A Novel Strategy-Selecting Hybrid Optimization Algorithm for Designing Electromagnetic Machines

J. W. Kang[1], H. J. Park[1], S. W. Jung[1], J. S. Ro[2] and H. K. Jung[1], *Senior Member, IEEE*

[1]Department of Electrical and Computer Engineering, Seoul National University, Seoul 151-744, Korea,
[2]School of Electrical and Electronics Engineering, Chung-Ang University, Dongjak-gu, Seoul, Korea,
jongsukro@gmail.com

Calculating electromagnetic fields requires a great amount of computation time when designing electromagnetic machines. To overcome the disadvantage of existing optimization algorithms, it is necessary to formulate a suitable algorithm which works situationally. A novel strategy-selecting hybrid optimization algorithm (SSHOA) is proposed to establish a strategy which offers a better fit for every iteration. The main characteristics of the SSHOA are analyzed, and a permanent magnet machine is then designed to verify electromagnetic performance capabilities of the proposed algorithm.

***Index Terms*—Learning (artificial intelligence), Finite element analysis, Genetic algorithms, Design optimization.**

I. Introduction

Social cognitive theory maintains that observational learning enables humans to expand their knowledge and achieve experience vicariously. The acquired knowledge gives the ability to predict the outcome and consequently gives influence when making decisions [1]. A number of models addressing observational learning have been developed in the fields of cognitive science and artificial intelligence (AI), considering factors that affect the learnings and the impact they have on behavioral responses [2], [3].

Optimal designing electromagnetic machinery requires algorithms to solve global optimization problems with the least amount of iteration in finite element analysis [4], [5]. Considering that all optimization algorithms have trade-off disadvantages, such as diversity versus convergence, a strategy used in one instance may not always be efficient during the enumeration of the algorithm. Changing certain parameters or the search strategy to make them more suitable under certain circumstances can maximize the efficiency, and possibly reduce unnecessary calculations.

The aim of this paper is to model an artificial strategy selecting system that mimics human decision making process by means of hybrid optimization algorithms. By observing changes in the population, the algorithm learns and predicts to help utilize suitable strategies and adjust the population size [6].

II. Observation & Learning

The flow chart of the proposed algorithm is designed and shown in the following figure 1. There are two major steps that affect decision making in strategy-selecting hybrid optimization algorithm (SSHOA). A detailed flow chart of these steps is shown in figure 2.

The first step is the Observation and Learning step. In this stage, information is collected from the population, and from repeated observations the convergence state is learned. To process the collected information, two factors are used. The observation factor (Ob) records the information. The learning factor (Lrn) learns to predict convergence.

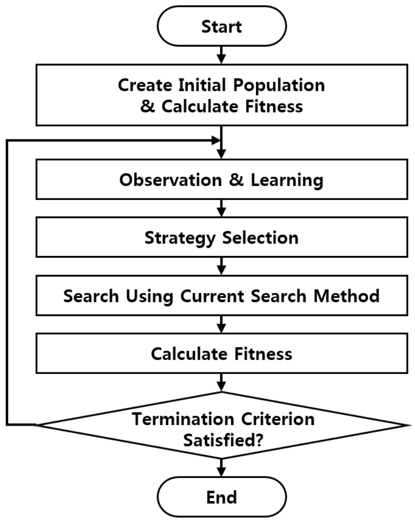

Fig. 1 The flow chart of the proposed algorithm.

A. Observation Factor

Assumption 1: The observation factor (Ob) refers to the number of iterations the best solution does not change. It increases as the same x_{best} is repeated across multiple iterations, and reaches zero when the best particle is drastically improved. The information obtained from the observation factor is the criterion for learning to predict or deny convergence.

B. Learning Factor

Assumption 2: The learning factor (Lrn) is a one-digit binary number with a value of 0 or 1. When the algorithm assumes that global search is needed, the learning factor remains 0, but when convergence is predicted, the factor becomes 1.

III. Strategy Selection

The second part of decision making is the Strategy Selection step. In this step, a new strategy for the next iteration is chosen based on the two factors defined in the previous section.

A. Activation Threshold

Assumption 3: Based on the observation factor, the activation threshold determines when to modify the strategy.

TABLE I
ACTIVATION THRESHOLD VALUES

Threshold	Value
Th1 (Population Change)	10
Th2 (Search Method Change)	5, 15
Th3 (Convergence Prediction)	20
Tolerance	1%

As shown in Table I, there are three types of thresholds (Th1, Th2 and Th3) with different strategies. When the observation factor increases and exceeds each activation threshold, the strategy corresponding to the threshold value is modified. Th1 increases or decreases the population, Th2 changes the search method, and Th3 assumes whether a possible global optimal solution is found, and changes the learning factor to 1. The figures in table I have not yet been optimized.

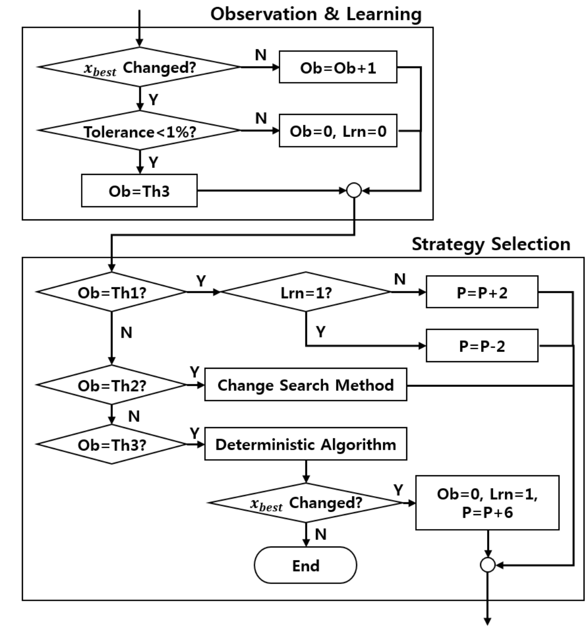

Fig. 2 A partial flow chart of the proposed algorithm about Observation & Learning and Strategy Selection. P refers to population size.

IV. HYBRID GA WITH STRATEGY SELECTION

The strategy selection algorithm is applied to optimization algorithms to test its performance. Based on genetic algorithm (GA), particle swarm optimization (PSO) and the Newton method were chosen as candidate search methods from which the strategy selection algorithm to choose. As PSO requires previous values of personal bests and velocities, the values of the closest particle were used for the new particles generated by the GA. Further applications to other good performing algorithms and the resulting performances will be described in the full paper.

V. NUMERICAL TESTS AND RESULTS

Conventional test functions are applied to evaluate the performance of the proposed algorithm. To assess the improvement of the algorithm, it is compared with standard GA and PSO as applied to the strategy selection algorithm.

For a meaningful statistical analysis, each algorithm was run 100 times at a fixed tolerance of $\varepsilon < 10^{-4}$. Population sizes for the GA and PSO were fixed at 30, and the proposed hybrid algorithm had a limited population size of $10 \le popsize \le 50$. As shown in Table II, the average numbers of function calls have dramatically decreased compared to conventional GA and PSO.

TABLE II
OPTIMIZATION RESULTS FOR TEST FUNCTIONS

	GA	PSO	Hybrid
Rastrigin's Function*			
Avg. num. function calls	4074.6	11027.7	1314.4
Avg. function values	1.0757	1.0015	1.0346
Standard deviation	0.3821	0.0068	0.1494
Rosenbrock Function**			
Avg. num. function calls	23034.6	10991.7	1592.4
Avg. function values	1.0153	1.0177	1.0092
Standard deviation	0.0564	0.1526	0.0535

* $f(x_1, x_2) = 21 + x_1^2 + x_2^2 - 10(\cos 2\pi x_1 + \cos 2\pi x_2),\ f_{\min} = 1$

** $f(x_1, x_2) = 100(x_2 - x_1^2)^2 + (x_1 - 1)^2 + 1,\ f_{\min} = 1$

To verify the feasibility of the proposed algorithm with regard to the design of electric machinery, it is applied to minimize cogging torque of a permanent magnet (PM) machine. Details will be presented in the full paper.

VI. CONCLUSION

In this paper, we propose a new strategy-selecting hybrid optimization algorithm. The concept of changing strategies while the optimization is running is novel and can be a solution to circumvent the No Free Lunch Theorem [7]. Also, the algorithm is similar to artificial intelligence (AI) that predictions are made through simple information gatherings. Moreover, it is possible to apply more various and concrete methods for convergence prediction. The performance of this algorithm is proven through comparisons with conventional methods, and it is applied to optimize the design of a permanent magnet machine.

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