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A. Plot, P. Besnier, B Azanowsky. Efficient EMC Risk Analysis of PCB Using Iterative Surrogate-Model Enrichment and Morris Sensitivity Analysis. International Symposium on Electromagnetic Compatibility (EMC Europe), Sep 2022, Gothenburg, Sweden. 10.1109/EMCEUROPE51680.2022.9901313 . hal-03884542

**HAL Id: hal-03884542**

**<https://hal.science/hal-03884542>**

Submitted on 5 Dec 2022

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# Efficient EMC Risk Analysis of PCB Using Iterative Surrogate-Model Enrichment and Morris Sensitivity Analysis

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**Abstract**—This document describes a new methodology for building surrogate model dedicated to EMC analysis of printed circuit boards. Stochastic approaches have recently showed their interests for EMC phenomena simulations because of their ability to replace costly computations. The proposed method is composed of two process stages. The first one is a pre-processing step which consists in filtering inputs that are not significant regarding output variations. The second one consists in an iterative learning technique of the surrogate model avoiding the requirement for prior determination of the sample size. The method is tested from a representative scenario of an EMC problem. The gain in computation time offered by the method makes it possible to build surrogate models more efficiently.

**Index Terms**—Surrogate model, EMC risk analysis, Morris analysis, kriging.

## I. INTRODUCTION

This paper deals with a methodology which aims at efficiently training a surrogate model in order to study the electromagnetic behavior of a printed circuit board (PCB). The design of sophisticated multilayer PCBs with huge number of interconnections requires the determination of strict guidelines to reduce the risk of non-compliant EMC tests. Investigation about guidelines often requires numerical simulations. Regarding radiated emission they are based on solving Maxwell equations with 3D numerical solvers. However, using such solvers can be very time and resource consuming especially when carrying out parametric analysis with a large number of parameters. One way to overcome this problem is to use a replacement model called a surrogate-model (SM) or meta-model. SMs are a set of mathematical tools that approximate or interpolate a true function using known experiments. SMs have become very popular in many engineering fields to efficiently evaluate model output(s) as a function of its inputs only [1]. SMs can be used for problem optimization [2], dimension reduction [3], sensitivity analysis [4] and for visualization of output(s). Different types of SMs can be found in the literature such as support vector machine (SVM), Gaussian process, polynomial chaos or neural networks, to name a part of them. Here we focus on a technique called kriging (or Gaussian process). One of its main advantages is its ability to determine

a prediction error. Furthermore, kriging has already shown promising performances for EMC problems [5] [6] [7] [8].

Nevertheless, kriging has also drawbacks regarding high dimension problems as many other SMs. This is classically designated as the curse of dimensionality. More specifically, kriging is associated with the calculation of a covariance matrix whose size increases with the number of input variables. This inevitably leads to an increase in the computation time of the covariance matrix inversion. Furthermore, kriging involves the optimization of the hyper-parameters (one per input) requiring the computation of the covariance matrix several times. Recent works have attempted to solve these problems. For instance, [9] proposed a method combining partial least squares regression and kriging to reduce the number of hyper-parameters. Another work [10] proposed a simplification of the model using additivity. In addition to the above limitation, the question of the size of the learning sample arises when constructing a SM. Indeed, the amount of data required to build an accurate SM is not known in advance. One possible answer is to use a design of experiment (DOE) whose size is increased gradually until a certain criterion is met. Different types of enrichment are possible. In [11], an iterative latin hypercube samplig (iLHS) technique was applied in association with a neural network. More complex techniques that optimize the placement of the next point also exist [12].

In this article, we present a new strategy for kriging-SM construction technique using on the one hand a pre-processing of the inputs based on Morris sensitivity analysis and on the other hand an iterative enrichment of the DOE. The pre-processing is potentially useful in the frame of EMC analysis for which non essential parameters could be rapidly discarded reducing the dimensional of the problem at the same time. The proposed and simple iterative DOE enrichment is then relevant to avoid the determination of a badly chosen sample size. Section II details the proposed method whereas Section III describes the validation criteria of the method and its application to a test case, looking at extreme values of the total radiated power.

## II. ITERATIVE KRIGING SURROGATE MODEL COMBINED WITH MORRIS SENSITIVITY ANALYSIS

### A. Kriging and Morris sensitivity analysis

The advanced SM construction method introduced in this paper is based on an iterative kriging approach and takes advantage of the Morris method for sensitivity analysis. Kriging approach and Morris analysis are briefly described in the following paragraphs.

1) *Kriging*: Kriging was introduced by Danie Gerhardus Krige and formalised by George Matheron [13]. This method was first used in the field of geology and was then extended as a meta-modeling technique. The kriging method consists in approaching the response of a model with  $M$  inputs variables described by an input vector  $\mathbf{X}$  of the corresponding size. The response  $f(\mathbf{X})$  is then evaluated from:

$$\forall x \in D^M, f(\mathbf{X}) = \mu(\mathbf{X}) + \varepsilon(\mathbf{X}) \quad (1)$$

In this equation,  $\mu$  is a deterministic function of  $\mathbf{X}$  and represents the mean or the trend of the process. For an ordinary kriging, it is considered as a known constant. The term  $\varepsilon$  is a Gaussian process of random variables which is found by optimizing hyperparameters from known values. Hyperparameters are tunable parameters of the Gaussian Process. The process  $\varepsilon$  is supposed to be stationary (regarding the first and the second moment), which means that the dependence function between random variables  $\varepsilon(\mathbf{X}_1)$  and  $\varepsilon(\mathbf{X}_2)$  does not depend on their local coordinates in the input space. It is generally defined as a function of the Euclidean distance between  $\mathbf{X}_1$  and  $\mathbf{X}_2$  only. Thus, the correlation function  $C$  can be written as:

$$\forall \mathbf{X}_1, \mathbf{X}_2 \in D^M \times D^M, C(\|\mathbf{X}_1 - \mathbf{X}_2\|_\theta) = C(h_\theta) \quad (2)$$

where  $\theta$  is the vector of hyperparameters. A typical parameterized correlation function must be selected. These hyperparameters will then be determined by optimization. A commonly used function is the Matérn one:

$$C(h, \theta, \nu) = \frac{1}{2^{\nu-1} \Gamma(\nu)} (2\sqrt{\nu} h_\theta)^\nu K_\nu(2\sqrt{\nu} h_\theta) \quad (3)$$

where  $\Gamma$  is the Euler function,  $K_\nu$  is the Bessel function,  $\nu$  is a scalar parameter. In the rest of this paper, the commonly used by default Matérn function with  $\nu = \frac{5}{2}$  is selected.

2) *Morris sensitivity analysis*: The Morris method is a global method for sensitivity analysis. It was first introduced in [14]. Its principle is to vary the inputs one at a time and to measure the corresponding variation of the output. This method is particularly effective when the number of inputs is large and the model is expensive in terms of computation time. Indeed, it allows sensitivity analysis for a limited number of calls to the model.

Two indices are calculated from a Morris analysis:

- $\mu$  which measures the overall influence of inputs on output. It is the average of elementary effects over all trajectories as defined below.

- $\sigma$  which measures the non-linear influence of inputs on output and the interaction between inputs. It is the standard deviation of elementary effects over all trajectories.

The Morris method consists in calculating an elementary effect caused by the variation of a  $\Delta$  step of a given input. The elementary effect for the input  $x_i$  of  $\mathbf{X}$  is calculated as follows:

$$E_i(\mathbf{X}) = \frac{f(x_1, \dots, x_i + \Delta, \dots, x_M) - f(x_1, \dots, x_i, \dots, x_M)}{\Delta} \quad (4)$$

where  $\mathbf{X} = (x_1, \dots, x_i, \dots, x_M)$  is a given random realisation of  $X$  and  $\Delta$  is the experiment step which is equal to a multiple of  $\frac{1}{p-1}$  where  $p$  is the number of grid levels (grid is built from input space).

The calculation of elementary effects for all  $M$  inputs is repeated  $r$  times to achieve  $r$  independent trajectories. Then, the mean over all trajectories of the absolute value of the elementary effect of the  $i$ -th input parameter and the standard deviation are calculated such as:

$$\mu_i = \frac{1}{r} \sum_{t=1}^r |E_i^t| \quad (5)$$

$$\sigma_i = \sqrt{\frac{1}{r} \sum_{t=1}^r \left( E_i^t - \frac{1}{r} \sum_{t=1}^r (E_i^t) \right)^2} \quad (6)$$

Based on the values of  $\mu_i$  and  $\sigma_i$ , it is possible to classify input variables into 3 categories: i) negligible effects ii) large linear effects without interactions iii) large non linear effects.

The total cost of Morris experiment is  $r(M+1)$  (i.e. the number of calls to the model) where  $r$  is the number of trajectories in the input space [15]. This is the result of changing one variable at a time for each trajectory once a first random input vector is initialized.

In the Morris analysis, the main factors influencing the precision of the result are  $r$  and  $p$ . In [16], the authors demonstrated that the choice of  $p = 4$  and  $r = 10$  produces good results, whereas in [17] a sample with  $r = 4$  is used. In this paper, we use  $p = 4$  and  $r = 10$ .

### B. Description of the proposed methodology

The proposed methodology consists in creating efficiently a kriging-type metamodel based on a sensitivity pre-analysis and on iterative learning.

It is schematized in Fig. 1. The first step is to define the case study. This includes the definition of the input parameters ( $M$ ), their domain of definition as well as the output(s) of interest. The next step is the prior sensitivity analysis. It allows determining the parameters which influence the output the most and those with less importance. We can then consider the unimportant variables as constants, thus reducing the dimension of the problem treated. From there we have a scenario with  $M^* = M - d$  parameters, where  $d$  is the number of parameters identified as insignificant regarding output variations.

The third step is to gradually train a SM while increasing the size of the training sample until a certain criterion is reached. This step is called "iterative training".

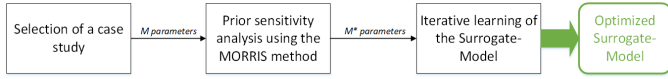


Fig. 1. Global methodology for the creation of a kriging metamodel with prior Morris analysis

1) *Morris Analysis*: As described in section II-A2, the Morris method is a global sensitivity analysis method based on the quantification of elementary effects observed at the output with respect to variations at inputs. According to the values of  $\mu_i$  defined in (5), it is possible to classify each input variable by order of importance. To better identify important parameters, we first normalize the  $\mu_i$  and  $\sigma_i$  indices.

$$\mu_i^{norm} = \frac{\mu_i}{\mu_{total}}, \quad \sigma_i^{norm} = \frac{\sigma_i}{\sigma_{total}}, \quad i \in [1, M] \quad (7)$$

where  $\mu_{total}$  and  $\sigma_{total}$  corresponds to the total mean and standard deviation over the M input variables, respectively. Then we plot the Morris graph  $\sigma_i^{norm}$  as a function of  $\mu_i^{norm}$ . The higher  $\mu_i^{norm}$ , the more sensitive is the corresponding  $i$  input. From there, a selection may be performed among all the variables. To better visualize the impact of parameters with regard to the output, the cumulative contribution for a group of parameters is computed by summing their normalized contributions after sorting them in decreasing order.

If the chosen parameters give a cumulated contribution  $\mu_{cumulated}$  greater of equal to 80%, we assume that this group of variables is sufficient to predict the output response. Thus, the other ones are discarded from the SM construction by fixing them to their nominal values.

2) *Iterative training*: After having identified the essential parameters of the problem, we can build a SM using only essential parameters. The classical way to build it is first to set up a DOE of a given size  $N$ , then to run the model (typically a time consuming numerical simulation) as many times to compute the corresponding output(s). However, there is no a priori knowledge of the relevant size to be selected. Given that the size of the DOE greatly influences the quality of the SM, we propose here a method to construct the SM by increasing the size of the DOE step by step until reaching a satisfaction criterion. Several sampling methods exist. The classical LHS is one of the most common sampling method and is selected in this study due to its good properties for small sample sizes. The propose iterative procedure is detailed in the algorithm Alg. 1.

$N_{ini}$  sets the initial number of experiments contained in the DOE. A rule of thumb consists of choosing  $N_{ini} = 10 \times M$ .  $N_{step}$  defines the number of points added at each iteration. It can be constant or dynamic. The algorithm is based on LHS enrichment, which consists in adding new points to an existing DOE, preserving the LHS nature of the complete sample.

### Algorithm 1 Iterative sampling approach

- 1: **Input** : A costly function  $f$  with  $M$  parameters
- 2: **Output** : A Kriging surrogate model  $\hat{f}$
- 3: Generate an initial DOE  $X = [x_1, \dots, x_{N_{ini}}]^T$  of size  $N_{ini}$  using LHS
- 4: Call  $f$  to compute the output of each experiment of DOE  $y = [f(x_1), \dots, f(x_{N_{ini}})]^T$
- 5: Construct the initial Kriging SM  $\hat{f}(x)$  using  $X$  and  $y$
- 6: **While** stopping criterion is not met **do**
- 7:   **Add new points**:
- 8:   Generate  $N_{step}$  points based on the initial DOE and using iLHS technique  $X' = [x'_1, \dots, x'_{N_{step}}]^T$
- 9:   Call  $f$  to compute the output of the added points  $y' = [f(x'_1), \dots, f(x'_{N_{step}})]^T$
- 10:   **Update information**:
- 11:    $X = X \cup X'$  and  $y = y \cup y'$
- 12:   Construct a new Kriging SM using the new DOE with added points
- 13: **return** The final surrogate model  $\hat{f}(x)$

## III. VALIDATION OF THE METHOD

### A. Validation setup

An application of the iterative kriging surrogate model combined with Morris sensitivity analysis is now illustrated and compared to a direct kriging approach. It is applied to a use-case representative of a typical EMC scenario encountered for PCB design. The use-case is described in Fig. 2.

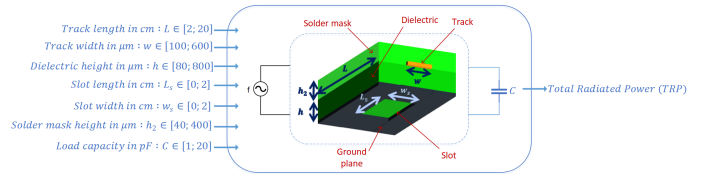


Fig. 2. Slot scenario

It represents a simple micro-strip line with a slot inserted in the ground plane. The total radiated power of the micro-strip line is observed when it is supplied with a voltage generator at one of its ports and over the 200 MHz - 2 GHz frequency range by step of 2 MHz which makes 901 frequencies. The frequency being not included as a random variable one SM is built up at each frequency, i.e 901 SMs in total. The total radiated power is analysed with regard to variations of 7 different inputs (M=7).  $L$  and  $w$  are the length and the width of the track,  $h$  and  $h_2$  are the dielectric and solder mask thicknesses,  $L_s$  and  $w_s$  are the length and width of the slot and  $C$  is the load capacity. these inputs are considered as random variables uniformly distributed over their respective intervals indicated in Fig. 2. The uniform distribution was selected for geometrical parameters since they can be freely chosen by the designer within some ranges. Regarding the load capacity, the uniform distribution is arbitrary.

The total radiated power is computed from a well known full wave solver using CST microwave studio configured with temporal solver. We use UQLAB/Matlab to build the kriging

SM and the Morris analysis. The code is interfaced with CST to obtain data automatically.

From an EMC design point of view we are interested in studying the set among all input parameters that mostly explain the fluctuations of the total radiated power. More precisely, high values of the total radiated power should be avoided. Once an adequate SM is set up, it may be used to look for design solution reaching this goal. To do so, we perform a complete sensitivity analysis and extreme values analysis using the constructed SM.

Therefore, the cornerstone of this EMC design analysis is to ensure the construction of a valid SM. Both iterative kriging and Morris aspects of our methodology are validated sequentially. For that, 3 different SMs (described in Table I) will be constructed

TABLE I  
DENOMINATION OF SMS

| Denomination            | Nb of parameter | Learning sample size   | Description  |
|-------------------------|-----------------|------------------------|--|
| $SM_{reference}$        | $M = 7$         | $N_{reference}$        | SM constructed with independent sample in order to validate $SM_{iterative}$ |
| $SM_{iterative}$        | $M = 7$         | $N_{iterative}$        | SM constructed iteratively   |
| $SM_{MORRIS-iterative}$ | $M^*$           | $N_{MORRIS-iterative}$ | SM with reduced number of parameter and constructed iteratively              |

1) *iterative kriging*: First, the incremental sampling approach is validated on a stand-alone basis without resorting to Morris analysis. To do this, we construct a SM called  $SM_{iterative}$  using iterative sampling approach.  $N_{iterative}^{ini}$  is chosen at  $10 \times M = 70$ .  $N_{step}$  is chosen to be an increase of 20% of the previous learning sample size at each step (see Table II).

TABLE II  
EVOLUTION OF SAMPLE SIZE

|             | Iteration 1 | Iteration 2 | Iteration 3 | ... | Iteration n             |
|-------------|-------------|-------------|-------------|-----|-------------------------|
| Sample size | 70          | 84          | 101         | ... | $N_{iterative}^{final}$ |
| N_step      | 0           | 14          | 17          | ... | $N_{step}^{final}$      |

To quantify the quality of a SM, several indicator definitions exist. We choose to use the leave-one-out error (LOO) which has the advantage of not requiring any additional sample for the validation. It consists in leaving one realization aside building the SM with the remaining  $N - 1$  observations. The unused observation is then used to validate the SM. It is repeated  $N$  times by permutation. As we build one SM per frequency, we compute the mean LOO error of all these SMs. Thus, the stopping criterion defined at line 6 of Alg. 1 is based on an error threshold. For EMC problems, we assume that an LOO error of 10% is accurate enough for a qualitative SM as we are more interested in the tendency of the phenomena.  $N_{iterative}^{final}$  is the size of the final learning sample size.

Then a second SM called  $SM_{reference}$  is constructed using a new DOE of size  $N_{iterative}^{final}$ . By this way, we ensure that the two surrogate models are built from two DOEs of the same

size but completely independent. To validate this method, the two corresponding SM errors  $\epsilon_{LOO}^{iterative}$  and  $\epsilon_{LOO}^{reference}$  are then compared.

2) *Morris approach*: Once the incremental approach is validated, we consider  $SM_{iterative}$  as the new reference. The Morris sensitivity analysis is applied to the slot scenario. This requires a preliminar sample of size  $N_{morris}$  evaluated from the true (CST) model. From that set of simulations an indication about the relative importance of each of the 7 input parameters is expected. The proposed criterion based on the cumulated mean of elementary effects will be discussed to discard the less important one. Then, a new SM called  $SM_{MORRIS-iterative}$  is built using the iterative approach but discarding irrelevant parameters. The results of extreme value analysis are then displayed for both models  $SM_{iterative}$  and  $SM_{MORRIS-iterative}$  for comparison.

## B. Results

1) *Iterative learning*: First, the iterative sampling method is applied to the slot scenario. The evolution of the mean error over the entire frequency range is given in Fig. 3.

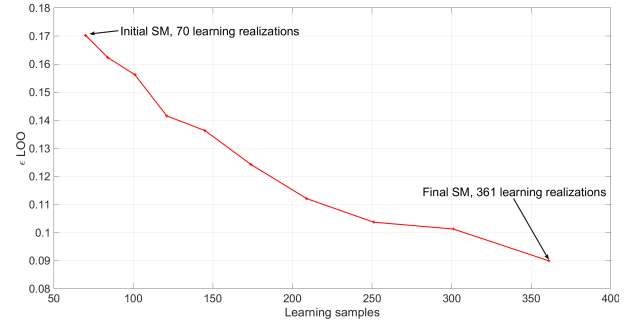


Fig. 3. Mean over frequency of LOO error as a function of the number of learning realizations

The LOO error decreases until reaching the stopping criterion of 10%, with  $N_{iterative}^{final} = 361$  as the final sample size. A set of 10 iterations is necessary to achieve this result. Thus, the SM of reference  $SM_{reference}$  is constructed using a new LHS DOE of size  $N_{iterative}^{final} = 361$ . Fig. 4 shows the LOO errors as function of frequency for both SMs, i.e.  $SM_{reference}$  and  $SM_{iterative}$ . Error curves as a function of the frequency look very similar. The differences observed are attributable to statistical fluctuations due to random sampling. We conclude that the iterative SM constructed with the proposed methodology is of the same quality as the reference. The LOO error tends to increase with frequency. This is related to the resonating behavior of the microstrip line, involving stronger sensitivity to the combination of input variations.

2) *Morris approach*: The Morris sensitivity analysis is computed using  $r = 10$  and  $N = (M + 1) \times r = 80$  input data. A sensitivity analysis is calculated for each frequency. The mean and standard deviation are calculated to display the result on a single graph.

Fig. 4 shows the result of Morris analysis. The spread of  $\mu$  and  $\sigma$  in frequency are illustrated has horizontal and vertical

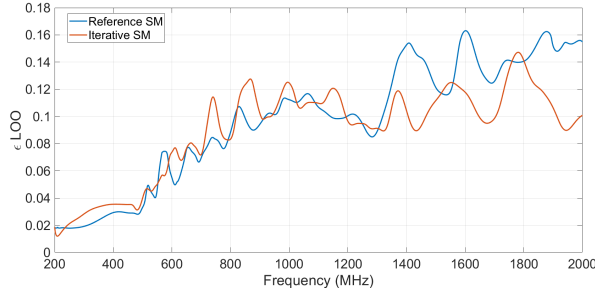


Fig. 4. Comparative error of  $SM_{reference}$  and  $SM_{iterative}$  versus frequency

bars, respectively with  $\pm$  the standard deviation. The larger the value of  $\mu$ , the more sensitive is the output variation of the corresponding variable. The parameter  $\sigma$  measures the linearity of the interaction between the variable and the output. As seen from this figure,  $w_s$  is clearly the most important parameter whereas  $L$  shows a large variance, which means that its influence depends a lot on the considered frequency.

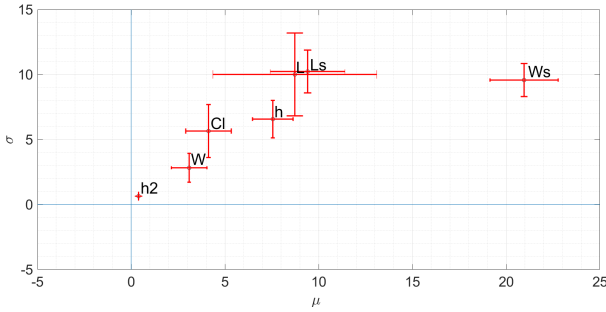


Fig. 5. Result of the Morris analysis: spread ( $\pm$  the standard deviation) of  $\mu$  and  $\sigma$  over the entire frequency range and for each input variable

From this representation of the Morris analysis, it is difficult to make a decision about the relative importance of each input variable. Thus, we consider another representation where  $\mu$  are normalized as introduced in II-A2. The cumulative contribution of a group of variables is then plotted, after sorting them in decreasing order according to  $\mu$ . No standard criteria have been defined in the literature to retain the only most important parameters. We therefore make an arbitrary choice that will be further validated. Fig. 6 shows two configurations. The first one is the aggregate of 4 parameters with the highest average  $\mu$  ( $w_s$ ,  $L_s$ ,  $h$  and  $L$ ). The  $Cl$  parameter is then added to form the second one.

We assume that 80% of cumulative contribution is sufficient to explain output variations. According to Fig. 6 5 parameters are required to fulfill this condition. Therefore, only the parameters  $w_s$ ,  $L_s$ ,  $h$ ,  $L$  and  $Cl$  are retained as random variables for the SM training. Consequently,  $h2$  and  $w$  are discarded from the SM analysis, and chosen to be constant and fixed at  $220 \mu\text{m}$  and  $350 \mu\text{m}$ .

In this specific scenario, we managed to reduce the problem dimension from 7 to 5 with only 80 simulations. In case the

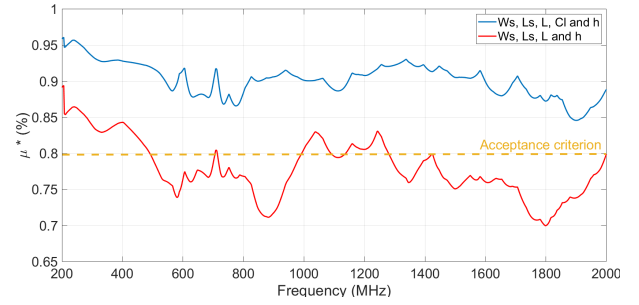


Fig. 6. Cumulative contribution for two configurations

Morris analysis does not allow discarding any input variable, it is worth mentioning that these simulations remain available for the iterative SM training.

The iterative learning is now applied to the reduced set of remaining 5 input random variables. Fig. 7 shows the compared error evolution as a function of the learning sample size for the iterative SM and this reduced Morris SM. As a result, the LOO error decreases much faster with the  $SM_{MORRRIS-iterative}$  SM and the 10% error is reached after 8 iterations with 179 realizations, not including the 80 realizations used for Morris analysis (instead of 361 for  $SM_{iterative}$  SM).

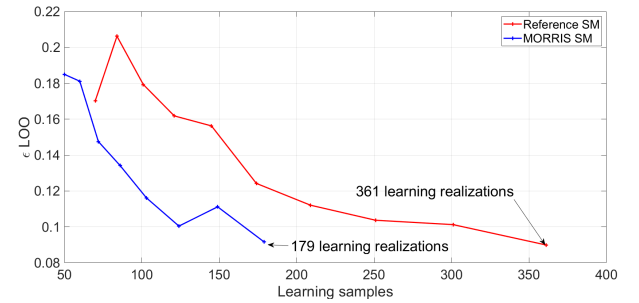


Fig. 7. LOO error as a function of the number of learning realizations for both  $SM_{iterative}$  and  $SM_{MORRRIS-iterative}$  SMs

Also,  $SM_{MORRRIS-iterative}$  allows a significant reduction of the total computation time. This is composed of the full-wave solver simulation time and of the learning time to compute SMs is determined for both  $SM_{MORRRIS-iterative}$  and  $SM_{iterative}$ . For  $SM_{MORRRIS-iterative}$ , the total computation time also includes the Morris analysis time and the full-wave simulation time required for this analysis. The synthesis of the total computation time for each case is given in Table III.

The total computation time of the Morris method is 40% lower than the total time of the iterative kriging.

Extreme value study is now conducted. It consists in evaluating a new LHS DOE of size 100 000 via SM and to isolate the 5000 (5%) highest values of total radiated power. Contribution of each parameter to this subset is then studied. Here we focus only on  $w_s$ .

First, the distribution function of  $w_s$  calculated via  $SM_{iterative}$  only is drawn in Fig. 8 for the complete set and for the set of the 5% extreme values. It clearly evidences that



TABLE III  
TIME RESULTS

| Time (minutes)                                 | iterative   | Morris-iterative |
|--|-------------|------------------|
| Simulation of realizations for MORRIS analysis | N/A         | 1223.4           |
| Morris analysis                                | N/A         | 1243.7           |
| Simulation of learning realizations            | 5451.1      | 2665.3           |
| Learning of SM                                 | 4595.2      | 17.1             |
| Total  | 10046.3 min | 5149.5 min       |

no extreme values are produced if  $w_s \leq 8$  mm. Thus, we decide to limit possible values of  $w_s$  to 8 mm.

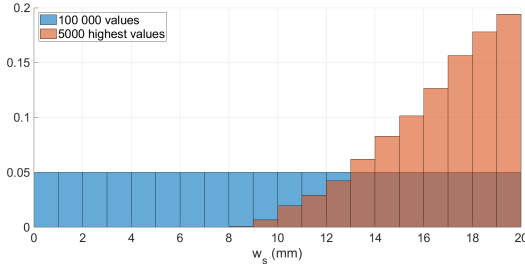


Fig. 8.  $w_s$  distribution of all DOE and 5% most radiating realizations for the iterative SM

We now have to demonstrate that  $SM_{MORRIS-iterative}$  and  $SM_{iterative}$  give similar results regarding the consequence of limiting  $w_s$  to a lower value. In the following, three empirical probability density function (epdf) using two independent LHS DOE are determined:

- 1) with  $SM_{iterative}$
- 2) with  $SM_{iterative}$  and  $w_s < 8$ mm
- 3) with  $SM_{MORRIS-iterative}$  and  $w_s < 8$ mm

Fig. 8 shows the result of such an analysis. Both  $SM_{iterative}$  and  $SM_{MORRIS-iterative}$  for  $w_s < 8$ mm provide similar distributions and confirm that this restriction provides a significant decrease of extreme values.

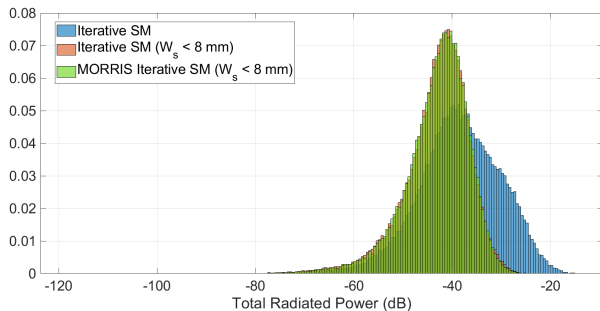


Fig. 9. PDF of SMs output

#### IV. CONCLUSION

In this article, we presented a new methodology that allows fast building of kriging SM for EMC studies. It is based

on the use of a preliminary Morris analysis to retain only significant input parameters for assessing a SM that is learned iteratively. The methodology was applied to a 7-parameter use case representative of a common EMC situation found on PCBs. The sensitivity analysis has identified that only 5 parameters are necessary to explain the output. Using extreme value analysis, conclusions about restricting the range of the slot width variation to decrease the total radiated power allows to validate the Morris approach.

Further work deals with increasing the complexity of scenarios and include other strategies to cope with the problem of dimensionality.

#### REFERENCES

- [1] A. Franczyk, "Engineering design via surrogate modelling: a practical guide", John Wiley and Sons, 2008
- [2] T. W. Simpson, V. Toropov, V. Balabanov and F. A. C. Viana, "Design and Analysis of Computer Experiments in Multidisciplinary Design Optimization: A Review of How Far We Have Come or Not," 12th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Victoria, 10-12 September 2008.
- [3] Y. Xia, H.I. Tong, W.K. Li and L.X. Zhu. "An Adaptive Estimation of Dimension Reduction Space." Journal of the Royal Statistical Society. Series B (Statistical Methodology) 64, no. 3 (2002): 363–410. <http://www.jstor.org/stable/3088779>.
- [4] B. Sudret, "Global sensitivity analysis using polynomial chaos expansions," Reliab. Eng. Syst. Saf., vol. 93, no. 7, pp. 964–979, 2008.
- [5] S. Salio, F. Canavero, D. Lecoine, and W. Tabbara, "Crosstalk prediction on wire bundles by Kriging approach," in IEEE International Symposium on Electromagnetic Compatibility. Symposium Record (Cat. No.00CH37016), 2002, vol. 1, pp. 197–202 vol.1.
- [6] V. Rannou, F. Brouaye, P. De Doncker, M. Helier, and W. Tabbara, "Statistical analysis of the end current of a transmission line illuminated by an elementary current source at random orientation and position," in 2001 IEEE EMC International Symposium. Symposium Record. International Symposium on Electromagnetic Compatibility (Cat. No.01CH37161), 2002, vol. 2, pp. 1078–1083 vol.2.
- [7] E. S. Siah, T. Ozdemir, J. L. Volakis, P. Y. Papalambros, and R. W. Wiese, "Optimization for RF coupling and interference reduction of devices in complex systems," in 2003 IEEE International Symposium on Electromagnetic Compatibility, 2003. EMC '03, 2003, vol. 2, pp. 1062–1065 Vol.2.
- [8] T. Bdour, L. Diaz, C. Guiffaut, A. Reineix, C. Miry, and P. Baraton, "Emulation of an expensive FDTD code with mixed quantitative and qualitative factors for analysis of lightning-induced transient responses," IEEE Trans. Electromagn. Compat., vol. 58, no. 5, pp. 1678–1681, 2016.
- [9] M. A. Bouhlef, N. Bartoli, A. Otsmane, and J. Morlier, "An improved approach for estimating the hyperparameters of the kriging model for high-dimensional problems through the Partial Least Squares method," Math. Probl. Eng., vol. 2016, pp. 1–11, 2016.
- [10] N. Durrande, D. Ginsbourger, and O. Roustant, "Additive Covariance kernels for high-dimensional Gaussian Process modeling," Ann. Fac. Sci. Toulouse Math. (6), vol. 21, no. 3, pp. 481–499, 2012.
- [11] A. Nuchitprasittichai and S. Cremaschi, "An algorithm to determine sample sizes for optimization with artificial neural networks," AIChE J., vol. 59, no. 3, pp. 805–812, 2013.
- [12] J. N. Fuhg, A. Fau, and U. Nackenhorst, "State-of-the-art and comparative review of adaptive sampling methods for kriging," Arch. Comput. Methods Eng., vol. 28, no. 4, pp. 2689–2747, 2021.
- [13] G. Matheron, "Principles of Geostatistics," Economic Geology, vol.58, no. 8, pp. 1246–1266, 1963
- [14] M. D. Morris, "Factorial sampling plans for preliminary computational experiments," Technometrics, vol. 33, no. 2, p. 161, 1991.
- [15] Alexander I. J. Forrester, András Sóbester and Andy J. Keane, "Using the Morris sensitivity analysis method to assess the importance of input variables on time-reversal imaging of seismic sources", 2019
- [16] F. Campolongo and A. Saltelli, Sensitivity analysis of an environmental model: an application of different analysis methods", 1997
- [17] M. D. Morris, "Factorial sampling plans for preliminary computational experiments," Technometrics, vol. 33, no. 2, pp. 161–174, 1991.