PAPER

Cloud Annealing: A Novel Simulated Annealing Algorithm Based on Cloud Model

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SUMMARY As one of the most popular intelligent optimization algorithms, Simulated Annealing (SA) faces two key problems, the generation of perturbation solutions and the control strategy of the outer loop (cooling schedule). In this paper, we introduce the Gaussian Cloud model to solve both problems and propose a novel cloud annealing algorithm. Its basic idea is to use the Gaussian Cloud model with decreasing numerical character *He* (Hyper-entropy) to generate new solutions in the inner loop, while *He* essentially indicates a heuristic control strategy to combine global random search of the outer loop and local tuning search of the inner loop. Experimental results in function optimization problems (i.e. single-peak, multi-peak and high dimensional functions) show that, compared with the simple SA algorithm, the proposed cloud annealing algorithm will lead to significant improvement on convergence and the average value of obtained solutions is usually closer to the optimal solution.

key words: *simulated annealing, Gaussian Cloud model, cooling schedule, solution perturbation, optimization algorithm*

1. Introduction

Simulated annealing (SA) algorithm is a typical well-studied heuristic approach of a one-point iterative search in the field of operations research with the following advantages: simple to implement, easy to calculate and effective for large-scale problems. It is an approximate global optimization algorithm to find a good solution by random perturbation of the current solution [1]. A worse solution is accepted as the new solution with a probability that decreases as the solution space is explored. Since proposed by Metropolis in 1953 [2], [3], it has been widely used in complex combinatorial optimization and function optimization problems.

The current research focus of the optimization algorithm is how to avoid trapping in local optima (i.e., premature convergence) [4], [5]. Considering the global optimization ability of the SA algorithm to find an optimal or near-optimal solution, some research works mainly focus on combining SA algorithm with other local search algorithms to solve complex optimization problems, such as simulated annealing with genetic algorithm [6]–[8], parallel regeneration simulated annealing algorithm (PRSA) [9], simulated annealing with particle swarm optimization algorithm [10]. Other few research works attempt to improve the mechanism of the SA algorithm as well as solution convergence and solution accuracy. For example, Ingber L [11] proposed a very fast simulated annealing which has been developed to fit empirical data to a theoretical cost-function over a D-dimensional parameter-space; Jing Geng [12] employed chaotic sequence and cloud theory to improve the original shortcomings of the simulated annealing algorithm to avoid premature convergence. Although the above research improved SA algorithm from different perspectives, almost no work involved in the research about the heuristic control strategy to combine global random search of the outer loop and local tuning search of the inner loop.

In this paper, we propose a novel cloud annealing algorithm that introduces the Gaussian cloud model to design a heuristic control strategy of SA algorithm to combine global random search and local tuning search. Experimental results show that, compared with the simple SA algorithm, the proposed method requires no user-specified parameters, leads to significant improvement on convergence, and the average value of obtained solutions is always closer to the optimal solution for various function optimization problems including single-peak, multi-peak, and high dimensional functions.

In Sect. 2 we introduce the related backgrounds including the principle of the simulated annealing and the cloud model. In Sect. 3 we describe our cloud annealing algorithm. By evaluating high dimensional functions and multi-peak functions the results of cloud annealing comparing with the classical simulated annealing are presented in Sect. 4. In Sect. 5 we put forward the conclusion.

2. Related Backgrounds

2.1 Simulated Annealing

As seen in Fig. 1, a simulated annealing algorithm includes three functions and two criteria. The inner loop includes the acceptance criterion (Metropolis criterion), the new solution's generation function (the perturbation of solutions) and the probability function; the outer loop includes stop criterion and temperature decrease function (cooling schedule).

The inner loop shows that the optimal solution at this temperature can be found as long as the number of perturbations is sufficient. Due to the perturbation of solutions in a constant step length, we think that the new solution

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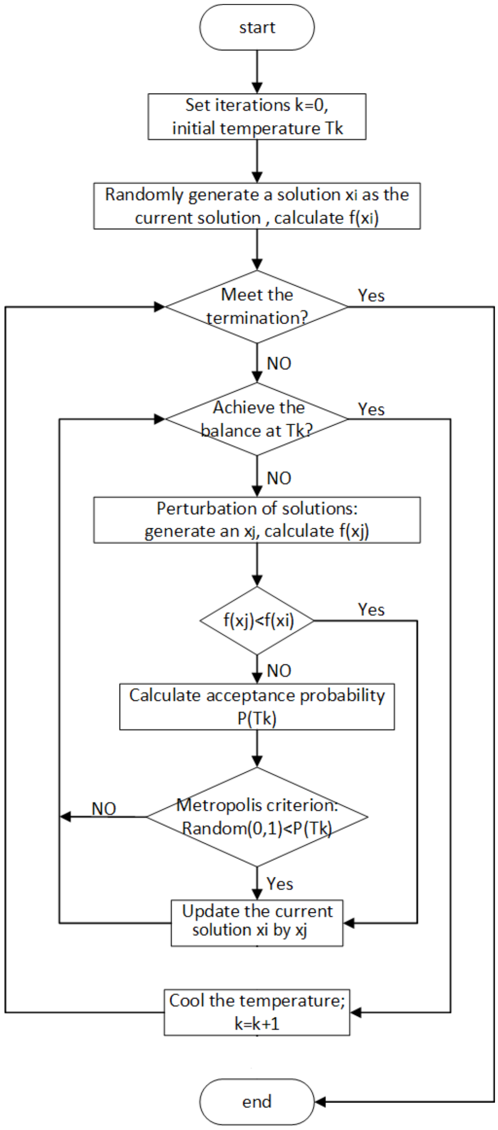

Fig. 1 Flow of the simulated annealing algorithm

generated by the inner loop has a stable tendency of uncertainty. **The outer loop** refers to temperature decrease during the entire simulated annealing process (cooling schedule). As long as the initial temperature is high enough and slow enough to fall, the global optimum solution can be found. Since the selection of initial temperature and the mode of temperature decrease have random uncertainty, these are disadvantages of the simulated annealing algorithm.

From the analysis above, a conclusion is that in order to increase the efficiency and accuracy of the simulated annealing algorithm, we can improve it from two aspects. One is the perturbation method of solutions and the other is the control strategy of the outer loop. The improvement will be discussed later.

2.2 Cloud Model

The cloud model was first proposed by Professor Li Deyi [13], [14], which can synthetically describe randomness, fuzziness and their relationship. This theory has been successfully applied in many fields, such as scenario prediction [15], stochastic optimization [16], and path planning [17].

The cloud model uses three numerical characteristics, namely Ex (expectation), En (entropy) and He (hyper entropy), to depict the intension and extension of a concept, the following describes the meaning of each parameter [18]. Cloud model consists of many cloud drops, and each cloud drop is a point in which the qualitative concept is mapped to the space of number fields, i.e. the implementation of a sample reflecting the quantity. This implementation is uncertain, and the model also provides the degree to which this point can represent the definition of the qualitative concept. Let X be a general set and $X = \{x\}$ can be called the universe of discourse.

1. Ex (Expectation): The mathematical expectation of the cloud drops belonging to a concept in the universal can be regarded as the most representative and typical sample of the qualitative concept.
2. En (Entropy): En is used to figure the granularity scale of the concept. On the one hand, En is a measurement of randomness, which reflects the dispersing extent of the cloud drops; on the other hand, it is also a measurement of fuzziness, which reflects the range of cloud drops in the universe of discourse.
3. He (Hyper-entropy): The entropy of En, He is used to depict the uncertainty of the concept granularity.

The Gaussian Cloud model is an important kind of cloud models. The definition of a Gaussian Cloud model is as follows:

Definition 1 [13]: Let U be the universe of discourse and the Gaussian Cloud $C(Ex, En, He)$ be a qualitative concept in U. If $x \in U$ is a random instantiation of concept C, x obeys Gaussian distribution $N(Ex, En'^2)$, where En'^2 is a random instantiation that obeys Gaussian distribution $N(En, He^2)$; the certainty degree of x to C is:

$$\mu = e^{\frac{-(x-Ex)^2}{2(En')^2}}. \tag{1}$$

The Gaussian Cloud model has an important property:

Property 1 [14]: The cloud drop generated by the Gaussian Cloud model is a random variable with expectation Ex and variance $En^2 + He^2$.

The proposed cloud annealing algorithm is based on the Gaussian Cloud model.

3. Methodology

3.1 The Main Idea of Cloud Annealing Algorithm

In this algorithm, we have three clear targets in mind. Our first goal is to propose a one-point search procedure that does not use an experience-based cooling schedule. The second goal is to effectively use the information collected during previous iterations of the search. The third goal is to make a heuristic control strategy to combine global random search of the outer loop and local tuning search of the inner loop. The cloud annealing algorithm proposed is an improved simulated annealing algorithm based on a Gaussian cloud model with decreasing numerical character He (Hyper-entropy) to generate new solutions in the inner loop, while He essentially indicates a heuristic control strategy to combine global random search of the outer loop and local tuning search of inner loop. In the inner loop, the simulated annealing algorithm uses a constant step length to search for the optimal solution, which results in slow convergence, while we adjust the search step by controlling the change of He to speed up the convergence in the cloud annealing algorithm. Because a cloud drop is a possible new solution in the cloud annealing, Property 1 shows that each cloud drop generated by the Gaussian cloud model is subject to normal distribution $(Ex, En^2 + He^2)$. As He becomes smaller, the variance of cloud drops becomes smaller and the distribution of cloud drops becomes dense. He controls the condensation degree of cloud drops which indicates the aggregation state of the distribution of solutions. When optimization begins, the cloud annealing has a good global random search capability because of the large search steps that result from large initial He. As iterations go on increasing, He becomes smaller and the local tuning search range becomes smaller. In outer loop, the role of He in cloud annealing algorithm is analogous to the role of temperature in the simulated annealing algorithm, which is used to control the rate of the iterations. However, unlike the temperature only participating in the outer loop, He participates in both outer loop and inner loop. In conclusion, the cloud annealing algorithm improves optimization performance from two aspects, the perturbation of solutions and the control strategy of the outer loop.

3.1.1 The Perturbation of Solutions

In cloud annealing algorithm, we use the Gaussian Cloud generator to generate a new solution. The current solution is chosen as Ex. The perturbation of solutions is

$$x_{new} = cloud(x, En, He), \tag{2}$$
$$x_{new} \sim N(Ex, En'^2), \tag{3}$$
$$En' \sim N(En, He^2). \tag{4}$$

3.1.2 The Control Strategy of Outer Loop

1. The initial value of He in cloud annealing
   The outer loop is a process that narrows the optimal range of the cloud from a wide scope, and it needs to increase the degree of condensation of the cloud drops. When He decreases, the overall tendency of cloud drops is to concentrate on Ex and the search radius is reduced. That is to say, we can control the degree of aggregation of cloud drops around Ex by changing He, thus controlling the selection range of the new solution. Figure 2 shows the distribution of cloud drops generated by the Gaussian Cloud Model on the condition of different He. Let $Ex = 0$, $En = 0.1$, the number of cloud drops be $n = 1000$, $He = 1, 0.1, 0.01$ respectively. It can be seen that as He decreases, all the cloud drops tend to be concentrated around the core,

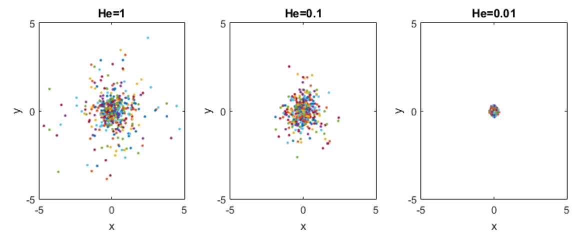

Fig. 2 Influence of changes in *he* (hyper-entropy) on cloud

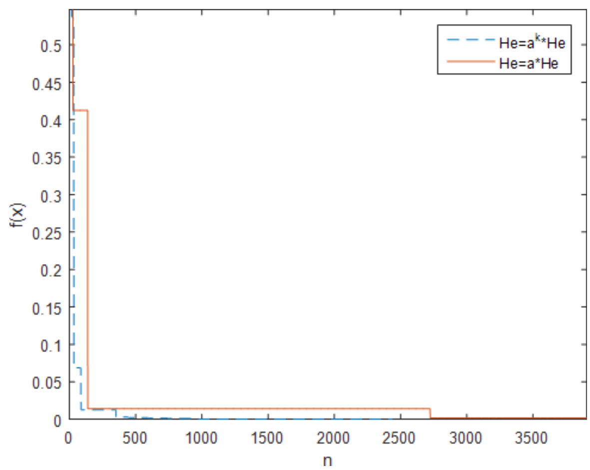

Fig. 3 Comparison of different control strategies

Algorithm 1 Cloud annealing algorithm

Input: iterations k, tolerance YZ, expectation Ex, entropy En, hyper-entropy He, attenuation coefficient α, the inner loop number (Markov chain length) L
Output: optimal solution

Choose a random x_k as the current solution and calculate its fitness value $f(x_k)$. Randomly initialize of an x_{best} as the last optimal solution.
while $f(x_{best}) - f(x_k) > YZ$ **do**
  for $i = 1 : L$ **do**
    $Ex = x_k$
    $x_{new} = cloud(Ex, En, He)$
    if $f(x_{new}) < f(x_k)$ **then**
      $x_k = x_{new}$
      if $f(x_k) < f(x_{best})$ **then**
        $x_{best} = x_k$
      else
        $P(He_k) = e^{-[f(x_{new}) - f(x_k)]/He_k}$
        Generate a random number $\lambda \in (0, 1)$
        if $\lambda < P(He_k)$ **then**
          $x_k = x_{new}$
        end if
      end if
    end if
  end for
  $He_{k+1} = \alpha^k \times He_k$
  $x_{k+1} = x_k$
  $k = k + 1$
end while

and the number of cloud drops around Ex becomes larger.

He finally will be infinitely close to 0, so that the function converges to the optimal value. When He is large enough, the perturbation of solutions can traverse the entire universe of discourse in order to find the optimal solution space containing the minimum energy value, so the choice of the initial value of He becomes significant. If the initial value of He chooses too small, it may find the local optimal solution; conversely, the iterative time is too long, affecting convergence speed. Compared with the uncertainty of initial temperature selection in the simulated annealing algorithm, the initial He of cloud annealing algorithm can be calculated by the following Eq. (7).

Let $x \in (x_{min}, x_{max})$, which can be seen from Property 1 that the cloud drop $x \sim N(Ex, En^2 + He^2)$. According to the 3σ property of the Gaussian distribution, the probability of cloud drops falling outside $(Ex - 3\sigma, Ex + 3\sigma]$ is less than 0.3%. It can be concluded that:

$$6\sigma = \|x_{max} - x_{min}\|, \tag{5}$$

$$\sigma^2 = En^2 + He^2, \tag{6}$$

$$He = \sqrt{\frac{\|x_{max} - x_{min}|^2}{36} - En^2}. \tag{7}$$

2. Comparison of control strategies in outer loop
   In order to choose a better way of the outer loop, we compare two methods of the control strategy. All the other conditions are the same, but the way of He decrease is different, calculate the minimum value of Sphere function. α is the attenuation coefficient between 0 and 1, and k is the number of iterations. The results of the calculation are shown in Fig. 3. It can be seen from Fig. 3 that the two outer loops both behave well and the values of cost function decrease rapidly. $He = \alpha^k \times He$ performs better, the convergence speed is faster and the accuracy is higher. Therefore, the cloud annealing algorithm adopts $He = \alpha^k \times He$ as outer loop mode.

3.2 Cloud Annealing Algorithm Steps

Based on the above analysis, the flow of cloud annealing algorithm is shown as Fig. 4. In cloud annealing, the significance of numerical characteristics (Ex, En, He) are as follows. (1) Ex is the current solution. The cloud is generated with Ex as the center. The farther away from Ex, the greater the difference in cost function values may be. (2) $En^2 + He^2$ reflects the deviation of cloud drops from the current solution, the degree of cloud drops dispersion, representing the scope of the search. (3) He is an outer loop switch, a measure of the uncertainty of the search. By changing He, the density of the entire cloud drops can be flexibly adjusted, and the cohesion and diffusion of cloud drops can be controlled.

4. Numerical Experiments

4.1 An Experiment on the Effectiveness of the Initial Value of Hyper-Entropy

The numerical experiment below demonstrates whether

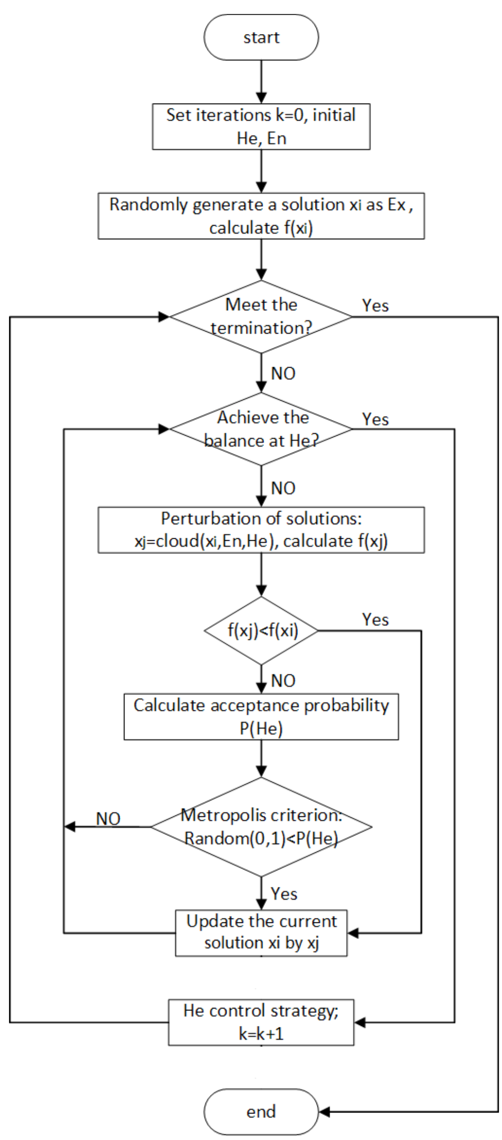

Fig. 4 Flow of cloud annealing algorithm

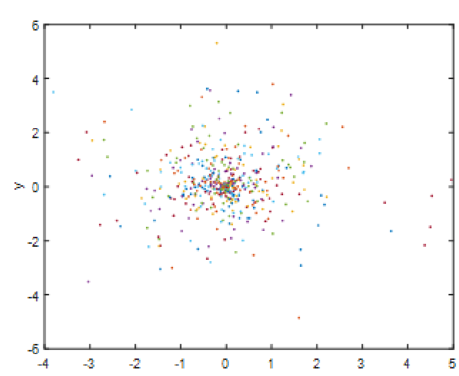

Fig. 5 The distribution of cloud drops

Table 1 Test function set

Function name	Test function
Sphere	$f_1(x) = \sum_{i=1}^{D} x_i^2$
Rosenbrock	$f_2(x) = \sum_{i=1}^{D-1} 100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2$
Ackley	$f_3(x) = 20 + exp(1) - 20exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}) - exp(\frac{1}{n}\sum_{i=1}^{n} cos(2\pi x_i))$
Griewank	$f_4(x) = \sum_{i=1} D\frac{x_i^2}{4000} - \prod_{i=1}^{D} cos\frac{x_i}{\sqrt{i}} + 1$
Rastrigin	$f_5(x) = \sum_{i=1}^{D} x_i^2 - 10cos(2\pi x_i) + 10$
Bohachevsky	$f_6(x) = \sum_{i=1}^{D-1} x_i^2 + 2x_{i+1}^2 - 0.3cos(3\pi x_i) - 0.4cos(4\pi x_{i+1}) + 0.7$
Matyas	$f_7(x) = 0.26(x_1^2 + x_2^2) - 0.48x_1x_2$

Table 2 Test functions scope

	range	minimum	dimension
f_1	[-10,10]	0	20
f_2	[-100,100]	0	10
f_3	[-32,32]	0	3
f_4	[-600,600]	0	10
f_5	[-5.12,5.12]	0	10
f_6	[-15,15]	0	2
f_7	[-10,10]	0	2

Table 3 Average function value error between SA and CA

	method	Optimal value	mean error ∓ standard deviation
f_1	SA	1.3400E-03	1.6000E-03∓ 1.7387E-03
	CA	4.5680E-04	5.4800E-04∓4.2071E-04
f_2	SA	7.0921E-07	1.3511E-05∓ 2.1689E-05
	CA	1.6497E-09	2.7188E-08∓3.7146E-08
f_3	SA	1.1021E-03	1.8504E-03∓ 4.9185E-01
	CA	3.5230E-04	5.2327E-04∓ 1.0271E-02
f_4	SA	4.4310E-02	5.4086E-02∓9.7075E-02
	CA	1.1660E-02	3.2252E-02∓1.0042E-03
f_5	SA	1.3096E-03	1.9997E-02∓ 5.8930E-01
	CA	7.2420E-07	8.0898E-07∓ 9.7536E-02
f_6	SA	1.9552E-07	1.6467E-06∓ 1.3938E-06
	CA	4.2004E-09	4.4111E-08∓ 7.9103E-08
f_7	SA	1.3120E-08	6.9318E-08∓ 8.0525E-06
	CA	6.2196E-09	3.3543E-08 ∓ 3.9906E-08

cloud drops generated by the initial value of He can cover the entire universe of discourse or not. Let $x \in [-3, 3]$, $y \in [-3, 3]$, $Ex = 0$, $En = 0.1$, $n = 1000$, according to Eq. (7), $He = 0.995$, draw the cloud as Fig. 5.

The initial He calculated by Eq. (7) is applied to a Gaussian Cloud generator in Fig. 5. Generated cloud drops can reach the boundary of the universe of discourse $x \in [-3, 3]$, $y \in [-3, 3]$. As long as the number of cloud drops n is large enough that all the cloud drops can cover the entire universe of discourse. This illustrates the completeness of cloud annealing algorithm, that is, all the values in the universe of discourse can be obtained.

4.2 Performance Experiments of Cloud Annealing Algorithm

In order to observe the quality of solutions and the convergence rate of cloud annealing, we have chosen single-peak functions and multi-peak functions to carry out the experiments. Sphere is a single-peak function. Rosenbrock is a single-peak function in two and three dimensions, but can be regarded as a multi-peak function in more dimensions [19]. The rest functions are multi-peak functions with many local extreme points [20]. Parameters set: Markov chain length $L = 200$, $En = 0.01$, attenuation parameter $\alpha = 0.998$, tolerance $YZ = 10^{-8}$. For a more scientific and objective comparison, we conduct 50 independent experiments under the same configuration environment and parameters. The test functions are in Table 1, Table 2.

4.2.1 Quality Analysis of Solutions

The quality of the solution is expressed as "mean error ∓ standard deviation", SA for simulated annealing, and CA for cloud annealing. The results are shown in Table 3.

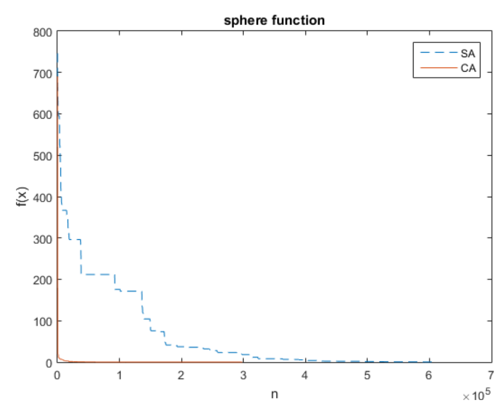

Fig. 6 Sphere function

As can be seen from Table 3, the optimal solution of the CA algorithm is closer to the real optimal solution 0 than that of the SA algorithm. Meanwhile, the average error and standard deviation of the CA algorithm are much smaller than that of SA algorithm, especially in f_2, f_5 and f_6. The results show that the cloud annealing algorithm significantly improves the accuracy and stability of the solution both in single-peak functions and multi-peak functions.

4.2.2 Convergence Rate Analysis

In the case of the same experimental parameters, we compare the convergence speeds of the different functions using simulated annealing and the cloud annealing algorithms.

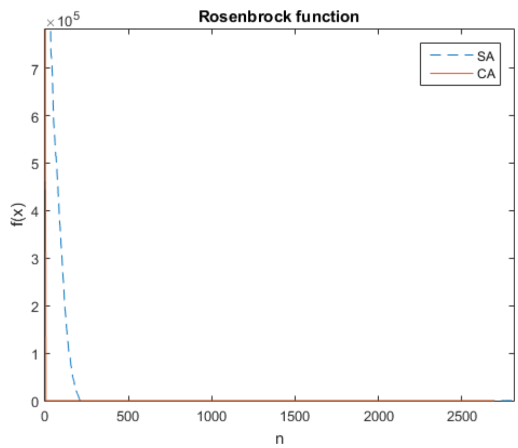

Fig. 7 Rosenbrock function

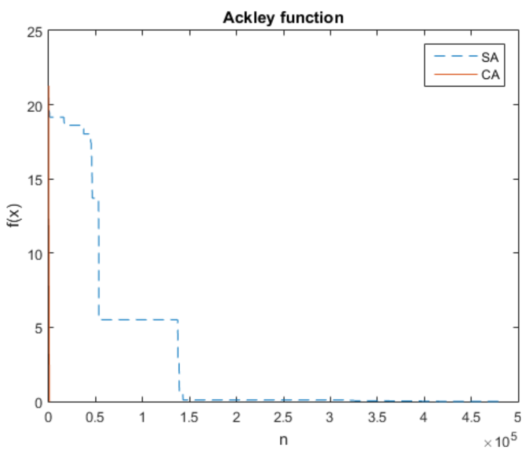

Fig. 8 Ackley function

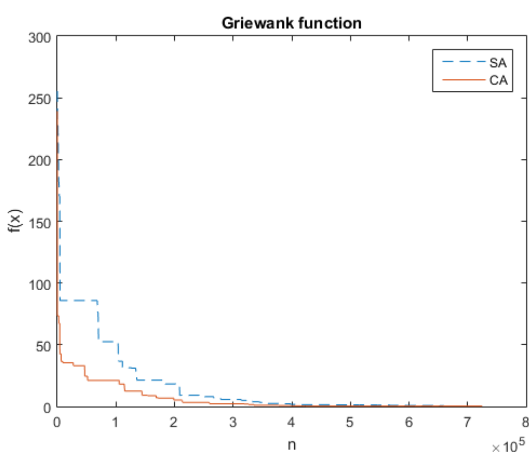

Fig. 9 Griewank function

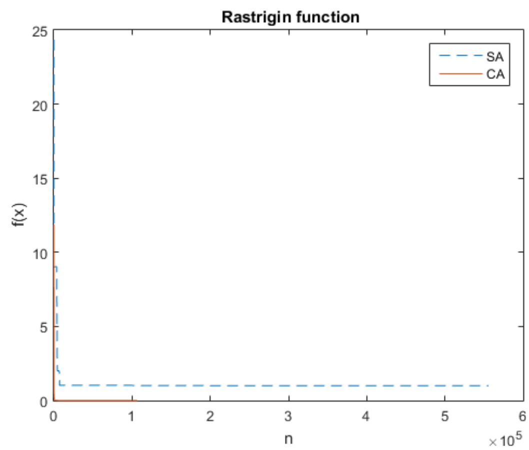

Fig. 10 Rastrigin function

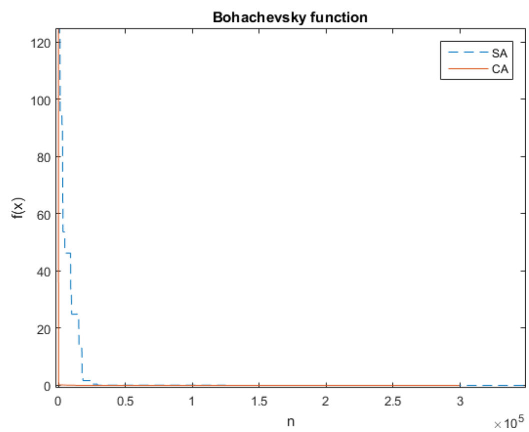

Fig. 11 Bohachevsky function

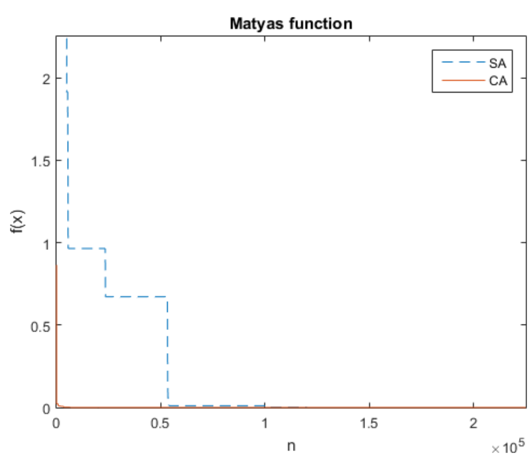

Fig. 12 Matyas function

The results are shown in Figs. 6, 7, 8, 9, 10, 11, 12. The ordinate represents the function value and the abscissa represents the number of iterations. Figure 6 shows the different performance of f_1 function using the simulated annealing algorithm and the cloud annealing algorithm. At the same number of iterations, the function value obtained by the cloud annealing algorithm is far less than that obtained by the simulated annealing algorithm. The cloud annealing algorithm converges faster than the simulated annealing algorithm. Figures 7, 8, 9, 10, 11 are the same as Fig. 6. The convergence rate of the cloud annealing algorithm is significantly better than that of the simulated annealing algorithm.

Table 4 The average number of iterations that converge to the error threshold

function	error threshold	SA iterations	CA iterations
f_1	10^{-3}	6.779E+05	1533
f_2	10^{-6}	9.372E+04	8.251E+04
f_3	10^{-3}	4.828E+05	1018
f_4	10^{-2}	2.324E+03	3675
f_5	10^{-6}	-	568
f_6	10^{-6}	6.132E+05	1688
f_7	10^{-8}	9.273E+05	3.808E+05

It can be seen from Table 4 that when reaching to the same error threshold, the iterative times of the cloud annealing is obviously less than that of the simulated annealing. In f_1, f_3, f_4, f_6, the cloud annealing algorithm greatly reduced iterative times. In f_5, the simulated annealing algorithm did not reach the error threshold, cloud annealing algorithm performed better.

5. Conclusion

In this paper, we presented an advanced cloud annealing algorithm based on Gaussian Cloud model whose selection mechanism was controlled by He (hyper-entropy). It was a heuristic control strategy to combine global random search of the outer loop and local tuning search of the inner loop in terms of finding global optimal solutions by controlling the change of He. We have made several experimental comparisons of the cloud annealing with the simulated annealing on different types of functions. The results showed that the cloud annealing could improve the accuracy and convergence speed of solutions. Through the above research on cloud annealing algorithm from the principle to numerical experiments, we can get the following conclusions:

1. Based on the idea of the cloud model, we proposed an original perturbation method of solutions which can adjust the search step by changing the He (hyper-entropy).
2. We proposed a way for calculating the initial value of He (hyper-entropy) and a heuristic control strategy in the outer loop.

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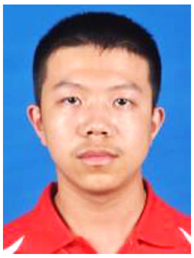

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