Comparison of Efficient Global Optimization and Output Space Mapping on the bi-objective optimization of a safety isolating transformer

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Abstract — The optimal design of electromagnetic devices needs to address two particular aspects: the use of accurate tools, and the limited time budget affected to this task. In order to respond to these issues, two low evaluation budget multi-objective optimization techniques - Efficient Global Optimization (EGO) and Output Space Mapping (OSM) - are investigated in this paper with regard to a bi-objective optimization benchmark. The device to be optimally sized is a low-voltage safety isolating transformer, represented through two levels of modeling: coarse (analytical model) and fine (numerical 3D FEM). A new idea for making use of the synergies given by the combined use of the two available models of the device within the EGO algorithm is proposed. The bi-objective comparison of the two techniques on the transformer benchmark is discussed.

I. INTRODUCTION

With the development of powerful computational resources, the use of CAD software becomes more and more frequent in product design. The integration of CAD tools directly into the optimization process replaces the classical trial-and-error process, though allowing for a non-negligible design time saving.

Expressing all the goals of a design within the form of a single objective (SO) function is not always obvious, nor desired, sometimes. The designer may wish for a set of compromise designs, to make his final choice. In order to obtain a set of trade-off solutions, a multi-objective (MO) technique is to be used. However, the amount of model evaluations required by a MO technique, though of total computing time, is more substantial than for the SO case.

The two low evaluation budget techniques considered in this paper are the Efficient Global Optimization (EGO) and the Output Space Mapping (OSM). Both techniques aim to obtain satisfactory results with a minimum number of FEM evaluations. The former, EGO, uses Kriging models as surrogates for fine model, in order to guide the search for optimal points. Recently, EGO was used for the optimization of two electromagnetic devices: a microwave filter and a textile antenna [1]. The latter, OSM, maps the fine model's responses at the site of the optimal solution using a coarse model, an analytical model in this case. The optimization is done using the coarse model, which is corrected using the fine model. The effectiveness of this technique was proven through the application on two electromagnetic test problems in [2]. A first comparison of the two optimization techniques was carried on for the SO case [3]. The single-objective comparison of the two optimization techniques, over the considered benchmark, revealed the domination of OSM over EGO in terms of total fine model evaluations. The main causes for the OSM's advance over EGO were the good quality of the analytical model and the highly constraint character of the benchmark. A well-known issue of the EGO algorithm is represented by its constraint handling difficulty. In this paper, the repositioning of the two algorithms, in the light of the new scenario of bi-objective comparison, is studied.

The paper is organized in three parts. First, the considered optimization benchmark is presented. Secondly, the two optimization techniques are briefly presented. To conclude, the comparison of the two techniques through the new scenario of bi-objective benchmark is discussed.

II. OPTIMIZATION BENCHMARK

The optimization problem considered in this paper consists of the optimal sizing of a single-phase low voltage safety isolating transformer proposed as benchmark to the electromagnetic community [4]. The optimization problem formulation is expressed in (1).

$$
\begin{aligned}
&\underset{\mathbf{x}}{\text{Minimize}}\, F(\mathbf{x}) = \begin{bmatrix} f_1(\mathbf{x}) \\ f_2(\mathbf{x}) \end{bmatrix} = \begin{bmatrix} mass(\mathbf{x}) \\ 1-\eta(\mathbf{x}) \end{bmatrix} \\
&s.t.\quad T_{copper} \le 120°C \quad T_{iron} \le 100°C \quad f_1 \le 0.5 \\
&\qquad \frac{I_{10}}{I_1} \le 0.1 \quad \frac{DV_2}{V_2} \le 0.1 \quad f_2 \le 0.5 \\
&with \quad \mathbf{x} = [a, b, c, d, n_1, S_1, S_2] \\
&\quad 3\,mm \le a \le 30\,mm \quad 14\,mm \le b \le 95\,mm \\
&\quad 6\,mm \le c \le 40\,mm \quad 10\,mm \le d \le 80\,mm \\
&\quad 0.15\,mm^2 \le S_1 \le 19\,mm^2 \quad 200 \le n_1 \le 1200 \\
&\quad 0.15\,mm^2 \le S_2 \le 19\,mm^2
\end{aligned}
\qquad (1)
$$

The device to be optimally sized is represented by two models, with different levels of accuracy: a coarse - analytical model and a fine - numerical (3D finite element) model. The 3D FE model is in fact a coupling model of 3 sub-models: two 3D magnetic models (full-load and no-load), and a 3D thermal model. The coupling between the 3 sub-models is managed through an IDF multi-disciplinary formulation. One coupling model evaluation takes up to 2 hours. The analytical model is less accurate than the numerical one, but it is able to capture the trend of the objective and constraint functions. The bi-objective optimization problem resides in determining the optimal mass-efficiency trade-off configurations of the device with respect to 6 geometrical and physical constraints. One particular feature of the benchmark is the extremely narrow feasible domain sub-space, which makes difficult the solving of the optimization problem [3].

III. EFFICIENT GLOBAL OPTIMIZATION

The Efficient Global Optimization (EGO) is a surrogate-assisted optimization technique which uses Kriging models as surrogates for the fine model. The fine model is evaluated in order to build Kriging surrogate models for each objective and constraint function of the optimization problem. Along with the prediction of the objective/constraint function, the Kriging model also supplies an estimate of the prediction error. The two measures are used within the formulation of an infill point selection criterion (IC) which guides the search for optimal solutions and improves the surrogate models global accuracy.

The pseudo-distance criterion employed here naturally balances the search for optimal solutions and model improvement. The bi-objective character of the problem is though naturally accounted for by the multi-objective infill criterion. In order to improve the quality of the surrogate models, and to make use of the information given by the analytical model, the coarse model was integrated within the EGO formulation. This way, the global trend of the objective/constraint functions is given by the analytical model; the Kriging models fit only the discrepancy between the fine and the coarse model, as in (4).

$$\delta(\mathbf{x}) = y_f(\mathbf{x}) - y_c(\mathbf{x}) \quad (3)$$

$$\hat{y}_f(\mathbf{x}) = y_c(\mathbf{x}) + \hat{\delta}(\mathbf{x}) \quad (4)$$

where $\delta(\mathbf{x})$ is the discrepancy between the two models – fine and coarse, $y_f(\mathbf{x})$ represent the outputs of the fine model, $y_c(\mathbf{x})$ are the outputs of the coarse model, $\hat{\delta}(\mathbf{x})$ is the Kriging prediction of the discrepancy between the two models, and $\hat{y}_f(\mathbf{x})$ is the surrogate model prediction of the fine model's outputs. This improvement allows for a better prediction of the constraint functions, which is a key point of the optimization benchmark.

IV. OUTPUT SPACE MAPPING

The Output Space Mapping (OSM) technique is a space projection method which is a common approach for the optimization of electromagnetic devices using accurate, but time consuming models. The technique requires two models of the device to be designed, with different levels of accuracy. OSM aligns iteratively the coarse model and the fine one by adding correctors to the coarse model. The optimization is carried on with the coarse model (analytical in this case) and the results are then validated using the fine model. The coarse model is then corrected in order to map the fine model's output.

In order to account for the two objectives of the optimization benchmark, an epsilon-constraint technique was set in place. The bi-objective optimization problem is transformed in a constrained single-objective problem by keeping η as objective and passing the *mass* in constraint. The rephrased optimization problem is expressed as in

$$\underset{\mathbf{x}}{\text{Maximize}}\ f\big(\mathbf{x},\theta(\varepsilon)\big) = \eta\big(\mathbf{x},\theta(\varepsilon)\big) \quad (2)$$

$$s.t.\ \begin{cases} c\big(\mathbf{x},\theta(\varepsilon)\big) = mass\big(\mathbf{x},\theta(\varepsilon)\big) \le \varepsilon \\ g_i\big(\mathbf{x},\theta(\varepsilon)\big) \le 0 \qquad i = 1..6 \end{cases}$$

where $\theta(\varepsilon)$ represents the vector of correctors, $g_i\big(\mathbf{x},\theta(\varepsilon)\big)$ represent the 6 constraints of the initial optimization problem, and ε represents different limit levels for the mass, used in order to spread the solutions along the Pareto front. For each value of ε, a new single-objective optimization takes place, determining a new point on the Pareto front.

V. DISCUSSION

To improve EGO's constraint handling, two ideas are tested. First, the analytical model is introduced within EGO to improve global surrogate model accuracy. Then, an allowed constraint overpassing progressive reduction scheme is applied. A preliminary comparison of the two algorithms is visually presented in Fig. 1. One can see that the two algorithms face some difficulties in finding non-dominated solutions with smaller mass values. Also, for about the same number of fine model evaluations, the EGO's Pareto front is close to the one obtained with OSM. The repositioning of the two techniques, face to the new bi-objective scenario and the stated improvements will be developed. Whilst OSM uses a transformation technique (epsilon constraint) and interpolation models of the correctors in order to account for the two objectives, the MO character of the problem is naturally accounted for by the expression of EGO's MO infill criterion, leading though to less fine model evaluations.

VI. REFERENCES

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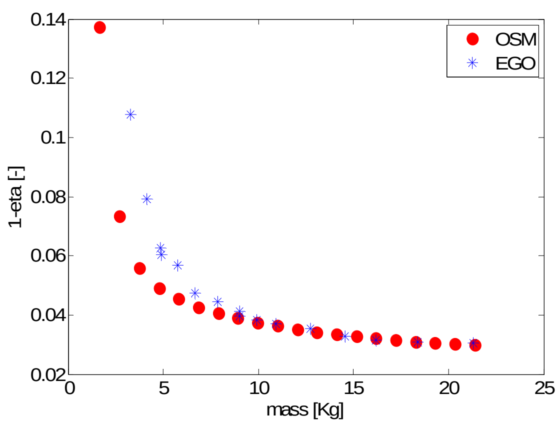

Fig. 1. Pareto front of the bi-objective transformer benchmark