An Intelligent Economic Approach for Dynamic Resource Allocation in Cloud Services

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Abstract—With Inter-Cloud, distributed cloud and open cloud exchange (OCX) emerging, a comprehensive resource allocation approach is fundamental to highly competitive cloud market. Oriented to infrastructure as a service (IaaS), an intelligent economic approach for dynamic resource allocation (IEDA) is proposed with the improved combinatorial double auction protocol devised to enable various kinds of resources traded among multiple consumers and multiple providers at the same time enable task partitioning among multiple providers. To make bidding and asking reasonable in each round of the auction and determine eligible transaction relationship among providers and consumers, a price formation mechanism is proposed, which is consisted of a back propagation neural network (BPNN) based price prediction algorithm and a price matching algorithm. A reputation system is proposed and integrated to exclude dishonest participants from the cloud market. The winner determination problem (WDP) is solved by the improved paddy field algorithm (PFA). Simulation results have shown that IEDA can not only help maximize market surplus and surplus strength but also encourage participants to be honest.

Index Terms—Cloud, resource allocation, combinatorial double auction, price formation, reputation

1 Introduction

Cloud computing provides virtually unlimited computing power as utility service to consumers. It enables different provisioning models for on-demand access to applications (software as a service, or SaaS), platforms (platform as a service, or PaaS), and computing infrastructures (IaaS). It has created a competitive market where consumers pay providers for using resources and are usually billed using a pay-as-you-go model. To facilitate trading, a market mechanism should be explored to allocate and utilize resources within their capacities without over-provisioning or under-provisioning [1].

Resources in the cloud are usually geographically distributed; may be heterogeneous and owned by multiple organizations with different usage and cost policies. A large number of self-interested providers and consumers coexist. Resource allocation and reclamation can occur at any time with supply and demand relation varying frequently, and resource usage cannot be fully anticipated. Many issues, such as automatic resource provisioning, multi-objective multi-task scheduling, and workflow scheduling, must be solved [2], [3]. Especially, resource allocation must cater to the nature of decentralization, heterogeneity, and dynamics of cloud. Since economics is concerned with resource allocation among individuals with different objectives in human societies, many economic models have been applied to cloud resource allocation [4].

Although the fixed-price based approaches (for example, commodity market model and posted price model) are used in cloud, they are economically inefficient [5]. In contrast, auction-based approaches are economically efficient and belong to dynamic pricing [5]. Components of a cloud market can be categorized into buyers (consumers), sellers (providers), and auctioneers. Buyers are charged for their consumed resources based on their valuations, and thus competitions among buyers and also among sellers are encouraged. Auction offers incentive not only for sellers to provide their resources to get profits, but also for buyers to back off when necessary, regulating supply and demand to arrive at market equilibrium. It can cope with diverse and conflicting interests of participants, match dynamic supply and demand, and enable participants to make independent decisions.

Due to the above highly desirable advantages of the auction, many auction based resource allocation approaches have been proposed (see Section 2 for details), and some cloud service providers have already used auction to sell their resources, for example, spot instances in Amazon's EC2 [6]. With cloud computing becoming more and more popular and commercial cloud services being widely available, especially as Inter-Cloud, distributed cloud, and OCX are emerging, a cloud market is now really complex and increasingly competitive [7], [8], [9]. In such an environment, a consumer may apply for and a provider may provide various kinds of services and their combinations in

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terms of resources, making the problem more difficult than focusing on only one of them and calling for combinatorial auction [10]; at the same time, appropriate resources may be available from a number of providers, and a large number of consumers may compete for the same resources, that is, providers and consumers are treated symmetrically with providers submitting asks and consumers submitting bids, calling for double auction [11]; hence, combinatorial double auction should be provided [11]. In addition, the resources demanded by a consumer may be offered by one provider alone, or by multiple providers jointly in order to, for example, optimize market profits, balance system load, or partition an extra-large task among several providers, which cannot be accommodated by any single provider, especially in Inter-Cloud or distributed cloud. This cannot be supported by [10], [11] and other related solutions. Therefore, we improve the combinatorial double auction further to enable task partitioning among multiple providers.

In each round of the auction, consumers and providers submit their bidding and asking prices. Both price-related factors (for example, budget) and non-price factors (for example, resource usage time-frame) can significantly influence their offers. Not only instant market status (for example, supply and demand relation) but also historical market experience (for example, historical transaction price) affects their pricing decisions. Thus, a price formation mechanism, which is adaptive to cloud market dynamics, is highly desired. It can be done automatically with agents introduced on behalf of participants, not only freeing participants from such complex decision making but also representing them to make rational offers and determine eligible transaction relationship. This not only significantly reduces or even eliminates possibility of participants to perform strategic behaviors, but also helps greatly speed up the auction process.

There inevitably exist some dishonest participants in cloud market. Auction is vulnerable to strategic behaviors of participants, and its trustfulness depends on participants' honesty and their free competition. Trustful design for auction, for example, the randomized auction, can be devised to discourage participants from dishonest behaviors, and its effectiveness of the resultant auction mechanism has been proven by [10], [11], [12], [13], [14]. Reputation [15] is another good way to motivate honest interaction among participants, and participant reputation can significantly affect resource allocation decision. A reputation system can enforce confidence among participants and suppress their strategic behaviors [16]. For example, one hospital wants to outsource its patients' medical records to a cloud. With reputation system, the hospital can choose a cloud provider which is honest enough to ensure all medical records kept in privacy with a reasonable service billing, and the cloud provider can ascertain that the hospital is an honest consumer which never intentionally damages or misuses cloud resources with an guaranteed paying. In this paper, a novel reputation system is proposed and integrated into IEDA, and then free competition is encouraged and trustful auction is boosted.

At the end of the auction, which provider offers the demanded service to which consumer based on the eligible transaction relationship at the same time whether and how a demanded service should be carried out by multiple providers jointly are decided. A winner determination algorithm (WDA) is needed so that those participants, who can not only bring high economic efficiency but also have good reputation, are chosen as winners.

The interactions during the auction, such as bidding, asking, reputation judgment, and winner determination, should be done automatically without human intervention as much as possible to improve participant quality of experience (QoE) [17] and enhance auction trustfulness.

In fact, a comprehensive cloud resource allocation approach is really fundamental in such a challenging cloud market. Oriented to IaaS, we propose IEDA to allocate the following basic resources: processing, memory, storage, network bandwidth. In particular, we consider the following basic services: virtual machine service (*VMS*), computation service (*CPS*), database service (*DBS*), and storage service (*STS*). The major contributions of this paper are as follows. (1) With integration and necessary improvement of existing techniques, the IEDA system framework is proposed to comprehensively deal with the aforementioned resource allocation challenges, and agents are introduced to enable process automation. (2) An improved combinatorial double auction protocol is devised to enable various kinds of resources traded among multiple consumers and multiple providers, and at the same time enable task partitioning among multiple providers. (3) A price formation mechanism is devised. A BPNN [18] based price prediction algorithm is proposed with instant and historical price and non-price factors considered to make bidding and asking reasonable; a price matching algorithm is proposed to determine eligible transaction relationship among consumers and providers. (4) A reputation scheme is devised based on the performance of a participant in the auction to exclude the dishonest one from the market. (5) The PFA [19] is improved and a WDA is proposed, called WDAPFA. Participants, who can bring the maximum market surplus and surplus strength and have the highest reputations, are preferred to be winners. Thus, IEDA is economic efficient and trustful.

The rest of this paper is organized as follows. In Section 2, we review related works and compare our work with them. In Section 3, we provide the IEDA system framework. In Section 4, we describe the proposed reputation system. In Section 5, we present the improved combinatorial double auction protocol, including tender description, price formation, and winner determination. In Section 6, we describe simulations and performance evaluations. We draw conclusions in Section 7.

2 Related Work

A lot of auction based cloud resource allocation researches have been done. In [20], several resource allocation strategies based on a reverse auction model for allocating one type of cloud resource from different providers are investigated. In [21], a reverse batch matching auction is proposed for allocating various kinds of cloud resources from different providers. In [14], a truthful online auction mechanism is proposed for a provider to allocate one type of cloud resource among consumers with heterogeneous demands. In [22], a continuous double auction mechanism is designed

to enable consumers and providers to bid and offer one type of cloud resource. In [23], a knowledge based continuous double auction model is proposed to trade one type of cloud resource. In [24], a non-additive negotiation model is proposed with multiple objectives considered, by which a provider can efficiently allocate various kinds of resources to a consumer. In [13], cloud resource allocation is done through the auction of different types of *VM* instances, and a randomized combinatorial auction is proposed, which is computationally efficient and truthful in expectation with guaranteed social welfare approximation factor. In [10], an online combinatorial auction framework is proposed, which can optimize system efficiency across temporal domain and model dynamic provisioning of heterogeneous *VM* types. In [12], a suite of truthful and computationally efficient auction mechanisms for cloud resource pricing are proposed with the multi-unit combinatorial auction problem solved. In [11], a combinatorial double auction cloud resource allocation model is proposed, allowing double-sided competition and bidding on bundles of items. However, the aforementioned researches cannot deal with transactions of various kinds of resources among multiple consumers and multiple providers with task partitioning among multiple providers enabled, which is solved by our work. In addition, we consider *VMS*, *CPS*, *DBS*, and *STS*, which usually provided in IaaS cloud; in contrast, [10], [11], [12], [13] only consider *VMS*.

A lot of price formation mechanisms have been proposed. In [5], [14], [21], [24], [25], [26], bidding and asking prices are given directly, not reflecting supply and demand relation. In [27], the asking price is determined by a dynamic pricing scheme based on instant supply and demand information. In [20], the asking price is calculated based on instant capacity information or historical win/loss ratio information. In [22], bidding and asking prices are determined by a two-stage game strategy based on historical price information. In [23], bidding and asking prices are determined by a learning algorithm based on historical price information. In [28], a genetic model based on both price and non-price historical information is proposed to offer suitable price, however, it does not adapt to rapid market changes. Encouraged by the successful application of the artificial neural network (ANN), for example, in stock market forecasting [29], we propose an ANN based price prediction algorithm, and especially due to BPNN's strong self-adaptability, we choose BPNN. We use historical transaction samples to train BPNN and input instant information to BPNN to predict bidding and asking prices. We further propose a price matching algorithm to determine eligible transaction relationship among consumers and providers. Different from the [5], [14], [20], [21], [22], [23], [24], [25], [26], [27], [28], our method considers instant and historical price and non-price factors, which all influence bidding and asking prices, and at the same time has strong adaptability. It focuses on cloud rather than stock market with factors considered different from those surveyed in [29].

There have been researches on solving WDP. In [20], [22], [23], winners are simply determined by price matching. In [5], winners are determined by bid density greedily during combinatorial auction provision to maximize provider profit. In [21], an immune evolutionary algorithm is applied to solve WDP to maximize the difference between asking price and bidding price. In [14], WDP is solved to maximize the consumer utility gain with an auxiliary pricing function. In [24], a consumer chooses the provider to maximize the defined non-additive utility function. In [25], based on Karush-Kuhn-Tucker (KKT) conditions in the convex optimization theory, winners are determined to minimize task executing time. In [26], WDP is solved by the linear mixed integer programming to maximize the total difference between consumer budgets and provider costs. Our goal is different; we try to maximize market surplus, surplus strength and participant reputation with task partitioning among providers under multiple constraints. Due to the NP-hardness of WDP in combinatorial double auction [26], the improved PFA is devised to find the optimal solution.

Participant honesty is necessary to ensure auction trustfulness. In [5], [20], [21], [22], [23], [24], [25], [26], participants are simply assumed honest. In [10], [11], [12], [13], [14], trustful auction mechanisms are designed without reputation system integrated. In [30], a cheat-proof trust model is proposed to make participants be honest to others. The overall trust from *A* to *B* has two parts, one is what *A* directly knows about *B*, and the other is what the others say about *B*. Different from [30] and others, our proposed reputation system does not aim at any special kind of dishonest behaviors. It derives a participant's honesty from his actual performance in the auction and can effectively deal with participant dishonesty.

3 System Framework

At the outset, we list in Table 1 the abbreviations used throughout this paper.

The system framework of the proposed IEDA consists of five roles: *CSP*, *PA*, *CSC*, *CA*, and *AI*, shown in Fig. 1. A *CSP* provides services in terms of resources. A *CSC* generates service demands and leases resources. The *PA* and the *CA* provide necessary support to *CSP* and *CSC*, for example, submitting tender, predicting price, etc. *AI* is an agent in charge of, for example, collecting tender, running WDA, informing auction result and managing reputation system, etc. *AI*, *PA* and *CA* together relieve *CSC*s and *CSP*s of the complicated interaction process for efficient resource allocation. What a *CSC* and a *CSP* need to do is to provide the related information, wait for the result, and then evaluate his partner's performance.

The workflow of the proposed IEDA is described as follows and shown in Fig. 2.

At first, when a *CSC* requests services, he provides the related information to his *CA*, such as the demanded resources and his own budget, then the *CA* makes the initial tenders; when a *CSP* can provide services, he provides the related information to his *PA*, then the *PA* makes the initial tenders; see Section 5.1 for details.

Second, the *CA* and the *PA* use price prediction algorithm (see Section 5.2.1) to get bidding and asking prices, put these prices into the corresponding initial tenders, and then submit these updated tenders to *AI*.

Third, *AI* collects tenders and performs the price matching algorithm (see Section 5.2.2) to determine the eligible transaction relationship among *CSC*s and *CSP*s.

TABLE 1
Abbreviations

Abbreviation	Full Name	Abbreviation	Full Name
CSP	Cloud Service Provider	CSC	Cloud Service Consumer
PA	Provider Agent	CA	Consumer Agent
AI	Auction Intermediary	CID	Consumer IDentifier
DS	Demanded Service	BPoDS	Bidding Price of DS
ToDS	Type of DS	SToDS	Starting Time of DS
EToDS	Ending Time of DS	CPUSDS	CPU Speed of DS
MI	Million Instructions	MIPS	MI Per Second
MEM	MEMory	MEMCDS	MEM Capacity of DS
GB	Giga Bytes	STO	STOrage
STOCDS	STO Capacity of DS	NETB	NETwork Bandwidth
NETBDS	NETB of DS	TS	Task Size
DV	Data Volume	MPN	Maximum Partition Number
P&SoDS	Platform and Software of DS	MREPCSP	the required Minimum REPutation to CSP
PID	Provider IDentifier	SS	Supplied Service
PoCPUoSS	Price of CPU of SS	CPUSSS	CPU Speed of SS
PoMEMoSS	Price of MEM of SS	MEMCSS	MEM Capacity of SS
PoSTOoSS	Price of STO of SS	STOCSS	STO Capacity of SS
PoNBoSS	Price of NETB of SS	NETBSS	NETB of SS
SToSS	Starting Time of SS	EToSS	Ending Time of SS
P&SoSS	Platform and Software of SS	MREPCSC	the required Minimum REPutation to CSC
SDR	Supply and Demand Ratio	BUD	BUDget
REP	REPutation	CST	CoST
TF	Time-Frame	APoRU	Asking Price of the Resource per Unit
TLS	TotaL Surplus	TUS	Total Unit Surplus
TRP	Total RePutation	MOO	Multi-Objective Optimization
SOO	Single-Objective Optimization	WSM	Weighted Sum Method
GA	Genetic Algorithm	SPD	SuPeriority Degree
AHP	Analytic Hierarchy Process	LSIA	Local Search Improvement Algorithm
CDA	Continuous Double Auction	SCDA	Stable CDA
TWR	Total Winning Rate	DWR	Dishonest Winning Rate
GM	Greedy Method	Mbps	Million bits per second

Fourthly, *AI* runs WDAPFA (see Section 5.3) to determine the auction winners and informs *CSC*s and *CSP*s of the result. Then, the *CSP* winners provide services to the *CSC* winners with payments from the latter to the former.

Finally, after the auction, each *CSC*/*CSP* evaluates his partner's performance according to his own QoE on the transaction and submits his evaluation to *AI*, and then *AI* updates *CSC* and *CSP*'s reputation correspondingly (see Section 4).

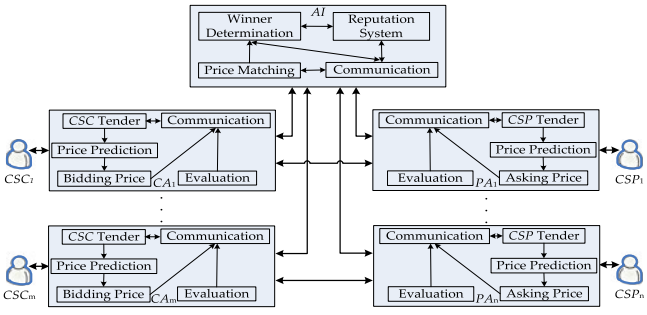


Fig. 1. The IEDA system framework.

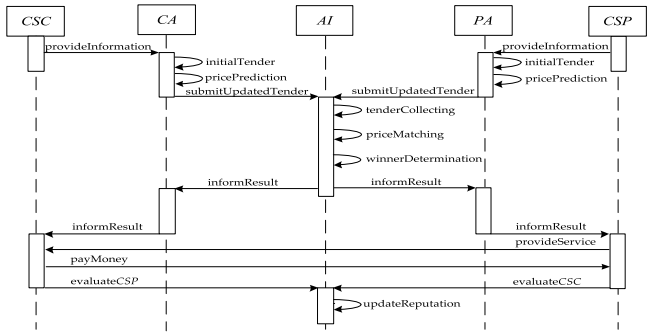


Fig. 2. The IEDA workflow.

From the above IEDA workflow, one possibility for a *CSC* to tell lies is that he provides a misleading budget on his demanded service at the beginning of the auction. If his provided budget was intentionally increased, even if he won the auction, he would pay a higher bid than what he should pay because of the competition, which is not what he expects. If his provided budget was intentionally reduced, he would lose the winning opportunity in the competition due to his lower bids. Another possibility is that he dishonestly evaluates his partner's performance after the auction, and his dishonest behavior will be punished by our proposed reputation system. There are no other chances for a *CSC* to tell lies during the auction due to IEDA process automation. For a *CSP*, he can provide a misleading cost on his offered service or dishonestly evaluate his partner's performance; the situation is similar to that of a *CSC*. Therefore, with price formation, reputation, WDAPFA and agent integrated, IEDA can promote the economic efficiency and the trustfulness of the auction.

The following simple illustration example will be used throughout this paper to help clarify the discussion: there are four *CSC*s and six *CSP*s, all *CSP*s only provide *STS* and all *CSC*s only consume *STS*.

4 Reputation System

4.1 Basic Idea

Our proposed reputation system obeys the following intuitions. (I1) If a participant takes part in auction frequently and his turnover is high, his reputation should be high, and vice versa. (I2) If a participant gets high evaluations on QoEs from his trading partners, his reputation should be high, and vice versa. (I3) If a participant evaluates his trading partners objectively, that is, he is honest to his partners, his evaluations on his partners should be creditworthy, and vice versa. During the auction, *AI* makes participants with good reputations winning chance high. After the auction, each participant evaluates his partners' actual performances based on his QoEs on the transactions, and *AI* updates these participants' reputations. If a participant's evaluation value is much different from his partner's previous reputation, *AI* considers him to be slightly or seriously dishonest according to how big the difference is. If a participant has been considered slightly dishonest the prescribed consecutive times or seriously dishonest once, he is excluded from the market. Thus, the honesty is encouraged and the dishonesty is punished.

4.2 Reputation Computation

The *CSP*'s reputation is computed as follows:

$$p\_rep_{jk} = de(\Delta t_{k-1}^{k}) \times \frac{total\_tr_{j(k-1)}}{total\_tr_{jk}} \times p\_rep_{j(k-1)} + \left(1 - de(\Delta t_{k-1}^{k})\right) \times \frac{\sum_i RPM_{ijk} \times price_{ijk} \times QoE_{ijk} \times CR_{ijk}}{total\_tr_{jk} - total\_tr_{j(k-1)}} \tag{1}$$

$$de(\Delta t_{k-1}^{k}) = \begin{cases} 1 & \Delta t_{k-1}^{k} < t_{\min} \text{ and } k > 1 \\ \frac{t_{\max} - \Delta t_{k-1}^{k}}{t_{\max} - t_{\min}} & t_{\min} \le \Delta t_{k-1}^{k} \le t_{\max} \text{ and } k > 1 \\ 0 & t_{\max} < \Delta t_{k-1}^{k} \text{ or } k = 1 \end{cases} \tag{2}$$

$$CR_{ijk} = \frac{N_{ijk} - N_{ijk*}}{N_{ijk}}. \tag{3}$$

Here, p_rep_{jk} is the CSP_j's reputation after the kth auction. $total\_tr_{jk}$ is the accumulated turnovers of CSP_j after the kth auction. RPM_{ijk}, $price_{ijk}$ and $RPM_{ijk} \times price_{ijk}$ are trading volume, transaction price and turnover between CSP_j and CSC_i in the kth auction respectively. $QoE_{ijk} \in [0, 1]$ is the evaluation of CSC_i on CSP_j's performance in the kth auction which reflects his QoE to CSP_j, where 1 denotes complete satisfaction and 0 entire dissatisfaction, and CSC_i submits it to *AI* after the auction. $de(\Delta t_{k-1}^{k})$, defined in (2), is the time decay coefficient to reflect the decrement degree of reputation with time passing, where Δt_{k-1}^{k} is the time interval between the kth auction and the (k-1)th auction which CSP_j took part in, t_{min} and t_{max} are the lower and upper experienced threshold respectively. CR_{ijk} is creditworthiness degree of CSC_i to CSP_j in the kth auction and defined in (3). If $Diff = \left|QoE_{ijk} - p\_rep_{j(k-1)}\right|$, that is, the difference between CSP_j's current evaluation value on CSP_j and CSP_j's previous reputation, is too big, *AI* considers that the CSC_i's evaluation on CSP_j is not objective, and whether CSC_i is slightly or seriously dishonest depends on how big $Diff$ is. N_{ijk} is the total times of CSC_i evaluating CSP_j up to the kth auction, and N_{ijk*} is the times which CSC_i is considered to be dishonest.

The reputation value is between 0 and 1. Initially, all participants' reputation values, for example, p_rep_{j0}, are set to be 0.5, that is, their default honesties are "average", because *AI* has no experience with them and cannot evaluate their honesties before they enter the cloud market.

The *CSC*'s reputation computation is similar to *CSP*'s. Due to limited space, we do not describe it in detail.

For the example in Section 3, assume that in the 10th auction CSC_1 and CSC_2 have transactions with CSP_1 and have the following data: $total\_tr_{1,9} = \$56$, $p\_rep_{1,9} = 0.6$, $RPM_{1,1,10} = 0.5, RPM_{2,1,10} = 0.5, QoE_{1,1,10} = 0.5$, $QoE_{2,1,10} = 0.6, price_{1,1,10} = \$9.3, price_{2,1,10} = \$8.6, \Delta t_9^{10} = 400$ hour, $t_{min} = 300$ hour, $t_{max} = 800$ hour, $N_{1,1,10} = 10, N_{1,1,10*} = 0$, $N_{2,1,10} = 10, N_{2,1,10*} = 1$, we get $de(\Delta t_9^{10}) = 0.8$, $total\_tr_{1,10} = total\_tr_{1,9} + RPM_{1,1,10} \times price_{1,1,10} + RPM_{2,1,10} \times price_{2,1,10} = \$65.0$, $CR_{1,1,10} = 1$, $CR_{2,1,10} = 0.9$, then after the 10th auction, the reputation of CSP_1 is updated as $p\_rep_{1,10} = 0.5$ by (1). By the way, in this paper, just for simplicity, when we do calculation for the example in Section 3, we only keep one decimal place in the calculation result.

TABLE 2
CSC Tenders

Attribute \ Service	*VMS*	*CPS*	*DBS*	*STS*
CID	√	√	√	√
BPoDS	√	√	√	√
ToDS	√	√	√	√
SToDS	√	√	√	√
EToDS	√	√	√	√
CPUSDS	√	√	×	×
MEMCDS	√	×	√	×
STOCDS	√	×	√	√
NETBDS	√	×	√	×
TS	×	√	×	×
DV	×	×	√	×
MPN	×	√	√	√
P&SoDS	√	√	√	√
MREPCSP	√	√	√	√

5 Combinatorial Double Auction Protocol

5.1 Tender Description

5.1.1 CSC Tender

The attributes, which a *CSC* tender could have, are as follows: *CID*, to identify a *CSC* uniquely in the cloud market; *BPoDS*, to denote a *CSC*'s bidding price to the demanded service with unit \$; *ToDS*, to denote the type of service that a *CSC* demands; *SToDS*, to denote when the *CSC* demanded service begins; *EToDS*, to denote when the *CSC* demanded service ends; *CPUSDS*, to denote the CPU speed asked by the *CSC* demanded service with unit MIPS; *MEMCDS*, to denote the memory capacity asked by the *CSC* demanded service with unit GB; *STOCDS*, to denote the storage capacity asked by the *CSC* demanded service with unit GB; *NETBDS*, to denote the network bandwidth asked by the *CSC* demanded service with unit Mbps; *TS*, to denote the size of the executed task asked by the *CSC* demanded service with unit MI; *DV*, to denote the volume of the processed data asked by the *CSC* demanded service with unit GB; *MPN*, to denote the maximum allowed number of *CSP*s to execute the *CSC* demanded service jointly (A task could be partitioned to be executed by several *CSP*s; however, it should not be partitioned into too many tiny parts in order to avoid too much communication and coordination overhead. A *CSC* can set *MPN* to do so.); *P&SoDS*, to denote the specific platform and software environment needed by the *CSC* demanded service; *MREPCSP*, to denote the required minimum reputation to *CSP*.

In fact, the tenders of a *CSC* to *VMS*, *CPS*, *DBS* and *STS* are subsets of the above attributes, listed in Table 2, where '√' means that the tender has the corresponding attribute and '×' means no.

5.1.2 CSP Tender

The attributes, which a *CSP* tender could have, are as follows: *PID*, to identify a *CSP* uniquely in the cloud market; *PoCPUoSS*, to denote the CPU price of the *CSP* supplied service with unit \$/(MIPS × hour); *CPUSSS*, to denote the CPU speed of the *CSP* supplied service with unit MIPS; *PoMEMoSS*, to denote the memory price of the *CSP*

TABLE 3
CSP Tenders

Attribute \ Service	*VMS*	*CPS*	*DBS*	*STS*
PID	√	√	√	√
PoCPUoSS	√	√	×	×
CPUSSS	√	√	×	×
PoMEMoSS	√	×	√	×
MEMCSS	√	×	√	×
PoSTOoSS	√	×	√	√
STOCSS	√	×	√	√
PoNBoSS	√	×	√	×
NETBSS	√	×	√	×
SToSS	√	√	√	√
EToSS	√	√	√	√
P&SoSS	√	√	√	√
MREPCSC	√	√	√	√

supplied service with unit \$/(GB × hour); *MEMCSS*, to denote the memory capacity of the *CSP* supplied service with unit GB; *PoSTOoSS*, to denote the storage price of the *CSP* supplied service with unit \$/(GB × hour); *STOCSS*, to denote the storage capacity of the *CSP* supplied service with unit GB; *PoNBoSS*, to denote the network bandwidth price of the *CSP* supplied service with unit \$/(Mbps × hour); *NETBSS*, to denote the network bandwidth of the *CSP* supplied service with unit Mbps; *SToSS*, to denote when the *CSP* supplied service begins; *EToSS*, to denote when the *CSP* supplied service ends; *P&SoSS*, to denote the platform and software environment of the *CSP* supplied service; *MREPCSC*, to denote the required minimum reputation to *CSC*. The tenders of a *CSP* are listed in Table 3.

For the example in Section 3, the tenders of four *CSC*s and six *CSP*s are labeled as c_exp1-4 and p_exp1-6 respectively and given as follows.

c_exp1:{"CSC_1",\$3.1,STS,2015-6-5-6:00,2015-6-10-9:00,,, 100GB,,,,3, {Linux},0.4},

c_exp2:{"CSC_2",\$4.0,STS,2015-6-2-5:00,2015-6-6-00:00,,, 120GB,,,,3, {Linux},0.5},

c_exp3:{"CSC_3",\$7.0,STS,2015-6-8-7:00,2015-6-11-10:00,,, 200GB,,,,4, {Linux},0.5},

c_exp4:{"CSC_4",\$9.0,STS,2015-6-12–8:00,2015-6-17-9:00,,, 150GB,,,,3, {Linux},0.4}.

p_exp1:{"CSP_1",,,,,\$0.00026/(GB×hour),120GB,,,2015-6-1-0:00,2015-6-20-0:00,{Linux},0.7},

p_exp2:{"CSP_2",,,,,\$0.00031/(GB×hour),100GB,,,2015-6-1-1:00,2015-6-21-21:00, {Linux},0.6},

p_exp3:{"CSP_3",,,,,\$0.00029/(GB×hour),120GB,,,2015-6-1-2:00,2015-6-17-20:00, {Linux},0.6},

p_exp4:{"CSP_4",,,,,\$0.00037/(GB×hour),95GB,,,2015-6-1-3:00,2015-6-20-18:00, {Linux},0.8},

p_exp5:{"CSP_5",,,,,\$0.00045/(GB×hour),80GB,,,2015-6-1-4:00,2015-6-21-17:00, {Linux},0.5},

p_exp6:{"CSP_6",,,,,\$0.00055/(GB×hour),150GB,,,2015-6-1-5:00,2015-6-20-15:00, {Linux},0.7}.

For example, c_exp1 means that CSC_1 is willing to pay \$3.1 for 100 GB storage between 2015-6-5-6:00 and 2015-6-10-9:00, the maximum allowed number of *CSP*s is 3, the supporting platform and software environment is *Linux*, and the *CSP*'s reputation is at least 0.4; p_exp1 represents that CSP_1's storage unit price is \$0.00026/(GB×hour), it can provide 120 GB storage between 2015-6-1-0:00 and 2015-6-20-0:00, the supporting platform and software environment is *Linux*, and the *CSC* reputation is at least 0.7.

5.2 Price Formation

5.2.1 Price Prediction

A price prediction algorithm is proposed for *CA*s and *PA*s respectively. Just for simplicity, we only consider *SDR*, *BUD*, *REP*, *TF* for *CSC*s, and *SDR*, *CST*, *REP*, *TF* for *CSP*s. Among them, *SDR*, *BUD* and *CST* are price factors and others are none-price ones.

If *SDR* is lower, the *CSC*/*CSP* bidding/asking price should be higher, otherwise lower. *BUD* is the *CSC*'s budget of the demanded service and is the upper bound of his bidding price. *REP* is the lowest reputation that a *CSC*/*CSP* asks *CSP*s/*CSC*s to have. *TF* is the period during which the *CSC*'s demanded service is used; if it is in peak period or prime time, the *CSC*/*CSP* bidding/asking price should be higher, otherwise lower. *CST* is the *CSP*'s cost of the supplied service and is the lower bound of his asking price.

In this paper, the linear exponential smoothing method [31] is used to estimate the expected *SDR* of each type of service in the *k*th price matching, denoted as $SDR_k^{P,TS}$.

$$SDR_k^{P,TS} = \psi SDR_{k-1}^{A,TS} + (1-\psi)SDR_{k-1}^{P,TS}. \tag{4}$$

Here, ψ is the smoothing coefficient, $0 \le \psi \le 1$; $SDR_{k-1}^{P,TS}$ and $SDR_{k-1}^{A,TS}$ are predicted and actual *SDR* of *TS* service in the $(k-1)$th price matching, *TS* represents *VMS*, *CPS*, *DBS* or *STS*. We assume that the initial supply and demand are in balance with $SDR_0^{P,TS} = SDR_0^{A,TS} = 1$. *AI* calculates the actual *SDR* of each type of resource by (5) in the *k*th price matching and publishes it after the *k*th price matching.

$$SDR_k^{A,TR} = \frac{\sum_{j=1}^{n} SUP_{j,k}^{TR}}{\sum_{i=1}^{m} DEM_{i,k}^{TR}}. \tag{5}$$

Here, $SUP_{j,k}^{TR}$ and $DEM_{i,k}^{TR}$ are the amount of *TR* resource supplied by CSP_j and the amount of *TR* resource demanded by CSC_i in the *k*th price matching, *TR* represents CPU, MEM, STO and NETB. Then, *CSC* obtains the actual *SDR* of each type of service in the *k*th price matching by (6)-(9).

$$SDR_k^{A,VMS} = \min(SDR_k^{A,CPU}, SDR_k^{A,MEM}, SDR_k^{A,STO}, SDR_k^{A,NETB}) \tag{6}$$

$$SDR_k^{A,CPS} = SDR_k^{A,CPU} \tag{7}$$

$$SDR_k^{A,DBS} = \min(SDR_k^{A,MEM}, SDR_k^{A,STO}, SDR_k^{A,NETB}) \tag{8}$$

$$SDR_k^{A,STS} = SDR_k^{A,STO}. \tag{9}$$

VMS is involved in CPU, MEM, STO and NETB usage, and we use the minimum of their *SDR*s to be *VMS*'s *SDR*. The *SDR*s of *CPS*, *DBS* and *STS* are defined similarly.

We use BPNN to predict price based on historical samples if sufficient, which accumulated from previous

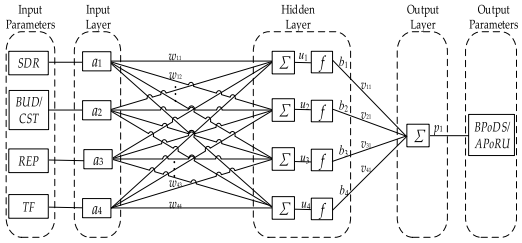


Fig. 3. The BPNN structure.

auctions (see line 24 of WDAPFA and the last paragraph in Section 5.3.2), and instant input information. The BPNN has three layers, shown in Fig. 3. Its hidden layer contains four nodes corresponding to the four considered factors and *f* is the log_sigmoid function as follows.

$$f(x) = \frac{1}{1 + e^{-x}}. \tag{10}$$

The *CA*'s BPNN based bidding price prediction algorithm is described as follows.

At first, Algorithm1 judges whether BPNN has been trained with sufficient samples (line 3): if so, the bidding price is predicted by BPNN (lines 11-22) and the supply-and-demand relation is adjusted between two successive calls of Algorithm1 (line 12); otherwise, it is determined directly without BPNN (lines 4-9), because insufficient training often lead to bad prediction results from BPNN.

Algorithm 1. Price_prediction

Input: *SDR, BUD, REP, TF, sample-base, Label* (indicating whether this is the first call to Algorithm1, 1 means yes, 0 means no)
Output: *BPoDS*
1: Set *MNoS* be the required minimum number of samples in *sample-base* to train BPNN;
2: Set *N* be the number of samples recorded in *sample-base*;
3: **if** $N < MNoS$ **then**
4: **if** $Label == 1$ **then**
5: Set *BPoDS* be a random number between 0 and *BUD;*
6: **else**
7: Get ΔBP randomly from the uniform distribution within the interval [0, *BUD-BPoDS*]; /*ΔBP is the bidding price adjustment amplitude.*/
8: $BPoDS = BPoDS + \Delta BP$;
9: **end if**
10: **else**
11: **if** $Label == 0$ **then**
12: Update *SDR* by (4);
13: **end if**
14: $a_1 = SDR$, $a_2 = BUD$, $a_3 = REP$, $a_4 = TF$;
15: **for** $j \in \{1, 2, 3, 4\}$ **do**
16: $u_j = \sum_{i=1}^{4} w_{ij} a_i$;
17: **end for**
18: **for** $j \in \{1, 2, 3, 4\}$ **do**
19: $b_j = f(u_j)$;
20: **end for**
21: $p_1 = \sum_{i=1}^{4} v_{i1} b_i$;
22: $BPoDS = p_1$;
23: **end if**
24: **return** *BPoDS*;

MNoS should satisfy the following condition:

$$MNoS = O(W/e). \tag{11}$$

Here, e is the permitted output error; W is the total number of BPNN's free parameters (i.e., synapse weights and bias values) and calculated as follows [32].

$$W = M \times L_1 + L_1 + d. \tag{12}$$

Here, M, L_1 and d are the number of the input, hidden and output layer nodes respectively.

The *PA*'s price prediction algorithm is almost the same as the *CA*'s. However, its input and output are changed to {*SDR, CST, REP, TF, sample-base, Label*} and *APoRU* respectively, line 7 is changed to "Get ΔAP randomly from the uniform distribution within the interval [0, *APoRU-CST*]; /*ΔAP is the asking price adjustment amplitude.*/", and line 8 is changed to "$APoRU = APoRU - \Delta AP$;".

The *CA*'s and *PA*'s sample formats are {*SDR, BUD, REP, TF, BPoDS*} and {*SDR, CST, REP, TF, APoRU*} respectively. Here, *BPoDS* is the final bidding price of a *CSC* to the demanded service, and *APoRU* is the final asking price of a *CSP* to the resource per unit. After each auction, we get samples (see line 24 of WDAPFA and the last paragraph in Section 5.3.2) and we can use them to train BPNN offline. After trained by *MNoS* samples, BPNN can be used to predict price.

5.2.2 Price Matching

What a *CSP* offers is the resource unit price, thus *AI* needs to get total asking price of a *CSP* to the *CSC* demanded service and match it with the *CSC*'s bidding price to find the eligible transaction relationship among *CSC*s and *CSP*s. For *VMS*, *CPS*, *DBS*, and *STS*, the total asking price of CSP_j to CSC_i is calculated in (13)-(16) respectively.

$$\begin{aligned} ask\_price_{ij} = (&CPUSDS_i \times PoCPUoSS_j \\ &+ MEMCDS_i \times PoMEMoSS_j \\ &+ STOCDS_i \times PoSTOoSS_j \\ &+ NETBDS_i \times PoNBoSS_j) \times length_i \end{aligned} \tag{13}$$

$$ask\_price_{ij} = TS_i \times PoCPUoSS_j \tag{14}$$

$$\begin{aligned} ask\_price_{ij} = (&MEMCDS_i \times PoMEMoSS_j + STOCDS_i \\ &\times PoSTOoSS_j) \times length_i + DV_i \times PoNBoSS_j \end{aligned} \tag{15}$$

$$ask\_price_{ij} = STOCDS_i \times PoSTOoSS_j \times length_i \tag{16}$$

$$length_i = EToDS_i - SToDS_i. \tag{17}$$

For the example in Section 3, assume that CSC_1 demands *STS* from CSP_1. Based on c_exp1 and p_exp1, the total asking price is calculated as follows.

$$ask\_price_{11} = 100 \text{ GB} \times \$0.00026/(GB \times hour) \times 123 \text{ hour} = \$3.2. \tag{18}$$

The price matching algorithm is described as follows.

In Algorithm2, price matching is done *MRN* rounds to prompt trading among *CSC*s and *CSP*s as much as possible. After each round, a *CSC*/*CSP*, whose bidding/asking price does not match any *CSP*/*CSC* asking/bidding price, is notified to re-bid/re-ask (line 21/line 26). Here, re-bid is done by Algorithm1, re-ask is done by *PA*'s price prediction algorithm and (13)-(16).

Algorithm 2. Price_matching

Input: *MRN* (the maximum round number), *TCT* (the tender collection time at each round)
Output: $ask\_price_{m\times n}$
1: Set m and n be the number of *CSC*s and *CSP*s respectively;
2: Initialize all elements in matrix $flag_{m\times n}$ to be 0; /* $flag_{ij}$ indicates whether price matching between CSC_i and CSC_j succeeds, 1 means yes, 0 means no.*/
3: $k = 1$;
4: **while** ($k \leq MRN$) **do**
5: Collect tenders from *CSC*s and *CSP*s until *TCT* timeouts;
6: **for** $i \in \{1, 2, \ldots, m\}$ **do**
7: **for** $j \in \{1, 2, \ldots, n\}$ **do**
8: **switch** (type of CSC_i's tender)
9: **case** *VMS*:
Calculate ask_price_{ij} by (13); break;
10: **case** *CPS*:
Calculate ask_price_{ij} by (14); break;
11: **case** *DBS*:
Calculate ask_price_{ij} by (15); break;
12: **case** *STS*:
Calculate ask_price_{ij} by (16);
13: **end switch**
14: **if** $BPoDS_i \geq ask\_price_{ij}$ **then**
15: $flag_{ij} = 1$;
16: **end if**
17: **end for**
18: **end for**
19: **for** $i \in \{1, 2, \ldots, m\}$ **do**
20: **if** (all elements of ith row in $flag_{m\times n}$ are 0) **then**
21: Notify the CSC_i to re-bid;
22: **end if**
23: **end for**
24: **for** $j \in \{1, 2, \ldots, n\}$ **do**
25: **if** (all elements of jth column in $flag_{m\times n}$ are 0) **then**
26: Notify the CSP_j to re-ask;
27: **end if**
28: **end for**
29: $k = k + 1$;
30: **end while**
31: **return** $ask\_price_{m\times n}$;

For the example in Section 3, we get $initial\_ask\_price_{4\times 6}$ and $initial\_flag_{4\times 6}$, e.g., $initial\_ask\_price_{11} = \$3.2$, *BPoDS* of CSC_1 is \$3.1, then $initial\_flag_{11} = 0$. From $initial\_flag_{4\times 6}$, we can see that the CSC_1/CSP_6's bidding/asking price does not match any *CSP*/*CSC*'s asking/bidding price, then *AI* notifies them to try again. Finally, we get $BPoDS_1 = \$5.0$, $BPoDS_2 = \$4.0, BPoDS_3 = \$7.0$, $BPoDS_4 = \$9.0$, $final\_ask\_price_{4\times 6}$ and $final\_flag_{4\times 6}$. See Fig. 4 for details.

$$initial\_ask\_price_{4\times 6}\begin{bmatrix} 3.2 & 3.8 & 3.6 & 4.6 & 5.5 & 6.8 \\ 2.8 & 3.4 & 3.2 & 4.0 & 4.9 & 6.0 \\ 3.9 & 4.7 & 4.4 & 5.6 & 6.8 & 8.3 \\ 4.7 & 5.6 & 5.3 & 6.7 & 8.2 & 10.0 \end{bmatrix}(a)\quad initial\_flag_{4\times 6}\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 \end{bmatrix}(b)$$

$$final\_ask\_price_{4\times 6}\begin{bmatrix} 3.2 & 3.8 & 3.6 & 4.6 & 5.5 & 4.9 \\ 2.8 & 3.4 & 3.2 & 4.0 & 4.9 & 4.4 \\ 3.9 & 4.7 & 4.4 & 5.6 & 6.8 & 6.0 \\ 4.7 & 5.6 & 5.3 & 6.7 & 8.2 & 7.3 \end{bmatrix}(c)\quad final\_flag_{4\times 6}\begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix}(d)$$

Fig. 4. Matrices in the example.

5.3 Winner Determination

5.3.1 Problem Formulation

In this paper, winner determination is used to get the optimal solution in which the trading volume at the transaction price between each *CSC* and his partner *CSP* is decided. As a result, WDP becomes one to find an optimal partition matrix $RPM_{m\times n}$, of which RPM_{ij} is the proportion of the demanded service that CSC_i receives from CSP_j, $RPM_{ij} \in [0, 1]$, $1 \leq i \leq m$, $1 \leq j \leq n$.

The *CSC* bidding price should not be less than the *CSP* asking price in one transaction, and the balance between them is called market surplus [33]. We call the balance between the total bidding prices of all *CSC*s and the total asking prices of their partner *CSP*s, the balance between their total unit time prices, and their total reputations as *TLS*, *TUS*, and *TRP*, calculated in (19)-(21) respectively.

$$\begin{aligned} TLS(RPM_{m\times n}) = &\sum_{i=1}^{m}\sum_{j=1}^{n}(RPM_{ij} \times BPoDS_i) \\ &- \sum_{i=1}^{m}\sum_{j=1}^{n}(RPM_{ij} \times ask\_price_{ij}) \end{aligned} \tag{19}$$

$$\begin{aligned} TUS(RPM_{m\times n}) = &\sum_{i=1}^{m}\sum_{j=1}^{n}\left(RPM_{ij} \times \frac{BPoDS_i}{length_i}\right) \\ &- \sum_{i=1}^{m}\sum_{j=1}^{n}\left(RPM_{ij} \times \frac{ask\_price_{ij}}{length_i}\right) \end{aligned} \tag{20}$$

$$\begin{aligned} TRP(RPM_{m\times n}) = &\sum_{i=1}^{m}\sum_{j=1}^{n}(RPM_{ij} \times c\_rep_i) \\ &+ \sum_{j=1}^{n}\sum_{i=1}^{m}(RPM_{ij} \times p\_rep_j). \end{aligned} \tag{21}$$

Here, c_rep_i and p_rep_j are CSC_i's and CSP_j's reputation respectively.

We want to optimize *TLS*, *TUS* and *TRP* so that not only gross surplus but also surplus strength are tried to be maximized at the same time honest participants are encouraged with high economic efficiency and trustfulness attained. It is a MOO problem and can be dealt with by, e.g., GA [28] and WSM [34]. GA can be effective regardless of the nature of the objective functions and constraints, but has relatively high computational expense. WSM is computationally efficient and easy-to-use, but needs to determine the relative importance of multiple objectives. Due to its computation efficiency, we use WSM to convert MOO into SOO and define *SPD* of $RPM^a_{m\times n}$ to $RPM^b_{m\times n}$ as follows.

$$\Omega_b^a = \alpha \frac{TLS(RPM_{m\times n}^a) - TLS(RPM_{m\times n}^b)}{TLS(RPM_{m\times n}^b)} + \beta \frac{TUS(RPM_{m\times n}^a) - TUS(RPM_{m\times n}^b)}{TUS(RPM_{m\times n}^b)} + \gamma \frac{TRP(RPM_{m\times n}^a) - TRP(RPM_{m\times n}^b)}{TRP(RPM_{m\times n}^b)}. \quad (22)$$

Here, α, β and γ are the weights of three objectives and their values can be determined, e.g., by experiments or by AHP [35], $\alpha+\beta+\gamma=1$, $\alpha>0$, $\beta>0$, $\gamma>0$. We determine them by experiments (see Section 6.2.1).

Assume that we have a list of partition matrices, $RPM_{m\times n}^1$, $RPM_{m\times n}^2$, ..., $RPM_{m\times n}^{LT}$, and LT is the list length. We select $RPM_{m\times n}^{\#}$ as the benchmark and get $\Omega_{\#}^i$, $i=1,\ldots,LT$. Denote the biggest $\Omega_{\#}^i$ as $\Omega_{\#}^{BT}$, then $RPM_{m\times n}^{BT}$ corresponding to $\Omega_{\#}^{BT}$ is the optimal partition matrix, $BT\in\{1,2,\ldots,LT\}$.

We formulate WDP in this paper as follows.

$$\text{maximize} \quad \Omega_{\#}^i \quad (23)$$

s.t.

$$BPoDS_i \geq ask\_price_{ij}, \forall RPM_{ij}\neq 0 \quad (24)$$

$$p\_rep_j \geq MREPCSP_i, \forall RPM_{ij}\neq 0 \quad (25)$$

$$c\_rep_i \geq MREPCSC_j, \forall RPM_{ij}\neq 0 \quad (26)$$

$$\sum_{j=1}^{n} \lceil RPM_{ij} \rceil \leq MPN_i, \forall i \quad (27)$$

$$RPM_{ij}\in[\varepsilon,1]\cup\{0\}, \forall_i, \forall_j \quad (28)$$

$$\sum_{j=1}^{m} RPM_{ij}\in\{0,1\}, \forall i \quad (29)$$

$$SToDS_i \geq SToSS_j, \forall RPM_{ij}\neq 0 \quad (30)$$

$$EToDS_i \leq EToSS_j, \ \forall RPM_{ij}\neq 0 \quad (31)$$

$$P\&SoDS_i \subseteq P\&SoSS_j, \forall RPM_{ij}\neq 0 \quad (32)$$

$$CPUSSS_j \geq CPUSDS_i, \forall RPM_{ij}\neq 0 \quad (33)$$

$$MEMCSS_j \geq MEMCDS_i, \forall RPM_{ij}\neq 0 \quad (34)$$

$$STOCSS_j \geq STOCDS_i, \forall RPM_{ij}\neq 0 \quad (35)$$

$$NETBSS_j \geq NETBDS_i, \forall RPM_{ij}\neq 0. \quad (36)$$

Here, (24) says that the *CSC* bidding price cannot be lower than the *CSP* asking price. (25), (26) require that the *CSP*/*CSC*'s reputation cannot be lower than the *CSC*/*CSP* requirement. (27) means that at most MPN_i *CSP*s are allowed to carry out the *CSC* demanded service jointly. (28) means that the partition granularity cannot be too fine and ε is its lower bound. (29) requires that the *CSC* demanded service must be provided by *CSP*(s) completely or none. (30)-(36) mean that the *CSP* service starting time, service ending time, platform and software environment, CPU, memory, storage and network bandwidth must satisfy the corresponding *CSC* requirement. Among them, (24)-(32) are common constraints satisfied by all types of services. However, each type of service has specific constraints to be satisfied, in particular, *VMS*, *CPS*, *DBS*, *STS* need to satisfy (33)-(36), (33), (34)-(36), (35) respectively.

$$RPM_{4\times6}^1 = \begin{bmatrix} 0.5 & 0 & 0.5 & 0 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.3 & 0.4 & 0.3 \\ 0 & 0 & 0.4 & 0 & 0 & 0.6 \end{bmatrix} \quad (a)$$

$$RPM_{4\times6}^2 = \begin{bmatrix} 0.5 & 0.5 & 0 & 0 & 0 & 0 \\ 0.4 & 0.4 & 0.2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.4 & 0.6 \\ 0 & 0 & 0.4 & 0.6 & 0 & 0 \end{bmatrix} \quad (b)$$

$$RPM_{4\times6}^3 = \begin{bmatrix} 0.4 & 0.3 & 0.3 & 0 & 0 & 0 \\ 0.4 & 0.4 & 0.2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.1 & 0.2 & 0.7 \\ 0.2 & 0.1 & 0.2 & 0.5 & 0 & 0 \end{bmatrix} \quad (c)$$

Fig. 5. Initial seeds.

5.3.2 Winner Determination Algorithm

We improve PFA to solve WDP. PFA is bio-inspired and seeds correspond to problem solutions. When sown in field, seeds which fall into places with the favorable conditions tend to grow to become the healthy plants. Such plants are capable of producing more seeds than less fortunate ones. The healthiest plant of the population corresponds to the optimum which can be determined by a fitness function. A high plant density would increase pollination chance, thus the higher the plant density, the more likely the chance of proper pollination. Then, the seeds of these plants are scattered in field and become new plants, and the cycle continues. PFA has strong global search ability and low computation overhead. It does not depend heavily on initial values. However, its local search ability is not very good, thus we improve it with the simplex algorithm (SA) [34]. In addition, we devise a customized seed refinement procedure to make the solution feasible to satisfy (24)-(36). If a seed corresponds to a feasible solution, it is healthy, otherwise it is ill. The key operations of WDAPFA are described as follows.

(1) *Sowing*. The *INoS* seeds are generated randomly as initial solutions and *INoS* is population size. Each seed is a matrix $RPM_{m\times n}$ and RPM_{ij} is uniformly distributed within [0, 1]. One seed is randomly chosen as the benchmark. The *SPD* of each seed to the benchmark is defined as its fitness value to measure its health.

Corresponding to the example in Section 3, we generate initial seeds $RPM_{4\times6}^1$, $RPM_{4\times6}^2$, and $RPM_{4\times6}^3$, shown in Fig. 5. According to (24)-(32) and (35), the former two are healthy and the latter one is ill.

(2) *Seed refinement*. We can refine an ill seed to a healthy one so that an infeasible solution is changed into a feasible one. If price, reputation, time-frame, platform and software, or capacity constraints ((24), (25), (26), (30), (31), (32), or (33)-(36)) violated, we just set the corresponding RPM_{ij} be 0. If partition number, partition granularity, or service constraints ((27), (28), or (29)) violated, the refinement is complex.

(a) Partition number constraint violation handling.

If there exists $\sum_{j=1}^{n} \lceil RPM_{ij} \rceil > MPN_i$, that is, the partition number is too big, we do the following refinement.

Step 1: $i=1$.

Step 2: If $i>m$, go to Step 7.

Step 3: If $\sum_{j=1}^{n} \lceil RPM_{ij} \rceil \leq MPN_i$, go to Step6.

Step 4: Find the minimum and second minimum elements $RPM_{i,min}$ and $RPM_{i,smin}$, $RPM_{i,smin}=RPM_{i,smin}+RPM_{i,min}$, $RPM_{i,min}=0$.

$$RPM^{3}_{4\times 6}{}' = \begin{bmatrix} 0.4 & 0.3 & 0.3 & 0 & 0 & 0 \\ 0.4 & 0.4 & 0.2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.1 & 0.2 & 0.7 \\ 0.2 & 0 & 0.3 & 0.5 & 0 & 0 \end{bmatrix}$$

Fig. 6. Refined seed.

Step 5: If $\sum_{j=1}^{n} \lceil RPM_{ij} \rceil > MPN_i$, go to Step 4.

Step 6: $i = i + 1$, go to Step 2.

Step 7: Refinement ends.

We merge the proportion of CSP_{min} into that of CSP_{smin} and CSP_{min} is no longer a provider in Step 4, then the partition number decreases by 1. This iteration continues until (27) is satisfied.

(b) Partition granularity constraint violation handling.

If there exists $RPM_{ij} < \varepsilon$, that is, there exists too fine partition, we do the following refinement.

Step 1: $i = 1$.

Step 2: If $i > m$, go to Step 8.

Step 3: Find $RPM_{i,min}$.

Step 4: If $RPM_{i,\min} \geq \varepsilon$, go to Step 7.

Step 5: Find $RPM_{i,smin}$.

Step 6: $RPM_{i,smin} = RPM_{i,smin} + RPM_{i,min}$, $RPM_{i,min} = 0$, go to Step 3.

Step 7: $i = i + 1$, go to Step 2.

Step 8: Refinement ends.

We merge the proportion of CSP_{min} into that of CSP_{smin} and CSP_{min} is no longer a provider in Step 6. Then, the partition granularity minimum is increased. This iteration continues until (28) is satisfied.

(c) Service constraint violation handling.

If there exist $\sum_{j=1}^{n} RPM_{ij} \neq 1$ and $\sum_{j=1}^{n} RPM_{ij} \neq 0$, that is, the *CSC* demanded service cannot be provided properly, we do the following refinement.

Step 1: $i = 1$.

Step 2: If $i > m$, go to Step 8.

Step 3: If $\sum_{j=1}^{n} RPM_{ij} = 1$ or $\sum_{j=1}^{n} RPM_{ij} = 0$, go to Step 7.

Step 4: Find the maximum element $RPM_{i,max}$.

Step 5: $Temp = \sum_{j=1}^{n} RPM_{i,j} - RPM_{i,max}$.

Step 6: If $Temp \leq 1$, $RPM_{i,\max} = 1 - Temp$, go to Step 7, else $RPM_{i,max} = 0$, go to Step 3.

Step 7: $i = i + 1$, go to Step 2.

Step 8: Refinement ends.

We adjust the proportion of CSP_{max} in Step 6 to make $\sum_{j=1}^{n} RPM_{ij} = 1$ or $\sum_{j=1}^{n} RPM_{ij} = 0$ until (29) is satisfied.

By refinement, $RPM^{3}_{4\times 6}$ becomes $RPM^{3'}_{4\times 6}$, see Fig. 6.

(3) *Selection*. After seeds are sown into the field and plants are produced, only the very healthy plants are selected, so that plants do not grow explosively. In this paper, we sort all plants in descending order based on their fitness values and only select the first *INoS* plants as new population.

(4) *Seeding*. Each plant P produces a number of seeds based on its fitness and the number is calculated as follows.

$$S_P = \left\lceil q_{\max} \frac{\Omega^{P}_{\#} - \Omega^{WT}_{\#}}{\Omega^{BT}_{\#} - \Omega^{WT}_{\#}} \right\rceil. \tag{37}$$

Here, $q_{\max}$ is the number of seeds produced by the plant with the highest fitness value, and $\Omega^{WT}_{\#}$ is the smallest fitness value of the plant.

(5) *Pollination*. It determines whether the seeds survive or not. If euclidean distance between two plants is smaller than a preset threshold r, they are considered as neighbors. Pollination depends on the number of neighbors of a particular plant. The more neighbors a plant has, the better its pollination is. Thus, a pollination factor for P is introduced and calculated as follows.

$$u_P = e^{\frac{v_P}{v_{max}} - 1}. \tag{38}$$

Here, v_P is the number of neighbors of P, and v_{max} is the number of neighbors of the plant with the most neighbors in the population.

After pollination, the number of the survived seeds produced by P is calculated as follows.

$$S_P = \left\lceil u_P q_{\max} \frac{\Omega^{P}_{\#} - \Omega^{WT}_{\#}}{\Omega^{BT}_{\#} - \Omega^{WT}_{\#}} \right\rceil. \tag{39}$$

(6) *Dispersion*. Each new seed gets its value randomly which conforms to normal distribution with σ as dispersion spread, that is, $RPM^{new}_{ij} \sim N(RPM^{old}_{ij}, \sigma)$. The spreading of seeds within the parameter space promotes that if the healthiest plant of a particular iteration corresponds to a local optimum, the dispersing seeds may fall in the parameter space corresponding to the global optimum.

(7) *Local search ability improvement*. SA is effective and computationally compact. It adapts itself to the local landscape and contracts on to the optimum. The simplex corresponds to problem solution. At first, its *mirror center* is built. Then, *reflection* is carried out to generate a new simplex at the mirror center, *expansion* to accelerate the reduction of the simplex to a better simplex, and *contraction* to keep the simplex in good position. We use SA to improve PFA's local search ability. The LSIA based on SA is described as follows.

In LSIA, line 6, line 7, lines 12–7 and lines 20-27 correspond to building *mirror center*, *reflection*, *expansion* and *contraction* respectively.

The proposed WDAPFA is described as follows.

In line 24, we get samples from successful transactions in the auction to train BPNN (see Section 5.2.1). If there is only one seed in OSS, it is the problem solution; otherwise, choose one seed randomly or by some user-specified rule (for example, *TLS* preferred, *TUS* preferred, or *TRP* preferred) from OSS as the problem solution.

6 Simulations and Performance Evaluations

6.1 Simulation Setup

The proposed IEDA is implemented based on Simjava2.0 on Eclipse platform. The services and resource prices are set referring to Amazon and Ali clouds [6], [23], [36]. The resource capacity is set referring to TeraGrid [37]. The supply and demand relation is divided into four types, shown in Table 4. The market scale is classified into six categories according to the numbers of *CSC*s and *CSP*s in cloud market, shown in Table 5. The parameters of PFA and BPNN are set referring to [19] and [38], shown in Tables 6 and 7 respectively. ψ in (4) is set to be 0.5 referring to [39].

TABLE 4
Supply and Demand Ratio

Supply and demand ratio	Value
Scarce Supply(SS)	[0.4, 0.9)
BaLance(BL)	[0.9, 1.1]
Over Supply(OS)	(1.1, 2]
Over sufficienT(OT)	(2, 4]

Algorithm 3. LSIA

Input: $X_1, \ldots, X_P$ (seeds), *MNoI* (the maximum iteration number)
Output: $X_1, \ldots, X_P$ (the improved seeds)
$i = 1$;
while $i \leq MNoI$ **do**
  Choose one seed randomly as the benchmark $X_{\#}$;
  Calculate the *SPD* of each seed to $X_{\#}$;
  Set X_{max} and X_{min} be the seeds with the maximum and minimum *SPD* respectively (if multiple, choose one randomly);
  Average $X_1, X_2, \ldots, X_P$ to be X_0;
  $X_r = X_0 + \delta(X_0 - X_{min})$;
  if $\Omega_{\#}^{\min} \leq \Omega_{\#}^{r} \leq \Omega_{\#}^{\max}$ **then**
    Replace X_{min} by X_r;
  end if
  if $\Omega_{\#}^{r} > \Omega_{\#}^{\max}$ **then**
    $X_e = X_0 + \xi(X_r - X_0)$;
    if $\Omega_{\#}^{e} > \Omega_{\#}^{r}$ **then**
      Replace X_{min} by X_e;
    else
      Replace X_{min} by X_r;
    end if
  end if
  if $\Omega_{\#}^{r} < \Omega_{\#}^{\min}$ **then**
    $X_c = X_0 + \rho(X_{min} - X_0)$;
    if $\Omega_{\#}^{c} > \Omega_{\#}^{\min}$ **then**
      ReplaceX_{min}byX_c;
    else
      for $j \in \{1, \ldots, p\}$ **do**
        $X_j = (X_j + X_{max})/2$;
      end for
    end if
  end if
  $i = i + 1$;
end while
return $X_1, X_2, \ldots, X_P$;

TABLE 5
Market Scale

Market scale	*CSC*	*CSP*
TinY(TY)	8	4
SmalL(SL)	16	8
MediuM(MM)	32	8
LarGe(LG)	64	16
HuGe(HG)	128	16
OversiZed(OZ)	128	32

TABLE 6
PFA Parameter

Parameter	Value
Maximum iteration number	20
Maximum seeds produced by a plant	10
Population size	20
Maximum spread	0.1
Minimum spread	0.02
Radius	0.2

In order to evaluate economic efficiency and trustfulness of IEDA, we use simulation to verify its effectiveness and compare its performance with its counterpart which applies SCDA [40] to resource allocation. In SCDA, a compulsory bidding adjustment layer is added to CDA to promote continuous matching and immediate allocation with low runtime overhead. In particular, it deals with resource allocation among self-interested participants in a dynamic and distributed market, and resource providers and consumers have their own asking/bidding strategies. Due to the treatment situation similarity and the auction nature, we choose the counterpart which applies SCDA as the comparison benchmark to IEDA. The performance data used in the following are the average of 20 trials in corresponding simulation settings.

Algorithm 4. WDAPFA

Input: *INoS* (population size), *MNoI* (the maximum number of iterations)
Output: *OSS* (the optimal seed set)
Do sowing to generate *INoS* seeds initially and do seed refinement;
Choose one seed randomly as the benchmark;
Calculate the *SPD* of each seed to the benchmark;
Set $MSPD^{BT}$ and $MSPD^{*}$ to be the maximum *SPD* and initialize *OSS* with all seeds corresponding to $MSPD^{BT}$;
$i = 1$;
while $i \leq MNoI$ **do**
  Do seeding;
  Do pollination;
  Do dispersion;
  Improve local search ability;
  Do seed refinement;
  Calculate the *SPD* of each seed to the benchmark;
  Set $MSPD^{BT}$ be the current maximum *SPD*;
  if $MSPD^{BT} > MSPD^{*}$ **then**
    Replace *OSS* with all seeds corresponding to $MSPD^{BT}$;
    $MSPD^{*} = MSPD^{BT}$;
  end if
  if $MSPD^{BT} == MSPD^{*}$ **then**
    Put all seeds corresponding to $MSPD^{BT}$ into *OSS*;
  end if
  Do selection;
  $i = i + 1$;
end while
Get necessary information from *CSC* and *CSP* winners as samples and put them into the corresponding *PA*'s and *CA*'s *sample-base*.
return *OSS*;

TABLE 7
BPNN Parameter

Parameter	Value
Learning factor	0.5
Output error	0.05
MNoS	400

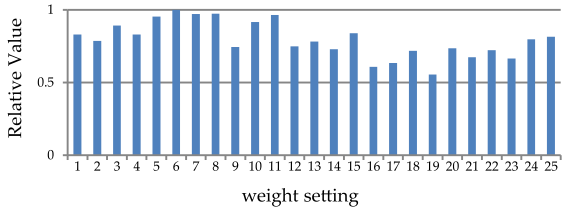


Fig. 7. SPD under different weight settings.

6.2 IEDA Effectiveness

When we do simulations in this section, we assume a cloud market with medium scale and balanced supply and demand.

6.2.1 Objective Weight Determination

We compare IEDA performances under different settings of α, β and γ, shown in Table 8. In Fig. 7, we use the relative value of *SPD* to make the comparison more visualized, that is, we set the largest value of *SPD* be 1 and others be the ratios to 1. It can be seen that the best performance is produced under $\alpha = 0.5$, $\beta = 0.4$, and $\gamma = 0.1$. Thus, we use this weight setting in the following performance evaluations.

6.2.2 Reputation System

We define TWR as the ratios of the number of winners to the number of all participants in one auction, and DWR as the proportion of winners in dishonest participants respectively. They are computed under two different scenarios. In Scenario 1 (S1), IEDA is equipped with the proposed reputation system, and in Scenario 2 (S2) without. Specifically, when we do simulations, after the auction, if a participant A gives his partner B a QoE which is different from B's previous reputation no more than 40 percent, A is considered by *AI* honest; if more than 40 percent but no more than 70 percent, A is considered slightly dishonest; if more than 70 percent, A is considered seriously dishonest. If considered slightly dishonest three consecutive times or seriously dishonest once, A is excluded from the cloud market.

TABLE 8
Weight Settings

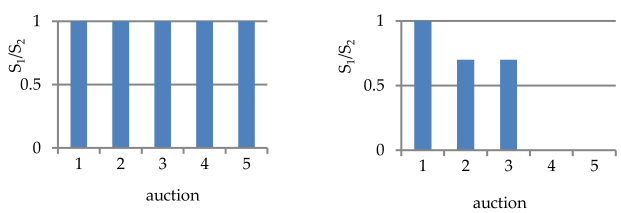
Weight setting	α	β	γ
1	0.6	0.2	0.2
2	0.6	0.3	0.1
3	0.6	0.1	0.3
4	0.5	0.3	0.2
5	0.5	0.2	0.3
6	0.5	0.4	0.1
7	0.5	0.1	0.4
8	0.2	0.6	0.2
9	0.3	0.6	0.1
10	0.1	0.6	0.3
11	0.3	0.5	0.2
12	0.2	0.5	0.3
13	0.4	0.5	0.1
14	0.1	0.5	0.4
15	0.2	0.2	0.6
16	0.1	0.3	0.6
17	0.3	0.1	0.6
18	0.2	0.3	0.5
19	0.3	0.2	0.5
20	0.4	0.1	0.5
21	0.1	0.4	0.5
22	0.4	0.2	0.4
23	0.2	0.4	0.4
24	0.4	0.4	0.2
25	0.33	0.33	0.33

Fig. 8a shows the ratio of TWR under S1 to that under S2 in a cloud market without dishonest participants. It can be seen that their TWRs are the same, that is, if all participants are honest, there is no need for reputation system.

We further evaluate the effectiveness of the proposed reputation system on suppressing the dishonest participants. Fig. 8b shows the ratio of DWR under S1 to that under S2 in a cloud market where 10 percent *CSC*s and 10 percent *CSP*s are dishonest. Among dishonest participants, 30 percent are seriously dishonest and others are slightly dishonest. We can see that in the first auction, the DWRs are the same under S1 and S2, because at the beginning the reputation system does not identify those dishonest participants, thus it seems to be ineffective. However, after the first auction, all dishonest participants are identified. In the second auction, the DWR under S1 is much lower than that under S2, because at this time all seriously dishonest ones have already been excluded from the market. The situation in the third auction is the same as that in the second auction, because all slightly dishonest participants still take part in the auction although they are already suspected. From the fourth auction on, the DWR under S1 becomes 0, because all dishonest participants have been excluded from the market.

6.2.3 Price Formation and Winner Determination

We compare *TLS*, *TUS*, *TRP* and *SPD* under Scenario 3 (S3) and Scenario 4 (S4), Scenario 5 (S5) and Scenario 6 (S6) to evaluate the effectiveness of our proposed price formation mechanism (see Fig. 9a) and winner determination method (see Fig. 9b) respectively. In S3, IEDA is equipped with the proposed price formation mechanism while in S4 with GM inspired from [41]. GM means that the *CSC* with the highest bidding price transacts with the *CSP* with the lowest asking



(a) TWR without Dishonest Participants (b) DWR

Fig. 8. TWR without dishonest participants and DWR.

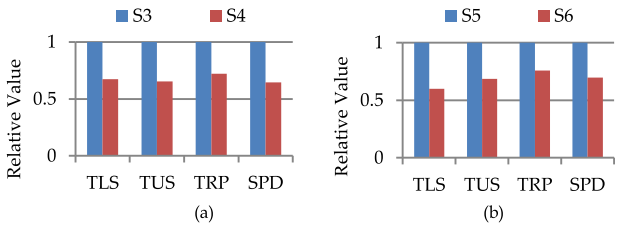


Fig. 9. Price formation and winner determination effectiveness.

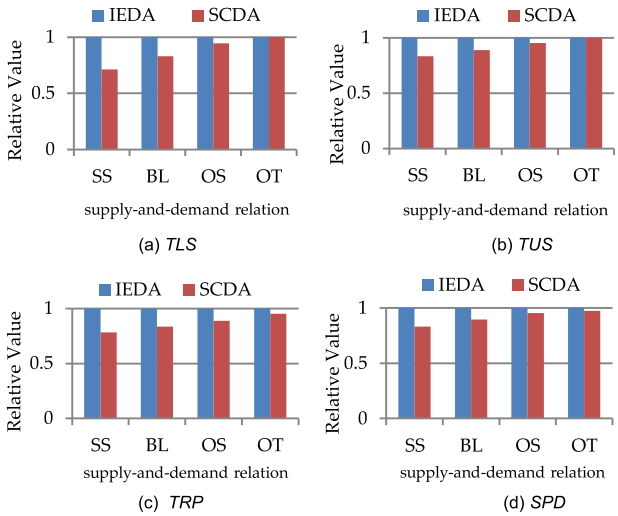


Fig. 10. Under different supply-and-demand relations.

price. In S5, IEDA is equipped with WDAPFA while in S6 with GM. In Figs. 9a and 9b, we use the relative values of *TLS*, *TUS*, *TRP* and *SPD*, that is, we set their values in S3 and S5 be 1, and their values in S4 and S6 be the ratios to 1. It can be seen that our proposed methods are effective.

6.3 IEDA and SCDA Comparison

In this section, when we compare performance between IEDA and SCDA, we use the relative values of *TLS*, *TUS*, *TRP*, *SPD*, transaction number and runtime overhead, that is, we set their values in IEDA be 1, and their values in SCDA be the ratios to 1.

6.3.1 TLS, TUS, TRP and SPD

(1) *Under different supply and demand relations*. Fig. 10 shows comparison of *TLS*, *TUS*, *TRP* and *SPD* under different supply and demand relations in a cloud market with medium scale. It can be seen that IEDA outperforms SCDA, however, as the *SDR* increases, the superiority of IEDA decreases. This is because the *CSC* demanded service cannot be partitioned to and carried out by multiple *CSP*s in SCDA, and thus some *CSC* demanded services cannot be accommodated due to insufficient resources, leading to *TLS*, *TUS*, *TRP* and *SPD* of IEDA better than those of SCDA. The scarcer the resources, the better the performance of IEDA than that of SCDA. When resources are over-sufficient, a *CSC* can always get resources from one *CSP*, thus IEDA and SCDA get almost the same performance.

(2) *Under different market scales*. Fig. 11 shows comparison of *TLS*, *TUS*, *TRP* and *SPD* under different market scales in a cloud market with balanced supply and demand relation. It can be seen that IEDA outperforms SCDA. However, as the market scale increases, the performance of IEDA tends to decrease slightly, because the stability of the bio-inspired PFA becomes worse when the problem space gets larger.

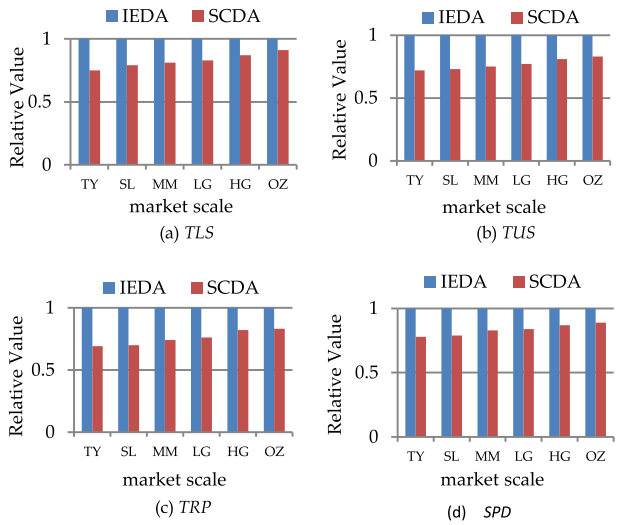


Fig. 11. Under different market scales.

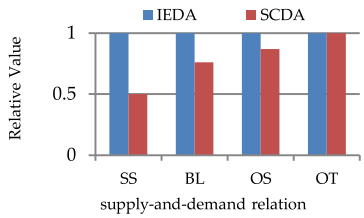


Fig. 12. Transaction number.

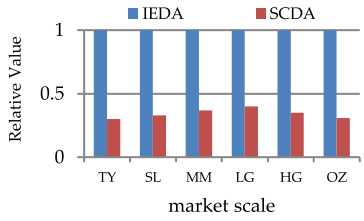


Fig. 13. Runtime overhead.

6.3.2 Transaction Number and Runtime Overhead

(1) *Transaction number*. Fig. 12 shows comparison of transaction number between IEDA and SCDA under different supply and demand relations with medium scale. It can be seen that the number of transactions successfully dealt with in IEDA is the same as that in SCDA when resources are over-sufficient; however, in other cases, it is larger in IEDA than that in SCDA, because one *CSC* demanded service can be partitioned to and carried out by multiple *CSP*s in IEDA, then more transactions are accommodated.

(2) *Runtime overhead*. Fig. 13 shows comparison of runtime overhead between IEDA and SCDA under different market scales with balanced supply and demand relation. It can be seen that the runtime overhead of IEDA is larger than that of SCDA. The main reason is that IEDA has

integrated the BPNN-based price prediction, the PFA-based winner determination and the devised reputation system. At the cost of runtime overhead, IEDA not only brings good market surplus and surplus strength but also suppresses dishonest participants. SCDA emphasizes the instant resource allocation, thus its runtime overhead is low, but it does not offer the advantages of IEDA.

7 Conclusion

Based on economic method and bio-inspired algorithm, an intelligent combinatorial double auction based dynamic resource allocation approach is proposed for cloud services. The system framework is devised to provide a comprehensive solution. A reputation system is used to suppress dishonest participants. A price formation mechanism is proposed to predict price and determine eligible transaction relationship. WDP is optimally solved by the improved PFA. Simulation results validate the effectiveness of our proposed approach and demonstrate its superiority on economic efficiency and trustfulness. In the near future, we expect to implement our proposed approach in a prototype system and do experiment on CERNET2 [42], which can deploy and provide cloud services to faculties and students at universities, to make it more practical.

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