Harmony Search Optimization Algorithm Based on Normal Cloud

Lifu Wang, Zhi Kong, Xingang Wang
College of Control Engineering, Northeastern University at Qinhuangdao, Qinhuangdao, China
e-mail: wlfkz@qq.com

***Abstract*—The pitch adjusting rate (PAR) is an important parameter in harmony search algorithm, which indicates that the algorithm will choose a neighboring value with a probability. The traditional harmony search algorithm uses fixed value for PAR. However, PAR should be increased when all objective values are centralized and decreased when the function values are scattered in the solution space. In this paper, a new cloud harmony search algorithm (CHS) is proposed. We introduce cloud model theory to adjust the value PAR in the harmony search to improve the global search ability and make faster convergence speed of the algorithm. The improved harmony search algorithm is tested on some benchmark functions and the results are compared with the result of the traditional harmony search. Experimental results indicate that the improved harmony search algorithm has a good performance in the global search ability and convergent speed.**

Keywords- cloud model; harmony search; optimization; the pitch ajusting rate (PAR)

I. INTRODUCTION

Over the last four decades, a large number of algorithms have been developed to solve various engineering optimization problems. Recently, Geem et al. [1] developed a new harmony search algorithm (HS). The ideal of harmony search comes from the musicians. The harmony in music corresponds with the solution in optimization problem, and the musician's improvisations correspond with the search schemes in optimization techniques. However, harmony search algorithm is not efficient in performing local search for applications, Kong et al. introduced adaptive harmony search algorithm[2]. Mahdavi et al. proposed an improved harmony search algorithm (IHS) [3]. In the harmony search, there is an important parameter, the pitch adjusting rate (PAR). PAR should be increased when all objective values are centralized and decreased when the function values are scattered in the solution space. However, the traditional harmony search algorithm uses fixed value for PAR, which is disadvantageous to the convergence speed and global optimization.

Clouds are a ubiquitous feature of our world[4]. Since the cloud model [5] is proposed, researchers put more attentions on it. Especially the cloud theory is applied in optimization to adjust the parameters[6-9].

In this paper, we proposed the improved harmony search algorithm based on cloud theory. Using normal cloud to adjust the parameter PAR in the harmony search, the PAR is varying with the procedure of optimization algorithm.

II. HARMONY SEARCH ALGORITHM

The new HS algorithm was derived by adopting the idea that existing meta-heuristic algorithms are found in the paradigm of natural phenomena. The algorithm was based on natural musical performance processes that occur when a musician searches for a better state of harmony, such as during jazz improvisation. Jazz improvization seeks to find musically pleasing harmony (a perfect state) as determined by an aesthetic standard, just as the optimization process seeks to find a global solution (a perfect state) as determined by an objective function. The pitch of each musical instrument determines the aesthetic quality, just as the objective function value is determined by the set of values assigned to each decision variable. The optimization procedure of the HS algorithm consists of Steps 1 through 5[1]:

Step 1. Initialize the optimization problem and algorithm parameters.

Step 2. Initialize the harmony memory (HM).

Step 3. Improvise a new harmony from the HM.

Step 4. Update the HM.

Step 5. Repeat Steps 3 and 4 until the termination criterion is satisfied.

1. Initialize the Optimization Problem and Algorithm Parameters

In this step, the optimization problem is specified as follows:

$$\text{Minimize} \quad z = f(x) \quad \text{subject to } x_i \in X_i \quad i = 1, 2, \cdots, N \qquad (1)$$

where $f(x)$ is the objective function to be minimized, x_i are the decision variables, X_i are the set of possible ranges of each variable, and N is the number of decision variables. The governing parameters of HS algorithm which are the harmony memory size (HMS), harmony memory considering rate (HMCR), pitch adjusting rate (PAR), and the termination criterion are also specified in this step. Note that the HM is a memory matrix in which all the decision variables are stored. The HMCR and PAR are the used solution parameters and both of them will be defined in Step 3.

2. Initialize the Harmony Memory (HM)

In this step, HM matrix is filled with randomly generated solution vectors as many as the HMS and corresponding fitness function values are calculated as

$$\begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_{N-1}^1 & x_N^1 \\ x_1^2 & x_2^2 & \cdots & x_{N-1}^2 & x_N^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^{HMS-1} & x_2^{HMS-1} & \cdots & x_{N-1}^{HMS-1} & x_N^{HMS-1} \\ x_1^{HMS} & x_2^{HMS} & \cdots & x_{N-1}^{HMS} & x_N^{HMS} \end{bmatrix} \Rightarrow \begin{bmatrix} f(x^1) \\ f(x^2) \\ \vdots \\ f(x^{HMS-1}) \\ f(x^{HMS}) \end{bmatrix} \quad (2)$$

3. Improvise a New Harmony From the HM

In this step, a new harmony vector $x' = (x_1', x_2', \cdots, x_N')$ is generated by considering three rules. These are the memory consideration, pitch adjustment, and random selection. In the memory consideration, the value of the first decision variable x_1' for the new vector is selected from any values in the HM range $(x_1^1, x_1^2, \cdots, x_1^{HMS})$. Values of the other decision variables $(x_2', \cdots, x_N')$ are selected in the same manner. The parameter HMCR, which varies between 0 and 1, is the probability of selecting one value from HM whereas (1 -HMCR) is the probability of randomly selecting from possible range. The selection procedure for HMCR is

$$x_i' = \begin{cases} x_i' \in \{x_i^1, x_i^2, \cdots, x_i^{HMS}\} \text{ with probability } HMCR \\ x_i' \in X_i \text{ with probability } 1\text{-}HMCR \end{cases} \quad (3)$$

After the memory consideration, each decision variable is evaluated to determine whether pitch adjustment is necessary or not. This evaluation is carried out with PAR parameter which is the probability of pitch adjusting and identified as follows:

$$x_i' = \begin{cases} x_i' \pm \text{Rnd}(0;1) \times \text{bw with probability } PAR \\ x_i' \text{ with probability } 1\text{-}PAR \end{cases} \quad (4)$$

In Eq. (4), bw is an arbitrary bandwidth, Rnd(0;1) is a uniform random number between 0 and 1. As can be seen in Eq. (4), decision variable x_i' is replaced with $x_i' \pm \text{Rnd}(0;1) \times \text{bw}$ with probability PAR while doing nothing with probability (1-PAR). While HMCR is introduced to find global optimum solution by generating the new solutions vectors from current HM and possible data range whereas PAR is adopted for improving solutions, which were found by HMCR, and escaping local optima. The procedure works as follows:

for each $i \in [1, N]$ do
  if $U(0,1) \le HMCR$ then
    begin
      $x_i' = x_i^j$, where $j \sim U(1, \cdots, HMCR)$.
      if $U(0,1) \le PAR$ then
        begin
          $x_i' = x_i' \pm r \times bw$, where $r \sim U(0,1)$ and bw is an arbitrary distance bandwidth.
        endif
  else
      $x_i' = x_{\min} + r \times (x_{\max} - x_{\min})$
    endif
done

4. Update the Harmony Memory

In this step, the comparison between new harmony vector $x' = (x_1', x_2', \cdots, x_N')$ and worst harmony in the HM is performed in terms of their objective function values. If the new harmony vector is better than worst harmony, the new harmony vector is included to the HM and worst harmony is excluded.

5. Check the Termination Criterion

In this step, the optimization process continues with the computation by iterating Steps 3–5 until the given termination criterion is satisfied.

III. THE IMPROVED HARMONY SEARCH ALGORITHM

A. Normal Cloud Mode

The cloud model is a model of the uncertain transition between a linguistic term of a qualitative concept and its numerical representation [10, 11]. The cloud model is as follows:

Let U be the set $U = \{u\}$, as the universe of discourse, and T a linguistic term associated with U. The membership degree of u in U to the linguistic term T, $C_T(u)$, is a random number with a stable tendency. $C_T(u)$ takes the values in [0,1]. A compatibility cloud is a mapping from the universe of discourse U to the unit interval [0,1]. That is, $C_T(u): U \to [0,1]$, $\forall u \in U$, $u \to C_T(u)$. Namely, the random distribution of $C_T(u)$ in U is called (membership) cloud. When $C_T(u)$ obeys the normal distribution, cloud is called normal cloud model.

A normal cloud is defined with three digital characteristics, expected value E_x, entropy E_n, and hyper-entropy H_e. The expected value E_x is the position at U corresponding to the center of gravity of the cloud. The entropy E_n is a measure of the coverage of the concept within the universe of discourse. The hyper-entropy H_e is the entropy of the entropy of the entropy E_n. It is a measure of dispersion of the cloud drops.

B. Harmony Search Algorithm Based on Normal Cloud

The pitch adjusting rate (PAR) is an important parameter in harmony search algorithm, which indicates that the algorithm will choose a neighboring value with a probability. The traditional harmony search algorithm uses fixed value for PAR. However, PAR should be increased when all objective values are centralized and decreased when the function values are scattered in the solution space. In this paper, we introduce cloud model theory to adjust the value

PAR in the harmony search to improve the global search ability and make faster convergence speed of the algorithm.

The optimization procedure of the improved harmony search algorithm consists of 5 steps, which is similar to the traditional harmony search algorithm. However, the value of PAR is different from that of the traditional harmony search algorithm.

For the value PAR, it can be obtained as follows:

1. Set the maximum of PAR is $PAR_{\max}$, the minimum of PAR is $PAR_{\min}$.

1. Calculate the fitness function value $f(x^i)$ for each solution vector.

2. Calculate the average fitness F_{ave} and the best fitness F_{best} using the following equations:

$$F_{ave} = \sum_{i=1}^{HMS} f(x^i)/HMS$$

$$F_{best} = \min\{f(x^i)\}$$

3. Select a variable x_i' in the harmony memory corresponding to the fitness value $f(x_i')$.

if $f(x_i') < F_{best}$

PAR= $PAR_{\max}$

elseif $f(x_i') > F_{best}$

PAR= $PAR_{\min}$

else

$E_x = F_{best}$

$E_n = (f(x_i') - F_{best})/c_1$

$H_e = E_n / c_2$

$E_n' = normrnd(E_n, H_e)$

$$PAR = PAR_{\max} - PAR_{\min} e^{-\frac{(f(x_i') - F_{best})}{2E_n'^2}}$$

end

where c_1 and c_2 are two parameters. Generally, $c_1 = 3$, $c_2 = 10$.

IV. SIMULATION RESULTS

The harmony size is set to 10 in harmony search algorithms. Five prevalent benchmarks described in [8] are employed, and their configuration is listed in Table 1.

TABLE I. Benchmark configuration for simulation

Function	Name	Domain	Minimum
f1	Sphere	[-1000,1000]	0
f2	Rosenbrock	[-30,30]	0
f3	Schaffer	[-5.12,5.12]	0
f4	Ackley	[-30,30]	0
f5	Griewank	[-600,600]	0

The benchmark functions as follows:

Sphere:

$$f_1 = \sum_{i=1}^{n} x_i^2$$

Rosenbrock:

$$f_2 = \sum_{i=1}^{n} (100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2)$$

Schaffer:

$$f_3 = 0.5 + \frac{\sin^2(\sqrt{x^2 + y^2}) - 0.5}{(1 + 0.001(x^2 + y^2))^2}$$

Ackley:

$$f_4 = -20\exp\left(-0.2\sqrt{1/n\sum_{i=1}^{n} x_i^2}\right) - \exp\left(1/n\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$$

Griewank:

$$f_5 = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$$

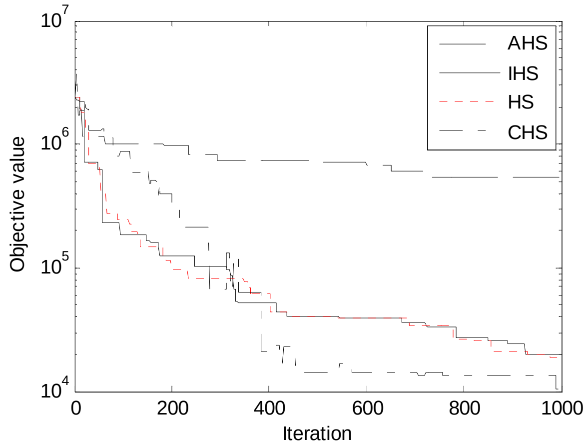

Figure 1. Sphere function

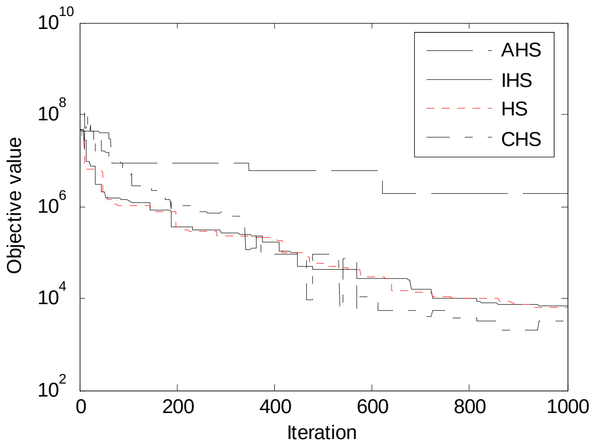

Figure 2. Rosenbrock function

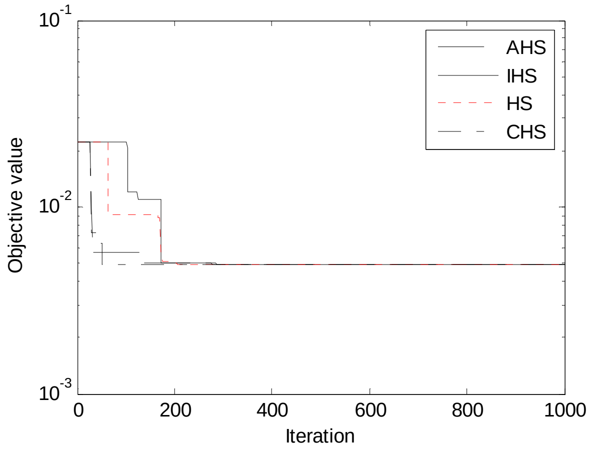

Figure 3. Schaffer function

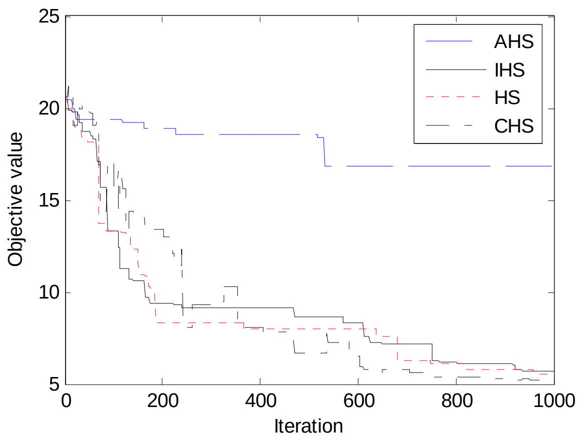

Figure 4. Ackley function

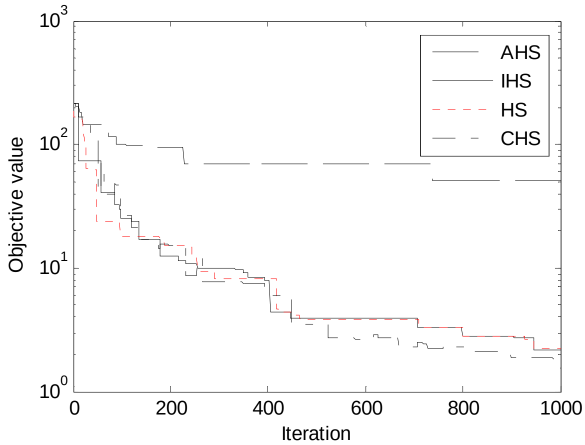

Figure 5. Griewank function

Comparing with the optimization algorithms, adaptive harmony search algorithm (AHS), improved harmony search algorithm (IHS), and traditional harmony search algorithm (HS), the new cloud harmony search algorithm (CHS) is better. The experimental results are listed through Figures 1-5. In order to compare four algorithms distinctively, log-scale vertical and horizontal ordinates are used to denote the objective function value and iteration times, in Figure 1-3 and Figure 5. From Figure 4, we can see CHS algorithm rapidly converges to the global optimum. From Figure 1-3, and Figure5 CHS has the better precision error than other algorithms.

V. CONCLUSIONS

This paper has introduced a cloud harmony search algorithm that uses cloud theory to adjust parameter PAR in harmony search algorithm. And several benchmarks are used to test CHS algorithm. The results are better than those previously reported in the literature.

ACKNOWLEDGMENT

This work is supported by the Natural Science Foundation of Hebei under Grant No. F2012501030, the Fundamental Research Funds for the Central Universities under Grant No. N100323012, No. N100323011, and National Natural Science Foundation of China under Grant No. 51105068.

REFERENCES

[1] Z. W. Geem, J. H. Kim and G. V. Loganathan, “A new heuristic optimization algorithm: Harmony search,” Simulation, vol.76, no.2, pp.60-68, 2001.

[2] Z. Kong, L.Q. Gao, L.F. Wang, and Y.F. Ge, “On Adaptive Harnony Search Algorithm,” International Journal of Innovative Computing, Information and Control, vol. 5, no.9, pp.2551-2560, 2009.

[3] M. Mahdavi, M. Fesanghary and E. Damangir, “An improved harmony search algorithm for solving optimization problem,” Applied Mathematics and Computation, vol.188, pp.1567-1579, 2007.

[4] Mark J. Harris, William V.Baxter III, Thorsten Scheuermann, Anselmo Lastra, “Thrsten Scheuermann.Simulation of Cloud Dynamics on Graphics Hardware”. Graphics Hardware (2003).

[5] D.Y. Li, “Uncertainty reasoning based on cloud models in controllers,” Computer science and Mathematics with Application, vol. 35, no. 3, pp. 99-123, 1998.

[6] J. Zhoa, J. SUN, and W. Xu. “Quantum-behaved Particle Swarm Optimization with Normal Cloud Mutation Operator,” Computational Intelligence and Software Engineering, 2009 Wuhan, pp. 1-4.

[7] G. Yan, and Z. Hao. “A Novel A tmosphere Clouds Model Optimization Algorithm,” International Conference on Computing, Measurement, Control and Sensor Network. 2012, Taiyuan, pp. 217-220.

[8] J. Wen and B. Cao. “A Modified Particle Swarm Optimizer Based on Cloud Model,” Proceedings of the 2008 IEEE/ASME International Conference on Advanced Intelligent Mechatronics July, 2008, Xi'an, China, pp, 1238-1241.

[9] J. Wen, X. Wu, K. Jiang and B. Cao, “Particle Swarm Algorithm Based on Normal Cloud,” IEEE World Congress on Computational Intelligence, Hangkong, China, pp.1492-1496.

[10] C. Dai, Y. Zhu, W. Chen, “Cloud Theory-Based Genetic Algorithm,” Journal of Southwest Jiao Tong University, 2006, 41(6), pp.729-732.

[11] Li D.; Meng H.; Shi X.. “Membership Clouds and Membership Cloud Generators” [J]. Journal of Computer Research and Development, 1995,32 (6), pp.15-20.