A Novel Multimodal Optimization Algorithm Using a Subgroup Concept for the Design of Electric Machines

Han-Kyeol Yeo[1], Hyeon-Jeong Park[1], Dong-Kuk Lim[1], Sang-Yong Jung[2], Jong-Suk Ro[3], and Hyun-Kyo Jung[1]

[1]Department of Electrical and Computer Engineering, Seoul National University, Seoul 08826, Korea
[2]School of Electronic and Electrical Engineering, Sungkyunkwan University, Suwon 16419, Korea
[3]School of Electrical and Electronics Engineering, Chung-Ang University, Seoul 06974, Korea

The design of electric machines is a multivariable and multimodal problem which requires much time to find the optimal design results. To address this problem, we propose a novel multimodal optimization algorithm using a subgroup concept (MS), which uses a grey wolf optimizer, a subgroup, a Kriging surrogate model, a scout, and an adaptive coefficient. In multivariable and multimodal design problems, the proposed novel algorithm is more rapid, exact, and reliable compared to the conventional algorithms such as niching genetic algorithm (NGA) and auto tuning NGA. The validity of the proposed method was confirmed via test functions. For the verification of the application to electric machines, interior permanent-magnet synchronous motors for electric vehicles was designed using the proposed algorithm.

***Index Terms*—Grey wolf optimizer (GWO), IPMSM, Kriging, multimodal optimization, surrogate model.**

I. Introduction

THE finite-element method (FEM) is generally used for the design of electric machines, as it can precisely calculate the performances of electric machines with complex structures and easily take into account magnetic saturation effects [1]. However, the FEM is too time-consuming directly to determine many design variables via a trial-and-error method. Therefore, optimization algorithms are widely used in order to reduce the computational costs significantly by reducing the number of objective function evaluations by the FEM [2]-[4].

Most electric machine designs are multivariable and multimodal optimization problems given that there are many design variables and conflicting objectives. Conventional metaheuristic algorithms have been improved in terms of their ability to solve multimodal optimization problems such as a niching genetic algorithm (NGA) [3], [4]. More appropriate and feasible designs of electric machines can be obtained via these improved algorithms, which provide diverse solutions to multimodal optimization problems.

The recently proposed grey wolf optimizer (GWO) is a metaheuristic algorithm inspired grey wolves [5]. This algorithm mimics the social hierarchy and hunting mechanism of grey wolves. The competitive performance of the GWO was verified using various test functions. However, the GWO cannot guarantee to find local optima as well as a global optimum, since solutions of that tend to converge into a global optimum. In other words, it is impossible for the GWO to solve multimodal and multiobjective optimization problems.

To solve these problems of the conventional GWO, we propose a novel multimodal optimization algorithm by using the GWO, a subgroup concept, a Kriging surrogate model, scouts for diverse solutions, and an adaptive coefficient for balance between exploration and exploitation. Hence, we termed the proposed algorithm as a multimodal optimization algorithm using a subgroup concept (MS) in this paper. The performances as the convergence speed, accuracy, and the reliability of the proposed MS is verified through the application into mathematical test functions and a practical electric machine.

II. The Proposed MS

The proposed MS utilizes subgroups determined by a Kriging surrogate model in order to effectively search for multiple solutions and achieve a rapid convergence. The proposed algorithm can secure the diversity of solutions by using scouts directly exploring to non-search area instead of inefficient methods such as mutation in a genetic algorithm and a mathematical model of obstacles to approaching prey in the GWO. Moreover, an adaptive coefficient is used in the MS for balancing exploration and exploitation effectively, which is defined considering a degree of convergence. The flowchart of the MS is shown in Fig. 1 and the detailed procedure of that is explained in Table I.

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}\cdot\vec{D} \tag{1}$$

$$\vec{A} = 2a\vec{r}_1 \tag{2}$$

$$\vec{D} = \left|\vec{X}_p(t) - \vec{X}(t)\right| \tag{3}$$

where t indicates the current iteration, $\vec{A}$ is a coefficient vector, $\vec{X}_p$ is the position vector of the prey, $\vec{X}$ is the position vector of a grey wolf. $\vec{r}_1$ is random vectors in [-1,1].

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{4}$$

$$\vec{X}_1(t+1) = \vec{X}_\alpha(t) - \vec{A}_1\cdot\vec{D}_\alpha, \quad \vec{D}_\alpha = \left|\vec{X}_\alpha(t) - \vec{X}(t)\right| \tag{5}$$

$$\vec{X}_2(t+1) = \vec{X}_\beta(t) - \vec{A}_2\cdot\vec{D}_\beta, \quad \vec{D}_\beta = \left|\vec{X}_\beta(t) - \vec{X}(t)\right| \tag{6}$$

$$\vec{X}_3(t+1) = \vec{X}_\delta(t) - \vec{A}_3\cdot\vec{D}_\delta, \quad \vec{D}_\delta = \left|\vec{X}_\delta(t) - \vec{X}(t)\right| \tag{7}$$

where $\vec{X}_\alpha$, $\vec{X}_\beta$, and $\vec{X}_\delta$ are the position vectors of *α*, *β*, and *δ*.

TABLE I
PROCEDURE OF THE PROPOSED MS

Step 1 : Definition of basic parameters

The population number and the range of the design variables is set, and *a* is initialized to 2. *a* is an adaptive coefficient balancing exploration and exploitation, which is updated considering a degree of convergence in step 7.

Step 2 : Generation of initial samples

The initial samples are randomly generated in the predefined search region and their objective function values are calculated.

Step 3 : Construction of Kriging surrogate model

The Kriging interpolation method is known for a method which can efficiently approximate complex functions [6]. The performances of optimization algorithms can be improved by utilizing the Kriging surrogate model properly. In this step, the surrogate model is obtained in the predefined search region using the all sample data calculated in advance.

Step 4 : Determination of peaks and subgoups

The local peaks are estimated using the Kriging surrogate model, of which the objective function values of all peaks is calculated. All peaks have their respective subregions in the form of a circle. Each radius of circles is determined by using the distance between each peak and the nearest peak of the peak. Furthermore, the radius of a peak is set larger when the objective function value of a peak is better than that of the nearest peak of the peak. Each subgroup is composed of all populations in each subregion.

Step 5 : Determination of social hierarchy in main group and subgoups

The social hierarchy are composed of four types in this case alpha (*α*), beta (*β*), delta (*δ*), and omega (*ω*). The main group is composed of all of the conventional populations and the updated peaks. The hierarchy of the main group can be simply modeled by regarding the fittest solution, the second best solution, and the third best solution in the main group as the global *α*, *β*, and *δ*, respectively. In each subgroup, the best, the second, and the third best solutions in the conventional populations and the updated peak are determined as the local *α*, *β*, and *δ*.

Step 6 : Update of populations by encircling prey, hunting, and scouting

Encircling prey can be modeled by using (1)-(3) modified from [5]. In hunting stage, it is assumed that the hunt is guided by *α*, *β*, and *δ* and they have better information about location of prey. Therefore, the final position of a solution can be defined using (4)-(7) modified from [5]. The procedures of encircling prey and hunting are conducted using the local *α*, *β*, and *δ* in each subgroup respectively. The populations not included in any subgroups are updated using the global *α*, *β*, and *δ*.

There is no random factor except for $\vec{A}$ in order to minimize inefficient searches for exploration. Instead, the simple and effective exploration is conducted by scouts. The scouts is defined as grey wolves exploring non-search areas in this paper. The scouts perform an important role to secure the diversity of solutions, of which locations are determined in the sparse region.

Step 7 : Update of *a*

a of the conventional GWO is defined by iteration without consideration of a degree of convergence, although *a* is a crucial factor to balance exploration and exploitation. In the MS, *a* is properly determined by a degree of convergence, which is calculated by using the differences between values evaluated by the Kriging method and real values in all populations updated in the previous step.

Step 8 : Convergence check

If the termination criteria is met, the procedure is finished. Otherwise, repeat the procedure from step 3.

III. NUMERICAL TESTS AND RESULTS

The superiority of the proposed algorithm in terms of the optimization time and accuracy was confirmed by comparing the proposed method with the NGA and an auto-tuning NGA which are generally used for the multivariable and multimodal problem. Furthermore an interior permanent-magnet synchronous motor for an electric vehicle is optimally designed using the proposed algorithm to validate the possibility of its application to a practical machine. Fig. 2 shows a graph obtained using the MS. Detailed results will be presented in the full paper.

IV. CONCLUSION

In this paper, a novel optimization algorithm MS is proposed for a multivariable and multimodal problem which requires much time to find the optimal design result. It is remarkable in the aspect that the performance of the proposed MS algorithm is superior to the widely used conventional algorithms such as a NGA and an auto tuning NGA in the aspect of the convergence speed, accuracy, and reliability. Hence, this research is noteworthy in that the rapid and reliable optimization of an electric machine is possible using the proposed MS algorithm.

REFERENCES

[1] R. P. Deodhar, D. A. Staton, T. M. Jahns, and T. J. E. Miller, "Prediction of cogging torque using the flux-MMF diagram Technique," *IEEE Trans. Ind. Appl.*, vol. 32, no. 3, pp. 569-576, May/Jun. 1996.

[2] C. E. Klein, E. H. V. Segundo, V. C. Mariani, and L. S. Coelho, "Modified social-spider optimization algorithm applied to electromagnetic optimization," *IEEE Trans. Magn.*, vol. 52, no. 3, Mar. 2016, Art. ID 7208304.

[3] F. Campelo, F. G. Guimaraes, H. Igarashi, J. A. Ramirez, and S. Noguchi, "A modified immune network algorithm for multimodal electromagnetic problems," *IEEE Trans. Magn.*, vol. 42, no. 4, pp. 1111-1114, Apr. 2006.

[4] E. Dilettoso and N. Salerno, "A self-adaptive niching genetic algorithm for multimodal optimization of electromagnetic devices," *IEEE Trans. Magn.*, vol. 42, no. 4, pp. 1203-1206, Apr. 2006.

[5] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in Engineering Software*, vol. 69, pp. 46-61, Mar. 2014.

[6] A. Gonzalez, C. Hernandez, and M. A. Arjona, "A novel high-efficiency parallel-winding connection for a three-phase induction motor fed by a single-phase power supply," *IEEE Trans. Energy Conv.*, vol. 29, no. 2, pp. 269-277, Jun. 2014.

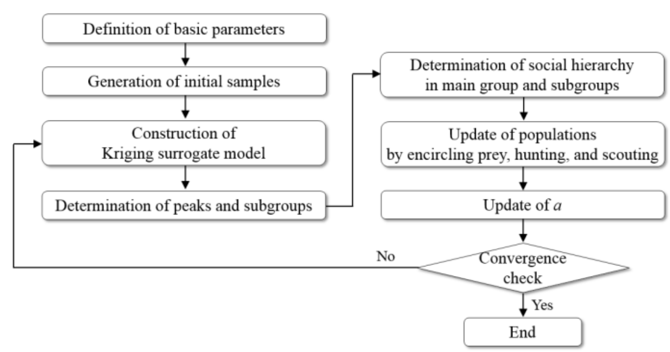
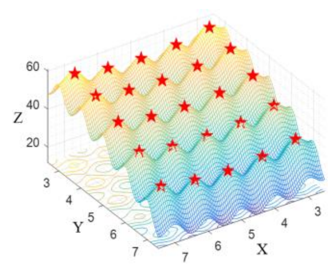


Fig. 1. Flowchart of MS.



	NGA	Auto tuning NGA	Proposed MS
No. of searched peaks	25	25	25
No. of function calls	7821	4586	550

$$f(x,y) = 50 - (x-2)^2 + 5\cos\{2\pi(x-3)\} + (y-5)^2 + 3\cos\{2\pi(x-3)\}, \quad (2.5 \le x, y \le 7.5)$$

Fig. 2. Optimization result for a test function.