



**HAL**  
open science

# Stochastic Modelling of 3D Electric Fields in Children Brain exposed to 50 Hz Magnetic Field with Uncertain Orientation

E Chiaramello, M. Parazzini, S. Fiocchi, M Bonato, Laurent Le Brusquet, P Ravazzani

► **To cite this version:**

E Chiaramello, M. Parazzini, S. Fiocchi, M Bonato, Laurent Le Brusquet, et al.. Stochastic Modelling of 3D Electric Fields in Children Brain exposed to 50 Hz Magnetic Field with Uncertain Orientation. 2018 IEEE International Conference on Environmental Engineering (EE) (IEEE EE 2018), Mar 2018, Milan, Italy. hal-01871323

**HAL Id: hal-01871323**

**<https://centralesupelec.hal.science/hal-01871323v1>**

Submitted on 10 Sep 2018

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Stochastic Modelling of 3D Electric Fields in Children Brain exposed to 50 Hz Magnetic Field with Uncertain Orientation

E. Chiaramello, M. Parazzini, S. Fiocchi, M. Bonato,  
P. Ravazzani  
Istituto di Elettronica e di Ingegneria dell'Informazione e  
delle Telecomunicazioni  
IEIIT CNR, Milano, Italy

L. Le Brusquet  
Département Signal et Statistiques  
Centrale Supélec  
Paris France

**Abstract**— This study focused on the evaluation of the electric field induced in the brain grey matter of a 5 years child when exposed to uniform magnetic field at 50 Hz with uncertain orientation. An innovative approach that combines Principal Component Analysis (PCA) and Gaussian process regression (Kriging method) in order to build space-dependent surrogate models was applied and validated. Preliminary results showed the feasibility of the approach.

**Keywords**—stochastic dosimetry, ELF-MF exposure, surrogate modelling

## I. INTRODUCTION

The ubiquity of Extremely Low-Frequency Magnetic Fields (ELF-MF), such as those generated by transmission of electricity power lines, contributes to the raising of public awareness over the potential adverse health effects due to the interaction of ELF-MF with the human body. The exposure to ELF-MF of high amplitude causes well known acute biological effects on the nervous system, such as nerve stimulation and induction of retinal phosphenes [1]. Starting from the late 1970s, many studies focused on a possible association, firstly suggested by [2], between long-term exposure to ELF-EMF and an increased risk of childhood cancer (see e.g. [3]), leading the International Agency for Research on Cancer (IARC) [4] to classify ELF-MF as “possibly carcinogenic to humans” (2002).

Many studies investigated the exposure to magnetic field at the specific frequency of 50 Hz, particularly focusing on children [5], [6] and fetuses [5], [7]–[10], for their precocity of exposure. Most of these studies investigated the assessment of the compliance to exposure guidelines when considering few specific exposure scenarios, providing no information about how the exposure changes in realistic and highly variable scenarios. Such an assessment is indeed a challenging task, due to the intrinsic variability of the parameters that influence the exposure, (e.g. morphology, anatomy and posture of the exposed subject, reciprocal position of the source and the exposed subject, polarization of the EMF field [11]). Classical electromagnetic computational techniques typically involve highly time-consuming simulations to obtain 3D spatial distributions of the electromagnetic fields induced in human tissues, making almost impossible to characterize how the exposure changes in variable conditions. Recently, stochastic dosimetry has been proposed as a method to face variability of

the EMF exposure scenario in the assessment of exposure. Stochastic dosimetry uses statistics to build surrogate models able to replace by analytical equations the heavy numerical simulations that would be needed to describe the highly variable exposure by electromagnetic computational techniques. Stochastic dosimetry proved to be a useful method to assess the EMF exposure both at radio frequency [12], [13] and at low frequency [10]. All these studies were exclusively dealing with surrogate models of EMF univariate variables, e.g. the 99<sup>th</sup> percentile calculated on the 3D domain of root mean square tissue-specific values of the electric field induced by ELF-MF [14]. However, a complete assessment should involve the complete description of the 3D spatial distribution the induced electric field in each tissue of the exposed subjects in variable conditions, as different spatial localization could involve different effect on the tissues. Such an assessment involves creating surrogate models able to describe the 3-dimensional spatial localization of the electric field induced in each tissue. Some recent studies focused on the developing of non-intrusive methods (i.e. methods in which the phenomenon to be approximated is treated as a “black-box”) for building surrogate models of space-temporal variables [15]–[17]. To the best of our knowledge, these methods were never applied before in the stochastic dosimetry framework.

In this study, the variability of the 3-dimensional spatial distribution of electric field induced in children brain tissues when exposed to a uniform 50 Hz magnetic field with uncertain orientation was investigated. An innovative approach that combines Principal Component Analysis (PCA) and Gaussian process regression (Kriging method) [15] in order to build space-dependent surrogate models was applied and validated.

## II. MATERIALS AND METHODS

Fig. 1 shows a schematic view of the exposure scenarios (left side) and the flow chart of the experimental procedure (right side). The electric field induced in the brain grey matter of a 5 years child was assessed by varying the orientation of a perfectly homogeneous 50 Hz  $\mathbf{B}$ -field of 200  $\mu\text{T}$  of amplitude, using 3D surrogate models. Each surrogate model describes how the 3D variable of interest  $Y$  (i.e., the electric field induced in the brain) was affected by the variability in the input parameters  $X$  (i.e., the different orientation of the  $\mathbf{B}$ -field).

Three main steps composed the experimental procedure. The first step, namely, “design of the experiment,” consisted of using deterministic dosimetry, that is, dosimetry based on computational methods, for the evaluation of a set of  $N$  experimental observations  $Y_0$  of the variable of interest  $Y$ , needed for the construction of the surrogate models. The second step, namely, “3D surrogate modelling,” focused on the development of a surrogate model  $\hat{Y}$ . The surrogate model thus obtained was validated in the “validation” step. Details about each step are as follows.

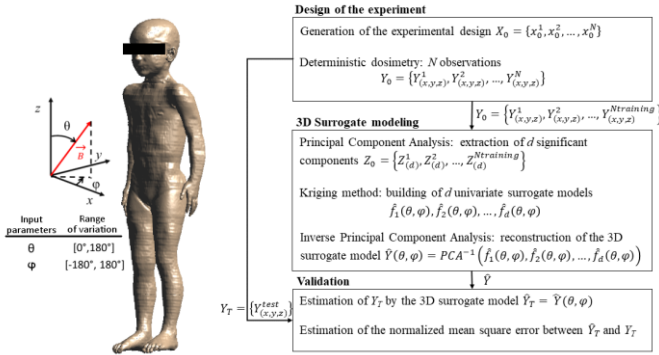


Figure 1: Schematic view of the exposure scenarios and flow chart of the experimental procedure.

### A. Design of the experiment

The random input vector  $X$  was defined as the two spherical angles theta ( $\theta$ ) and phi ( $\varphi$ ), which characterized the  $\mathbf{B}$ -field orientation (see Fig. 1). The experimental design  $X_0$  has been generated using a Latin Hypercube Sampling (LHS), using a selection criterion based on the maximum of the minimum distance between the points [18]. The variable of interest  $Y$  is the root mean square value of electric field induced in the child grey brain matter averaged on a 2 mm side cube, obtained by deterministic dosimetry based on Magneto Quasi-Static low frequency solver implemented on the simulation platform SEMCAD X (Schmid & Partner Engineering). The simulations were conducted using the 5 years Roberta model from the Virtual Classroom [19]. The dielectric properties (permittivity and conductivity values) in each tissue of the children were assigned according to the data available in literature [20], [21]. A total number of  $N = 150$  simulations, corresponding to 150 different orientations of  $\mathbf{B}$ -field were carried out to obtain the set of observation  $Y_0$ . Each observation is a matrix with dimensions 452x258x1494.

### B. 3D Surrogate Modelling

Similarly to the approach proposed by [15], the 3D surrogate modelling procedure is based on three main steps. First, a kernel PCA with linear kernel was applied. The rationale of using PCA is that the electric field induced at nearby spatial coordinates could be hypothesized to be highly correlated [22], and thus can be efficiently represented by a few  $d$  components.

As a second step, the Kriging method (see, e.g. [15]) was applied to develop a separate surrogate model for each of the  $d$  components identified by PCA. Kriging (a.k.a. Gaussian process modelling) is a stochastic interpolation algorithm that assumes that a model output a realization of a Gaussian

process indexed by  $x \in D_X \subset \mathbb{R}^M$ . A Kriging surrogate model is described by the following equation:

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

where  $\beta^T f(x)$ , is the mean value of the Gaussian process and it consists of the regression coefficients  $\{\beta_j, j = 1, \dots, P\}$  and the basis functions  $\{f_j, j = 1, \dots, P\}$ ,  $\sigma^2$  is the variance of the Gaussian process and  $Z(x, \omega)$ , a zero mean, unit variance, stationary Gaussian process. The underlying probability space is represented by  $\omega$  and is defined in terms of a correlation function  $R$  (a.k.a. correlation family) and its hyperparameters  $\theta$ . In this study, a Matérn correlation function  $R$  was used and its hyperparameters  $\sigma^2$  and  $\theta$  were estimated by Maximum Likelihood Estimation (MLE).

The third step in the 3D surrogate modelling procedure consisted of using the inverse Principal Component analysis to reconstruct, from the univariate surrogate models  $\hat{f}_1, \hat{f}_2, \dots, \hat{f}_d$  obtained by Kriging method, the 3D spatial distribution of the electric field induced in the brain of the child.

For more details about each step and about the whole 3D surrogate modelling procedure, see [15].

### C. Validation

The validation of the 3D surrogate model was based on a leave-one-out cross-validation approach, a technique developed in statistical learning theory (see, e.g., [23]) and here used to reduce at minimum the size of the experimental design. To that purpose, the set of observation  $Y_0$ , obtained by deterministic dosimetry from the experimental design of size  $N$ , was recursively divided into two subsets:  $Y_{training}$ , containing all the observations except for the  $i^{th}$  one, and  $Y_{test}$ , containing only the excluded observation. A 3D surrogate model  $\hat{Y}$  was built using the subset  $Y_{training}$  and then its prediction of the excluded  $i^{th}$  point ( $\hat{Y}_T(\theta_i, \varphi_i)$ ) was compared with  $Y_{test}$ . The normalized Mean Square Error (MSE) was calculated by computing the mean of the errors calculated at each iteration, as:

$$MSE = 100 * \sum_{i=1}^N \frac{\|\hat{Y}_T(\theta_i, \varphi_i) - Y_T\|^2}{\|Y_T - \text{mean}(Y_0)\|^2} \quad (2)$$

## III. PRELIMINARY RESULTS

Fig. 2 shows the leave-one-out MSE versus the number  $d$  of principal components considered in the 3D surrogate modelling procedure. For  $d$  equal to 5, the MSE was equal to 0.34%, thus indicating that a very low number of components was sufficient to represent the 3D distribution of the electric field induced in the brain grey matter.

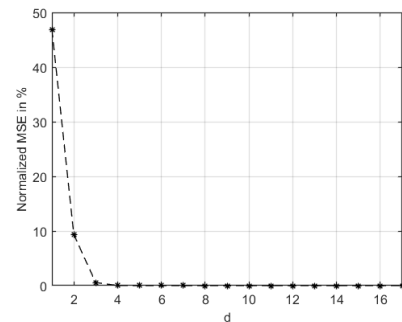


Figure 2: Leave-one-out MSE versus the number  $d$  of components considered in the 3D surrogate modelling procedure.

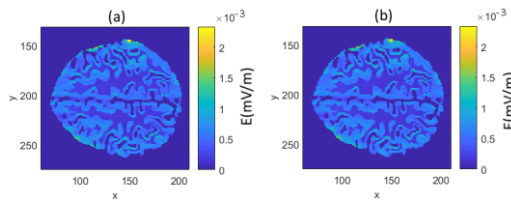


Figure 3: Spatial distribution of the electric field induced on one slice of the brain grey matter obtained by 3D surrogate model (a) and deterministic dosimetry (b).

Fig. 3 shows, as an example, the spatial distribution of the electric field induced on one slice of the brain obtained for one specific orientation ( $\theta$  and  $\phi$  equal to  $89^\circ$  and  $72^\circ$ , respectively) of the incident  $\mathbf{B}$ -field by the 3D surrogate model (fig. 3a) and by deterministic dosimetry (fig. 3b). Fig. 3a and fig. 3b appear to be almost identical, confirming the feasibility of the proposed approach.

Preliminary results showed that the proposed approach is feasible to assess the 3D spatial distribution of the electric field induced in human tissues when exposed to a uniform magnetic field with variable orientation. 3D surrogate models will be created to assess the variability of the spatial distribution of the electric field induced in different tissues of children of different ages. The proposed method will allow not only to assess the exposure to ELF-MF in variable conditions in terms of univariate variables resuming the level of exposures, but to investigate how the spatial distribution of the EMF field induced in the human tissue is influenced by the variability intrinsic to realistic exposure scenarios.

#### ACKNOWLEDGMENT

This research is supported by the French National Research Program for Environmental and Occupational Health of ANSES (2015/1/202): Project ELFSTAT - In depth evaluation of children's exposure to ELF (40 – 800 Hz) magnetic fields and implications for health risk of new technologies, 2015-2019. The authors wish to thank Schmid and Partner Engineering AG ([www.speag.com](http://www.speag.com)) for having provided the simulation software SEMCAD X/SIM4Life.

#### REFERENCES

- [1] R. D. Saunders and J. G. R. Jefferys, "A neurobiological basis for ELF guidelines," *Health Phys.*, vol. 92, no. 6, pp. 596–603, 2007.
- [2] N. Wertheimer and E. Leeper, "Electrical wiring configurations and childhood cancer," *Am. J. Epidemiol.*, vol. 109, no. 3, pp. 273–284, 1979.
- [3] L. Kheifets, A. Ahlbom, C. M. Crespi, G. Draper, J. Hagihara, R. M. Lowenthal, G. Mezei, S. Oksuzyan, J. Schüz, J. Swanson, A. Tittarelli, M. Vinceti, and V. Wunsch Filho, "Pooled analysis of recent studies on magnetic fields and childhood leukaemia," *Br. J. Cancer*, vol. 103, no. 7, pp. 1128–1135, 2010.
- [4] Iarc, "International Agency for Research on Cancer Iarc Monographs on the Evaluation of Carcinogenic Risks To Humans," *Iarc Monogr. Eval. Carcinog. Risks To Humans*, vol. 96, p. i-ix+1-390, 2002.
- [5] P. Dimbylow and R. Findlay, "The effects of body posture, anatomy, age and pregnancy on the calculation of induced current densities at 50

- Hz.," *Radiat. Prot. Dosimetry*, vol. 139, no. 4, pp. 532–538, 2010.
- [6] J. F. Bakker, M. M. Paulides, E. Neufeld, a Christ, X. L. Chen, N. Kuster, and G. C. van Rhoon, "Children and adults exposed to low-frequency magnetic fields at the ICNIRP reference levels: theoretical assessment of the induced electric fields," *Phys. Med. Biol.*, vol. 57, no. 7, pp. 1815–1829, 2012.
- [7] R. Cech, N. Leitgeb, and M. Padiaditis, "Fetal exposure to low frequency electric and magnetic fields.," *Phys. Med. Biol.*, vol. 52, no. 4, pp. 879–888, 2007.
- [8] A. Zupanic, B. Valic, and D. Miklavcic, "Numerical assessment of induced current densities for pregnant women exposed to 50 Hz electromagnetic field," *Int. Feder. Med. Biol. Eng. Proc.*, vol. 16, pp. 226–229, 2007.
- [9] I. Liorni, M. Parazzini, S. Fiocchi, M. Douglas, M. Capstick, M.-C. Gosselin, N. Kuster, and P. Ravazzani, "Dosimetric study of fetal exposure to uniform magnetic fields at 50 Hz," *Bioelectromagnetics*, vol. 597, no. 35(8), pp. 580–97, 2014.
- [10] I. Liorni, M. Parazzini, S. Fiocchi, and P. Ravazzani, "Study of the Influence of the Orientation of a 50-Hz Magnetic Field on Fetal Exposure Using Polynomial Chaos Decomposition," *Int. J. Environ. Res. Public Health*, vol. 12, no. 6, pp. 5934–5953, 2015.
- [11] J. Wiart, *Radio-Frequency Human Exposure Assessment: From Deterministic to Stochastic Methods*. John Wiley & Sons, ISTE, 2016.
- [12] E. Chiaromello, M. Parazzini, S. Fiocchi, P. Ravazzani, J. Wiart, and S. Member, "Assessment of Fetal Exposure to 4G LTE Tablet in Realistic Scenarios : Effect of Position , Gestational Age and Frequency," *IEEE J. Electromagn. RF Microwaves Med. Biol.*, 2017.
- [13] I. Liorni, M. Parazzini, N. Varsier, A. Hadjem, P. Ravazzani, and J. Wiart, "Exposure assessment of one-year-old child to 3G tablet in uplink mode and to 3G femtocell in downlink mode using polynomial chaos decomposition," *Phys. Med. Biol.*, vol. 61, no. 8, pp. 3237–3257, 2016.
- [14] E. Chiaromello, S. Fiocchi, P. Ravazzani, and M. Parazzini, "Stochastic Dosimetry for the Assessment of Children Exposure to Uniform 50 Hz Magnetic Field with Uncertain Orientation," *Biomed Res. Int.*, vol. 2017, pp. 1–14, 2017.
- [15] T. Chen, K. Hadinoto, W. Yan, and Y. Ma, "Efficient meta-modelling of complex process simulations with time – space-dependent outputs," *Comput. Chem. Eng.*, vol. 35, no. 3, pp. 502–509, 2011.
- [16] O. T. Kajero, R. B. Thorpe, T. Chen, B. Wang, and L. Le, "Kriging Meta-Model Assisted Calibration of Computational Fluid Dynamics Models," *AIChE J.*, vol. 62, no. 12, pp. 4308–4320, 2016.
- [17] L. Hawchar, C. El Soueidy, and F. Schoefs, "Principal component analysis and polynomial chaos expansion for time-variant reliability problems," *Reliab. Eng. Syst. Saf.*, vol. 167, pp. 406–416, 2017.
- [18] G. Blatman, "Adaptive sparse polynomial chaos expansions for uncertainty propagation and sensitivity analysis," Université Blaise Pascal, Clermont-Ferrand, 2009.
- [19] M.-C. Gosselin, E. Neufeld, H. Moser, E. Huber, S. Farcito, L. Gerber, M. Jedensjö, I. Hilber, F. Di Gennaro, B. Lloyd, E. Cherubini, D. Szczerba, W. Kainz, and N. Kuster, "Development of a new generation of high-resolution anatomical models for medical device evaluation: the Virtual Population 3.0.," *Phys. Med. Biol.*, vol. 59, no. 18, pp. 5287–5303, 2014.
- [20] C. Gabriel, S. Gabriel, and E. Corthout, "The dielectric properties of biological tissues .1. Literature survey," *Phys. Med. Biol.*, vol. 41, no. 11, pp. 2231–2249, 1996.
- [21] C. Gabriel, a Peyman, and E. H. Grant, "Electrical conductivity of tissue at frequencies below 1 MHz.," *Phys. Med. Biol.*, vol. 54, no. 16, pp. 4863–4878, 2009.
- [22] J. Rougier, "Efficient emulators for multivariate deterministic functions," *J. Comput. Graph. Stat.*, vol. 17, pp. 827–843, 2008.
- [23] G. Blatman and B. Sudret, "Adaptive sparse polynomial chaos expansion based on least angle regression," *J. Comput. Phys.*, vol. 230, no. 6, pp. 2345–2367, 2011.