Surrogates and Infill Criteria to solve Electromagnetic Problems

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***Abstract*—The Surrogate Based Optimization is largely used in engineering design to find optimal performance characteristics of computational expensive simulations such as Finite Element Method (FEM). An original multiple surrogate based optimization criterion is proposed. The approach was tested on Loney's solenoid benchmark problem. Simulation results and comparisons with some traditional Kriging based global optimization (TKO) methods show that the proposed method can be used very effectively in electromagnetic design optimization.**

***Index Terms*—Metamodeling, Optimization.**

I. Introduction

Surrogate Methods become a popular tool to solve electromagnetic optimization problems due to its capability to save computation time, particulary when the FEM is used. This work proposes a multiple surrogate based optimization with two kriging surrogate models and the corresponding infill samping criteria (ISC). One of the surrogates/infill criteria is tuned as a global explorator and chooses the region where the other surrogate/infill criterion, designed to improve the local exploitation, makes a local search to find the optimum.

II. Proposed Searching Method

The generic Multiple based on Efficient Global Optimization method (MEGO) used in this work is a sampling strategy that aims the identification of the global optimum of a deterministic function based on ISC and can be summarized as follows: a) Start with a set of points (SP) usually arranged in a space-filling pattern using some DoE technique (e.g., latin hypercube sampling) and fit a global Kriging model to this set; b) Then pick the next design to be evaluated (in a computer experiment) by optimizing an ISC (using a global search criterion); c) With this point and a subset of points highly correlated with it, withdrawn from SP, fit a new local Kriging model; d) Then add an evaluation to the subset of points, at the location where a new ISC is optimized (using a local search criterion), and update the local Kriging model; e) Repeat these last steps until the evaluation converge to a minimum; f) Next add the recent sampled points to SP and repeat all these steps until some stopping criterion is achieved.

In the problem that follows, MEGO was used in two different configurations, one with a lower confidence bounding (LCB) ISC [1] and the other one with a modified form of WB_2[2], here called Weighted WB_2 (WWB_2). In both configurations, the ISC have parameter values that allow them to make a global (steps a-b) and a local search (steps c-e). The WWB_2 is a ISC weighted sum of the Kriging predicted value and of the Expected Improvement function (EI)[1].

III. Loney's Solenoid Benchmark Problem

The two MEGO and the TKO with EI, LCB and WB_2 infill criteria [2] have been applied to solve the optimal design problem for the Loney's solenoid problem [3]. The optimization problem consists in determining the separation (s) and size of two correcting coils (l) in order to minimize the dishomogeneity of the magnetic induction, $F(s,l)$, within a subregion of the axis of the main solenoid. In the domain of F there exists three different basins of attraction of local minima corresponding to the values of $F > 4\text{x}10^{-8}$ (High Level region-*HL*), $3\text{x}10^{-8} < F < 4\text{x}10^{-8}$ (Low Level region-*LL*) and $F < 3\text{x}10^{-8}$ (Global Minimum region-*GM*). The simulation results of 100 runs for each optimization method, with a stopping criterion of 200 objective function evaluations for each run, are reported in Table I. The results show that

TABLE I
Simulation Results of $F(s,l) \times 10^{-8}$ in 100 runs

Method	F_{min}	F_{avg}	F_{max}	n_{GM}	n_{LL}	n_{HL}	$t_{avg}(s)$
EI	3.77	7.83	30.28	0	7	93	522
LCB	3.22	7.42	66.81	0	6	94	236
WB2	3.59	8.57	186.45	0	6	94	255
MEGO-LCB	2.59	3.88	6.28	4	57	39	104
MEGO-WWB_2	**2.15**	**3.77**	**4.89**	**6**	65	**29**	**97**
Tribes-1 [3]	2.27	3.65	4.51	9	88	3	-
Tribes-2 [3]	2.06	3.49	3.95	18	82	0	-

the proposed MEGO-LCB and MEGO-WWB_2 outperform the TKO methods in all items of the table. As shown, the TKO methods can hardly find solutions in the *LL* region (only 7 for EI, against 57 and 65 for MEGO-LCB and MEGO-WWB_2, respectively), their best values are similar to the average values of the proposed approach, their worse values are in average more than 10 times bigger than the proposed approach worse values, and all this for a run average CPU time, that is approximately between 2.5 and 5 times higher than the proposed approach. The results obtained with the proposed approach seem to be also very competitive when compared with other optimization algorithms that do not use a sample strategy as Particle Swarm Tribes[3]. The Tribes-1 and Tribes-2 values were obtained with 1000 and 2000 evaluations.

References

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