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Research Article

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Uncertainty quantification in the design of wireless power transfer systems

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Abstract: The paper addresses the uncertainty quantification of physical and geometrical material parameters in the design of wireless power transfer systems. For 3D complex systems, a standard Monte Carlo cannot be directly used to extract statistical quantities. So, surrogate models based on Kriging or polynomial chaos expansions are built to study the impact of variable parameters on the radiated magnetic field and efficiency. Such fast prediction of uncertainties in the parameters of the system can improve the design of inductive power transfer systems taking into account human exposure recommendations and variability of the parameters.

Keywords: EMC, wireless transfer, uncertainty quantification, shielding, efficiency

1 Introduction

In recent years, inductive power transfer (IPT) systems have been widely developed in several fields such as biomedical engineering, consumer electronics, and automotive industry. In automotive applications, the coupling between the transmitter, which is placed on the ground, and the receiver, which is placed under the floor of the vehicle, leads to a large gap. This large space implies a high level of stray field near the coils, which can pose a problem of exposure to magnetic fields for passengers or persons likely to approach

the vehicle during charging operations [1–5]. The stray field depends on the power level and shielding effectiveness (SE) of the charging pads. It is therefore important to evaluate the efficiency of the system and the SE. The properties of shields are very dependent on many parameters (thickness, number of layers, electromagnetic properties, etc.) [6] and these parameters may be affected by uncertainties (measurements errors, approximations) having a significant impact on the performances of the system.

For such uncertainty propagation studies, statistical methods based on Monte Carlo approaches are used [7]. For example, analytical simulations illustrate in ref. [8] the influence of material properties on the SE of planar sheets with a Monte Carlo technique. Two simple standard configurations were analyzed. The first case considers a source loop in a low frequency range of 0–100 kHz. Such standard geometry is a basic situation in IPT [9]. The second one deals with a plane wave in a high frequency range of 0–10 GHz which is relevant to general electromagnetic compatibility (EMC) studies involving composite materials [10].

However, with such a Monte Carlo approach, a large set of inputs are 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 metamodels (or surrogate models). A metamodel is an approximated model, built with a reduced set of input data, and whose behavior is representative of the original model for all data. Metamodeling is a well-known procedure in reliability and uncertainty propagation in mechanics. It is based on stochastic techniques (Kriging, polynomial chaos expansions [PCE]). In electromagnetics, similar approaches have been developed in electromagnetic compatibility problems and human exposure evaluation [11–13]. Recently, the quantification of uncertainty relevant to electrical parameters of a simple wireless transfer system was studied using a PCE [14]: both the transmitter and receiver units have simple shapes and only consist of a resonant coil (helical or spiral) and a matching loop. In ref. [15] Kriging was combined with a finite element software for the design of an IPT system.

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This paper presents the study of uncertainty propagation in the design of 3D wireless power systems taking into account the shielding structures. It extends the work presented in ref. [16] where preliminary results dealing with the stray field emitted from an IPT system were considered. A Monte Carlo approach cannot be applicable because of too heavy computational cost. Instead, surrogate models based on Kriging and PCE are presented and applied to two simplified but realistic 3D IPT systems. The first one was built in Politecnico di Torino [16,17] and the second one in GeePs [18]. The stochastic techniques easily take into account the variability of different parameters defining the 3D configurations. In particular, the results show that with a reduced set of input data, accurate predictions relevant to the stray field or mutual inductance can be obtained over a wide range of parameters. This allows making easier any sensitivity analysis when designing the system with appropriate shielding structural parts.

2 Wireless power system (Polito di Torino)

2.1 Studied configuration

The structure considered in this section contains two rectangular coils (the transmitter and the receiver) and two ferrite plates. This test case corresponds to an existing inductive power system that has been built in Politecnico di Torino, Italy [17]. Preliminary results have been published in ref. [16]. The design includes a steel plate that represents the chassis of the electric vehicle (Figure 1). The dimensions of the system are shown in Table 1. The relative permeability of ferrite is 2,200. 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

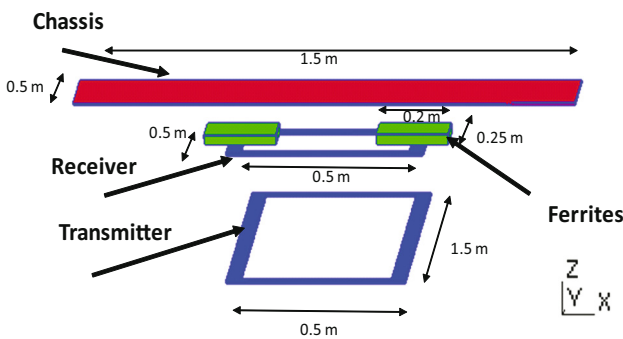


Figure 1: Studied configuration of the wireless transfer system.

Table 1: Dimensions of the wireless power transfer system

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

the current in the transmitter at 36 A and the current in the receiver at 75 A.

2.2 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 inputs x [19]:

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

The first term in (1) is the mean value of the Gaussian process (trend) and it consists of the regression coefficients β_j ($j = 1, \dots, P$) and the basis functions f_j ($j = 1, \dots, P$). The second term in (1) consists of σ^2 , the (constant) variance of the Gaussian process and $Z(x, \omega)$, 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. The correlation function describes the correlation between two samples of the input space and depends on the hyperparameters. In the context of metamodeling, it is of interest to calculate a prediction $M^K(x)$ for a new point x , given $X = (x_1, \dots, x_n)$, the experimental design and $y = (y_1 = M(x_1), \dots, y_n = M(x_n))$, the corresponding (noise-free) model responses. A Kriging metamodel (Kriging predictor) provides such predictions based on the Gaussian properties of the process.

2.3 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 $\Psi(X)$ made of orthogonal polynomials. A truncation of this polynomial expansion can be written as follows:

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

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, 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 .

2.4 Numerical results – three parameters (chassis conductivity and misalignment between emitter and receiver)

Kriging has been applied in the configuration of Figure 5 in order to check the compliance regarding the maximum admissible values of the radiated magnetic field. For the frequency of interest (85 kHz), the maximum admissible value of the magnetic flux density is $27 \mu\text{T}$ according to the ICNIRP Guidelines (2010) [5]. The experimental design is evaluated by the finite element method (Figure 2). The magneto-dynamic problem is solved with a 3D vector potential formulation using the software COMSOL.

The accuracy of the metamodel is checked thanks to the leave-one-out (LOO) cross-validation defined according to [19]:

$$\text{LOO} = \sum_{i=1}^N (M(x_i) - M^{-i}(x_i))^2 / \text{Var}[Y] \quad (3)$$

This quantity involves in each sampling point x_i the error between the value provided by the model and the Kriging prediction by using all the sampling points except x_i . If the LOO is close to 1, the metamodel is highly modified if one data point is erased, whereas the smallest it is, the least it will be modified.

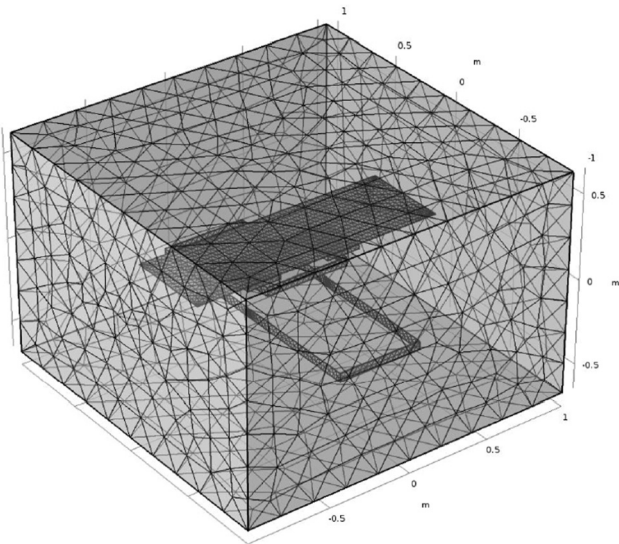


Figure 2: Finite element mesh used for computing sampling data.

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

In this example, the variability regarding the frame conductivity, distance between coils and length of reception coil is investigated. Here, σ , d , and L are the chassis conductivity, distance between coils, and length of reception coil, respectively. The range of variation is shown in Table 2.

Regarding the conductivity, the range includes typical values relevant to composite materials which are used in automotive applications. 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.

For the studied case, the metamodel is constructed with 10 randomly selected data points out of 27 (three samples for each of the three parameters). The computing cost for one simulation (three given parameters) is less than 2 min 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 metamodel is then calculated on the remaining 17 points out of 27 to get the LOO (Table 3). Regarding Kriging, a significant lower LOO is obtained using a linear or quadratic term compared to an ordinary trend.

In order to study the influence of the number of samples on the predictions, the metamodels were constructed on 8, 10, and 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 3: Comparison of different metamodels

	LOO
Kriging (ordinary trend)	2.1×10^{-4}
Kriging (linear trend)	1.7×10^{-6}
Kriging (quadratic trend)	1.3×10^{-5}
PCE	1×10^{-6}

Table 4: LOO values for different numbers of samples

	8 points	10 points	15 points
Kriging (ordinary trend)	8.8×10^{-6}	2×10^{-4}	1.6×10^{-4}
Kriging (linear trend)	1.3×10^{-3}	1.7×10^{-6}	1.2×10^{-8}
Kriging (quadratic trend)	5×10^{-3}	1.3×10^{-5}	8.8×10^{-7}
PCE	2.2×10^{-3}	1×10^{-6}	8.1×10^{-7}

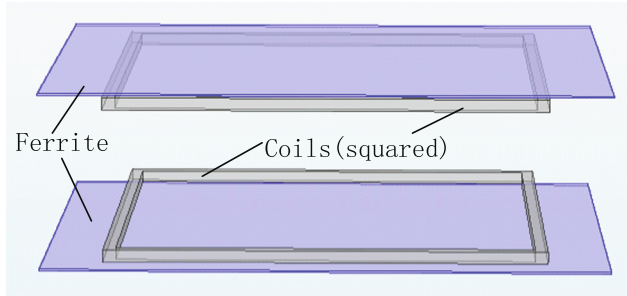


Figure 3: IPT system [18].

3 Wireless power system (GeePs)

3.1 Studied configuration

The IPT system considered in this section has been studied in GeePs and is presented in ref. [18] (Figure 3). There are two squared coils and rectangular ferrite plates. The power transfer efficiency can be expressed as [15]:

$$\eta \propto \frac{1}{1 + \frac{R_1 R_L}{(\omega L_{12})^2}} \quad (4)$$

where ω is the angular frequency, R_1 is the series transmitter coil resistance, R_L is the series load resistance, and L_{12} is the mutual inductance between the two coils.

It is clear from (4) that when the structure of the coils and the frequency of the IPT system have been fixed, the efficiency is directly related to the mutual inductance.

The dimensions of the IPT systems are shown in Table 5. The design of the ferrites plates of a IPT system has a relatively strong effect on the power transfer efficiency. Here, the uncertainty lies in the distance between the ferrite plate and the coil (d), the thickness (w), and the relative permeability (μ_r) of the ferrite plate. A surrogate model is built in order to study the influence on the mutual inductance in the IPT system.

3.2 Sensitivity analysis

A PCE is used to find the most influential parameters and to perform a first sensitivity analysis. To illustrate, the

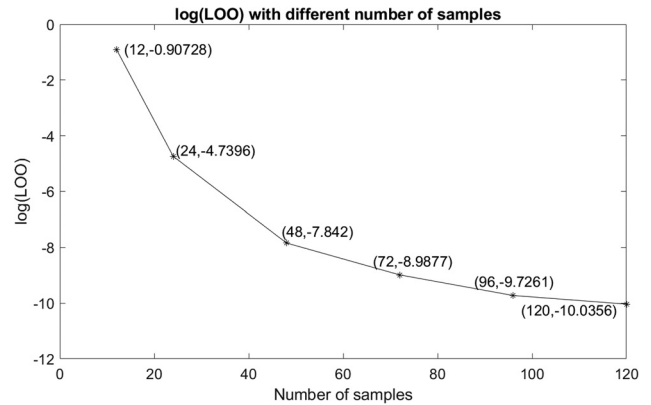


Figure 4: log(LOO) error versus different number of samples.

Table 5: Dimensions of the IPT system

Parameter	Value
Coil length	468 mm
Coil height	13 mm
Ferrite width	600 mm
Ferrite length	500 mm
Ferrite height	2 mm
Distance between coils	150 mm
Frequency	85 kHz
Current in one coil	42 A rms

metamodel is built with 120 samples, each sample including three values corresponding to the three parameters. The parameters are chosen uniformly distributed over the range of variations (Table 6). As Figure 4 shows, the LOO error rapidly decreases with the number of these datapoints. Around 20 datapoints is a sufficient number to obtain a value of M with less than 5% compared to the value computed with the 3D finite element model.

In order to perform a sensitivity analysis regarding the mutual inductance L_{12} , the Sobol indices [20] are determined. These Sobol indices are statistical quantities that can be obtained at low cost using the metamodels instead of a classical Monte Carlo approach. They are known analytically with a PCE metamodel. The first order Sobol index related to the parameter p is defined as in ref. [21] with the first statistical moments:

Table 6: Parameters: range of variation

Parameter	Min	Max
μ_r	1,000	3,000
d (mm)	0	10
w (mm)	0	2

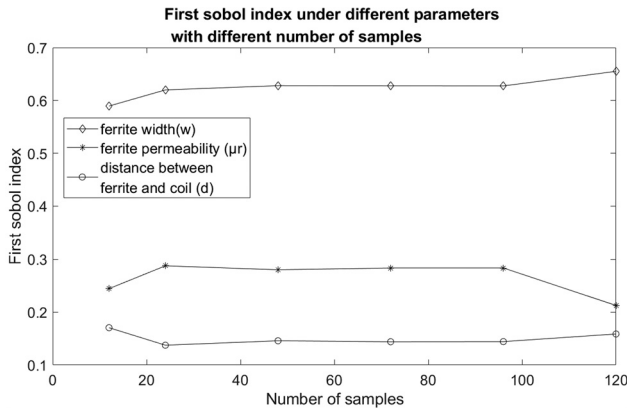


Figure 5: First Sobol index versus number of samples.

$$S_p = \text{Var}(E\{L_{12}|p\}) / \text{Var}[L_{12}] \quad (5)$$

If S_i is close to one, it describes the highest impact on the mutual inductance L_{12} . Figure 5 contains the first-order Sobol index for the three parameters. It is clear that no matter how the number of samples changes, the Sobol index for each parameter is nearly the same and the thickness of the ferrite plate appears to influence the most. Therefore, this parameter should be paid more attention when designing the system.

4 Conclusion

Predictions of magnetic field and related quantities have been obtained from a statistic approach Monte Carlo and stochastic models. In case of a 3D complex configuration, metamodels based on Kriging or PCE provide efficient approaches to consider the uncertainties regarding different physical or geometrical parameters. The interest of such surrogate models was demonstrated in case of two simplified but realistic inductive power systems. With a reduced number of samples, a metamodel can be used as a fast predictor to check if reference levels fit the guidelines for human exposure, for example, or to improve the efficiency of the transfer. The paper has validated the approach with synthetic numerical data: In a next step, predictions of the metamodels will be compared with measured values. The work will also be extended to investigate more complex configurations involving a higher number of parameters and taking into account the global structure of the vehicle.

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