Assessment of Human Exposure in Case of Wireless Power Transfer for Automotive Applications using Stochastic Models

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Abstract **─** In this paper, different non-intrusive stochastic approaches are compared in view of human exposure assessment from an inductive power transfer system at 85 kHz, dedicated to automotive applications. The stochastic approaches are combined with a 3D finite element method to build adequate meta-models based on Kriging and Polynomial Chaos Expansion. These models are used to consider the uncertainty and variability of several parameters defining the electromagnetic problem. Such fast predictions of uncertainties may help to improve the design of shields for inductive power transfer systems considering health and safety standards.

Index Terms **─** Human exposure, Stochastic models, wireless power transfer.

I. INTRODUCTION

During recent years, inductive power transfer (IPT) systems have been widely developed in several fields such as biomedical engineering, consumer electronics and the automotive industry [1-7]. With such increasing use, the human exposure to the radiated electromagnetic fields from these systems in day to day life must be deeply investigated. It is therefore needed to evaluate the compliance to health and safety guidelines [8].

International guidelines for human exposure safety (such as ICNIRP 2010) include two recommendations: reference levels and basic restrictions. The first recommendation to be checked is the reference level. If the reference level is exceeded, then a dosimetry analysis (involving the human body) has to be performed in order to be compliant to the guidelines. The work presented in this paper deals with the reference level. At the standard frequency for inductive power system for wireless charging, 85 kHz, the maximum magnetic flux density allowed according to the ICNIRP in 2010 is 27 μT (reference level).

In order to assess human exposure near IPT systems in automotive applications, adequate modeling methods need to be developed. Nowadays 3D computational models are studied and applied to solve the electromagnetic problem involving the wireless system, the vehicle and the human body (in the vehicle or located beside it) [4-7]. Such full wave computational approaches give reliable results for the radiated fields around the system or the induced quantities in the human body. This may lead to heavy computations that must be repeated for each new configuration. A major point in such problems is that the level of field is highly dependent on various parameters: the shape or size of coils, the geometrical characteristics of the system (structural parts of the vehicle, shielding plates), materials properties (ferrite, frame of the vehicle), the possible misalignment between transmitter and receiver while charging, the position of the human body in case of dosimetry analysis. Moreover, each physical or geometrical parameter may be affected by some uncertainty. For such uncertainty propagation studies, statistical methods based on Monte Carlo simulations may provide reliable results [9]. With this approach, a large set of inputs is considered, and many evaluations of a model response are needed. This leads to a heavy computational cost in case of complex system configurations. To avoid the computational burden and deal with a large variability of data, it can be very useful to build adequate meta-models (or surrogate models). A meta-model is an approximated behavioral model, built with a reduced set of input data, whose behavior is representative of the original model for all data. Metamodeling is a well know procedure in reliability and uncertainty propagation in mechanics. It often relies on stochastic techniques (Kriging, polynomial chaos expansions). In electromagnetics, similar approacheshave been developed and applied to various problems (electromagnetic compatibility problems, microwave devices design, etc.) [10-12]. Recently the quantification of the uncertainty relevant to electrical parameters of a simple wireless transfer system was studied using a polynomial chaos expansion [13]: both the transmitter and receiver units have simple shapes and only consist of a resonant coil (helical or spiral) and a matching loop. Also, Kriging provides an efficient approach that was combined with a finite element software for the design of an inductive power transfer system in [14] and used to verify the compliance of power transfer systems

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regarding human exposure [15].

This paper presents a comparison of surrogate models, Kriging-based and Polynomial chaos-based for the prediction of radiated field in the case of a simplified but realistic 3D inductive power transfer system [16]. In [6] the level of exposure of this system was studied through a parametric analysis involving only the possible misalignment of the two coils. Nevertheless, in practice it is highly desirable to be able to determine the impact of different parameters involved in the electromagnetic analysis. The stochastic techniques used in this paper consider the variability of different parameters defining the 3D configuration in order to evaluate the impact on the radiated magnetic field. In particular, the results show that with a reduced set of input data, accurate predictions can be obtained over a wide range of parameters. These approaches are used to check if the reference levels relevant to the magnetic field are compliant with the recommendations. A sensitivity analysis is performed to evaluate the relative impact of the different parameters.

II. STOCHASTIC MODELING

A. Studied wireless power system

The structure considered in this paper contains two rectangular coils (the transmitter and the receiver), and two ferrite plates [16]. This test case corresponds to an existing inductive power system that has been built in Politecnico di Torino, Italy; the structure studied in this paper involves the main parts of the coupling system. The design also includes a steel plate that represents the chassis of the electric vehicle (Fig. 1). Previous studies [6] have shown that such a simplified chassis is sufficient to evaluate its impact on the results. The dimensions of the system are shown on Table 1. Each coil has 10 turns. This system has been designed for dynamic charging but only static charging is considered in this study. The power electronics controls and keeps the rms value of the current in the transmitter at 36 A and the current in the receiver at 75 A.

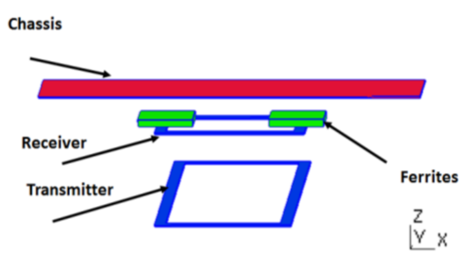

Fig. 1. Wireless power system.

Table 1: Dimensions of the system

	Width (m)	Length (m)
Transmitter	0.5	1.5
Receiver	0.5	0.25
Ferrite	0.2	0.3
Frame	1.5	0.5

B. Kriging

Kriging is a stochastic interpolation algorithm which assumes that the model output M(x) is a realization of a Gaussian process indexed by the input x. A Kriging meta-model is described by the following equation:

$$M(x) \sim M^K(x) = \beta^T f(x) + \sigma^2 Z(x, \omega). \qquad (1)$$

The first term in (1), is the mean value of the Gaussian process (trend) and it consists of the regression coefficients β_j (j = 1,…P) and the basis functions f_j (j = 1,…P). Ordinary Kriging has a constant trend. A trend based of linear or quadratic polynomial can also be used. The second term in (1) consists of σ^2, the (constant) variance of the Gaussian process and Z(x, ω), a zero mean, unit variance, stationary Gaussian process. The underlying probability space is represented by ω and is defined in terms of a correlation function R and its hyper-parameters θ. The correlation function R = R(x; x_0 ; θ) describes the correlation between two samples of the input space, *e.g.*, x and x_0 and depends on the hyper-parameter θ. In the context of meta-modelling, it is of interest to calculate a prediction $M^K(x)$ for a new point x, given X = (x_1,…x_n), the experimental design and y = (y_1 =M(x_1),…,y_n = M(x_n)), the corresponding (noise-free) model responses. A Kriging meta-model (Kriging predictor) provides such predictions based on the Gaussian properties of the process.

B. Polynomial chaos expansion

The polynomial chaos is a spectral method and consists in the approximation of the system output in a suitable finite-dimensional basis Ψ(X) made of orthogonal polynomials. A truncation of this polynomial expansion can be written as follows:

$$M(x) \sim M^{PC}(x) = \sum_{j=0}^{P-1} \propto_j \Psi_j(X), \qquad (2)$$

where M(x) is the system output, X is the random input vector made of the input parameters x_i, Ψ_j are the multivariate polynomials belonging to $\Psi(X)$, α_j are the coefficients to be estimated, ε is the error of truncation, and P is the size of the polynomial basis $\Psi(X)$. Each multivariate polynomial Ψ_j is built as a tensor product of univariate polynomials orthogonal with respect to the probability density function of each input parameter x_i:

$$\Psi_\alpha(X) = \prod_{i=1}^{N} \Psi_i(x_i). \qquad (3)$$

Here, inputs Gaussian distributions are used, and the corresponding polynomial families Ψ_i are the Hermite polynomials families. The coefficients in (2) can be estimated by using spectral projections or least-square regressions [21].

C. Polynomial chaos – Kriging

Kriging interpolates the local variations of the output as a function of the neighbouring experimental design points, whereas PCE approximates well the global behaviour of the output. By combining the global and local approximation of these techniques, a more accurate meta-model is achieved. Polynomial Chaos-Kriging (PC-Kriging) can be understood as a universal Kriging model the trend of which consists of a set of orthonormal polynomials:

$$M(x) \sim M^{PCK}(x) = \sum_{j=0}^{P-1} \propto_j \Psi_j(X) + \sigma^2 Z(x, \omega), \quad (4)$$

where the first term in the right-hand side is a weighted sum of orthonormal polynomials describing the trend of the PC-Kriging model, and where the second term includes the variance and the zero mean, unit variance, stationary Gaussian process respectively.

The three meta-models summarized above and used in this paper are proposed in the framework for uncertainty quantification are freely available [17]. Kriging (with different trends), Polynomial Chaos Expansion based on the Least Angle Regression (PCE), Kriging combined with Polynomial Chaos Kriging (PCK) are applied to check the compliance regarding the reference levels of radiated magnetic field. For the frequency of interest (85 Hz), the maximum admissible value of the magnetic flux density is 27 µT according to the ICNIRP Guidelines (2010). The experimental design is evaluated by the finite element method using the commercial software COMSOL. The magneto-dynamic problem is solved with a 3D vector potential formulation. The mesh includes around 8000 first order tetrahedral finite elements (Fig. 2). The average size of edges is around 30 mm in coils, ferrite and frame. The mean of the flux density provided by the meta-models in a vertical line, located at 50 cm from the frame representing the possible location of a bystander.

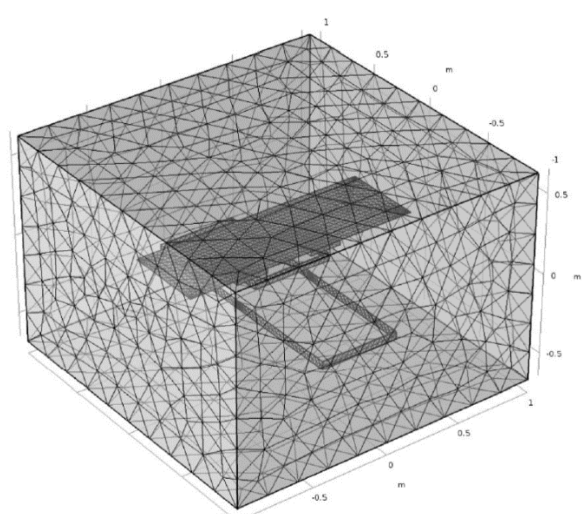

Fig. 2. Finite element mesh used for the computations.

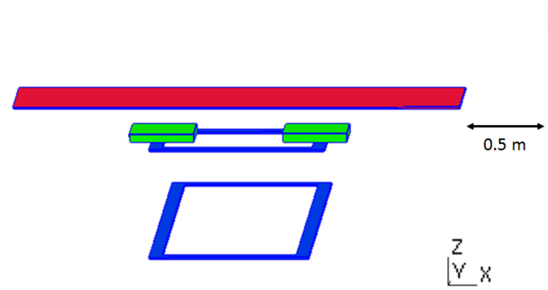

Fig. 3. Position of the observation points (blue line).

III. NUMERICAL RESULTS

A. Configuration with 3 parameters

In the first example, the uncertainty regarding the frame conductivity, distance between coils and length of reception coil is investigated. Here, σ, d, L are the frame conductivity, distance between coils and length of reception coil respectively. The range of variation is shown in Table 1. Regarding the conductivity, the range includes typical values relevant to composite materials which are used in automotive applications [18,19]. These three parameters are important for such analysis since once a park or a road is equipped with defined transmitter coils, different kinds of vehicle may be charged by the system. The level of radiated field then depends on the type of the receiver system (L and d) and car body (σ). They may strongly vary according to the vehicle. The relative permeability of ferrite is 2200.

Table 2: Parameters: Range of variations

Parameter	Min	Max
σ (S/m)	10^4	10^6
d (m)	0.	1.
L (m)	0.2	0.3

The accuracy of the meta-model is checked thanks to the LOO (leave-one-out) cross-validation provided by each meta-model and defined according to [16]:

$$LOO = \sum_{i=1}^{N} (M(x_i) - \widehat{M}^{-i}(x_i))^2 / \sum_{i=1}^{N} (M(x_i) - m)^2. \quad (5)$$

This quantity involves N meta-models $\widehat{M}^{-i}$, each one created on a reduced experimental design excluding x_i and comparing the prediction to the real value $M(x_i)$. In equation (5), m is the mean of the experimental design response. If the LOO is close to 1, the meta-model is highly modified if one data point is erased, whereas the smaller it is, the least it will be modified.

In order to measure the accuracy of the output model according to the number of sampling points, another estimate of the accuracy can be defined, the OSE (Out-of-Sample Error):

$$OSE = \frac{1}{N-k}\sum_{i=1}^{N-k}\left(\frac{M(x_i)-M^k(x_i)}{M(x_i)}\right)^2 , \tag{6}$$

where M^k is the predictor that was trained using k data-points among the N available.

The OSE is a measure of the accuracy of the meta-model with a reduced set of sampling values.

For the studied case, the meta-model is constructed with 10 randomly selected data points out of 27 (3 samples for each of the three parameters). The computing cost for one simulation (three given parameters) is less than 2 minutes on a work station DELL XEON E5-1630 V3 (64 Go). The number of 27 data inputs points (full wave computations) was chosen as a compromise between accuracy and reasonable computing time in view of an engineering-oriented tool. The accuracy of the meta-model is then calculated on the remaining 17 points out of 27 to get the OSE and the LOO (Table 3). Regarding Kriging, a significant lower LOO is obtained using a linear or quadratic term compared to an ordinary trend. Among the three types of approaches PCK clearly appears as the more accurate.

Table 3: Comparison of different meta-models

	OSE Eq.(5)	**LOO** Eq.(6)
Kriging (ordinary trend)	$2.1\ 10^{-6}$	$2.1\ 10^{-4}$
Kriging (linear trend)	$7.\ 10^{-6}$	$1.7\ 1^{-6}$
Kriging (quadratic trend)	$1.4\ 10^{-5}$	$1.3\ 10^{-5}$
PCK	$7.\ 10^{-6}$	$5.2\ 10^{-11}$
PCE	$7.\ 10^{-6}$	$1.\ 10^{-6}$

In order to study the influence of the number of samples on the predictions, the meta-models were constructed on 8,10,15 randomly selected points out of 27 data points. The values of LOO for different methods and for the three given cases are shown in Table 4. In practice it was shown that using more than 10 points is unnecessary to get a sufficiently accurate surrogate model.

Table 4: LOO values for different numbers of samples

	8 points	**10 points**	**15 points**
Kriging (ordinary trend)	8.8×10^{-6}	$2. \times 10^{-4}$	1.6×10^{-4}
Kriging (linear trend)	1.3×10^{-3}	1.7×10^{-6}	1.2×10^{-8}
Kriging (quadratic trend)	$5. \times 10^{-3}$	1.3×10^{-5}	8.8×10^{-7}
PCK	$1. \times 10^{-3}$	5.2×10^{-11}	3.7×10^{-13}
PCE	2.2×10^{-3}	$1. \times 10^{-6}$	8.1×10^{-7}

B. Configuration with 5 parameters

In this second example, the uncertainty regarding the frame conductivity (σ), distance between coils (d), length of reception coil (L), shift between coils (D) and frame relative permeability (μ) is studied. By increasing the number of parameters, the objective is to evaluate the quality of the meta-models to deal with a larger variability of practical configurations. The distance D refer to a possible misalignment between the transmitter and receiver due to the vehicle position, while charging. The permeability of the frame refers to different type of steel material of the car body. The range of variation of the parameters is shown in Table 5.

Table 5: Parameters: range of variations

Parameter	**Min**	**Max**
σ (S/m)	10^4	10^6
d (m)	0.	1.
L (m)	0.	0.5
D (m)	0.	0.5
μ (H/m)	1000.	3000.

The efficiency of the different meta-models is checked in case of 20 randomly selected data points among 243 (3 samples for each of the five parameters). The corresponding values of the LOO and the OSE are shown in Table 6.

Table 6: Comparison of different meta-models

	OSE	**LOO**
Kriging (ordinary trend)	3.2×10^{-3}	$1. \times 10^{-3}$
Kriging (linear trend)	1.7×10^{-4}	4.1×10^{-4}
Kriging (quadratic trend)	8.2×10^{-4}	8.1×10^{-4}
PCE	2.1×10^{-4}	4.2×10^{-6}
PCK	6.3×10^{-3}	1.5×10^{-4}

The influence of the number of samples is described in Table 7. Again, PCK provides the lowest error.

Table 7: LOO values for different number of samples

	15 points	**20 points**	**25 points**
Kriging (ordinary trend)	6.9×10^{-3}	$1. \times 10^{-3}$	8.4×10^{-4}
Kriging (linear trend)	1.1×10^{-2}	4.1×10^{-4}	5.5×10^{-5}
Kriging (quadratic trend)	2.6×10^{-2}	8.1×10^{-4}	3.5×10^{-5}
PCK	1.7×10^{-3}	4.2×10^{-6}	5.2×10^{-7}
PCE	$6. \times 10^{-2}$	1.4×10^{-4}	1.6×10^{-5}

The maximum mean value of the B field recorded on the vertical line shown on Fig. 3 occurs in front of the air gap between the coils. If the number of samples is sufficient (above 20 in the present case) the three meta-models give the same outputs: the relative error between the field obtained but the meta-model and that deduced from the finite element method remains below 0.6% for all the values computed along the vertical line. The predictions remain under the ICNIRP limit of 27 µT.

Table 8 gives the values of the Sobol indices which quantify the impact of uncertain input variables on the output [20]. These indices may be useful in case of a sensitivity analysis. The higher the Sobol index, the stronger the influence of the related input in the output uncertainty. The Sobol indices are directly and analytically extracted from the polynomial chaos expansion [21]. This is a key interest of PCE: the results are obtained sensitivity indices and are computed at almost no additional cost with a computing time which is several orders of magnitude lower compared to a standard Monte Carlo analysis. As expected in this simplified studied case, the distance between the coils has the greatest impact on the magnetic field. Because of the position of the observation point, the physical properties of the plate has negligible effect. The two other parameters which have a significant impact are the shift between the coils and the length of the reception coil. Of course, in the case of a dosimetry analysis involving a realistic human exposure situation, the field has to be evaluated accurately using many observation points near the system (and not only on the vertical line of interest) and in the biological tissues [22-24]. Then the conclusions may be different.

Table 8: Sensitivity of parameters

Parameter	**Sobol Index**
σ (S/m)	1. x 10^{-8}
d (m)	0.83
L (m)	0.3
D (m)	0.15
µ (H/m)	1. x 10^{-8}

IV. CONCLUSION

Predictions of the radiated magnetic field have been obtained from stochastic models based on Kriging and Polynomial chaos expansions in the case of a simplified but realistic wireless power transfer system. This feasibility analysis shows that meta-models provide efficient approaches to consider uncertainties of different physical or geometrical parameters. With a reduced number of samples, the combination of Kriging and Polynomial chaos expansions can be used as a fast predictor to check if reference levels fit the guidelines for human exposure. The work is now extended to investigate more complex configurations, which consider the global structure of the vehicle. Such an approach will also make any sensitivity analysis when designing the system with appropriate shielding structural parts easier.

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