Resource Scarcity-Based Pricing for Cloud Manufacturing Service Platform

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Abstract. Based on the architecture and key technologies of cloud manufacturing (CMfg) are becoming increasingly perfect, it is of great significance for the development and application of CMfg to study the resource pricing under the specific transaction environment of cloud manufacturing service platform (CMSP). Hence, an optimal pricing strategy model adapted to the CMSP environment was proposed in this paper. Firstly, the transaction process of CMSP is analyzed, then the static Bayesian model is selected and improved from three aspects. Finally, through the solution of the model and parameter analysis, the advantages of the model are proved, and the pricing strategy is provided for the platform resource providers.

1. Introduction

Cloud manufacturing is a manufacturing mode of sharing, collaboration and interconnection based on cloud manufacturing service platform (CMSP) and the concept of "manufacturing as a service" by using network and cloud computing technology [1-2].

The research in the field of CMfg can be divided into two parts: CMfg architecture and key technologies in CMfg, both of which have rich research results. In terms of CMfg architecture, Xu et al. [3] put forward the key technology and structure framework from cloud computing to cloud manufacturing, and elaborated the centralized management process of resources and the role of CMSP in the whole manufacturing life cycle. From the application level, Ren et al. [4] proposed a public cloud manufacturing platform for small and medium-sized enterprises, summarizing the concept, architecture, key technologies and implementation process of the cloud manufacturing platform. Yi Shuping et al. [5, 6] summarized the research process and achievements of the above six key technologies of cloud manufacturing services, and revealed possible future research trends and development directions of cloud manufacturing services.

However, we have noticed that most of the existing studies are keen on the construction of cloud manufacturing architecture model and the design of various algorithms. In order to promote the implementation and application of CMSP, we realize that the operation mode and economic characteristics of cloud manufacturing platform deserve more attention.

Therefore, this paper regards the CMSP as the market, taking manufacturing tasks in CMSP as an example, researching the optimal pricing problem under the specific transaction environment of CMSP.
The rest of the paper is structured as follows. In Section 2, we review some related works on the pricing model of cloud platform. Section 3 introduces the transaction process of CMSP. Then in Section 4, we expand the improvement and innovation of the basic Bayesian model under the background of CMSP. Next, the pricing strategy model of CMSP is completed and solved. Subsequently, we analyze the influence of model parameters through simulation experiments in Section 5. Finally, we summarize our work and plan for future work in Section 6.

2. Related Works

In this section, we will review some of the existing literature on cloud platform pricing. Through the analysis and summary of a large number of literatures, we divide the pricing research of cloud platform into three categories from the perspective of the prototype of the model.

2.1. Fixed pricing mechanism represented by cloud computing service charges

Anandasivam et al. [7] proposed two basic pricing models for cloud computing: a pay-per-use pricing model and an on-demand pre-paid pricing model. Butrico et al. [8] pointed out that any pricing model must combine one or more of per unit pricing, tiered pricing, and predetermined pricing. Weinhardt et al. [9-10] introduced the mainstream pricing mechanism used by major cloud computing platforms, and analyzed various practical factors affecting these pricing strategies. Yeo et al. [11] analyzed and compared the advantages and disadvantages of the fixed pricing mechanism adopted by cloud computing platforms from the aspects of demand, efficiency and service, and discussed the dynamic pricing algorithm. However, this kind of pricing method is tailored for cloud computing resources and is not suitable for a broader cloud platform.

2.2. Dynamic pricing model based on bilateral market

Friedma et al. [12] proposed a dynamic resource pricing model based on double action. In bilateral auctions, multiple cloud users and cloud platforms can be freely quoted by bilateral auctions. Samimi et al. [13-15] also studied the cloud platform and cloud user quotation algorithms in bilateral auctions, and Shi et al. [16] analyzed the pricing strategy based on the bilateral auction mechanism. The model of the bilateral market is very suitable for the pricing of the cloud platform, and the dynamic pricing scheme is more reasonable, but some competition factors between the platforms are ignored.

2.3. Game model considering competition

Some researchers use the game theory of economics to analyze platform pricing by focusing on competitive factors. Truong-Huu et al. [17] analyzed how the cloud platform is priced in a competitive environment in a simplified game model, and Qin et al. [18] assumed that in the cloudy platform competition environment, most cloud platform pricing will follow an active cloud platform, and then based on the reinforcement learning algorithm to analyze the pricing strategy of the active cloud platform. Shi Yuliang et al. [19] proposed a service pricing model based on Pareto optimum idea, considering the benefits of multi-user and cloud platform, and multi-objective particle swarm optimization algorithm was used to obtain the global optimal resource allocation and pricing scheme.

3. Transaction Process of CMSP

The participants in the CMSP are as follows: cloud manufacturing service resource providers, CMSP provider, and cloud manufacturing service demanders. The CMSP provider creates an open service platform for providers and demanders to facilitate their transactions. Fig. 1 shows the architecture and transaction process of the CMSP.
Firstly, the requirement information of manufacturing task is submitted to the CMSP. The platform decomposes tasks into sub-tasks, and each sub-task can correspond to a specific manufacturing capability on the platform. Each sub-task generates an order separately, and the platform matches the resource of the resource pool according to the specific demand information of the order, and finally selects the candidate supplier set.

Secondly, the candidate providers and the demander enter the trading platform together. At this time, candidate resource providers make their own bids based on various factors, such as resource valuation based on cost accounting, historical transaction price information, competitive environment and platform resource information, etc.

After the resource provider bids, the platform finally determines the transaction and generates an order with the complete transaction information. At this point, the entire transaction process is over.

4. Improved Static Bayesian Model for CMSP

4.1. The basic model of the static Bayesian game

The basic model of the static Bayesian game is as follows:

The basic assumptions of the model:
Suppose there are n bidders, and each bidder is rational.

Assuming that the valuation of auction items is \( v \), \( v \) is a random variable, and \( v \in [\underline{v}, \bar{v}] \), \( \underline{v}, \bar{v} \) are the lowest and highest possible values respectively, and the distribution function \( F(v) \) is the consensus among bidders. Assume that each bidder has his own valuation \( V_i \), \( V_i \in [\underline{v}, \bar{v}] \). \( V_i \) is private information, and only the i-th bidder knows that other bidders do not know when they are quoting.

The bidder's optimal strategy function \( b_i(v) \) is a strictly increasing function of its valuation \( v \). For each bidder, the optimal strategy function is the same, except that they have different valuation \( v \), so the i-th bidder's strategy function is \( b_i = b_i(V_i) \), and there is \( b_i \in [\underline{v}, \bar{v}] \), that is, the bidder's actual bid cannot be higher than his own valuation of the manufacturing service, otherwise it would be unprofitable.

Payoff function hypothesis:
If the i-th bidder wins the bid, its net utility is expressed as $b_i - v_i$, and other bidders have a utility of 0 because they failed to win the bid. The winning bidder's quote is the lowest of all quotes, $b_i = \min (b_1, ..., b_n)$, so the bidder's payoff function can be expressed as:

$$u_i(b_i, b_j, v_i) = \begin{cases} 
    b_i - v_i, & \text{if } b_i < b_j, j = 1, ..., i - 1, i + 1, ..., n \\
    \frac{1}{n}(b_i - v_i), & \text{if } b_i = b_j, j = 1, ..., i - 1, i + 1, ..., n \\
    0, & \text{if } \exists j, b_i > b_j 
\end{cases} \quad (1)$$

When n bidders offer the same price, the order is randomly distributed among n bidders. And the subjective probability that the i-th bidder evaluates other bidders is:

$$p(v_1, v_2, ..., v_{i-1}, v_{i+1}, ..., v_n|v_i) = \frac{p(v_1, v_2, ..., v_n)}{p(v_i)} \quad (2)$$

The process of analyzing the Bayesian game is to solve the Bayesian Nash equilibrium in consideration of the maximum benefit of the bidder.

### 4.2. Improved Static Bayesian Model

The pricing strategy of this paper is aimed at maximizing the profit of the resource provider in CMSP. The composition of its profit is the difference value between final transaction price (quotation price) and resource provider’s valuation price. Therefore, the objective function can be expressed as:

$$\max U_i = (P_i - v_i)M_i \quad (3)$$

$$U_i = \begin{cases} 
    (P_i - v_i)M_i, & \text{if } P_i < P_j, j = 1, ..., i - 1, i + 1, ..., n \\
    \frac{1}{n}(P_i - v_i)M_i, & \text{if } P_i = P_j, j = 1, ..., i - 1, i + 1, ..., n \\
    (P_i - v_i)M_i^*, & \text{if } \exists j, P_i > P_j 
\end{cases} \quad (4)$$

According to Bayesian Nash Equilibrium, each resource provider's pricing goal is to maximize the expected return. For each resource provider i, satisfy:

$$\max \left[ \left( P_i - v_i \right) M_i \right] \quad (5)$$

Then $P_i, P_j$ ($i \neq j$) are Bayesian Nash equilibrium, that is, the optimal pricing strategy for i-th, j-th resource provider are $P_i, P_j$ respectively.

According to the model hypothesis, the resource providers participating in the bidding are independent of each other, and the quotation of the other party cannot be known at the time of quotation. Therefore, $P(P_i < d)$ and $P(P_j = d)$ are two independent events, thence:

$$P(P_i < d | P_j = d) = \frac{P(P_i < d \cap P_j = d)}{P(P_j = d)} = \frac{P(P_i < d)P(P_j = d)}{P(P_j = d)} = P(P_i < d) \quad (6)$$

And formula (1) can be simplified as:

$$U = \max \left\{ \left( (P_i - v_i)M_i \right)P(P_i < P_j) + \left[ (P_i - v_i)\varepsilon M_i \right]P(P_i > P_j) \right\} \quad (7)$$
\( V_i \) represents the valuation of the i-th provider and \( V_i \) obeys truncated normal distribution \([v_{\min}, v_{\max}]\):

\[
f(v; \mu, \sigma, v_{\min}, v_{\max}) = \frac{1}{\phi \left( \frac{v_{\max}-\mu}{\sigma} \right) - \phi \left( \frac{v_{\min}-\mu}{\sigma} \right)} \]

\( P_i = v_i (1 + \alpha) \)

\[
U = \max \{ \left[ (P_i - v_i)M_i \right] P(P_i < P_j) + [(P_i - v_i)\epsilon M_i] P(P_i > P_j) \} = \max \left\{ \left[ (P_i - v_i)M_i \right] \left[ 1 - \int_{v_{\min}}^{P_i} \frac{1}{\phi \left( \frac{v_{\max}-\mu}{\sigma} \right) - \phi \left( \frac{v_{min}-\mu}{\sigma} \right)} dx \right] + [(P_i - v_i)\epsilon M_i] \int_{v_{\min}}^{P_i} \frac{1}{\phi \left( \frac{v_{max}-\mu}{\sigma} \right) - \phi \left( \frac{v_{min}-\mu}{\sigma} \right)} dx \right\}
\]

Solve the partial derivative of \( P_i \) of the above formula and make it equal to 0, the following result can be obtained:

\[
\frac{1}{1 - \epsilon} - \int_{v_{\min}}^{P_i} \frac{1}{1 + \alpha} = \frac{P_i - v_i}{1 + \alpha} \frac{1}{\phi \left( \frac{v_{max}-\mu}{\sigma} \right) - \phi \left( \frac{v_{min}-\mu}{\sigma} \right)}
\]

Remember \( k = \Phi \left( \frac{v_{max}-\mu}{\sigma} \right) - \Phi \left( \frac{v_{min}-\mu}{\sigma} \right) \), the above formula can be simplified as follows:

\[
\frac{k \sigma}{1 - \epsilon} - \int_{v_{\min}}^{P_i} \phi \left( \frac{x-\mu}{\sigma} \right) dx = \frac{P_i - v_i}{1 + \alpha} \frac{1}{\phi \left( \frac{v_{max}-\mu}{\sigma} \right) - \phi \left( \frac{v_{min}-\mu}{\sigma} \right)}
\]

According to the model calculation results, the final quotation price decision depends on:

- \( v_i \): The valuation of the i-th resource provider.
- \( \mu, \sigma, v_{\max}, v_{\min} \): Estimation of the distribution parameters of competitors' quotation price.
- \( \epsilon \): The Estimation of the available resource requirement quantity.
- \( \alpha \): The premium factor based on the resource scarcity.

The valuation price of each resource provider \( v_i \) can be obtained according to the resource cost. Due to the difference in cost and the strategic orientation of the resource provider, the valuation shows a large difference; the minimum value of the interval \( v_{\min} \) can be determined by the industry's lowest cost estimate for the resource. The maximum value of the interval \( v_{\max} \) can be determined by the minimum value plus the industry's largest profit bonus; the mean of the interval \( \mu \) can be estimated by the average historical transaction price of the resource on the platform; the estimated parameters of the demand obtained \( \epsilon \) are determined based on the resource provider's subjective estimate of the likely demand. The premium factor \( \alpha \) is determined by the resource scarcity of the current state platform.

5. Sensitivity Analysis

\( \mu \) is the estimation of the distribution parameter of competitors' quotation price. In this paper, the truncated normal distribution is chosen as the quotation distribution function of the platform supplier. \( \mu \) as a mean parameter reflecting the quotation of resource providers, its changes will greatly affect the final quotation strategy.
Figure 2. The optimal quotation corresponding to the change of $\mu$.

As shown in the Fig.2, by setting $v_i = 500, v_{min} = 10, v_{max} = 1000, \sigma = 50, \alpha = 0.5$, the optimal quotation corresponding to the change of $\mu$ in this scenario is finally obtained. As $\mu$ continues to increase, the corresponding optimal quotation is higher under the same conditions, but the trend of synergistic growth gradually slows down. In practice, $\mu$ can be estimated by the average historical transaction price of the resource on the platform. Uniform distribution has no average parameters of quotation information, only the upper and lower bounds of quotation range. Therefore, in this case, the historical average transaction price will not affect the optimal quotation of resource providers at all. Here we can see one advantage of choosing truncated normal distribution. Truncated normal distribution can optimize the optimal bidding model by measuring the average bidding information of platform resource providers.

Figure 3. $v_i - p_i$ for different $\mu$.

As shown in the Fig.3, the quotation curves $v_i - p_i$ for $\mu=200$, $\mu=400$, and $\mu=600$ are plotted respectively, and other parameter values remain the same. It can be seen from the figure that when the value of $\mu$ is different, the curve of the quotation basically has the same trend. The higher the value of $\mu$, the higher the corresponding optimal quotation for the same valuation. However, as the valuation increases, the effect of the $\mu$ value on the quotation will decrease, and the last three curves will
continue to approach. In practice, it is not difficult to understand that when the resource provider's valuation of a resource reaches the maximum value of the industry valuation, the impact of the average quotation level will be minimal.

6. Conclusion
This paper analyzes the transaction process of CMSP, then proposes the optimal pricing strategy model of the CMSP for resource providers. This model is based on the basic Bayesian model, and improves and innovates from three aspects: the distribution function of competitor valuation, the existence of multiple winners and the scarcity of platform resources according to the cloud platform trading environment. By solving the model, it is concluded that the final quotation price decision of resource providers depends on: the resource evaluation value based on cost accounting; the estimation of the distribution parameters of competitors' quotation price; the estimation of available quantity and the resource scarcity index of the platform. In the subsequent research, the specific estimation method of the parameters can be further studied to provide guidance for the resource provider in CMSP.

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