Improved Sequential Optimization Method for Multiobjective Electromagnetic Device Design Problems

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Abstract — In this paper, we extend sequential optimization method (SOM) to deal with multiobjective optimization design problems of electromagnetic devices. Firstly, we construct Kriging models for all the objectives and constraints, get a surrogate multiobjective optimization model. Secondly, we implement multiobjective optimization algorithm for the gained surrogate model and get the Pareto optimal solutions. Thirdly, new updating method of the design space is presented with the comparison of the Pareto points between the surrogate multiobjective model and finite element model (FEM). Finally, to illustrate the efficiency of the proposed method, a classic test function and the TEAM Workshop Problem 22 are investigated.

I. INTRODUCTION

Many electromagnetic devices are designed by means of finite element model (FEM) with direct optimization algorithms, such as genetic algorithm. However, the higher the accuracy of design objective is, the more expensive the direct optimization is expected. Sometimes, this cost may be prohibitive, especially for the three dimensional complex design problems. As an alternative, many approximate models, such as response surface model, are employed to ease computational burden of direct optimization method. However, they are proved fast, but not very accurate [1].

In order to make up for the low fidelity of approximate model and the expensive cost of optimization algorithm, we have introduced sequential optimization method (SOM) to solve such problems [2], [3]. SOM can optimize the model and algorithm simultaneously and it was proved to be efficient for the electromagnetic design problems. However, SOM has only discussed for single objective problems. There are many multiobjective problems in the practical application, so we extend SOM to solve those problems in this work.

II. MULTIOBJECTIVE SOM

Fig. 1 is the flowchart of the extended SOM for multiobjective problems. There are mainly four steps.

Firstly, we constructed the surrogate multiobjective model. In traditional methods, all the models are constructed with the same sample points. However, the optimal points for these objectives are different, so we should sample different data for each objective to improve the model accuracy. Fortunately, SOM can provide different sample data. After this process, we can get the surrogate multiobjective optimization model as

$$\begin{aligned} \min: & \ \tilde{f}_1(\vec{x}), \tilde{f}_2(\vec{x}), ..., \tilde{f}_m(\vec{x}) \\ \text{s.t.}: & \ \tilde{g}_i(\vec{x}) \le 0, \quad , \\ & \ \tilde{h}_j(\vec{x}) = 0 \end{aligned} \tag{1}$$

Secondly, we implemented the multiobjective optimization of model (1) with non-dominated sorting genetic algorithm II (NSGA II) [4]. The gained Pareto optimal points set are denoted as $P_a^{(t)}$. Then these points with FEM are computed and we can get a subset $P_r^{(t)}$ in which the points are also the Pareto solutions for the FEM.

Thirdly, we updated the surrogate multiobjective model with new space updating strategy similar to space reduction strategy in SOM. This is the most important step in this method. We use the following strategy to determine the step size for each variable,

$$r^{(t)} = N(P_r^{(t)}) / N(P_a^{(t)}) . \tag{2}$$

$r^{(t)}$ is a measure factor for the degree of approximation between surrogate model and FEM. $r^{(t)} \to 1$ means a higher accuracy of the model. The aim of the space updating process is to maximize this value.

Finally, we terminated the optimization process with the step size $l^{(t)}$ of the each variable. If $|\Delta l^{(t)} / l^{(1)}| \le \varepsilon$, we stop and output the optimal value. Otherwise, the model with the Pareto points is updated.

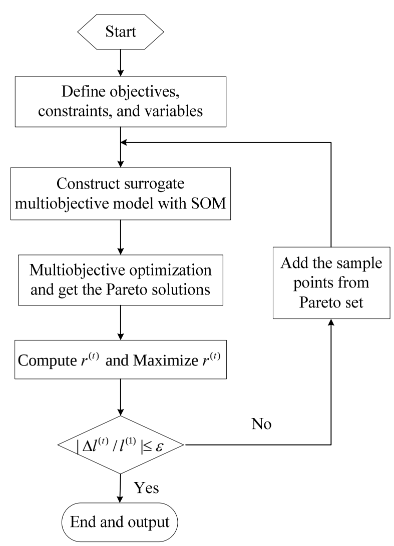

Fig. 1. Flowchart of the multiobjective SOM

III. EXPERIMENTS

A. *Test function*: *POL function*

POL function is a classic test function for multiobjective optimization [4]. It has the form as

$$\min:\begin{cases} f_1(x_1,x_2)=1+(A_1-B_1)^2+(A_2-B_2)^2 \\ f_2(x_1,x_2)=(x_1+3)^2+(x_2+1)^2 \end{cases} \quad (3)$$

$$A_1=0.5\sin1-2\cos1+\sin2-1.5\cos2,$$
$$A_2=1.5\sin1-\cos1+2\sin2-0.5\cos2,$$
$$B_1=0.5\sin x_1-2\cos x_1+\sin x_2-1.5\cos x_2,$$
$$B_2=1.5\sin x_1-\cos x_1+2\sin x_2-0.5\cos x_2,$$
$$-\pi\le x_1,x_2\le\pi.$$

B. *TEAM Problem 22*

This benchmark problem was proposed for the optimization of superconducting magnetic energy storage (SMES) [5], [6]. Fig. 2 shows the design model. All parameters should be optimized to minimize the mean stray fields (B_{stray}) while keeping the stored energy (E) close to 180 MJ and a quench condition. B_{stray} is root mean square of 21 equidistant points on lines a and b. Two objectives and a constraint are defined as follows.

$$\min:\begin{cases} f_1(\vec{x})=B_{stray} \\ f_2(\vec{x})=|E-180| \end{cases}$$
$$s.t.\quad g_1(\vec{x})=B_{max}-4.92+\beta\le 0\ . \quad (4)$$
$$g_2(\vec{x})=f_2/180-\lambda\le 0$$

It should be noted that there are two additional parameters β and λ. β is used to ensure the robustness of optimal solutions, and 5% is selected in this work. As the main objective of this problem is the energy, we only need to consider the Pareto solutions satisfying that $\lambda=5\%$.

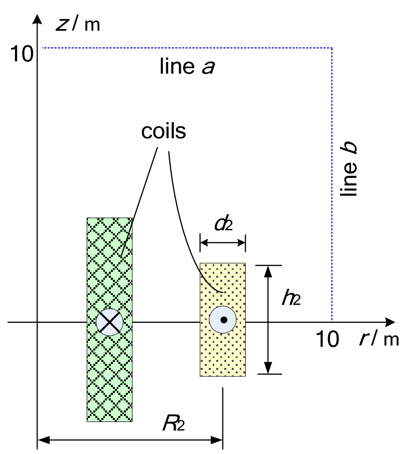

Fig. 2. Design model of three variables case of SMES

IV. DISCUSSIONS AND RESULTS

Fig. 3 is the Pareto solutions for the POL function gained by three model updating processes. From the figure, we can see that the Pareto curve from the last surrogate model fits that from the true function very well.

Fig. 4 is the Pareto solutions for SMES gained by six model updating processes. The Pareto solutions from the last Kriging model and FEM model are illustrated in the figure. From the figure, we can see that the proposed method can also provide good solutions. Furthermore, the needed FEM sample points is 317, which is less than 1/10 of that from direct optimization with NSGA II, which is 4630.

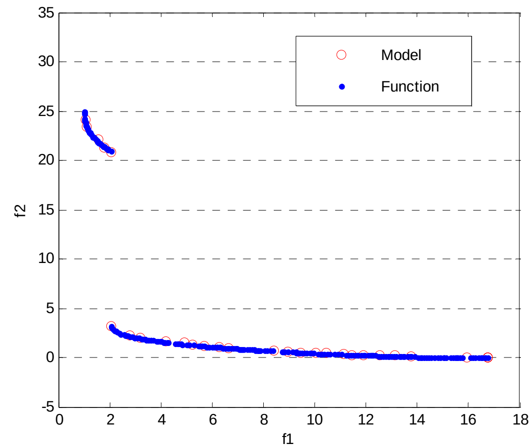

Fig. 3. Pareto solutions for POL function

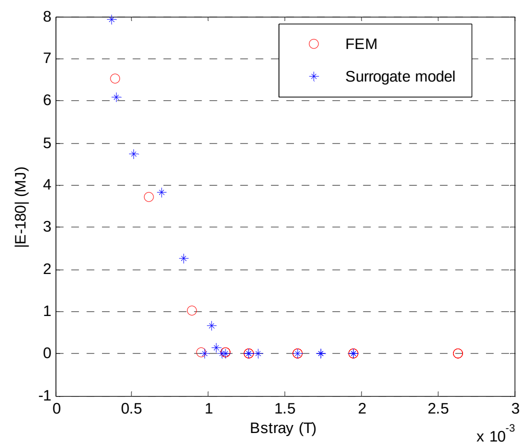

Fig. 4. Pareto solutions for SMES

V. REFERENCES

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