

Research Article

A Possibilistic Approach for the Prediction of the Risk of Interference between Power and Signal Lines Onboard Satellites

Nicola Toscani , Flavia Grassi , Giordano Spadacini , and Sergio A. Pignari 

Dipartimento di Elettronica, Informazione e Bioingegneria, Politecnico di Milano, Milano, Italy

Correspondence should be addressed to Flavia Grassi; flavia.grassi@polimi.it

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This work presents a hybrid random/fuzzy approach for uncertainty quantification in electromagnetic modelling, which combines probability and possibility theory in order to properly account for both aleatory and epistemic uncertainty, respectively. In particular, a typical intrasystem electromagnetic-compatibility problem in aerospace applications is considered, where some parameters are affected by fabrication tolerances or other kinds of randomness (aleatory uncertainty) and others are inherently deterministic but unknown due to human's lack of knowledge (epistemic uncertainty). Namely, a differential-signal line in a satellite is subject to crosstalk due to a nearby dc power line carrying conducted emissions generated by a dc-dc converter in a wide frequency range (up to 100 MHz). The nonideal features of the signal line (e.g., weak unbalance of terminal loads) are treated as random variables (RVs), whereas the mutual position of signal and power line is characterized by possibility theory through suitable fuzzy variables. Such a hybrid approach allows deriving a general and exhaustive description of uncertainty of the target variable of interest, that is, the differential noise voltage induced in the signal line. The obtained results are compared versus a conventional Monte Carlo simulation where all parameters are treated as RVs, and the advantages of the proposed approach (in terms of completeness and richness of information gained about sensitivity of results) are highlighted.

1. Introduction

In recent years, development and application of novel statistical techniques have received increasing attention from researchers and engineers working in the electromagnetic-compatibility (EMC) field, since EMC problems usually involve several parameters with unknown or variable values. Several alternative techniques to the traditional Monte Carlo (MC) method have been proposed, with the objective to alleviate the computational burden associated with the repeated-run simulations required by MC. Among these, advanced techniques based on implementation of polynomial-chaos expansion [1–4] and stochastic collocation [5], as well as stochastic reduced-order models [6, 7], are worth mentioning, since they allow getting fast and accurate estimates of the statistical moments, characterizing the variability of output quantities, with few computational resources.

All these techniques are based on the representation of uncertain parameters by random variables (RVs) assigned with suitable probability distribution functions (pdfs). Such

a priori knowledge and statistical insight, however, are somehow unfeasible for all uncertain parameters. Indeed, the uncertainty affecting some parameters is actually due to lack of knowledge, rather than due to stochastic variability. This is for instance the case of uncontrolled but deterministic parameters, whose values are unknown because they are dependent on the specific, yet not controlled, realization of the system (e.g., the position of a cable in a test setup, which depends on the choice of the human operator running the test). From the theoretical viewpoint, assuming a specific pdf rather than another one for these parameters is not justified by the available knowledge and may prevent obtaining reliable estimates of the actual variability of output quantities.

This problem is common in several engineering sectors, such as, for instance, in the field of risk assessment [8–10] and structural reliability [11–14]. In these sectors, the concept of epistemic (rather than aleatory) uncertainty as well as the use of nonprobabilistic approaches has been introduced several years ago, with the objective of properly managing the aforesaid lack (of) and/or imprecise knowledge.

In particular, several contributions (nonlimited to the aforesaid sectors) make use of possibility theory and represent system parameters affected by epistemic uncertainty through fuzzy variables (FVs). Their variability is described by possibility distributions assigned by experts based on the plausibility—rather than on the actual frequency of occurrence, as in probability theory—of a given event. Since real-case systems usually involve parameters affected by epistemic and stochastic/aleatory uncertainty, a great deal of effort was put in the development of uncertainty quantification (UQ) techniques that are able to manage hybrid problems characterized by the presence of both fuzzy and random variables [8, 15–17].

Little has been done so far in the field of EMC and Signal Integrity (SI) [18, 19], which anyway highlights the limitations of classical probabilistic approaches also in this field. For instance, in [18] a fuzzy-based approach was proposed to evaluate the risk of susceptibility to electromagnetic radiation of electronic systems. In [19], a polynomial-chaos-based technique was presented for the propagating epistemic uncertainty in high-speed circuits. In these examples, however, fully possibilistic problems are addressed, where all uncertain parameters are modelled through FVs.

This work presents the application of a hybrid possibilistic-probabilistic approach in a typical intrasystem EMC problem in the aerospace industry. Namely, conducted emissions (CE) generated by a dc-dc converter in the electric system of a satellite are coupled to a victim differential-signal line through crosstalk, since the line runs in parallel and in close proximity to the dc power bus where CE are propagating. Different uncertainties characterize the problem, including the unknown position of the victim signal line with respect to the power bus (epistemic uncertainty), and the unbalance of terminal loads due to fabrication tolerances and/or parasitic effects (aleatory uncertainty). Suitable RVs and FVs are defined and a hybrid probabilistic/possibilistic algorithm based on MC simulation is applied to predict the noise voltage induced in the signal line in a wide frequency range (up to 100 MHz) and to characterize its uncertainty. Although significant simplifications to the real-case scenario were introduced, the proposed analysis allows highlighting the advantage in terms of completeness of the obtained information with respect to a fully probabilistic MC approach.

The paper is organized as follows. A brief introduction to possibility theory and fuzzy sets is presented in Section 2 to explain the fundamental concepts exploited in this work. The hybrid UQ method used to account both for FVs and for RVs is presented in Section 3. On such basis, the intrasystem EMC problem is presented and solved in Section 4. Completeness and quality of the obtained results are critically discussed. Finally, Section 5 draws concluding remarks.

2. Possibility Theory and Fuzzy Sets

According to possibility theory [20], imprecise or lack of information on the variability of input parameters is represented through possibility distribution functions, $\pi(x)$:

$$\pi : \mathbb{R} \longrightarrow [0, 1], \quad \exists x \in \mathbb{R} : \pi(x) = 1, \quad (1)$$

which provide convex mapping of the real-number interval $[0, 1]$. The values of $\pi(x)$ represent the degree of plausibility of an event, that is, the likelihood that a value x of variable X may lie in a given interval $[x_1, x_2]$. Accordingly, possibility $\pi(x) = 0$ is assigned to impossible values, whereas $\pi(x) = 1$ denotes fully plausible values for x . Since such an assignment has nothing to do with the frequentist interpretation underlying probability distributions, but it rather represents a plausibility estimation provided by experts, possibility distributions do not undergo any area constraint.

The mathematical framework to deal with possibility distributions is the theory of fuzzy sets [20]. The uncertainty affecting the variable X is therefore modelled through a FV, that is, through a convex membership function coincident with the possibility distribution $\pi(x)$. Depending on the available information on X , different membership functions can be assigned (i.e., rectangular, triangular, trapezoidal, etc.). For instance, the rectangular possibility distribution shown in Figure 1 well represents total lack of knowledge (or total ignorance) about the distribution of X on the assigned interval $[x_1, x_2]$.

Possibility, Π , and necessity, N , measures associated with the possibility distribution $\pi(x)$ in (1) are introduced as

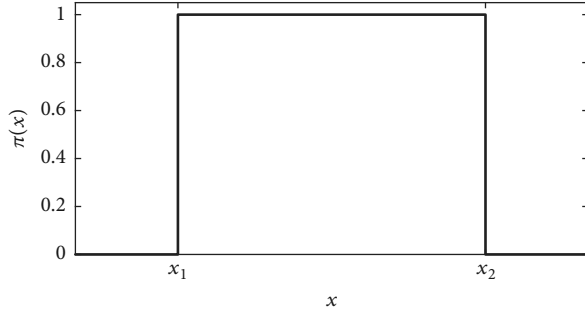
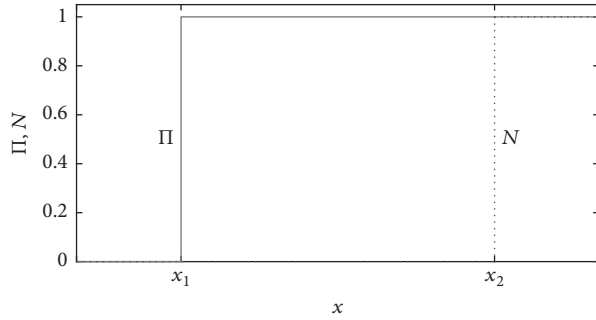
$$\begin{aligned} \Pi(A) &= \sup_{x \in A} \pi(x), \\ N(A) &= 1 - \sup_{x \notin A} \pi(x), \end{aligned} \quad (2)$$

where A is a subset of \mathbb{R} . The former measure estimates the consistency of A with the knowledge described by $\pi(x)$. The latter evaluates how much an event is implied by the knowledge of $\pi(x)$. For a subset A , Π and N always satisfy the inequality $N(A) \leq \Pi(A)$, as it can be easily appreciated in Figure 2, where possibility and necessity measures associated with the rectangular possibility distribution in Figure 1 are shown. Moreover, given the interval $A = (-\infty, x]$, these measures can be interpreted as upper and lower bounds [21] to the family of infinite probability cdfs, $P(A)$; that is, $N(A) \leq P(A) \leq \Pi(A)$. This property implies that imprecision of the input (and output) parameters is modelled by a set of cdfs instead of by a specific cdf, whose choice is usually not supported by the available knowledge.

FVs can also be interpreted as a series of nested confidence intervals, known as α -cuts $A_\alpha = [\inf_\alpha, \sup_\alpha]$, as shown in Figure 3 for a triangular membership function. The degree of confidence that X is contained in A_α is equal to

$$N(A_\alpha) = 1 - \sup_{x \notin A_\alpha} \pi(x) = 1 - \alpha. \quad (3)$$

The α -cut corresponding to $\alpha = 0$ is the support of $\pi(x)$ with $N(A_\alpha) = 1$, whereas the interval that corresponds to $\alpha = 1$ is the core of the possibility distribution and is characterized by $N(A_\alpha) = 0$. Hence, a FV is fully identified either by its member function, or, equivalently, by the knowledge of a sufficient number of α -cuts $A_\alpha = [\inf_\alpha, \sup_\alpha]$, $\forall \alpha \in [0, 1]$.


 FIGURE 1: Rectangular possibility distribution with support $[x_1, x_2]$.

 FIGURE 2: Possibility Π and necessity N measures associated with the rectangular possibility distribution in Figure 1.

3. Uncertainty Propagation

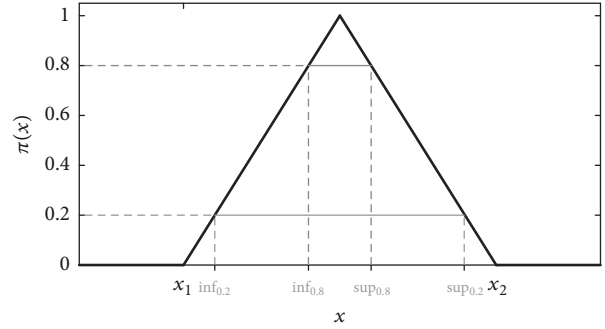
In common engineering problems, only a few of the parameters usually call for a fully possibilistic representation, since the availability of experimental data as well as a deep insight into the underlying physical phenomena often allow providing most unknown parameters with a reliable representation in terms of probability distribution functions. Hence, a great deal of mathematics has been developed for UQ in hybrid problems, in which random parameters, characterized by probability distribution functions, coexist with fuzzy parameters, whose epistemic uncertainty requires a representation in terms of possibility distributions.

A possible approach is to transform the probability distribution functions associated with the random variables into the corresponding possibility functions (by the transformation in [22, 23]) and to solve a purely possibilistic problem.

Conversely, the hybrid approach here exploited retains the random/fuzzy nature of the involved parameters and resorts to MC repeated runs and aggregation of the obtained results in order to propagate the uncertainty [8, 15].

3.1. MC Hybrid Algorithm. Let us consider the generic model $z = f(x_1, \dots, x_M, x_{M+1}, \dots, x_N)$, characterized by M probabilistic parameters x_1, \dots, x_M and $N-M$ possibilistic parameters x_{M+1}, \dots, x_N . The uncertainty of z can be evaluated by the following algorithm.

First, a realization of the M probabilistic parameters is generated. For this specific realization, a specific α -cut


 FIGURE 3: Examples of α -cuts (i.e., $A_{\alpha=0.2}$ and $A_{\alpha=0.8}$) for a triangular possibility distribution.

is considered for the $M-N$ probabilistic variables, and the extreme values of the interval $A_\alpha = [\inf_\alpha, \sup_\alpha]$ of the output variable z are evaluated. Repeating this for all α -cuts from $\alpha = 0$ to $\alpha = 1$ allows determining the possibility distribution function of the specific MC realization under analysis. This procedure, repeated for every MC realization of the M probabilistic parameters, yields a cluster of membership functions, describing the variability of the output parameter z .

If the simple model $z = f(x, y) = yx^2$, where x is a FV with triangular membership function with support $[2, 4]$ and mode 3 and y is a RV with normal probability distribution, $N(\mu, \sigma)$, with mean value $\mu = 1$ and standard deviation $\sigma = 1$, the result of the aforesaid hybrid MC algorithm is the family of curves plotted in Figure 4(a), obtained by fifty different realizations of the probabilistic variable y .

3.2. Aggregation. To aggregate the cluster of curves obtained by MC simulation in a single membership function characterizing the variability of the output variable z , the method proposed by Guyonnet et al. [15] is adopted. For every α -cut of z , the extreme values \inf_α, \sup_α are evaluated by computing the corresponding cdfs and by choosing a quantile q , so that \inf_α corresponds to the $(1 - q)$ quantile of minimum values and \sup_α to the q quantile of maximum values. For the model $z = f(x, y) = yx^2$, such an aggregation procedure is exemplified in Figures 4(b)–4(d) for $q = 0.95$. In Figure 4(b), the cdfs of the minimum (red curve) and maximum (blue curve) values of the generic α -cut of the output variable z are evaluated, and the extreme values \inf_α, \sup_α for such an α -cut are evaluated as the 5% quantile of the minimum and 95% quantile of the maximum values. Repeating this evaluation for all α -cuts yields the possibility distribution function in Figure 4(c) and the possibility measures Π, N shown in Figure 4(d), which characterized the variability of the output variable z .

4. An Intrasystem Compatibility Case Study

In this section, the MC hybrid approach is applied to the solution of an intrasystem compatibility problem often arising in complex systems, where sensitive signal lines coexist in close proximity with power lines. Particularly, the specific

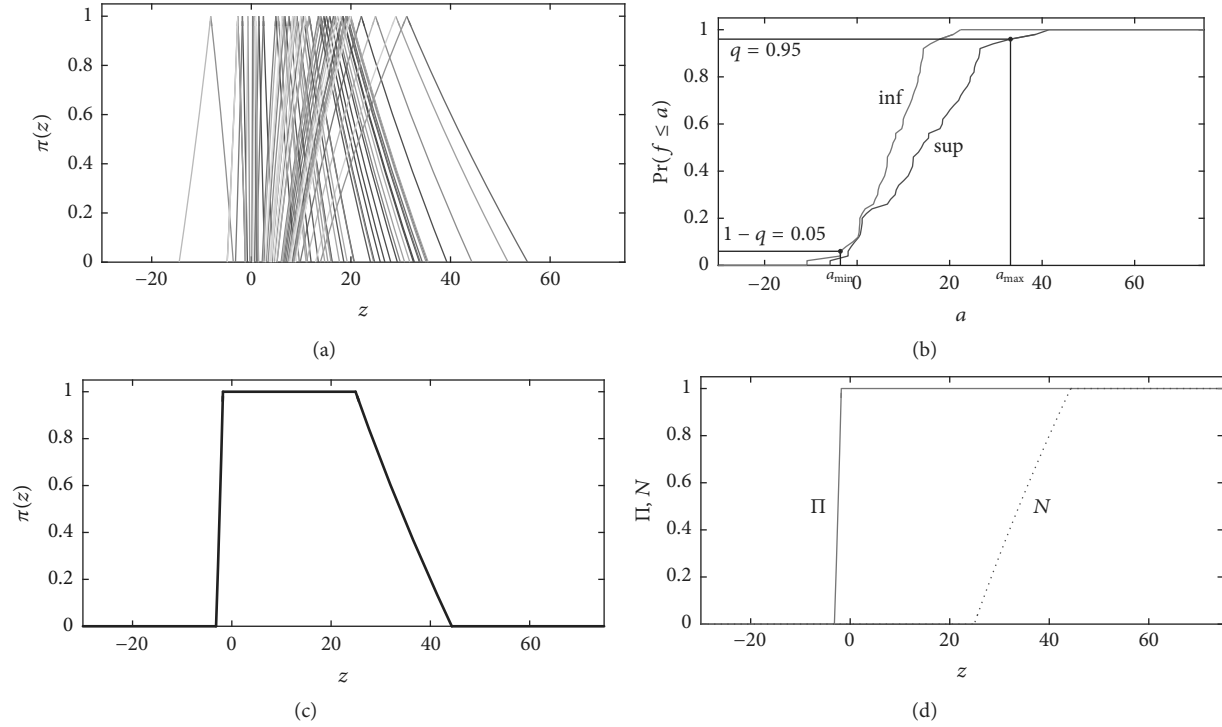


FIGURE 4: Hybrid MC approach and aggregation procedure for the hybrid model $z = f(x, y) = yx^2$: (a) family of membership functions obtained by hybrid MC simulation, (b) application of the aggregation method [15] for a generic α -cut, resulting (c) possibility distribution π , and (d) possibility, Π , and necessity, N , measures characterizing the variability of the output variable z .

case study here analyzed is developed with reference to typical signal and power lines exploited onboard satellites. Indeed, in these systems the electrical power is generally distributed through 24-V dc power busses equipped with dc-dc converters to adapt the 24-V distribution voltage to the actual voltage levels required by sensors and payloads. The conducted emissions generated by these switching devices propagate along the dc bus and may couple through crosstalk (i.e., near-field coupling) with nearby signal lines, thus possibly interfering with signal transmission. Due to stringent space constraints, the final arrangement of the involved signal and power lines is usually unknown to the designer. Furthermore, RF leakage due to improper connection of components, nonideal shielding of cables, connectors, and metallic enclosures, and nonideal realization of the involved circuitry, for example, possible asymmetries leading to imbalance, has to be considered, since they may unpredictably contribute to the susceptibility of the signal line, thus possibly leading to communication failure. All these aspects suggest that evaluating the risk of interference requires a statistical instead of a deterministic approach to the problem.

4.1. Description and Modelling of the Test Setup. Since the objective here is to investigate the potential and possible advantages of the above-described hybrid approaches in addressing EMC problems rather than to provide an exhaustive description of the complexity of the system under analysis, a simplified model of the test setup is here exploited,

which involves a reduced number of uncertain/uncontrolled parameters.

A principle drawing is shown in Figure 5. In this test setup, a two-conductor power line running above ground (representative for the satellite chassis) is connected at the left end to a dc-dc converter for aerospace applications. The other line end is terminated with a Line Impedance Stabilization Network (LISN), whose circuit diagram (see Figure 5) and values of involved circuit components (i.e., $C_p = 1.5 \mu\text{F}$, $C_g = 1 \text{ pF}$, $L = 2 \mu\text{H}$, and $R = 50 \Omega$) conform with [24] and are the most suitable to represent the output impedance of power conditioning and distribution units used onboard satellites. A differential line (victim circuit) runs parallel to the power line and is terminated in communications units with differential front-ends.

For the sake of modelling, the behavioral model in [25, 26] is exploited for the dc-dc converter. Accordingly, the active part of the converter is represented by means of two current sources (connected between each wire in the power line and ground), whose frequency spectra are exacted from measurement data. For the specific dc-dc converter here considered, the spectra of such current sources are shown in Figure 6. Moreover, the passive part of the converter is modelled by a 2×2 matrix of admittances, whose frequency response (not reported here for the sake of brevity) was retrieved from the scattering parameters measured at the input pins of the dc-dc converter switched off.

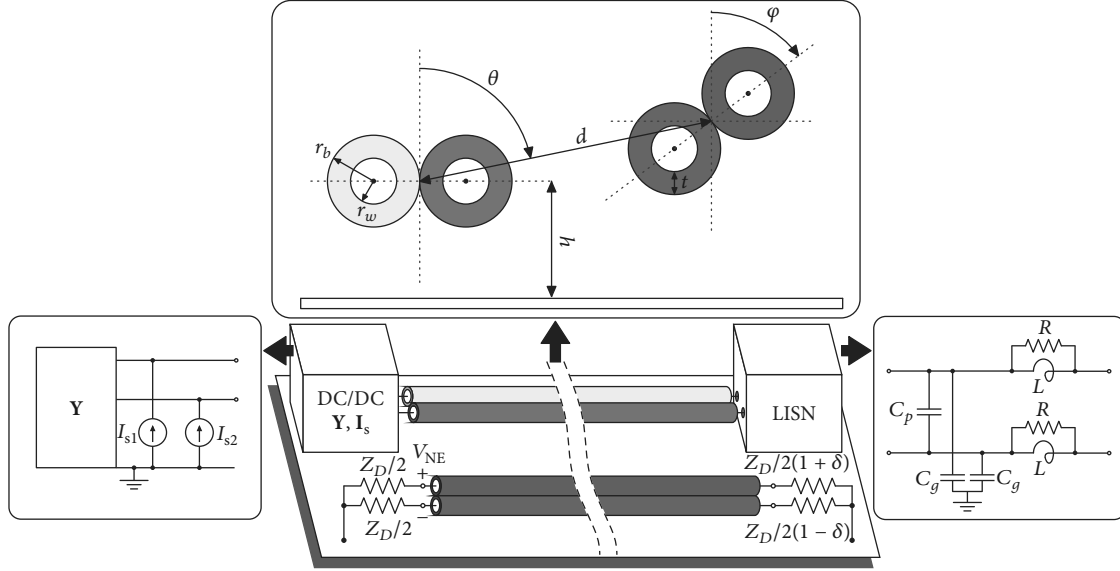


FIGURE 5: Principle drawing of the system under analysis: on the left, the mode of the dc-dc converter is reported. At the top of the picture there is a cross-sectional view of the power (left) and signal (right) lines under analysis. On the right the circuit diagram of a typical Line Stabilization Network (LISN) foreseen by aerospace standard is shown [24].

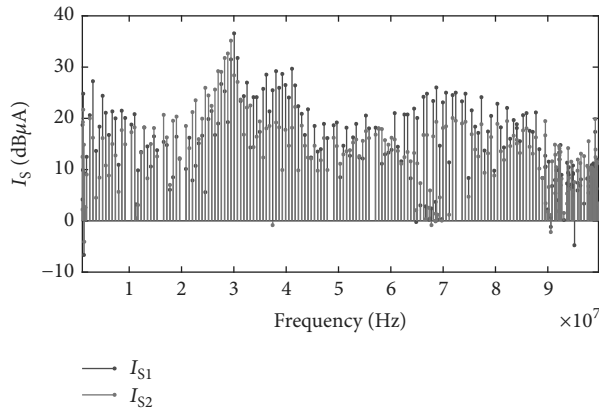


FIGURE 6: Frequency spectra of the equivalent current sources I_{s1} , I_{s2} modelling the active part of the dc-dc converter [25, 26].

To predict the interference induced by crosstalk at the terminations of the signal line, the communications units are treated as passive circuits and simply modelled by 2×2 impedance matrices with expression

$$\mathbf{Z}_{NE} = \text{diag} \left\{ \frac{Z_D}{2}, \frac{Z_D}{2} \right\}, \quad (4)$$

$$\mathbf{Z}_{FE} = \text{diag} \left\{ \frac{Z_D(1+\delta)}{2}, \frac{Z_D(1-\delta)}{2} \right\}, \quad (5)$$

where Z_D denotes the differential-mode (DM) characteristics impedance of the signal line. In (5), coefficient δ is introduced to account for possible imbalance affecting the terminal units. Without loss of generality, in this example only the far-end

unit is assumed to be affected by imbalance. The random variability of the associated coefficient δ will be characterized in the following subsection.

Eventually, a cross-sectional view of the wiring structures under analysis is shown in Figure 5. Without loss of generality, geometrical and electrical characteristics of the wires belonging to the power and the signal lines are assumed to be the same; that is, inner radius $r_w = 0.4$ mm, thickness and permittivity of the dielectric jacket $t = 0.2$ mm (hence, $r_b = r_w + t = 0.6$ mm), and $\epsilon_r = 2.3$, respectively. Both lines are 2-m long. The power line is sketched on the left, and its layout is assumed to be constant and fully known, with height above ground $h = 50$ mm. Conversely, unknown positioning and layout of the signal line (sketched on the right) with respect to the power line are described by three geometrical parameters d , θ , and ϕ , whose variability will be characterized in terms of RVs or FVs in the following subsection.

4.2. Definition of Random and Fuzzy Variables. In this subsection a suitable possibilistic/probabilistic description of the unknown variability affecting the parameters δ , d , θ , and ϕ is provided. As previously observed, not all these parameters can be considered to be affected by epistemic uncertainty, and therefore not all of them require a description in terms of FVs.

This is, for instance, the case of coefficient δ in (5), whose value (ideally equal to zero) is strictly related to tolerances and nonideal realization of the involved circuit components [27]. Based on this interpretation, this coefficient can be better described by an RV with normal distribution $N(\mu_\delta, \sigma_\delta)$ and mean value $\mu_\delta = 0$. In this specific example, a standard deviation $\sigma_\delta = 0.1$ is assumed.

Similar reasoning leads to a probabilistic description also for the angle ϕ , which identifies the rotation of the two wires

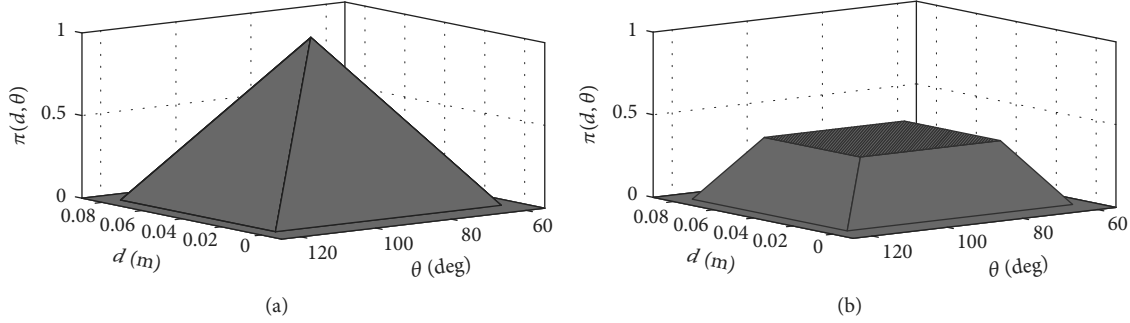


FIGURE 7: (a) Joint possibility distribution $\pi(d, \theta)$ and (b) one of its generic α -cuts.

in the signal line around their axis. Indeed, this parameter may randomly change along the cable axis even after system installation. Hence, such a purely random variability can be adequately represented by an RV with uniform distribution in the interval $[0^\circ, 180^\circ]$.

The geometrical parameters describing reciprocal positioning of the signal line (victim circuit) with respect to the power line (generator circuit) are conversely represented by means of FVs, since their variability is not known nor certain, as they are strongly dependent on the specific installation. Hence, with the objective to account for different plausible arrangements, the parameters θ and d are hereinafter modelled by means of suitable possibility distributions. To this end, identification of a preferable value as well as a reasonable interval of variation for these parameters allows representing their variability by means of triangular possibility distribution. More precisely, a triangular possibility distribution with support $[60^\circ, 120^\circ]$ and preferable value (mode) 90° is assigned to θ .

Conversely, as far as d is concerned, a triangular distribution with support spanning from $4 \cdot r_b$ (minimum distance obtained when the inner wires of the two lines are in contact, for $\varphi = 0$) up to 8 cm, and mode 4 cm, is exploited.

The joint possibility distribution $\pi(d, \theta)$ associated with the possibilistic variables (FVs) d, θ is shown in Figure 7(a). From this 3D plot, the possibility distribution of each FV can be retrieved by projection on the π - d and on the π - θ plane, respectively.

4.3. Prediction of the Voltage Induced at the Terminals of the Signal Line. In order to get statistical estimates of the undesired voltages induced at the terminations of the signal line, a distributed circuit model [28] of the four-wire transmission line running above ground (with variable cross-section in Figure 5) is combined with the hybrid MC procedure described in Section 3.1. To this end, 100 random extractions of the stochastic parameters δ and φ were combined with 51 α -cuts of the possibilistic parameters d, θ (a generic α -cut is shown in Figure 7(b)). For each line cross-section, a numerical routine based on the method of moments [29] was used to efficiently evaluate the per unit length parameters required for line solution. Particularly, the analysis reported in the following focuses on the spread of the voltage V_{NE} induced at the termination of the signal line closer to the

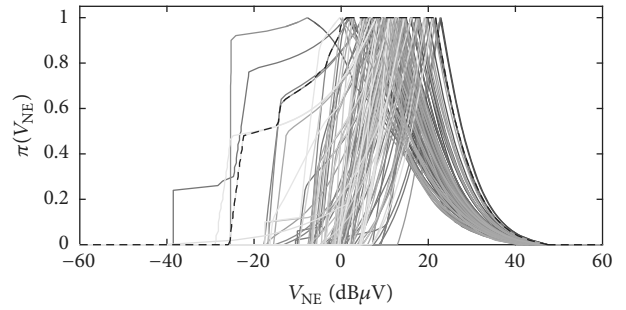


FIGURE 8: Near-end voltage V_{NE} at $f = 92.22$ MHz: family of 100 possibility distributions (colored curves) and aggregated possibility distribution (black-dashed curve).

dc-dc converter (near end, NE), since the maximum interference is expected at this termination.

Plausible values of V_{NE} are represented frequency by frequency by a family of scattered possibility distributions, as those shown in Figure 8, which were obtained at frequency $f = 92.22$ MHz. These curves are then aggregated frequency by frequency according to the Guyonnet method (see Section 3.2), choosing a conservative quantile $q = 0.95$. For the generic frequency $f = 92.22$ MHz, the aggregated possibility distribution is represented by the solid-black curve in Figure 8. Equivalently, the aggregation method can be directly applied to the corresponding possibility Π and necessity N measures. This is exemplified in Figure 9, where the black-solid and black-dashed curves represent the aggregated Π and N measures obtained at $f = 92.22$ MHz, respectively. For each frequency, the obtained limiting cdfs include the 95% of the possible values that V_{NE} may assume at every frequency.

4.4. Comparison versus a Conventional Full-Probabilistic Approach. Eventually, the obtained results are compared versus those provided by purely stochastic MC simulation, where all random variables are assigned probabilistic instead of possibilistic distributions. To this end, also parameters d and θ , previously modelled as FVs, are here treated as probabilistic random variables, and their variability is modelled through uniform probability distributions having the same support as the possibility distributions π

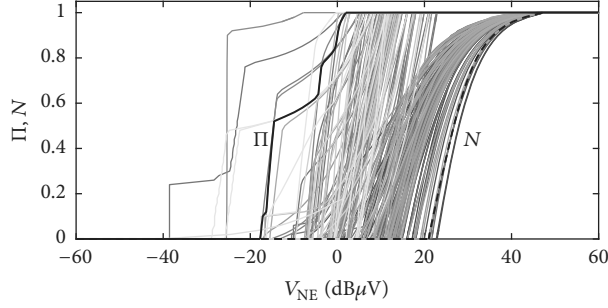


FIGURE 9: Near-end voltage V_{NE} at $f = 92.22$ MHz: family of 100 possibility, Π , and necessity, N , measures (yellow-red and green-blue curves, resp.) and aggregated Π and N measures (black-solid and black-dashed curves, resp.).

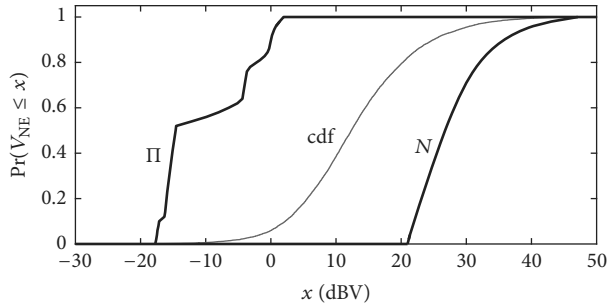


FIGURE 10: Near-end voltage V_{NE} at $f = 92.22$ MHz: comparison between the possibility, Π , and necessity, N , measures predicted by the hybrid method, and the cdf obtained by purely stochastic MC simulation.

previously exploited. Ten thousand extractions of the resulting random parameters δ , φ , d , θ are considered for MC simulation.

Comparison of purely stochastic MC results versus those obtained by the hybrid method puts in evidence the potential of the possibilistic/probabilistic approach to provide a more complete description of the variability of the output voltage V_{NE} . As a matter of fact, at every frequency point, the cdf of the voltage V_{NE} predicted through the purely stochastic MC method is bounded by the possibility and necessity measures predicted by the hybrid approach, as shown in Figure 10 for the specific frequency $f = 92.22$ MHz. By the light of (3), it is worth noting that the probabilistic cdf is just one among infinite others that are possible, similarly bounded by Π and N , since it is a strict consequence of the uniform probability distributions assumed for d and θ (by improperly adding unjustified information, on the viewpoint of epistemic uncertainty).

The frequency response of the near-end voltage V_{NE} in the frequency interval from 1 up to 100 MHz is shown in Figure 11. In this figure, the cluster of colored lines represents the 10^4 frequency responses obtained by full-probabilistic MC simulation. Conversely, black curves represent upper and lower bounds obtained by selecting for every frequency point the 0.025 and 0.975 α -cut of the possibility Π and the

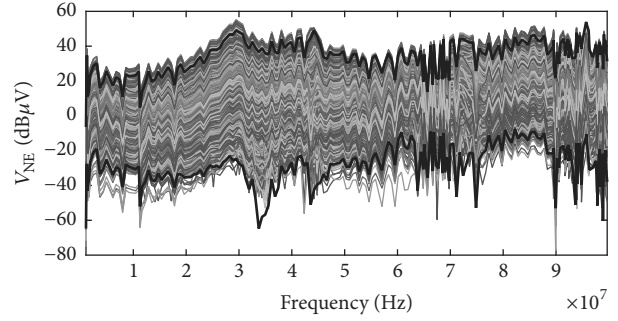


FIGURE 11: Spread of the frequency responses of the near-end voltage V_{NE} : colored lines are obtained by 10^4 purely stochastic MC simulations; black lines are upper and lower bounds obtained by the hybrid approach.

necessity N measures, respectively, obtained by the hybrid approach. One can appreciate that such a 97.5% confidence interval represents a tight bound for the 10^4 full-probabilistic MC simulations and exclude only a few very improbable outliers.

5. Conclusion

In this work, a hybrid random-fuzzy approach (involving both FVs and RVs) has been applied to UQ in an intrasystem EMC case study, dealing with crosstalk between differential-signal lines and power lines in a satellite. Target of the analysis has been the differential-mode voltage induced in the weakly unbalanced terminal loads of the signal line due to CE generated by a dc-dc converter flowing into the power bus. The mutual position between signal line and power line has been considered as unknown but deterministic (due to lack of knowledge); hence the relevant epistemic uncertainty has been characterized through FVs. Conversely, some aleatory and nonideal characteristics of the signal line such as the tilt angle and the weak unbalance of terminal loads have been characterized through RVs.

Although simplified, since several other nonidealities should be considered in order to get reliable intrasystem compatibility assessment, such a model and the obtained results confirm that the proposed approach has the potential to provide a general and complete characterization of output sensitivity to model parameters affected both by aleatory and epistemic uncertainty. This fact has been demonstrated by the comparison versus conventional MC approach, where all uncertain parameters are treated as RVs. It turns out that more rich information about UQ of the induced noise voltage is provided by the hybrid random-fuzzy approach (like possibility and necessity measures) than the mere statistical characterization offered by the cdf obtained through conventional MC. In particular, the possibility of providing lower and upper bounds to the frequency responses of the output quantities (in this case the induced DM voltage) and of assigning these limit curves with a more/less conservative confidence level turn out to be attractive not only in the

aerospace case study here analyzed, but also in EMC problems in general. As a matter of fact, the degree of susceptibility of complex systems usually depends on compliance with noise thresholds that are set by experts in the relevant field but are often identified through qualitative, rather than quantitative, observations of the system vulnerability [18].

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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