Utilizing Adaptive Dynamic Taylor Kriging Assisted Multi-Objective DE Algorithm for Optimization Design of Electromagnetic Device

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***Abstract*—A multi-objective global optimization strategy is developed by incorporating an adaptive dynamic Taylor Kriging (ADTK) into an improved multi-objective differential evolution algorithm (MODE) to achieve a numerically efficient multi-objective optimization algorithm. The basis functions of the ADTK are optimally, adaptively and dynamically selected so that the Kriging model may have better accuracy than any other Kriging model, and the MODE has an improved mutation algorithm.**

***Index Terms*—Adaptive sampling, basis function, Kriging, multi-objective optimization.**

I. Introduction

Most multi-objective optimal designs of electromagnetic devices have primarily been developed based on the use of non-deterministic optimization algorithms such as genetic algorithm, particle swarm optimization (PSO) and differential evolution (DE) and finite element method (FEM) for the calculation of objective function values [1]. In the designs, however, the computational cost of evaluating the objective function values is in general very expensive.

This paper, therefore, proposes a novel adaptive dynamic Taylor Kriging (ADTK) to provide accurate surrogate objective functions with minimum required number of samples, and it is incorporated into multi-objective differential evolution (MODE) algorithm. In the ADTK the basis functions are optimally selected by using binary version of PSO (BPSO). A reliable guidance for the minimum required number of sampling is also proposed.

II. ADTK Assisted MODE Algorithm

A. Adaptive dynamic Taylor Kriging methodology

With the N sampling data, the ADTK satisfies:

$$\sum_{i=1}^{N}\lambda_i(\mathbf{x})b_k^*(\mathbf{x}_i)=b_k^*(\mathbf{x}),\quad k=0,1,\cdots,K \tag{1-a}$$

$$\begin{aligned}&\sum_{i=1}^{N}\lambda_i Cov[Z(\mathbf{x}_i),Z(\mathbf{x}_j)]+\sum_{k=0}^{K}\delta_k b_k^*(\mathbf{x}_j)\\&\quad=Cov[Z(\mathbf{x}),Z(\mathbf{x}_j)],\quad j=1,\cdots,N\end{aligned} \tag{1-b}$$

where the basis function, $b_k^*(\mathbf{x})$, is optimally selected by BPSO [2].

Then, if the fitting error of ADTK model is not small enough, new sampling points are selected adaptively among the test points, $\mathbf{X}_{\text{test}}$, based on the following rule using (2)

$$\mathbf{X}_{\text{new}}=\left\{\mathbf{x}\,\middle|\,E_{\text{fit}}(\mathbf{x})>\varepsilon,\ \mathbf{x}\in\mathbf{X}_{\text{test}}\right\} \tag{2}$$

where the tolerance ε is, in this paper, set to 10^{-4} and $E_{\text{fit}}(\mathbf{x})$ is the fitting error for the test point [2].

Table I compares the multi-objective optimization results obtained by using various methods including the proposed ADTK for an analytic function.

$$\begin{aligned}&\min\ f_1(x,y)=x^2+y^2\\&\min\ f_2(x,y)=(x-5)^2+(y-5)^2\\&s.t.\ -5\le x_1,\,x_2\le 10\end{aligned} \tag{3}$$

From the results, the proposed ADTK gives almost same optimal solution with true one. This means the ADTK has a higher fitting accuracy even with relatively small number of samples.

B. Improved MODE Assisted by ADTK

The overall flow of the proposed optimization is summarized as follows.

Step 1: Generate sampling data in the whole design space.
Step 2: Generate randomly the population and evaluate their objective and constraint function values by the ADTK.
Step 3: Generate mutant population by adaptive mutation (4).
Step 3: Find the Pareto-optimal solutions by using the improved MODE with ADTK.
Step 4: Terminate if the stopping criteria are satisfied.
Step 5: Insert new sampling data and go to *Step* 2.

$$\mathbf{v}_{i,g}=\mathbf{x}_{i,g}+F_1\cdot(\mathbf{x}_{r1,g}-\mathbf{x}_{r2,g})+F_2\cdot(\mathbf{x}_{r1,g}-\mathbf{x}_{\text{best},g}) \tag{4}$$

where mean and standard deviation of F_1 is decreased, while those of F_2 is increased within [0.5, 1.0] by iteration increasing.

On the stopping criteria and insertion of new sampling data will be discussed in detail in the version of full paper.

References

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TABLE I
OPTIMIZATION RESULTS FOR ANALYTIC FUNCTION

Algorithm	Extreme solutions		FEA calls	
	($f_{1,\min}$, f_2)	(f_1, $f_{2,\min}$)	f_1^*	f_2^*
MODE	(0.022, 50.076)	(48.736, -0.018)	600	600
OK-MODE	(0.105, 46.751)	(45.346, 0.206)	50	50
ADTK-MODE	(0.085, 49.557)	(48.736, -0.113)	35	43

* Number of function evaluations