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Metamodel multi-objective optimization of 3F3 Ferrites Core in a WPT system for automotive applications

Meta-modélisation pour l'optimisation multi-objectifs des ferrites d'un système de recharge inductif pour véhicules électriques

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Abstract/Résumé

This paper shows the useful combination of a gradient-based particle swarm optimization (GPSO) method with a metamodeling process in order to save computation time for the design of a Wireless Power Transfer (WPT) system for automotive applications. The goal of this analysis has been to investigate new configurations for $3F3$ ferrite cores in an existing WPT system regarding both the coupling factor and the ferrite volumes. An innovative gradient-based multi-objective optimization method has been coupled to an adaptive sampling algorithm for Polynomial-Chaos Kriging (PCK) metamodeling.

Cet article vise à montrer l'utilisation de la meta-modélisation pour l'optimisation par essaims particulaires avec gradient (GPSO). Le but est d'économiser du temps de calcul pour le design optimal d'un système de transfert de puissance sans contact pour la recharge inductive des véhicules électriques. En partant d'un modèle partiellement optimisé, la configuration des ferrites $3F3$ a été analysée en fonction du facteur de couplage et du coût de construction (proportionnel au volume de ferrites utilisé). L'optimisation multi-objectifs par GPSO a été couplée à un algorithme adaptatif pour le calcul d'un métamodèle Polynôme Chaos-Krigeage.

1 Introduction

Metamodels have been initially developed to perform sensitivity analysis at a low computation cost. They are widely used for various modeling applications, and are especially handy for trade-off optimization problems on complex computational models. The main interest of using an accurate metamodel for optimization is its direct analytical expression which can be called instead of the real model for computing many datapoints. In the field of electromagnetics, many metamodel-based optimization have already been developed such as Kriging-based optimization [1] or PCE-based optimization [2]. The novelty of the metamodel-based optimization presented here consists in extracting the gradient of the cost function directly from its analytical expression. Indeed, instead of calling the PCK predictor during the optimization process, the gradient is directly computed from the meta-parameters, thus, saving a lot of computation time in the case of complex high-dimensional models. The works aims at investigating new configurations for the design of $3F3$ ferrite cores on an available WPT system [3] which had not been done before.

2 Optimization problem

2.1 Optimization method

The considered surrogate model consists in a combination of a Polynomial Chaos Expansion (PCE) and a Gaussian process (Kriging) : a Polynomial-Chaos Kriging (PCK) metamodel. An accurate predictor can be computed from a given parameter space using a previously developed active learning algorithm, which combines PCK with an adaptive sequential sampling method based on the quad-tree algorithm [4]

The optimization is performed by the Gradient Particle Swarm Optimization (GPSO) which adds a local gradient-based term to the motion equation of particles in the PSO optimization [5]. The gradient computation is usually a heavy burden but thanks to the PCK predictor it can be performed easily. Indeed, the main advantage of using a PCE-based metamodel is its direct analytical expression which allows an easy computation of its gradient [6].

2.2 WPT model

The combination of an already developed active learning metamodelling algorithm with the aforementioned GPSO optimization method has been used for finding an optimal design for the $3F3$ ferrites of an existing WPT system [3] (see figure 1). Thanks to this fast and accurate optimization method, this problem, never treated before on such a WPT system, could be computed easily. The considered relevant parameters, displayed on table 1, are the (x_f, y_f) position of the ferrite along with its dimensions (w_f, h_f, l_f). Both ferrites are taken symmetrical regarding (O, y, z).

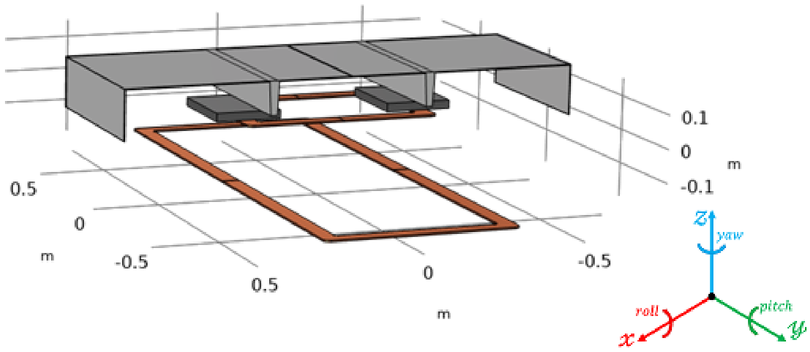

Figure 1: WPT model for the optimisation problem with 3F3 ferrites cores and an optimized shielding structure

The objectives of the geometry optimization are to :

- Maximize: $k = \dfrac{M}{\sqrt{L_R L_T}}$ the coupling factor between the transmitting coil (self-inductance L_T) and the receiving coil (self-inductance L_R) with M the mutual inductance
- Minimize: $V = w_f.h_f.l_f$ the ferrite volume used in the design

3 Results

3.1 Optimization

A prior global sensitivity analysis and single-objective optimization (maximizing k) has been conducted on the metamodel, built with $n_{samples} = 517$ and a $LOO \simeq 6.907 \cdot 10^{-10}$. The results are displayed on table 1. Due to the low influence of the size parameters on the model regarding the ferrite position, an evident factor simplification has been made with x_f and y_f set to their nominal values for the multi-objective optimization.

Table 1: Optimized parameters for maximizing the coupling factor k with their Sobol' indices ($LOO \simeq 6.907 \cdot 10^{-10}, n_{samples} = 517$)

variable	value	S^T	description
w_f	$0.1167\,\text{m}$	$5.856 \cdot 10^{-5}$	ferrite width
h_f	$0.0304\,\text{m}$	$7.004 \cdot 10^{-5}$	ferrite height
l_f	$0.1760\,\text{m}$	$7.727 \cdot 10^{-5}$	ferrite length
$x_f(\Delta x = 0)$	$0.2627\,\text{m}$	0.881	x position of the ferrite
$y_f(\Delta y = 0)$	$-0.0049\,\text{m}$	0.161	y position of the ferrite

For the multi-objective optimization on the size parameters only (w_f, h_f, l_f) for the ferrite cores, an accurate metamodel ($n_{samples} = 35$, $LOO \simeq 3.698 \cdot 10^{-5}$) has been built for an unidimensional output : the coupling factor k. The two objectives are to minimize both $1 - k$ and the ferrite volume V. The Pareto front is displayed on figure 2. Due to convexity of the Pareto front, the knee point solution ($k = 0.0950, V = 5.806 \cdot 10^{-4}\text{m}^3$,, drawn in red on figure 2) has been chosen as the most optimal solution as it minimises the distance to the ideal point $(0, 0)$ for both objectives. The corresponding parameters values and their Sobol' indices are displayed on table 2.

Table 2: Optimized parameters for maximizing the coupling factor k and minimizing the ferrite volume V with their Sobol' indices ($LOO \simeq 3.698 \cdot 10^{-5}, n_{samples} = 35$)

variable	value	S^T	description
w_f	0.246 m	0.876	ferrite width
h_f	0.0102 m	$8.855 \cdot 10^{-3}$	ferrite height
l_f	0.234 m	0.126	ferrite length

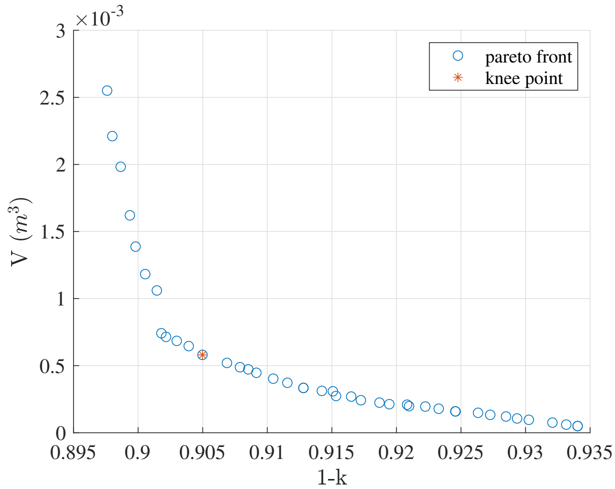

Figure 2: Pareto front for the multi-objective optimization to minimize the ferrite volume V and maximize the coupling factor k

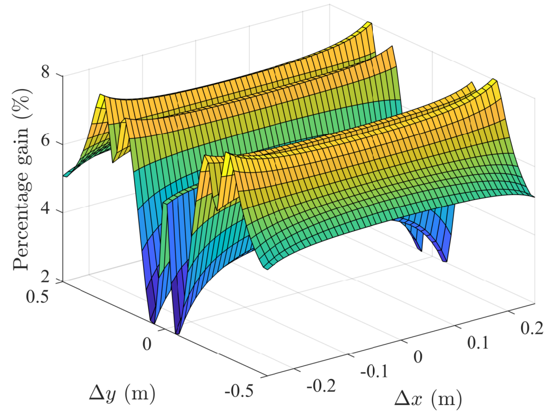

Figure 3: Percentage gain for the coupling factor k with the optimized geometry from the coupling factor with the nominal geometry k_0 against the misalignments Δx and Δy

3.2 Validation

Using the optimized ferrite geometry, for each possible misalignment $(\Delta x, \Delta y)$, the resulting coupling factor $k(\Delta x, \Delta y)$ has been predicted along with its nominal value $k_0(\Delta x, \Delta y)$, using the active learning algorithm with $(\Delta x, \Delta y) \in [-0.25\text{m}, 0.25\text{m}] \otimes [-0.5\text{m}, 0.5\text{m}]$. The gain in percentage $\left(\dfrac{k - k_0}{k_0}\right)$ from the nominal coupling factor is displayed on figure 3. Over the wide domains of variations of Δx and Δy the percentage gain is ranging from 2% to 8% with an average value of 6.1%. Thanks to the optimization, the cost of 3F3 ferrites can be divided by 2 on a practical system using the optimal set of parameters, while not diminishing, but slightly increasing the WPT coupling factor.

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