A Modified Harmony Search Algorithm for Optimization Problems

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***Abstract*—Harmony search (HS) algorithm is a new meta-heuristic optimization algorithm inspired from the music improvisation process. Though the excellent performance makes it wildly used in many areas, it is easy to get trapped in local minima. This paper is to introduce a modified harmony search algorithm to improve the performance of HS algorithm. The method is implemented by adding an "innovative" process on global harmony search algorithm (GHSA), a variant of HS algorithm. This modification would be easy to make a balance of diversification and intensification. The benchmarks are designed to test the performance of the modified HS algorithm and the results show that the innovative HS algorithm has a better performance than the basic HS algorithm and its variants. In addition, to investigate the influence of parameter bw on the algorithm's performance, the tests are also conducted under the parameter bw with different types.**

Keywords- Harmony search algorithm, Evolutionary algorithms, Global optimization.

I. INTRODUCTION

For complex optimal problems, evolutionary computation methods become the popular ways to solve these problems, such as genetic algorithm (GA), evolution strategy (ES), particle swarm optimization (PSO), ant colony optimization (ACO), and so on. These methods are mostly inspired from biological intelligence or natural evolution mechanisms and they are easy and efficient to be used in many optimization problems.

Nowadays, a new evolutionary computation method --- harmony search algorithm (HSA), is proposed by Zong Woo Geem et al. in 2001[1]. Harmony search algorithm is also a meta-heuristic global optimization algorithm and is inspired from the music improvisation process, through which the musicians search a better state of harmony. Due to the algorithm's simplicity, efficiency and flexibility, harmony search algorithm has been successfully used in many optimization issues (like TSP problem[1]) and practical engineering problems such as combined heat and power dispatch problem[2] , schedule problem of multiple dam system[3], structural optimization[4], PID controller design[5], circle detection[6] and so on.

Though the harmony search algorithm has excellent performance in global optimization problems, it also has the trouble in performing local search for numerical applications[7]. In order to enhance the performance of HS algorithm, many studies have been conducted and many methods have been proposed to modify the basic HS algorithm. This paper will propose a new method to improve the performance of HS algorithm through the introduction of an "innovative" process to a variant of HS algorithm--- global-best harmony search (GHS).

The paper is organized as follows: section II gives an overview of basic harmony search algorithm and the related works. The modified algorithm is introduced in section III. Section IV presents the benchmarks designed to test the performance of the algorithms and experiment setup, section V gives the test results. The paper is concluded in section VI.

II. HARMONY SEARCH ALGORITHM

A. The Basic Harmony Search Algorithm

The harmony search algorithm is simulating the process of musician tune the musical instruments to find a better harmony state[8], which can also be considered as an optimization process. The procedure of HS algorithm concluded as the following steps [1, 8]:

Step 1: Initialize HS algorithm (parameter and memory);
Step 2: Improvise a new harmony;
Step 3: Check the new harmony and update the memory;
Step 4: Check the stop condition.

The detail content of these steps is shown in Fig 1.

B. Related works

After the harmony search algorithm been first proposed, many modifications have been made to improve the performance of HS algorithm. The methods they adopted can mainly be classified into two ways: the modification of the parameters or strategies in improvisation and hybrid the HS algorithm with other evolutionary computation algorithms.

Mahdavi *et al.*[7] put forward an Improved Harmony Search algorithm (IHS), which enhance the accuracy of final solution through the change of parameter PAR and bw on the course of evolution instead of the constant value in the basic HS algorithm. This modification has been tested to be better than the basic HS algorithm and the parameters are changing according the following rules:

$$PAR(t) = PAR_{\min} + \frac{(PAR_{\max} - PAR_{\min})}{NI} \times t \tag{1}$$

$$bw(t) = bw_{\max} \times e^{\left(\frac{\ln\left(\frac{bw_{\min}}{bw_{\max}}\right)}{NI} \times t\right)} \tag{2}$$

Where, t is the current generation number.

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Inspired by the main principle of PSO algorithm, Omran and Mahdavi [9] proposed a Global-best Harmony Search algorithm (GHS), which replaced the pitch adjust operation by setting the i-*th* variable as an random variable of the best harmony in HM. This would reduce the parameter bw and add a social dimension to the algorithm [9] and outperform other modifications in the ten benchmark functions given by the authors.

Y.M. Cheng *et al*. [10] modify the HS algorithm with a strategy that the harmony with better fitness value has greater chance to be selected for the generation of the new harmony in step 2 and the worse the less. This approach was found to be more efficient than the basic HS algorithm in the slope stability analysis.

More recently, Swagatam Das *et al*. [11] firstly gave an theoretical analysis of the expected population variance of HS algorithm. Through the final mathematical results, they proposed an Explorative Harmony Search algorithm (EHS), which just modify the parameter bw be proportional to the standard deviation of current harmony memory, and demonstrated this method was better than the three HS variants introduced before through benchmark test.

The modifications of HS algorithm are all the modification of the parameters or strategies in improvisation, the methods of hybrid HS algorithm with other algorithm include PSO[12], GA[13], SA[14], Differential Evolution[15], Simplex Algorithm[16], Ant System [17]and so on.

// Step 1: Initialization
Specify the objective function: $f(x)$;
Set the parameter: N, HMS, HMCR, PAR, bw, NI, the bound of search space $[x_{iL}, x_{iU}]$ $(1 \leqslant i \leqslant N)$;
Randomly generate the harmony memory in search space and calculate the fitness value of each harmony in HM, find the best harmony x_b and the worst harmony x_w;
Set impv_cnt=0.
// Step 2: Improvise a new harmony
impv_cnt = impv_cnt+1;
For i=1 to N
If (rand(0,1) < HMCR)
a is randomly select in [1,2,HMS]
$x_{new}(i)=x_a(i)$;
If (rand(0,1) < PAR)
$x_{new}(i)= x_{new}(i)+rand(-1,1)*bw(i)$;
End If
Bound $x_{new}(i)$ in $[x_{iL}, x_{iU}]$
Else
$x_{new}(i)= x_{iL} +rand(0,1)*(x_{iU} - x_{iL})$
End If
End For
// Step 3: Check the new harmony and update HM
Calculate the fitness value of the new harmony, denoted as f_{new};
If ($f_{new} < f_w$)
$x_w=x_{new}$;
Find the best harmony x_b and the worst harmony x_w;
End If
// Step 4: Check the stop condition
If (impv_cnt $\leqslant$ NI)
Repeat Step 2 and Step 3;
Else
Output the best solution found so far;
Terminate the algorithm.
End If

Fig 1 Procedure of the basic Harmony Search Algorithm

III. INNOVATIVE HS ALGORITHM

This section introduces the method we proposed to enhance the performance of harmony search algorithm on the base of the proposed IGS and GHS algorithms.

Although the basic HS algorithm demonstrates good global optimal search ability in optimization problems, it also comes to the problem of premature convergence and easily traps into the local minima. The performance of the meta-heuristic algorithms is mainly dependent on two properties of the algorithm: diversification and intensification, also mentioned as exploration and exploitation [18]. Intensification or exploitation is to search better solution in the adjacent space of the best solution and diversification or exploration is to make the searched domain of the search space as large as possible. A good optimal algorithm should make an appropriate balance between intensification and diversification [18, 19].

Therefore, to improve the performance of HS algorithm on the base of making a balance of intensification and diversification, we make a modification of GHS algorithm. The GHS algorithm reduces the parameter bw and replaces the process of disturbance of the new harmony by randomly select the variable in the current best harmony, which would optimize the new harmony but reduce the diversification and intensification of the algorithm. So, our modification is to add this random disturbance process after the pitch adjustment process of GHS algorithm, which would seem as the musician make an innovative try to improve the harmony state on the base of accumulative experience. Thus, the modification is call "innovative" harmony search algorithm.

Making use of the idea of IHS algorithm, let the parameters PAR and bw be adjusted through the evolution of the algorithm. The varying bw would determine the diversification and intensification of the algorithm, bigger bw would increase diversification and smaller bw would be favorable to intensification, which would let us make a balance between diversification and intensification.

After modification, the improvisation procedure of the modified algorithm is shown as Fig 2.

In addition, the parameters PAR and bw have a great influence on the performance of the algorithm, so we would also study the performance of the algorithm under the parameter bw with different types.

```
// Step 2: Improvise a new harmony
   impv_cnt = impv_cnt+1;
   calculate the varying parameter PAR
   For i=1 to N
      calculate the varying parameter bw(i)
      If (rand(0,1) < HMCR)
         a is randomly select in [1,2,…,HMS]
         x_new(i)=x_a(i);
         If (rand(0,1) < PAR)
            k is randomly select in [1,2,…,N]
            x_new(i)= x_best(k);
         End If
         // Impose the innovative search
         x_new(i)= x_new(i)+rand(-1,1)*bw(i);
         Bound x_new(i) in [x_iL, x_iU]
      Else
         x_new(i)= x_iL +rand(0,1)*( x_iU - x_iL)
      End If
   End For
```

Fig 2 improvisation procedure of the “innovative” HS Algorithm

IV. EXPERIMENT SETUP

In order to test the performance of the innovative HS algorithm, we use a series of test benchmarks to test the innovative HS algorithm under the situations of many local minima and stochastic disturbance.

As the harmony search algorithm is a random optimization algorithm, all experiments would be run 30 times to eliminate the random factors and use the average value as the final results.

A. *Test Functions*

To test the performance of the innovative HS algorithm under different situations, three benchmarks are designed to test its convergence, robustness and the effect of parameter bw. The detail of the functions used here can be found in [20, 21].

1) Benchmark 1: The Convergence Test

In this benchmark, six general global optimization problems are selected to test the general convergence performance of the modified HS algorithm. The test functions are listed in Table 1.

2) Benchmark 2: The Robustness Test

The robustness test is to add disturbances on the test functions to investigate the performance of an algorithm. The test functions are listed as following:

- *Schwefel's Problem 1.2*

$$f_7 = \sum_{i=1}^{N_d}\left(\sum_{j=1}^{i} x_j\right)^2 \quad -100 \le x_i \le 100$$

With $x^*=0$ $f_{\min}=0$.

- *Schwefel's Problem 1.2 with noise*

$$f_8 = f_7 * (1 + 0.4\left|N(0,1)\right|) \quad -100 \le x_i \le 100$$

With $x^*=0$ $f_{\min}=0$.

3) Benchmark 3: The Effect of the parameter bw Test

In this subsection, the test of parameter bw in different types is conducted to investigate the performance of the modified HS algorithm. The parameter would be tested in the following types:

(denote μ as $\mu = \dfrac{\ln(\frac{bw_{\min}}{bw_{\max}})}{NI}$)

Table 1 Test Functions for Benchmark 1

Function	Function Equation	Variable Range	x^*	$f_{\min}$
Rosenbrock Function	$f_1 = \sum_{i=1}^{N_d}\left(100*(x_{i+1}-x_i^2)^2 + (x_i-1)^2\right)$	$-30 \le x_i \le 30$	(1,1,…,1)	0
Swefel’s Problem 2.26	$f_2 = 418.9829N_d - \sum_{i=1}^{N_d}\left(x_i * \sin(\sqrt{\lvert x_i\rvert})\right)$	$-500 \le x_i \le 500$	(420.9687,…, 420.9687)	0
Generalized Rastrigin's Function	$f_3 = \sum_{i=1}^{N_d}\left(x_i^2 - 10*\cos(2\pi x_i) + 10\right)$	$-5.12 \le x_i \le 5.12$	**0**	0
Ackley's Function	$f_4 = -20\exp\left(-0.2\sqrt{\frac{1}{N_d}\sum_{i=1}^{N_d} x_i^2}\right) - \exp\left(\frac{1}{N_d}\sum_{i=1}^{N_d}\cos(2\pi x_i)\right) + 20 + \mathrm{e}$	$-32 \le x_i \le 32$	**0**	0
Generalized Griewank's Function	$f_5 = \frac{1}{4000}\sum_{i=1}^{N_d} x_i^2 - \prod_{i=1}^{N_d}\cos(\frac{x_i}{\sqrt{i}}) + 1$	$-600 \le x_i \le 600$	**0**	0
Six-Hump Camel-Back function	$f_6 = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4 + 1.0316285$	$-5 \le x_i \le 5$	(-0.08983, 0.7126)	0

Table 2 Test results of Benchmark 1

		f_1	f_2	f_3	f_4	f_5	f_6
HSA	Mean	3522.081	561.3671	91.7330	4.2079	2.3034	5.3698e-8
	Std.	1173.722	116.9446	6.9962	0.1606	0.1439	8.2688e-9
IHSA	Mean	142.888	3.8187e-4	0.3355	3.9324e-5	0.0025	**4.6510e-8**
	Std.	238.037	6.3412e-9	0.4750	4.7847e-6	0.0053	**8.1806e-15**
GHSA	Mean	37.401	0.0119	9.2708e-4	0.0091	0.0454	3.2540e-5
	Std.	50.0037	0.0154	0.0013	0.0112	0.1390	6.2185e-5
Innovative HSA	Mean	**28.5323**	**3.8186e-4**	**5.8023e-9**	**3.8601e-5**	**2.2189e-8**	4.6512e-8
	Std.	**0.0947**	**6.0884e-9**	**9.7307e-10**	**3.3866e-6**	**6.2956e-9**	1.4142e-12

$$bw1(t)=\frac{(bw_{\max}-bw_{\min})\times t}{NI}+bw_{\min} \tag{3}$$

$$bw2(t)=bw_{\max}\times\exp\left(\mu\times t\right) \tag{4}$$

$$bw3(t)=(bw_{\max}-bw_{\min})\frac{1-\exp\left(\mu\times(NI-t)\right)}{1+\exp\left(\mu\times(NI-t)\right)}+bw_{\min} \tag{5}$$

$$bw4(t)=\frac{(bw_{\max}-bw_{\min})}{2}\left(\left(\frac{NI-2t}{NI}\right)^3+1\right)+bw_{\min} \tag{6}$$

$$bw5(t)=\frac{bw_{\max}}{1+\exp(2\mu\times(NI-2t))} \tag{7}$$

The curves of the parameter be are shown in Fig 3.

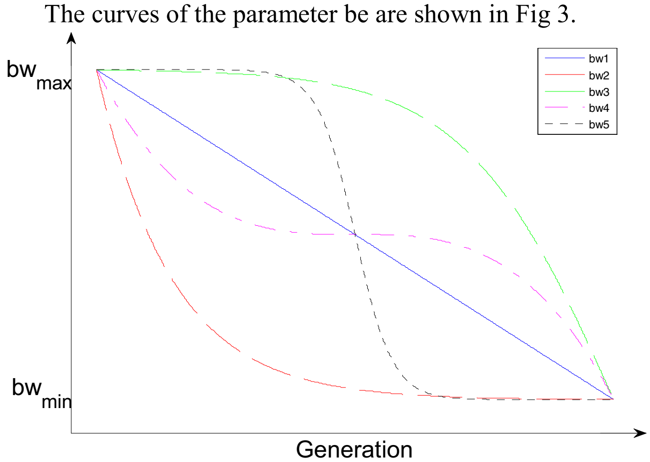

Fig 3 Curves of the parameter bw variation

B. Parameter Configurations

Except the test function f6, the dimensions of other test functions are all 30, that is NI=30. Other parameters are set as: HMCR=0.9, HMS=7, NI=10000, PAR_{max}=0.9, PAR_{min}=0.4, $bw_{max}=0.05*|x_U-x_L|$, bw_{min}=0.00001.

V. EXPERIMENT RESULTS

The test results of all benchmarks are listed in Table2-4.The "Mean" row represents the average value of the final fitness values calculated for 30 times and the "Std." row for the standard deviation. The best result of each test function is bold to make a stress.

A. Results of Benchmark 1(Convergence Test)

Benchmark 1 is designed mainly to test the optimization performance or the convergence ability of the algorithms. The results are shown in Table 2.

The test functions in benchmark 1 include the functions with many local minima to test the global optimization ability. From the results in Table 2, we can see that the final results of innovative HS algorithm are better than other three algorithms both in the average value and the standard deviation except the test function f_6. As the test function f_6 is a 2-dimension optimization problem, the four algorithms all get good results and IHSA is little better than other three.

So, we can conclude that the innovative HS algorithm have a better optimization performance or convergence ability than other three HS algorithms.

B. Results of Benchmark 2(Robustness Test)

Table 3 Test results of Benchmark 2

		f_7	f_8
HSA	Mean	36334.822	44159.0944
	Std.	3935.941	4285.1114
IHSA	Mean	3.1147	29.2261
	Std.	3.1796	26.5459
GHSA	Mean	1.7289	74.5323
	Std.	3.2635	119.4047
Innovative HSA	Mean	**9.1746e-5**	**1.1968e-4**
	Std.	**2.8563e-5**	**3.8254e-5**

This benchmark is mainly used to test the robustness of an algorithm when the fitness function contains noise. Table 3 shows the results of the test function without and with noise.

Form the results of Table 3, innovative HS algorithm reveal a better performance both in the noise-free problem and the problem with noise. Because of the influence of noise, the results of four algorithms are all become worse compared with the situation without noise. But the innovative HS algorithm can also obtain a satisfied result under the noise effect.

C. Results of Benchmark 3(Parameter effect Test)

In this benchmark, the performance of innovative HS algorithm would be tested under the parameter bw with different types to investigate the effect of parameter bw. The results are shown in Table 4.

Table 4 Test results of Benchmark 3

		f_1	f_2	f_3	f_4	f_5	f_6
bw1	Mean	30.1327	0.7463	0.1047	0.1470	0.5847	1.0629e-7
	Std.	4.5213	0.4134	0.0824	0.0492	0.2349	4.2706e-8
bw2	Mean	28.5652	3.8186e-4	5.4367e-9	3.8442e-5	2.0727e-8	4.6512e-8
	Std.	**0.1036**	7.0412e-9	1.1716e-9	2.9166e-6	**3.7107e-9**	1.9310e-12
bw3	Mean	171.1874	25.7583	3.6113	1.2103	1.0733	2.3442e-6
	Std.	105.5228	12.8255	1.5354	0.4096	0.0391	1.8825e-6
bw4	Mean	56.4920	5.2416	0.9591	0.5398	0.9661	8.1792e-7
	Std.	34.1553	3.2483	0.5433	0.1993	0.1287	1.0342e-6
bw5	Mean	**3.8904**	**3.8183e-4**	**0**	**2.3573e-10**	**1.5339e-8**	**4.6510e-8**
	Std.	23.2553	**8.7214e-13**	**0**	**6.4873e-11**	6.0040e-8	**5.8312e-16**

From the results in Table 4, we can know that the innovative HS algorithm with bw2 and bw5 get better results than other three circumstances and all the best results are obtained in the case of bw5.

From the curve of bw5 in Fig 3, at the first half phase of evolution, the parameter bw is very big, which would increase the search scope and diversification of the algorithm. At the second half phase of evolution, bw is very small, as a result, the intensification or exploitation will be get improved. Thus, the innovative HS algorithm with bw5 is of excellent performance.

VI. CONCLUSIONS

This paper has proposed a new modified harmony search algorithm, which is to improve the performance of harmony search algorithm through the introduction of "innovative" process. The modification added an innovative process to the algorithm is to make a balance of diversification and intensification. To investigate the influence of parameter bw, the modified algorithm was tested under the parameter with different types. The results of benchmark tests shown that the innovative harmony search algorithm performed better than other algorithms in many aspects like convergence, robustness and so on.

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