A Machine Learning-Based Epistemic Modeling Framework for EMC and SI Assessment

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***Abstract*—A novel machine learning-based framework is presented to evaluate the effect of design parameters, affected by epistemic uncertainty, on the Signal Integrity (SI) and Electromagnetic Compatibility (EMC) performance of electronic products. In particular, possibility theory is leveraged to characterize the epistemic variations, which is combined with Bayesian optimization to accurately and efficiently perform uncertainty quantification (UQ). A suitable application example validates the proposed method.**

***Index Terms*—Bayesian optimization, epistemic uncertainty, fuzzy variables, Gaussian process**

I. Introduction

Uncertainty quantification problems for EMC and SI assessment are usually defined in a statistical framework, and design parameters under uncertainty effects are regarded as random variables with specific distributions [1], [2], [3], [4], [5], [6], [7]. Many statistical method have been applied to estimate the effect of stochastic variations of design parameters, such as the traditional Monte Carlo (MC) analysis, which requires a high number of simulations of the electronic product study, and the Polynomial Chaos (PC) based methods, which model the variations in terms of stochastic surrogates.

In fact, all these statistical methods provide legitimate results if the distribution of the random variables is known in terms of, for example, their joint probability density function (PDF). However, they fall short when design parameters under epistemic uncertainty effects are present, i.e., no characterization of the parameters' variability is known in a probabilistic sense.

To overcome this limitation of providing an adequate representation for epistemic uncertainty, a framework that leverages possibility theory for antenna design was introduced in [8]. Hybrid approaches which combines the effects of probabilistic and epistemic uncertainty in a common framework have been develop and applied in different engineering fields [9], [10], [11]. In an EMC context, a hybrid UQ algorithm was applied in [12] to estimate the radiated susceptibility of a non-ideally twisted wire pair (above ground) illuminated by a partially-unknown impinging electromagnetic (EM) field.

In this contribution, we present a machine learning-based framework for the solution of epistemic UQ problems for EMC and SI problems. The design parameters affected by epistemic uncertainty (fuzzy variables (FVs)) are assigned possibility distributions (PDs) and Bayesian Optimization (BO) is exploited to propagate this epistemic uncertainty. Efficiency and accuracy of the presented hybrid algorithm are validated by means of a suitable application example.

The manuscript is organized as follows. First, in Section II, the relevant features of possibility theory are presented, and their application to epistemic UQ problems is discussed. Section III briefly introduces BO, and the procedure to apply BO to EMC and SI problems. An application example is presented in Section IV. Conclusions are drawn in Section V.

II. Formulation of the Epistemic Uncertainty Problem

A brief overview of FVs (also referred to as epistemic variables) in the framework of possibility theory and their relevant features are introduced in Section II-A, whereas the epistemic UQ framework for EMC and SI assessment is discussed in Section II-B. For a more complete treatment of epistemic uncertainty problems and possibility theory, the interested reader is referred to [13], [14], [15], [16], [17].

A. *Epistemic Uncertainty and Fuzzy Variables*

In the framework of possibility theory, epistemic uncertainty finds its definition through the FVs and their possibility distributions (PDs) $\pi(x)$ which are defined as follows:

$$\pi : \mathbb{R} \to [0,1], \exists\ x \in \mathbb{R} : \pi(x) = 1. \tag{1}$$

The PD of an epistemic variable can be explained in analogy to the PDF of a stochastic random variable as such: while a PDF expresses the frequency of occurrence of an event, a PD represents how likely it is that an event may occur. Hence, the set [0,1] in 1 corresponds to different levels of confidence assigned to a FV over a certain interval, i.e., 0 corresponds to a impossible value and 1 corresponds to a perfectly possible value.

Different PDs are defined to represent different level of information. For instance, a rectangular (or uniform) PD (see Fig. 1(a)) represents a complete lack of knowledge about the value of a parameter or its distribution, i.e., all the values in the interval $[x_1, x_2]$ are equally plausible. However, a triangular

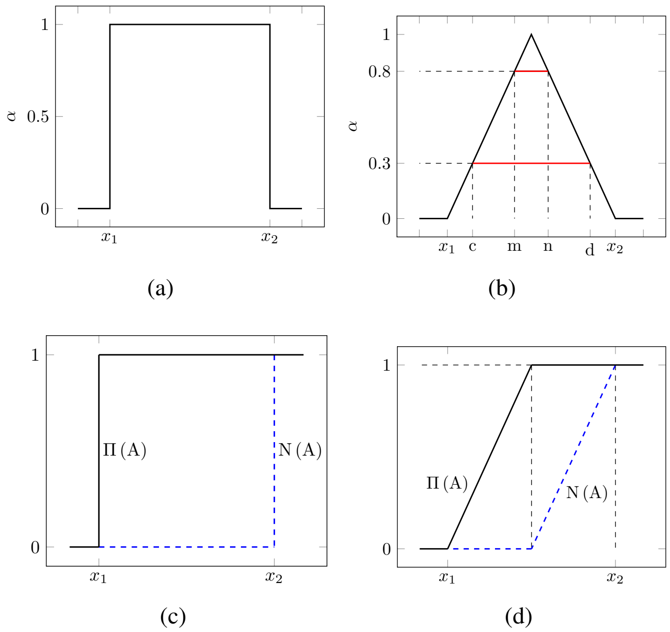

Figure 1: Rectangular (a) and triangular (b) PDs, $\pi(x)$, and their corresponding possibility Π (solid) and necessity N (dashed) measures in (c) and (d), respectively.

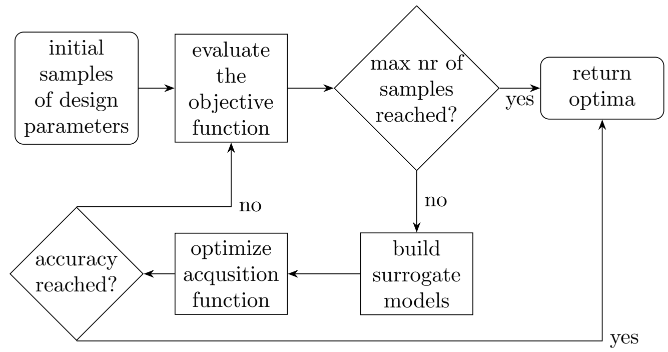

Figure 2: Flowchart of the BO algorithm.

PD (see Fig. 1(b)) is more suitable for cases where a parameter assumes levels of confidence which are higher around a mean value where $\pi(x) = 1$, and substantially decreasing ones for all the other values in the interval $[x_1, x_2]$.

In possibility theory, confidence levels of a FV are represented by α-cuts which are obtained by simply cutting the PD of a FV evenly at different levels in the interval [0,1]. Two α-cuts of a triangular PD are demonstrated on Fig. 1(b). Note that the α-cut at level 0.3 identifies the interval $[c_1, c_2]$, whereas the α-cut at level 0.8 determines the interval $[d_1, d_2]$.

A PD of a FV allows us to construct two important measures: the possibility $\Pi\mathrm{A}$ and the necessity $\mathrm{N}(\mathrm{A})$ functions of an event $\mathrm{A} \in \mathbb{R}$ are defined as:

$$\Pi(A) = \sup_{x \in A} \pi(x); \quad \mathrm{N}(A) = 1 - \sup_{x \notin A} \pi(x). \tag{2}$$

The measures Π and N can be interpreted as the minimum and the maximum bound of all possible cumulative distribution functions (CDFs), respectively, such that for a family of probability measures $P(\mathrm{A})$, the relation $\mathrm{N}(\mathrm{A}) \leq \mathrm{P}(\mathrm{A}) \leq \Pi(\mathrm{A})$ holds [17], [18]. These functions are demonstrated in Fig. 1(c) for a rectangular PD, and in Fig.1(d) for a triangular one.

B. Epistemic UQ Problems for EMC and SI Assessment

The quantity of interest of the electronic product under study (e.g., crosstalk level, DM-to-CM conversion, etc.), is denoted as $g(\mathbf{x})$, where $\mathbf{x}$ is a vector collecting the design parameters subject to epistemic uncertainty, which are regarded as FVs. The goal is to estimate the PD of the objective function $g(\mathbf{x})$ and, consequently, the corresponding possibility Π and necessity N measures encompassing all families of probability distributions $\mathrm{P}(\mathrm{A})$ [19].

In order to achieve this goal, we adopt the theory of FVs [20]. First, a finite set of N_α α-cuts is defined, by cutting the interval of possibility values $[0, 1]$ at different levels. Each value α delimits a domain $\mathbf{\Omega}_\alpha$ in the space of the pertinent FVs, in the vector $\mathbf{x}$. Next, for each α-cut, the minimum and maximum of the objective function are computed for $\mathbf{x} \in \mathbf{\Omega}_\alpha$. Finally, the possibility distribution of the objective function $\pi(g)$ is defined by the minima $\inf_\alpha$ and the maxima $\sup_\alpha$ for all the N_α α-cuts. Once the PD of the objective function is computed, the corresponding possibility and necessity functions can be obtained using (2).

Hence, a series of N_α minimization and maximization problems must be solved. Unfortunately, since time consuming full-wave simulations are often required to estimate the objective function, the standard "brute force" approach which adopt a dense sampling of $\mathbf{x} \in \mathbf{\Omega}_\alpha$ to evaluate $g(\mathbf{x})$ becomes cumbersome. Furthermore, it can offer only limited accuracy if the objective function is non-smooth in $\mathbf{\Omega}_\alpha$. These issues become especially relevant when the number of parameters effected by epistemic uncertainty, i.e., the number of FVs, increases. In order to overcome these limitations, a machine-learning based framework is proposed in Section III.

III. METHODOLOGY

A. Bayesian Optimization Framework

The goal of BO is to perform optimization on a surrogate model which is much cheaper than directly performing optimizing on the objective function $g(\mathbf{x})$. The flowchart of BO is shown in Fig. 2. First, the objective function is evaluated over a set of design parameters $[\mathbf{x}_\mathrm{k}]_{\mathrm{k}=1}^{\mathrm{K}} \in \mathrm{X}$ (chosen, e.g., according to a Latin hypercube). This allows to construct the first surrogate model of $g(\mathbf{x})$. Because the surrogate model in BO is, contrary to other surrogate-based optimization strategies, *stochastic* and not deterministic, the model uncertainty is used by the acquisition function to determine the location of the candidate optimum. This optimum is then evaluated via a new simulation, and when none of the stopping criteria is met, the surrogate model is updated. Therefore, each additional simulation refines the surrogate model, which increases the chance of finding the global optimum of the objective function.

In this contribution, Gaussian processes (GPs) [21] are chosen as stochastic surrogate models, owing to their analytic inference, accuracy, and modeling power. In particular, the Matérn (5/2) was chosen as GP kernel, due to its capability to model a wide class of functions (including nondifferentiable ones). Among the available acquisition functions, in this work the Expected Improvement (EI) [22] is adopted as sampling method. EI is defined as

$$\mathrm{E}\left[\mathrm{I}\left(\mathbf{x}\right)\right] = \mathrm{E}\left[\max\{0, g_{\min} - y\}\right] \tag{3}$$

where E is the expectation operator, $I\left(\mathbf{x}\right)$ is a suitable measure of improvement defined at the point $\mathbf{x}$, $g_{\min}$ is the current evaluated minimum of the objective function and y is the prediction of the GP surrogate model at point $\mathbf{x}$. Since y is a Gaussian random variable, the expectation in (3) can be calculated analytically. Moreover, the hyper-parameters σ^2 and ρ are optimized using maximum likelihood estimation via the GPyOpt package [23].

B. BO for Epistemic UQ problems in EMC and SI

BO is particularly suited for the solution of optimization problems with epistemic uncertainty where both $\inf_\alpha$ and $\sup_\alpha$ of all α-cuts need to be calculated. A possibility distribution is then constructed with these extreme values. To this purpose, the acquisition function (3) is modified as:

$$\mathrm{EI}_{\mathrm{mm}}\left(\mathbf{x}\right) = \max\{\mathrm{E}\left[\max\{0, g_{\min} - y\}\right], \mathrm{E}\left[\max\{0, y - g_{\max}\}\right]\} \tag{4}$$

This modification allows us to calculate the candidate points in the space of the design parameters with a higher potential of finding a minimum and a maximum at the same time. Indeed, as illustrated in Section IV, the proposed method is capable of finding both optima with a minimal number of evaluations of the objective function $g\left(\mathbf{x}\right)$.

Because α-cuts are always nested, regardless of the specific PD under consideration, BO is performed as follows. First, for a small number of initial samples, BO is applied at the top alpha level (α=1). Next, the optimization for all other α levels is performed progressively by making use of the samples already evaluated at the "upper" α levels and by evaluating only a few additional samples at each subsequent α level. Optimization of the objective function at all α levels is performed until the bottom α level ($\alpha = 0$) is reached. During this process, if a better optimum is found in the current α level, the optimum for previous levels can be updated accordingly, whenever applicable.

IV. Application Example

The proposed approach is applied to two coupled microstrip lines making a 90° bend [24] (see Fig. 3). For this example, we consider four independent epistemic variables: the lengths of both of line segments, l_1 and l_2, the relative permittivity ε_r, and the height h of the substrate. Their supports are as follows: $[48.75\,\mathrm{mm}, 51.25\,\mathrm{mm}]$, $[48.75\,\mathrm{mm}, 51.25\,\mathrm{mm}]$, $[3.36, 3.96]$, and $[1.374\,\mathrm{mm}, 1.674\,\mathrm{mm}]$, respectively. In particular, a uniform PD is assigned to l_1 and l_2, and a triangular one for ε_r and h, on their respective supports.

The goal is to estimate the effect of the design parameters affected by epistemic uncertainty, on the total differential mode

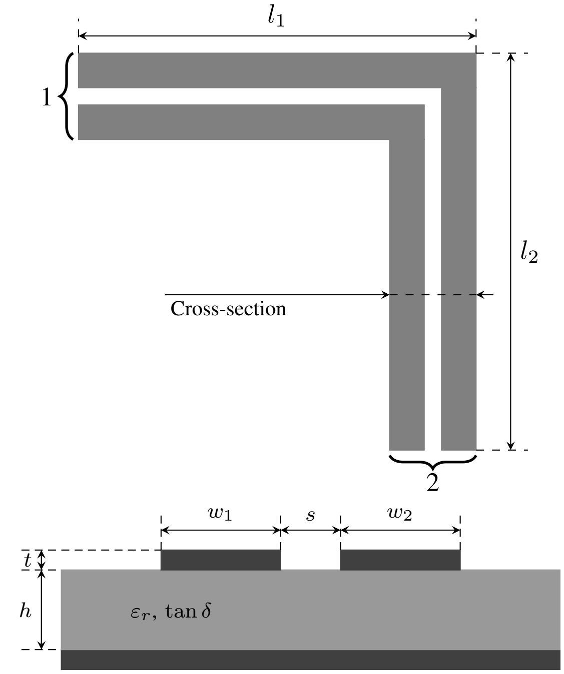

Figure 3: Bent microstrip lines: The top panel shows the layout of the bent microstrip lines, delimiting the line lengths l_1 and l_2. The two differential signaling ports are also indicated using braces. The cross-section of the bent microstrip lines is shown in the bottom panel, demarcating the remaining parameters. The fixed parameters are $s = 0.7\,\mathrm{mm}$, $t = 35\,\mathrm{\mu m}$, $\tan\delta = 0.003$, $w_1 = w_2 = 1.8\,\mathrm{mm}$, and the line conductivity is $4.1 \times 10^7\,\mathrm{S\,m^{-1}}$. The lengths l_1 and l_2, the relative permittivity ε_r, and the height h of the substrate are considered to be four independent epistemic variables.

(DM) to common mode (CM) conversion. Given that mode conversion is especially critical for bent interconnects, we construct an objective function that is a measure of the total DM-to-CM conversion [25], as follows:

$$f\left(\mathbf{x}\right) = C = \left[\int_{0\,\mathrm{GHz}}^{6\,\mathrm{GHz}} \left(\left|S_{cd11}\left(f\right)\right|^2 + \left|S_{cd21}\left(f\right)\right|^2\right) df\right]^{1/2}, \tag{5}$$

where S_{cd11} and S_{cd21} are the relevant frequency-dependent elements of the modal S-parameters matrix. Here, no analytical model for the S-parameters nor the cost function C is available. For a specific sample of the epistemic variables, the cost function is computed by first acquiring the S-parameters in the frequency range of interest [0-6 GHz] by means of full wave simulations, performed using Advanced Design System (ADS) [26]. Then, the modal scattering parameters are computed [24], and the integral in (5) is calculated using standard numerical techniques [25].

BO was performed on 51 α-cuts ranging from possibility level 1 to 0. First, a computational budget of 10 $(l_1, l_2, \varepsilon_r, h)$ samples is assigned for $\alpha = 1$, while a budget of 1.8 additional samples is given for each following α level, for a total maximum computational budget of 100 $(l_1, l_2, \varepsilon_r, h)$ samples.

For validation purposes the results of the proposed method

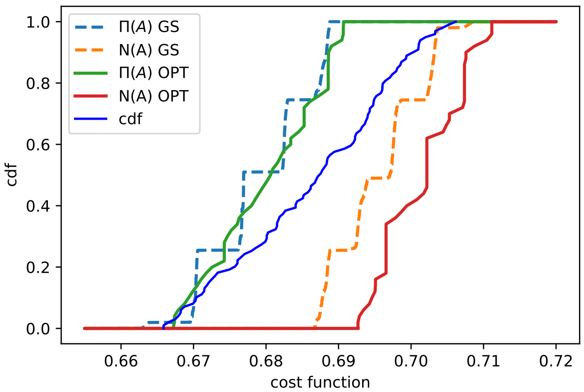

Figure 4: Possibility Π and necessity N functions for the cost function C (5), estimated with the grid search (GS) and the proposed BO-based method (BO) for different number of samples.

are compared to a grid search (GS) with a uniform grid of $9 \times 9 \times 9 \times 9\,(l_1, l_2, \varepsilon_r, h)$ samples. The elapsed time is 78 minutes for the BO-based method and 8 days and 6.5 hours for the grid search method, using a personal computer with 8 GB and 8 cores Intel(R) Core(TM) i7-2600 CPU @ 3.40GHz. The corresponding Π and N measures as well as an example CDF are presented in Fig. 4. The CDF was calculated with 10000 (h, ϵ_r, L, W) samples by treating all variables as probabilistic and assigning uniform distributions on their corresponding supports. As pointed out in Section II-A, the CDF is always in the domain defined by the possibility Π and necessity N functions. Clearly, the proposed method estimates a better N and a comparable, but smoother, Π function while requiring less computational resources.

V. Conclusion

A machine learning-based framework to propagate the epistemic uncertainty in EMC and SI problems is introduced in this contribution. The method characterizes epistemic variations using possibility theory, and leverages on the theory of fuzzy sets combined with a suitable BO-based approach to solve epistemic UQ problems. In contrast with stochastic approaches, no characterization of the parameters' variability in a probabilistic sense is needed. A suitable application example validates the efficiency and the accuracy of the proposed method.

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