A New Multimodal Optimization Approach and Its Application to the Design of Electric Machines

Chung-Hee Yoo [1]

[1]The 1st R&D Institute, Agency for Defense Development, Daejeon 34186, Korea, chyooch37@naver.com

The optimal shape and parameter search during the design of an electric machine is a nonlinear, multivariable and multimodal optimization problem that requires a great deal of computation time when calculating electromagnetic fields. To overcome these problems effectively, this paper proposes a new evolutionary multimodal optimization algorithm based on the water cycle algorithm and aided by a surrogate model using the theory of compressed sensing. Its efficiency is demonstrated by assessing the optimization results for test functions. Moreover, to evaluate the feasibility of its application to an electromagnetic problem, a permanent magnet machine is designed using the proposed algorithm. The obtained results confirm that the proposed method is more effective and efficient than other existing approaches.

***Index Terms*— Electric machine design, evolutionary algorithm, multimodal optimization, surrogate model**

I. INTRODUCTION

IN THE AREA of electric machine design, there are many design parameters, and their nonlinear behaviors must be considered as well to obtain reliable results. Furthermore, given that the structures of up-to-date electric machines are more complex than those of traditional machines, more accurate electromagnetic field analysis methods, such as 3D FEM, are needed. Therefore, electric machine designs are highly nonlinear, multivariable and multimodal optimization problems. Moreover, the actual computation time and costs associated with optimization increase significantly depending on the number of objective function evaluations [1].

To find effective solutions to such problems, it is often desirable to obtain not only the global optimum but also the local optima because various solutions provide insight into the nature of the target space and suggest alternative solutions under limited conditions [2]. This makes multimodal optimization the most feasible approach to solve these problems.

In recent years, many multimodal optimization algorithms based on evolutionary algorithms have been widely studied [3]-[4]. Most conventional evolutionary optimization algorithms, such as genetic algorithms, evolutionary strategies, and particle swarm optimization methods, find only a single global solution in what is known as a genetic drift. To solve this problem, many practical studies involving modifications of evolutionary algorithms have been done to find multiple solutions to multimodal optimization problems [5]-[6].

The water cycle algorithm (WCA) has been recently introduced as a new heuristic search algorithm which is based on the observation of water cycle process and how rivers and streams flow to the sea as in nature [7]. Because the WCA has a low computational cost and a high convergence speed, it is very efficient when the number of optimization parameters is high. The WCA has successfully been applied to tangible engineering areas [8]-[9].

Unfortunately, like other evolutionary algorithms, the WCA tends to converge towards the global optimum solution. Therefore, the standard WCA cannot simultaneously search for multiple solutions to multimodal problems. Thus far, research to develop a WCA to handle multimodal optimization problems has not been conducted. This paper deals with this problem, with several modifications applied to the standard WCA.

In this paper, we propose a new multimodal optimization algorithm based on the WCA and assisted by a surrogate model using compressed sensing (CS) theory. A niching technique is applied to the WCA to find multiple optimal solutions simultaneously. We use a surrogate model to determine the niche and its niche radius adaptively. The proposed algorithm reduces the computation time and cost significantly by eliminating the need for a large number of function evaluations, and the niche radius is adjusted adaptively according to the optimization results.

II. BRIEF OVERVIEW OF THE WCA

The WCA has a hierarchical structure, and its individuals are classified into three types according to their intensity of flow: streams, rivers, and a sea. Also, evapolation and raining process are defined to enhance its capability [7]-[8]. The WCA can be summarized by the pseudo-code in Fig. 1.

```
Initialize population (Raindrops) and Compute their fitness values
Determine intensity of flow and Assign streams, rivers and sea
Do While (Stop condition is not satisfied)
        Streams flow to rivers and sea
        Rivers flow to sea
        If (Evaporation condition satisfied)
                Start raining process
        End If
End Do
```

Fig. 1. Pseudo-code of the WCA.

III. PROPOSED ALGORITHM

In this research, we propose a new multimodal water cycle optimization algorithm assisted by a surrogate model using CS theory. Generally, in multimodal optimization algorithms, it is very difficult to determine a niche radius parameter which determines the size of the niche or species. Here, to ascertain the niche and its niche radius adaptively, we construct a surrogate model from selected samples and then find the peaks. The WCA is also utilized restrictively in the region within its niche radius.

The detailed process of the proposed algorithm is as follows.

Step 1—Generation of Initial Samples:

Generate initial samples randomly in the predefined search space and calculate their fitness function values. The position of the ith sample is defined as $\mathbf{x}^i$.

Step 2—Construction of the Surrogate Model using CS:

Surrogate models are able to estimate approximately real objective functions. The spatial distribution on a predefined lattice region can be obtained through various interpolation methods, such as response surface method and Kriging method. In this research, we apply a newly developed CS interpolation method. This interpolation method has the ability to reconstruct the objective function successfully with only a small number of selected samples. Consequently, it reduces the computational complexity more effectively.

Step 3—Assigning Niches and Calculating the Niche Radius:

In this step, the locations of local peaks are estimated on the points of a grid using the surrogate model.

The positions of the peaks are assigned as temporary niches, with each niche radius calculated based on the mutual distances of the peaks. The niche radius is determined by the Euclidian distance between the temporary niche and the nearest neighbor peak from it.

Step 4—Checking the Change of Niches:

The positions of the niches in the present iteration calculated during step 3 are compared to those of the niches one step behind and two steps behind the iteration. If all three step positions are nearly identical, the interpolation process is terminated and this algorithm goes to Step 6.

Step 5—Applying the WCA within Each Niche Radius :

The following WCA procedure is applied to a predefined number of nearest neighbor samples of each niche within its niche radius.

1. Streams ($\mathbf{x}_{str}^{ki}$), rivers ($\mathbf{x}_{riv}^{kj}$) and the sea ($\mathbf{x}_{sea}^{k}$) are defined depending on their intensity of flow. (k is the number of niches. ki and kj are the number of streams and rivers near each niche respectively)

2. Streams flow to rivers and the sea by using (1) and (2).

$$\mathbf{x}_{str}^{ki}(t+1) = \mathbf{x}_{str}^{ki}(t) + rand \times C \times (\mathbf{x}_{riv}^{kj}(t) - \mathbf{x}_{str}^{ki}(t)) \quad (1)$$

$$\mathbf{x}_{str}^{ki}(t+1) = \mathbf{x}_{str}^{ki}(t) + rand \times C \times (\mathbf{x}_{sea}^{k}(t) - \mathbf{x}_{str}^{ki}(t)) \quad (2)$$

where $rand$ is a uniformly distributed random number between 0 and 1, and C is a value between 1 and 2 (near to 2).

3. Rivers flow to the sea by using (3).

$$\mathbf{x}_{riv}^{kj}(t+1) = \mathbf{x}_{riv}^{kj}(t) + rand \times C \times (\mathbf{x}_{sea}^{k}(t) - \mathbf{x}_{riv}^{kj}(t)) \quad (3)$$

4. If the evaporation condition is satisfied, the raining process will occur by using (4) and (5).

$$\mathbf{x}_{str}^{k\_new}(t+1) = LB + rand \times (UB - LB) \quad (4)$$

$$\mathbf{x}_{str}^{k\_new}(t+1) = \mathbf{x}_{sea}^{k}(t) + \sqrt{\mu} \times randn(1, N_{\mathrm{var}}) \quad (5)$$

where LB and UB are lower and upper bounds defined by the given niche radius respectively, μ is a coefficient which shows the range of searching region near the sea, $randn$ is the normally distributed random number, and N_{var} is the number of design variables.

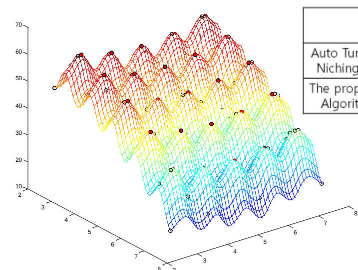
5. The best individual becomes the new sea. The position of the niche is updated if the fitness value of the new sea is larger than the fitness value of the existing niche for a maximization problem, which is an elitism strategy between the existing niche and the new sea. After checking the niche update condition, the execution of this algorithm goes back to Step 2.

Step 6—Searching for Niches in Detail within Their Niche Radii:

To find the precise niches in detail, an additional niche search process using the WCA is necessary. This process is performed within the niche radius of each niche obtained in step 3.

IV. Numerical Test and Result

To evaluate the performance of our algorithm, we applied it to test functions and electric machine designs. A detailed explanation will be presented in the full paper. Fig. 2 shows an example.



	Number of Peaks	Number of Function Call
Auto Tunning Niching GA	25	5039
The proposed Algorithm	25	821

Fig. 2. Optimization result on a test function.

References

[1] L. D. S. Coelho, H. V. H. Ayala, and P. Alotto, "A multiobjective Gaussian particle swarm approach applied to electromagnetic optimization," *IEEE Trans. Magn.*, vol. 46, no. 8, pp. 3289–3292, Aug. 2010.

[2] C. Stoean, M. Preuss, R. Stoean, and D. Dumitrescu, "Multimodal optimization by means of a topological species conservation algorithm," *IEEE Trans. Evol. Comput.*, vol. 14, no. 6, pp. 842–864, Dec. 2010.

[3] 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.

[4] 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.

[5] X. Zhang, X. Zhang, S. L. Ho, and W. N. Fu, "A Modification of Artificial Bee Colony Algorithm Applied to Loudspeaker Design Problem," *IEEE Trans. Magn.*, vol. 50, no. 2, Art. ID 7018204, Feb. 2014.

[6] E. Dilettoso, S. A. Rizzo, and N. Salerno, "A parallel version of the self-adaptive low-high evaluation evolutionary-algorithm for electromagnetic device optimization," *IEEE Trans. Magn.*, vol. 50, no. 2, Art. ID 7015604, Feb. 2014.

[7] H. Eskandar, A. Sadollah, A. Bahreininejad, and M. Hamdi, "Water cycle algorithm – A novel metaheuristic optimization method for solving constrained engineering optimization problems," *Comput. Struct.*, vol. 110, pp. 151–166, 2012.

[8] S. S. Haroon, "Evaporation rate based water cycle algorithm for the environmental economic scheduling of hydrothermal energy systems," *J. Renewable Sustainable Energy*, vol. 8, Art. ID 044501, 2016.

[9] M. A. El-Hameed, "Water cycle algorithm-based load frequency controller for interconnected power systems comprising non-linearity," *IET Gener. Transm. Distrib.* , vol. 10, pp. 3950–3961, 2016.