A Comparison Between SPSO and QPSO from View Point of Optimization

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Received: 29 November 2018 Accepted: 19 March 2019

Abstract

Particle swarm optimization (PSO) has magnetized different investigators who are concerned in dealing with different optimization problems, due to its ease of implementation and reasonable performance. However, PSO algorithm is trapped in the local optima easily because of the quick loss of the population variance. Hence, enhancement of the performance of PSO and detraction the relaying on factors are led to significant variants of SPSO. One important variant is the quantum behavior of particle swarm optimization (QPSO), which is dependent on the dynamical analysis of SPSO and quantum mechanics. This paper presents a notion for the optimization of nonlinear functions using swarm methodology and a comparison between SPSO and QPSO are given. These two algorithms are analyzed on both unimodal and multimodal, high and low dimensional continuous functions. The results on eight benchmark functions show that the QPSO algorithm can perform much better than the SPSO.

Keywords: SPSO, QPSO, benchmark functions, Meta-heuristic optimization.

مقارنة بين SPSO و QPSO من وجهة نظر المفاضلة

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الخلاصة

اجتذب مفاضلة سرب الجسيمات (PSO) العديد من الباحثين المهتمين بالتعامل مع مشاكل المفاضلة المختلفة، بسبب سهولة التنفيذ، وعدد قليل من المعلمات المضبوطة، والأداء المقبول. ومع ذلك، خوارزمية PSO سهلة الفخ في optima المحلية بسبب فقدان سريع للتنوع السكاني. لذلك يتم مفاضلة أداء PSO وتقليل الاعتماد على المعلمات إلى أشكال هامة من SPSO. أحد المتغيرات المهمة هو مفاضلة سرب الجسيمات المحسوب على الكم (QPSO) والذي يعتمد على التحليل الديناميكي لـ SPSO والميكانيكا الكمومية. في هذه الورقة، تم تقديم مفهوم لمفاضلة الوظائف غير الخطية باستخدام منهج سرب الجسيمات، تتم مقارنة بين SPSO و QPSO. يتم اختبار هذين الخوارزميتين على كل من الوظائف المستمرة أحادية الواسطة ومتعددة الوسائط، منخفضة وعالية الأبعاد. تظهر النتائج التجريبية على 8 وظائف معيارية، أن خوارزمية QPSO يمكن أن تكون أفضل بكثير من SPSO.

الكلمات المفتاحية: مفاضلة السرب الجزيئية القياسية، مفاضلة السرب الجزيئية الكمية، دوال قياسية ,الاستدلال الفوقي الأمثل.

Introduction

Swarm intelligence (SI) is the combined attitude of decentralized, natural or artificial, self-organized systems. SI systems are consisting of a population of simple representatives reacting locally with each other and with the environment [1]. These representatives obey very easy principles, and in spite of no centric control fabric dictating how individual representatives should behave local, and to some extent random. Influences between such representatives derive to the development of "intelligent" global behavior, unknown to the individual representatives. Some natural paradigms of SI cover bird flocking, ant colonies, animal herding, bacterial growth, and fish schooling [2].

Studies of the social behavior of creatures (individuals) in swarms motivated the design of very active optimization algorithms. For example, the PSO algorithm simulates the behaviors of bird flocking [3]. Researchers have proposed different modified variants of PSO to enhance its efficiency; nevertheless, a little convergence rate problems are yet still. In the PSO research, how to increase population diversity to enhance the precision of solutions and how to speed up convergence rate with the least computation cost are two vital issues. Lately, a new variant of PSO has been advanced, namely the QPSO algorithm [4].

QPSO algorithm is a new improved version of PSO presents quantum computing into the PSO algorithm, beginning from viewpoint of the quantum mechanics. In this paper, the performance of SPSO and QPSO is compared in solving global optimization problems.

This paper is organized as follows: sections 2 and 3 describe the SPSO and QPSO algorithms. Section 4 provides details of the simulation and analysis of both these algorithms on the benchmarking problems and compares their results. In section 5, conclusions from this work are drawn and suggestions for future research are given.

Standard Particle Swarm Optimization (SPSO)

The fundamental PSO [5] model contains a swarm of particles, which are started with a population of stochastic nominee solutions. They proceed iteratively through the problem space of d-dimensions to search for better solutions. The fitness (f) can be calculated as the specific qualities measure [6]. Particles have positions represented by position-vector (xi) (i is the index of the particle), and a velocity represented by a velocity vector (vi). Particles remember their own best positions in a vector and their d-dimensional values are pbest (pid) [6]. The best position vector is stored in the vector i-th, and its d-th dimensional value is gbest (pgd). Through the time (t) of iteration, Eq. 1 determines the update of the velocity (vid) from the previous velocity to the new velocity [6]. Eq. 2 determines the new position (xid) by the sum of the previous position and the new velocity [5].

$$V(id+1) = w * vid + c1 * r1 * (pgd - xid) + c2 * r2 * (pid - xid) \quad \textbf{(1)}$$

$$X(id+1) = xid + v(id+1) \quad \textbf{(2)}$$

DOI: https://dx.doi.org/10.24237/djps.15.03.497C
P-ISSN: 2222-8373
E-ISSN: 2518-9255

where: i =1, 2, …, N; inertia weight is (w), random numbers are (r1 and r2), over the period [0,1] in order to maintain the diversity of the population. Self-recognition component is a positive constant (C1). Coefficient of the social component is a positive constant (C2).

The particle determines the next move depending on Eq. 1 taking its experience in consideration which is its own best past position, and its most successful particle in the swarm

In order to direct the particles efficiently in the swarm space, the farthest moveable distance through one iteration should be clamped between the velocities [−vmax, vmax] [8]. The basic SPSO algorithm can be viewed in figure 1.

```
Begin
generate an initial random population positions and velocities with size m and the dimensions
d of the particles.
Repeat
for i = 1 to m do
if (f (xi) < f (pi) then pi = xi
G = argmax (f (pi))
for j = 1 to d do
update velocity with Eq. (1);
update Position with Eq. (2);
end;
end;
until termination criterion is met.
End
```

Figure 1: Pseudo Code of PSO Algorithm; After [5].

Quantum-Behaved – Particle Swarm Optimization algorithm (QPSO)

Recently, inspired by quantum mechanics and dynamical analysis of SPSO algorithm [32], Sun et al. proposed a new version of SPSO [4]. Quantum-Behaved Particle Swarm Optimization (QPSO) algorithm [4,9]. QPSO makes use of a strategy based on a quantum delta potential well δ model to sample around the SPSO best positions [4]. Also, the mean best position was introduced into the iterative equation of QPSO to enhance the global search ability of the particle [34]. As per classical PSO [6], a particle is stated by its position vector x and velocity vector v, which determine the trajectory.

Quantum Particle Swarm Optimization (QPSO)

In the QPSO algorithm, the state of a particle is drawn by wave function Ψ (x, t) instead of velocity and position. The movement of particles can be anywhere in the functional region, even a particle moves far away from the current position, depending on the potential field the particle lies in [9].

The movement of particles depend on the iterative equations (3 and 4) [8]:

$$x_{t+1} = p + \alpha \left| mbest - x_t \right| \ln \frac{1}{u} \qquad \text{if} \qquad k \geq 0.5 \tag{3}$$

$$x_{t+1} = p - \alpha \left| mbest - x_t \right| \ln \frac{1}{u} \qquad \text{if} \qquad k < 0.5 \tag{4}$$

Where: $Qp_{id} + (1 - Q)\, p_{gd}$ **(5)**

$$MBEST = \frac{1}{M} \sum_{i=1}^{m} p_i \tag{6}$$

The mean of the best positions of all particles is represented by (mbest). U, k, Q are stochastic uniformly distributed numbers on the interval [0, 1]. The factor α is called contraction-expansion factor. The pseudo code of QPSO algorithm is shown in figure 2.

```
Initialize the swarm
Begin
While the condition termination not met Do
Calculate mbest by equation (3)
Update particle positions by using equation (1)
Update pbest
Update gbest
End do
End
```

Figure 2: Pseudo Code of QPSO Algorithm; After [9]

Experimental Results and Discussion

A. Benchmark Test Functions

In order to compare the performance of the SPSO algorithm with the QPSO algorithm (8) benchmark functions have been used, including four unimodal and four multimodal functions [11]. The description of each function, along with their limits of functional space and global minimum values of the functions are shown in the table 1.

Functions are examined with dimension D = 3, 6 and 10. The population size is specified to 30. Algorithms are examined with (3000) iteration for each test function.

Table1: Benchmark Functions used in the experiments

Function name	Function definition	range	optimum
Sphere	$f1(x)=\sum_{i=1}^{D} x_i^2$	[-100,100]	0.0
Schwefel's P2.22	$f2(x)=\sum_{i=1}^{D} \lvert x_i \rvert + \prod_{i=1}^{D} \lvert x_i \rvert$	[-10,10]	0.0
Step	$f3(x)=\sum_{i=1}^{D} (\lvert x_i + 0.5 \rvert)^2$	[-100,100]	0.0
Rosenbrock	$f4(x)=\sum_{i=1}^{D-1} 100(x_i^2 - x_{i+1})^2 + (1-x_i)^2$	[-30,30]	0.0
Multimodal Schwefel's	$f5(x)=418.9829* D\sum_{i=1}^{n} - x_{i\sin\lvert\sqrt{x_i}\rvert}$	[-500,500]	0.0
Rastrigin	$f6(x)=\sum_{i=1}^{D}[x_i^2 10\cos(2\Pi x_i)+10)$	[-5.12,5.12]	0.0
Griewank	$f7(x)=\frac{1}{4000}\sum_{i=1}^{D} x_i^2 - \prod_{i=1}^{D} \cos\frac{x_i}{\sqrt{i}} + 1$	[-600,600]	0.0
Alpine 1	$f8(x)=\sum_{i=1}^{D} \lvert x_i \sin x_i + 0.1 x_i \rvert$	[-10,10]	0.0

B. Discussion

In the table 2, we can see that the solution quality (mean value) of QPSO algorithm is much better and can find the global optimal solutions on both multimodal and unimodal function on different search spaces. Also, the value of the standard deviation indicates that the result of

QPSO is more consistent. Therefore, we also conclude that QPSO has better stability than SPSO algorithms in different search spaces. The performance of (SPSO and QPSO) algorithms for Unimodal Sphere Function and Multimodal Rastrigin Function on 30D, 60D, and 100D search spaces are plotted in figure 3.

Table 2: Comparison between SPSO and QPSO on 8 standard benchmark functions.

Function name	Algorithm	Dimension	Mean Best Values	Standard deviation
Sphere	SPSO	30	2497969.367	377.870968028728
	QPSO		975.250333333333	466.517995925087
	SPSO	60	1036909.139	342.589026771309
	QPSO		468.127333333333	671.769462694633
	SPSO	100	4719710.12966667	1664.78076303771
	QPSO		101.816333333333	1137.75578297028
Schwefel's P2.22	SPSO	30	60119.689	6.23233333333343
	QPSO		34.5793333333333	23224459.8043513
	SPSO	60	36655.618	5.55699999999993
	QPSO		3.49633333333333	30730546.3481424
	SPSO	100	152520.447333333	35.7413333333333
	QPSO		16.0583333333333	443645358.67847
Step	SPSO	30	7662647.63733333	2329.46262676454
	QPSO		243.103666666667	1899.98723901219
	SPSO	60	19678057.464	697.488916590488
	QPSO		30.8833333333333	1821.45677605273
	SPSO	100	2768780.27466667	1300.90215670385
	QPSO		32.8046666666667	1623.40197967115
RosenBrock	SPSO	30	235695090.865	23725.2446666663
	QPSO		78580.1146666667	57782.566383228
	SPSO	60	826168511.27	50063.7686666658
	QPSO		91228.1256666667	78204.9609324502
	SPSO	100	393718479.651667	41714.4153333338
	QPSO		173186.361666667	6111.41907859525
Schwefel	SPSO	30	13135113.9150007	875628.172881195
	QPSO		4038417060.82427	47642037072.9023
	SPSO	60	8848918.84799965	275619.521107109
	QPSO		7564251521.1723	59952365306.7374
	SPSO	100	13235669.8110001	710088.029090923
	QPSO		24404182459.2012	45519416630.1825
Rastrigin	SPSO	30	7997.97466666667	2.35300000000006
	QPSO		2.93766666666667	2.58160701567267
	SPSO	60	8695.97266666667	1.45666666666664

	QPSO		3.55333333333333	1.58487458358815
	SPSO		10527.9836666667	3.50566666666675
	QPSO	100	3.52833333333333	3.80895861759071
	SPSO		9133.080939915703	0.176460750000001
	QPSO	30	0.177740795229174	0.848512530150701
	SPSO		1856.54149012814	0.395528333333321
Griewank	QPSO	60	0.385627850333332	0.663930405633507
	SPSO		174.760007393218	0.0277717500000016
	QPSO	100	0.0382736303541656	0.800576293451328
	SPSO		10329.9933333333	3.53166666666668
	QPSO	30	3.50633333333333	4.10468328001799
	SPSO		5923.99333333333	2.00600000000003
Alpine 1	QPSO	60	5.67933333333333	55259.4023332337
	SPSO		5987.99366666667	1.97800000000006
	QPSO	100	2.94533333333333	2.79236143694822

Figure 3 shows the mean best values of the QPSO algorithm on most of the test functions and with different search spaces is more closely to global optimal solutions because QPSO algorithm is more efficient in finding the best and closest points to optimum for each test function than SPSO algorithm as shown in table 2 and figure 3.

Conclusion

This paper presents a variant of the SPSO algorithm which is the QPSO algorithm by using quantum mechanism and dynamical analysis of SPSO. Both of these algorithms use swarm intelligence to find the global optimum value of continuous optimization problems. Experimental results on the eight standard benchmark problems for SPSO and QPSO demonstrate the effectiveness and competitiveness of the algorithms. The QPSO outperforms the SPSO algorithm in terms of the final solution quality in most of the functions.

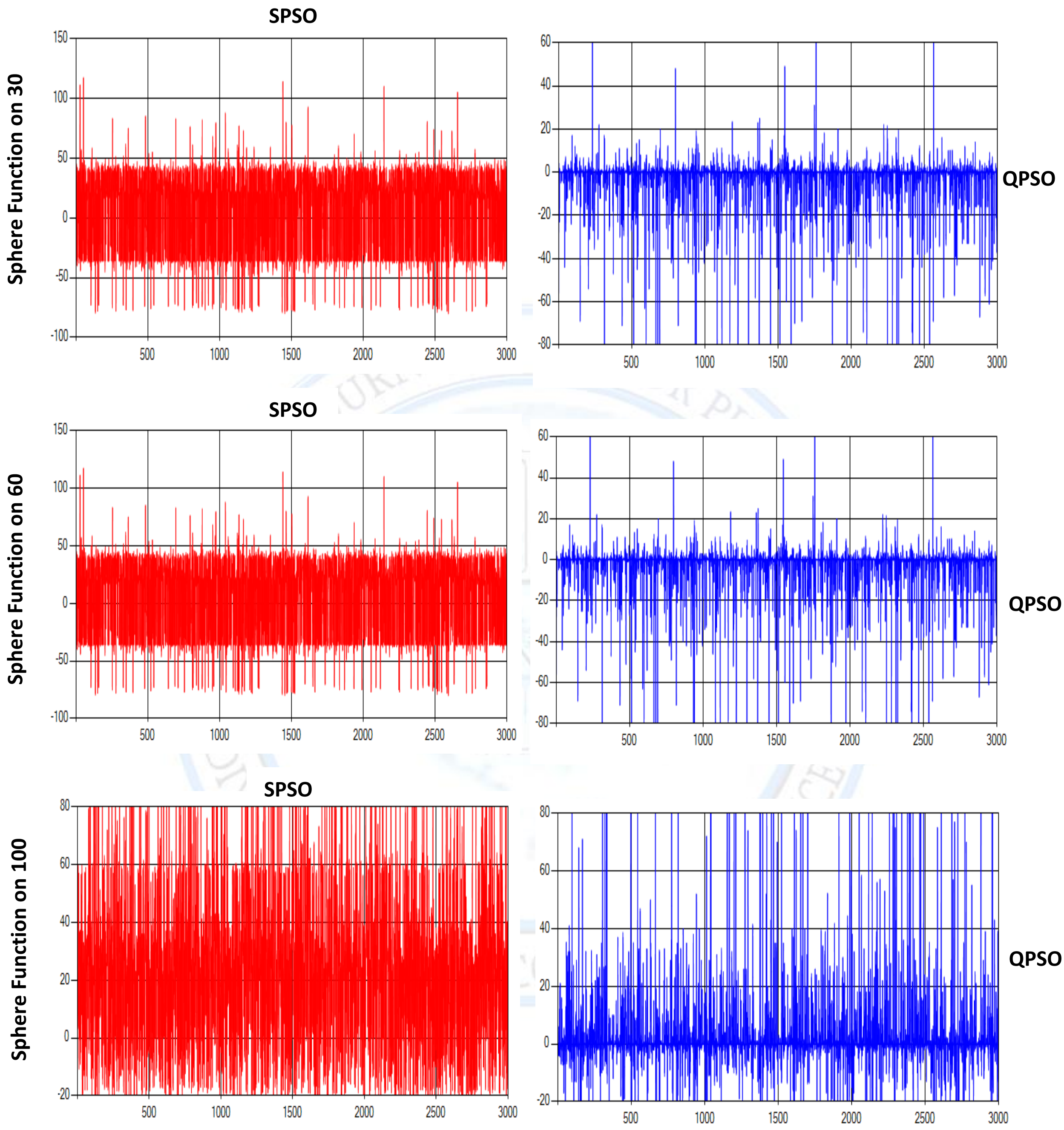

Figure 3: The performance of (SPSO and QPSO) algorithms for Unimodal Sphere Function and Multimodal Rastrigin Function on 30D, 60D and 100D search spaces

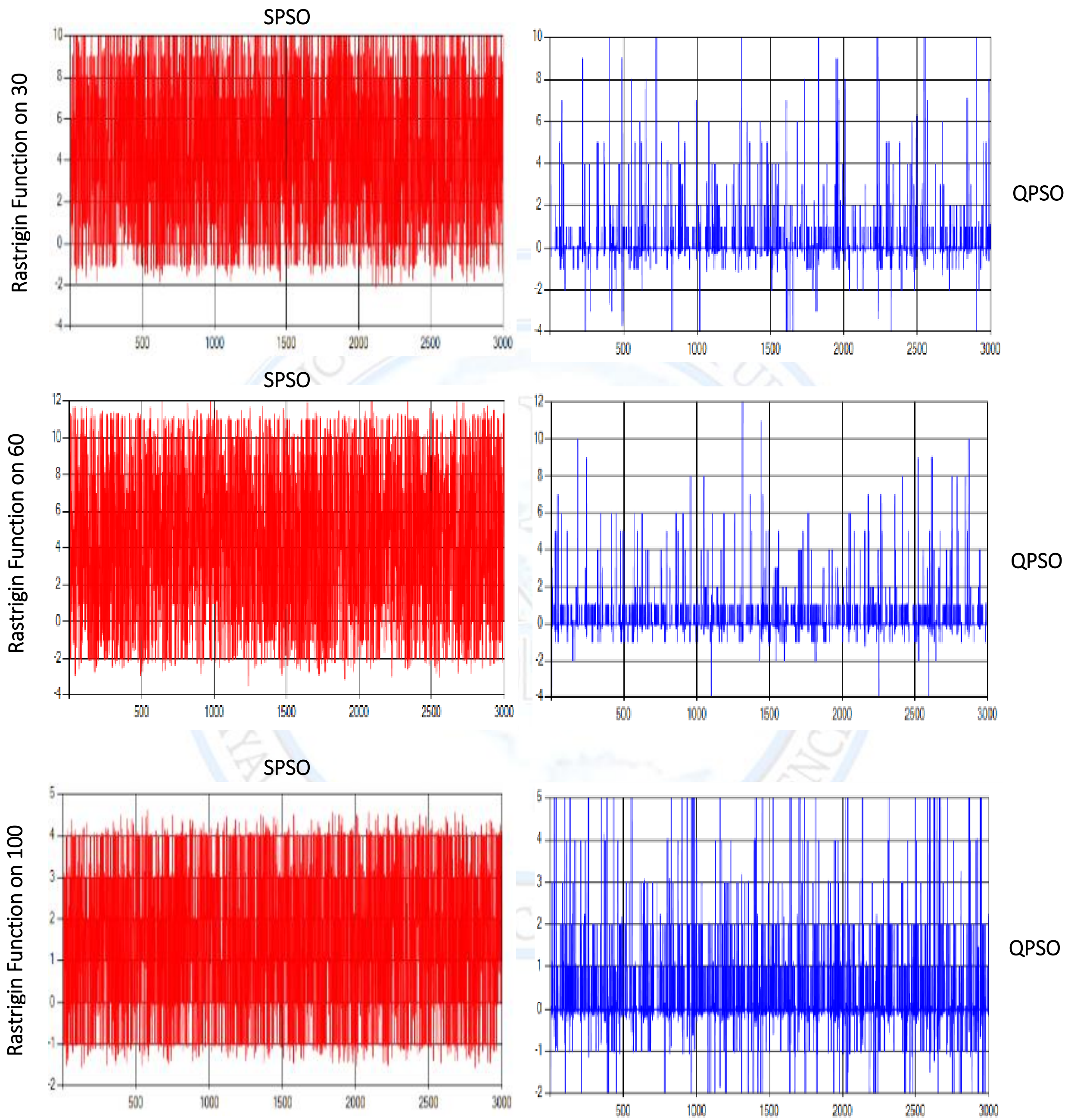

Figure 4: Continue of Figure 3

References

1. H. Ahmed, J. Glasgow, Swarm Intelligence Concepts, Models and Applications, Technical Report no. 2012-585, school of computation Queen's University Kingston, Ontario, Canada K7L3N6, (February 2012).
2. J. Sun, C. H. Lai, X. Jun, Particle Swarm Optimization Classical and Quantum Perspective, 1st ed. (Chapman & Hall / CRC Press, Boca Raton, 2012).
3. J. I. Fister, X. S. Yang, J. Brest, P. Fister, A Brief Review of Nature- Inspired Algorithm for Optimization, report no. 1307.4186, Review Scientific Paper 80(30), PP. 116-122, (2013).
4. W. Zhang, W. Shi, J. Zhuo, Quantum-PSO based system stabilizer optimization for shipboard power system, In: 35th Chinese Control Conference (CCC), (2016), Chengdu, pp. 9810-9814.
5. J. Kennedy, R. Eberhart, Particle swarm optimization (PSO), In: IEEE International Conference on Neural Networks, November (1995), Australia, pp. 1942–1948.
6. Z. T. M. Al-Ta'i, O.Y.A. Al-Hameed, International Journal of Engineering and Innovative Technology (IJEIT) ,3(1), 421- 425(2013).
7. M. Clerc, J. Kennedy, The particle swarm-explosion, stability, and convergence in a multidimensional complex space, In: IEEE Transactions on Evolutionary Computation, Feb. (2002), 6(1), pp. 58–73.
8. J. Sun, B. Feng, W. XU, A Global search strategy of quantum-behaved particle swarm optimization, In: IEEE Conference on Cybernetics and Intelligent Systems, (2004), Singapore, pp. 111-116.
9. J. Sun, W. Fang, X. Wu, V. Palade, W. Xu, Evolutionary Computation, 20(3), 349-393(2012).
10. A. Abraham, H. Guo, H. Liu, Swarm Intelligence: Foundations, Perspectives and Applications, Studies in Computational Intelligence, vol. 26, (Springer, Berlin, Heidelberg, 2006), pp. 3-25.
11. P. N. Suganthan, N. Hansen, J. J. Liang, K. Deb, Y. -P. Chen, A. Auger, S. Tiwari, Problem definitions and evaluation criteria for the CEC 2005, Technical Report, KanGAL report 2005005, Nanyang Technological University, Singapore, (2005).