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Virtual Machine Resource Allocation of Probabilistic Optimization Based on SME Algorithm

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Abstract

To further enhance optimizing effect of virtual machine resource allocation, virtual machine resource allocation algorithm of probabilistic optimization based on SME-FFD (Simulated Evolution – First Fit Decreasing) is proposed aiming at NP hard optimization problem in the process of virtual machine resource allocation in cloud computing. First of all, an optimization evaluation scheme of virtual machine resource allocation is proposed, and strong climbing optimization ability of simulated evolutionary algorithm is adopted to carry out iterative evolution to selection, evaluation and ranking of virtual machine resource allocation ; after that, based on SME algorithm obtaining resource allocation ordering, the secondary allocation on virtual machine and physical host resources ranked is conducted using FFD to improve efficiency and effectiveness of resource allocation; in the end, experimental comparison is conducted in CloundSim grid lab in the University of Melbourne and gridbus cloud simulation platform, the results show that CPU usage rate of proposed algorithm reaches up to 47%, memory usage rate reaches up to 56%, therefore, it may effectively reduce physical machine usage quantity and realize the goal of energy consumption.

Keywords*: Cloud computing; Resource allocation; Probabilistic optimization; NP solution optimization; simulated evolution*

1. Introduction

In recent years, data center, which is economical and convenient, based on cloud computing has become commonly used modes provided by mainframe and IT service. Gartner report indicated that a growth rate of public cloud is expected to be 20.5% in 2016, and its energy consumption has increased rapidly. In 2014, power consumption in data center is estimated to account for 1.3% to 1.8% of total electric power consumption of society, and it's expected to further climb up. Energy consumption is not only used for physical machine operation but also for infrastructure cooling in data center. In addition, large data centers are faced with restrictions of energy use regulation of green computing driven by governmental body. Therefore, how to reduce energy consumption is now the main objective for data center operation [1-2]. A heuristic simulated evolutionary algorithm is proposed to achieve finding the optimal problem-solving solution in the shortest time. Similar to other non-deterministic algorithm, SME algorithm also has strong climbing optimization ability. In the experiment of performance comparison, SA (simulated annealing) is selected, it's the first time that it adapts FFDimp and LLimp, of which two algorithms are proposed by literature [16] mended. Simulation results reveal that SME algorithm is more effective compared to above-mentioned algorithms.

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2. Proposed Algorithm

2.1. Simulated Evolution

SME is an iterative heuristic optimization proposed by Kling and Banerjee, such scheme integrates iterative improvement and structural perturbation and employs random fashion to protect it from being caught in local minimum. In SME, random walk, which differs from other non-deterministic algorithms, is the main creative point of such algorithm with intelligent mobility to accomplish spatial traversal search. SME algorithm framework of virtual machine allocation as shown in Figure 1.

Assume that it contains n mobile element (VMS), SME algorithm is set V that contains solution ϕ. Algorithm begins with initial scheme ϕ_i, then evolving method is adopted to weed out worse individuals in iterative process and optimal individuals are retained to achieve an optimization for optimal allocation scheme. Such algorithm is comprised of three basic steps: evolution, selection and distribution. Above three steps are conducted in sequence until optimal mean value of scheme reaches a maximal value or optimal value remains unchanged.

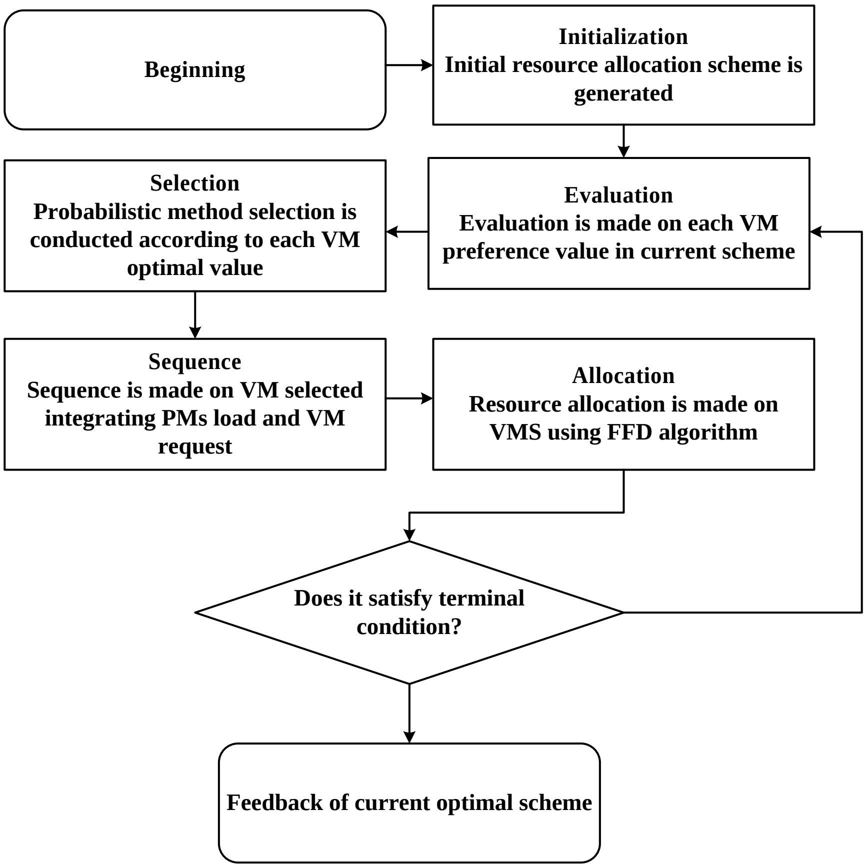


Figure 1. SME Algorithm Framework of Virtual Machine Allocation

2.2. Optimal Evaluation

The basis of optimization is to define optimal object, which is introduced in literature [7-11], in the process of virtual machine resource allocation literature, for example, literature [7] sets minimal quantity of physical machine resource allocation as optimal object (formula (3)); literature [8] sets energy consumption of physical host as optimal object; literature [9] sets the above two to construct multi-objective optimization problem.

Above-mentioned optimal objects all are rational, however, in practical use process, due to many a parameter and complex interference are involved, the algorithm will be stuck in local extremum and unable to jump out in optimization process, which results in a failure to final optimal object. An optimal object with indirect resource allocation is proposed, which is called optimal evaluation index to this problem, such index will dynamically adjust subsequent individual resource allocation according to current condition of resource individual allocation, repeated calculation will be reduced and computational efficiency will be improved when success rate of allocation is increased.

Steps of optimal evaluation include current scheme ϕ', an optimization g_i of PM p_k given by VM v_i allocation is calculated. Optimal measurement can be seen as knowledge optimization process. Optimal measurement value must be expressed with digital form within an range of $[0,1]$. For virtual machine allocation problem, optimal definition as follows:

$$g_i = \frac{v_i^c + v_i^m}{p_k^c + p_k^m}, \ p_k^c \le T_k^c \ \& \ p_k^m \le T_k^m \tag{1}$$

In formula, v_i^c and v_i^m are CPU and memory resource requirements of virtual machine v_i, respectively. p_k^c and p_k^m are usable CPU and memory resource requirements, respectively, after virtual machine v_i is removed from physical host p_k in current scheme ϕ'. The form of minimum resource waste of PM p_k is given in equation (1). After v_i is added to p_k, $v_i^c = p_k^c$, $v_i^m = p_k^m$, then virtual machines v_i's optimal evaluation $g_i = 1$. It means the resource can be used with a maximum limit according to current v_i task allocation.

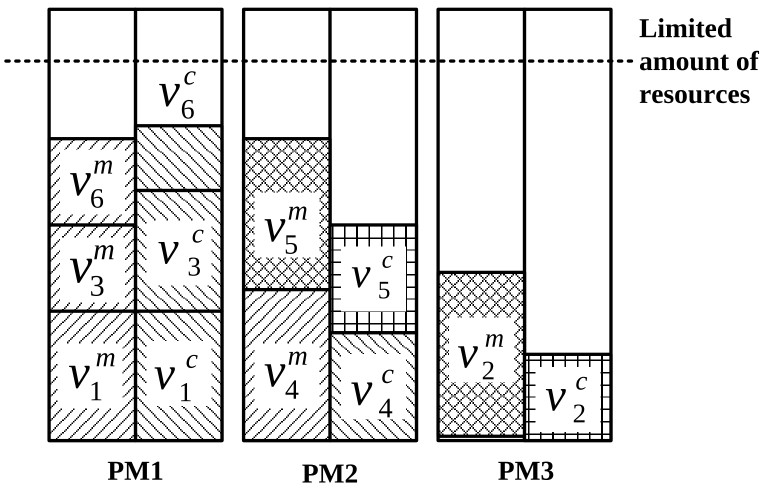


Figure 2. 3 Physical Resource Allocation of 6 Virtual Hosts

v_1, v_2 and v_3's optimal evaluation $g_1 = g_2 = g_3 = 1$ as shown in Figure 2, for its resource allocation may make a maximum using of physical host resources. On the other hand, when virtual machine v_i with minimum resource demand is allocated to physical host p_k, then $v_i^c \ll p_k^c$, $v_i^m \ll p_k^m$, here $g_i \approx 0$, just like the virtual host v_6, in Figure 2, optimal evaluation value of it is close to 0. Notice that such optimal evaluation is closely related to objective of given problem. An approximation can be conducted for quality of solution according to total optimal evaluation of elements (VMS).

For optimal evaluation problem of D dimension, formula (1) can be expanded as:

$$g_i = \frac{v_i^{d_1} + v_i^{d_2} + \cdots v_i^{d_D}}{p_k^{d_1} + p_k^{d_2} + \cdots p_k^{d_D}} \tag{2}$$

$$s.t. \quad p_k^{d_1} \le T_k^{d_1}, p_k^{d_2} \le T_k^{d_2}, \cdots, p_k^{d_D} \le T_k^{d_D} \tag{3}$$

2.3. Selection

Probabilistic algorithm is adopted to reallocate selection element. Individuals of smaller optimal value has a high probability to be selected, ϕ' is divided into two disjoint sets in selection steps, one selection set V_s and one local selection set, which remaining elements of solution set ϕ' are contained. Each element of solution set is independent relative to other elements. It's entirely up to its optimal value g_i on deciding whether allocate such element to set V_s or not. Selection operator has nondeterministic aspect, that is, there's one non-zero probability in individuals with high optimal value is allocated to selection set V_s. Just because of this uncertainty, the element individual has ability to escape from local minimum. Selection mode of probabilistic optimization is:

$$Random \le (1 - g_i + B) \tag{4}$$

Deviation (B) is selected to make up for optimization error estimate. The purpose of it is to generate swell and shrinkage action to element optimization value. Selective probability is decreased by a higher positive value B , however, negative value is opposite. Select a major selection set might bring a better solution, however, a higher running time is required. On the other hand, small selection helps accelerate algorithm and increase probability of premature convergence to sub-optimization solution (local minimum). Value range of deviation B $[-0.2, 0.2]$. In most cases, $B = 0$ is the selection mode in common use.

2.4. FFD Resource Allocation

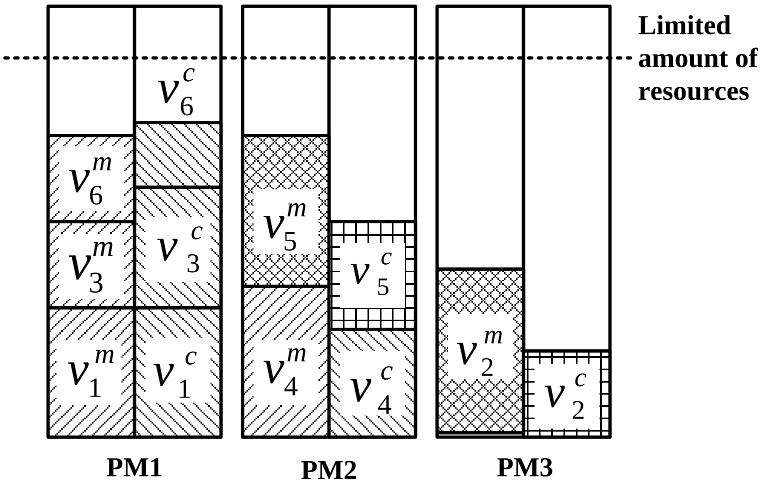
SME resource allocation has a great influence on quality of solution set, SME operation is the basis of FFD resource allocation in algorithm design. V_s is used as input for FFD allocation, total solution ϕ' is generated from partial solution ϕ_p and V_s allocation strategy variation. The objective of resource allocation is to perfect previous generation allocation, but not to adopt excessive greed mode. FFD heuristic mutation is adopted to process resource allocation in this work. Descending sort of VMS selection is made according to its bytes of resource request:

$$Rv_i = (v_i^c)^2 + (v_i^m)^2 \tag{5}$$

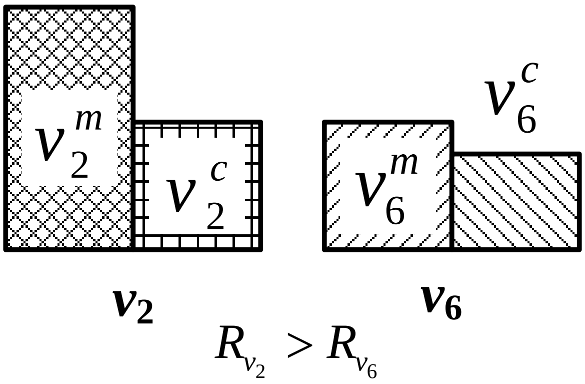
Descending order of PMS in local solution set ϕ_p is conducted according to its linear summation Op_k of occupied resources, Op_k calculation form is:

$$Op_k = (1 - Pk^c) + (1 - Pk^m) \tag{6}$$

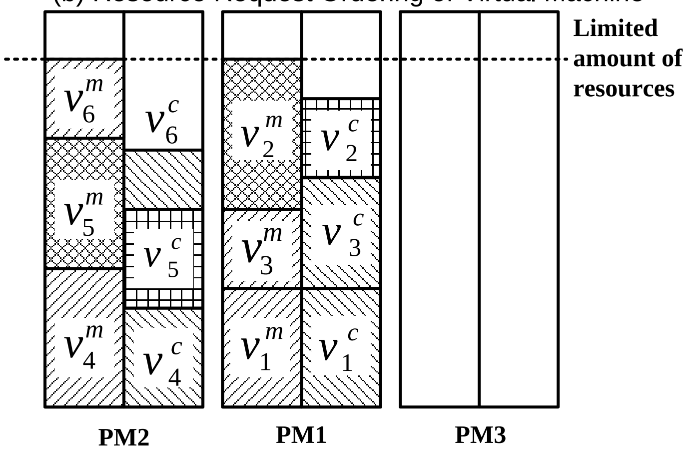
To illustrate this point, placement scheme is taken into consideration in Figure 4. Assume that v_2 and v_6 are selected to carry through resource reallocation. An ordering of VMS is conducted according to bytes of resource request and an ordering of PMs is conducted according to resource utilization rate. Detailed process as shown in Figure 3. Similar allocation strategy is also conducted to initial position ϕ_i , however, the difference is all virtual machines are regarded as conducting selection and allocation in null set PMS.



(a) Host Resource Ordering



(b) Resource Request Ordering of Virtual Machine



(c) Resource Allocation of Virtual Machine resurrect

Figure 3. 3 FFD Resource Allocation

After the process of FDD resource allocation in Figure 4, only 2 physical host resources, which there are 3 physical host resources in Figure 3, are required in Figure 4 (c) to save up host resource, at the same time, for above-mentioned resource allocation mode, to some degrees, a breakthrough can be made and flexibility of algorithm will be increased according to probabilistic selection mode.

3. Experimental Analysis

To verify validity of virtual machine resource allocation scheme of proposed SME, CloudSiim is selected to process simulation testing, this platform is a simulation platform of cloud computing which is cooperative development by grid computation laboratory of the University of Melbourne and Gridbus program, this platform supports users to conduct user-defined of virtual machine, physical host and upper application load as needed, auto set can be conducted to energy consumption with the help platform kernel. To give expression to advantages of algorithm, here two simulation comparison algorithms are selected: modified FFD algorithm (FFDimp) and modified minimum load algorithm (LLimp). Probability selection parameter $P = 0.5$ in formula (6).

3.1. Comparison of Physical Host Quantity

In the first place, contrast result of physical host quantity increasing with number of time units shall be provided. With a small quantity of physical hosts come with high efficiency of algorithm to each host, which means the number of aggregate resources required will be reduced. Above-mentioned three resource allocation algorithms of comparison are respectively adopted to put 100 virtual machine allocation into 50 physical hosts, in addition to different placement schemes employed, limited amount of resources, physical host properties and virtual host resource allocation task of these three comparison algorithms are consistent, 10min is selected as an experimental timing unit in simulation process, the change condition of physical host selection number of comparison algorithm in operational process is recorded to 10 timing units, and a mean value is calculated, experimental comparison data as shown in Figure 5.

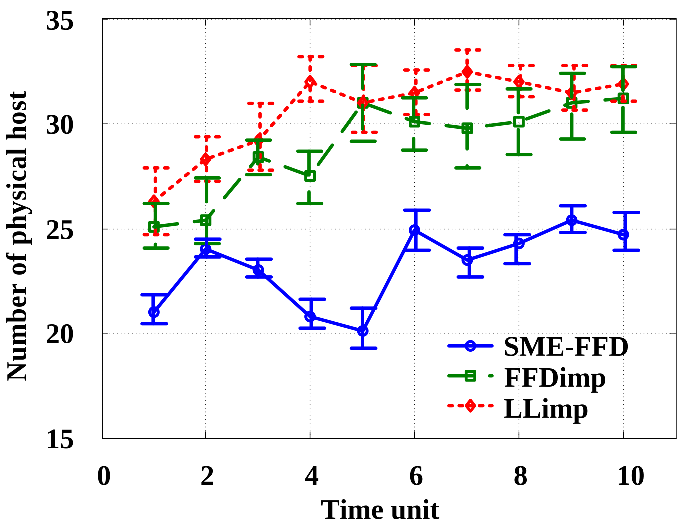
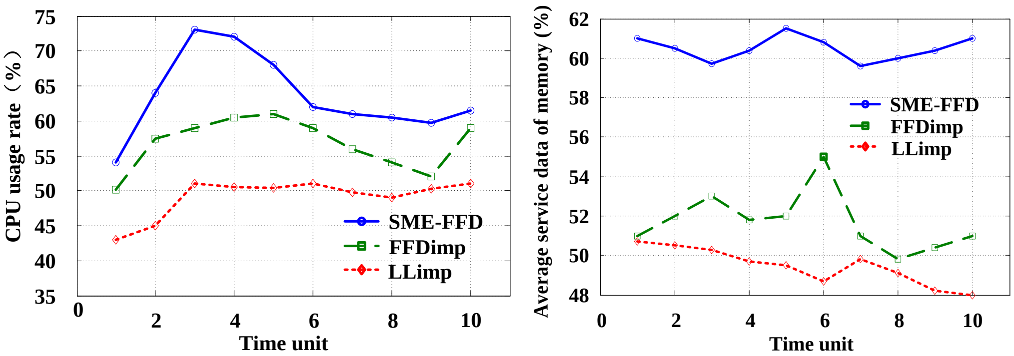


Figure 4. Comparison of Physical Host Request

Experimental data in Figure 4 shows that virtual machine resource allocation has a dynamic change trend to host quantity over time in algorithm iteration, in general, physical host request quantity of SME-FFD algorithm is lower than FFDimp and LLimp comparison algorithm. A major reason for this is that an optimal evaluation strategy is adopted by SME-FFD algorithm and evolution is made based on probabilistic selection, which help algorithm jump out of local extremum and realize global convergence, however, due to FFDimp and LLimp algorithm use minimum physical host quantity and minimum load as optimizing index, it will easily generate virtual machine pieces in practical use, which will result in algorithm being stuck in local peak, and global optimization of virtual machine task cannot be achieved. The reason why FFDimp algorithm is superior to LLimp algorithm is because FFDimp adopts a semi-random process in realization process, which help algorithm jump out of local peak, however, minor load optimization of LLimp algorithm will easily result in resource waste of physical host, and it's unable to allocate more virtual hosts. Analyzing from algorithm stability, the solution set distribution of SME-FFD algorithm is more centralized, which gives expression to stability of SME-FFD algorithm and its validity of virtual machine resource allocation.

3.2. Utilization Efficiency of Physical Resource

The actual comparison condition of physical host quantity required is given in previous section, utilization efficiency of algorithm to host resource can be given indirectly, this section will directly conduct experimental comparison on CPU utilization and memory usage of one host to verify computing resource utilization efficiency of algorithm. 10min is selected as a time unit in the comparison of average utilization index of CPU and memory obtained from above SME-FFD, FFDimp and LLimp algorithm in virtual machine resource allocation, experimental comparison data as shown in 5 (a) ~ (b).



(a) Average Service Rate of CPU (b) Average Service Data of Memory

Figure 5. Average Service Data of CPU and Memory

Figure 5 (a) shows that SME-FFD algorithm is superior to FFDimp and LLimp algorithm in terms of average service rate index of CPU, average service rate of CPU of it reaches up to above 60%, followed by FFDimp algorithm, average service rate index of CPU of LLimp algorithm being the lowest, which explains its CPU resource use efficiency is very low. For average service rate index of memory, average service rate of memory of SME-FFD algorithm is the highest, which is approximately 60%, however, usage rate index of memory of both FFDimp and LLimp algorithm are very low, which is approximately 50%, of which average usage rate index of memory of FFDimp algorithm is superior to LLimp algorithm. Above experiments give expression to advantages of SME-FFD algorithm to utilization efficiency of physical resource.

3.3. Running Time and Convergence Procedure of Algorithm

Random method is adopted to generate experimental subject, generating code as follows.

Pseudocode 2: generating code of experimental subject

For $i = 1 : n$ do

$v_i^c = rand\left(2\overline{v}^c\right)$; $v_i^m = rand\left(\overline{v}^m\right)$; $r = rand\left(1\right)$;

If $\left(r < P \wedge v_i^c \geq \overline{v}^c\right) \vee \left(r \geq P \wedge v_i^c < \overline{v}^c\right)$ then

$v_i^m = v_i^m + v^m$;

End if

End for

Virtual machine quantity is set as 200, distribution range of average service rate of CPU and memory is (0.5%), $\bar{v}^c$ is average CPU using ratio, $\bar{v}^m$ is average memory usage rate. The main function of probabilistic selection method adopted is to control correlation coefficient of utilization rate to CPU and memory so as to achieve harmonious enhancement of using ratio. When selecting probability parameter $P = 0.00$, 0.25, 0.50, 0.75, 1.0 and selecting $\bar{v}^c = \bar{v}^m = 25\%$ and $\bar{v}^c = \bar{v}^m = 45\%$, upper limit of the resource utilization of it is 98%, the comparison condition of running time of SME-FFD, FFDimp and LLimp as shown in Figure 7.

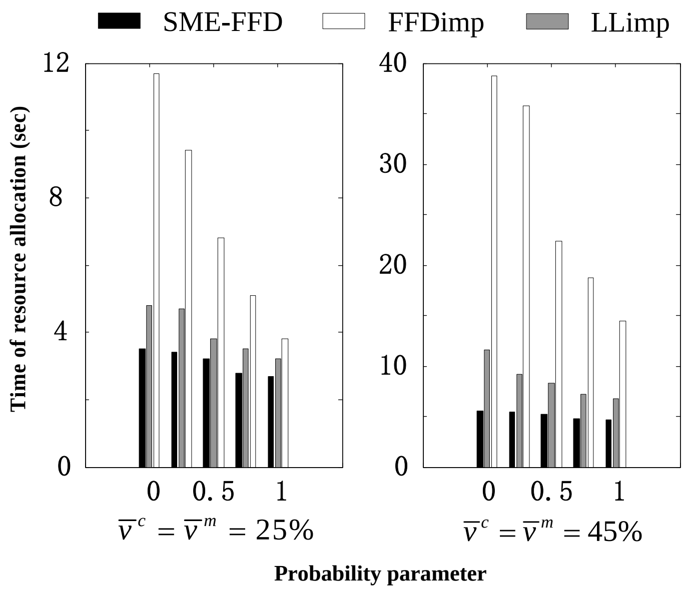


Figure 6. Comparison of Computation Time of Algorithm

Figure 6 presents the comparison result of three comparison algorithms on running time when $\bar{v}^c = \bar{v}^m = 25\%$ and $\bar{v}^c = \bar{v}^m = 45\%$, the figure reveals that the running time of three algorithms has a declining trend as the value of probability parameter is increased, the running time of SME-FFD is superior to FFDimp and LLimp algorithm. It gives expression to advantages of SME-FFD algorithm on computational efficiency.

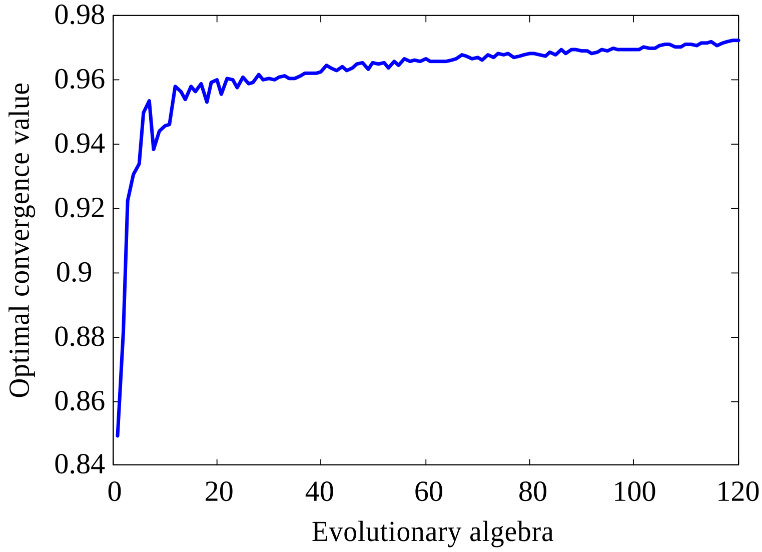


Figure 7. Optimal Convergence Value

Figure 7 represents convergence curves of optimal evaluation value of algorithm, the figure reveals that optimal index of algorithm is increasing and has a trend of convergence along with the iteration process, due to each host resource cannot be entirely occupied in the process of upper limit of physical resource and resource allocation, ultimately, the optimal convergence value is close to 1 but stands no chance equaling to 1.

4. Conclusion

Virtual machine resource allocation algorithm of probabilistic optimization based on SME-FFD algorithm in cloud computing is proposed virtual machine resource allocation problem in cloud computing. Further optimization of resource allocation is achieved according to optimal evaluation, probability selection evolution and FFD resource allocation *etc.* The experimental results show that proposed SME-FFD algorithm has better resource allocation and higher resource utilization rate, along with faster resource allocation speed, which give expression to performance advantage of algorithm and realize the goal of energy-saving and cost-reducing. The correlation of virtual machine performance will be introduced in algorithm research in future studies to enhance rationality of resource allocation.

References

[1] X. Song and Y. Geng, "Distributed Community Detection Optimization Algorithm for Complex Networks", Journal of Networks, vol. 9, no. 10, **(2014)**, pp. 2758-2765.
[2] K. Pahlavan, P. Krishnamurthy and Y. Geng, "Localization Challenges for the Emergence of the Smart World", Access, IEEE, vol. 3, no. 1, **(2015)**, pp. 1-11.
[3] J. He, Y. Geng, Y. Wan, S. Li and K. Pahlavan, "A cyber physical test-bed for virtualization of RF access environment for body sensor network", Sensors Journal, IEEE, vol. 13, no. 10, **(2013)**, pp. 3826-3836.
[4] Z. Lv, A. Tek and F. D. Silva, "Game on, science-how video game technology may help biologists tackle visualization challenges", PloS one, vol. 8, no. 3, **(2013)**, pp. 57990.
[5] T. Su, W. Wang and Z. Lv, "Rapid Delaunay triangulation for randomly distributed point cloud data using adaptive Hilbert curve", Computers & Graphics, vol. 54, **(2016)**, pp. 65-74.
[6] J. Hu, Z. Gao and W. Pan, "Multiangle Social Network Recommendation Algorithms and Similarity Network Evaluation", Journal of Applied Mathematics, vol. 2013, **(2013)**.
[7] S. Zhou, L. Mi, H. Chen and Y. Geng, "Building detection in Digital surface model", 2013 IEEE International Conference on Imaging Systems and Techniques (IST), **(2012)**.

[8] J. He, Y. Geng and K. Pahlavan, "Toward Accurate Human Tracking: Modeling Time-of-Arrival for Wireless Wearable Sensors in Multipath Environment", IEEE Sensor Journal, vol. 14, no. 11, **(2014)**, pp. 3996-4006.
[9] Z. Lv, A. Halawani and S. Fen, "Touch-less Interactive Augmented Reality Game on Vision Based Wearable Device", Personal and Ubiquitous Computing, vol. 19, no. 3, **(2015)**, pp. 551-567.
[10] G. Bao, L. Mi, Y. Geng, M. Zhou and K. Pahlavan, "A video-based speed estimation technique for localizing the wireless capsule endoscope inside gastrointestinal tract", 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), **(2014)**.
[11] D. Zeng and Y. Geng, "Content distribution mechanism in mobile P2P network", Journal of Networks, vol. 9, no. 5, **(2014)**, pp. 1229-1236.
[12] W. Gu, Z. Lv and M. Hao, "Change detection method for remote sensing images based on an improved Markov random field", Multimedia Tools and Applications, **(2015)**, pp. 1-16.
[13] Z. Chen, W. Huang and Z. Lv, "Towards a face recognition method based on uncorrelated discriminant sparse preserving projection", Multimedia Tools and Applications, **(2015)**, pp. 1-15.
[14] J. Hu and Z. Gao, "Distinction immune genes of hepatitis-induced heptatocellular carcinoma", Bioinformatics, vol. 28, no. 24, **(2012)**, pp. 3191-3194.
[15] T. Su, W. Wang and Z. Lv, "Rapid Delaunay triangulation for randomly distributed point cloud data using adaptive Hilbert curve", Computers & Graphics, vol. 54, **(2016)**, pp. 65-74.
[16] W. Gu, Z. Lv and M. Hao, "Change detection method for remote sensing images based on an improved Markov random field", Multimedia Tools and Applications, **(2015)**, pp. 1-16.

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