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— Robust optimization of electromagnetic devices with deterministic models —

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Context

Variability on dimensions or material properties of an electromagnetic device is introduced by the manufacturing process and operational condition [1]. It can introduce significant dispersions on the product performances. With the aim to have a robust optimization of the device, this variability has to be incorporated in the early design stage where a pre-sizing of the device is made by solving an optimization problem. The model of the electromagnetic device has to include uncertainty on design parameters, such as dimensions and material properties, but also uncertainty on operational conditions that are expressed through constraints. Moreover, the objectives of optimization are to minimize a probability of failure or maximize the expectation of performances.

To take into account the uncertainties of the input parameters of a model, the probabilistic approach can be used. The uncertain parameters are then modeled using random variables. The outputs of the model are also random variables. The characterization of such output can be made by Monte Carlo Simulation Method (MCSM) with a large number of model evaluations. Unfortunately, electromagnetic device modeling is very time consuming, particularly in the case of finite element model (FEM). Thus, more effective approaches are required for the robust optimization of electromagnetic devices. Methods based on approximation methods are also proposed [2]. The convergence to the solution is faster than the MCSM but those methods require a stochastic model.

Objective

Another approach is to use a surrogate model that is very fast and can be used in Monte Carlo simulations to compute probability. The surrogate model is a local model built with a reduced number of evaluations of FEM. Surrogate-based optimization is faster and without loss of precision [3].

Recent works [4] also suggest building the surrogate model by using information required during the optimization process, such as gradient of the objectives and constraints functions.

Work steps

The first step is a bibliographical synthesis on robust and reliability-based optimization techniques, surrogate-based optimization, and probability assessment. The similarity of information required for optimization and probability assessment has to be highlighted. The second step is to choose or build benchmarks in order to compare the computing time and precision of the reliability-based optimization techniques. In the third step, the most-promising techniques will be implemented in Matlab language and tested on an analytical benchmark. Finally, a novel approach for reliability-based optimization could be proposed.

References