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QUORUM SENSING BASED BACTERIAL SWARM OPTIMIZATION ON TEST BENCHMARK FUNCTIONS

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Abstract

The Bacterial swarm optimization is one of the latest optimization technique mainly inspired from the swarm of bacteria. This paper introduces an intelligent Quorum sensing based Bacterial Swarm Optimization (QBSO) technique for testing and validation. The quorum sensing senses the best position of the bacteria by knowing the worst place in search space. By knowing these positions, the best optimal solution is attained. Here in this proposed QBSO algorithm the exploration capability of the bacteria is well improved. The proposed technique is validated on the seven standard benchmark with unimodal and multimodal test function for its feasibility and optimality. The basic swarm based optimization algorithms such as Particle Swarm Optimization, Ant Colony Optimization, Biogeography Based Optimization, Simulated Bee Colony and conventional Bacterial Swarm Optimization with the standard parameters are simulated and associated with the proposed technique. The attained results evidently indicate that the proposed method outperforms from the considered optimization methods. Further, the proposed technique may apply to any engineering problems, especially for complex real time optimization problems.

Keywords: Swarm based Optimization Algorithm, Quorum Sensing based Bacterial Swarm Optimization, Test Benchmark Functions, Unimodal Function, Multimodal Function.

1. INTRODUCTION

In engineering domain, the term swarm denotes the group of representatives holding self-governing specific dynamics, but revealing closely combined activities and cooperatively accomplishing certain consignment. When concerning the field of natural science, the swarms are reserved for certain species. These species are in assuring behavioral modes for e.g., honey bees in pursuit of hive fission happens, the group of bacteria is in the search of high nutrient content, clusters of ants, groups of birds, schools of fishes, group of species, etc. these unique nature of every species has enthralled to apply these in the power optimization methods.

To create the standard protective swarm perception, the idea of defending representative came into existence. The main thing in the swarm is that the communication ability between the involved organisms or species. In natural science, this might be due to chemical communication (e.g., in bacteria The recent swarm optimization techniques include Particle swarm optimization algorithm (PSO) [1-6], Differential evolution algorithm (DE) [7-10], Ant Colony Optimization (ACO) algorithm [11-16], Artificial Bee Colony (ABC) or Simulated Bee Colony (SBC) algorithm [17,18], Biogeography based optimization [19-26], Bat Motivated Optimization [27], Social Spider Optimization [28], Bacterial Swarm Optimization (BSO) [29,30] etc.

The variants in BSO or Bacterial Foraging Optimization include least square-fuzzy BF strategy [31], Self-adaptation BFO [32], Adaptive computational chemotaxis [33], Adaptive BFO [34], Velocity modulated BFO [35] etc. Also the variants applied developed with BFO is applied to Economic operation of power system problem such as Dynamic adaptive BFO [36], Multiobjective BFO [37], Improved BFO [38], Hybrid multi-objective improved BFO [39], etc.

Bacterial swarm optimization (BSO) or BFO employs biochemical-identifying tissues to sense the intensity of nutritious affluences in its surroundings. The bacteria travels across the surroundings by the sequences of tumbling and trailing, evading the toxic ingredients and reaching nearer to nutrition spot ranges in the practice named chemotaxis. In addition, the bacteria can emit a biochemical mediator that fascinates its mates, ensuing in an ancillary practice of interaction. Stimulated through the E.Coli scavenging scheme it is used to apply for various optimization problems. In the conventional BSO, the foraging behaviour of bacteria explores the global optimum solution, which is administered by inertial, cognitive and collective behaviour. The memory and collective behaviour are the main apparatuses of the scavenging behaviour, which supports the swarm of bacteria to find nutrient gradients in optimal path. BSO is superior to PSO in provisions of convergence, sturdiness and accuracy. Even though the BSO is superior to other techniques, it suffers in exploring global optimum solution sometimes. Therefore, there is a need for new powerful technique.

& ants) or signals (e.g., honeybee waggle dance) or throughout the location.

In this paper, the intelligent Quorum sensing mechanism in the bacteria is added for the extra exploration rate. The quorum-sensing is a biochemical communication, i.e. the process of generating, releasing, sensing and responding to small hormone-like molecules called autoinducers [40]. These molecules are the mediators of quorum sensing. The communication signalling permits bacteria to organize the behaviour of the group (swarming behaviour). From the strategies QBSO algorithm is articulated, in this algorithm the bacterium uses Quorum Signalling (QS) trajectories to remember the earlier visited noxious substances (worst fittest points). By comparing the earlier visited best position (high nutrient gradient) and worst position (noxious substances) components. This formulation can able to explore the global best position.

This paper mainly focuses on testing the QBSO algorithm with unimodal and multi modal test benchmark functions. The proposed algorithm is compared with PSO, ACO, ABC, BBO and BSO techniques. It is also tested with the various populations and dimensions; this represents the superiority of the proposed algorithm. The proposed algorithm is applied to practical power scheduling problem [41] is not in the scope of this paper.

The fragments of this article are distributed into five sections. Section 2 formulates the conventional Bacterial Swarm Optimization. Section 3 presents the formulation of the proposed QBSO algorithm. Section 4 offers the validation of proposed algorithm with other techniques using test benchmark functions and Section 5 embraces the significant conclusion.

2. CONVENTIONAL BACTERIAL SWARM OPTIMIZATION (BSO)

stochastic search technique widely employed for solving distributed optimization and control. The main idea of the BSO is the accurate modelling and simulation of the food searching strategy of bacterial swarm. The simple biological foraging behaviour helps the researchers to solve real-world optimization problems. Every single bacterium signifies a feasible solution to the optimization problems. The bacteria swarm towards the random directions in the search space always forages towards the nutrient gradient in optimal path. The swarming of bacteria is influenced by three major mechanisms, namely velocity, cognitive and social behaviours. The inertial component represents the motile nature of bacteria to swim and tumble in the previous visited direction. The cognitive and collective component signifies the bacteria's memory about its previous best location of the swarm. Tumbling around the search space, the bacteria try to discover the best optimal solution (High nutrient concentration). From these behaviours, the novel BSO is modelled as follows

$$J^{SW}(i,j,k,l)) = \sum_{i=1}^{NB} J_{cc}(\theta(i,j,k,l)) = \left[\sum_{i=1}^{NB} \left[d_{attract}.\exp\left(w_{attract} \sum_{m=1}^{n} (\theta_{gbest} - \theta^{i}_{best})^{2} \right) \right] + \sum_{i=1}^{NB} \left[h_{repellant}.\exp\left(w_{repellant} \sum_{m=1}^{n} (\theta_{gbest} - \theta^{i}_{best})^{2} \right) \right] \right] \quad (1)$$

The cognitive and collective behaviour are the two main mechanisms of the foraging activity of the bacterial swarm. By controlling these behaviour, the exploration capability of bacteria can be improved.

3. PROPOSED QUORUM SENSING BASED BACTERIAL SWARM OPTIMIZATION

The quorum sensing is a biochemical communication, i.e. the process of generating, releasing, sensing and responding to small hormone-like molecules called autoinducers. These molecules are the mediators of quorum sensing. This sensing is natural among bacteria and helps to retain the bacteria in a good location. This assists the bacterial swarm from congestion (overcrowding) and avoids from noxious substances. The presented variant with quorum sensing enabled bacterial swarm optimization consistently tries to chase the more nutrient gradient locations and avoid harmful matters.

swarm towards the random directions in the search space always forages towards the nutrient gradient in

The proposed method models the bacteria's best and worst location. These locations identify the global best location. It is demonstrated by segregating both the memory and collective behaviours components of the conventional BSO. In the cognitive behaviour, the bacterial swarm collects both the best and worst experience position among the search space. When exploring, the bacteria remembers earlier visited best position (high nutrient gradient) and previously visited worst position (noxious substance). Based on the positions bacteria always explore towards the global best position in the selected search space. Correspondingly, the bacteria's collective behaviour is distributed into global best and worst experience mechanisms. The diffusion of noxious substances and the motion pattern will affect the grouping behaviour and move the bacteria towards complex paths. The projected QBSO variant deliberates these cognitive and grouping components to calculate the inertial movement of bacteria.

Then, the inertial update equation for the proposed technique is given by

$$J^{SW}(i,j,k,l) = \sum_{i=1}^{NB} J_{cc}(\theta(i,j,k,l)) = \left[\sum_{i=1}^{NB} \left[\begin{array}{l} r_1.d_{attract}.\exp\left(w_{attract}.\sum_{m=1}^{n} \left(\theta_{gbest} - \theta^{i}_{best}\right)^{2} \right) \\ + r_2.\left(\theta^{i}_{best} - \theta^{i}_{worst}\right) \end{array} \right] + \sum_{i=1}^{NB} \left[\begin{array}{l} r_3.h_{repellant}.\exp\left(w_{repellant}.\sum_{m=1}^{n} \left(\theta_{gbest} - \theta^{i}_{best}\right)^{2} \right) \\ + r_4.\left(\theta^{i}_{best} - \theta^{i}_{worst}\right) \end{array} \right] \right]$$

$$i = 1,2,\ldots\ldots,NB \qquad j = 1,2,\ldots\ldots,N_{ch} \quad (2)$$

Where r_1, r_2, r_3 and r_4 are the random values generated within 0 and 1.

By knowing the worst experience components, the bacterial swarm spends surplus exploration capability to the swarming behaviour. Through the worst experience positions, the bacteria continually try to avoid its previous worst positions (noxious substance locations) and move towards healthier location in the area of the search space (high nutrient gradient). i.e., finding the global best position in the search space.

3.1 Algorithm of Proposed QBSO

The step-by-step brief summary of the proposed method is as follows

[1] The QBSO algorithm is governed fundamentally by three main nested loops namely Chemotaxis, Reproduction, Elimination and Dispersal also has certain other internal loops. At first the initial bacterial population (randomly distribute across the search space) $i = 1,2,\ldots.,NB$ and the swimming length N_{sw}, number of chemotactic steps N_{ch}, reproduction steps N_{re} and elimination-dispersal events N_{ed} should be generated. For the swarming, set the parameters of the cell-to-cell attractant functions;

[2] In this step, the index of three main loops are set as zero $(j = k = l = 0)$

[3] Fix the counter of bacteria, $(i = 1)$ to implement the chemotaxis loop.

[4] For i^{th} bacterium the Fitness function of QBSO, represented by $FF(i,j,k,l)$, is computed as follows

$$FF(i, j, k, l) = AOF(i, j, k, l) + J^{SW}(i, j, k, l) \tag{3}$$

[5] In addition, the constructed $AOF(i,j,k,l)$ denotes augmented objective function, Where $J^{SW}(i, j, k, l)$ is given by the eqn. (2)

[4-a] For each bacterial position in this loop $J_{last} = FF(i,j,k,l)$ save fitness function to this value, meanwhile the better fitness can be calculated via a run.

The i^{th} bacterium position is updated and this step is known as tumble, is given by

$$\theta(i, j+1, k, l) = \theta(i, j, k, l) + C(i).\frac{\Delta(i)}{\sqrt{\Delta^T(i).\Delta(i)}} \tag{4}$$

Where $\Delta(i) \in R^p$ is the random vector, for each element $\Delta_m(i), m = 1, 2, \ldots..P$, Random numbers between [-1, 1]. This results in a step of size $C(i)$ in the direction of the tumble $[\Delta(i)/\sqrt{\Delta^T(i).\Delta(i)}]$ for bacterium i.

[6] The fitness function of bacterium i for subsequent iteration of chemotaxis loop $(j+1)$ is computed similar to eqn. (5) as follows

$$FF(i, j+1, k, l) = AOF(i, j+1, k, l) + J^{SW}(i, j+1, k, l) \tag{5}$$

[7] This step is called as swim. Initially, an internal counter for swim length is set to zero $(m=0)$ and the factor J_{last} is set as $J_{last} = FF(i, j, k, l)$ .Then the internal loop is executed as follows

[7-a] If $FF(i,j+1,k,l) < J_{last}$,go to step 7-b; Else leave the internal loop, Then go to step 8

[7-b] Set $J_{last} = FF(i, j+1, k, l)$ and the position of i^{th} bacterium is updated by incrementing $j+1$ once more as follows

$$\theta(i, j+1, k, l) = \theta(i, j+1, k, l) + C(i).\frac{\Delta(i)}{\sqrt{\Delta^T(i).\Delta(i)}} \tag{6}$$

Correspondingly, compute eqn. (4) once more with new $\theta(i,j+1,k,l)$ as obtained from above equation. In addition, if the bacterium is moving in the direction of tumble $[\Delta(i)/\sqrt{\Delta^T(i).\Delta(i)}]$ results in a best position with least fitness function for bacterium i, then the bacterium i should move single step forward in this path.

[7-c] Subsequently, increment the counter for swim length of the bacteria. $m = m+1$

[7-d] If $m < N_{sw}$, then drive back to step 7-a. Else exit the internal loop.

[8] If $i < NB$, go to step 9; Else go to step 10.

[9] Go to the next bacterium by incrementing i $(i = i + 1)$ and return to step 4.

[10] Increment the chemotactic loop index j $(j = j + 1)$.

[11] If $j < N_{ch}$, go to step 3. Continue chemotaxis meanwhile the trail of the bacteria is not over, Furthermore the length of the lifetime of the bacteria as measured by the number of chemotactic steps.

[12] Set the counter of bacteria as one $(i = 1)$ to implement the Reproduction

[12-a] For the bacterium i, $AFF(i)$ is computed as follows

$$AFF(i) = \sum_{j \in N_{ch}} FF(i, j, k, l) \tag{7}$$

Where $AFF(i)$ is the measure of effective bacterium i that climbs the nutrients over its lifetime by avoiding noxious substances (anti-predatory activity) in solving this optimization problem.

[12-b] If $i < NB$, go to step 12-c; Else go to step 12-d.

[12-c] Now increment i $(i = i + 1)$ and return to step 12-a.

[12-d] Sort all bacteria in the terms of $AFF(i)$ such that a least accumulated fitness function specifies a more successful bacterium (healthiest bacterium). Then B_r bacteria with the highest $AFF(i)$ values are discarded and the remaining B_r bacteria with least $AFF(i)$ values are copied and placed at the same location of discarded bacteria. Commonly set B_r as NB/2.

[13] The counter of reproduction loop k is incremented to $(k = k + 1)$.

[14] If $k < N_{rp}$, then go to step 15; Else go to step 16.

[15] By considering the above case, if the loop has not reached the number of indicated reproduction steps, then set $j = 0$ and start the next generation in the chemotactic loop. (step 4)

[16] As usual select the bacterium $i = 1$ to implement the Elimination-dispersal loop.

[16-a] Elimination-dispersal process is implemented for each bacterium i. For this procedure, a random number, consistently dispersed in the interval $[0,1]$ is generated. If this random number is worse than P_{ed}, then the bacterium i is eliminated (i.e., disperse the worse bacterium to a random location on the search space) and substitute again a randomly generated new bacterium within population limits. Else, the bacterium i is retained.

[16-b] If $i < NB$, go to step 16-c; Else go to step 17.

[16-c] Increment i $(i = i + 1)$ and return to step 16-a.

[17] Increment the counter for Elimination-dispersal loop $(l = l + 1)$

[18] If $l < N_{ed}$, then go to step 19; Else go to step 20.

[19] Fix the index for the chemotactic and reproduction loop as zero $(j = k = 0)$ and go back to step 3.

[20] The algorithm is terminated and the global best bacterium of the population possessing the least fitness function FF is reverted as a final solution of the considered optimization problem.

4. RESULTS AND DISCUSSIONS

All the calculations have been compiled on Intel(R) Core2Duo, 2.60 GHz CPU, 2 GB RAM with MATLAB R2014a compiler. Attributes of the proposed QBSO is done by using trial and error method using following parameters as follows:

No of bacteria S = 10, Number of chemotactic steps Nc= 5, No of reproduction step, Nre= 10, Elimination dispersal step Ned= 5, probability of elimination dispersal, ped= 0.25, Ns = 4, the depth of attractant

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released by the cell dattract= 0.1, the measure of width of the attractant signal wattract= 0.2, height of the repellant effect hrepellent= 0.1 & measures of the width of the repellant signal wrepellent= 1.0 are considered.

By using these parameters, the projected QBSO technique is validated for 40 epochs for some selected intricate benchmark functions shown in Table 1.

The below-mentioned following test function is simulated with 10 bacterial populations, 100 iterations with the indicated data for 40 epochs. The best convergence rate for all these functions with projected QBSO & conventional BSO, PSO, BBO, SBC, ACO is illustrated in Table 2. In this convergence table for better understanding of the results, the minimum, average and maximum fitness values are evaluated. From the Table 2 it is clear that the produced results of QBSO overrides the other techniques

Fn. No	Function	Objective function	Search space limits	Global optimal value
1	De Jong	$f(x)=\sum_{i=1}^{n} x_i^2$	$-5.12 \le x_i \le 5.12$ $i=1,\cdots\cdots n$	$f(x)=0$ $x_i=0, i=1,\cdots\cdots n$
2	Ackley	$f(x)=-a*\exp\left[-b*\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right] -\exp\left[\frac{1}{n}\sum_{i=1}^{n}\cos(cx_i)\right]+ [a+\exp(1)]$	$a=20, b=0.2, c=2\pi.$ $-32.768 \le x_i \le 32.768$ $i=1,2,\cdots\cdots n$	$f(x)=0$ $x_i=0, i=1,\cdots\cdots n$
3	Rastrigin	$f(x)=10n+ \sum_{i=1}^{n}\left[x_i^2-10\cos(a\prod x_i)\right]$	$-5.12 \le x_i \le 5.12$ $i=1,\cdots\cdots n$	$f(x)=0$ $x_i=0, i=1,\cdots\cdots n$
4	Rotated Hyper-ellipsoid	$f(x)=\sum_{i=1}^{n}\sum_{j=1}^{i} x_i^2$	$-65.536 \le x_i \le 65.536$ $i=1,\cdots\cdots n$	$f(x)=0$ $x_i=0, i=1,\cdots\cdots n$
5	Rosenbrock's valley	$f(x)=\sum_{i=1}^{n-1}\left[\begin{matrix}100(x_{i+1}-x_i^2) \\ +(1-x_i)^2\end{matrix}\right]$	$-2.048 \le x_i \le 2.048$ $i=1,\cdots\cdots n$	$f(x)=0$ $x_i=0, i=1,\cdots\cdots n$
6	Griewangk	$f(x)=\frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	$-600 \le x_i \le 600$ $i=1,\cdots\cdots n$	$f(x)=0$ $x_i=0, i=1,\cdots\cdots n$
7	Schwefel	$f(x)=\sum_{i=1}^{n} -x_i.\sin\left(\sqrt{\lvert x_i\rvert}\right)$	$-500 \le x_i \le 500$	$f(x)=-418.9829n,$ $x_i=420.9687,$ $i=1,\cdots\cdots n.$

Table: 1 Selected intricate benchmark functions

S. No	Test Function	Techniques	Maximum Fitness	Average Fitness	Minimum Fitness
1	De Jong's	ACO	5.5478e-2	3.1781e-3	3.201e-4
		SBC	9.5764e-3	1.915e-6	1.8457e-6
		BBO	6.2583e-4	2.7542e-8	9.738e-9
		PSO	6.2587e-1	3.4269e-2	5.0129e-2
		BSO	4.2564e-8	5.6899e-9	6.5894e-9
		QBSO	5.44e-10	2.94e-10	8.8700e-11
2	Rotated Hyper Ellipsoid	ACO	4.5210e-4	8.87e-7	9.1285e-9
		SBC	7.5616e-3	9.915e-6	1.5742e-6
		BBO	6.4784e-4	3.2176e-6	9.251e-8
		PSO	6.2583e-6	2.4754e-7	5.14579e-8
		BSO	4.2564e-6	5.6899e-8	6.7845e-8
		QBSO	1.5210e-8	7.20e-10	1.1285e-10
3	Rosenbrock's	ACO	0.6872	5.983e-1	2.997e-1
		SBC	0.8897	6.570e-1	0.985e-1
		BBO	0.8753	7.782e-1	0.46e-1
		PSO	0.3976	4.2347e-1	7.5941e-1
		BSO	0.0374	3.0378e-1	0.6220e-1
		QBSO	1.02e-2	4.317e-4	1.2072 e-4
4	Rastrigin's	ACO	0.274	0.3254e-2	7.98e-1
		SBC	0.6853	2.472e-1	3.9074e-1
		BBO	0.1917	1.2258e-1	4.5787e-1
		PSO	0.1564	5.49e-1	1.580e-1
		BSO	0.09789	1.838e-1	2.987e-2
		QBSO	4.9438e-2	2.841e-3	2.1355e-7
5	***Schwefel's***	ACO	-714.4896	-790.7219	-823.3882
		SBC	-712.7894	-799.5493	-831.6646
		BBO	-719.2437	-812.4623	-829.7727
		PSO	-684.4710	-782.7323	-837.9058
		BSO	-726.6114	-794.0880	-836.4460
		QBSO	-735.7197	-817.5371	-837.9752
6	Griewangk's	ACO	8.1267e-1	7.6328e-8	2.6834e-9
		SBC	4.5216e-1	1.2487e-4	7.5149e-7
		BBO	1.2971e-2	9.4051e-7	1.45e-9
		PSO	6.8547e-3	6.4716e-4	8.258e-4
		BSO	7.1464e-3	3.5468e-10	5.4178e-10
		QBSO	5.359e-3	1.15e-10	1.125e-12
7	Ackley's	ACO	7.245e-2	4.6543e-4	1.8975e-4
		SBC	9.7856e-2	7.5879e-3	9.654e-4
		BBO	0.9758e-1	3.75e-4	7.45e-4
		PSO	0.7124e-2	6.75e-5	9.93e-4
		BSO	0.4589e-2	6.8569e-6	8.0345e-7
		QBSO	0.0899e-2	3.55841e-7	3.90764e-7

Table: 2 Rate of convergence for the benchmark functions using QBSO and other optimization techniques

Firstly the De Jong's is Function with continuous, convex and unimodal in nature is simulated. The obtained solution is evidently illustrated in the Table 2. The presented QBSO technique yields the optimal results than the other techniques indicated. The fitness value is plotted with respect to the considered iterations for two dimensions are demonstrated in Figure 1. It is evident from the Figure 1. that the projected QBSO technique produces best optimal results with a few iterations.

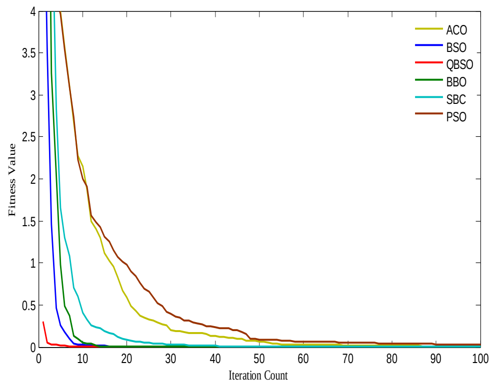

Figure: 1 Convergence curve of De Jong's function using QBSO and other considered algorithms

Concerning the coordinate axes, this function creates rotating hyper-ellipsoids. It is continuous, convex and unimodal in nature. The below Figure 2. specifies the convergence curve of rotated hyper-ellipsoid function using the presented QBSO and other techniques. For this test function, the optimal solution is produced with the fifth iteration itself.

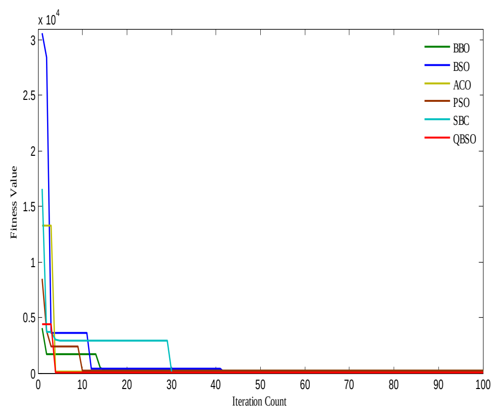

Figure: 2 Convergence curve of Rotated Hyper-Ellipsoid function using QBSO and other considered algorithms

Rosenbrock's function or banana function or consequent De Jong's function is a custom optimization problem. The global optimum for this function ruins within an extensive, tapered and parabolic shaped flat valley. To treasure the valley, this function is insignificant, though convergence to the global optimum is hard. This function is tested using the projected QBSO technique for its optimality and the convergence curve for this function is illustrated in Figure 3 below.

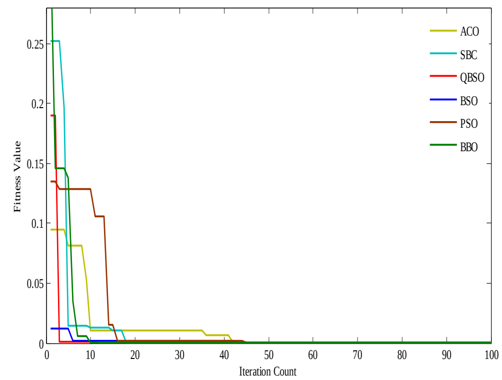

Figure: 3 Convergence curve of Rosenbrock's Valley function using QBSO and other considered algorithms

The Rastrigin's function is built on the De Jong function over the addition of cosine modulation with the objective to create recurrent local minima. Therefore, this function is multimodal in nature. Though, the positions of the minima are often scattered. Moreover, in this function the dimension of the problem increases the difficulty in encountering the global optimal solution, which is clear from Table 2. The dimension for this Rastrigin function is increased from 2, 3 & 5 with the population 10, 20 & 50 and their best results is presented in Table 3. As well as the dimension is increased the proposed optimization method always produce global optimum results evident from Table 3. The convergence characteristics of this function by projected QBSO and other deliberated algorithm is obtainable in Figure 4.

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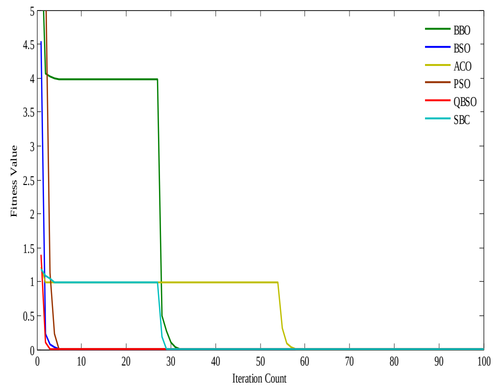

Figure: 4 Convergence curve of Rastrigin's function using QBSO and other considered algorithms

The global minimum of the Schwefel's function is symmetrically separated around the limitation space, subsequently accomplishing the best local minima. As an outcome, the traditional search algorithms are theoretically susceptible to convergence in the inaccurate direction.

When related to all other functions revealed in this work, for this function the conventional BSO algorithm is initially unsuccessful to treasure the global optimal solution in 20% of instances. Not only the BSO but also all other techniques stated above is stuck in the local minima. Normally owing to the randomization, it invents the global optimum. In proposed QBSO technique due to the exploration competence, the percentage of superiority results generated is beyond 95%. For cracking this problem, the exploration space range of bacteria is augmented twice. Even if the time encompasses in acquiring the global solution is amplified, it treasures the best optimum result revealed in Figure 5.

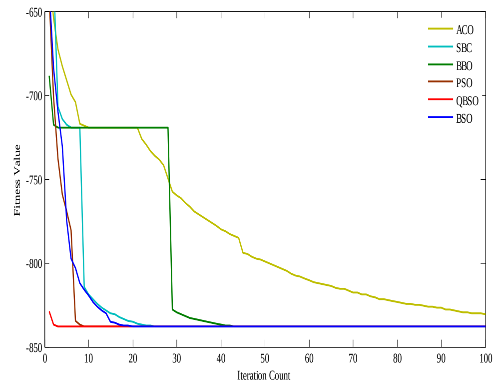

Figure: 5 Convergence curve of Schwefel's function using QBSO and other considered algorithms

The Griewangk's function is analogous to the Rastrigin function. It has numerous extensive local minima recurrently disseminated. Obtaining the global optimal spot is intricate in this function, but the proposed QBSO technique produces the optimal solution with initial iterations clear from Figure 6.

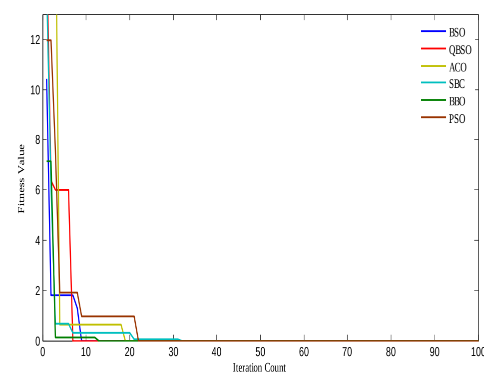

Figure: 6 Convergence curve of Griewangk's function using QBSO and other considered algorithms

This griewangk's function is an extensively employed multimodal benchmark function. The search space constraints are acquired from Table 2. In this, the exploration dimension is grabbed as two and the exploration space is termed as per the bounds. The intended QBSO technique recreates a major part for the intention that of the enriched swarming and chemotaxis step. Finally, from the Figure 7 it is obvious that the projected technique generates quality results with a less convergence period.

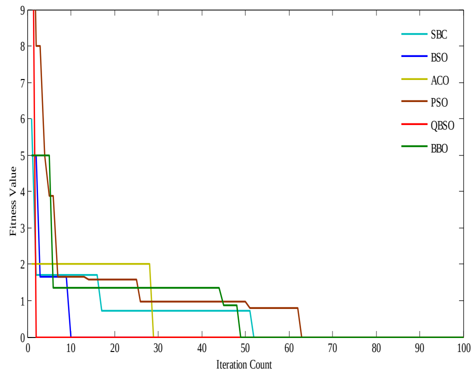

Figure: 7 Convergence curve of Ackley's function using QBSO and other considered algorithms

All these considered benchmark functions are tested with projected QBSO technique for 40 trial runs. This test is done with the bacterial populations of 10, 20 & 50 for the 2, 3 & 5 dimensions and the results are compared in Table 3.

S. No.	Functions	No. of population	Dimensions		
			5	3	2
1	De Jong's	50	1.134e-10	1.698e-11	3.396e-13
		20	8.870e-11	1.3112e-11	1.60e-13
		10	6.253e-11	2.6654e-12	2.32e-12
2	Rotated hyper-ellipsoid	50	9.5217e-7	8.4529e-9	1.8745e-11
		20	1.1285e-8	2.1720e-10	2.970e-12
		10	1.3484e-9	5.7900e-11	5.340e-12
3	Rosenbrock's valley	50	6.1247e-1	9.4758e-2	6.2478e-4
		20	2.3578e-1	7.254e-2	4.0749e-4
		10	7.025e-2	5.317e-3	1.2072 e-4
4	Rastrigin's	50	6.9518e-5	3.4795e-10	6.8864e-11
		20	1.0678e-7	5.8486e-9	9.82e-12
		10	4.7956e-8	6.3500e-9	2.2778e-11
5	Schwefel's	50	NA*	-710.741	-825.547
		20	-712.247	-772.316	-837.78
		10	-714.6114	-792.0880	-831.0880
6	Griewangk's	50	4.5217e-10	8.7523e-11	1.0824e-14
		20	0.331e-11	1.436e-13	1.353e-14
		10	1.1257e-12	4.87e-13	7.6e-14
7	Ackley's	50	4.7988e-4	2.3249e-4	2.8116e-6
		20	6.0653e-5	3.2583e-5	5.6785e-7
		10	1.0569e-5	1.3764e-6	1.1225e-10

*NA-No Amount

Table: 3 Comparison of output for considered functions with different populations & dimensions using QBSO Technique

The validation of the proposed technique is conducted for various dimensions to ensure its robustness. From the Table 3 it is clear that the dimensionality of the problem increases by the mean time the complexity increases. In addition, the population of the algorithm escalates the quality of the optimal solution, but the computational time taken for algorithm surges.

5. CONCLUSION

This paper articulates the detailed steps involved in proposed QBSO algorithm. The persistence of QBSO algorithm in acquiring the global optimum solution for the presented unimodal and multimodal test benchmark functions is simulated. The convergence rates of the projected algorithm with other techniques are trailed out and the results are presented. Finally, all the considered functions are tested with different population and dimensions. The assessment of the concluding solution substantiates the competence of the projected algorithm. Therefore, the QBSO technique is anticipated to apply for dynamic practical optimization problems.

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