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Impact of parameters variability on the level of human exposure due to inductive power transfer

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This paper shows the effectiveness in combining non-intrusive stochastic techniques with 3D modeling tools to build adequate surrogate models for the evaluation of human exposure close to a vehicle equipped with a wireless charging pad. A surrogate model is appropriate to deal with uncertainties and variabilities of parameters defining the electromagnetic problem. Numerical results obtained in case of a light passenger vehicle illustrate the proposed methodology.

Index Terms—Inductive power transfer, stochastic methods, human exposure.

I. INTRODUCTION

Inductive power transfer (IPT) is a key factor in the growth of electric mobility [1]. However, the large gap between transmitter and receiver implies a high level of stray field in the vicinity of the coils that, despite the presence of ferrite concentrators and aluminum shield, may represent a problem in terms of exposure to magnetic fields for passengers or by-standers during the charging operations. It is therefore needed to evaluate the level of exposure in order to be compliant with the relevant standards and guidelines for human exposure when designing a new IPT system.

In order to assess human exposure near IPT systems in automotive applications, adequate modeling methodologies have to be developed. The use of powerful 3D models involving the wireless power transfer (WPT) system and the car-body produced reliable results at heavy computational cost for the radiated field around the system or induced in the human body [2], [3] and more recently on the magnetic field produced by SAE J2954 coils [4]–[6]. The level of exposure is highly dependent on various physical and geometrical parameters: magnitude and phase of the currents in the coils, geometrical characteristics of the system, materials properties, possible misalignment and distance between transmitter and receiver, position of the human body and so forth. Moreover, when building the real system, every parameter (physical or geometrical) might come with some given uncertainty which also needs to be taken into account. Therefore, in order to fully predict the behaviour of the IPT system for human exposure, one cannot simply use 3D solvers.

Thus by using stochastic tools with a given set of inputs and their corresponding outputs, one can build a metamodel which interpolates the real model given by the 3D solver. This resulting metamodel is a mathematical function which can be used easily to predict the

outputs of the real model outside of the training dataset. Therefore it can be used to perform various analysis such as Sobol index sensitivity analysis [7] at a low computation cost. This allows to deal with the variability of all the parameters describing the electromagnetic problem. Such tools have already been used successfully in the past for the determination of specific rate absorption (SAR) in biological tissues due to mobile phones at microwaves frequencies [8], [9]. The same goes for an automotive WPT system in the case of a simplified 3D model, where Polynomial chaos and Kriging methods have been really efficient [10].

The objective of this paper is to show the effectiveness of non-intrusive methods based on a combination of polynomial chaos expansions with Kriging in case of a realistic passenger vehicle in assessing the sensitivity of the electromagnetic problem to several parameters. INRiM provided a 3D Finite Element Method (FEM) model of an electric vehicle charging station (EVCS) that includes a car-body of a S80 sedan car kindly provided by Volvo car company in the framework of the project [11]. The FEM model has been solved varying the physical parameters of the metal car body and charging pad. The GeePs used the various results to develop accurate metamodels using the UQLab framework [12] to perform decent sensitivity analysis using Sobol indices.

II. A REALISTIC MODEL

A. The charging station model

The studied EVCS has been modeled in the framework of the MICEV project [11] and it is considered with a central position for the IPT system (see Fig. 1). The 3D finite element mesh has been built by means of the OPERA 3D simulation software by Dassault Systèmes®. The system has been limited to the car-chassis and to the charging pad, whose rated power is up to 7.5 kW and the resonance frequency is 85 kHz. The current in

the two coils was taken as sinusoidal, the current in the receiving coil being the same amplitude as that in the transmitting coil, i.e. 26 A peak. Being 8 the turns the total magnetomotive force in the coils is 208 A peak, but the electric current in the receiving coil had a 90° phase lag. The distance between the coils was 150 mm. The metal thickness of the chassis is assumed to be 1 mm. Due to the important skin effect, a Surface Impedance Boundary Conditions (SIBC) is used [13].

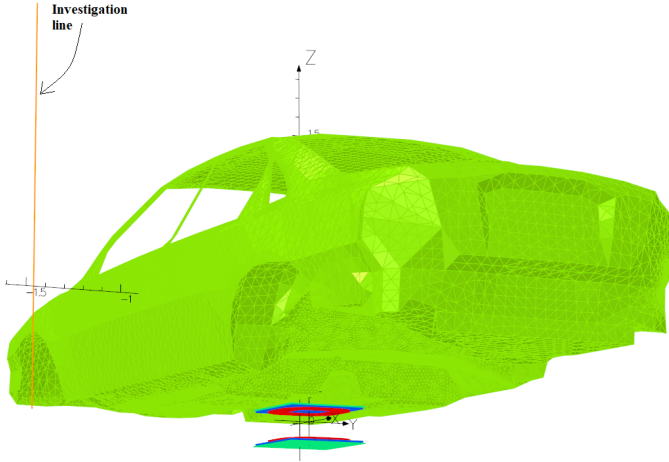


Fig. 1: 3D FEM model mesh of the chassis: the positions of the charging pad and the investigation line

The following input parameters have been considered for performing sensitivity analysis on our vehicle:

- the conductivity of the chassis σ
- the relative permeability of the chassis μ_r
- the relative permeability of the ferrite in the charging pad μ_f
- the radial misalignment between the center of the two coils Δx along the x-axis (axis of motion)
- the radial misalignment between the center of the two coils Δy along the y-axis
- the gap between the two coils Δz along the z-axis (vertical axis)

The output (B hereafter) of our model is the amplitude of the magnetic flux density evaluated along a vertical line (101 points) which embodies a by-stander position:

- $x = 0$ m
- $y = -1.5$ m
- 101 values for z uniformly distributed from 0 m to 2 m

With such a system, the built-in mesh has around $6 \cdot 10^6$ elements along with around $7.7 \cdot 10^6$ edges. Thus computing the model for a given set of input parameters is taking about 16 hours (CPU time).

B. Polynomial-Chaos-Kriging metamodeling

Kriging is a stochastic interpolation algorithm which interpolates the local variations of the output \mathbf{B} as a function of the neighbouring experimental design

points, whereas Polynomial-Chaos expansion approximates well the global behaviour of \mathbf{B} . By combining the global and local approximation, a more accurate stochastic process can be achieved. Polynomial-Chaos-Kriging (PCK) is defined as a universal Kriging model the trend of which consists of a set of orthonormal polynomials. Given an input X of the parameters, the output $B(X)$ can be estimated by:

$$\widehat{B}(X) = \sum_{\alpha \in \mathcal{A}} y_{\alpha} \psi_{\alpha}(X) + \sigma^2 Z(X, \omega) \quad (1)$$

where $\sum_{\alpha \in \mathcal{A}} y_{\alpha} \psi_{\alpha}(X)$ is a weighted sum of orthonormal polynomials describing the trend of the PCK model, σ^2 and $Z(X, \omega)$ denote the variance and the zero mean, unit variance, stationary Gaussian process, respectively. Hence, PCK can be interpreted as a universal Kriging model with a specific trend.

1) Consistency of the metamodel

Let's consider a set $\{(X_1, B_1), \dots, (X_n, B_n)\}$ of n datapoints : a given set of input and their corresponding outputs. Using this set, one can build a metamodel $\widehat{B}(X)$ with PCK. The accuracy of the metamodel is calculated using the mean Leave-One-Out error (LOO):

$$LOO = \frac{1}{n} \sum_{i=1}^n \left(\frac{\widehat{B}_{/i}(X_i) - B_i}{B_i} \right)^2 \quad (2)$$

where $\widehat{B}_{/i}$ is the mean predictor that was trained using all (X, Y) but (X_i, B_i) . The LOO enables us to evaluate the consistency of the metamodel considering its build. If the LOO is close to 1, the metamodel is highly modified if one datapoint is missing, whereas the smallest it is, the least it will be modified.

2) Accuracy of the metamodel

If one were to build a metamodel $\widehat{B}_k(X)$ using a subset of k datapoints out of the aforementioned n datapoints, the accuracy of the predictor on the $(n - k)$ remaining points $\{(X_1, B_1), \dots, (X_{n-k}, B_{n-k})\}$ can be calculated using the OSE (Out-of-sample-error):

$$OSE = \frac{1}{n - k} \sum_{i=1}^{n-k} \left(\frac{\widehat{B}_k(X_i) - B_i}{B_i} \right)^2 \quad (3)$$

The analysis of the OSE emphasizes something different than the LOO analysis does: if the OSE for k datapoints is extremely small, it means that, at the non-sampled points, there is almost no difference between the predictor and the real value. Hence, if the OSE for k datapoints is small enough, there was no need to compute n datapoints but k is enough.

III. NUMERICAL RESULTS AND DISCUSSION

PCK metamodeling has been used on several numerical results of our 3D model in order to predict its behaviour. Out of the available set of datapoints, only a part has been taken to build the metamodels in order to observe if the output model accuracy would be the same using all points or fewer.

A. First sweep: 3 input parameters, $n = 24$ datapoints

The first metamodells developed used an existing pre-computing dataset (table I) regarding the 3 input parameters: $X = (\sigma, \mu_r, \mu_f)$.

TABLE I: Our first dataset ($n = 24$)

μ_r	σ (Sm ⁻¹)	μ_f	μ_r	σ (Sm ⁻¹)	μ_f
1	0	2000	300	0	100
1	10 ⁶	2000	300	0	200
1	5 · 10 ⁶	2000	300	0	500
1	10 ⁷	2000	300	0	1000
100	0	2000	300	0	2000
100	10 ⁶	2000	300	10 ⁶	2000
100	5 · 10 ⁶	2000	300	2 · 10 ⁶	100
100	10 ⁷	2000	300	2 · 10 ⁶	200
200	0	2000	300	2 · 10 ⁶	500
200	10 ⁶	2000	300	2 · 10 ⁶	1000
200	5 · 10 ⁶	2000	300	5 · 10 ⁶	2000
200	10 ⁷	2000	300	10 ⁷	2000

Four different metamodells have been computed: one with the full set of $n = 24$ datapoints, then three metamodells calculated by randomly taking $k = 18, 12$ and 6 datapoints out of the full set. The goal was to observe using the OSE if initially computing less than 24 points would have still produced an accurate metamodel on the given domain. The results are displayed in table II.

TABLE II: LOO, OSE and Sobol sensitivity analysis for our first metamodells

Subset size (k samples)	LOO	OSE	S_{μ_r}	S_{σ}	S_{μ_f}
24	$2.29 \cdot 10^{-3}$	NaN	0	0.842	$4.34 \cdot 10^{-3}$
18	$1.97 \cdot 10^{-3}$	$6.50 \cdot 10^{-4}$	0	0.918	0
12	$3.26 \cdot 10^{-2}$	$5.67 \cdot 10^{-2}$	0	0.941	0
6	0.180	1.78	0	0.609	0

The first noticeable thing is the LOO which is even better with $k = 18$ instead of 24 datapoints, meaning that the metamodel produced with less randomly chosen points is more consistent with itself. Moreover the LOO for $k = 12$ samples is still good (less than 4%) and the OSE is also less than 6%, thus a metamodel with half the points could almost have been enough for the considered parameters domain. Unfortunately, 6 points are not enough to produce an accurate and consistent metamodel and perform a sensitivity analysis on our model. The significant parameter by far here is the conductivity of the frame while both relative permeabilities have almost no influence on the output B vector for this dataset. When plotting the B-field values against the distance for one of the 6 datapoints remaining when building the $k = 18$ datapoints metamodel (see figure 2), it can be observed that the metamodel can perfectly interpolate the input model to produce an estimate accurate enough to perform sensitivity analysis that could help designing a WPT system compliant to the safety guidelines.

Thus, this first attempt at metamodelling our WPT system is promising but, when looking at the dataset

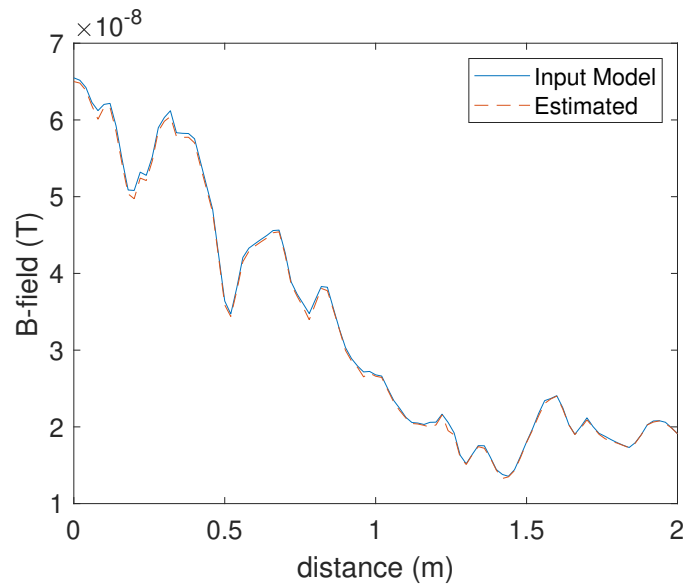


Fig. 2: B-field against the distance for the model with 18/24 datapoints (estimated) against the one with the full dataset (input model) for a given datapoint ($\mu_r = 200, \mu_f = 2000$ and $\sigma = 5 \cdot 10^6$ Sm⁻¹)

especially, its distribution in the parameter space (see figure 3), it can be seen that the sample distribution is highly nonuniform. By building a metamodel with fewer randomly chosen datapoints out of the given dataset, some area of the parameter space could be avoided and therefore a totally inaccurate metamodel would be computed. That is why for the next attempt we decided to compute a more uniformly distributed sweep on our WPT model.

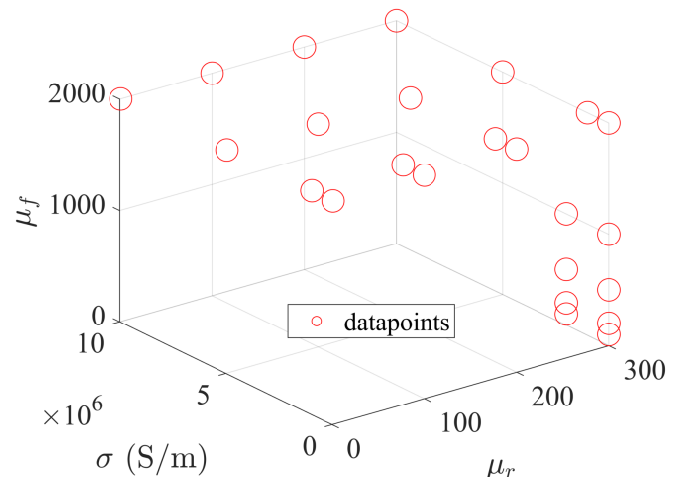


Fig. 3: Distribution of the different samples in the parameter space for our first dataset ($n = 24$)

B. Second sweep: 5 input parameters, $n = 78$ datapoints

For the second dataset the samples are uniformly distributed in the chosen parameter space:

$X = (\mu_r, \sigma, \Delta x, \Delta y, \Delta z)$. The following sweep has been computed on our WPT model:

- $\sigma \in \{0, 10^6\} \text{S m}^{-1}$
- $\mu_r \in \{1, 100, 300\}$
- $\Delta x \in \{-75, 75\} \text{mm}$
- $\Delta y \in \{-100, 0, 100\} \text{mm}$
- $\Delta z \in \{-50, 0, 50\} \text{mm}$

The same analysis as previous has been performed on this dataset of $n = 78$ points resulting in the LOO, OSE and sensitivity analysis displayed in table III.

TABLE III: LOO, OSE and Sobol sensitivity analysis for our second metamodels

Subset size (k samples)	LOO	OSE	S_{μ_r}
78	$2.76 \cdot 10^{-4}$	NaN	$1.79 \cdot 10^{-3}$
58	$1.11 \cdot 10^{-3}$	$4.62 \cdot 10^{-4}$	$1.67 \cdot 10^{-3}$
39	$1.53 \cdot 10^{-2}$	$5.61 \cdot 10^{-3}$	$2.45 \cdot 10^{-3}$
19	$4.02 \cdot 10^{-2}$	0.248	$2.28 \cdot 10^{-3}$
S_σ	$S_{\Delta x}$	$S_{\Delta y}$	$S_{\Delta z}$
0.690	$2.09 \cdot 10^{-4}$	$9.67 \cdot 10^{-2}$	0.123
0.656	$2.55 \cdot 10^{-3}$	0.120	0.141
0.581	$1.72 \cdot 10^{-4}$	0.127	0.231
0.584	$4.43 \cdot 10^{-4}$	$9.70 \cdot 10^{-2}$	0.253

This new metamodels are all consistent: Indeed, there is less than 5% of leave-one-out error even when sampling only a quarter ($k = 19$) of the dataset. But for this metamodel the OSE is too high ($> 20\%$) thus it cannot be used as an accurate predictor for the WPT system. The predictor with half the points ($k = 39$) is even more accurate ($OSE \simeq 6\%$) than the one from the first set. Using a more uniform parameter space enabled us to build a more consistent and more accurate metamodel with fewer points.

Even with more parameters as the previous analysis, the metamodels computed on this sweep allowed an equally accurate sensitivity analysis with the car-body conductivity still being the significant parameter against new geometrical parameters. The Sobol indices of the five parameters are here really useful for future computations. First, the influence of the relative permeability and the coils misalignment along the axis of motion is negligible against the misalignment along the y-axis and the z-axis and the car-body lamination conductivity. Thus, future sensitivity analysis on this five parameters can be reduced to three parameters, or less samples can be taken from the non-significant parameters and more samples can be given to the significant ones. Then, such an analysis can help with the design of real WPT systems where a greater care should be given to the uncertainties on dimensioning the chassis conductivity and the system along the y and z-axis.

IV. CONCLUSION

The stray magnetic field on a by-stander position has been obtained using a Polynomial-Chaos-Kriging metamodel in a modeled realistic EVCS. PCK metamodels enabled us to examine the effects of different physical

or geometrical parameters on the output field of our IPT system at a low computation cost. Less computed datapoints will be needed in the future in order to verify the compliance of the system with the guidelines for human exposure. The analysis presented in this paper will now be extended by using more realistic configurations: various possible positions around the car will be investigated and a full voxelized model for the human body will be used.

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