International Journal of the Physical Sciences Vol. 7(17), pp. 2554 - 2564, 23 April, 2012
Available online at http://www.academicjournals.org/IJPS
DOI: 10.5897/IJPS12.143
ISSN 1992 - 1950 ©2012 Academic Journals

Full Length Research Paper

Mixed intelligent optimization algorithm (MIOA): An algorithm for quality of service (QoS) based web service selection

Yanping Chen[1,2]*, Qinghua Zheng[1] and Jianke Zhang[3]

[1]Department of Computer Science and Technology, Xi'an Jiaotong University, 710049, Xi'an China.
[2]School of Computer Science, Xi'an University of Posts and Telecommunications, 710121, Xi'an China.
[3]School of Science, Xidian University, 710068, Xi'an China. 710071, Xi'an, China.

Accepted 10 April, 2012

With the rapid growth of abundant Web services on the World Wide Web, designing effective approaches for Web service selection, which satisfy service consumers' customized quality of service (QoS) requirement, has become a fundamental problem for the application of composed Web service. To address this problem, we propose, in this paper, a new algorithm, called Mixed Intelligent Optimization Algorithm (MIOA). MIOA optimizes service selection with multiple QoS constraints by taking advantage of both Maximum Entropy Method and Social Cognitive Optimization theory. Furthermore, Chaos method is also integrated into MIOA to improve the existing social cognitive optimization algorithm. Extensive analysis and simulations have been conducted. Our experimental results show that MIOA effectively selects high-quality service, and its convergence is also improved.

Key words: Web service, quality of service, service selection.

INTRODUCTION

Establishment on service oriented architecture (SOA), Web service composition has becomes one of the key technologies of business-level service composition. How to create robust composed service is the next step in Web services (Curbera et al., 2003), and attracts extensive research (Xiong et al., 2009; Liang and Huang, 2009).

In the past years, researches about Web service composition have gained considerable momentums. Service providers from different business organizations develop their individual Web services and publish them in a public service registry (e.g., UDDI). Then, by looking up this service registries, service consumers can find suitable services and compose them into one composition service to achieve their specific business goals. As the proliferation of available Web services, there are more and more services, which possess same functionality but different non-functional properties (that is, response time, price, etc.). In this paradigm, non-functional properties can be used for discriminating between functionally-equivalent Web service.

In this paper, we propose a new algorithm, called Mixed Intelligent Optimization Algorithm (MIOA). MIOA deals on Web service selection with multiple qualities of service (QoS) constraints by taking advantages of both Maximum Entropy Method and Social Cognitive Optimization theory. The remainder of this paper is organized as follows. Subsequently, the composition service selection model was discussed, on which, a new MIOA was designed, and thereafter, we concentrated on the technical aspects of MIOA with our problem scenario, before evaluating the experiments. Finally, this study was concluded.

COMPOSITION SERVICE SELECTION MODEL

Basic concept

Definition 1: Service class

Let $S = \{S_1, S_2, S_3, ..., S_p\}$, and S_p, be the *p*th ($p \in Z$)

*Corresponding author. E-mail: cyp.xjtu@gmail.com.

atomic service which developed by business organizations composer (the role that can carry on composition and provides composed services to consumers) divides *S* into *m* sets, named as Service Class (*SC*), atomic services in same as *SC* possess same functions but differ in QoS properties.

For example, let CS be a Composition Service, composer divides current services into *l* Service Classes $\{S_1, S_2, S_3, ..., S_l\}$, the number of candidate services in S_i is N_i, as for a candidate atomic service, it has its own QoS criteria, defined as a vector metrics $q = [q_1, q_2, ..., q_m]$. QoS of atomic services are provided by atomic service providers, let Q = $[Q_1, Q_2, ..., Q_m]$, Q represents QoS of CS which can be aggregated by atomic services QoS. In reality, Q can be defined as a vector similar to response time, cost, …, security level. Although, each service provider may design their own QoS properties to satisfy the customer's requirements individually, unified service QoS should be provided for further composition. Detailed QoS criteria will be discussed later

Composition service selection model

We propose a service selection model based on multi-QoS optimization problem, which can be defined as finding result $\mathrm{X} = [x_{11}, x_{12}, x_{1N_1} ..., x_{L1}, x_{L2}, ..., x_{LN_L}]^T$,

$$\begin{cases} \text{MAX} \quad f_i(X) \\ \text{St.} \quad x_{ij} = 0 \text{ or } 1 \end{cases} \tag{I}$$

where

$$f_i(X) = f_i[\sum_{j=1}^{N_1} q_i * x_{1j}, \sum_{j=1}^{N_2} q_i * x_{2j}, \sum_{j=1}^{N_3} q_i * x_{3j}, ..., \sum_{j=1}^{N_L} q_i * x_{Lj}]$$
$$i = 1, ..., L$$

Here, x_{ij} =1 indicates the qualified service j is selected from service class i; $f_i(X)$ is composition function that can figure out Q_i of CS by atomic services QoS. $Q(X) = [f_1(X), f_2(X), ..., f_m(X)]$ is a set of objective functions means we have to consider m-dimensional QoS targets while composing. In the process of service selection optimization, the purposes of selection are different, and the construction of composition functions is different, so do final results.

In Model I, as far as QoS, consumer expects some QoS criteria to be larger and some to be reverse. To solve this problem, we need to observe the maximal value of $f_i(X)$. So, constraint conditions should be added into Model I through the use of following equivalent:

$$\begin{cases} x_{ij} * (1 - x_{ij}) = 0 \\ \forall i = 1, ..., L, \ \sum_{j=1}^{N_i} x_{ij} = 1 \end{cases}$$

Here, the first constraint condition $x_{ij} * (1 - x_{ij}) = 0$ implies that the value of x_{ij} only has two possibilities, x_{ij} =0 means the *j*th atomic service in SC_i is not selected according to the QoS requirements of service consumer; x_{ij} =1 means the *j*th atomic service is selected. The second constrains $\sum_{j=1}^{N_i} x_{ij} = 1$ implies one service must be selected in SC_i.

The aforementioned two constraint conditions guarantee that only one atomic service will be selected from one SC_i. Hence**,** we can get Model II:

$$\begin{cases} MAX \quad f_i(X), \\ \text{St.} \quad x_{ij} * (1 - x_{ij}) = 0 \\ \forall i = 1, ..., L, \quad \sum_{j=1}^{N_i} x_{ij} = 1, \\ x_{ij} \geq 0, \ i = 1, ..., L, \ , \quad \mathrm{j} = 1, ..., L, \end{cases} \tag{II}$$

where

$$f(X) = f_i[\sum_{j=1}^{N_1} q_i * x_{1j}, \sum_{j=1}^{N_2} q_i * x_{2j}, \sum_{j=1}^{N_3} q_i * x_{3j}, ..., \sum_{j=1}^{N_L} q_i * x_{Lj}]$$
$$i = 1, ..., L$$

In this way, service selection problem can be considered as the 0-1 nonlinear programming problem. Therefore, by selecting and designing proper variables, we can get the minimal (or maximal) value of objective functions. Although, 0-1 linear programming problem belongs to linear problem, it also attributes to linear problem, it also belongs to NP hard problem or NP completeness problem.

The basic characteristic of 0-1 linear programming problem is that the value of designed variable can only be 0 or 1, this leads objective function and constraint function discontinuous in its feasible sets, results in non-differentiable problem in some optimized mathematical models, thus making many effective mathematical analytical methods for continuous-variable optimization meaningless. Here we use x_{ij} *(1- x_{ij})=0 to transfer a discrete problem into a smooth continuous function. These are the main aims of Model II.

The second constrains condition $\forall i=1,...,L, \sum_{j=1}^{N_i} x_{ij} = 1$ indicates in each SC, only one candidate service can be selected.

Model II is a nonlinear constraint as well as a multi-purpose continuous optimization problem. In this multiple-constraint service selection model, our purpose is to find a better composition plan which contains a group of atomic services $\{S_1^{\mathrm{i}}, S_2^{\mathrm{j}}..., S_L^x\}$ from $N_1 \times N_2 \times N_3 \times ... \times N_L$ kinds of existing composition plans, and $\{S_1^{\mathrm{i}}, S_2^{\mathrm{j}}..., S_L^x\}$ is a Pareto optimal solution. Finally, the selected result is denoted as $X = [x_{11}, x_{12}, x_{1N_1} ..., x_{L1}, x_{L2}, ..., x_{LN_L}]^T$, this result can straightly tell composer which candidate service has been selected.

DESIGN COMPOSITION SERVICE SELECTION OPTIMIZATION METHOD

Maximum entropy function method

In the past references of Web service selection optimization problem, they always merged multiple-QoS criteria into a single parameter, such as $\sum_{i=1}^{m} Weight_i * qos_i$, and then take this single parameter as an optimization algorithm's target function. The method ignore non-inferior solutions problem, we can solve this problem through maximum entropy function, at first we select the minimum from some objective QoS, then maximize, in this way, we can guarantee that every target is the maximum. Using Maximum Entropy Function Method, the selecting result of forenamed example is S_2.

Definition 2

Let $F_p(x) = \frac{1}{p} In\left\{\sum_{i=1}^{m} \exp[p * f_i(x)]\right\}$ be the maximum entropy function of $f(x)$ on $x \in \Omega \subset R^n$ (Li, 1994).

Theorem 1

As for every $x \in \Omega \subset R^n$, the value of function $F_p(x)$ is inversely proportional to that of parameter *p* (Li, 1994). And when $p \to \infty$, $f(x)$ is a limit value, such that:

$$F_s(x) \le F_r(x) \quad s \le r, \qquad \lim_{p\to\infty} F_p(x) = f(x) \tag{1}$$

Theorem 1 shows if *p* is large enough, we can use the maximum entropy function to substitute the target function $f(x)$, by this means, we can transform the former nonlinear minimization problem into a differentiable function of unconstrained optimization problem. Although, *p* is an approximate solution, if *p* is large enough, high accuracy can also be guaranteed.

Constrained nonlinear max-min problem in this paper is:

$$\underset{x}{MIN}\ f(x) \equiv \underset{1\le i\le m}{MAX}\{f_i(x)\} \qquad st. \quad g_j(x) \le 0, 1 \le j \le n \tag{2}$$

$f_i(x)$ and $g_j(x)$ are smooth functions with respect to $x \in \Omega \subset R^n$.

MIOA

Firstly, we can transform MAX $f_i(X)$ of Model II into following:

$$MAX \quad \underset{1\le i\le L}{MIN}\{f_1(X), f_2(X), ..., f_L(X)\} \tag{3}$$

Equates to:

$$\underset{x}{MAX}\ f(x) \equiv \underset{1\le i\le m}{MIN}\{f_i(x)\} \qquad st. \quad g_j(x) \le 0, 1 \le j \le n \tag{4}$$

Now, we could not simply use maximum entropy function of Theorem 1, Equation 3 is a MAX-MIN problem. In order to use maximum entropy function, we add negative sign to every target function $-f_i(x)$, then we can convert MAX-MIN expression into MIN-MAX one, as a result, Equation 3 is converted to:

$$MIN[-\underset{1\le i\le L}{MAX}\{-f_1(X), -f_2(X), ..., -f_L(X)\}] \tag{5}$$

So, maximum entropy function of our service selection problem can be denoted as:

$$F_p(x) = -\frac{1}{p} In\left\{\sum_{i=1}^{m} \exp[-p * f_i(x)]\right\} \tag{6}$$

Then, nonlinear constraints multi-object optimal problem of Model II is converted into single-object constraints optimal problem by using maximum entropy method in this paper. With this fitness function, we can improve current social cognitive optimization to solve QoS Based service selection problem. SCO is based on social cognitive theory, which is more applicable to solve large-scale constrained problem compared with particle swarm optimization (PSO) and genetic algorithm (GA) according to the experiments. SCO can gain good performance in solving nonlinear programming problem (Xie and Zhang, 2004).

Parameters of SCO includes: N_{pop}, N_c and T, N_{pop} represent the amount of knowledge points in library; N_c stands for the amount of learning agent is N_c. T indicates the times of learning cycle. Consider logistic mapping: $a_{k+1} = 4 * a_k * (1 - a_k)$, among them, K=1，2，… is iterative times, α is a controlled variable, reference has already proved that when α =4, logistic mapping becomes a subjective mapping to (0,1),and the system is in chaos totally, such that the input of system is ergodic within the range of (0,1) (Yang et al., 2009). So we can find a new point $\vec{x}_d^*$ in the neighborhood of SCO.

$$\vec{x}_d^* = \vec{x}_{1,d} + 2 * Rand(\ ) * (\vec{x}_{2,d} - \vec{x}_{1,d}) \tag{7}$$

Here, $Rand()$ is a random number within the range of (0, 1), α is a constant, $\vec{x}_1$ and $\vec{x}_2$ are defined as reference point and center point respectively. Now, in MIOA, we improved SCO by introducing $Chaos()$ instead of $Rand()$, so, Equation 7 can be converted as follows :

$$\vec{x}_d^* = \vec{x}_{1,d} + 2 * Chaos(\ ) * (\vec{x}_{2,d} - \vec{x}_{1,d}) \tag{8}$$

Within which, $Chaos()$ is a chaos factor which generated by $a_{k+1} = 4 * a_k * (1 - a_k)$ through logistic mapping. The main steps of improved SCO involve 4 steps, which are specified as follows.

Step 1: Initialization: (a) Create all the N_{pop} knowledge points from the library randomly (including every knowledge point's position and its level). (b) Allocate knowledge points in the library to every learning agent randomly, but each knowledge point can only be allocated once.

Step 2: Vicarious learning: (a) Model selection: Select more than two knowledge points from the library randomly (ordinary two is OK), but these selected knowledge points could not be repeated in learning agent itself, then we need to select a better knowledge point in these knowledge points based on the principle of competitive alternatives (Compare every knowledge point's adaptive value through function $F(x)$); (b) Observational learning: compare with the selected knowledge points and knowledge points of learning agent its own level, we select one point which have a better level (we make all these properties as large as possible) to be a center point, the worse point as reference point, then learning agent move the two points to a new knowledge point based on the principle of neighborhood searching, and then add the new point into library.

Step 3: Library refreshment: Remove N_c knowledge points with the worst levels from the library.

Step 4: Repeat procedures of step 2 to 4 till all stop conditions (for example, the result reached the number of iterations which fixed ahead, or reached the precision mentioned ahead) are satisfied. The total running time is $N_c * T + N_{pop}$.

While selecting CS, p is requested to be large enough, so it leads to $\exp[p * f_i(x)]$ overflow easily, we deal with this problem via computing as follows: if M>0, exp(M) is smaller than the greatest integer which computer stored, whereas exp(M+1) overflows is note down as follows:

$$f_k(x) = \max_{1 \le i \le m} \{ | f_i(x) | \}$$

(A) If $p * | f_k(x) | \le M$, fitness function is defined as:

$$F_p(x) = \frac{1}{p} In \left\{ \sum_{i=1}^{m} \exp[p * f_i(x)] \right\}$$

(B) If $p * | f_k(x) | > M$, fitness function is defined as:

$$F_p(x) = f_k(x)$$

REALIZATION OF MIOA

Design of problem scenario

We consider a composition service scenario, named TravelPlan, proving the travel planning (e.g. weather broadcasting, hotel booking, airplane booking and payment) for its customs. Assume a professor, Wang, wants to spend his vacation in Beijing, China . Service Composer firstly needs to search for a weather broadcasting service which can provide the weather condition of Beijing. If the weather is good for travel, then Service Composer will search a hotel booking service and airplane booking service according to prof. Wang's travel scheduling and his anticipate payout. After that, Service Composer will find a proper payments service support for Wang's credit card.

Figure 1 depicts this service composition (TravelPlan) scenario of four service classes: there are three candidate

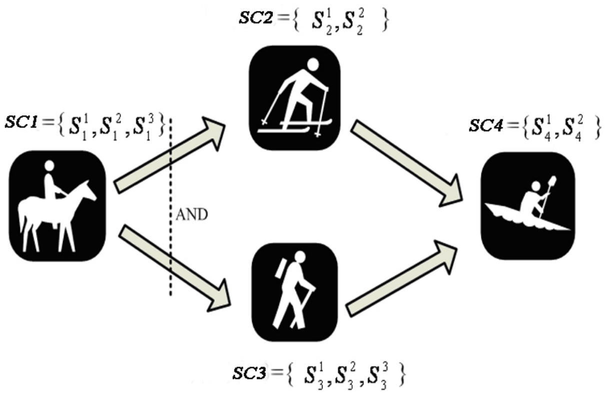

Figure 1. Experimental scenario.

services $\{S_1^1, S_1^2, S_1^3\}$ in SC_1 (Service Class of weather broadcasting); there are two candidate services $\{S_2^1, S_2^2\}$ in SC_2 (Service Class of hotel booking), three candidate services $\{S_3^1, S_3^2, S_3^3\}$ in SC_3 (Service Class of airplane booking) and two candidate services $\{S_4^1, S_4^2\}$in *SC*4 (Service Class of payment). CS should choose one atomic service from each *SC,* such that $\{S_1^i, S_2^j, S_3^k, S_4^l\}$ with $1 \le i \le 3, 1 \le j \le 2, 1 \le k \le 3, 1 \le l \le 2$.

QoS criteria

Despite the lack of standardized framework studying related solutions based on a consistent view of QoS service characteristics. In this paper, a five-dimensional QoS is proposed. A Web service should have defined a vector of QoS metric q , shown as $q = \{q_1, q_2, q_3, q_4, q_5\}$:

1) q_1=responseTime, indicates response time of an atomic service;
2) q_2= price, stands for the cost of an atomic service; the more a service costs, the more guaranteed functions it provides;
3) q_3=expireTime, represents the expire time of an atomic service; during these times, service availability can be guaranteed;
4) q_4= availability, denotes the availability of an atomic service;
5) q_5=securityLevel, delegates the security level of an atomic service.

Note that, this study does not intend to illustrate the non-functional concerns of Web service with an extensive list of QoS criteria, and presents their corresponding definitions in a practical manner.

As for a CS, every atomic service's $\{q_1, q_2, q_3, q_4, q_5\}$ is already known ($\{q_1, q_2, q_3, q_4, q_5\}$ is given by atomic service provider when they enroll service into registry center). Then, Q(CS) = [$f_1(X)$, $f_2(X)$, $f_3(X)$, $f_4(X)$, $f_5(X)$]. Function $f_i(X)$ $(1 \le i \le 5)$ represents the *i*th QoS dimension of Composition Service, and its scenario-dependent. According to the scenario in Figure 1, $f_i(X)$ can be got by employing the following equation:

1) $f_1(X)$=*ResponseTime*(*X*), response time of CS, as for consumers, a shorter response time corresponds to a better QoS. Considering in Figure 1, business flow of CS includes subsequent services, CPA (Zeng et al., 2003) is introduced to compute the response time. It is an algorithm to find critical path, response time of CS should be the summation of every atomic service's response time on critical path. *ResponseTime*(*X*) can be figured out by using the following equation:

$$f_1(X) = CPA\left[\sum_{j=1}^{3} q_1 * x_{1j}, \sum_{j=1}^{2} q_1 * x_{2j}, \sum_{j=1}^{3} q_1 * x_{3j}, \sum_{j=1}^{2} q_1 * x_{4j}\right]$$

2) $f_2(X)$=*Price*(*X*), *Price*(*X*) denotes cost of CS is the sum of the cost of every selected atomic service $\{S_1^i, S_2^j, S_3^k, S_4^l\}$ $(1 \le i \le 3,\ 1 \le j \le 2,\ 1 \le k \le 3,\ 1 \le l \le 2)$, as for consumers, they always want to spend less money on requisite service, so higher value of *Price*(*X*) indicates the lower quality, *Price*(*X*) is defined as:

$$f_2(X) = \left[\sum_{j=1}^{3} q_2 * x_{1j} + \sum_{j=1}^{2} q_2 * x_{2j} + \sum_{j=1}^{3} q_2 * x_{3j} + \sum_{j=1}^{2} q_2 * x_{4j}\right]$$

3) $f_3(X)$=*ExpireTime*(*X*), expire time of CS is decided by the minimum expire time of the selected atomic service, as for consumers, they expect the value of *ExpireTime*(*X*) as large as possible. *ExpireTime*(*X*) can be got by employing the following equation:

$$f_3(X) = MIN\left[\sum_{j=1}^{3} q_3 * x_{1j}, \sum_{j=1}^{2} q_3 * x_{2j}, \sum_{j=1}^{3} q_3 * x_{3j}, \sum_{j=1}^{2} q_3 * x_{4j}\right]$$

4) $f_4(X)$=*Availability*(*X*), stands for the availability of CS, as for consumers, the larger the better, it can be computed by:

$$f_4(X) = \left[\sum_{j=1}^{3} q_4 * x_{1j}\right] * MIN\left[\sum_{j=1}^{2} q_4 * x_{2j}, \sum_{j=1}^{3} q_4 * x_{3j}\right] * \left[\sum_{j=1}^{2} q_4 * x_{4j}\right]$$

5) $f_5(X)$ =*SecurityLevel*(*X*), indicates the security level of CS, we define that the minimum of $\{S_1^i, S_2^j, S_3^k, S_4^l\}$ is the final security level of CS, as for consumers, the larger the better:

$$f_5(X) = MIN\left[\sum_{j=1}^{3} q_5 * x_{1j}, \sum_{j=1}^{2} q_5 * x_{2j}, \sum_{j=1}^{3} q_5 * x_{3j}, \sum_{j=1}^{2} q_5 * x_{4j}\right]$$

Here,

1) In order to assess a CS better or worse, there should be a forwarded an evaluation function, called target function. In MIOA, $F(X) = -\frac{1}{P} In \sum_{i=1}^{5} e^{-p*f_i(X)}$ is employed to define the quality of knowledge points in SCO.
2) In the process of optimization problems, numeric QoS criteria can be classified as either positive or negative. For a positive attribute, e.g. *Availability*, a higher value indicates better quality. A negative attribute, e.g. response time, exhibits the opposite effect. In our model, we always require target functions $f_i(x)$ to be negative. Correspondingly, attribute values can be normalized by the following equations, where we can add negative notes before target functions $f_i(x)$ that are positive.

$$MIN[-\underset{1 \le i \le L}{MAX}\{-[-f_1(X)], -[-f_2(X)], -f_3(X), -f_4(X), -f_5(X)\}]$$

3) In order to guarantee high accuracy of maximum entropy function $F(X) = -\frac{1}{P} In \sum_{i=1}^{5} e^{-p*f_i(X)}$, here let P=10^5.

4) $X = [x_{11}, x_{12}, x_{13}, x_{21}, x_{22}, x_{31}, x_{32}, x_{33}, x_{41}, x_{42}]^T$, after implementing the service selection algorithm, if we get final value $X = [1,0,0,0,1,1,0,0,0,1]^T$ it means CS is composed by candidate services $\{S_1^1, S_2^2, S_3^1, S_4^2\}$.

Experimentations

In order to validate the usefulness of the method in this paper, we measure and test composition service selection model and MIOA algorithm based on Web service composition manage prototype system E-WsFrame (Xiong et al., 2009; Liang and Huang, 2009), in which we use Service Composition Management Language (SCML) to describe composition service. Such language evolves existing Business Process Execution Language for Web Service (BPEL4WS) with QoS values. And we use Extended Web Service Description Language (EWSDL) to describe atomic service, which proposed by extending current WSDL (EWSDL) with additional QoS values. The algorithm is implemented in JAVA and the results have been obtained by running the algorithm on a P4 2.3 GHZ computer with 4 GB of RAM.

Firstly, when service providers register a new service, concrete values of $\{q_1, q_2, q_3, q_4, q_5\}$ contained in its EWSDL, MIOA algorithm takes decision based on these values. According to our experimental scenario in Figure 1, there are four service class, concrete values of $\{q_1, q_2, q_3, q_4, q_5\}$ of each atomic service are shown in Figures 2 to 5:

Secondly, Chaos means a sensitive dependence recoverability non-periodic movement, which is generated by deterministic system. With development of computer technology, Chaos has become to be a deeply influential, fast-developed advancing science since it is proposed in 1972. Chaos is a nonlinear phenomenon existing in nature, which has features of randomicity, ergodic property and sensibility in initial conditions. It can traversal all states no-repeatedly according to its own discipline in a certain range. The result of Chaos optimization method is prominent while the searching space is small. Figure 3 shows allocating circumstances of 3000 points with the range of (0,1) using simple random number method Random() and Chaos method Logistic mapping $a_{k+1} = 4 * a_k * (1 - a_k)$.

From Figures 6 and 7, we can intuitively see that the distribution of points which Chaos method generated is more even, and ergodic property is more obvious. So, substituting random( ) with chaos( ) in SCO speeds up the velocity of service selection algorithm.

In MIOA, with T=1000, N=100, NL=350. For all experiments, we repeatedly run the algorithm 100 times, and take the average over the results in succeeding Figure 8. For higher accuracy, each experiment is carried out 100 runs. We can see, after 10 runs, S_1^2 should be selected from SC1; S_2^2 should be selected from SC2; S_3^1, S_3^2, S_3^3 can be selected from SC3; S_4^2 should be selected from SC4.

1) Combined with Figure 2, value of q_1 , q_2 of S_1^2 is the minimum in SC_1; q_3, q_4 , q_5 is the maximum in SC_1 (We defined that the smaller value of q_1 and q_2 are proportional to the QoS value, whereas q_3, q_4, q_5 are inversely proportional to the QoS value), so S_1^2 is the best among the three candidate services in SC_1, that is to say, we selected atomic service S_1^2 from SC_1 using service selection algorithm after computing 100 times. In the same way, we selected S_2^2 from SC_2 and selected S_4^2 from SC_4.

2) The candidate services of SC_3 are S_3^1, S_3^2, S_3^3 and selected times of them does not have obvious preference, the reason is that $\{q_1, q_2, q_3, q_4, q_5\}$ of these three

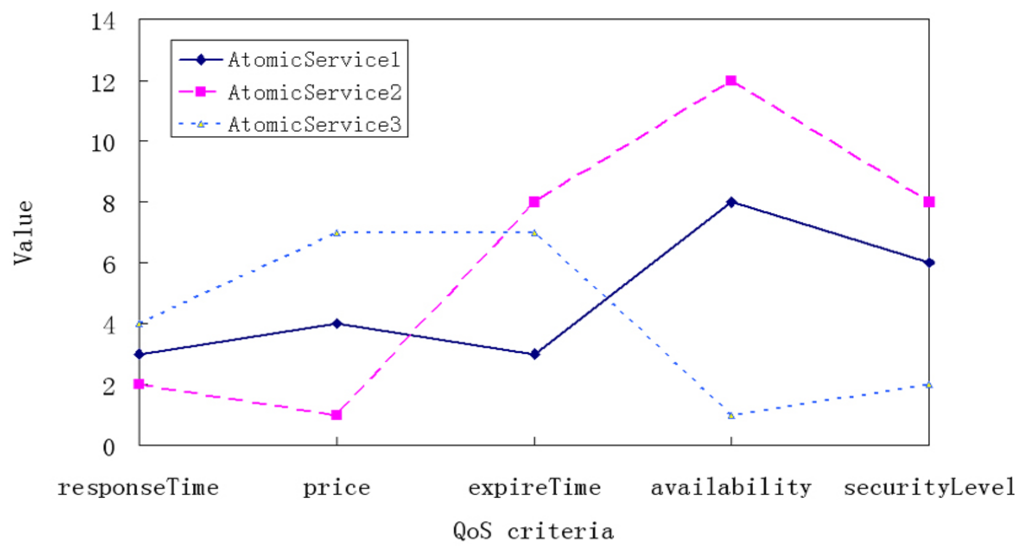

Figure 2. QoS of Atomic services in SC_1.

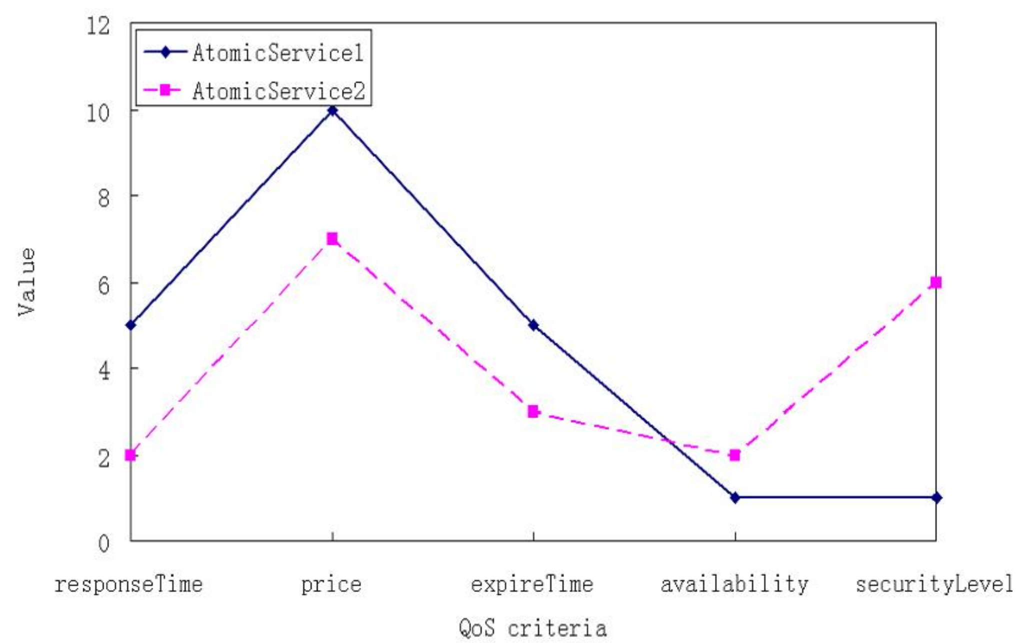

Figure 3. QoS of Atomic services in SC_2.

services are non-inferior, namely we could not determine which one is better.

Figures 8 and 9 show, MIOA can get a satisfactory solution after 230 iterations. But the SCO could not get satisfactory solution until 454 iterations.

Conclusion

In this paper, we discuss Web service compositon and the key elements in QoS Based service selection, we address a new service selection model, then give a novel algorithm MIOA to solve composition service selection problem. Our solution incorporates the following contributions: Firstly, this paper converted a service selection problem into a QoS constrained multipurpose composition optimal problem in the process of Web service composition management, which fill up deficiencies of local optimum method effectively; Web service composition selection model proposed in this is

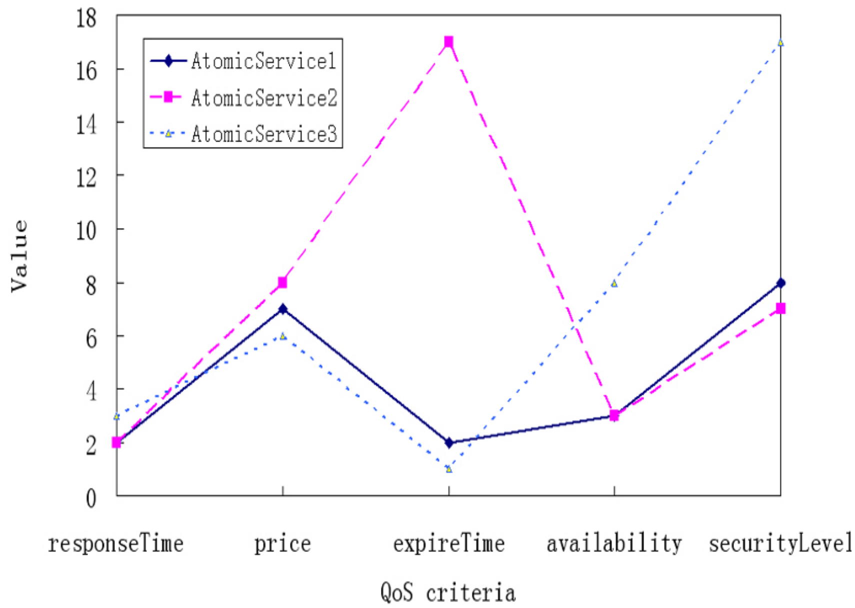

Figure 4. QoS of Atomic services in SC_3.

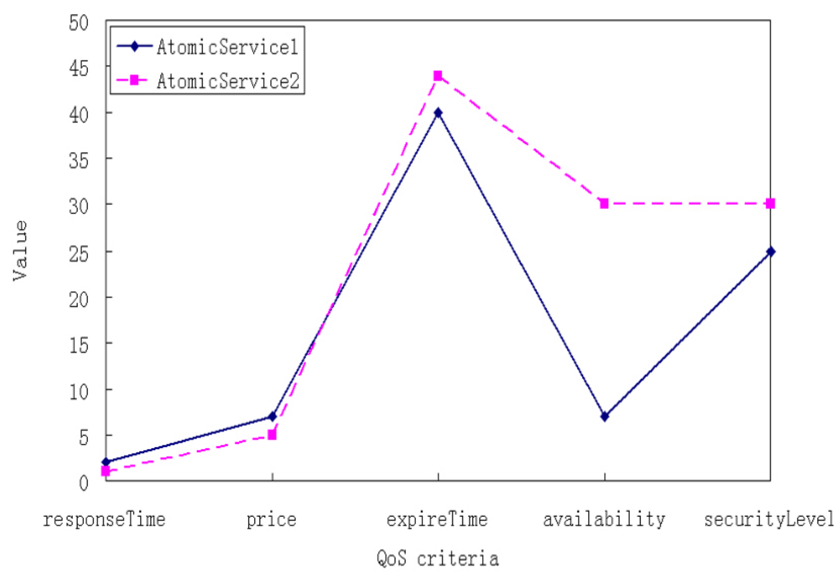

Figure 5. QoS of Atomic services in SC_4.

more efficient than previous study with wider application.

Secondly, in most current studies (Chen and Li 2007a, b; Zhang et al., 2007; Jin et al., 2005; Zeng et al., 2003, 2008; Yuan , 2005; Mohammad and Thomass, 2009) QoS criteria are always merged into one target function $\sum_{i=1}^{m} Weight_i * qos_i$ and then get Optimal Solutions. These methods can not directly tell consumers which atomic service is selected, so essentially speaking; these methods are optimization of QoS, not service selection method. The novel contribution of this paper is to tell consumers the result of selection; it is a real suitable service selection model.

Thirdly, this paper converts a discrete multipurpose integer planning problem (Chen and Li, 2007a, b; Zhang et al., 2007; Jin et al., 2005; Zeng et al., 2008, Mohammad and Thomass, 2009) into a continuous single purpose planning problem, but the method which solve discrete multi-purpose integer programming problem only

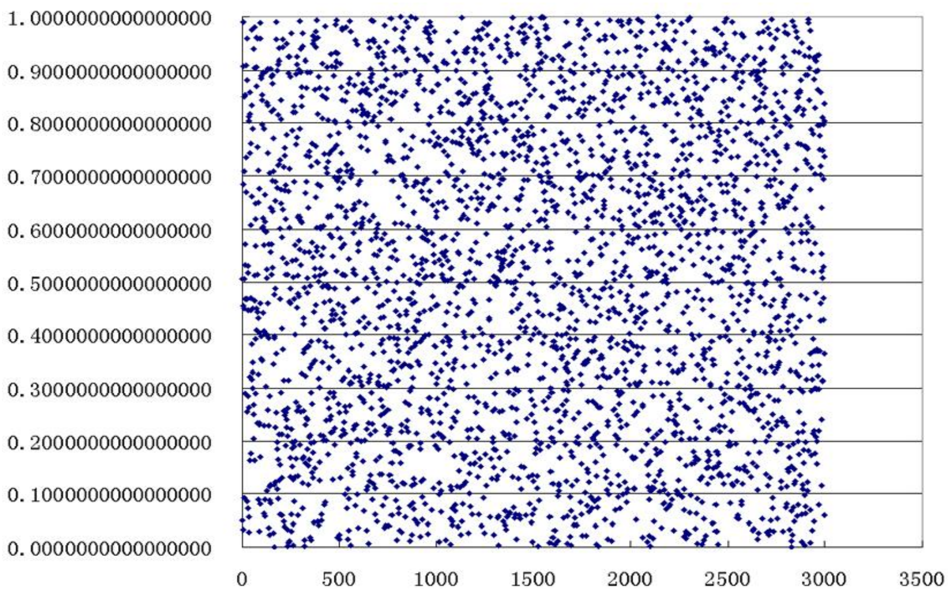

Figure 6. Sequence distribution figure of simple random number.

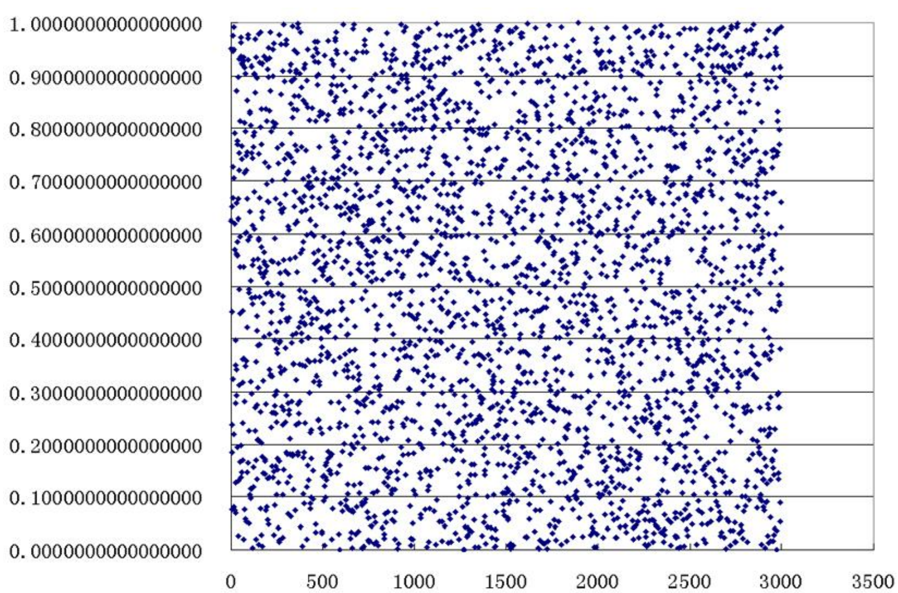

Figure 7. Sequence distribution figure of chaos.

applicable to small-scale problem, rather than service composition selection optimization. This continuous method kept away from uncontinuity of discrete variable optimization problem and combinatorial explosion problem, we can get primal problem's satisfactory solute-ion only needed to solve relevant continuous variable nonlinear programming problem, and we can get high accuracy.

Fourthly, as for current research, ordinary consumers give or get the weights of every property using multipurpose decision method, the weak point of this is: it does not guarantee that the largest weights is the best target, its only guarantee multipurpose $\sum_{i=1}^{m} Weight_i * qos_i$ is the largest. MIOA gets the minimum of several QoS and then maximize, which guarantees that every target is the result of maximization. Meanwhile, MIOA does not need to set every variable's value artificially at run-time, which ensures the promising availabilities of the approach.

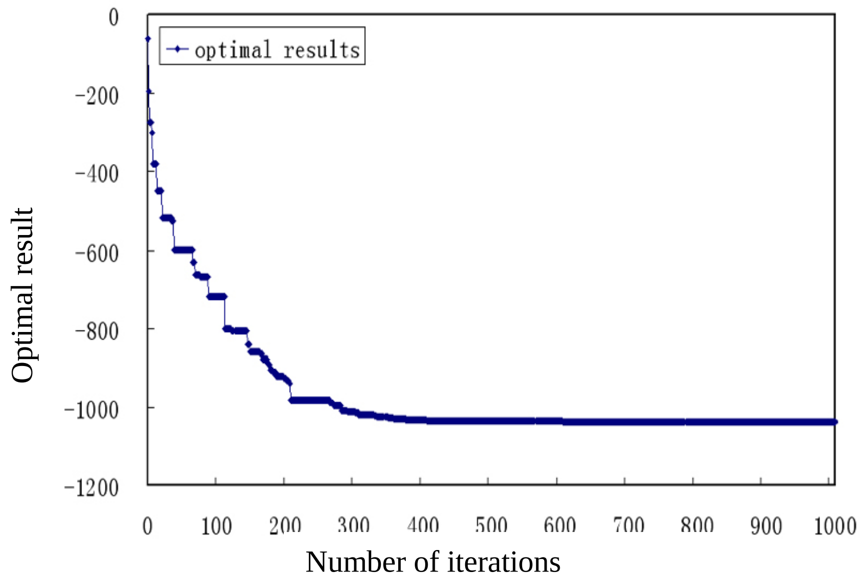

Figure 8. Iterative times of SCO.

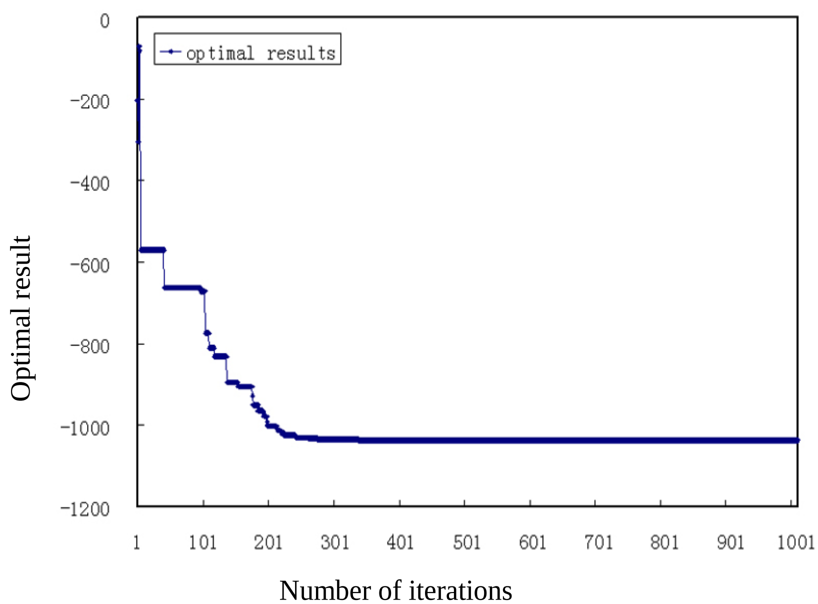

Figure 9. Iterative times of MIOA.

Finally, MIOA, combined with classic maximum entropy function and SCO, shows advantages of fast computed speed and good convergence while solving continuous optimization problem. In addition, Chaos method Logistic mapping of generating random numbers are more average.

In the current approach, the number of QoS criteria is fixed and need to be defined beforehand. Currently we are studying the impact of the applied method as well as the number of the selected QoS criteria on the performance and quality of the obtained results. We also aim at developing a self-adaptive approach, which optimizes itself by determining the best composition service at run-time based on the available QoS information.

ACKNOWLEDGEMENTS

The work presented in this paper was supported by

National Natural Science Foundation of China under Grant No. 60803162, 60825202; and Scientific Research Program Funded by Shaanxi Provincial Education Department (No.11JK1061).

REFERENCES

Chen YP, Li ZZ (2007a). E-Wsframe: A framework support QoS Based Web services composition, Inform. Technol. J., 6(3): 390-395.

Chen YP, Li ZZ (2007b). Study on Several Key Problems in Web Service Composition Management. Xi'an: Xi'an Jiaotong University.

Curbera F, Khalaf R, Mukhi N (2003). The next step in web services. Commnincation of the ACM. 46 (10): 29–34.

Jin H, Chen HW, Lv ZP, Ning XM (2005). QoS optimizing model and solving for composition service in CGSP job manager. Chinese J. Comput., 28(4): 578-588.

Liang WY, Huang CC (2009). The generic genetic algorithm incorporates with rough set theory - An application of the web services composition. Expert Systems with Applications, 36: 5549-5556.

Li XY (1994). An Effective Solution to Non-differentiable Optimization Problem.science in China, 24: 371-377.

Mohammad A, Thomass R (2009). Combining Global Optimization with Local Selection for Efficient QoS-aware Service Composition Efficient QoS-aware Service Composition. pp. 881-890.

Xie XF, Zhang WJ (2004). Solving engineering design problems by social cognitive optimization. Genetic and Evolutionary Computation, pp. 261-262.

Xiong PC, Fan YS, Zhou MC (2009). Web Service Configuration under Multiple Quality-of-Service Attribute, IEEE Trans. Auto. Sci. Eng., 6(2): 311-321.

Yang L, Song J, Jin Q (2009). New chaotic Elman neural network and its application. J. Comput., 02: 0549–0551.

Yuan L (2005). A Method of QoS-aware Service Components Composition for Pervasive Computing Environments. Beijing: Institute of Software Chinese Academy of Sciences.

Zhang C, Su S, Chen J, DiGA (2007). Population diversity handling genetic algorithm for QoS-aware web services selection. Comput. Comm., 30: 1082-1090.

Zeng LZ, Benatallah B, Dumas M (2003). Quality Based Web Services Composition. Proc. of 12th International Conference on World Wide Web (WWW), Budapest, Hungary. pp. 411-421.

Zeng LZ, Anne HH, Ngu, Benatallah B, Podorozhny R, Lei H (2008). Dynamic composition and optimization of Web services. Distrib. Parallel Databases, 24: 45–72.