The International Journal Of Engineering And Science (IJES)
|| Volume || 4 || Issue || 3 || Pages || PP.39-43|| 2015 ||
ISSN (e): 2319 – 1813 ISSN (p): 2319 – 1805

Adaptive Optimization of Cloud Security Resource Dispatching SFLA Algorithm

[1,] Xiaoxi Hu
[1,] School of Computer and Communication Engineering, University of Science and Technology Beijing, Beijing, 100083, China

ABSTRACT
According to the present problem of cloud computing resources dispatching model as low safety performance, a cloud computing resources safety dispatching model is proposed based on the adaptive optimization SFLA algorithm. First of all to adaptive optimize the learning factor of standard SFLA algorithm, at the same time of the continuation of the last update inertial step, also to learn to the history optimal value of individual neighborhood in the memory, expand the search area of the individual, maintaining the diversity of the population, and as the original algorithm is easy to fall into local optimal problem, the Cauchy mutation operator is introduced into the basic SFLA algorithm, and improve the locally adaptive update strategy. Simulation experiments show that the proposed cloud computing resources security dispatching model has better convergence effect and application effect based on adaptive optimization SFLA algorithm.

Keywords *- SFLA, Adaptive optimization, Cloud computing resource dispatching, Security dispatching, Local update strategy, Learning factor*

Date of Submission: 09 March 2015 Date of Accepted: 20 March. 2015

I. INTRODUCTION

With the rapid development of cloud computing, cloud amount and internal server number of each cloud platform are also in rapid growth, the operation of those large number of server cluster depends on the cloud computing system. Cloud computing users access to information resource service through the network conveniently on-demand as easily as get water and electricity; On the other hand, cloud computing can compatible with a variety of based resources of software and hardware, enables the different resources to division of labor to work together, to implement the dynamic flow of resources; The two basic function is the core of the cloud computing system. Thus, resource scheduling strategy in cloud computing system for the operation of cloud platform is particularly important, it directly affect the speed of cloud users experience, cloud platform equipment utilization, cloud service cost and economic benefit etc.

Scholars at home and abroad research on safety scheduling of cloud computing resources is essentially revolve around the following aspects. Amazon provides the cloud IaaS (infrastructure as a service) products, provides computing power, storage, and other services for users, according to Amazon, its Web service allows you to use the global computing infrastructure of Amazon.com, this is Amazon's retail business and the core of corporate affairs. Trusted computing technology is used to protect the cloud computing environment, the premise of set up the scheme is to establish a trusted computing base, and then use the trusted computing base to control and manage the upper service software, Santos et al. propose a trusted cloud computing platform TCCP, based on the platform, IaaS cloud computing service providers can provide users with a closed box execution environment, to ensure that the user virtual chance the confidentiality. In addition, it also allows users to inspect IaaS cloud computing service provider's service is safe or not before starting virtual machine. Companies such as EMC, Intel and VMware announce the cooperation project of "trusted cloud architectures", and put forward a proof of concept system. Boneh put forward a kind of support other authorized user retrieval scheme, cipher processing focuses on privacy homomorphism encryption algorithm design. Mowbray et al. propose a privacy management tool on client bases, and put forward the trust model with user-centric, to help users to control their sensitive data in the cloud storage and use. Rankova et al. propose an anonymous data search engine, can make interactive search on each other's data, to obtain data information what you want, at the same time ensure that the content of search inquiry will not be known by each other, search with request irrelevant information will not be obtained. In cloud computing environment, when sharing and protecting the resources, must formulate a reasonable and mutually acceptable access control policy for shared resources. Therefore, we need to compound support strategy. Mclean first raised the issue in mandatory access control framework, he compound two safety synthesis to a new lattice structure, constructs a synthetic framework of mandatory access control strategy. Synthesis strategy should not only guarantee the safety of the new strategy, but also ensure that new synthetic strategies cannot contrary to the original access control policy of each domain. Therefore, Gong put forward the principles of autonomy and safety. Bonatti presents a synthetic algebra of access control policy, based on set theory using synthetic operator for synthesis of security policy. Wijesekera put forward strategy based on authorized state change to composite algebraic framework, Agarwal structure strategy synthetic solution of semantic Web services, Shafiq put forward for more than a trust domain RBAC synthesis strategy, focus on strategies in the synthesis of solution and the domain the consistency problem of original strategy.

According to the characteristics of cloud computing, a cloud computing resources safety dispatching model based on the adaptive optimization SFLA algorithm is proposed, in order to improve the security of cloud computing resources dispatching.

II. DISPATCHING SFLA ALGORITHM OF RESOURCES SECURITY

Hybrid leapfrog algorithm (SFLA) algorithm is a bionic optimization algorithm of global collaborative search, the algorithm is inspired by the frog foraging behavior: a group of frogs living where there are many stones, frog by jumping between stones and looking for food. Each frog looks for different stones to improve their ability to search for food, and communicate ideas with each other between frogs to achieve information sharing.

For optimization problem of M dimensional space, suppose that the frog population size as S , frog i marked $U(i)=\{U_{i1},U_{i2},...,U_{ij},...,U_{iM}\}$ as a solution of solution space, $1\le i\le S$, $1\le j\le M$. Compute fitness value of each frog within the population, descending order according to the fitness value. The entire frog populations were divided into m groups, each group contains n frogs, which meet the relationship $S=m\times n$. At the same time, according to the following rules to sort frog population: first frog into the first group, second frog into 2 groups, and the rest can be done in the same manner, the m frog into the m groups. And then, the $m+1$ frog into the first group, the $m+2$ frog into second groups, such as the cycle distribution, until finish all the frogs were assigned.

The best and the worst of the fitness value of the frog in ethnic groups, respectively as P_b and P_b. The best fitness value of frogs in the population as P_g . Before reach the preset local the number of iterations, local search in the group of all nationalities, through the study manner of P_w in ethnic groups to the groups P_b, to achieve the optimization for P_w. After local search in each group, the frog jumps between ethnic groups to mix into a population, so that complete a global search.

Shuffled Frog Leaping Algorithm (SFLA) can be basic divided into three processes as global search, local search and mixed operation. The global search process is as follows:

1) Algorithm parameters. Number of ethnic groups m, local search the maximum number of iterations $J_{\max}$, global maximum number of iterations $Q_{\max}$, each group contained in the number of frogs n, The frog population size $S=m\times n$, the dimensions of the optimization problem solution space M, and upper and lower limits of search space respectively marked as: H , L ;

2) Initialize the population. In M dimension the feasible solution space, randomly generated S frogs marked as $U(1),U(2),...,U(S)$, the i frog marked as $U(i)=\{U_{i1},U_{i2},...,U_{ij},...,U_{iM}\}$, $1\le i\le S$, $1\le j\le M$, $U_{ij}\in[L,H]$;

3) Fitness function. Through fitness function $f(i)$ to evaluate performance of each frog solution $U(i)$;

4) The frog population division. Frog rank: according to fitness function $f(i)$, the S frogs descending order according to the fitness, generates an array $P=\{U(i),f(i),i=1,2,...,S\}$, the frog $U(1)$ is the best individual in the frog populations as global extreme value $P_g=U(1)=\{U_{11},U_{12},...,U_{1j},...,U_{1M}\}$; The frog divided race: according to the equation (1) to divide the frog population.

$$Z_k(i)=U(k+m\times(i-1)) \tag{1}$$

In equation, $i=1,2,...,n$, $k=1,2,...,m$, distributing the sorted frogs into m groups $Z_1,Z_2,...,Z_m$, each group contained n frogs; for example $m=3$, $n=2$, that is $S=6$, the frog $U(1)$ into $U(1)$ groups, $U(2)$ enter into Z_2, $U(3)$ enter into Z_3, $U(4)$ enter into Z_1 , $U(5)$ enter into Z_2 ,$U(6)$ enter into Z_3.

Perform evolution within each group. Within the group, the frog is affected by the other frogs' individuals culture within the same ethnic, through evolution, to make each frog learning approach to extremum in their ethnic local.

III. ADAPTIVE OPTIMIZATION OF SFLA ALGORITHM

3.1 Adaptive Optimization of Learning Factors

Because the frog individuals with memory function, can remember the last update step length and its own history optimal value of individual neighborhood, and so P_w learn not only from P_b or P_g in iteration process, at the same time of the continuation of the last update inertial step, also to learn the history optimal value from individual neighborhood in the memory, with the increase of the number of iterations, learning factors impact on individual update strategy is linear weakening trend. While this update strategy speed up the convergence, expand the individual search area, to maintain the population diversity, a certain extent, expanded the search ability of the algorithm. Specific update strategy such as equations (2) ~ (4).

$$\begin{aligned} Dis(t+1) = W(R_1 Dis(t) + R_2 His(P_w)) \\ + R_3(P_b - P_w) \end{aligned} \tag{2}$$

$$W = W_e + (W_s - W_e)\frac{T_{\max} - t}{T_{\max}} \tag{3}$$

$$P_w(t+1) = P_w(t) + Dis(t+1) \tag{4}$$

In equation, R_1, R_2, R_3 are a random number between 0 and 1, Dis is moving step of P_w, t is the number of iterations, $T_{\max}$ is the total number of iterations, W is a weighting factor, W_s and W_e is the initial value and end value weighting factor, in this paper, the values are respectively 0.9 and 0.4, $His(P_w)$ is individual neighborhood history optimal value of P_w .

3.2 Adaptive Optimization of Local Update Strategy

In basic SFLA, each iteration only to update operation of ethnic group X_w, and each use equation (1) update the frog individuals. If the frog ignore some search domain, the algorithm is easy to fall into local optimum. Aiming at this problem, to make full use of information among groups, SFLA algorithm was proposed based on disturbance Cauchy distribution.

Cauchy distribution, is very important application of probability distribution to many areas such as a mathematical theory, engineering application. Cauchy density function is defined as:

$$f(x) = \frac{\beta}{\pi[\beta^2 + (x-\alpha)^2]} \tag{5}$$

Usually express by $C(\alpha, \beta)$, its Cauchy probability distribution function is:

$$F(x) = 0.5 + \frac{\arctan((x-\alpha)/\beta)}{\pi} \tag{6}$$

When $\alpha = 0$, $\beta = 1$, known as the standard Cauchy distribution, to remember as $C(0,1)$. Cauchy distribution is the shape of two relatively flat, wide and pattern is a located above the horizontal axis of peak type curve (as shown in figure 1).

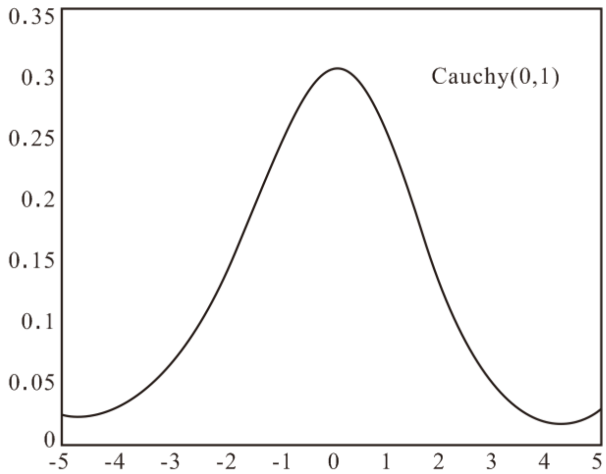

Fig.1: Cauchy Distribution Function

The Cauchy mutation operator is introduced into the basic SFLA algorithm, the local update strategy was improved, the worst individual X_w to subgroup within individual X_b according to the equation (7) the best learning update, the update strategy for:

$$D(t+1) = rand \times (X_b - X_w) \times C(0,1) \tag{7}$$

Compared to Gauss mutation, Cauchy mutation with larger probability, in a broader space domain, finds the best solution. By adding random disturbance, improve diversity of the group, the lower the possibility of the frog “into” local optimal domain, improve local escape ability of the algorithm. Compared with Gaussian mutation, although Cauchy mutation are more likely to escape from the local optimal area, when the algorithm into the late search, near the global optimal extremum, because of its high Cauchy mutation operator variable step length easily over a better search area, is not conducive to the depth of local search. To reduce the dramatic differences between the individual spaces by local update operation, put forward a kind of Cauchy mutation hybrid leapfrog algorithm based on probability of disturbance. Local update strategy is as follows:

$$D(t+1) = \begin{cases} rand \times (X_b - X_w) \times C(0,1), R \le Q \\ rand \times (X_b - X_w), R > Q \end{cases} \tag{8}$$

$$X_w(t+1) = X_w(t) + D(t+1) \tag{9}$$

In equation, R is random number $rand$ of $[0,1]$, Q probability of disturbance.

IV. THE SIMULATION OF ALGORITHM

In order to verify the effectiveness of the improved algorithm proposed in this paper, simulation experiments on it. First Sphere function f_1, Rosenbrock function f_2 and Rastrigin function f_3, Griewank function f_4 and Schaffer function f_5 were introduced in standard SFLA algorithm and the improved SFLA algorithm for testing. The results are shown below:

Tab.1: The Test Results of Standard Algorithms and Improved Algorithm

f	Algorithm	Average optimal value	Standard deviation	Running time
f_1	SFLA	0.0062	0.0047	0.9
	IM-SFLA	0.0028	0.0001	1.4
f_2	SFLA	124.9740	53.1455	1.0
	IM-SFLA	45.9851	27.2636	1.7
f_3	SFLA	11.4995	3.6283	1.4
	IM-SFLA	10.2293	4.3324	1.9
f_4	SFLA	0.5815	0.2399	1.5
	IM-SFLA	0.1536	0.0805	1.9
f_5	SFLA	19.6511	5.1459	3.1
	IM-SFLA	19.3725	7.8156	3.7

Seen from the data in table 1, under the same number of iterations and precision, based on the improved SFLA algorithm can obviously get the better average optimal value than the standard hybrid leapfrog algorithm, and its standard deviation is smaller, means that improved leapfrog algorithm has better stability.

Then the standard SFLA algorithm and the improved SFLA algorithm in cloud computing resources safety scheduling optimization, test its convergence, the result is as follows:

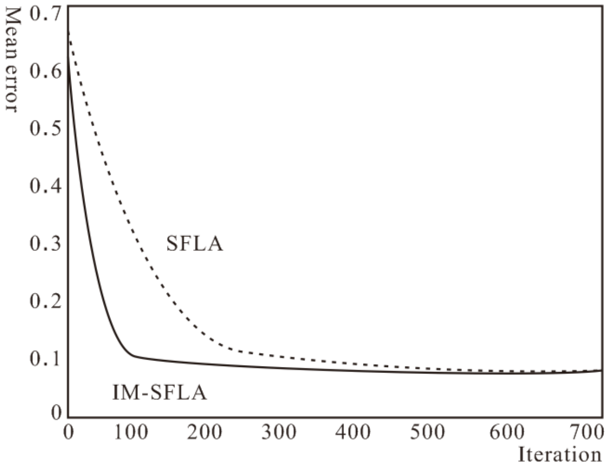

Fig.2: Convergence Test Results of Standard algorithms and Improved algorithm

Seen from the simulation results, the proposed improved SFLA algorithm has good convergence, and has good application in cloud computing resources safety dispatching optimization.

REFERENCES

[1] Zhang Yan. A Novel Improved Bat Algorithm for Cloud Computing Resources Scheduling Optimization, *Bulletin of Science and Technology*. 2014, 30: 117-121.

[2] Yin Fan. Algorithm of Multi-Agent Genetic Based on Cloud Computing Resource Scheduling. *Bulletin of Science and Technology*. 2014, 30: 247-249.

[3] Lv Shuhong. Research on the Cloud Computing Resource Scheduling Based on Chaos Strategy and Bat Optimization Algorithm. *Bulletin of Science and Technology*. 2014, 30: 144-149.

[4] YE Feng. Application of Two-Way Convergence Ant Colony Algorithm in QoS of Cloud Computing Resource Scheduling. *Electronics Optics ＆ Control*. 2014, 21: 93-96.

[5] Zhang Hengwei. Cloud resource scheduling method based on estimation of distribution shuffled frog leaping algorithm. *Application Research of Computers*. 2014, 31: 3225-3228.

[6] Ji Keke. Application of Improved SFLA Algorithm in Resource Scheduling of Cloud Computing, *Bulletin of Science and Technology*. 2014, 4: 225-228.

[7] Xu Bingyuan. Virtual Resources Dispatching Algorithm Based on Multipath Traversal Priority Selection in Cloud Computing, *Electric Power*. 2014,8: 139-143.

[8] Feng Guofu. Maximum Profit Oriented Adaptive Scheduling of Cloud Resources, *Mini-micro Systems*. 2014, 35: 1717-1721.

[9] Ma Junbo. Security-constrained workflow scheduling in cloud computing environments, *Computer Engineering ＆ Science*. 2014, 36: 607-614.

[10] Luo Liang. Energy Modeling Based on Cloud Data Center, *Journal of Software*. 2014, 25: 1371-1387.

[11] Xu Bo. Virtual Machine Resource Scheduling Multi-objective Optimization in Cloud Computing, *Journal of System Simulation*. 2014, 26: 592-595.

[12] Hao Liang. A cost constrained resource scheduling optimization algorithm for reduction of energy consumption in cloud computing, *High Technology Letters*. 2014, 5: 458-464.