A Game-Based Price Bidding Algorithm for Multi-Attribute Cloud Resource Provision

Junyan Hu, Kenli Li, *Senior Member, IEEE*, Chubo Liu, and Keqin Li, *Fellow, IEEE*

Abstract—The pricing mechanism of cloud-computing resources is an essential issue for both cloud customers and service providers, especially from the point of multi-provider competition. Although various mechanisms for resource provision are proposed, few studies have focused on multi-attribute resource provision with the objective of improving benefits of both cloud customers and service providers. To address the issue, we propose a price bidding mechanism for multi-attribute cloud-computing resource provision from the perspective of a non-cooperative game, in which the information of each player (customers and providers) is incomplete to others and each player wishes to maximize his/her own benefit. More specifically, considering the fairness pricing competition, we propose a novel and incentive resource provision model referring to the Quality-of-Service (QoS) and the bidding price. Then, combining with the resource provision model, the problem of price bidding is formulated as a game to find a proper price for each cloud provider. We demonstrate the existence of Nash equilibrium solution set for the formulated game model by assuming that the quantity function of provided resources from every provider is continuous. To find a Nash equilibrium solution, we propose an Equilibrium Solution Iterative (ESI) algorithm, which is proved to converge to a Nash equilibrium. Finally, a Near-equalization Price Bidding (NPB) algorithm is proposed to modify the obtained Nash equilibrium solution. Extensive simulated experiments results and the comparison experiments with the state-of-the-art and benchmark solutions validate and show the feasibility of the proposed method.

Index Terms—Cloud computing, Nash equilibrium, non-cooperative game theory, price bidding strategy, resource provision

1 Introduction

1.1 Motivation

Benefiting from excellent computing power and elastic resource allocation, cloud computing is widely applied in various applications, such as Amazon EC2, Microsoft Azure and Google AppEngine [1]. It offers an attractive paradigm for the dynamic provisioning of computing services in a *pay-as-you-go* manner [2]. Customers use and pay for services on-demand without considering the upfront infrastructure costs and the subsequent maintenance costs [3], while cloud providers are not concerned about the overprovisioning or underprovisioning. It is a significant issue on how customers select resources combinations from cloud providers to maximize their profits, while satisfying the optimal profit of each provider at the same time.

For cloud customers, the profit is determined by the provided resources and the profit brought by each resource [4], [5], [6], [7]. Cloud providers submit different multi-attribute parameters and bidding prices for the resource provision competition. Each customer compares the Quality-of-Service (QoS) in terms of multi-attribute, such as bandwidth, latency and the reputation of the corresponding cloud provider. Moreover, due to economic reasons, a rational customer might not purchase all the cloud resources from the same provider. If the ratio of the QoS to the price of a provider's cloud resource is relatively high, the customer will purchase more resources from the provider. Otherwise, the customer will buy less resources or refuse to buy them, even if the quality of the resources is excellent. In addition, the resource provision mechanism is affected by the bidding prices that determine the profit of each provider. Besides, the resources provided by each provider are affected by the decisions of other ones. It is essential to propose an incentive resource provision model and construct a pricing strategy to maximize each cloud provider's profit and satisfy each customer's optimal profit [5], [7], [8], [9], [10], [11], [12].

In this paper, we mainly focus on maximizing the benefits of both cloud customers and service providers. A customer can purchase cloud resources from multiple cloud providers instead of one. The non-cooperative game can be described as each participant choosing his/her strategy from the perspective of maximizing his/her own benefits without considering the benefits of others or the overall situation. We hope to find a price equilibrium point to maximize the benefits of each participant (customers and providers). Each participant updates his/her optimal strategy based on information of the previous round until no change occurs. That is, the optimal solution to the discussed issue can be well calculated using an iterative algorithm.

Numerous studies have discussed the auction mechanisms, which include the relationship between procurement parties, supplier bidding behaviors and strategies, and the

- *J. Hu, K. Li, and C. Liu are with the College of Computer Science and Electronic Engineering, Hunan University, and National Supercomputing Center in Changsha, Hunan 410082, China. E-mail: {junyanhu, lkl, liuchubo}@hnu.edu.cn.*
- *K. Li is with the College of Computer Science and Electronic Engineering, Hunan University, and National Supercomputing Center in Changsha, Changsha, Hunan, 410082, China, and also with the Department of Computer Science, State University of New York, New Paltz, New York 12561 USA. E-mail: lik@newpaltz.edu.*

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(Corresponding authors: Kenli Li and Keqin Li.)
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design of optimal mechanisms [5], [7], [8], [13], [14], [15], [16], [17], [18]. These are all bidding mechanisms that consist of a series of auction rules that determine who is the winner and how much it should pay. Prasad and Rao [8] proposed three kinds of auction mechanisms for achieving automated procurement in cloud. These auction mechanisms are suitable for a single resource, which is extended in [18] for multiple resources from several cloud providers, i.e., a combinatorial auction in hybrid cloud. However, the existing results do not consider the cloud resource procurement issue from the perspective of optimizing the benefits of both cloud customers and service providers, but only from the perspective of determining a winner for each customer. In this work, we consider that a customer can be served by multiple providers. Therefore, based on the non-cooperative game theory, we propose an iterative algorithm to optimize the benefits of both cloud customers and service providers and give the convergence analysis of the iterative algorithm solutions.

1.2 Our Contributions

In this paper, we focus on the price bidding mechanism for cloud providers resource provision competition from the perspective of non-cooperative game. Our main contributions are listed as follows:

- With the perspective of non-cooperative game, a mechanism of pricing strategy for resource provision is constructed to maximize the profits of both the cloud customers and service providers.
- Regarding the quantity of the resource provision from each provider as a fraction to get continuous benefit functions, we prove the existence of Nash equilibrium solution for the proposed game model.
- An ESI algorithm is proposed to compute the Nash equilibrium solution, and the convergence of the solution sequence obtained by the ESI algorithm is analyzed.
- An approximate price bidding NPB algorithm is proposed to modify the solutions. Two equilibrium solutions obtained by the ESI and NPB algorithms are compared respectively.

The remainder of the paper is organized as follows. In Section 2, we introduce the related work. Section 3 describes the system model and presents the problem that needs to be solved. In Section 4, we consider the problem as a non-cooperative game. An ESI algorithm and a NPB algorithm are proposed respectively. In Section 5, extensive experiments and the comparison experiments results with others indicate the feasibility of our algorithms. We conclude the works of this paper in Section 6.

2 Related Work

We present a review of the related work centered around cloud-computing resource provision, bidding price, and non-cooperative game.

Resource provision has been extensively studied for customers' resource requirement in cloud computing [5], [7], [8], [9]. In [5], the issue of online combinatorial auction was first proposed for the cloud computing paradigm. In [7], Baranwal et al. proposed a multi-attribute combinatorial reverse auction for cloud resource procurement, which considers both price and non-price attributes. In [8], Prasad et al. proposed mechanisms to help a user to choose an appropriate provider that would offer resources with reasonable prices. Zhao et al. considered the significant cost of the high volume of data generated by cloud applications in terms of storage and transfer in [9]. Similar works and models can be found in [10], [11], [12], [13]. However, existing efforts did not consider the optimal profits of both cloud customers and service providers. In contrast, our work addresses the problem by proposing a multi-attribute resource provision model.

Bidding price of cloud resources [19] plays an important role in increasing the profits of cloud customers and service providers. It is widely used in various areas for effective resource management, such as smart grid and cloud computing [20], [21]. Numerous studies focused on bidding price in cloud-computing resource provision schemes [13], [14], [15], [16], [17], [22], [23]. In [13], a price formation mechanism was proposed to make bidding and determine eligible transaction relationship among providers and consumers. In [14], two mechanisms, CA-LP (Linear Programming) and CA-GREEDY, were introduced to solve the problem of virtual machine allocation in cloud computing environment as a combinational auction problem. In [15], a distributed algorithm using a group formation game was proposed to determine which users and providers will trade resources through their cooperative decision. Similar works and models can be found in [22], [23], [24]. In addition, dynamic pricing mechanisms establish healthy competition among cloud service providers and improve the overall resource utilization [25]. Heuristically, our work introduces a dynamic bidding price mechanism in the provision of multi-attribute cloud-computing resources.

Game theory is the study of mathematical models of conflict and cooperation between intelligent rational decision-makers. It plays an increasingly important role in computer science [22], [26], [27], [28], [29], [30]. Cao et al. reviewed the disadvantages of the leader-follower game and proposed a cooperative game to provide a better solution for all players [26]. Truong et al. formulated a non-cooperative stochastic game to address the problem of providers competition, which was modeled as a Markov decision process [29]. Liu et al. focused on strategy configurations of multiple users to make cloud reservation [22]. By considering the problem as a non-cooperative game among the multiple cloud users, they proved that there exists a Nash equilibrium solution set for the formulated game. However, Ref. [22] did not consider the resource multi-attribute problem and resource satisfaction for every customer. In our system, we not only consider these problems, but also show that it is an incentive mechanism. Besides, different from most of the existing cooperative or non-cooperative algorithms, we address the price bidding problem in an iterative way, which achieved a good effect in subsequent algorithm evaluation and performance evaluation.

3 System Model

3.1 Participants of Cloud Resource Provision

Our model can be applied to the multi-customer and multi-provider condition. We focus on how customers purchase multi-attribute resources provided by multiple providers,

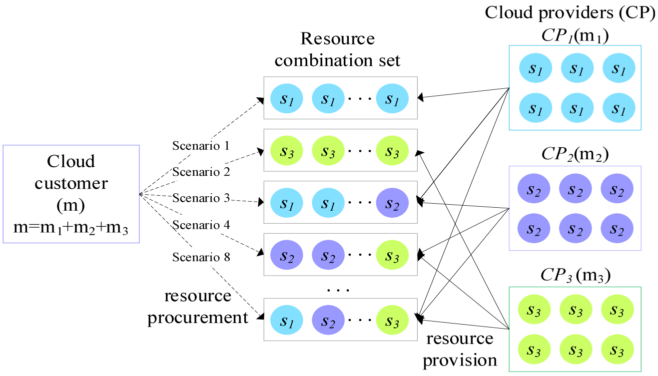


Fig. 1. Multi-attribute cloud resource provision model.

and how providers set pricing strategies to maximize the benefits of both customers and providers. During the purchasing process, there is no contact (cooperative or competition) among multiple customers. From the perspective of maximizing the benefits of each provider, each provider adopts different price strategies for each customer. In the case of multi-customer and multi-provider, if the equilibriums (resource procurement and prices) between each customer and multiple providers maximize the benefits of participants, then multi-customer and multi-provider condition can be parallelized into one customer and multi-provider condition satisfying that the benefits of both customers and providers are maximized. Therefore, we focus on the single customer (one customer) and multi-provider condition in detail in the paper.

3.1.1 One Customer

The customer chooses m cloud resources from n cloud providers, considering k non-price attributes and price attributes of the resources. The index set of k resource attributes can be denoted as $\mathcal{K} = \{1, \ldots, k\}$. We denote the set of resource attribute values provided by cloud providers as $\mathcal{Q} = \{Q_1, \ldots, Q_k\}$, which consists of k dimension vectors. Then, the attribute values of resources are denoted as a vector $q = (q_1, \ldots, q_k)$, where $q \in \mathcal{Q}$ and $q_j \in Q_j$. There are customers with varying attribute preferences based on different demands. The customer submits the highest reservation price for one resource is $\bar{p}$. However, due to the privacy consideration of each provider, customers do not know the resource cost of each provider.

3.1.2 Multiple Cloud Providers

The set of n cloud providers is denoted as $\mathcal{N} = \{1, \ldots, n\}$. For convenience, the ith cloud provider ($i \in \mathcal{N}$) is denoted as CP_i. CP_i submits his/her attribute values and resource prices to the customer. We denote the attribute values of of the resources provided by CP_i as a vector $q^i = (q_1^i, \ldots, q_k^i)$ and the price of provider i as p_i. The price set of each CP_i is $\mathcal{P}_i$ ($p_i \in \mathcal{P}_i$). Each CP_i has a reserved price r_i, which is the lowest acceptable price. According to the attribute values and the price submitted by CP_i, the customer decides to purchase m_i resources from CP_i, satisfying the condition of $\sum_{i \in \mathcal{N}} m_i = m$.

Fig. 1 shows an example of the cloud resource provision model with 3 CPs, the attributes of which are presented as Table 1 in the following Section 3.2.1. After the customer submitting his/her resource requirement and the number m, the three CPs raise their resources with the corresponding attributes and price. The three CPs constitute a resource combination set, which consists of 2^3 scenarios. Then, the customer can select one scenario and determine m_1, m_2 and m_3, where m_i ($i \in \{1,2,3\}$) is the provided number of CP_i. Hence, the key problem is how the customer selects a subset of the resources to maximize the profits of both the cloud customer and providers.

TABLE 1
Mapping of Multi-Attribute Values

	CP_1	CP_2	CP_3	D
Bandwidth (kpb)	300 20	500 40	800 50	[1-100]
Latency (ms)	10 50	5 80	20 30	[1-100]
Main Memory	4G 20	16G 60	8G 40	[1-100]

3.2 QoS Evaluation Function

The comparison of QoS parameters is an issue on multiple resource attributes decision making. A simple additive weighting (SAW) method is used in [18] to perform the comparison of quality attributes.

3.2.1 Mapping of Multi-Attribute Values

Assume that provider CP_i offers the resources at price p_i and resource attributes q^i based on the resource purchase requirements submitted by the customer. The attribute values are mapped to a unified non-dimensional interval D. Let $f_j : Q_j \rightarrow D$ be the customer's evaluation function for the jth attribute value. Especially, if a customer does not want to purchase any resource provided by service provider i, then he/she can set $f_j(q_j^i) = 0$ ($j \in \mathcal{K}$). An example of the mapping of multi-attribute values of the cloud-computing resources is shown in Table 1.

3.2.2 Customer's Resource Attribute Preferences

The customer's QoS evaluation function for CP_i is defined:

$$w(\rho, q^i) = \sum_{j \in \mathcal{K}} \rho_j f_j(q_j^i), \tag{1}$$

where $\rho = (\rho_1, \ldots, \rho_k)$ is a vector of attribute preferences that satisfy the condition that $\sum_{j \in \mathcal{K}} \rho_j = 1, \rho_j \geq 0$. For further simplicity, we use w_i to indicate $w(\rho, q^i)$.

To obtain an accurate attribute preferences ρ, we use the Analytic Hierarchy Process (AHP) [18] to approximate the calculation of attribute preferences. Based on resource requirements provided by the customer, we can get a judgment matrix $A = (a_{ij})_{k \times k}$, where a_{ij} ($i, j \in \mathcal{K}$) represents the degree of importance of attribute i over attribute j. If attribute i is more important than attribute j, a_{ij} is an integer in the range $1 \leq a_{ij} \leq 9$, which increases with the degree of importance of attribute i over attribute j. Moreover, $a_{ji} = 1/a_{ij}$, and $a_{ii} = 1$.

The Square Root Method (SRM) is introduced in this paper to qualitatively and simply approximate the attribute preferences ρ. The SRM method involves two stages:

(1) Calculating the geometric mean $\bar{\rho}_i$ of all the elements in each row of the judgment matrix A, $\bar{\rho}_i$ is defined:

TABLE 2
Attribute Preferences of One Customer

	Bandwidth	Latency	Main Memory
Bandwidth	1.000	5.000	8.000
Latency	0.200	1.000	1.600
Main Memory	0.125	0.625	1.000

$$\bar{\rho}_i = \left(\prod_{j \in \mathcal{K}} a_{ij} \right)^{1/k} \qquad i \in \mathcal{K}, \tag{2}$$

where $\bar{\rho} = (\bar{\rho}_1, \ldots, \bar{\rho}_i, \ldots, \bar{\rho}_k)$.

(2) Standardizing the attribute preference ρ_i, which is defined:

$$\rho_i = \frac{\bar{\rho}_i}{\sum_{j \in \mathcal{K}} \bar{\rho}_j} \quad i \in \mathcal{K}, \tag{3}$$

where $\rho = (\rho_1, \rho_2, \ldots, \rho_k)$ is the resource attribute preferences.

We illustrate the QoS comparison with a simple numerical computation. The attribute values are assigned arbitrarily for illustration. In Table 1, the first column of each provider represents his/her resource attributes and the second column is the corresponding mapping values. Table 2 represents the attribute preference matrix A of one customer. Therefore, the attribute preference is computed as $\rho = (0.75, 0.15, 0.10)$. The final QoS values of the resources provided by three providers are 24.5, 47.9, and 46.0, respectively.

3.3 Cloud-Computing Resource Provision Model

We consider the up-rounding and down-rounding method in the cloud-computing resource provision model. Let $b_i = \langle p_i, w_i \rangle$ be the bid ordered pair of CP_i. The cloud-computing resource provision model is defined:

$$\overline{m}_i(b_i, \boldsymbol{b}_{-i}) = \frac{\frac{w_i}{p_i}}{\sum_{j \in \mathcal{N}} \frac{w_j}{p_j}} \cdot m, \tag{4}$$

where $\boldsymbol{b}_{-i}$ is the cloud providers tuple without CP_i, i.e., $\boldsymbol{b}_{-i} = (b_1, b_2, \ldots, b_{i-1}, b_{i+1}, \ldots, b_n)$. Since the quantity of the provided resources cannot be a fraction, $\overline{m}_i(b_i, \boldsymbol{b}_{-i})$ is rounded:

$$m_i(b_i, \boldsymbol{b}_{-i}) = \begin{cases} \lfloor \overline{m}_i(b_i, \boldsymbol{b}_{-i}) \rfloor & \overline{m}_i - \lfloor \overline{m}_i \rfloor < 0.5, \\ \lceil \overline{m}_i(b_i, \boldsymbol{b}_{-i}) \rceil & \overline{m}_i - \lfloor \overline{m}_i \rfloor \geq 0.5, \end{cases} \tag{5}$$

where $\lfloor x \rfloor$ denotes the largest integer not greater than or equal to x, and $\lceil x \rceil$ denotes the smallest integer greater than or equal to x. From the following analysis and experimental charts, we can know that the cloud provider with higher QoS value has a higher bidding price and more benefits. It presents that the proposed cloud-computing resource provision model is in line with the incentive mechanism.

3.4 Architecture Model and Problem Formulation

Based on the price bidding strategy, we structure the resource provision model from the perspective of non-cooperative game.

Based on the QoS evaluation function w_i calculated from the resource attribute values q^i, each CP_i provides the resources with price p_i. If $p_i > \bar{p}$, the customer will eliminate CP_i. In turn, if $p_i < r_i$, CP_i will abandon the competition. At the beginning, we consider the number of resources m_i that will be offered by the ith provider as a fraction in the resources provision model. Each m_i is a continuous function with respect to p_i and w_i. The resources provision model is modified:

$$m_i(b_i, \boldsymbol{b}_{-i}) = \begin{cases} \frac{\frac{w_i}{p_i}}{\sum_{j \in \mathcal{N}} \frac{w_j}{p_j}} \cdot m & p_i \in [r_i, \bar{p}], \\ 0 & \text{otherwise}. \end{cases} \tag{6}$$

The customer has a benefit function u, which is the total benefits from the resources provided by all of the cloud providers. In [8], Prasad assumed that cost and QoS are correlated. Similarly, the benefit of the customer is correlated with QoS. Because QoS is only determined by q, the revenue function v of customer can represent as $v(q)$, where $v : \mathcal{Q} \rightarrow R \ (q \in \mathcal{Q})$ is the customer's revenue function with respect to resource attribute values. The benefit function u is defined:

$$u(b_i, \boldsymbol{b}_{-i}, q^i) = \sum_{j \in \mathcal{N}} m_j(b_j, \boldsymbol{b}_{-j})(v_j - p_j), \tag{7}$$

where $v_i = v(q^i)$. We assume that v_i is monotonically increasing with respect to q^i.

It is reasonable to consider that each cloud customer is selfish. When choosing cloud providers, the customer tends to maximize his/her own interests. The customer's resource procurement strategy set of selecting providers is Θ, where Θ is a subset group of set $\mathcal{N}$, i.e., $\Theta = 2^{\mathcal{N}}$. We denote J as a set of the customer's resource procurement strategy, i.e., $J \in \Theta$. According to the selection of the provider, the customer optimizes the objective function, which is defined:

$$\begin{aligned} \max \quad & u(b_i, \boldsymbol{b}_{-i}, q^i) = \sum_{j=1}^{n} m_j(b_j, \boldsymbol{b}_{-j}) \cdot (v_j - p_j), \\ \text{s.t.} \quad & p_j \in \mathcal{P}_j, q^j \in \mathcal{Q}. \end{aligned} \tag{8}$$

Every cloud provider CP_i has a benefit function π_i, which is composed of revenues and costs. The cost function of CP_i with respect to resource attribute values is denoted as $c : \mathcal{Q} \rightarrow R \ (q \in \mathcal{Q})$. The benefit function $\pi_i \ (i \in \mathcal{N})$ is defined:

$$\pi_i(b_i, \boldsymbol{b}_{-i}, q^i) = m_i(b_i, \boldsymbol{b}_{-i})(p_i - c_i), \tag{9}$$

where $c_i = c(q^i)$. It is reasonable that c_i is monotonically increasing with respect to q^i.

Similar to the customers, the providers are also considered as selfish to maximize their benefits. Each provider continually changes his/her strategy until reaching a steady state. The strategy set of CP_i is $\mathcal{B}_i$, where $b_i = \langle w_i, \ p_i \rangle \in \mathcal{B}_i$. According to the bidding price p_i, CP_i optimizes his/her objective function, which is calculated:

$$\begin{aligned} \max \quad & \pi_i(b_i, \boldsymbol{b}_{-i}, q^i) = m_i(b_i, \boldsymbol{b}_{-i}) \cdot (p_i - c_i), \\ \text{s.t.} \quad & p_i \in \mathcal{P}_i, q^i \in \mathcal{Q}. \end{aligned} \tag{10}$$

3.5 Calculation of Critical Price

Given the non-price attributes q^i of the resources provided by CP_i, the cost c_i of CP_i and the customer's benefits f_i is

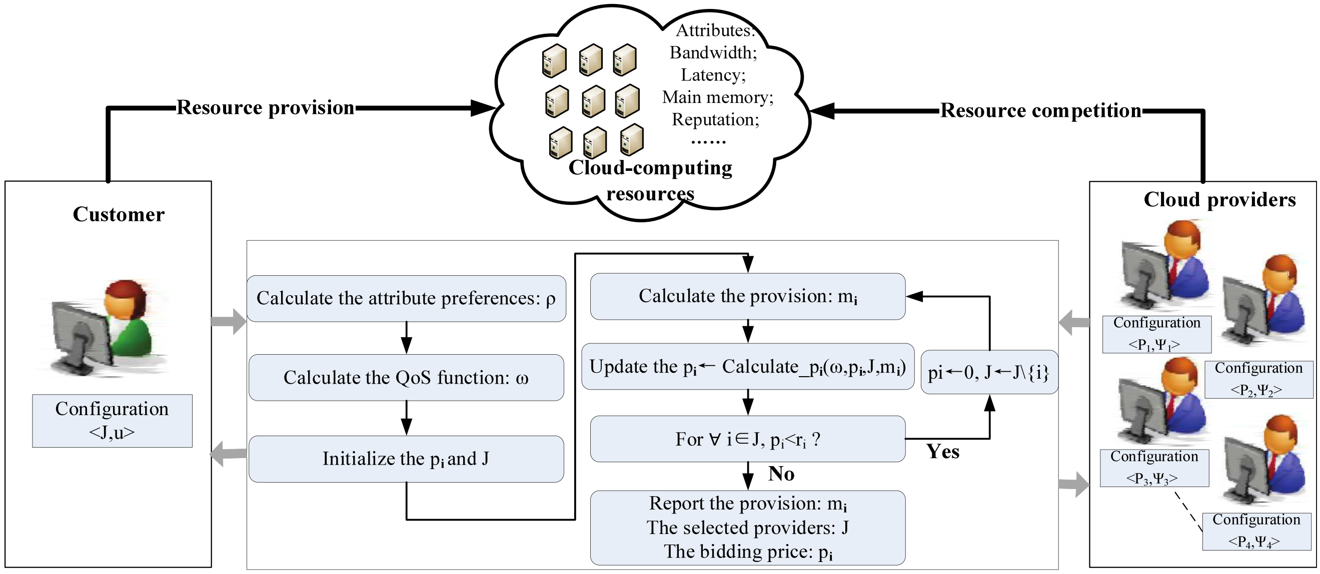


Fig. 2. Game-based price bidding mechanism for cloud-computing resource provision.

evaluated. In every round of bidding, the price of CP_i is related to the quantity of the provided resources, which affects the benefit functions of cloud customer and provider i. At the beginning of the bidding price, the customer's strategy $J = \mathcal{N}$. In each round, CP_i submits the bid price p_i ($p_i \leq \bar{p}$). Without selecting CP_i, we denote the benefit function of the customer:

$$u(\boldsymbol{b}_{-i}) = \sum_{j \in J \backslash \{i\}} m'_j(b_j, \boldsymbol{b}_{-j}) \cdot (v_j - p_j), \tag{11}$$

where $m'_j(b_j, \boldsymbol{b}_{-j})$ is the quantity of resources from CP_j ($j \neq i$, and $i, j \in J$). If $u(\boldsymbol{b}_{-i}) > u(b_i, \boldsymbol{b}_{-i}, q^i)$, $J \leftarrow J \backslash \{i\}$.

To win the competition, the bid price p_i ($r_i \leq p_i \leq \bar{p}$) of CP_i satisfies the condition $u(b_i, \boldsymbol{b}_{-i}, q^i) \geq u(\boldsymbol{b}_{-i})$. Without selecting CP_i ($i \in J$), the number of resources provision is written:

$$m'_{j, j \in J \backslash \{i\}}(b_j, \boldsymbol{b}_{-j}) = \frac{\frac{w_j}{p_j}}{\sum_{k \in J \backslash \{i\}} \frac{w_k}{p_k}} \cdot m. \tag{12}$$

Based on the condition $u(\boldsymbol{b}_{-i}) \leq u(b_i, \boldsymbol{b}_{-i}, q^i)$, we obtain:

$$p_i \leq v_i - \frac{\sum_{j \in J \backslash \{i\}} \frac{w_j}{p_j} \cdot (v_j - p_j)}{\sum_{j \in J \backslash \{i\}} \frac{w_j}{p_j}}. \tag{13}$$

The right side of the inequality is the critical price of CP_i. In addition to $p_i \leq \bar{p}$, the critical price of provider i p'_i is updated:

$$p'_i = \min \left\{ v_i - \frac{\sum_{j \in J \backslash \{i\}} \frac{w_j}{p_j} \cdot (v_j - p_j)}{\sum_{j \in J \backslash \{i\}} \frac{w_j}{p_j}}, \bar{p} \right\}. \tag{14}$$

If $p'_i < r_i$, the provided resources m_i of CP_i is zero.

4 Game Formulation and Analyses

4.1 Game Formulation

We give the definition of Nash equilibrium and three elements of the game on the proposed problem of cloud-computing resource provision. We also propose a game-based bidding price mechanism for cloud-computing resource provision, as illustrated in Fig. 2. The cloud customer submits the requirement of cloud resources, and providers compete for providing the resources to the customer. Providers repetitive submit their prices to the customer, which determines the resource provision. After a series of price bidding iterations, it reaches a steady state. Namely, it reaches a Nash equilibrium solution.

Definition 4.1 (Nash Equilibrium). *In a strategy profile, all participants are facing with a situation where the strategy is the best one when others do not change their strategies.*

The participants in our game model are one cloud customer and n providers. The strategy and the benefit function of the customer are J and $u(b_i, \boldsymbol{b}_{-i}, q^i)$, respectively. Corresponding, the strategy and the benefit function of CP_i are $\mathcal{B}_i$ and $\pi_i(b_i, \boldsymbol{b}_{-i}, q^i)$. Considering the maximal benefits of the customer, the bidding price for each cloud provider keeps changing until it comes to an equilibrium. Since b_i is composed of p_i and w_i, and w_i is represented by q^i, we denote Eq. (9):

$$\Psi_i(p_i, \boldsymbol{p}_{-i}, q^i) = -\pi_i(b_i, \boldsymbol{b}_{-i}, q^i), \tag{15}$$

where $\boldsymbol{p}_{-i}$ is the bid price p_i ($p_i \in \mathcal{P}_i$) of cloud provider tuple without CP_i, i.e., $\boldsymbol{p}_{-i} = (p_1, p_2, \ldots, p_{i-1}, p_{i+1}, \ldots, p_n)$. We denote $\mathcal{P} = \mathcal{P}_1 \times \mathcal{P}_2 \times \cdots \times \mathcal{P}_n$. Then the benefit function of CP_i is modified:

$$\min \Psi_i(p_i, \boldsymbol{p}_{-i}, q^i) = \begin{cases} \frac{\frac{w_i}{p_i} \cdot m \cdot (c_i - p_i)}{\sum_{j \in J} \frac{w_j}{p_j}} & p_i \in [r_i, \min\{p'_i, \bar{p}\}], \\ 0 & \text{otherwise}, \end{cases} \tag{16}$$
$$\text{s.t. } \langle p_i, \boldsymbol{p}_{-i} \rangle \in \mathcal{P}, q^i \in \mathcal{Q}.$$

The customer's strategy set is Θ and the benefit function is $u(b_i, \boldsymbol{b}_{-i}, q^i)$. We denote $\Psi = \Psi_1 \times \Psi_2 \times \cdots \times \Psi_n$. The price bidding game is used to represent G, where $G = \{\mathcal{P}, \Theta; \Psi, u\}$. We have the following definition.

Definition 4.2 (Nash Equilibrium of the Pricing Model). *A Nash equilibrium* $\langle \boldsymbol{p}^*, J^* \rangle$ *of the game* $G = \{\mathcal{P}, \Theta; \Psi, u\}$ *satisfies*

$$\boldsymbol{p}^* \in \arg\min_{p_i \in \mathcal{P}_i} \Psi_i(p_i, \boldsymbol{p}_{-i}, q^i),\ \boldsymbol{p}^* \in \mathcal{P}, \tag{17}$$

$$J^* \in \arg\max_{J \in \Theta} u(b_i, \boldsymbol{b}_{-i}, q^i), J^* \in \Theta, \tag{18}$$

for the customer and each provider.

For all cloud providers, $\boldsymbol{p}^* = (p_1^*, p_2^*, \ldots, p_n^*)$ is the best countermeasure. That is to say, for CP_i and any $p_i \in \mathcal{P}_i$, there is $\Psi_i(p_i, \boldsymbol{p}_{-i}^*, q^i) \geq \Psi_i(p_i^*, \boldsymbol{p}_{-i}^*, q^i)$.

4.2 Nash Equilibrium Existence Analysis

There are many studies of equilibrium solution existence analysis [31], [32]. [31] expanded the two-person games to n-person games to find Nash equilibrium, which satisfies the conditions that $\mathcal{P}_i$ is a compact convex set in an euclidean space, Ψ_i is a continuous function on $\mathcal{P}$, and Ψ_i is a convex function on $\mathcal{P}_i$ with respect to p_i. In [32], Facchinei et al. considered a generic convex optimization problem:

$$\begin{aligned} &\text{minimize} && f(x), \\ &\text{subject to} && x \in \mathcal{K}, \end{aligned} \tag{19}$$

where f is called the objective function and $\mathcal{K}$ is the constraint set. There is a minimum principle that a feasible point $x^* \in \mathcal{K}$ is an optimal solution if and only if $(y - x^*)^T \triangledown f(x^*) \geq 0, \forall y \in \mathcal{K}$.

Theorem 4.1. *Given the non-price resource attributes* q $(q \in \mathcal{Q})$ *and* $p_i \leq \min\{p_i', \bar{p}\}$, *non-cooperative game strategies for* n *cloud providers* $\mathcal{M} = (\mathcal{N}, \{\mathcal{P}_i\}, \{\Psi_i\})$ *have a Nash equilibrium* $\boldsymbol{p}^*$ $(\boldsymbol{p}^* \in \mathcal{P})$.

Proof. First, for each CP_i, $\mathcal{P}_i$ is a one-dimensional closed interval. Thus, $\mathcal{P}_i$ is compact. For any $x_1, x_2 \in \mathcal{P}_i$, there is $\lambda x_1 + (1 - \lambda) x_2 \in \mathcal{P}_i$, for any $\lambda \in [0, 1]$. And $\mathcal{P}_i$ is considered as a convex set. Second, when $r_i \leq p_i \leq \min\{p_i', \bar{p}\}$, we can know Ψ_i is a continuous function on $\mathcal{P}_i$. The Ψ_i is expanded to obtain:

$$\begin{aligned} \Psi_i(p_i, \boldsymbol{p}_{-i}, q^i) &= \frac{\frac{w_i}{p_i} \cdot m \cdot (c_i - p_i)}{\sum_{j \in \mathcal{N}} \frac{w_j}{p_j}}, \\ &= \frac{\frac{w_i}{p_i} \cdot m c_i}{\sum_{j \in \mathcal{N}} \frac{w_j}{p_j}} - \frac{w_i \cdot m}{\sum_{j \in \mathcal{N}} \frac{w_j}{p_j}}. \end{aligned} \tag{20}$$

Taking a derivative with respect to p_i yields:

$$\begin{aligned} \frac{\partial \Psi_i}{\partial p_i} &= \frac{-\frac{w_i c_i m}{p_i^2} \left(\sum_{j \in \mathcal{N}} \frac{w_j}{p_j} \right) + \frac{w_i^2 c_i m}{p_i^3}}{\left(\sum_{j \in \mathcal{N}} \frac{w_j}{p_j} \right)^2} - \frac{\frac{w_i^2 m}{p_i^2}}{\left(\sum_{j \in \mathcal{N}} \frac{w_j}{p_j} \right)^2}, \\ &= \frac{-\frac{w_i c_i m}{p_i^2} \left(\sum_{j \in \mathcal{N} \setminus \{i\}} \frac{w_j}{p_j} \right) - \frac{w_i^2 m}{p_i^2}}{\left(\sum_{j \in \mathcal{N}} \frac{w_j}{p_j} \right)^2} < 0. \end{aligned} \tag{21}$$

Taking the second derivative with respect to p_i obtains:

$$\begin{aligned} \frac{\partial^2 \Psi_i}{\partial p_i^2} &= \frac{\left(\sum_{j \in \mathcal{N} \setminus \{i\}} \frac{w_j}{p_j} \right) \cdot \frac{2 w_i c_i m}{p_i^3} + \frac{2 w_i^2 m}{p_i^3}}{\left(\sum_{j \in \mathcal{N}} \frac{w_j}{p_j} \right)^2} \\ &\quad - \frac{\frac{2 w_i^2 c_i m}{p_i^4} \left(\sum_{j \in \mathcal{N} \setminus \{i\}} \frac{w_j}{p_j} \right) + \frac{2 w_i^3 m}{p_i^4}}{\left(\sum_{j \in \mathcal{N}} \frac{w_j}{p_j} \right)^3}, \\ &= \frac{\frac{2 w_i c_i m}{p_i^3} \left(\sum_{j \in \mathcal{N} \setminus \{i\}} \frac{w_j}{p_j} \right)^2 + \frac{2 w_i^2 m}{p_i^3} \left(\sum_{j \in \mathcal{N} \setminus \{i\}} \frac{w_j}{p_j} \right)}{\left(\sum_{j \in \mathcal{N}} \frac{w_j}{p_j} \right)^3} \\ &> 0. \end{aligned} \tag{22}$$

Then we can know that $\Psi_i(p_i, \boldsymbol{p}_{-i}, q^i)$ is a convex function on $\mathcal{P}_i$. At last, due to the Eq. (21), $\frac{\partial \Psi_i}{\partial p_i} < 0$ for $\forall p_i \in \mathcal{P}_i$. To satisfy the condition that $(p_i - p_i^*)^T \triangledown \Psi_i(p_i, \boldsymbol{p}_{-i}, q^i) \geq 0$ for $\forall p_i \in \mathcal{P}_i$ and $p_i \leq \min\{p_i', \bar{p}\}$, then p_i^* is the maximum value in the intersection of $\mathcal{P}_i$ and interval $[0, \min\{p_i', \bar{p}\}]$. The proof of the theorem has been completed. □

Based on Theorem 4.1, we can prove that there exists a Nash equilibrium for the game $G = \{\mathcal{P}, \Theta; \Psi, u\}$.

Theorem 4.2. *Given the non-price resource attributes* q $(q \in \mathcal{Q})$ *and the bidding price* $\boldsymbol{p}$ $(\boldsymbol{p} \in \mathcal{P})$, *there exists a Nash equilibrium solution set for formulated game* $G = \{\mathcal{P}, \Theta; \Psi, u\}$.

Proof. At the beginning, we set the initial value of J to $\mathcal{N}$. According to Theorem 4.1, there exists a Nash equilibrium $\boldsymbol{p}^*$ for $\mathcal{M} = (\mathcal{N}, \{\mathcal{P}_i\}, \{\Psi_i\})$. If the bidding price p_i^* of each CP_i satisfies $r_i \leq p_i^* \leq \bar{p}$, the customer's optimal choice is $J = \mathcal{N}$. That is to say, game $G = \{\mathcal{P}, \Theta; \Psi, u\}$ has reached the Nash equilibrium. Otherwise, the customer can update $J = J \setminus \{i\}$ to maximize the revenue, meanwhile, $p_i^* = 0$. Based on Theorem 4.1, the customer updates J until J does not change. Then the Nash equilibrium for game $G = \{\mathcal{P}, \Theta; \Psi, u\}$ is obtained. The proof of the theorem has been completed. □

The profit of the customer is increased or not reduced based on the analysis in Section 3.5. Besides, the profit of each service provider will be reduced whether he/she intentionally bids a high or low price from Theorem 4.1. From selfishness and rationality, each player will not make a deceptive strategy to decrease his/her profit.

4.3 Nash Equilibrium Solution Computation

An Equilibrium Solution Iterative algorithm is presented to find the equilibrium solution. The initial value of customer's resource procurement strategy J is equal to the set of cloud providers $\mathcal{N}$. After each cloud provider bidding, the provider CP_i has a critical price p_i'. Each CP_i $(i \in J)$ bids continually until the change of p_i' is less than a threshold. Assuming that the maximum price offered by the customer is $\bar{p}$, if $p_i' > \bar{p}$, we set $p_i' = \bar{p}$, and $p_i' = \bar{p}$ is the best choice for CP_i. Then we can assume that $p_i' \leq \bar{p}$. As mentioned in Section 4.2, $\Psi_i' < 0$ and $\Psi_i'' > 0$, we can know that:

(1) If there is $r_i \leq p_i' \leq \bar{p}$ for each CP_i $(i \in J)$, it is true that

$$p_i' = v_i - \frac{\sum_{j \in J \setminus \{i\}} \frac{w_j}{p_j'} \cdot (v_j - p_j')}{\sum_{j \in J \setminus \{i\}} \frac{w_j}{p_j'}}. \tag{23}$$

The equilibrium solution of the model $\mathcal{M} = (J, \{\mathcal{P}_i\}, \{\Psi_i\})$ is $p^* = (p_1^*, p_2^*, \ldots, p_n^*)$, where $p_i^* = p_i'$. The optimal strategy for the customer is $J = \mathcal{N}$. The equilibrium solution of the formulated game $G = \{\mathcal{P}, \Theta; \Psi, u\}$ is $\langle p^*, J \rangle$.

(2) If there are providers that each CP_i of them satisfies $r_i > p_i'$, $p_i^* = 0$. We update $J = J \setminus \{i\}$, which is obtained by removing CP_i. In addition, we repeat update J until J does not change. The value of p^* in the equilibrium solution is calculated:

$$p_i^* = \begin{cases} v_i - \dfrac{\sum_{j \in J \setminus \{i\}} \frac{w_j}{p_j^*} \cdot (v_j - p_j^*)}{\sum_{j \in J \setminus \{i\}} \frac{w_j}{p_j^*}} & i \in J r_i \leq p_i^* \leq \bar{p}; \\ \bar{p} & i \in J p_i^* > \bar{p}; \\ 0 & i \in \mathcal{N} \setminus J. \end{cases} \tag{24}$$

The detailed steps of the ESI algorithm are described in Algorithm 1.

Algorithm 1. Equalization Solution Iterative Algorithm

Input: $\mathcal{N}$, A, $Q_{n \times k}$, f, v, r, ϵ.
Output: $\boldsymbol{p}_{\mathcal{N}}$, J.
1: calculate the attribute preference $\rho \leftarrow \rho(A)$;
2: calculate the QoS function $w \leftarrow w(\rho,\ Q_{n \times k})$;
3: initialize p_i for each cloud provider CP_i;
4: $r \leftarrow 0$;
5: $J^{(0)} \leftarrow \mathcal{N}$;
6: **for** each cloud provider $CP_i \in J$ **do**
7:

$$p_i^{(r+1)} \leftarrow \min\left\{ v_i - \frac{\sum_{j \in J^{(r)} \setminus \{i\}} \frac{w_j}{p_j^{(h)}} (v_j - p_j^{(r)})}{\sum_{j \in J^{(r)} \setminus \{i\}} \frac{w_j}{p_j^{(r)}}}, \bar{p} \right\};$$

8: $J^{(r+1)} \leftarrow J^{(r)}$;
9: **if** ($p_i^{(r+1)} < r_i, i \in J$) **then**
10: $\quad p_i^{(r+1)} \leftarrow 0$;
11: $\quad J^{(r+1)} \leftarrow J^{(r)} \setminus \{i\}$;
12: $r \leftarrow r + 1$;
13: **if** ($J^{(r)}$ is not equal to $J^{(r-1)}$ or $\left\| \boldsymbol{p}_{J^{(r)}} - \boldsymbol{p}_{J^{(r-1)}} \right\| > \epsilon$) **then**
14: $\quad$ repeat steps 7 to 12;
15: **return** $\boldsymbol{p}_{\mathcal{N}}^{(r)}$ and J.

The input of Algorithm 1 is $\{\mathcal{N},\ A,\ Q_{n \times k},\ f,\ v,\ r,\ \epsilon\}$, where $\mathcal{N}$ is a set of n cloud providers, A is the judgment matrix of the customer to the resources, $Q_{n \times k}$ is the resource attribute values of the providers. f is the customer's function tuple with respect to $Q_{n \times k}$, and v, r are the customer's revenue function tuple with respect to a resource attribute value and the reservation price of the provider, respectively. ϵ is an arbitrarily small number.

The algorithm begins to iterate from the 7. In each iteration, the system computes the critical price of each provider at first, and then determines whether the critical price of each provider to meet the condition that $r_i \leq p_i^{(r+1)}$. If not, the system updates the bidding price and customer's strategy by lines 6 to 12. The iteration loop will continue until the conditions $J^{(r)} = J^{(r-1)}$ and $\|\boldsymbol{p}_J^{(r)} - \boldsymbol{p}_J^{(r-1)}\| \leq \epsilon$ are satisfied.

4.4 Convergence of the Iterative Algorithm

Depending on the Algorithm 1, we verify that whether the obtained solution sequences converge to the Nash equilibrium. If the solution sequences are proved to be monotonic and bounded, we can draw the conclusion that the solution sequences must converge to an equilibrium.

Theorem 4.3. *Supposing the Nash equilibrium solution of non-cooperative game strategies for n cloud providers $\mathcal{M} = (J, \{\mathcal{P}_i\}, \{\Psi_i\})$ as $\boldsymbol{p}^*$ ($\boldsymbol{p}^* \in \mathcal{P}$), sequence solutions $\boldsymbol{p}^{(h)}$ obtained by the proposed ESI algorithm converge to $\boldsymbol{p}^*$.*

Proof. Here, an inductive method is utilized to prove the theorem. First, we know that the price sequence of each provider CP_i is bounded. Second, we prove its monotonicity as shown below.

The initial value is given as $p_i^{(0)} = \bar{p}$. We know that $p_i^{(1)} \leq \bar{p} = p_i^{(0)}$. Then, supposing $h = s$ satisfies $p_i^{(s)} \leq \bar{p} = p_i^{(s-1)}$, we need to prove $p_i^{(s+1)} \leq \bar{p} = p_i^{(s)}$ in the next iteration. At last, if $p_i^{(s)} = \bar{p}$, $p_i^{(s+1)} \leq \bar{p} = p_i^{(s)}$. Otherwise, Eq. (14) is written:

$$p_i = v_i - \sum_{j \in J \setminus \{i\}} \frac{1}{\mathcal{H}_j}, \tag{25}$$

where

$$\mathcal{H}_j = \frac{\sum_{k \in J \setminus \{i,j\}} \frac{w_k}{p_k}}{\frac{w_j v_j}{p_j} - w_j} + \frac{1}{v_j - p_j}. \tag{26}$$

We observe p_i as a continuous function of p_j $(j \in J \setminus \{i\})$. Taking the derivative of $\mathcal{H}_j$ with respect to p_j, we get

$$\frac{\partial \mathcal{H}_j}{\partial p_j} = \frac{\sum_{k \in J \setminus \{i,j\}} \frac{w_k}{p_k} w_j v_j}{(w_j v_j - w_j p_j)^2} + \frac{1}{(v_j - p_j)^2} > 0. \tag{27}$$

We take derivative of p_i with the respect to p_j, and we have

$$\frac{\partial p_i}{\partial p_j} = \sum_{k \in J \setminus \{i\}} \frac{1}{\mathcal{H}_j^2} \frac{\partial \mathcal{H}_j}{\partial p_j} > 0. \tag{28}$$

That is to say, p_i increases with p_j. Since $p_i^{(s+1)}$ is calculated by $p_j^{(s)}$ $(j \in J \setminus \{i\})$ and $p_i^{(s)} \leq p_i^{(s-1)}$ $(i \in J)$, we can obtain $p_i^{(s+1)} \leq p_i^{(s)}$ $(i \in J)$. □

4.5 Near-Equilibrium Price Bidding Algorithm

Based on the ESI algorithm for the Nash equilibrium solution, we propose a Near-equilibrium price bidding algorithm for the cloud-computing resource provision model. As mentioned in Section 3.3, we view m_i $(i \in \mathcal{N})$ as a fraction. However, m_i should be an integer. And, according to Eq. (5), the quantity of the resources available to the customer might not be equal to m. To get the desired result, we revise the model based on the ESI algorithm and propose a near-equilibrium price bidding algorithm. We propose a Resource Quantity Calculation (RQC) algorithm to compute the quantity of resource provision m_i. The calculation process of the quantity of cloud resources m_i is defined as $Calculate\_m_i(J, m, w_i, p_i, \bar{p})$, as described in Algorithm 2.

TABLE 3
Comparison of Cloud-Computing-Resource Provision Models

Model	Auction	Multi-attribute	QoS	Incentive	Game theory	Allocation/Provision	Algorithm
$\mathcal{CA}$ [18]	yes	no	yes	no	no	allocation	
FMCDAM [16]	yes	yes	yes	no	no	allocation	
C-DSIC, C-BIC, C-OPT [8]	yes	yes	yes	yes	no	provision	
Chonho et al. [15]	no	no	yes	yes	yes	provision	heuristic
$\mathcal{NPBA}$ [22]	no	no	no	no	yes	allocation	iterative
ESI and **NPB**	**no**	**yes**	**yes**	**yes**	**yes**	**provision**	**iterative**

Algorithm 2. Resource Quantity Calculation Algorithm

Input: $J, m, w_i, p_i, \bar{p}$.
Output: m_i.
$flag \leftarrow$ ***true***;
$s \leftarrow 0, m_s \leftarrow m, m_J \leftarrow m$;
while ($flag$ and m_J is not equal to 0) **do**
  initialize $m_i \leftarrow 0$ for each cloud provider;
  $m^{(s)} \leftarrow 0$;
  for each provider CP_i **do**
    $m_i^{(s)} \leftarrow$ Eq. (5);
    $m_i \leftarrow m_i + m_i^{(s)}$;
    $m^{(s)} \leftarrow m^{(s)} + m_i^{(s)}$;
  $m_J \leftarrow m_J - m^{(s)}$;
  if ($m^{(s)}$ equals to 0) **then**
    flag $\leftarrow$ ***false***;
    else $s \leftarrow s + 1$;
return m_i.

We develop a calculation process of the resource price to modify the benefits of CP_i. The resource Bidding Price Calculation (RBPC) algorithm is executed in each iteration process. The calculation process of the bidding price p_i in the current iteration is defined as $Calculate\_p_i(J,\ m,\ w_i,\ \bar{p})$, as described in Algorithm 3.

Next, we focus on the approximate calculation of bidding price p_i. Combining with Algorithm 2, we propose Algorithm 3 to find the equilibrium price in J. In Algorithm 3, we first use Algorithm 2 to compute m_i, and further calculate m_j^i for each $i \in J$, where m_j^i is a vector of the quantity of cloud-computing resource provisions for every CP_j ($j \in J^{(r)} \backslash \{i\}$). In the inner $while$ loop, we use the dichotomy to compute $p_i^{(h)}$ of each CP_i. We set pl and pr to the left and right borders, respectively. The outer $while$ loops are executed until reach the condition of $\left\| \boldsymbol{p}^{(h)} - \boldsymbol{p}^{(h-1)} \right\| \leq \epsilon$.

We modify the ESI algorithm according to Algorithm 3 and require a NPB algorithm. The improvement of Algorithm 4 is to update the bidding price in line 7. Assuming that the computation time of the RQC algorithm is $O(a)$, the $while$ loop of the RBPC algorithm is $O(b)$, and the iterative RBPC algorithm is $O(d)$. The one computation iteration time of the NPB algorithm in the worst case is $O(na + b \log p)$. The time complexity of the NPB algorithm in the worst case is $O(d(na + b \log p))$.

5 Experiments

Related models are compared with our proposed ESI and NPB algorithms from some properties in Table 3. Due to the different selected parameters of various models, we compare the main features of various models from 7 aspects and to highlight the difference in our model. In the following sections, we draw the graphs from the ESI and NPB algorithms and comparison experiments with three mechanisms in [8] to validate the above theoretical analysis based on the data analysis.

Algorithm 3. Resource Bidding Price Calculation Algorithm

Input: $J, m, w_i, \bar{p}$.
Output: p_i.
$J \leftarrow \mathcal{N}$;
$h \leftarrow 0$;
initialize $p_i^{(0)} \leftarrow \bar{p}$ for each cloud provider CP_i;
while ($\| \boldsymbol{p}^{(h)} - \boldsymbol{p}^{(h-1)} \| > \epsilon$) **do**
  for (each provider $CP_i \in J$) **do**
    $m_j^i \leftarrow \mathcal{C}alculate\_m_j(J^{(r)} \backslash \{i\}, m, w_j, p_j^{(h-1)}, \bar{p})$;
  for (each provider $CP_i \in J$) **do**
    $pl \leftarrow 0$; $pr \leftarrow \bar{p}$;
    $p(0) \leftarrow \bar{p}$; $p(1) \leftarrow (pl + pr)/2$;
    $r \leftarrow 1$;
    while ($\| p(r) - p(r-1) \| > \epsilon$) **do**
      $m_i \leftarrow \mathcal{C}alculate\_m_i(J, m, w_i, \langle p_{-i}^{(h-1)}, p(r) \rangle, \bar{p})$;
      $u1 \leftarrow u(\boldsymbol{b}_{-i})$;
      $u2 \leftarrow u(\langle p(r), w_i \rangle, \boldsymbol{b}_{-i})$;
      if ($u1 > u2$) **then**
        $pr \leftarrow p(r)$;
      if ($u1 < u2$) **then**
        $pl \leftarrow p(r)$;
      $r \leftarrow r + 1$;
      $p(r) \leftarrow (pl + pr)/2$;
    $p_i^{(h)} \leftarrow p(r)$;
  $h \leftarrow h + 1$;
return $p_i^{(h)}$.

5.1 Experiment Setup

In the following simulation experiments, the number of cloud providers is varied in the range of 10 to 100. Table 4 lists the entire system parameters and the corresponding functions. The number of resource attributes k is varied from 0 to 100 with increment 5 when we analyse the influence of multi-attribute. The customer gives the relative importance of the k attributes, where $a(1, :)$ is the importance of the first attribute relative to other attributes. The resource attribute mapping value of each provider is varied from 1 to 100. We assume that the customer's revenue and the cost of providers are in exponential form. m is set as 1000. Besides, the parameter of controlling the iteration is set at 0.01.

5.2 Algorithm Evaluation

Table 5 lists the specific parameters of an example to validate our conclusions.

TABLE 4
System Parameters

System parameters	Variable range
Quantity of resource attributes (k)	[0, 100]
Comparison of the first attribute with other attributes $(a(1,:))$	random in [1, 9]
Number of cloud providers (n)	[10, 100]
Evaluation function (f_j)	random in [1, 100]
Customer's revenue function (v_i)	$\sum_{j\in\mathcal{K}} \alpha \cdot (q_j^i)^\beta / k$
Cost function of provider i (c_i)	$\sum_{j\in\mathcal{K}} \theta (q_j^i)^\eta / k$
Conservative bidding price (r_i)	λc_i
Quantity of resources required (m)	1000
Other parameter (ϵ)	0.01

Algorithm 4. Near-Equalization Price Bidding Algorithm

Input: $\mathcal{N}$, A, $Q_{n\times k}$, f, v, r, ϵ.
Output: $p_{\mathcal{N}}$, J.
1: calculate the attribute preferences $\rho \leftarrow \rho(A)$;
2: calculate the QoS function $w \leftarrow w(\rho,\ Q_{n\times k})$;
3: initialize p_i for each cloud provider CP_i;
4: $r \leftarrow 0$;
5: $J^{(0)} \leftarrow \mathcal{N}$;
6: $p_{\boldsymbol{i}}^{(r)} \leftarrow Calculate\_p_i(J^{(r)}, m, w_{\boldsymbol{i}}, \bar{p})$;
7: $J^{(r+1)} \leftarrow J^{(r)}$;
8: **if** $(p_i^{(r)} < r_i, i \in J)$ **then**
9: $\quad p_i^{(r)} \leftarrow 0$;
10: $\quad J^{(r+1)} \leftarrow J^{(r+1)} \backslash \{i\}$;
11: $r \leftarrow r + 1$;
12: **if** $(J^{(r)}$ is not equal to $J^{(r-1)}$ or $\|\boldsymbol{p}_{J^{(r)}}^{(r)} - \boldsymbol{p}_{J^{(r-1)}}^{(r-1)}\| > \epsilon)$ **then**
13: $\quad$ repeat steps 7 to 11.
14: **return** $\boldsymbol{p}_{\mathcal{N}}^{(r)}$ and J.

5.2.1 Convergence of Algorithm ESI and NPB

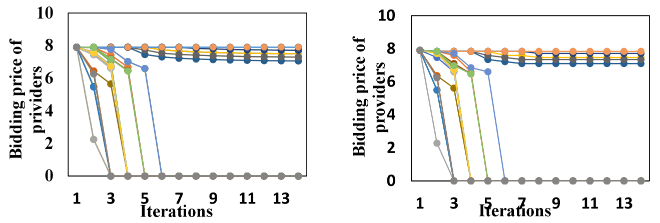
Parameters from the project described in Table 5 are used in the experiments. The experimental results are presented in Figs. 3 and 4.

Figs. 3a and 3b show the convergence process of bidding price by executing ESI and NPB algorithms, respectively. As the number of iterations increases, the bidding price of each cloud provider is decreasing and tends to a relatively stable state in two algorithms. In the iterative process, some providers withdraw the competition when the condition satisfies $p_i < r_i$. Fig. 3 shows that the iterative process and results in ESI close to the ones in the NPB algorithm. Moreover, it can be seen that the bidding prices reach a stable state after 10 iterations, which shows high efficiency of our developed algorithms.

Fig. 4 analyzes the iterative process of two randomly selected CPs (CP_5, CP_{16}) between two algorithms, individually. In the iterative process, the descent speed of bidding

TABLE 5
Specific Parameters for an Example

Parameter	n	k	α	β	η	θ	λ	$\bar{p}$
Value	20	10	0.8	0.7	1.0	0.4	1.5	7.9



(a) ESI algorithm (b) NPB algorithm

Fig. 3. Bidding prices process of cloud providers.

price and the reached stable value of each CP are consistent in both algorithms. The maximal pricing error ranges of CP_5 and CP_{16} are 1.52 and 2.76 percent, respectively, which show that how close the convergence of two algorithms is.

5.2.2 Comparison of Algorithm ESI and NPB

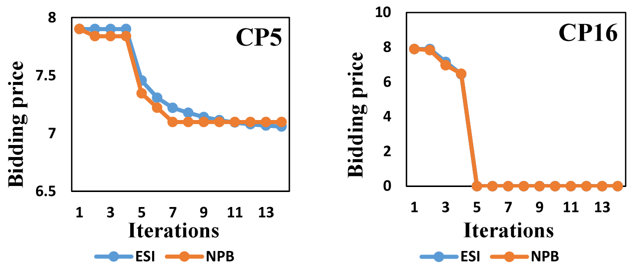
To illustrate how close a near-equilibrium solution found by our proposed NPB algorithm to the solution computed by ESI, experiments are performed for the ESI and NPB algorithms. The parameters are outlined in Table 5. The experimental results are presented in Fig. 5.

Fig. 5 analyzes the comparison the ESI and NPB algorithms from four different views. The blue and orange columns represent the values calculated by ESI and NPB, respectively. The selected providers are CP_2, CP_5, CP_7, CP_9, and CP_{12}. Meanwhile, bidding prices of other providers are zero. The maximal error of two algorithms in Fig. 5a is 1.10 percent. The values of resources provided by each CP between two algorithms are very close, whose maximal error is 1.30 percent. In Fig. 5c, obviously, the former is the benefit value computed from the Nash equilibrium solution and smaller than that of the latter. Specifically, differences of bidding prices between ESI and NPB are in the range from 0 to 0.46 percent. Similarly, Fig. 5d shows that the bidding prices between two algorithms are close. Based on the comparison of the convergence process and four different views, the percent differences are extremely small, which reflect that our NPB algorithm can obtain a very well near-optimal solution.

5.3 Profits Analysis of One Customer and Providers

5.3.1 Multi-Attribute Analysis

The values of resource multi-attribute are relevant to QoS, the cost of each CP, and the benefit of customers. To illustrate that how multiple attributes influence on the selected CPs, the parameters are selected as follows. Assuming that $n = 200$, the attribute projection evaluation value of each CP



(a) (b)

Fig. 4. Bidding price process of CP_5 and CP_{16}.

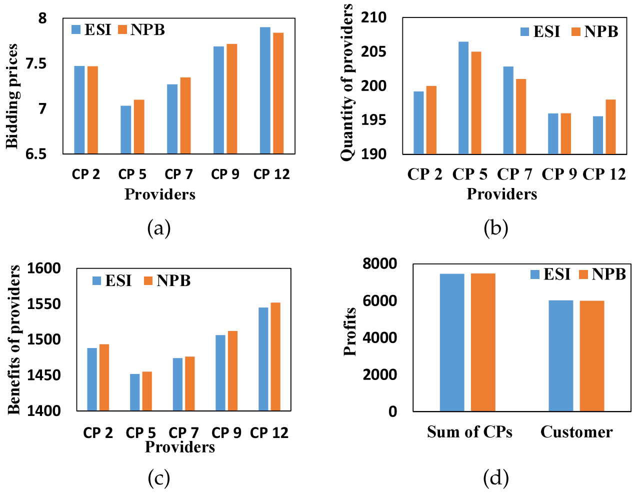


Fig. 5. Comparison of algorithms ESI and NPB.

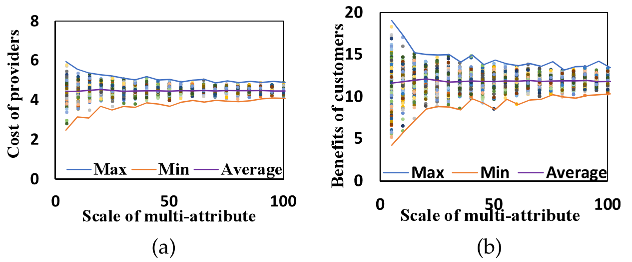


Fig. 6. Influence of different scales of attributes.

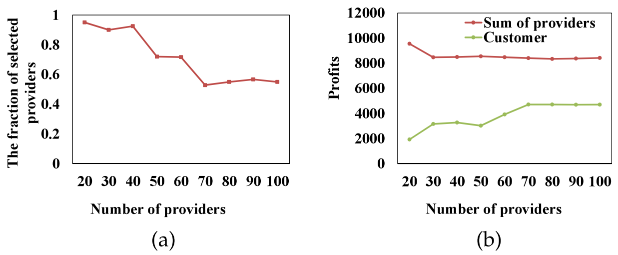


Fig. 7. Influence of different quantities of providers.

is randomly chosen from the interval of 1 to 100, and k increases by 5 from 5 to 100. The experimental results are presented in Figs. 6a and 6b.

Figs. 6a and 6b show the range of each selected provider's resource cost and one customer's benefit with the increment of k, respectively. The general trend of the blue line is decreasing, whereas the orange line is increasing. The average value maintains at a relatively stable state. This phenomenon reflects that the more attributes one customer considers, the narrower the range of cost of the selected providers is, and it is earlier to select the appropriate providers.

5.3.2 *Analysis of the Different Quantities of Providers*

We illustrate the relevance between the number of providers and profits of customer and providers. Assuming that $k = 10$, n is a variable, which fetches the value from 20 to 100 with the increment of 10. The experimental results are presented in Fig. 7.

Fig. 7 shows the influence of increasing the number of providers. Total profits of CPs decrease to a stable value, whereas the benefit of customer increases at first and reaches a

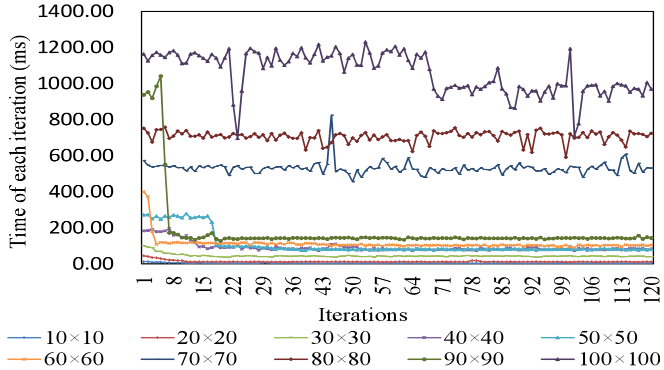


Fig. 8. Iterative times of different scales of resource attributes and providers.

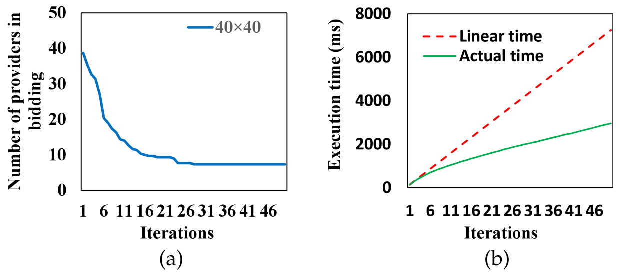


Fig. 9. Number of selected providers and execution time.

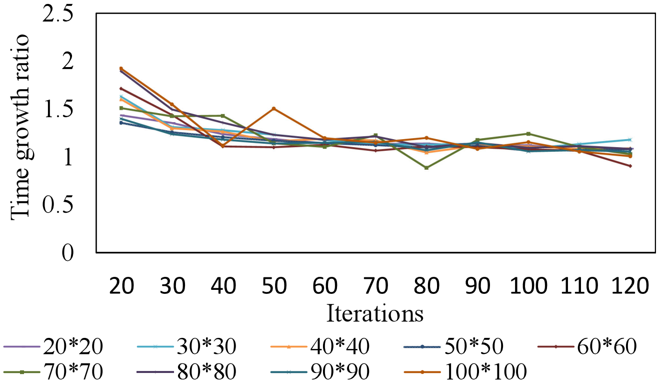


Fig. 10. Time growth ratio of different scales of resource attributes and providers.

relatively stable state. When the number of providers n increases, providers are posing growing competition for resource provision, which results in decrease of the fraction of selected CPs. Despite the fraction of selected CPs decreases, the number of selected CPs tends to be stable. This is the reason that the benefits of total profits of providers and the customer's profit tend to a relatively stable state, respectively.

5.4 Performance Evaluation

The time performance of the proposed algorithms is evaluated in terms of execution time. The variables are the number of attributes k and providers n. The other parameters are the same as in Table 5. We denote the case of k attributes and n providers as $k \times n$. The variables of k and n increase by 10 from 20 to 100, respectively. The experimental results are presented in Figs. 8, 9a, 9b, and 10, respectively.

Fig. 8 shows the time curve of each iteration for each $k \times n$. On the whole, the iteration time of each curve is relatively large at the beginning, then reaches a stable state after a certain number of iteration. In Fig. 8, it is shown that the

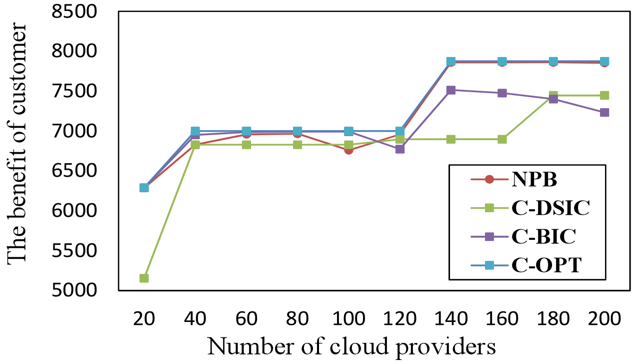


Fig. 11. Comparison of NPB, C-DSIC, C-BIC and C-OPT.

larger the values of k and n, the longer each iteration time, excluding the case of 90×90. The reason is that in the term of 90×90, the number of providers in bidding is small after several iterations. This results in very little time overhead of each iteration.

We give an example of 40×40 to analyze the time performance in detail. Fig. 9a presents the number of providers in bidding with the increase in number of iterations. The curve is monotonically decreasing at the beginning, and finally reaches a steady value of 7 after almost 28 iterations. Fig. 9b shows the execution time of each iteration. The red dotted line represents a linear time with a slope of 145, which is the first execution time. It is observed that the time growth ratio is gradually reduced as the number of iterations increases. This phenomenon can also explain that the time of each iteration is monotonically decreasing to a steady state in Fig. 8.

Fig. 10 shows the time growth ratio of each iteration for each case of $k \times n$. As the number of iterations increases, the time growth ratio of each curve is gradually decreasing and stabilizes to the value of 1, which explains the curve change of Fig. 9b in detail.

Generally speaking, the near-equilibrium solution obtained by our proposed NPB is extremely close to the equilibrium solution obtained by ESI. Second, the convergence rate of the two algorithms is very fast. Again, the benefits of the customer and providers are affected by the multiple attributes and the number of providers. At last, the time complexity of algorithms is less than linear, which is much better than the worst case time.

5.5 Comparison with C-DSIC, C-BIC and C-OPT

Prasad and Rao [8] proposed a multi-attribute cloud resource procurement approach, where three possible auction mechanisms (C-DSIC, C-BIC, and C-OPT) were presented. All of these mechanisms consider the multi-attribute cloud resource provision from a cost perspective. In C-DSIC and C-BIC mechanisms, the cloud resource provider that charges the lowest cost per unit QoS is declared the winner. The C-OPT overcomes the limitation of C-DSIC that is not balanced budget and the limitation of C-BIC that is not individually rational. The cloud vendor with the least virtual cost is declared the winner. The virtual cost considers the reverse hazard rate related to cost and QoS $\frac{F_i(.)}{f_i(.)}$ and is defined as

$$H_i(c_i, q_i) = c_i + \frac{F_i(\frac{c_i}{q_i})}{f_i(\frac{c_i}{q_i})},$$

where c_i is the bidding cost of each cloud vendor, q_i is the mapping value of the promised QoS parameters, $F(.)$ is the cumulative distribution function (CDF), and $f(.)$ is the density of the marginal function. Different from these mechanisms, in our work, we consider the same issue from the perspective of profit. We focus on improving the benefits of both cloud customers and service providers instead of just customers.

To perform the comparison experiments, we made some modifications to the three mechanism algorithms. In C-DSIC and C-BIC, the cloud vendor who charges the largest profit multiplied by QoS is declared the winner. In C-OPT, the cloud vendor with the most virtual profit is declared the winner. In the comparison experiments, assuming that $k = 10$, $m = 1000$, and n is a variable, which fetches the value from 20 to 100 with the increment of 20. Besides, the distribution of random variables in C-BIC and C-OPT is uniformly distributed. The comparison between NPB algorithm and the three mechanisms is shown in Fig. 11.

In Fig. 11, as the number of providers increases, the profit trend of the cloud customer in each algorithm first rises and then stays steady. In addition, the profit of NPB is higher than that of C-DSIC and C-BIC, and the variance of NPB and C-OPT is small. In terms of customer benefits, the algorithms ESI and NPB have absolute advantages. In addition, we also maximize the benefit of each provider through competition between service providers, which is not considered in algorithms C-DSIC, C-BIC, and C-OPT.

6 Conclusions

Our study focuses on the problem of multi-attribute cloud resource provision about pricing strategy for profit maximization consisting of both cloud customers and service providers from the perspective of non-cooperative game theoretical method. The existence of Nash equilibrium solution is proved. To calculate the solution, we propose ESI and NPB algorithms, which are proved to converge to a Nash equilibrium. Extensive simulated experiments results and the comparison experiments with the state-of-the-art and benchmark solutions validate and show the feasibility of the proposed method.

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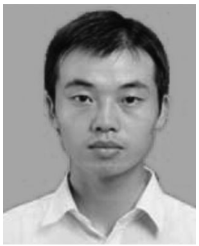
Junyan Hu is currently a PhD candidate in the College of Computer Science and Electronic Engineering, Hunan University, China. Her research interest includes tensor analysis, game theory, grid computing and cloud computing.

Kenli Li received the PhD degree in computer science from the Huazhong University of Science and Technology, China, in 2003. He was a visiting scholar with the University of Illinois at Urbana-Champaign from 2004 to 2005. He is currently a full professor in computer science and technology with the Hunan University and deputy director of National Supercomputing Center in Changsha. His major research areas include parallel computing, high-performance computing, grid and cloud computing. He has published more than 220 research papers in international conferences and journals such as the *IEEE Transactions on Computers*, the *IEEE Transactions on Parallel and Distributed Systems*, the *Journal of Parallel and Distributed Computing*, ICPP, CCGrid. He is an outstanding member of CCF. He is a senior member of the IEEE and serves on the editorial board of *the IEEE Transactions on Computers*.



Chubo Liu received the BS and PhD degrees in computer science and technology from Hunan University, China, in 2011 and 2016, respectively. His research interests include mainly in modeling and scheduling of distributed computing systems, approximation and randomized algorithms, game theory, grid, and cloud computing. He has published several papers in journals such as the *IEEE Transactions on Parallel and Distributed Systems*, the *IEEE Transactions on Cloud Computing*, *Future Generation Computing Systems*, and *Tata Consultancy Services*.

Keqin Li is a SUNY Distinguished professor of computer science. His current research interests include parallel computing and high-performance computing, distributed computing, energy-efficient computing and communication, heterogeneous computing systems, cloud computing, big data computing, mobile computing, service computing, Internet of things and cyber-physical systems. He has published more than 580 journal articles, book chapters, and refereed conference papers, and has received several best paper awards. He is currently or has served on the editorial boards of the *IEEE Transactions on Parallel and Distributed Systems*, the *IEEE Transactions on Computers*, the *IEEE Transactions on Cloud Computing*, the *IEEE Transactions on Services Computing*, the *IEEE Transactions on Sustainable Computing*. He a fellow of the IEEE.