A trust-based resource selection algorithm in Cloud Computing

Tong Qin[1], Xinran Liu[2*]

[1]*Information Security Center, Beijing University of Posts and Telecommunications, 100876 Beijing, China*

[2]*National Computer Network Emergency Response Technical Team/Coordination Center of China (CNCERT/CC), 100029 Beijing, China*

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Abstract

From the point of the safety in Cloud Computing and the virtual resource under the Cloud, here proposed a cognitive trust model of Cloud virtual resource, based on Bayesian, and the model supports the effective resource selection as a basis. Furthermore, on the basis of the description of process and question in virtual resource selection, here comes a Trust and Resource Scheduling oriented Cloud resource selection model which takes QoS, trust, resource scheduling and other indexes into account. After applying the improved CHC-TSSM Genetic Algorithm in the model, the simulation experiment confirms the feasibility and efficiency of the algorithm, which can resolve the trust and scheduling problem in resource selection effectively.

Keywords: resource selection, trust, Cloud Computing

1 Introduction

Cloud computing, Internet of things and big data considered as driven forces of the information innovation have become crucial to economic development and social stability [1]. With the emerging market opportunities, many businesses begin to take the advantage of Cloud computing for business upgrade. For example, Amazon develops its own data management centre and virtualizes its resources, providing customers with services as storage, computing, transmission and Internet data. Public Cloud, community Cloud, private Cloud and hybrid Cloud have taken shape [2] to provide services in the form of infrastructure service, platform service and software service. Cloud virtual resource is featured by large quantity and commerciality. It becomes an important issue to select resources that meet the users' demand from vast resources with similar functions [3]. Cloud computing is dynamic, distributed, changeable and in a large scale [4]. Effective resource selection process and method are of great value to meet the users' demand, enhance the selection satisfaction and optimize resources. Service computing has yielded fruitful results and is inspiring Cloud resource selection, which wins attraction from domestic and foreign researchers [5].

2 Related researches

Virtual resource selection under the Cloud mainly rests upon a resource discovery and selection model based on function matching. A new similarity algorithm is proposed based on resource description and relation reasoning. With the algorithm, the matching speed of function and demand and the query rate can be calculated [6]. Cloud resource selection algorithm constructed on semantic reasoning largely improves the efficiency and efficacy of searching [7]. However, the quality of the Cloud resource is hard to measure and control. Users' increasing attention to QoS (Quality of Service) and individual preference also present challenges to it. Virtual resource evaluation and selection under the Cloud is constructed and fuzzy set theory is introduced to address the dynamic QoS [8, 9].

Menascé et al. [10] and OHSC [11] use heuristic algorithm to address the automatic selection of Cloud resources. D.A. Menascé proposes a restriction of user's QoS and uses genetic algorithm to address this problem [12]. Dillon takes into consideration of the sematic information of resources and QoS level and uses genetic algorithm to address the problem of the optimized resources portfolio [13]. Feng Dengguo and some others introduces trust evaluation into the Cloud computing and enhances the probability of success [14]. Hu Chunhua uses trust spanning tree to construct a trusted set of Cloud resources and trusted evolving mechanism, which addresses the problem of malicious resource node [15]. Xie Xiaolan uses Game Theory to construct a reward matrix for resource nodes. She also proposes a node trust evaluation model and incentive mechanism [16]. Du Ruizhong proposes a trust and user preference oriented Cloud resource selection model and analyses the influence of trust [17].

Based on previous researches, this paper proposes a trust model of Cloud resource based on Bayesian theory. This model combines direct trust and recommendation trust while taking into consideration time-effectiveness and relationship of trust. On the basis of resource node trust computing, virtual resource scheduling is given a place. This paper constructs a virtual Trust and Resource Scheduling oriented Resource Selection Model. After

* ***Corresponding author*** e-mail: lxr@cert.org.cn

applying the improved CHC-TSSM Genetic Algorithm in the model, the simulation experiment confirms the feasibility and efficiency of the algorithm, which can solve the trust and scheduling problem in resource selection effectively. Finally, this paper concludes and discusses space for further researches.

3 Trust model of cloud resource based on Bayesian theory

Resource trust refers to the ability of the target resource node to provide reliable services. It is evaluated by historical transaction record and through recommendation from other nodes [18]. Suppose any two Cloud resource nodes x and y have direct and indirect interactions with other nodes, so the probability of successful cooperation is θ. And the successful rate of direct trust degree is expressed by θ_{dt}. For indirect node *z*, if there is a direct interaction between *x* and *z* and *y* and *z*, then the successful rate of indirect interaction between x and y is expressed by recommendation trust degree θ_{rt}.

$$f\left(\lambda_0\cdot\theta_{dt}+\left(1-\lambda_0\right)\cdot\theta_{rt}\right),\lambda_0\in\left(0,1\right). \tag{1}$$

Under non-empty set, for all $\theta_{dt},\theta_{rt}\in S,\lambda\in\left(0,1\right)$

$$f\left(\lambda\cdot\theta_{dt}+\left(1-\lambda\right)\cdot\theta_{rt}\right)\le\lambda f\left(\theta_{dt}\right)+\left(1-\lambda\right)f\left(\theta_{rt}\right).$$

So $f\left(\cdot\right)$ is the function for aggregated trust degree with the feature of a convex function.

Therefore the aggregated trust function is $\hat{\theta}=\lambda\cdot\theta_{dt}+\left(1-\lambda\right)\cdot\theta_{rt},\lambda\in\left(0,1\right)$. If the node is prone to trust direct experience, then there is $\lambda>0.5$.

3.1 ANALYSIS ON TRUST RELATIONSHIP

The relationship of two nodes falls into four categories according to direct trust and (or) recommendation interaction between nodes. When *dt*=1 or 0, node *x* and *y* have (or don't have) direct interaction. When *rt*=1 or 0, node *x* and *y* have indirect recommendation relationship. Four types of relationship can be expressed by *TR*(*dt*,*rt*).

3.2 TIMELINESS ATTENUATING ATTRIBUTE OF TRUST

Trust of resource node dies out with time. Recent transaction does influence the trust. Time is measured by day, reflecting the change of trust degree. Out of convenience for calculation, suppose the interaction order of node is *i*, the successful interaction times and the failed interaction times are u_i and v_i respectively. The information formula that has considered time attenuating attribute is expressed as:

$$u\left(n\right)=\sum_{i=1}^{n}u_i\cdot\eta^{\left(n-i\right)},v\left(n\right)=\sum_{i=1}^{n}v_i\cdot\eta^{\left(n-i\right)}, \tag{2}$$

$0\le\eta\le1$, $u\left(n\right)$ and $v\left(n\right)$ refer to successful times and failed times after *n* interactions. When $\eta=1$, all interaction records are aggregated. When $\eta=0$, only the latest service record is used for trust calculation. Recursive method is introduced to address the redundancy of historical records.

$$u\left(i\right)=u\left(i-1\right)\cdot\eta+u_i\ ,v\left(i\right)=v\left(i-1\right)\cdot\eta+v_i\ . \tag{3}$$

3.3 DIRECT TRUST

Suppose *x* and *y* are two service nodes in the Cloud virtual resource system. Their interaction can be explained by binomial expression to describe success or failure. When two resource nodes conduct *(n+1)* transaction and if *u* times are successful, *v* times are failure, and then at (*n+1*) times, the probability of successful cooperation is $\hat{\theta}_{dt}$. The posterior probability of successful cooperation between resource nodes *x* and *y* is in accordance with Bayesian distribution. The density function is:

$$Beta\left(\theta\middle|u,v\right)=\frac{\Gamma(u+v+2)}{\Gamma(u+1)\Gamma(v+1)}. \tag{4}$$

The direct trust degree of resource node is expressed as:

$$\hat{\theta}_{dt}=E\left(Beta\left(\theta\middle|u+1,v+1\right)\right)=\frac{u+1}{u+v+2}. \tag{5}$$

At this time $0<\theta<1\ and\ u,v>0$.

Without effective evidence it is necessary to evaluate the direct trust degree by intervals. $\left(\hat{\theta}_{dt}-\varepsilon,\hat{\theta}_{dt}+\varepsilon\right)$ refers to the confidence interval of node $\hat{\theta}_{dt}$ and it is expressed as:

$$\gamma=P\left(\hat{\theta}_{dt}-\varepsilon<\theta_{dt}<\hat{\theta}_{dt}+\varepsilon\right)=\frac{\int_{\hat{\theta}_{dt}-\varepsilon}^{\hat{\theta}_{dt}+\varepsilon}\theta^{u-1}(1-\theta)^{v-1}d\theta}{\int_0^1\theta^{u-1}(1-\theta)^{v-1}d\theta} \\ =\frac{\Gamma(u)\Gamma(v)}{\Gamma(u+v)}\int_{\hat{\theta}_{dt}-\varepsilon}^{\hat{\theta}_{dt}+\varepsilon}\theta^{u-1}(1-\theta)^{v-1}d\theta. \tag{6}$$

A balance needs to be addressed between confidence and the accuracy of the interval. When the interaction reaches a certain times, the two cannot be enhanced at the same time. Suppose the cap of the confidence is γ_0, when the accuracy reaches an acceptable level-that is when $\gamma\ge\gamma_0$, resource trust can be evaluated under such condition. Suppose the there has been n_0 interactions, the relationship between γ_0 and ε is expressed as:

$$n_0 \geq -\frac{1}{2\varepsilon^2}\ln\left(\frac{1-\gamma_0}{2}\right). \tag{7}$$

3.4 RECOMMENDATION TRUST

Recommendation trust consists of several direct interactions among nodes. Recommendation nodes are selected through the calculation of trust degree of other nodes. Suppose resource node *x* and *y*, and *y* and *z* have direct transaction but are independent from each other. Each pair has n_1 and n_2 times of interaction, u_1 and u_2 times of successful cooperation and v_1 and v_2 times of failure service. Through the recommendation of node *z*, the recommendation trust of *x* to *y* is:

$$\hat{\theta}_{rt} = E\left(Beta\left(\theta \middle| u_1+u_2+1, v_1+v_2+1\right)\right) = \frac{u_1+u_2+1}{n_1+n_2+2}. \tag{8}$$

When there are several recommendation nodes, the comprehensive recommendation trust according to the above expression and the confidence level is expressed as:

$$\hat{\theta}_{rt} = \frac{\sum_{\gamma\geq\gamma_0} u+1}{\sum_{\gamma\geq\gamma_0}(u+v)+2}. \tag{9}$$

Recommendation of trust of node *y* to node *x* equals to the ratio of actual interaction times to demand times:

$$w_{xy} = \begin{cases} \dfrac{n_{xy}}{n_0}, & if\ n_{xy} < n_0 \\ 1, & otherwise \end{cases}. \tag{10}$$

Given that the overall trust is influenced by active and passive feedback, and the value mapping of $\hat{\theta}_{rt} \in [-1,1]$, the expression is further adjusted to:

$$\hat{\theta}_{rt} = \frac{\sum w\cdot(u-v)}{\sum w\cdot(u+v)+2}. \tag{11}$$

4 Resource selection algorithm based on trust

A trust-based resource selection method oriented Cloud virtual resource is proposed while considering important factors of resource selection and function matching. It is expected to maximize the Cloud computing performance, realize resource selection as well as the effective implementation of the portfolio.

4.1 DESCRIPTION OF QUESTION

To give a better description of our questions, we introduce some specific definitions and symbols in new resource selection method.

Definition 1. R (resource) refers to units that can implement tasks in the resource pool in cloud computing. It is expressed as:

R= (RID, Group ID, SA, DA, TR, Location).

Namely, resource identifier (RID), Group identifier (Group ID), Static Attribute (SA), Dynamic Attribute (DA), Trust Degree (TD) and Location.

Definition 2. Resource Cluster (RC) refers to a set of Cloud resource nodes that have same or similar functions. It is described as RC= (Group ID, FunSet). All Cloud resource clusters are aggregated to the Resource Cluster Set (RCS) and RCS={ RC_1, RC_2,…,RC_i,…, RC_n}.

Definition 3. RFlow (resource flow) is the process in which resource portfolio is motivated to work out. It is expressed as RFlow= (FlowID, FlowFunSet). All these processes form the Resource Flow Set (RFlowS).

Definition 4. RPool (resource pool) refers to a set of resource type and service mode provided by resource cluster or resource flow. It is expressed as:

RPool = (PoolID, PoolName, RCS, RFlowS, PoolOwner)

Service Set or Service Flow carry out semantic search in the resource pool and match the candidate resource nodes that meet the demand of service node to form a candidate service set. Then conduct resource selection on the basis of QoS and trust level and calculate the efficiency and optimal target according to resource scheduling to match every service node with the optimal resource. Finally, the optimal resource portfolio is dawn at sight according to multi-objective optimized model.

4.2 MODEL FACTORS

Factors of resource selection showed in table 1 involves with service quality, trust degree and resource scheduling (location, waiting length, utilization efficiency). After a deep analysis with relevant index calculations, this paper paves the way for constructing a multi-objective programming model based on trust and service scheduling.

(1) Trust degree

Trust degree is crucial to virtual resource selection. It lifts users' satisfaction on resource matching and reduces failures during the implementation of resource services. Direct trust $\hat{\theta}_{dt}$ and indirect trust $\hat{\theta}_{rt}$ both have a place. This paper analyses the time-effectiveness of information interaction. Users have preference for current trust level. The overall trust is aggregated as: $\hat{\theta} = \lambda\cdot\theta_{dt} + (1-\lambda)\cdot\theta_{rt}, \lambda\in(0,1)$.

(2) QoS indexes

Users under the Cloud computing is paying more and more attention to service quality. QoS indexes vary from each other with different types and levels of service. If

$Q=\left(Q^1,Q^2,\cdots,Q^K\right)$ is used to show the preference order of users to indexes, then Q^1 wins the most preference and Q^2 follows it. QoS indexes are available from the resource description and at the registration center.

(3) Indexes of service resource scheduling.

Virtual resource scheduling means to schedule the resources in the pool in an optimized way that plays the performance of the system to the most and yields the most profit. Utilization efficiency R1, load balance R2 and location R3 are given a place. Supervise the parameters of the service state (SSta) where resource $S_{i,j}$ locates. When the server is open, $X_{i,j}$=1, otherwise $X_{i,j}$=0. R1 is calculated as:

$$R1=\sum_{i=1}^{I}\sum_{j=1}^{J_i}\left(X_{i,j}Y_{i,j}SSta_{ij}\right), \tag{12}$$

$$X_{i,j}\in\{0,1\}, i=1,2,...,\mathrm{I}, j=,2,...,J_i\,.$$

TABLE 1 Relevant symbols and description

Symbol	Description
i	the number of resource node
j	Service ID in ResourceSet
$S_{i,j}$	resource node j of resource combinations i
$Y_{i,j}$	$Y_{i,j}=\{0,1\}$, when resource j is selected by service i, $Y_{i,j}=1$, otherwise $Y_{i,j}=0$
$t_{i,j}$	execution time of resource $S_{i,j}$ instantiation
$wt_{i,j}$	For current users, real waiting time of the selected resource $S_{i,j}$ is decided by waiting time and execution time
Q^K	QoS of selected resource combinations

ServerUtlizRation (*SUR*) refers to the utilization efficient in virtual server. Resources in the server that has the least utilization efficiency are chosen. The load balance R2 is calculated as:

$$R2=\sum_{i=1}^{I}\sum_{j=1}^{J_i}\left(X_{i,j}Y_{i,j}\left(1-SSta_{ij}\right)\times SUR_{ij}\right). \tag{13}$$

In the process of resource selection, those resources in the server that is the closest to users are given priority. *location*$_{i,j}$ refers to the location of resources. *Uerlocation* refers to the location of users. *R3* is calculated as:

$$R3=\begin{cases} Distf\left(\sum_{j=1}^{J_i}Y_{i,j}location_{i,j},Uerlocation\right), I=1 \\ \frac{1}{I}\sum_1^I Distf\left(\sum_{j=1}^{J_i}Y_{i,j}location_{i,j},Uerlocation\right) \\ \quad+\sum_1^{I-1}Z_{i,j}Distf\left(\sum_{j=1}^{J_i}Y_{i,j}location_{i,j},\sum_{j=1}^{J_i}Y_{i,j}location_{i+1,j}\right), I>1 \end{cases} \tag{14}$$

(4) Calculating rules.

Based on previous researches of service flow, resources flow falls into four categories, namely, series type, parallel type, conditional type and circular type. Each has a different way of calculating QoS and the overall trust. Luckily, there have been successful researches on index calculation. This paper draws merits from these researches to aggregate the indexes. Indexes need to be normalized as they have different types of properties. Normalization serves to the calculation of the multi-objective programming model.

4.3 MULTI-OBJECTIVE PROGRAMMING MODEL OF RESOURCE SELECTION

This paper chooses flow cost, responding time, trust degree and resource scheduling as four objectives of the model together with the ideal plan of users.

(1) The priority of objectives is as follows. First is the flow cost, second is the responding time, third is the trust degree and fourth is the resource scheduling.

(2) The model is mainly restricted by QoS and trust degree.

Based on above objectives and restrictions, TSSM based on trust and resource scheduling is constructed and shown below:

$$lex,\min\left\{d_c^+V0,d_t^+V0,d_{tr}^-V0,d_c^+V0\right\}, \tag{15}$$

$$\begin{aligned}ObjFunc&=\alpha_1\left(d_c^+V0\right)+\alpha_2\left(d_t^+V0\right)+\alpha_3\left(d_{tr}^-V0\right)\\&+\alpha_4\left(P1\times R1V0+P1\times R1V0+P2\times R2V0+P3\times R3V0\right)\end{aligned}, \tag{16}$$

$$s.t.d_c^+=C-C_0, d_t^+=T-T_0, d_{tr}^-=TR-TR_0, \tag{17}$$

$$\sum_{j=1}^{J_i}c_{i,j}Y_{i,j}\le C_i, i=1,2,3....,I, \sum_{j=1}^{J_i}t_{i,j}Y_{i,j}\le T_i, i=1,2,3....,I, \tag{18}$$

$$\sum_{j=1}^{J_i}tr_{i,j}Y_{i,j}\ge TR_i, i=1,2,3....,I, \sum_{j=1}^{J_i}sh_{i,j}Y_{i,j}\le SH_i, i=1,2,3....,I \tag{19}$$

$$\sum_{j=1}^{J_i}Y_{i,j}=1, i=1,2,3....,I\,. \tag{20}$$

Weight of objectives is determined by their priorities. Equation (17) refers to the objective restriction. Equations (18) - (19) are QoS restriction, trust restriction and resource scheduling restriction. Equation (20) is decision variable restriction, which indicates that every node in the process binds with a certain service resource.

4.4 VIRTUAL RESOURCE SELECTION ALGORITHM BASED ON CHC-TSSM

Resource combination is a typical NP problem. The increase of candidate resources means more accessible solutions, which makes the problem even more complicated. The improved CHC-TSSM algorithm makes it possible to obtain the optimal trust service portfolio.

(1) Gene code.

If the resource portfolio is paralleled to chromes, then the integer code with fixed length is expressed as:

$$Y_i = \left[-1, y_1, y_2, \cdots, y_1, -1\right] y_i \,, \tag{21}$$

y_i accords with number j service ws_{ij} in the candidate service set of the resource portfolio. If the resource doesn't show in the portfolio, the value shall be given 0.

(2) Group initialization.

The initialized group is parallel to the initial virtual resource service set. From the beginning to the end of the resource portfolio, the chromes are of the same length. If it is a small-scale group, the limited searching space of the algorithm may result in convergence and knowledge optimal settings.

(3) Adaptive function

Utilization efficiency R1 is expressed as bellow.

$$R1 = \sum_{i=1}^{I} \sum_{j=1}^{J_i} \left(X_{i,j} Y_{i,j} SSta_{ij} \right) \tag{22}$$

and $X_{i,j} \in \{0,1\}, i = 1, 2, ..., \mathrm{I}, j =, 2, ..., J_i$.

According to the objective of virtual resource selection, load balancing R2 is calculated by equation (23).

$$R2 = \sum_{i=1}^{I} \sum_{j=1}^{J_i} \left(X_{i,j} Y_{i,j} \left(1 - SSta_{ij}\right) \times SUR_{ij} \right). \tag{23}$$

The adaptive function limited by distance (R3) is expressed as follow:

$$R3 = \begin{cases} Distf\left(\sum_{j=1}^{J_i} Y_{i,j} location_{i,j}, Uerlocation \right), I = 1 \\ \frac{1}{I} \sum_1^I \begin{matrix} Distf\left(\sum_{j=1}^{J_i} Y_{i,j} location_{i,j}, Uerlocation \right) \\ + \sum_1^{I-1} Z_{i,j} Distf\left(\sum_{j=1}^{J_i} Y_{i,j} location_{i,j}, \sum_{j=1}^{J_i} Y_{i,j} location_{i+1,j} \right) \end{matrix}, I > 1 \end{cases}. \tag{24}$$

(4) Genetic operation

Genetic operation involves in selection, crossover, mutation and others. The cross-generational elitist selection strategy is introduced for selection. Calculation of adaption degree is done on the basis of combining the group of previous generation and individual group produced through cross connection. Finally N1 individuals with relatively large adaptation degree will stand out as the group of next generation. The crossover is improved in this paper in the way that if the binary digit number of two different parent generations is M, then individuals at M/2 will be selected. Individuals are picked up randomly. Conduct the multi point cross operation according to cross probability P_c and form N2 new individuals. When the group evolves to T/2 generation, N3 individuals will be selected according to the adaption degree $F(Y_i)$. Select chromes according to the mutation probability and empower them with value randomly.

(5) Selection of controlling parameters.

Controlling parameters play an important role to the performance and convergence of the improved CHC genetic algorithm. They include group scale, crossover probability P_c, mutation probability P_m and the maximum evolutionary generations T. Generally speaking, the group scale is from 10 to 200, and generations T from 100 to 1000. P_c is proper from 0.4 to 0.99. If it is too big, the convergence will not be satisfying. The mutation probability $\mathrm{P_m}$ is better to take smaller value from 0.1 to 0.6.

(6) Group evolution.

After selection, crossover and mutation, there are (N1+N2+N3) new individuals or chromes. Then calculate the adaptive value $F(Y_i)$ of each individual by adaptive function, and select the best N1 as group of the next generation. As a result, some service portfolio with low trust and inefficient use of resources will be left out.

(7) The optimal plan

After repeating the process, the group will evolve to generation T, or the adaptive degree of the optimal plan will become less than the minimum value. The improved CHC genetic algorithm is adapted to objectives and restrictions. Finally, the best individuals and chromes will obtain the best virtual service plan after decoding.

5 Experimental evaluations

This paper proposes a trust-based resource selection model. It takes into consideration the optimal resource portfolio by QoS, trust degree of virtual resource and resource scheduling. The simulation experiment is conduced to ensure of the accuracy and the efficiency.

5.1 EXPERIMENTAL ENVIRONMENT AND PARAMETERS SETTING

Experience environment is designed as CPU Intel Core 4.0GHz, memory DDRII4G, operating system Windows7.0 Pro, Java programming language, software environment jdk.5.0-08.

Existing data about virtual resource and Cloud computing is far from enough and is limited by law. Therefore, this paper proposes to produce experiment data randomly according to relevant researches and expertise. Parameters: the maximum generation G=1000, group scale 20-100, penetration coefficient is set 3, the crossover probability P_c=0.6, the mutation probability P_m=0.5, decrement is 0.5. The following two experiments have same parameters.

5.2 RESULT ANALYSIS

All experiments based on above environment and parameters have gone through 50 times of weight average. The trust model and the CHC-TSSM algorithm have been evaluated in terms of effectiveness.

(1) The effectiveness of the trust model

Here designed four types of resource trust relationships together with calculation method to prove the effectiveness of the cognitive trust model. Suppose the direct trust and the indirect trust are both 0.5 and the best sample capacity is 200. Scheduling resources at 6 time (by day), each time (day) represents the trust degree and the evolutionary process of the resource node. Compare the trust weight with trust degree and time-effectiveness. The trust evaluation result is shown in Figure 1:

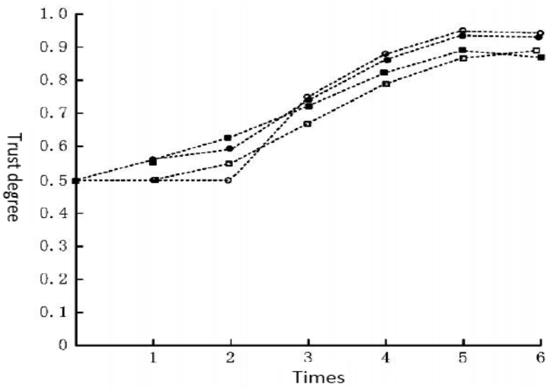
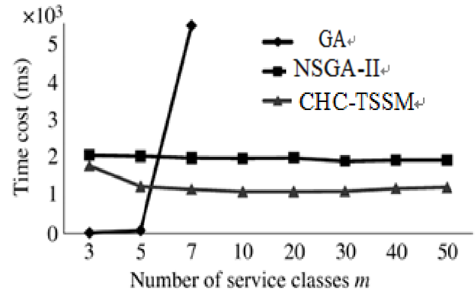


FIGURE 1 Evaluation of trust degree

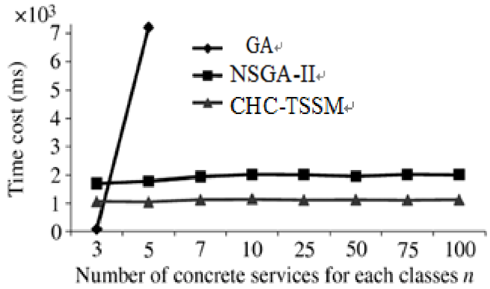
At the beginning, the trust degree of node x to y is 0.5. Only consider direct trust to address, λ_1=1, λ_2=0. At time 2, the interaction fails to reach the optimal 200 times, but the trust degree is still 0.5. At time 5 and 6, the trust degree becomes stable. And the confidence interval is [0.90, 0.95]. Only consider *z* recommendation trust, λ_2=1, λ_1=0. At time 4, the interaction of *z* to *y* reaches the optimal with the capability of recommendation trust. At time 5 and 6, trust degree becomes stable with the recommendation trust of 0.90 and the confidence interval of [0.8255, 0.9325]. The latter two circumstances are based on the previous two with similar calculation. According to Figure 1, the direct trust and the recommendation trust decrease with the time, which proves the hypothesis of time-effectiveness of trust.

(2) Convergence of CHC-TSSM algorithm

Factors that influence the scale of solutions to the resource portfolio include the number of service class m, the number of concrete service for each cluster and trust degree. Three parameters and the time of CHC-TSSM algorithm are applied to the test. CHC-TSSM algorithm is made comparison with NSGA-II and GA algorithm. The resource cluster m ranges from 5~60 and the candidate resource service of each cluster ranges from 4~100. The test results are shown in Figure 2 (a) and 4 (b).



2a)



2b)

FIGURE 2 The relationship between the algorithm time and the number of resource classes well as the number of candidate resource node

6 Conclusions

The trust-based resource selection model considers indexes such as the trust degree of the resource node, QoS and resource scheduling. It offers different index calculation under various service flows constructs a multi-objective programming model and works out relevant restrictions. This paper also proposes an improved CHC-TSCM algorithm with detailed descriptions to address the NP-hard problem. The simulation experiment confirms the feasibility and efficiency of the algorithm featured by an increase of successful rate of resource selection. But there is still space to improve the trust evaluation model or propose new models that may address the increase of QoS indexes or users' preferences.

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Authors

Tong Qin, born in February, 1984, Dandong, Liaoning, China

Current position, grades: Ph.D. candidate in Information security center at Beijing University of Posts and Telecommunications.
University studies: M.Sc. degree in software engineering from Beijing University of Posts and Telecommunications (BUPT) in 2007.
Scientific interest: network security and distributed computing.

Xinran Liu, born in February, 1971, Jixi, Heilongjiang, China

Current position, grades: researcher in National computer network emergency response technical team/coordination centre of China (CNCERT/CC), a doctoral supervisor in Information security centre at Beijing University of Posts and Telecommunications.
University studies: Ph.D. in computer architecture from Harbin Institute of Technology in 1998.
Scientific interest: distributed computing and information security.