Diversity-Controlled Quantum-Behaved Particle Swarm Optimization Based on Local Search

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***Abstract*—Quantum-behaved particle swarm optimization (QPSO) algorithm has shown an effective performance for solving variant benchmark and real-world optimization problems. However, it suffers from premature convergence because of quick losing of diversity. In order to enhance its performance, this paper proposes a new algorithm, called DCSQPSO, which employs a diversity-controlled into QPSO enhancing mechanism and local search strategies to improve the solution quality. A comprehensive experimental study is conducted on a set of benchmark functions, Comparison results show that DCSQPSO obtains a promising performance on the majority of the test problems.**

***Index Terms*—Quantum-behaved particle swarm optimization, diversity-controlled, local search, global optimization.**

I. Introduction

Particle swarm optimization (PSO) is a kind of stochastic optimization algorithms proposed by Kennedy and Eberhart [1] that can be easily implemented and is computationally inexpensive. The core of PSO is based on an analogy of the social behavior of flocks of birds when they search for food. PSO has been proved to be an efficient approach for many continuous global optimization problems. However, as demonstrated by F. Van Den Bergh [2], PSO is not a global convergence guaranteed algorithm because the particle is restricted to a finite sampling space for each of the iterations. This restriction weakens the global search ability of the algorithm and may lead to premature convergence in many cases.

Recently, a new variant of PSO called quantum-behaved particle swarm optimization (QPSO) [3], which is inspired by quantum mechanics and particle swarm optimization model. QPSO has only the position vector without velocity, so it is simpler than standard particle swarm optimization algorithm. Furthermore, several benchmark test functions show that QPSO performs better than standard particle swarm optimization algorithm. Although the QPSO algorithm is a promising algorithm for the optimization problems, like other evolutionary algorithm, QPSO also confronts the problem of premature convergence, and decrease the diversity in the latter period of the search. Therefore a lot of revised QPSO algorithms have been proposed since the QPSO had emerged. Differential mutation operation was adopted to enhance the global search ability in QPSO [4]. In Sun *et al*. [5], the mechanism of Gaussian distribution was proposed to make the swarm more efficient in global search. In reference [6], Niu combined QPSO with a selective probability operator to solve the economic dispatch (ED) problems with valve-point effects and multiple fuel options. Sun *et al*. [7] proposed a new scheme for clustering gene expression datasets based on a modified version of Quantum-behaved Particle Swarm Optimization (QPSO) algorithm, known as the Multi-Elitist QPSO (MEQPSO) model.

In this paper, diversity-controlled QPSO with local search (DCSQPSO) is introduced. This strategy is to prevent the diversity declining of particle swarm declining in the search of later stage.

II. QPSO Algorithm

In the PSO with M individuals, each individual is treated as volume-less particle in the D-dimensional space, with the current position vector and velocity vector of particle *i* at the n^{th} iteration represented as $X_{i,n} = (X_{i,n}^1, X_{i,n}^2, \cdots, X_{i,n}^D)$ and $V_{i,n} = (V_{i,n}^1, V_{i,n}^2, \cdots, V_{i,n}^D)$. The particle moves according to the following equations:

$$V_{i,n+1}^j = w \cdot V_{i,n}^j + c_1 r_{i,n}^j (X_{i,n}^j - P_{i,n}^j) + c_2 R_{i,n}^j (X_{i,n}^j - G_n^j) \quad (1)$$

$$X_{i,n+1}^j = X_{i,n}^j + V_{i,n+1}^j \quad (2)$$

Vector $P_{i,n} = (P_{i,n}^1, P_{i,n}^2, \cdots, P_{i,n}^D)$ is the best previous position (the position giving the best objective function value or fitness value) of particle i and called personal best (pbest) position, and vector $G_n = (G_n^1, G_n^2, \cdots, G_n^D)$ is the position of the best particle among all the particles in the population and called global best (gbest) position. G_n can be found by $G_n = P_{g,n}$, where $g = \text{argmax}_{1 \le i \le M} [f(P_{i,n})]$. The parameters $r_{i,n}^j$ and $R_{i,n}^j$ are sequences of two different sequences of random numbers distributed uniformly within (0, 1), which is denoted by $r_{i,n}^j, R_{i,n}^j \sim U(0,1)$. Generally, the value of $V_{i,n}^j$ is restricted in the interval $[-V_{max}, V_{max}]$.

Trajectory analysis in [8] showed that convergence of the PSO algorithm may be achieved if each particle converges to its local attractor

$$p_{i,n}^j = \varphi_{i,n}^j \cdot P_{i,n}^j + (1 - \varphi_{i,n}^j) \cdot G_n^j \quad (3)$$

where $\varphi_{i,n}^j = c_1 r_{i,n}^j / (c_1 r_{i,n}^j + c_2 R_{i,n}^j)$ with regard to the random numbers $r_{i,n}^j$ and $R_{i,n}^j$ in Eq. (1). $\varphi_{i,n}^j$ is a sequence of

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uniformly distributed random numbers within (0, 1). As a result, Eq. (3) can be restated as

$$p_{i,n}^j = \varphi_{i,n}^j \cdot P_{i,n}^j + (1 - \varphi_{i,n}^j) \cdot G_n^j,\ \varphi_{i,n}^j \sim U(0,1) \tag{4}$$

Using Monte Carlo method, we can measure the j^{th} component of position of particle *i* at the (*n*+1) iteration by

$$X_{i,n+1}^j = p_{i,n}^j \pm \frac{L_{i,n}^j}{2} ln(1/\mu_{i,n+1}^j) \quad \mu_{i,n+1}^j \sim U(0,1) \tag{5}$$

where $\mu_{i,n+1}^j$ is a sequence of random numbers uniformly distributed within $(0,1)$. The value of $L_{i,n}^j$ is determined by:

$$L_{i,n}^j = 2\alpha \cdot |X_{i,n}^j - C_n^j| \tag{6}$$

where $C_n = (C_n^1, C_n^2, \cdots, C_n^D)$ is called mean best (mbest) position defined by the average of the pbest position of all particles, i.e.

$$C_n^j = (1/M) \sum_{i=1}^M P_{i,n}^j \quad (1 \le j \le D) \tag{7}$$

Thus the position of the particle updates according to the following equation:

$$X_{i,n+1}^j = p_{i,n}^j \pm \alpha \cdot |X_{i,n}^j - C_n^j| \cdot ln(1/\mu_{i,n+1}^j) \tag{8}$$

The parameter α in Eq. (6) and (8) is called contraction-expansion (CE) coefficient, which can be adjusted to balance the local search and the global search of the algorithm during the optimization process.

$$\alpha = (1.0 - 0.5) \times \frac{MAXITER - T}{MAXITER} + 0.5 \tag{9}$$

III. DCSQPSO Algorithm

A. Diversity-Controlled Mechanism

QPSO is a promising optimization problem solver that outperforms PSO in many real application areas. The introduced exponential distribution of positions makes QPSO global convergent. But it suffers from premature convergence. At the beginning of the search, the diversity of the population is relatively high after initialization. With the development of evolution, the convergence of the particle makes the diversity been declining, which is enhancing the local search ability (exploitation) but weakening the global search ability (exploration) of the algorithm. At early or middle stage of the evolution the decline of the diversity is necessary for the particle swarm to search effectively. However, after middle or at later stage, the particles may converge into such a small region that the diversity of the swarm is very low and further search is difficult. At that time, if the particle with global best position is at local optima or sub-optima, premature convergence occurs.

To avoid the premature convergence and improve the performance of the algorithm, we introduce a diversity control method into QPSO. The population diversity of the DCSQPSO is denoted as diversity(pbest) and is measured by average Euclidean distance from the particle's personal best position to the mean best position, namely

$$\text{diversity}(pbest) = \frac{1}{M \cdot |A|} \cdot \sum_{i=1}^M \sqrt{\sum_{j=1}^D \left(pbest_{i,j} - \overline{pbest_j}\right)^2} \tag{10}$$

where M is the number of the population, *D* is the dimension of the problem, and $|A|$ is the length of longest the diagonal in the search space.

But unlike to Uresem and Riget [9], [10], in DCSQPSO, only low bound d_{low} is set for diversity(pbest)to prevent the diversity from constantly decreasing. The procedure of the algorithm is as follows. After initialization, the algorithm is running in convergence mode.

On the course of evolution, if the diversity measure diversity(pbest) of the swarm drops to below the low bound d_{low}, the mean best position is reinitialized.

B. Local Search Strategy

For each particle, its neighborhood may cover better solutions. To improve the ability of exploitation, a local neighborhood search strategy is proposed. During searching the neighborhood of a particle P_i, a trial particle LX_i is generated as follows [11]:

$$LX_i = r_1 \cdot X_i + r_2 \cdot pbest_i + r_3 \cdot (X_c - X_d) \tag{11}$$

where X_i is the position vector of the ith particle, $pbest_i$ is the previous best particle of P_i, X_c and X_d are the position vectors of two random particles in the k-neighborhood radius of P_i, $c, d \in [i-k, i+k] \wedge c \ne d \ne i$, r_1 r_2 and r_3 are three uniform random numbers within (0,1), and $r_1 + r_2 + r_3 = 1$. The random numbers r_1 r_2 and r_3 are the same for all $j = 1, 2, \cdots, D$ and they are generated a new in each generation.

Besides the local neighborhood search, a global neighborhood search (GNS) strategy is proposed to enhance the ability of exploration. When search the neighborhood of a particle P_i another trial particle G_i is generated as follows [11]:

$$GX_i = r_4 \cdot X_i + r_5 \cdot gbest + r_6 \cdot (X_e - X_f) \tag{12}$$

where gbest is the global best particle, X_e and X_f are the position vectors of two random particles chosen for the entire swarm, $e, f \epsilon [1, N] \wedge e \ne f \ne i$, r_4 r_5 and r_6 are three uniform random numbers within (0, 1), and $r_4 + r_5 + r_6 = 1$. The random numbers r_4 r_5 and r_6 are the same for all $j = 1, 2, \cdots, D$ and they are generated a new in each generation. The GNS strategy is helpful to solve multimodal problems. Particles are located at different regions. Therefore, if the current particle falls into local minima, particles in other regions may pull the trapped particle forward.

C. The Proposed Approach

In every generation, if the particle's current position is better than its parent then replaced with current particle position; otherwise, we keep parent particle unchanged. After this operation, the local search strategy is conducted with p_{ns} probability. If the probability p_{ns} is satisfied, two particle LX_i and GX_i are generated. Then, the fittest particle among X_i, LX_i and GX_i is selected as the new P_i.

Procedure of DCSQPSO:

Step 1: Initialize particles with random position; set the pbest position and gbest position of each particle;

Step 2: For *n*=1 to $n_{\max}$ (maximum number of iterations), execute the following steps;

Step 3: Calculate the mean best position among the particles according to Eq. (7);

Step 4: Compute the value of α according to Eq. (9);

Step 5: Measure diversity(pbest) according to Eq. (10). If $\text{diversity}(pbest) < d_{low}$ then the mean best position is reinitialized.

Step 6: For each particle, execute Step 6 to Step 9;

Step 7: Computer its objective function $f(X_{i,n})$, If $f(X_{in}) < f(\mathrm{P_{i,n}})$ then $P_{i,n} = X_{i,n}$

Step 8: Select the current gbest position;

Step 9: if $\mathrm{rand}(0,1) \le p_{ns}$ then generate a trial particle LX_i and GX_i according to Eq. (11) and Eq. (12).

Step 10: Calculate the objective function $f(X_{i,n})$, $f(LX_{i,n})$ and $f(GX_{i,n})$.

Step 11: Select the fittest one among X_i, LX_i and GX_i

Step 12: Update pbest position and gbest position;

Step 13: For each dimension of each particle, get the stochastic position P by Eq. (8).

Step 14: Update each component of the current position by Eq. (11) and return to Step 2.

IV. EXPERIMENTS AND RESULTS

To test the performance of the DCSQPSO, eight widely known benchmark functions listed in Table I. DCSQPSO are tested for comparison with Standard PSO (SPSO), QPSO, QPSO-RS [12]. Functions f_1-f_s are unimodal and functions f_4 -f_s are multimodal. These functions are all minimization problems with minimum objective function values zeros. The fitness value is set as function value and the neighborhood of a particle is the whole population.

As in [12], for each function, three different dimension sizes are tested. They are dimension sizes: 10, 20 and 30. The maximal number of generations is set as 1000, 1500, and 2000 corresponding to the dimensions 10,20, and 30 for functions f_1−f_8, respectively. In order to investigate whether the DCSQPSO algorithms are well or not, different population sizes are used for each function with different dimensions. They are population sizes of 20, 40, and 80.

In experiments, for SPSO, we used Standard PSO 2007 (SPSO) available on the particle Swarm Central. For QPSO and QPSO-RS, the value of CE Coefficient varies from 1.0 to 0.5 linearly over the running of the algorithm as in Sun *et al*. [3], while in DCSQPSO, the value of CE Coefficient also decreases from 1.0 to 0.5 linearly, *k*=2, $p_{ns} = 0.6$ [11]. We had 50 trial runs for every instance and recorded mean best fitness and standard deviation.

The mean best function values found in the last generation and the standard deviation are recorded in Table II to Table IX.

From the comparison of DCSQPSO with other algorithms, DCSQPSO achieved better results than other algorithms averagely. It shows the diversity-controlled QPSO with local search strategy were effective for most test functions. For function f_1, f_2, f_4, f_5, f_7, DCSQPSO has the best performance among all of the tested algorithms. In some case, these functions obtain minimum objective function values zeros. For function f_3, QPSO has the minimum value when the swarm size is 40 and dimension is 10, the swarm is 80 and dimension is 10 and 20, while DCSQPSO outperforms for the rest functions. For function f_6, SPSO has the best results in three cases. For function f_8, QPSO-RS algorithm has the minimal value in some cases.

TABLE I: EXPRESSION OF THE SEVEN TESTED BENCHMARK FUNCTIONS

	Function Expression	Search	Initial Range
Sphere	$f_1(x) = \sum_{i=1}^{n} x_i^2$	[-100, 100]	[50, 100]
Unimodal Schwefel's 2.21	$f_2(x) = 10^6 x_1^2 + \sum_{i=2}^{n} (x_i^2)^2$	[-100, 100]	[50，100]
Schwefel's 2.22	$f_3(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	[-10, 10]	[5, 10]
Rosenbrock	$f_4(x) = \sum_{i=1}^{n} (100 \cdot (x_{i-1} - x_i^2)^2 + (x_i - 1)^2)$	[-30, 30]	[15, 30]
Rastrigin	$f_5(x) = \sum_{i=1}^{n} (x_i^2 - 10 \cdot cos(2\pi x_i) + 10)$	[-5.12, 5.12]	[2.56, 5.12]
Griewank	$f_6(x) = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} cos\,(\frac{x_i}{\sqrt{i}} + 1)$	[-600, 600]	[300, 600]
Ackley	$f_7(x) = 20 + e - 20e^{\frac{1}{5}\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}} - e^{-\frac{1}{n}\sum_{i=1}^{n} cos\,(2\pi x_i)}$	[-32, 32]	[16, 32]
Multimodal Schwefel	$f_8(x) = 418.9829n - \sum_{i=1}^{n} (x_i sin\sqrt{\lvert x_i \rvert})$	[-500, 500]	[250, 500]

Functions f_1−f_3 are unimodal; Functions f_4-f_8 are multimodal.

TABLE II: SIMULATION RESULTS OF SPHERE FUNCTION

M	Dim	Gmax	SPSO		QPSO		QPSO-RS		DCSQPSO	
			Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.
	10	1000	1.47e-041	4.27e-041	3.19e-043	2.20e-042	4.94e-044	1.84e-043	**5.89e-082**	2.51e-081
20	20	1500	2.12e-032	1.13e-031	1.92e-024	7.16e-024	1.82e-024	3.86e-024	**2.16e-063**	5.30e-063
	30	2000	5.06e-023	2.02e-022	7.37e-015	2.18e-014	4.17e-015	1.26e-014	**3.44e-049**	7.28e-048
	10	1000	1.92e-047	5.17e-047	2.76e-076	1.90e-075	9.90e-076	3.82e-075	**0**	0
40	20	1500	7.46e-042	2.49e-041	3.92e-044	1.84e-043	3.07e-044	9.87e-043	**7.49e-097**	1.85e-097
	30	2000	8.51e-037	1.74e-036	2.64e-031	6.39e-031	3.36e-032	3.73e-031	**5.91e-084**	2.64e-083
	10	1000	8.91e-053	1.44e-052	2.56e-103	6.48e-103	2.39e-103	4.83e-103	**0**	0
80	20	1500	6.52e-050	1.83e-049	1.41e-068	7.45e-068	1.56e-068	2.44e-068	**0**	0
	30	2000	3.27e-013	9.16e-046	6.58e-050	3.60e-049	4.16e-050	3.28e-049	**0**	0

TABLE III: SIMULATION RESULTS OF UNIMODAL SCHWEFEL FUNCTION

M	Dim	Gmax	SPSO		QPSO		QPSO-RS		DCSQPSO	
			Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.
	10	1000	1.08 e-002	9.80 e-003	2.40e-021	9.94e-021	1.96e-053	1.39e-052	**0**	0
20	20	1500	8.01e-007	1.65e-006	3.06e-010	2.01e-009	1.48e-029	8.11e-029	**3.26e-047**	9.61e-047
	30	2000	2.43e-011	4.04e-011	2.39e-008	5.60e-008	5.85e-019	1.38e-018	**3.77e-038**	5.69e-037
	10	1000	1.51 e-002	2.70 e-002	2.78e-027	1.92e-026	1.00e-097	4.28e-097	**0**	0
40	20	1500	5.60e-007	8.00e-007	6.80e-017	1.56e-016	1.18e-056	7.82e-056	**0**	0
	30	2000	1.39e-011	1.71e-011	1.33e-011	1.96e-011	9.02e-038	5.73e-037	**4.73e-064**	8.52e-064
	10	1000	1.32 e-002	1.23 e-002	2.59e-028	8.73e-028	8.71e-132	6.14e-131	**0**	0
80	20	1500	7.38e-007	1.10e-006	3.99e-017	7.72e-017	6.92e-090	2.88e-089	**0**	0
	30	2000	2.14e-011	3.44e-011	7.62e-012	8.46e-012	2.58e-064	1.40e-063	**0**	0

TABLE IV: SIMULATION RESULTS OF SCHWEFEL'S 2.22 FUNCTION

M	Dim	Gmax	SPSO		QPSO		QPSO-RS		DCSQPSO	
			Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.
	10	1000	3.89e-013	3.84e-013	1.16e-023	5.82e-023	1.12e-014	1.47e-014	**5.09e-031**	8.62e-030
20	20	1500	1.97e-008	4.49e-008	9.39e-015	1.79e-014	9.26e-009	4.99e-008	**7.51e-024**	3.48e-024
	30	2000	8.14e-006	2.31e-005	3.64e-009	1.64e-008	9.94e-007	1.89e-006	**6.20e-018**	5.37e-017
	10	1000	4.32e-015	7.31e-015	**3.72e-041**	2.33e-040	5.60-015	4.24e-015	8.57e-035	3.14e-034
40	20	1500	2.74e-010	4.31e-010	8.88e-025	5.00e-024	4.76e-010	2.54e-010	**2.18e-041**	4.07e-040
	30	2000	5.71e-008	1.04e-007	1.30e-017	5.71e-017	1.98e-007	2.13e-007	**9.42e-029**	6.80e-029
	10	1000	8.34e-017	2.18e-016	**7.77e-058**	3.62e-057	5.88e-015	3.24e-015	5.82e-047	4.27e-047
80	20	1500	5.42e-012	5.91e-012	**4.47e-039**	2.78e-038	6.00e-010	8.51e-010	6.19e-028	1.07e-028
	30	2000	2.16e-009	3.81e-009	2.03e-028	1.28e-027	2.45e-007	1.57e-007	**4.51e-044**	3.64e-044

TABLE V: SIMULATION RESULTS OF ROSENBROCK FUNCTION

M	Dim	Gmax	SPSO		QPSO		QPSO-RS		DCSQPSO	
			Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.
	83.15	1000	18.96	49.87	9.56	16.63	6.91	0.90	**1.32**	0.05
34.06	20	1500	34.06	83.15	82.42	138.24	35.50	31.49	**12.14**	15.29
	30	2000	103.74	118.04	98.79	122.57	72.91	55.23	**35.27**	28.96
	10	1000	8.86	18.82	8.99	17. 02	5.19	6.03	**1.16**	0.02
40	20	1500	18.71	34.40	40.74	41.17	19.48	11.89	**8.25**	5.34
	30	2000	58.13	64.95	43.55	38.05	42.02	25.28	**10.53**	4.68
	10	1000	8.59	25.36	6.83	0.33	5.09	6.82	**0.06**	3.87
80	20	1500	22.02	35.49	33.52	31.64	17.09	0.23	**6.52**	2.27
	30	2000	43.74	58.09	44.59	31.67	27.17	0.20	**9.35**	5.22

Fig. 1 shows the convergence process of the four algorithms on the eight benchmark functions with dimension 30 and swarm size 40 averaged on 50 trail runs. It is shown that, although DCSQPSO converge more slowly than the

SPSO and QPSO during the early stage of search, it may catch up with SQPSO and QPSO at later stage and could be generated better solutions at the end of search.

TABLE VI: SIMULATION RESULTS OF RASTRIGIN FUNCTION

M	Dim	Gmax	SPSO		QPSO		QPSO-RS		DCSQPSO	
			Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.
	10	1000	5.64	2.53	4.00	2.14	3.73	2.78	**4.91e-002**	5.29 e-002
20	20	1500	20.34	5.36	15.06	6.07	14.96	11.55	**1.35 e-001**	2.58e-001
	30	2000	41.86	11.45	28.30	12.56	23.76	5.06	**6.44e-001**	3.10 e-001
	10	1000	3.43	1.21	2.64	1.53	2.01	1.64	**5.87e-003**	4.88e-002
40	20	1500	17.65	4.48	11.31	3.59	11.92	6.15	**1.06e-001**	3.29e-001
	30	2000	39.52	8.45	18.92	4.83	15.44	7.43	**2.18 e-001**	6.27 e-001
	10	1000	2.28	1.02	2.26	1.48	1.46	2.54	**2.61 e-003**	3.29 e-003
80	20	1500	10.23	2.56	8.41	2.57	7.74	3.79	**8.69e-002**	4.71 e-002
	30	2000	25.12	5.84	14.85	5.04	14.67	4.03	**1.28e-001**	3.64e-001

TABLE VII: SIMULATION RESULTS OF GRIEWANK FUNCTION

M	Dim	Gmax	SPSO		QPSO		QPSO-RS		DCSQPSO	
			Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.
	10	1000	6.00 e-002	2.59 e-002	7.39 e-002	5.59 e-002	6.57 e-002	5.02 e-002	**3.20 e-002**	4.74 e-002
20	20	1500	**1.00 e-002**	2.08 e-002	1.90 e-002	2.08 e-002	2.62 e-002	2.27 e-002	1.26 e-002	1.53e-002
	30	2000	6.50 e-003	1.86 e-002	7.51 e-003	1.14 e-002	8.24 e-003	2.35 e-002	**7.16 e-004**	2.91 e-003
	10	1000	**5.49 e-003**	3.41 e-002	4.87 e-002	2.41 e-002	5.81 e-002	8.22 e-002	2.46 e-002	1.82e-002
40	20	1500	1.16 e-002	2.87 e-002	2.06 e-002	1.97 e-002	1.35 e-002	4.31 e-002	**8.41e-003**	5.25e-003
	30	2000	7.60 e-003	2.67 e-002	7.93 e-003	9.24 e-003	2.07 e-003	1.23 e-002	**1.94 e-004**	3.76 e-004
	10	1000	**1.47 e-002**	1.54 e-002	4.16 e-002	3.23 e-002	4.24 e-002	6.82 e-002	3.48 e-002	5.92 e-002
80	20	1500	8.60 e-003	1.02 e-002	1.37 e-002	1.35 e-002	5.00 e-003	1.03 e-002	**4.83e-004**	7.16 e-003
	30	2000	1.45e-004	1.01e-004	7.10e-003	1.09 e-002	**1.05e-006**	5.31e-006	6.73e-005	8.04e-005

TABLE VIII: SIMULATION RESULTS OF ACKLEY FUNCTION

M	Dim	Gmax	SPSO		QPSO		QPSO-RS		DCSQPSO	
			Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.
	10	1000	3.32	7.12	15.20	8.63	1.60	5.48	**2.38e-002**	8.64e-002
20	20	1500	12.43	9.03	18.60	5.58	3.66	7.73	**4.51e-002**	7.89e-002
	30	2000	17.61	5.14	20.14	2.91	3.98	7.75	**9.64e-002**	5.60e-002
	10	1000	2.38	6.53	14.82	8.77	1.37	4.53	**3.12e-008**	4.16e-008
40	20	1500	10.75	9.75	18.37	1.62	4.28	5.29	**2.38e-006**	2.55e-006
	30	2000	12.22	8.99	20.52	0.06	7.74	1.27	**3.51e-004**	3.57e-004
	10	1000	1.43	1.01	12.37	9.78	1.06	3.81	**3.02e-010**	8.24e-010
80	20	1500	6.57	9.22	17.40	6.97	3.06	5.93	**7.21e-009**	2.81e-009
	30	2000	10.60	9.56	18.61	5.80	6.44	5.24	**1.14e-008**	4.35e-008

TABLE IX: SIMULATION RESULTS OF MULTIMODAL SCHWEFEL FUNCTION

M	Dim	Gmax	SPSO		QPSO		QPSO-RS		DCSQPSO	
			Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.	Mean Best	St. Dev.
	10	1000	8.57 e-014	1.54 e-013	5.46 e-038	9.05 e-038	**1.04 e-076**	1.57 e-076	8.64 e-069	6.71e-068
20	20	1500	5.69 e-018	4.59 e-017	3.46 e-045	2.18 e-044	1.33 e-087	9.49 e-087	**2.57 e-096**	4.31 e-095
	30	2000	1.77 e-021	6.38 e-021	7.65 e-054	3.51 e-053	2.51 e-095	1.70 e-094	**0**	0
	10	1000	4.28 e-011	9.24 e-011	1.42 e-032	3.88 e-031	**9.65 e-066**	1.98 e-065	5.61 e-057	8.44 e-056
40	20	1500	3.10 e-017	3.13 e-016	2.84 e-038	2.10 e-038	1.70 e-054	1.02 e-054	**8.29 e-070**	4.60 e-070
	30	2000	1.27 e-020	5.84 e-020	6.66 e-041	2.99 e-041	4.01 e-088	1.70 e-087	**0**	0
	10	1000	2.37 e-024	7.97 e-023	7.10 e-059	2.84 e-058	**4.22 e-081**	9.13 e-080	7.24 e-077	6.14e-076
80	20	1500	3.25 e-031	3.29 e-031	1.75 e-061	1.31 e-061	2.09 e-084	7.70 e-083	**3.67e-091**	5.08 e-090
	30	2000	1.12 e-035	5.88 e-035	5.71 e-064	2.81 e-063	4.87 e-102	9.89 e-101	**0**	0

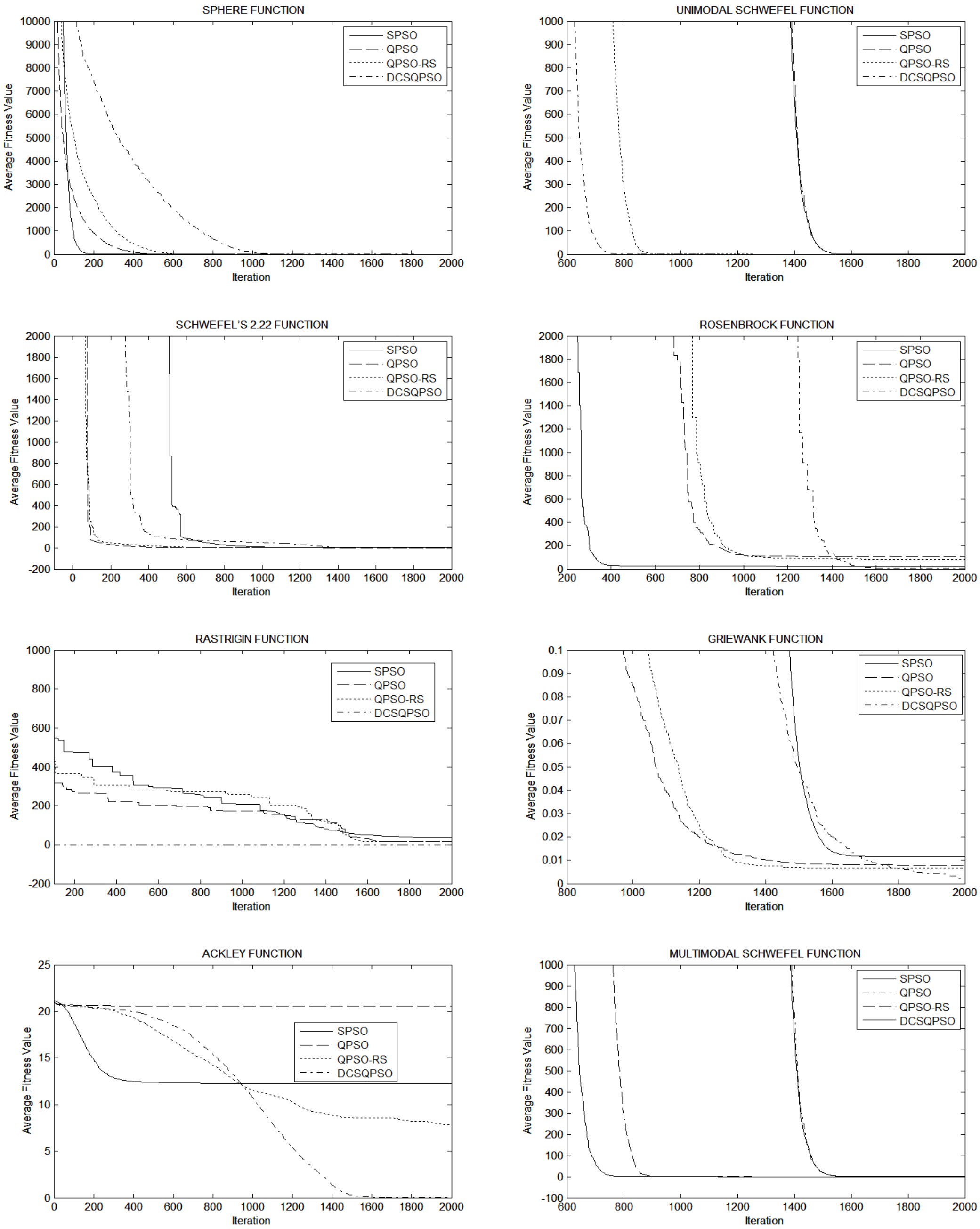

Fig. 1. Convergence process of the four algorithms on the functions f_1-f_8 with swarm size 40 and dimension 30 averaged on 50 trail runs.

V. Conclusions

This paper presents an enhanced QPSO algorithm called DCSQPSO to solve complex optimization problems. The proposed approach explores diversity enhancing mechanism and local search strategies. To verify the performance of DCSPSO, different types of benchmark functions are tested in the experiments.

Our future work for DCSQPSO will focus on the values of the parameters p_{ns} which affect the performance of DCSPSO.

References

[1] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. IEEE Int. Conf. Neural Networks*, 1995, pp. 1942–1948.

[2] F. Van den Bergh, *An Analysis of Particle Swarm Optimizers*, University of Pretoria, South Africa, 2001.

[3] J. Sun, X. J. Wu, V. Palade *et al.*, "Convergence analysis and improvements of quantum-behaved particle swarm optimization," *Information Sciences*, vol. 193, pp. 81-103, 2012.

[4] S. F. Lu, C. F. Sun, and Z. D. Lu, "An improved quantum-behaved particle swarm optimization method for short-term combined economic emission hydrothermal scheduling," *Energy Conversion and Management*, vol. 51, no. 3, pp. 561–571, 2010.

[5] J. Sun, W. Fang, and P. Vasile, "Quantum-behaved particle swarm optimization with Gaussian distributed local attractor point," *Applied Mathematics and Computation*, vol. 218, no. 7, pp. 3763–3775, 2011.

[6] Q. Niu, Z. Zhou, H. Y. Zhang, and J. Deng, "An improved quantum-behaved particle swarm optimization method for economic dispatch problems with multiple fuel options and valve-points effects," *Energies*, vol. 5, no. 9, pp. 3655-3673, 2012.

[7] J. Sun, W. Chen, W. Fang *et al.*, "Gene expression data analysis with the clustering method based on an improved quantum-behaved particle swarm optimization," *Engineering Applications of Artificial Intelligence*, vol. 25, no. 2, pp. 376–391, 2012.

[8] M. Clerc and J. Kennedy, "The particle swarm: explosion, stability, and convergence in a multi-dimensional complex space," *IEEE Transactions on Evolutionary Computation*, Piscataway, vol. 6, pp. 58-73, 2002.

[9] R. K. Ursem, "Diversity-Guided Evolutionary Algorithms," in *Proc. the Parallel Problem Solving from Nature Conference*, 2011, pp. 462-471.

[10] J. Riget and J. Vesterstroem, "A diversity-guided particle swarm optimizer-the ARPSO," Department of Computer Science, University of Aarhus, 2002.

[11] H. Wang, H. Sun, C. H. Li *et al.*, “Diversity enhanced particle swarm optimization with neighborhood search,” *Information Sciences*, vol. 223, pp. 119–135, 2013.

[12] H. X. Long, J. Sun, X. G. Wang *et al.*, “Using selection to improve quantum-behaved particle swarm optimization”, *International Journal of Innovative Computing and Applications*, vol. 2, no. 2, pp. 100-114, 2010.

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