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Trust assessment of business service workflow based on complex trust network①

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Abstract

For business service workflow, QoS-based services selection can't guarantee whether the composite service satisfies user's requirement after delivery, because once any service interrupts or quality of service (QoS) maliciously reduces, the quality of workflow will be reduced. Trustworthy services can provide reliable QoS, so trustworthiness research could improve the efficiency of services selection. This paper investigates trust assessment in the perspective of workflow. Firstly, trust network of business service workflow (TN-BSW) is proposed to analyze trust attributes; then, the trust measurement system of TN-BSW is investigated to assess the trust value quantitatively; and then, a trust-aware service recommendation model (TaSRM) is proposed to enhance the efficiency of QoS-basedservices selection; finally, experiment shows the feasibility of TN-BSWand the performance of TaSRM.

Key words: business service workflow, trust attributes, trust assessment, quality of service (QoS), service selection

0 Introduction

The function of business service workflow is achieved by the composition of different abstract services, such as logistic service and payment service. Many concrete services can achieve the function of abstract service, such as EMS and UPS both of which can provide logistic service, but their qualities of service (QoS) are different.

How to select service is the key problem of service system. Some previous works[1-6] investigated services selection problems based on QoS. Ref. [1] proposed the QoS framework for services selection. Ref. [2] proposed the ranking of services by QoS assessment. Refs[3-5] focused on composite services by QoS composition calculation. Ref. [6] proposed context-aware QoS to deal with dynamic services selection. Based on QoS, service with high QoS value and service workflow with high aggregated QoS value can be selected.

However, these works ignored the problem: "Advertising QoS published before delivery might change after delivery". The reason is: Business service has the characteristics of social, dynamic and subjective. In real case, once any service provider loses credibility, such as interrupting service and reducing QoS maliciously, the whole workflow will be affected. On one hand, the quality of workflow after delivery will deviate from advertising QoS; on the other hand, the whole workflow may be terminated with uncompleted response, so it can't achieve user's requirement. Obviously, QoS-based services selection can't be aware of credit losses, while credit losses often happen in real business service scenario.

For this shortage of QoS-based services selection, some works [7-9] research credit rating to measure services' credit from users or third-party monitoring. By comparing the credits, services with low credit can be filtered. However, service's credit might be deliberately rated high by its own providers or rated low by competitors. Therefore, malicious behaviors detecting[10,11] is to make credit rating more believable. However, in general, these two methods only deal with one type abstract service while not service workflow. One service with credible QoS can't represent that the whole workflow's quality is credible.

In conclusion, credit rating and malicious behaviors detecting make QoS-based services selection more

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reliable, but it still can't guarantee that the composite QoS satisfies user's requirement after delivery.

Trust relationship is the key factor to solve this shortage. On one hand, trustworthy services can provide reliable QoS; on the other hand, in services interaction, a high credible service tends to cooperate with others having the same or higher credit. Thus, if service workflow can be provided by trustworthy services, meanwhile, these services have good cooperative relationship, the quality of workflow could be guaranteed more reliably.

By this motivation, two questions on the research of trust relationship should be solved.

(1) How to measure the trustworthiness of a service and the trust relationship of business service workflow?

(2) How to utilize this trust measurement in business services selection?

This paper devotes to solve these two questions and contains 5 sections. Section 1 proposes trust network of business service workflow (TN-BSW); Section 2 presents the measurement system of TN-BSW; Section 3 proposes a Trust-aware Service Recommendation Model (TaSRM) and its algorithms to solve services selection problem; Experiment in Section 4 is to verify TN-BSWandTaSRM; Section 5 presents the conclusions.

1 TN-BSW

For business service, business correlations are formed gradually in the long-term interactions, such as partner and price alliance. It can be depicted by graph structure with nodes and links, as shown in Fig. 1: node represents service, link represents business correlation, such as $C(1,2)$ represents the correlation between service 1 and 2; they can also form a loop correlation.

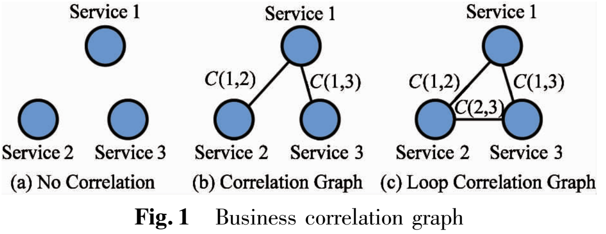

Fig. 1 Business correlation graph

Service tends to cooperate with others having the same or higher credit, business correlations reflect trust relationships. We call it business correlation trust and classify it into Node-trust and Link-trust. For business service, reputation, business scope and transaction volume are main attributes and they affect trust relationships significantly. Further more, Node-trust can be measured by reputation level (RL), and Link-trust can be measured by business scope compatibility (BSC) and business compactness degree (BCD), which are corresponding to business scope and transaction volume.

(1) **Node-trust**: Real service systems provide various reputation mechanisms to assess reputation. For example, Amazon defines five stars[12]; Alibaba defines gold supplier and a series of authentications[13]. Thus, reputation mechanism can be utilized to assess Node-trust.

(2) **Link-trust**: On one hand, business scope reflects service function, such as payment service. BSC represents business scope compatibility between two services' business scopes, for example, accessory manufacturer A only provides a special accessory to auto manufacturer B, another accessory manufacturer C can provide the same accessory and other accessories. To a certain extent, as the more compatiblescope, A can concentrate more on serving for B, and the intensity of trust between A and B is higher than C and B. On the other hand, BCD represents business compactness degree between two services, and it is reflected by transaction volume. The transaction might be product purchasing or service consumption. Stronger BCD reflects the deeper trust relationship.

By the combination of Node-trust and Link-trust, a trust network of business service workflow (TN-BSW) is established as Fig. 2 to illustrate the trust relationship.

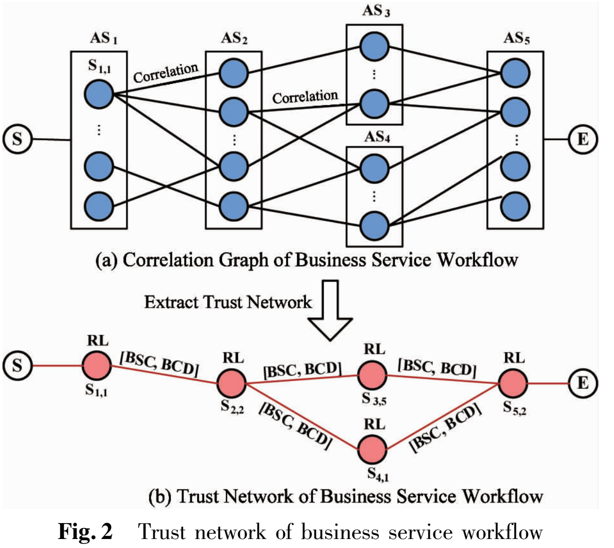

Fig. 2 Trust network of business service workflow

As shown in Fig. 2, circles marked with "S" and "E" respectively represent the start and end of workflow. This workflow is composed of 5 abstract services

(AS). AS_3 and AS_4 form a parallel structure and others form a sequential structure. Each AS has many candidate services, e.g., $S_{1,1}$ is the first service in AS_1, $S_{3,5}$ is the fifth service in AS_3. Cooperation between services in different abstract services forms business correlation.

Then, trust network can be extracted with Node-trust and Link-trust. As an example, one workflow instance path marked with Node-trust and Link-trust is shown in Fig. 2(b). By TN-BSW, trust relationships of business service workflow can be shown intuitively and clearly.

2 Trust measurement system

TN-BSW considers service trust (Node-trust) and business correlation trust (Link-trust). This section presents detailed trust measurement of TN-BSW.

2.1 Reputation level

Take $S_{i,j}$ represents the j^{th} service in the i^{th} abstract service, herein, $i = 1, 2, \cdots, I$. and $j = 1, 2, \cdots, J_i$; I represents the number of abstract service and J_i represents the number of services in the i^{th} abstract service. Reputation level of $S_{i,j}$ is depicted as $R(S_{i,j})$.

2.2 Business scope compatibility

$$BSC(S_{i,j}, S_{k,l}) = \frac{S(S_{i,j}) \cap S(S_{k,l})}{S(S_{i,j}) \cup S(S_{k,l})} \tag{1}$$

where $S(S_{i,j})$ and $S(S_{k,l})$ represent the business scope of service $S_{i,j}$ and $S_{k,l}$. They can be obtained by service tags, which are more concrete than service categories. For example, in the website (www.programmable web.com), the API "Google Maps" is categorized as mapping and annotated with the tags of mapping, places, viewer and display. These tags reflect its business scope. The business scope compatibility between $S_{i,j}$ and $S_{k,l}$ is calculated by similarity measurement of business scope[14]. $S(S_{i,j}) \cap S(S_{k,l})$ gets the number of matched scopes; $S(S_{i,j}) \cup S(S_{k,l})$ gets the total number of their scopes. Thus, the value domain of $BSC(S_{i,j}, S_{k,l})$ is $[0, 1]$. $BSC(S_{i,j}, S_{k,l}) = 0$ represents their business scopes are irrelative; $BSC(S_{i,j}, S_{k,l}) = 1$ represents their business scopes are matched absolutely; $0 < BSC(S_{i,j}, S_{k,l}) < 1$ represents their business scopes are partially matched.

2.3 Business compactness degree

$$BCD(S_{i,j}, S_{k,l}) = \frac{V(S_{i,j}) \cap V(S_{k,l})}{V(S_{i,j}) \cup V(S_{k,l})} \tag{2}$$

where $V(S_{i,j})$ and $V(S_{k,l})$ represent the total transaction volume of service $S_{i,j}$ and $S_{k,l}$. They can be obtained by transaction history and formatted as transaction times. The business compactness degree between $S_{i,j}$ and $S_{k,l}$ is calculated by similarity measurement of transaction volume[14]. $V(S_{i,j}) \cap V(S_{k,l})$ gets the transaction times between them; $V(S_{i,j}) \cup V(S_{k,l})$ gets the max transaction times. Thus, the value domain of $BCD(S_{i,j}, S_{k,l})$ is $[0, 1]$. $BCD(S_{i,j}, S_{k,l}) = 0$ represents no transaction between them; $BCD(S_{i,j}, S_{k,l}) = 1$ represents their transactions are absolutely from each other; $0 < BCD(S_{i,j}, S_{k,l}) < 1$ represents they have some transactions.

Then, for a service workflow instance path p, as in Fig. 2(b), the utility value of RL, BCD and BSC can be respectively calculated as Eq. (3). W_R represents the reputation weight vector of service, W_{BSC} represents the BSC weight vector of business correlation, W_{BCD} represents the BCD weight vector of business correlation, $U_R(p)$ represents the weighted average reputation of p, $U_{BSC}(p)$ represents the aggregated BSC value of p, and $U_{BCD}(p)$ represents the aggregated BCD value of p.

$$\begin{cases} U_R(p) = \dfrac{W_R \times R}{I} \\ U_{BSC}(p) = W_{BSC} \times BSC \\ U_{BCD}(p) = W_{BCD} \times BCD \end{cases} \tag{3}$$

The concrete measurement can be expressed as:

$$\begin{cases} U_R(p) = \dfrac{\sum_{i=1}^{I} w_R^i \times R(s_{i,j})}{I} \\ U_{BSC}(p) = \sum_{i=1}^{I-1} w_{BSC}^{i,i+1} \cdot BSC(S_{i,j}, S_{i+1,l}) \\ U_{BCD}(p) = \sum_{i=1}^{I-1} w_{BCD}^{i,i+1} \cdot BCD(S_{i,j}, S_{i+1,l}) \end{cases} \tag{4}$$

Herein, weights satisfy $\sum_{i=1}^{I} w_R^i = 1$, $\sum_{i=1}^{I-1} w_{BSC}^{i,i+1} = 1$ and $\sum_{i=1}^{I-1} w_{BCD}^{i,i+1} = 1$ for normalization. Weight vectors reflect user's preference. For example, if user expects a specific abstract service with high reputation, its reputation weight should be set larger; if user attaches importance to the transaction of two specific services, BCD weight between these two services should be set larger.

Finally, the trust utility value of path p integrated with Node-trust and Link-trust is expressed as

$$U(p) = \delta_1 U_R(p) + \delta_2 U_{BSC}(p) + \delta_3 U_{BCD}(p) \tag{5}$$

Herein, parameters δ_1, δ_2 and δ_3 are adjustable factors and satisfy $\delta_1 + \delta_2 + \delta_3 = 1$, by which the performance of trust assessment can be adjusted. In detail, if the service system emphasizes on reputation, it should set a greater δ_1, e.g. C-C/B-C e-commerce attaches importance to trust; if the service system emphasizes on the matching of business scopes, it should set a greater δ_2, e. g. sophisticated manufacturing needs a precise business scope matching; if the service system emphasizes on cooperation, it should set a greater δ_3, e. g. service workflow focuses on workflow stability, and the cooperative transaction is the most important evidence. For concrete case, Analytical Hierarchy Process (AHP)[15] method can be applied to determine the assignment of weight parameters (w_R^i, $w_{BSC}^{i,i+1}$, $w_{BCD}^{i,i+1}$) and adjustable factors (δ_1, δ_2, δ_3).

3 TaSRM and algorithms

3.1 TaSRM

Based on the trust measurement system, Trust-aware service recommendation model (TaSRM) is established as Fig. 3 to measure the trust of business service workflow instance paths (BSW-IP) and get the trustworthy BSW-IP.

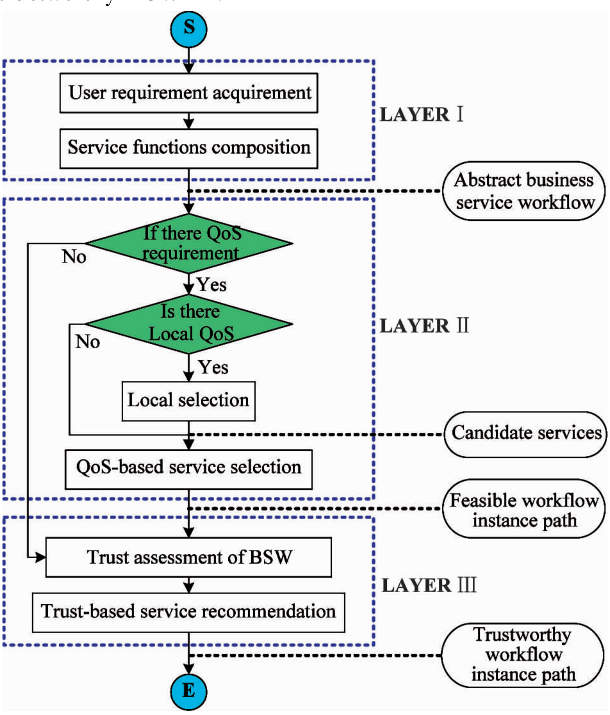

Fig. 3 Trust-aware service recommendation model

TaSRM sets two judgments and three layers.

Judgment Ⅰ: "Is there QoS requirement?"

It represents that if a user has QoS requirement? This judgment can distinguish different users. User without QoS requirement is like a new user who isn't familiar with QoS index or does not know their concrete requirement.

Judgment Ⅱ: "Is there local QoS?"

It represents that if QoS requirement contains local QoS requirement? Local QoS requirement can be applied to some specific scenarios, for example, user specifies the accommodation fee or transportation cost in travel service.

Layer Ⅰ: User requirement acquirement

User requirement contains requirements of function and QoS. Through service functionscomposition, abstract business service workflow can be obtained.

Layer Ⅱ: QoS-based services selection

This layer gets the feasible BSW-IP. If the user has local QoS requirement, firstly local selection is triggered to select services by local QoS; then, use QoS-based services selection to optimize composite QoS by global QoS requirement to get the feasible BSW-IP.

Layer Ⅲ: Trust-based service recommendation

This layer gets the trustworthy BSW-IP by trust measurement system. When there is no QoS requirement, directly adopt this layer to get service recommendation.

3.2 Algorithms of TaSRM

3.2.1 QoS-based services selection algorithm

In this stage, input the service workflow *SW* and QoS requirement (QoS^R); firstly, if there is local QoS requirement (QoS_{Local}^R), by "LocalSelection" to select candidate services, and then by "Compute Path" to compute the candidate BSW-IP; finally, comparing the aggregated QoS ($QoS_{Aggregated}^A$) of composite services with global QoS requirement (QoS_{Global}^R) to select the feasible BSW-IP (*FWP*), and then insert into the list of *FWP*. This stage is shown as Table 1.

Table 1 QoS-based services selection algorithm

Input	$SW = \{AS_1, AS_2, \cdots, AS_I\}$ $QoS^R = \langle QoS_{Global}^R, QoS_{Local}^R \rangle$
Output	FWP_List
Algorithm	1. Begin 2. If QoS_{Local}^R = empty 3. $CandidateServices$ = LocalSelection (QoS_{Local}^R, SW) 4. Else $CandidateServices = SW$ 5. End 6. $CandidatePath$ = ComputePath ($CandidateServices$) 7. For each p_i in $CandidatePath$ 8. $QoS_{Aggregated}^A = \{q_1^A, q_2^A, \cdots, q_M^A\}$ 9. For each q_i^A in $QoS_{Aggregated}^A$ 10. For each q_j^R in QoS_{Global}^R 11. If $q_i^A \leqslant q_j^R$ break; 12. End 13. End 14. Insert p_i in FWP_List 15. End 16. End

3.2.2 Trust-based service recommendation algorithm

In this stage, input FWP_List and TN-BSW; firstly, set weight vectors (W_R, W_{BSC}, W_{BCD}), and set parameters δ_1, δ_2 and δ_3; then compute trust utility value of each FWP by Eqs (4) and (5) to get $U(p_i)$; finally, sort $U(p_i)$ to get the list of trustworthy BSW-IP. This stage is shown as Table 2.

Table 2 Trust-based services recommendation algorithm

Input	FWP_List, $TN-BSW$,
Output	TWP_List
Algorithm	1. Begin 2. Set weight vectors W_R, W_{BSC}, W_{BCD} 3. Set parameters δ_1, δ_2 and δ_3 4. For each p_i in FWP_List 5. $U(p_i)$ = ComputeTrust (p_i) 6. End 7. Sort U_i in FWP_List 8. Insert p_i in TWP_List 9. End

In conclusion, TN-BSW and its measurement system are applied into TaSRM. TaSRM is to get the trustworthy BSW-IP on the premise of meeting QoS requirement.

4 Experiments and analysis

Experiments should investigate two issues.

(1) Whether TaSRM can detect malicious behaviors and provide the trustworthy BSW-IP?

(2) How about the execution efficiency of TaSRM?

4.1 Paremeters setting

4.1.1 Common parameter definitions

Common parameter definitions are shown as Table 3.

Table 3 Common parameter definitions

Parameters	Notation	Description
Abstract Service	AS_i	$i \in I$, $I = N^+$
Concrete Service	$S_{i,j}$	$j \in J_i$, $J_i = N^+$
Required QoS	QoS_R	User required QoS
Threshold QoS	QoS_T	User QoS threshold
Advertising QoS	QoS_A	Service advertising QoS
Execution QoS	QoS_E	Service execution QoS

4.1.2 Evaluation indicators definition

There are two types of QoS: 1) Cost QoS, and users expect it lower, such as price and execution time; 2) Benefit QoS, users expect it higher, such as reputation and usability. Besides, three indexes are defined:

QoS deviation degree represents the degree that QoS_E deviates from QoS_R. It is formulized as

$$\rho_D = \begin{cases} (QoS_E - QoS_R)/QoS_R; \ Cost\ QoS \\ (QoS_R - QoS_E)/QoS_R; \ Benefit\ QoS \end{cases} \quad (6)$$

User acceptance degree represents the degree that deviates from. It is formulized as

$$\rho_A = \begin{cases} (QoS_T - QoS_R)/QoS_R; \ Cost\ QoS \\ (QoS_R - QoS_T)/QoS_R; \ Benefit\ QoS \end{cases} \quad (7)$$

Recommendation Success Function represents if the selection result satisfies user's requirement. For cost and benefit QoS, $\rho_D \leqslant \rho_A$ indicates that users accept the deviation, so the recommendation is successful; and $\rho_D > \rho_A$ indicates that the deviation exceeds user's acceptance, so the recommendation is failed. It is formulized as

$$S(p) = \{1, \rho_D \leqslant \rho_A 0, \rho_D > \rho_A \quad (8)$$

In addition, behaviors of service providers reflect the trustworthy degree of their services. Classify providers into three types (#A, #B, #C) and $P(A)$, $P(B)$ and $P(C)$ respectively represent the proportion of their numbers.

Provider A represents providers with high credible, who advertise QoS truth fully. They would make QoS_E consistent with QoS_A even if at a profit loss.

Provider B represents providers with medium credit, who try to guarantee user's benefit, although QoS_E varies from QoS_A as uncertain commercial factors.

Provider C represents fraudulent providers, who maliciously overstate advertising QoS for more benefit, resulting that QoS_E deviates much from QoS_A.

4.2 Simulation experiments

The algorithms are programmed by Matlab 2009a and then run the experiments on DELL Optiplex 380 (Intel Core2 E7500 2.93GHz CPU, 1.96GB RAM).

4.2.1 Common parameters assignment

Common parameters assignment is shown as Table 4.

Firstly, set 6 abstract services and each one has 200 services. Select price and reputation as QoS examples, and set value domains as [0,100] and [0,1]; then generate QoS_A randomly in the value domain, and set QoS_R respectively as 60 and 0.8. Set 4 different user acceptance degree [#1,#2,#3,#4] as [5%, 10%, 20%, 30%]; it indicates different QoS thresholds: QoS_T ($Price$) = [63, 66, 72, 78] and QoS_T ($Reputation$) = [0.76, 0.72, 0.64, 0.56]. Set each weight vectors (W_R, W_{BSC}, W_{BCD}) as $[\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}]$, i.e., each service are considered to be equally important; then set adjustable factors ($[\delta_1, \delta_2, \delta_3]$) as $[\frac{1}{3}, \frac{1}{3}, \frac{1}{3}]$, i.e., RL, BSC and BCD

Table 4 Common parameter assignment

Parameters	Value	Description
I	6	Abstract service number
J_i	{200, …, 200}	Service number
{*Price*, *Reputation*}	[0,100], [0,1]	QoS examples
QoS_A	$q_i^A \sim Random$	Service advertising QoS
QoS_R	60, 0.8	User required QoS
ρ_A	[#1, #2, #3, #4]	[5%, 10%, 20%, 30%]
W_R, W_{BSC}, W_{BCD}	[1/6, …, 1/6]	Weight vectors
$[\delta_1, \delta_2, \delta_3]$	[1/3, 1/3, 1/3]	Adjustable factors

are considered to be equally important; finally, generate a certain business correlations randomly.

4.2.2 Experiment parameters assignment

Three group experiments are designed to show the performance of TaSRM as to different service providers. Table 5 sets the parameters of three group experiments.

Table 5 Experiment parameters assignment

NO.	Parameters	Value
1	$P(A)$	100%
	$P(B)$	0
	$P(C)$	0
2	$P(A)$	[100% → 0]
	$P(B)$	[0 → 100%]
	$P(C)$	0
	$q_i^E \sim N(q_i^A, \sigma_i^2)$	$\sigma_i = 0.1$
3	$P(A)$	[100% → 70%]
	$P(B)$	0
	$P(C)$	[0 → 30%]
	$q_i^E \sim N(q_i^A, \sigma_i^2)$	$\sigma_i = 0.4$

Herein, assume the total service number is fixed, and satisfies $P(A) + P(B) + P(C) = 1$. Set execution QoS obey Gaussian distribution as $q_i^E \sim N(q_i^A, \sigma_i^2)$. For Provider A, $q_i^E = q_i^A$; for Provider B, q_i^E has a variation with a standard deviation as $\sigma_i = 0.1$, and the expectation QoS is q_i^A; for Provider C, q_i^E has a variation with a larger standard deviation as $\sigma_i = 0.4$. For cost QoS, q_i^E is larger than q_i^A and for benefit QoS, q_i^E is less than q_i^A.

4.2.3 Model performance experiment

Comparative experiment is designed to verify TaSRM. QoS-SSM (QoS-based services selection model) refers to another of our papers[16], which supports QoS correlationin QoS-based services selection, while does not consider the trust impact. The following shows the three group experiments respectively for Provider A, B and C.

(1) For Provider A

a) Observation

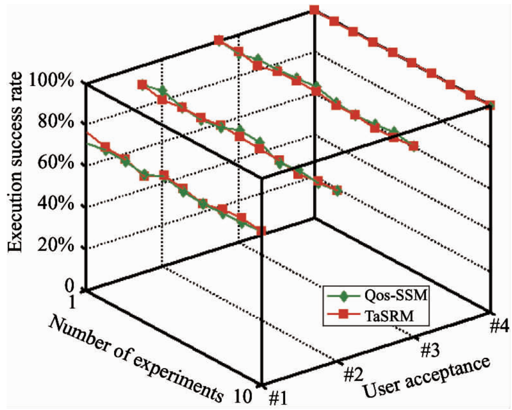

Fig. 4 ESR distribution by interacting with Provider A

b) Description

Table 6 Coordinates of Fig. 4

Coordinate	Value	Description
X	#1, #2, #3, #4	4 types of user acceptance
Y	[1, 10]	Experiment times
Z	[0%, 100%]	Execution success rate

Table 6 shows the coordinates of Fig. 4. For one type user acceptance, one experiment repeats 30 execution times with random QoS to calculate execution success rate (ESR) as Eq. (9). $S(p)$ refers to Eq. (8), which represents the execution times.

$$ESR(p) = \frac{\sum_1^N S(p)}{N} \tag{9}$$

c) Analysis

All services are provided by Provider A. When user acceptance ranges from #4 to #1, user demand becomes stricter and ESR becomes lower. At #4, both models can recommend services satisfying QoS_R at each time, i.e. ESR = 100%, but with acceptance degree decreasing, both models have failed recommendation, i.e. ESR < 100%.

The reason is: all services are credible and QoS_E is equal to QoS_A. Both models can get the optimal BSW-IP by QoS_A. But for stronger user demand, QoS_E of optimal BSW-IP might dissatisfy QoS_R.

(2) For Provider B

a) Observation

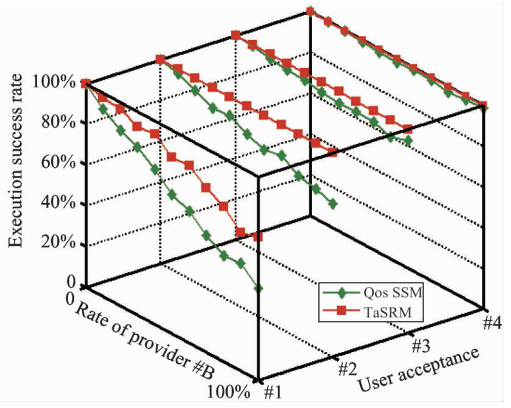

Fig. 5 ESR distribution by interacting with Provider B

b) Description

Table 7 Coordinates of Fig. 5

Coordinate	**Value**	**Description**
X	#1, #2, #3, #4	4 types of user acceptance
Y	[0%, 100%]	Number proportion of Provider B
Z	[0%, 100%]	Execution success rate

Table 7 shows the coordinates of Fig. 5. Coordinate Y represents the proportion of Provider B; the other is Provider A. For one type user acceptance and a certain rate of Provider B, one experiment repeats 30 execution times by random QoS to calculate ESR.

c) Analysis

On one hand, comparing with Fig. 4, ESR of both models is decreasing; on the other hand, for one specific user acceptance type, with the increasing of Provider B rate, TaSRM achieves a higher ESR than QoS-SSM.

(3) For Provider C

a) Observation

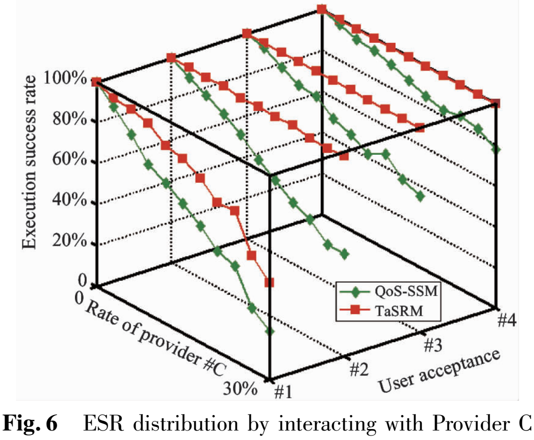

Fig. 6 ESR distribution by interacting with Provider C

b) Description

Table 8 shows the coordinates of Fig. 6. Coordinate Y represents the proportion of Provider C; the other is Provider A. For one type user acceptance and a certain rate of Provider C, one experiment repeats 30 execution times by random QoS to calculate ESR.

Table 8 Coordinates of Fig. 6

Coordinate	**Value**	**Description**
X	#1, #2, #3, #4	4 types of user acceptance
Y	[0%, 30%]	Number proportion of Provider C
Z	[0%, 100%]	Execution success rate

c) Analysis

Fig. 6 and Fig. 5 have different coordinate Y scales, one is [0%, 30%] and the other is [0%, 100%]. It indicates that ESR falls severely when Provider C increases and an example is shown in Table 9.

Table 9 ESR Comparison (Provider B and Provider C)

User Acceptance	**Proportion**	**ESR of QoS-SSM**	**ESR of TaSRM**
#1	$P(B) = 30\%$	74.31%	88.12%
#1	$P(C) = 30\%$	23.37%	47.52%

Obviously, if $P(C)$ continues increasing, ESR will fall more severely, and even no successful recommendation.

In conclusion, Provider B and C can't guarantee $QoS_E = QoS_A$ after delivery. QoS-SSM just depends on QoS_A, so it is unaware of QoS change, and ESR will decrease more certainly. For TaSRM, before delivery, TaSRM evaluates and sorts the trust value of feasible BSW-IP, then selects the most trustworthy one. According to QoS_A, BSW-IP by TaSRM might not have the optimal composite QoS, but it's the most trustworthy one to make QoS_E consistent with QoS_A. Thus, TaSRM can identify malicious services and resist their selection.

In conclusion, from Fig. 5 and Fig. 6, ESR of TaSRM is obviously higher than QoS-SSM, especially when the number of malicious services is increasing.

D. Execution efficiency experiment

An appropriate execution time can make recommendation effective. Herein, change the number of abstract service and service to simulate different service workflows. 5 type workflows are constructed in Table 10.

a) Observation

b) Description

Coordinate X represents different workflow types, and coordinate Y represents execution time. Execution time of QoS-SSM contains one step[16] and TaSRM contains two steps: QoS-based services selection (Step 1) and Trust-based services recommendation (Step 2).

Table 10 Scale of services workflows

NO.	Abstract Service Number	Service Number
#1	6	[200, …, 200]
#2	6	[400, …, 400]
#3	10	[400, …, 400]
#4	15	[400, …, 400]
#5	20	[400, …, 400]

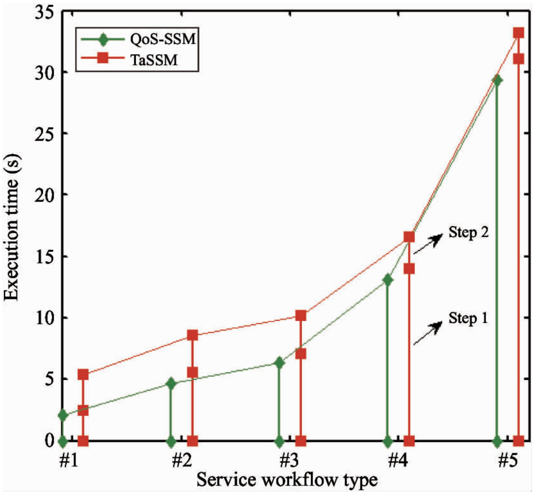

Fig. 7 Statistics of execution time

c) Analysis

The statistics of Fig. 7 is presented in Table 11.

Table 11 Statistics of execution time

NO.	QoS-SSM	TaSRM: Step 1	TaSRM: Step 2
#1	2.1	2.3	2.9
#2	4.6	5.1	3.0
#3	6.3	7.1	3.1
#4	13.1	14.1	2.3
#5	29.3	31.1	2.2

With workflow's scale increasing, the execution times of two models are increased. The execution time of TaSRM's Step 1 is close to QoS-SSM; TaSRM's Step 2 adds an execution time with the range of [2.2s, 3.1s].

Through analysis, QoS-SSM is to optimize the nonlinear combination of multi dimensional QoS[16], thus QoS-SSM depends on the numbers of abstract service and service; while trust measurement in TaSRM (Step 2) depends on the limited number of feasible BSW-IP from Step 1. Thus, Step 2 in TaSRM is less-complex than Step 1 and consumes less time.

Therefore, although TaSRM adds a certain time comparing with QoS-SSM, it can get the trustworthy BSW-IP within the effective execution time. Further, TaSRM can recommend more reliable BSW-IP to users, as considering both QoS and trust for selection.

E. Empirical study and insight

For the real service system, an online marine logistic service platform (OMLSP)[17] is selected for investigation. It is a typical business services system with 5 main abstract services, including forwarder, ship owner, ship agency, insurance agency and online payment service. OMLSP just provides QoS query with single abstract service, e.g. querying ship agency by freight charge or reputation will return a list of ranked ship agencies. But it may be hard for users to select other services and composite a whole BSW-IP. Therefore, if assess trust value and apply TaSRM, the trustworthy BSW-IP can be obtained. For example, BSW-IP recommendation might be {forwarder 1, ship owner 4, ship agency 5, insurance agent 2, payment 2}, while not a single {ship agency 3}.

In this perspective, trust assessment mechanism and TaSRM is feasible and effective to enhance the recommendation accuracy and user experience.

5 Conclusions

Services selection is a significant problem in business service management. This paper devotes to a trustworthy service recommendation to enhance the accuracy and reliability of QoS-based services selection.

First, TN-BSW is established to combine service reputation (Node-trust) and business correlation trust (Link-trust); then the corresponding trust measurement system is proposed to calculate the trust utility value; based on it, the trust-aware service recommendation model can filter unreliable service and recommend trustworthy BSW-IP; finally, an experiment verifies the feasibility of TN-BSW and the performance of TaSRM.

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