A Hybridized Vector Optimal Algorithm for Multiobjective Designs of Inverse Problems

Hu Guanzhong[1], Yang Shiyou, Li Yuling, and Shafi Ullah Khan

College of Electrical Engineering, Zhejiang University, 310027, Hangzhou, China, [1]gz_hu@yahoo.com

Problem with multiple objectives is a natural fashion in most disciplines of the real world, and multi-objective evolutionary algorithm is a technique which has a challenge of achieving a series of best solutions with respect to fitness and spread. In this regard, it is essential to keep the balance of local and global search abilities. Quantum-behaved Particle Swarm Optimization (QPSO) is a population-based swarm intelligence algorithm, and Differential Evolutionary (DE) is another simple population based stochastic search method for global optimization with real valued parameters. Although the two techniques have been successfully employed to solve a wide range of problems, they also suffer from the premature convergence and the lack of diversity in the latter searching stages. This is probably due to the insufficient dimensional searching strength, especially for multi-objective optimization problems with many decision parameters. In this study, a new multi-objective non-dominated optimization methodology combining QPSO, DE and Tabu search algorithm (QPSO-DET) is proposed to guarantee the balance between the local and global searches. The performances of the proposed QPSO-DET are compared with those of other two widely recognized vector optimizers using different case studies.

Index Terms**—DE, multi-objective optimization, QPSO, tabu search method.**

I. Introduction

THE evolutionary multi-objective optimization (EMO) has significantly grown in the last few years, giving rise to a wide variety of algorithms in engineering applications, due to multi-criteria nature of most real-world problems. In contrast to the single–objective optimization, where the optimal solution is clearly well defined, the objectives of multi-objective optimization problems may be conflicting to each other. Therefore, it is impossible to obtain, for all objectives, the global optimum at the same point. Thus, the concept of Pareto optimality and the Pareto set, called the Pareto Front (PF), is introduced. Based on the concept of PF, EMO researchers have developed some well recognized algorithms to maintain the diversity, such as the adaptive grid used by the Pareto Archive Evolutionary Strategy (PAES) [1] and the Non-dominated Sorting-based Genetic Algorithm (NSGAII) [2].

Quantum-behaved Particle Swarm Optimization (QPSO) is a global convergence guaranteed method inspired by a quantum delta potential well model. QPSO has been found to be successful in a wide variety of optimization problems, but until recently only lukewarm efforts have been devoted to extend QPSO to solve multi-objective optimal problems. In this study, a new multi-objective optimization methodology (QPSO-DET) is introduced by combinging the charcteristics of QPSO, Differential Evolutionary (DE) and Tabu search algorithm. The performance of the proposed QPSO-DET is compared to those of NSGA-II and PAES.

II. The Proposed QPSO-DET

A. The Proposed QPSO-DET

The proposed multi-objective optimal QPSO-DET is a hybridized methodology of QPSO, DE and tabu search algorithm. In a QPSO, a particle i updates its position using:

$$X(t+1) = P_i \pm (L/2)\cdot \ln(1/\mathrm{u}) \tag{1}$$

$$P_i = \varphi \cdot pBest_i \pm (1-\varphi)\cdot gBest_i \tag{2}$$

$$L = 2\cdot \beta \cdot \left| mBest - X(t) \right| \tag{3}$$

$$mBest = \sum_{i=1}^{N} pBest_i / N \tag{4}$$

P_i is the potential global optimal position which lies on the straight line between the personal and global best; The position *mBest*, called the mainstream thought point, is used to measure the vital parameter L which controls the probability of lying in the new position x; u is a random number uniform distributed in [0, 1]; and β is a linearly deceasing factor from 1 to 0.5. For multi-objective optimizations, QPSO suffers from the deficiency of information sharing and the relatively low local search ability. In this point of view, it is proposed to integrate DE and tabu search method into the iterative procedure of QPSO to keep the balance between local and global search abilities. In the proposed hybrid method, the whole swarm is divided into three sub-swarms with swarm sizes of N_1, N_2 and N_3, respectively for QPSO, DE, and Tabu method. In each sub-swarm, the particles (individuals) will be updated using the corresponding mechanism of the adopted method. The iterative procedures of the proposed QPSO-DET are described in details in Fig. 1.

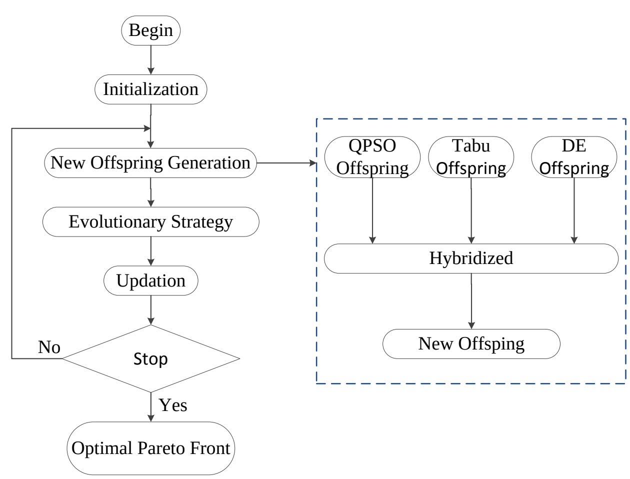

Fig. 1. The iterative procedures of the proposed QPSO-DET.

B. Validation

To validate the performance of QPSO-DET, five bench problems (ZDT1~ZDT4, ZDT6 from Table I of [2]) are solved and compared to PAES and NSGA-II. All of these test functions have two objectives and have no extra constraints except the bounds on the decision parameters. For PAES, the suggested parameters are used according to the original article. For NSGA-II, the crossover probability of P_c=0.9 and the mutation probability of P_m=1/n or 1/l are used, and the distribution indexes for the crossover and the mutation operators are, respectively, η_c=20 and η_m=20 [2].

Foe a fair comparison, the maximum iterative number for each algorithm is 25000 for one single run. To obtain the stochastic performance metrics, every algorithm runs randomly and independently 30 times. The performance measurements used are the two metrics as suggested in [2]. The first metric, α, measures the extent of convergences to a known set of true Pareto-optimal solutions; and the smaller this metric, the better convergent performance toward the true Pareto front. The second metric, γ, is a diversity measure, and the smaller the metric, the more uniform distribution of the searched non-dominated solutions. Tables I and II tabulate the corresponding comparison results of different algorithms.

From Table I, it is observed that; in view of the convergence; (1) the proposed QPSO-DET is significantly superior to PAES for functions ZTD1~ZTD3, and ZTD6 while it has almost the same convergence performance as that of PAES for ZDT4; (2) The proposed algorithm outperforms significantly NSGAII for functions ZDT1, ZDT3 and ZDT6, and has the same behavior as NSGA-II (Binary) for ZDT2.

From Table II, it is obvious that; in view of the diversity performance; (1) the proposed QPSO-DET is significantly superior to PAES; (2) the proposed QPSO-DET outperforms NSGA-II for nearly all test functions except ZDT4. However, the final solutions searched by NSGA-II are not the global optimal Pareto solutions but just parts of the local ones. As demonstrated in [2], ZDT4 has 21^9 different local Pareto-optimal fronts. As a result, it is not surprising that NSGA-II can not find the global Pareto optimal solutions. Nevertheless, the proposed algorithm finds the best solutions of ZDT4, as depicted in Fig. 2.

III. Application

The temperature field optimization for a prototype device of magnetic fluid hyperthermia [3] is then selected as a case study for engineering applications of the proposed algorithm. This problem includes two objectives, one objective f_1 is used to measure the uniformity of the temperature field while f_2 to scale the temperature gradient between the boundary B and the average temperature of the tumor region. The total number of decision parameter is 26 and the decision space is very broad while the feasible region is limited. The final solutions obtained using the proposed QPSO-DET are compared to those of the original QPSO-DE [3] in Fig.3. Obviously, the final solutions of the proposed algorithm are superior to those of QPSO-DE.

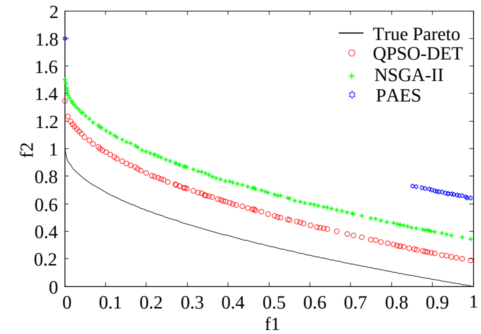

Fig. 2. The searched Pareto solutions by using different algorithms for ZDT4.

TABLE I
MEAN (FIRST ROW) AND VARIANCE (SECOND ROW) OF THE METRIC α

Algorithm	ZDT1	ZDT2	ZDT3	ZDT4	ZDT6
NSGAII (Real)	0.033482	0.072391	0.114500	0.513053	0.296564
	0.004750	0.031689	0.007940	0.118460	0.013135
NSGAII (Binary)	0.000894	0.000824	0.043411	3.227636	7.806798
	0.0	0.0	0.000042	7.307630	0.001667
PAES	0.082085	0.126276	0.023872	0.854816	0.085469
	0.008679	0.036877	0.000010	0.527238	0.006664
QPSO-DET	0.000123	0.000837	0.004723	0.300333	0.000824
	0.000019	0.000011	0.000067	0.046851	0.000013

TABLE II
MEAN (FIRST ROW) AND VARIANCE (SECOND ROW) OF THE METRIC γ

Algorithm	ZDT1	ZDT2	ZDT3	ZDT4	ZDT6
NSGAII (Real)	0.390307	0.430776	0.738540	0.702612	0.668025
	0.001876	0.004721	0.019706	0.064648	0.009923
NSGAII (Binary)	0.463292	0.435112	0.575606	0.479475	0.644477
	0.041622	0.024607	0.005078	0.009841	0.035042
PAES	1.229747	1.165942	0.789920	0.870458	1.153052
	0.004839	0.007682	0.001653	0.101399	0.003916
QPSO-DET	0.268132	0.274531	0.489937	0.611581	0.272134
	0.004325	0.005012	0.005354	0.027618	0.004839

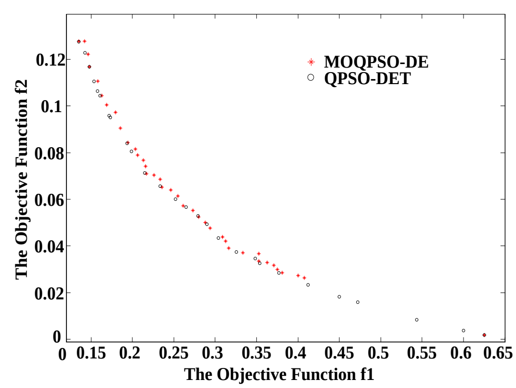

Fig. 3. The searched PF for the case study of application.

References

[1] Knowles, J. AND Corne, D., "The pareto archived evolution strategy: A new baseline algorithm for multiobjective optimization," *Proceedings of the Congress on Evolutionary Computation*, vol.1, pp. 98-105, 1999.

[2] Kalyanmoy Deb, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary computation*, vol.6, No.2, pp. 182-197, Apr. 2002.

[3] Guanzhong Hu, Yuling Li, Shiyou Yang, Yanan Bai, "Temperature field optimization and magnetic nanoparticles optimal approximation of MFH for Cancer Therapy," *IEEE Transactions on Magnetics*,2015(in press).