A Novel Memetic Algorithm Using Modified Particle Swarm Optimization and Mesh Adaptive Direct Search for PMSM Design

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Optimization algorithm is used in many engineering fields and validated of its effectiveness. Therefore, it is frequently applying to designing electric machines. In order to increase performance and minimize design time, search efficiency of an optimization method is important. In this paper, explorative-particle swarm optimization (E-PSO) combined with mesh adaptive direct search (MADS) is newly proposed and applied to design of permanent magnet synchronous machine (PMSM). The memetic algorithm which is modified from PSO improves search time and the number of function call drastically. Unlike any existing method, newly used start point selection takes advantage of minimizing search time. By applying proposed algorithm to PMSM, we minimize torque ripple.

***Index Terms*—Particle Swarm Optimization, Mesh Adaptive Direct Search, Optimal Design, Permanent Magnet Synchronous Machine, Torque Ripple**

I. Introduction

Optimization algorithm has been used in many engineering fields, which can be classified into global and local optimization. Particle swarm optimization (PSO) is one of the most popular global optimization methods, which employs the behavior principle of a population of social organisms without merely converging to their local optima [1]-[4]. PSO has strong advantage for the problem whose cost function is multimodal because of the communication ability and memory of each agent. However, PSO requires longer computation time than most local optimization methods in convergence phase.

In recent study, there have been many attempts to modify PSO in order to improve performance. We propose a new memetic algorithm which employs PSO with some modification and mesh adaptive direct search (MADS). The modified PSO is named as Explorative Particle Swarm Optimization (E-PSO). In proposed algorithm, the exploration of proposed algorithm is complimented using E-PSO and the exploitation is complimented by MADS. E-PSO searches promising clusters and memorizes the discovered clusters before MADS set out from centroid of discovered clusters.

In this paper, optimal design of permanent magnet synchronous machine (PMSM) is conducted using proposed algorithm. Target PMSM is 1kW surface mounted permanent magnet synchronous machine (SPMSM). By applying proposed optimization algorithm to SPMSM, ultimate goal is to validate effectiveness of proposed algorithm and to find optimal topology for electric machine [5],[6].

II. Basic Theory of Proposed Algorithm

A. Explorative Particle Swarm Optimization

Despite the high exploration capability of PSO, it takes a relatively long time for PSO to converge to global minima within assigned tolerance. Therefore, a local search method such as MADS can supplement PSO and accelerate the convergence to an adjacent local minimum. For this type of combined optimization, PSO needs to search as many promising regions or clusters as possible, which are then carried over to MADS for exploitative search.

In the present work, promising cluster is considered as a dense set of elite particles selected at the current iteration with respect to cost values. Moreover, in case of multimodal cost function, the discovered cluster is stored in memory and a new cluster needs to be explored far from it. The proposed PSO modifies the velocity equation of the *i*-th particle on dimension *d*, which determines its velocity and position vectors as

$$v_i^d = \omega v_i^d + c_1 rand_1^d (pBest_i^d - x_i^d) + c_2 rand_2^d (nBest_i^d - x_i^d)$$
$$x_i^d = x_i^d + v_i^d \qquad (1)$$

where ω is the inertia weight, c_1 and c_2 are the acceleration coefficients, and $rand_1^d$ and $rand_2^d$ are two uniformly distributed random numbers generated within [0,1]. $pBest_i$ is the personal best point for the *i*th particle and $nBest_i$ is neighbor best point which is a novel concept of the present work.

The neighbor best point depends on the quality of the current particle. That is, when the current particle is included in the present elite members, $nBest_i$ becomes a centroid of $x\_elite\_far\_lbc$, i.e., the particles with low cost and sufficient distance from the local best clusters found so far. Otherwise, $nBest_i$ is replaced with the nearest elite particle.

For diversification, a local best cluster can be newly enrolled if more than n_{cls} $x\_elite\_far\_lbc$ points gather with radius of smaller than r_{cls}, and then E-PSO randomly scatters all the particles again to seek for another possible cluster. If no more adjacent particles that are sufficiently far from all the local best clusters are found, E-PSO is terminated and followed by MADS which starts from the centroid of the best clusters attained.

Below Fig. 1 shows notion of E-PSO.

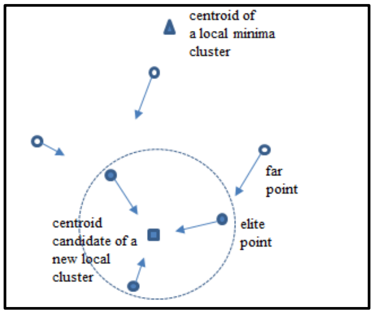


Fig. 1. Notion of E-PSO

B. Mesh Adaptive Direct Search

MADS is a local search algorithm which has powerful advantage to have fast convergence. However, MADS also has critical disadvantage to easily converge local optimum. When to supplement convergence of local optimum, MADS is very powerful to search optimal solution.

In Fig. 2, border line is frame and represents category of solution region to search optimal solution. The parameter which is related to selection of neighbor solution is called poll size parameter, Δ_k^p . Current solution, x_k , is called frame center which becomes center of mesh. Parameter related to selection of generating mesh is called mesh size parameter, Δ_k^m . When improved solution is deducted in neighborhood, it becomes new frame center. This new frame center regenerate frame and iterate searching process. Unless there is better solution in neighbor, it searches optimal solution by decreasing mesh size parameter. Finally, when mesh size approaches to assigned error rate, it determines to search optimal solution and terminates search.

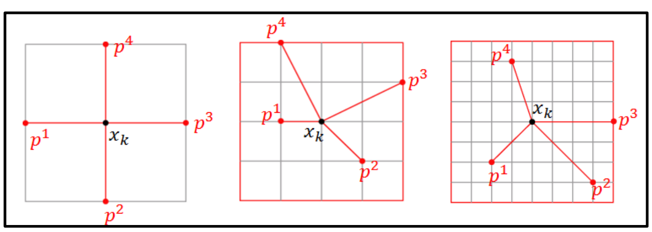
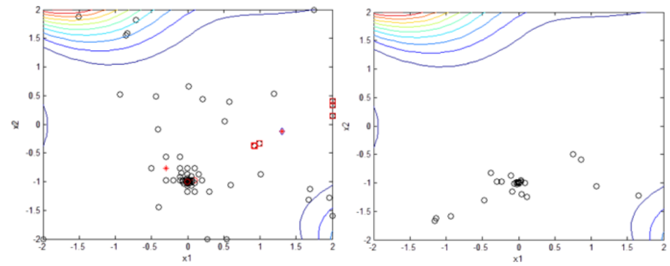


Fig. 2. Example of MADS frames

III. Comparison Proposed Algorithm with Conventional PSO

The biggest difference is while conventional PSO directly searches global optimum, E-PSO searches approximate optimal point in terms of PSO and then start local search method to search accurate solution. The key point of E-PSO is that *gBest* is substituted by *nBest*. In order to search accurate solution, conventional PSO should take minimum error rate. As a result, the number of function call ought to rise. However, in the case of E-PSO, user can properly regulate minimum error rate in terms of PSO, and then at the centroid of found clusters MADS is followed. As a result, the function call number of pro can be highly minimized. The test function is Goldstein-Price function which is more complicated than Branin function. Fig. 3 shows the result of PSO and proposed algorithm. In the test, the number of particle is fixed as 30 on stage PSO.



(a) Proposed Algorithm (b) Conventional PSO

Fig. 3. Comparison Proposed Algorithm with Conventional PSO

The result of the iteration is shown below Table 1.

TABLE I
The Result of Iteration

Iterative number	Conventional PSO		Proposed algorithm	
	The number of iteration	The number of function call	The number of iteration	The number of function call
1st	154	4650	31	259
2nd	166	5010	20	189
3rd	81	2460	45	341
4th	142	4290	87	432
5th	134	4050	38	261

Table 1 represents the result which shows the performance of proposed algorithm is by far better than conventional PSO.

IV. Conclusion

In this paper, new memetic algorithm is proposed. Although PSO is very powerful method for searching global optimum, it takes very slow convergence time and too many function call. Therefore, in order to improve these disadvantages, we propose memetic algorithm of E-PSO and MADS. In test function, proposed algorithm takes less the number of iteration and function call than conventional PSO. Finally, proposed algorithm is applied to designing SPMSM.

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