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A Comparative Study on the Impact of One-Way and Two-Way Matching Strategies on the Evolution of Cloud Manufacturing Ecosystems

YUANFA DONG[1,2,3], LEI WANG[2], WEI PENG[2], RONGHUA MENG[2], AND ZHENGJIA WU[2]

[1]Hubei Key Laboratory of Hydroelectric Machinery Design and Maintenance, China Three Gorges University, Yichang 443002, China
[2]College of Mechanical and Power Engineering, China Three Gorges University, Yichang 443002, China
[3]Yichang Key Laboratory of Robot and Intelligent System, China Three Gorges University, Yichang 443002, China

Corresponding author: Wei Peng (wpeng@ctgu.edu.cn)

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ABSTRACT The supply-demand matching (SDM) strategy is an important part of the transaction mechanism design of cloud manufacturing (CMfg) platforms, which has a significant impact on the evolution trend of cloud manufacturing ecosystems (CMEs). To help CMfg platform operators choose the appropriate SDM strategy, first, the evolution process of the CME was qualitatively analyzed, and the evolution process was divided into three stages: the germination period, the growth period and the stable period. Then, three types of market agent behavior models, service demanders (SDs), service providers (SPs) and platform operators (POs), were established, and a multiagent behavior simulation experiment was conducted. Finally, the evolution of CMEs with one-way and two-way SDM strategies for POs was compared and analyzed from three aspects: the overall utilization rate of SPs, the diversity of CMEs and the total output of CMEs. Simulation experiments show that, compared with the CME that adopts the one-way SDM strategy, the CME that adopts the two-way SDM strategy is approximately 33% faster to reach ecological balance, the overall utilization rate is approximately 98.7% higher, the diversity is approximately 6% higher, and the total output is approximately 91% higher. The two-way SDM strategy that comprehensively considers the respective preferences of SDs and SPs is more conducive to the healthy development of CMEs.

INDEX TERMS Cloud manufacturing, matching strategy, ecosystem, simulation analysis.

I. INTRODUCTION

With the development of the Internet of Things (IoT), cloud computing, artificial intelligence (AI) and other advanced information technologies, a new service-oriented networked manufacturing paradigm known as cloud manufacturing (CMfg) was introduced with the aim of solving more complex manufacturing problems and carrying out larger-scale collaborative manufacturing [1]. Drawing inspirations from cloud computing, heterogeneous manufacturing resources are virtualized and encapsulated as services, and then integrated into a cloud-based service center. All users connected to this center can make manufacturing service requests to the CMfg service center for various manufacturing activities such as product design, manufacturing, simulation and testing. The CMfg service platform will intelligently match, search, recommend and execute services in the cloud and transparently provide all kinds of manufacturing services to users to achieve the goal of providing highly sharable manufacturing capacity [2].

The key to the industrialization of CMfg is the development of a reasonable business model by fully considering the preferences and behaviors of market participants, the ability to attract a large number of market participants to engage in the platform, and the formation of a sustainable cloud manufacturing ecosystem (CME). The CMfg platform serves as the link between massive demand and manufacturing services. The supply-demand matching (SDM) strategies of platform

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operators (POs) directly affect the service experience of service demanders (SDs) and the business quality of service providers (SPs), which in turn affect SDs' and SPs' willingness to enter the CMfg platform, and ultimately affect the industrialization of the CMfg. However, most of the existing studies focus on specific strategies and methods for matching supply and demand from the micro individual perspective and rarely focus on the sustainable development of the CME from the macro system perspective. As a result, to the best of our knowledge, there are still few CMfg platforms that achieve large-scale commercial use. Therefore, it is necessary to analyze the impact of different SDM strategies on the evolution process of CMEs from the perspective of POs, to lay the foundation for the design of the transaction mechanism of the CMfg platform, and to provide guidance for the later operation and maintenance of the CMfg platform.

Existing research mainly focuses on three aspects: SDM strategies, negotiation strategies and the CME evolution model. In terms of SDM strategies, Argoneto *et al.* formulated the problem of capacity sharing for a set of independent firms as a cooperative game and identified a capacity sharing solution using the Gale–Shapley model. The proposed allocation rule takes into account the utility functions of the involved firms, and simulation shows that truth telling is a dominant strategy under this allocation rule [3]. Zhao and Li [4] constructed a two-sided matching mechanism with agents' expectations for CMfg resources. Zhao and Wang [5] proposed a two-sided matching model of cloud services based on the quality of service (QoS). Simulation results showed that the proposed model could accurately select the most suitable cloud service for both sides. Bi *et al.* [6] presented a resource mapping matching algorithm to map resources from both granularity and views to improve the accuracy and recall of supply-demand matching. Li *et al.* [7] proposed an intelligent search and matching method for CMfg services based on a formal description of CMfg services. Xue *et al.* [8]–[9] proposed a computational experiment-based evaluation framework to analyze the evolution of manufacturing service ecosystems, which can simulate all kinds of actual scenarios to verify the performance of service matching strategies. Joseph and Jitesh [10] formulated the resource allocation problem as a bipartite matching problem and analyzed four bipartite matching mechanisms, namely, deferred acceptance (DA), top trading cycle (TTC), Munkres, and FCFS, with respect to the desired properties of the mechanisms, such as individual rationality, stability, strategy proofness, consistency, monotonicity and Pareto efficiency. Additionally, the appropriateness of matching mechanisms for different scenarios in cloud-based design and manufacturing, such as fully decentralized, partially decentralized and totally monopolistic, is assessed. Zheng *et al.* [11] proposed a hybrid energy-aware resource allocation approach to help requestors acquire energy-efficient and satisfied manufacturing services. Liu and Wang [12] considered the overall benefit of both the cloud service provider and the cloud service demander as the optimization target and proposed a novel market-based continuous bidding mechanism by applying game theory. Li *et al.* [13] proposed a novel RIM (recommendation incentive mechanism) approach by building a cooperative agent recommendation system. In terms of negotiation strategies, Renna *et al.* proposed a game theory coordination mechanism for a network of independent plants, and the simulation results show that the proposed mechanism could be considered a valid alternative to the more usual negotiation approaches in several market conditions [14]. Zheng *et al.* proposed an approach that mixed concession and tradeoff strategies for cloud service negotiation [15]. Baarslag *et al.* introduced a taxonomy of currently existing opponent models in the bilateral negotiation setting based on their underlying learning techniques [16]. Rajavel *et al.* proposed a novel adaptive probabilistic behavioral learning system for managing opponents with unpredictable random behaviors, which contains a behavioral inference engine to analyze the sequence of negotiation offers received by the broker to effectively learn the opponent's behavior over several stages of the negotiation process [17]. Considering that the existing strategies cannot react to the stochastic, rational, emotional, and unknown behavior of opponents due to their deterministic behavior, they also proposed a stochastic behavioral learning negotiation (SBLN) strategy to further maximize the unity value and success rate [18]. In terms of the evolution model of CME, Geng *et al.* [19] proposed a three-stage basic evolution process of the CMfg platform and established a CMfg platform evolution model by virtue of complex network theory with five diffusion forces identified. Peng *et al.* [20] proposed an evolutionary model of the cooperative and competitive relationships of individuals to analyze the participants' cooperative and competitive relationships in CMEs and their impact on individual development and the stability and balance of the system. Zhang *et al.* [21] proposed a model of the ecological evolution of manufacturing service systems (MSS) driven by service providers (SPs) and adopted a predation cellular genetic algorithm to optimize this evolution. He *et al.* [22] established an evolutionary game model of knowledge transfer between CMfg enterprises and customers by using evolutionary game theory and proposed countermeasures and suggestions to promote knowledge transfer between CMfg enterprises and customers. Wang *et al.* simulated the CMfg diffusion process by considering the commission rate, government subsides, user membership fee of the cloud platform and user acceptance intention. The results show that subsidies for enterprise users are better than those for CMfg service providers in promoting the diffusion of the CMfg mode [23].

There are many existing studies on the behavioral strategies of various market agents, but there are still few studies on the impact of different SDM strategies on the evolution of CMEs from the perspective of POs. Therefore, this paper establishes three kinds of market agent behavior models, SDs, SPs, and POs, and designs a multiagent behavior simulation experiment. Considering the perspectives of POs, the evolution of CMEs with one-way and two-way SDM strategies was compared and analyzed from three aspects: the overall utilization rate of SPs, the diversity of CMEs and the total output of CMEs.

II. ANALYSIS OF THE EVOLUTION OF CMEs

The cloud manufacturing platform is not only an e-commerce service platform for the manufacturing industry but also a ''living'' organization. Individuals participating in the organization can survive and develop in the system through interaction, influence, choice and adaptation. CMEs consist of three types of market agents: SPs, SDs and POs. POs are the managers of CMEs. By building the CMfg service platform and formulating platform access conditions and transaction rules, CMEs can attract high-quality manufacturing resources to gather and provide manufacturing services via the CMfg service platform. The accumulation of a large number of high-quality SPs will attract SDs to use the services provided by the CMfg service platform. The increase in service demand in turn will attract more manufacturing resources to the CMfg service platform, thus forming a virtuous circle. In addition, POs promote the sustainable development of CMEs by establishing a reasonable QoS evaluation mechanism. The development of CMEs occurs in multiple stages, mainly including the germination period, growth period and stable period.

A. GERMINATION PERIOD

The germination period of CMEs is the early stage of the CMfg service platform. In this stage, the PO and some core SPs reach a strategic cooperation agreement. The core SPs encapsulate related manufacturing resources as a manufacturing service based on digital twin technology, make their services available to users via the CMfg service platform, and transfer part of their offline business to the platform, creating a demonstration effect and accumulating experience for future large-scale operations. This stage mainly focuses on verifying the effectiveness of the technical aspects and exploring various strategies. During this stage, the scale of CMEs will not change significantly, and the number of participants will slowly increase.

B. GROWTH PERIOD

The growth period of CMEs refers to the stage in which the number of main participants in the system rapidly increases. In this stage, the platform technology and transaction mode gradually mature. The PO carries out intensive market promotion activities based on the early success of the application. It continuously improves the platform service quality and introduces incentive policies and other related measures to attract more SPs and SDs to the platform, thereby forming a scale effect. During this stage, the number of participants in the system increases exponentially, and quality varies. Some SPs and SDs may quit the platform because their actual experience does not conform to their expectations, but these exits will not affect the overall upward trend. Whether the CME can develop mainly depends on the operation strategy used by the PO in this stage.

C. STABLE PERIOD

The stable period of CMEs refers to the later stage of platform operation when the number and structure of participants tend to be stable. At this stage, the trading mode and rules were widely accepted. The number of SPs is close to the upper limit of the ecosystem's capacity. Fierce competition will cause some SPs to temporarily or permanently withdraw from the platform. New SPs will enter the platform because they are attracted by stable demand and potential business opportunities. The number of participants in the system is in a state of dynamic equilibrium. In addition, the PO will further adjust the reward and punishment measures, establish the QoS evaluation system, and continuously optimize the group quality and the proportion of various types of participants in the system. As a negative entropy input, the operation and regulation strategy used by the PO is the main driving force to offset the disorder of the ecosystem and maintain the stable and healthy development of the ecosystem.

III. MODELING THE BEHAVIOR OF MARKET AGENTS

The transaction mechanism of the CME affects the transaction behavior of various market agents, and the behavior processes of a large number of market agents constitute the basis of the evolution of CMEs. At present, there are three common transaction modes: (1) Matchmaking. PO focuses on demand push, service push and matchmaking. The specific transaction is reached by the supply and demand parties according to negotiation. PO is responsible for dynamically updating the SD reliability and SP QoS based on the evaluation data. This type of transaction mode is similar to the free market and is suitable for manufacturing services with a relatively high degree of personalization. (2) Bidding. PO converts the demand information released by SD into bidding information and releases it to the SPs in the platform. The SPs determine whether to bid according to their own situation, and the SD determines the final winning SP according to the bidding situation. In this mode, market agents communicate frequently and require many resources. (3) Assignment. PO uniformly allocates service requirements and manufacturing services according to preset matching and scheduling rules. SD only needs to submit service requirements on the platform, and does not care about completing the service. SP can choose to accept or reject PO's task assignment. With the continuous development of technologies such as the Internet of Things, big data and digital twins, the assigned transaction mode is gradually becoming the main development direction of CMfg because it can give full play to the advantages of CMfg, such as high availability, flexibility and global optimization. This paper is mainly oriented towards the assigned transaction mode.

Figure 1 shows a schematic diagram of the main behavior process of the three types of market agents in the assigned transaction mode. The SD enters the platform to release service requirements. The PO selects suitable SPs according to preset matching rules and assigns tasks to candidate SPs.

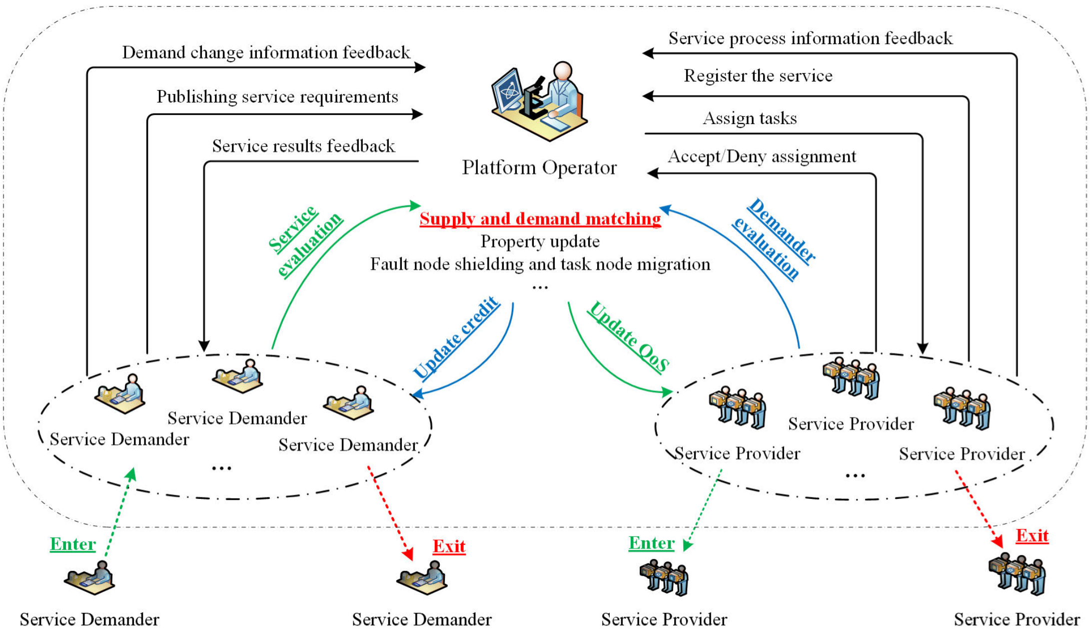


FIGURE 1. Schematic diagram of the main behavior process of the three types of market agents under the assignment mode.

Candidate SP can choose to accept or reject the assigned tasks according to its own circumstances. During the service process, PO performs dynamic scheduling according to the demand changes and service process information fed back by SDs and SPs, and carries out shielding and task migration of faulty nodes, and dynamic QoS updates. After the service ends, the SD and SP evaluate each other, and the PO updates the SD's reliability and SP's QoS based on the mutual evaluation data.

It can be seen from the figure that the degree of automation of the service process in the assigned transaction mode is relatively high. This paper refers to the analysis results in reference [24] and expert interviews, focusing on the behaviors that have a greater impact on the evolution of the CME, such as the entry and exit of SD, the entry and exit of SP, the SDM of PO and the QoS and reliability update mechanism. This section describes the development of behavior models for SPs, SDs and POs and lays a foundation for the multiagent behavior simulation experiment. PO behavior involves the use of either a one-way or two-way SDM strategy, which is the focus of the comparative analysis in this paper.

A. SP BEHAVIOR MODELING

The SP agent is defined as follows:

$$\text{SP}=(SP\_Information, P\_Information,\ SP\_Strategy) \quad (1)$$

where *SP_Information* represents the basic information of the SPs. *P_Information* represents the basic information of services provided by the SPs. *SP_Strategy* represents the strategy set of the SPs, including entering the platform, publishing their service, evaluating the services that have been provided and exiting the platform.

The *SP_Information* is defined as follows:

$$\begin{aligned} SP\_Information &= \{SP\_ID, SP\_Name, SP\_Address, \\ &\quad \times SP\_Rejection\_rate, SP\_QoS\} \quad (2) \\ SP\_QoS &= \{RP, Tl, RL\} \quad (3) \end{aligned}$$

where *SP_ID, SP_Name* and *SP_Address* represent the identity, name and address of the SP, respectively. *SP_Rejection_rate* represents the rejection rate of SP. *SP_QoS* represents the QoS indicator set of the SPs. *RP* represents the reputation of the SPs, mainly considered in terms of timeliness and product quality. *Tl* represents the technical level of the SPs, considering three main aspects: R&D capabilities, core technology level and personnel quality. *RL* represents the reliability of the SPs and mainly considers the difficulty of repairing and improving the service provided by the SPs under abnormal conditions.

The *P_Information* is defined as follows:

$$\begin{aligned} P\_Information &= \{P\_Name, P\_Type, P\_Capability, \\ &\quad \times P\_Price, P\_ExpCredit\} \quad (4) \\ P\_Capability &= \{ResClu, CapModel, CapLoad\} \quad (5) \end{aligned}$$

where *P_Name* represents the name of the service, *P_Type* indicates the type of service, and *P_Capability* represents service capability. *P_Price* represents the price of the manufacturing service. *P_Expcredit* represents the SP's expectation of the reliability characteristic attribute of its potential client SDs. *ResClu* represents the collection of resources encapsulated by CMfg services, such as personnel, machinery, equipment and materials. *CapModel* represents the capability description model, including the coupling mode of manufacturing resources [25] and the method used to determine capability. *CapLoad* represents the current load of the service.

There are three factors affecting SP access to the platform: ① the activeness of transactions in the system, where, generally speaking, the more active the transaction is, the greater the willingness of new SPs to enter the platform; ② the sensitivity of SPs to the activity level of transactions in the system; and ③ the number of SPs of the same type in the system. In the early evolution stage of CME, there is a small number of SPs, which has little influence on the number of SPs entering the platform. However, when the group size of similar SPs is close to the upper limit of the capacity of the CME, fierce competition within the group will greatly reduce the willingness of new SPs to enter the platform. The willingness of a new SP to enter the platform is characterized by probability as follows.

$$P_{\mathrm{SP}_{in}}(t) = \frac{1}{1+\rho^{\partial-1}}\left(1-\frac{1}{1+e^{-K(N_{\mathrm{SP}}(t)-Q)}}\right) \tag{6}$$

$$\partial = \frac{\sum C(t)}{N_{\mathrm{SP}}(t)} \in [0, +\infty] \tag{7}$$

where ∂ indicates the activity level of transactions in the system, $\sum C(t)$ is the total number of transactions in progress by SP of the same type at time t, $N_{\mathrm{SP}}(t)$ is the total number of SP of the same kind at time t. The coefficient ρ represents the sensitivity of SP to the activity level of transactions in the system, Q refers to the upper limit of certain SPs that CMEs can carry, and K is the adjustment coefficient.

Factors causing SPs to exit the platform include ① the business condition of the SP, which can be either good or bad. When an SP enters the system, it is less affected by its own business conditions, and its exit intention within protection period T_0 is subject to the current market normal turnover rate θ. When protection period T_0 has lapsed, the exit intention of an SP is mainly affected by its own business conditions. When the same kind of SP enters the system in the same period, the smaller the number of transactions is, the greater the exit intention of the SP. ② the sensitivity of the SP to its own business situation. The following piecewise probability function is used to characterize the willingness of a new SP to quit the platform.

$$P_{\mathrm{SP}_{out}}(t) = \begin{cases} e^{-\delta\cdot\gamma} & t > T_0 \\ \theta & 0 < t \le T_0 \end{cases} \tag{8}$$

where $\gamma \in [0, 1]$ represents the ratio of the cumulative transactions of an SP at time t to the transactions of the SP with the best performance among the SP group that entered the platform during the same period. The coefficient δ represents the sensitivity of SP to its own business conditions.

B. SD BEHAVIOR MODELING

The SD agent is defined as follows:

$$\mathrm{SD}=(SD\_Information, D\_Information, SD\_Strategy) \tag{9}$$

where *SD_Information* represents the basic information of the SDs. *D_Information* represents the basic demand information for SDs. *SD_Strategy* represents the strategy set of the SDs, including publishing demand and evaluating QoS.

The *SD_Information* is defined as follows:

$$\begin{aligned} SD\_Information &= \{SD\_ID, SD\_Name, SD\_Address, \\ &\quad \times SD\_Credit\} \end{aligned} \tag{10}$$

$$SD\_Credit = \{DPayment\_Speed, DReputation\} \tag{11}$$

where *SD_ID, SD_Name* and *SD_Address* represent the identity, name and address of the SD, respectively. *SD_Credit* represents the credit characteristic attribute of the SDs. *DPayment_Speed* represents the payment speed of the SDs: the time required to pay 95% of the total payment after the service agreement is reached (the other 5% is usually the quality assurance deposit). *DReputation* represents the reputation of the SDs, considering two aspects: the rate of breach of contract and the difficulty of communication.

The *D_Information* is defined as follows:

$$\begin{aligned} D\_Information = \{&D\_Name, D\_Type, D\_ExpCap, \\ &\times D\_ExpPrice, D\_ExpQoS\} \end{aligned} \tag{12}$$

where *D_Name* represents the name of the demand, *D_Type* represents the type of demand, *D_Expcap* represents the specific capacity demand for a service, *D_ExpPrice* represents the expected rate of demand, and *D_ExpQoS* represents the SD's expectation regarding the SP's service quality.

Factors influencing SD's publishing demand in CMfg platforms include ① the SP population size that can provide the required services in the system. In general, the more SPs that can provide high-quality service in the system, the greater the willingness of new SDs to release demand in the platform. ② Its sensitivity to the number of SPs that can provide the required services in the system. The willingness of a new SD to release demand in the platform is characterized by probability as follows.

$$P_{\mathrm{SD}_{in}}(t) = \frac{1}{1+k^{\sigma-0.5}} \tag{13}$$

where σ represents the scale factor of high-quality services that meets the needs of SDs, and it is measured as the ratio of the number of SPs whose matching degree with the new SD's demand [5] is greater than the given threshold value ξ to the number of SPs that can meet SD demand. The coefficient k represents the sensitivity of SDs to the number of SPs in the system that can provide the required services.

C. PO BEHAVIOR MODELING

The PO is mainly responsible for matching the appropriate SP for the service demand of an SD, and dynamically updating their QoS and credit attributes based on historical evaluation records.

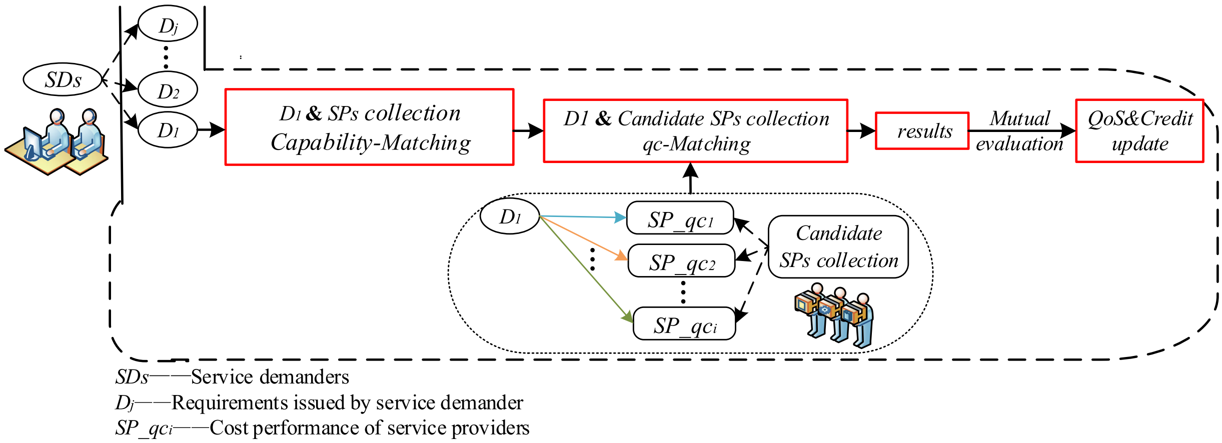


FIGURE 2. **Model for the one-way matching strategy used by CME based on QoS.**

1) DYNAMIC UPDATE OF QOS AND CREDIT ATTRIBUTES

The updated values of *SP_QoS* and *SD_Credit* are mainly based on the evaluation data of historical transactions and are dynamically obtained using the fuzzy comprehensive evaluation method [26]. Taking SP_QoS as an example, SD adopts a five-level system to evaluate the reputation (*RP*), technical level (*Tl*) and reliability (*RL*) of SPs that have provided services for it. The evaluation grade set is $V = \{$very high – 5 points, high – 4 points, medium – 3 points, low – 2 points, very low – 1 point$\}$. For reputation RP, the evaluation result of the reputation of SP_i in the historical evaluation record is:

$$R_{i1} = (\frac{n_1}{N_0}, \frac{n_2}{N_0}, \frac{n_3}{N_0}, \frac{n_4}{N_0}, \frac{n_5}{N_0}) \tag{14}$$

where N_0 represents the total number of evaluations obtained by $SP\ _i$, n_1 represents that the number of SP_i credibility ratings in the evaluation record is very high, and n_2, n_3, n_4 and n_5 correspond to the number of SP_i credibility ratings in the evaluation record that are high, medium, low, and very low, respectively. Similarly, the evaluation result of SP_i's technology level R_{i_2} and reliability R_{i_3} can be obtained. Thus, the fuzzy evaluation matrix R_i of SP_i can be obtained.

$$R_i = \begin{pmatrix} R_{i1} \\ R_{i2} \\ R_{i3} \end{pmatrix} \tag{15}$$

Considering the weight of each QoS index, the fuzzy comprehensive evaluation vector F_i of SP_i is calculated as follows.

$$F_i = A \cdot R_i = (f_{i1}, f_{i2}, \cdots, f_{i5}) \tag{16}$$

where A represents the weight vector of QoS indicators, which can be determined comprehensively by the analytic hierarchy process (AHP) and entropy weight method (EWM). The calculation method of SP_i's integrated service quality SP_i_QoS is as follows:

$$|SP_i\_QoS| = \sum_{k=1}^{5} (6-k) \cdot f_{ik} \tag{17}$$

2) SDM STRATEGY

At present, the SDM strategies used by POs are mainly divided into one-way and two-way strategies. The one-way SDM strategy only considers the demand preference of SD to match the most suitable SP for SD, while the two-way SDM strategy considers both SD's demand preference for SP and SP's service preference for SD and matches the SP that is suitable for both sides for SD.

➢ One-way SDM strategy

The one-way SDM process is shown in Figure 2. For demand D_j, the PO first selects candidate SPs that meet the service capability demands from the existing SP set and then selects the SP with the highest cost performance ratio (*qc*) from candidate SPs to match D_j. The *qc* of SP_i can be calculated by the following formula:

$$qc_i = \frac{Q_i}{p_i} \times R_i \tag{18}$$

$$R_i = 1 - \frac{1}{1 + e^{-\lambda * (r_i - 0.5)}} \tag{19}$$

where Q_i represents the normalized QoS of SP_i, p_i represents the normalized rate of SP_i, R_i represents the influence factor of SP_i's rejection rate on the matching degree, r_i represents the rejection rate of SP_i, and λ represents the steepness factor.

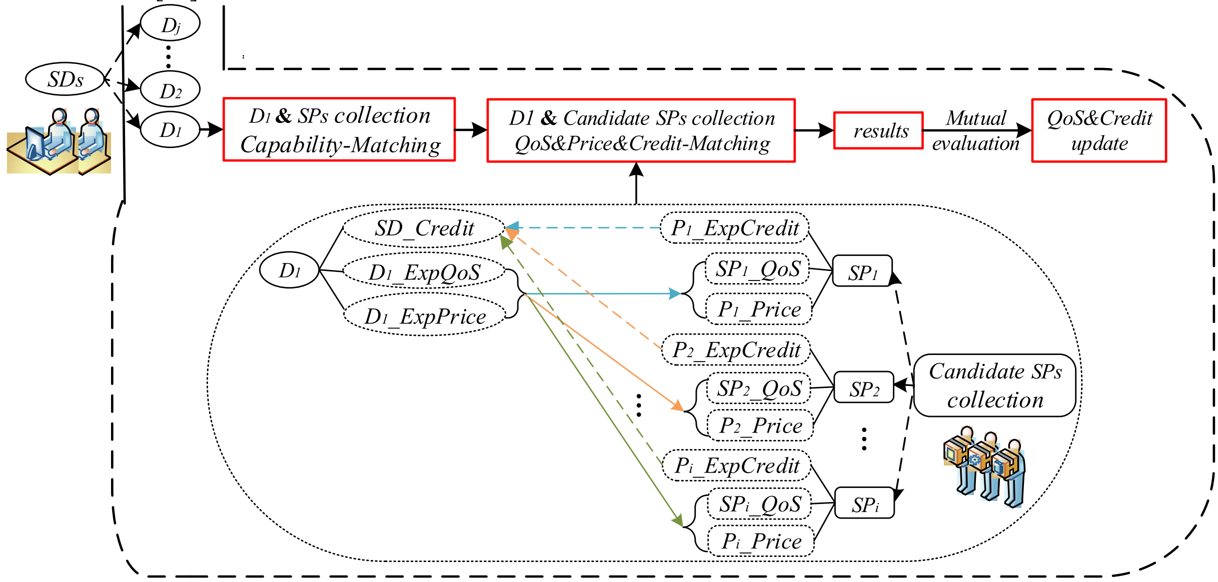
➢ Two-way SDM strategy

The two-way SDM process is shown in Figure 3. For demand D_j, the PO first selects candidate SPs that meet the service capability demands from the existing SP set. Then, the cosine similarity calculation method is used to calculate the two-way matching degree Sim_{ij} between the demand D_j and the candidate service SP_i. Finally, the SP with the highest bidirectional matching degree is selected to match D_j.

$$Sim_{ij} = \frac{\vec{P_i} \cdot \vec{D_j}}{\left\| \vec{P_i} \right\| \times \left\| \vec{D_j} \right\|} \times R_i \tag{20}$$

where $\vec{P_i}$ represents the vector formed by normalization of $P\_ExpCredit$, SP_QoS and P_Price of SP_i. $\vec{D_j}$ represents the

recall and accuracy of the matching method used in this paper are verified in [27].



SDs——Service demanders
D_j——Requirements issued by service demander
SD_Credit——Reliability of service demand
D_j_ExpQoS——SD's expectation regarding the SP's service quality
D_1_ExpPrice——SD's expectation of service rate

SPs——Service providers
P_1_ExpCredit——Service provider's expectation of SD credit
SP_1_QoS——Service quality of service provider
P_1_Price——Service rate of service provider

FIGURE 3. Two-way matching model of CME based on QoS.

vector formed by normalization of *SD_Credit*, *D_ExpQoS* and *D_ExpPrice* of D_j. R_i represents the influencing factor of SP_i's rejection rate on the matching degree, which is the same as formula (19). The recall and accuracy of the matching method used in this paper are verified in [27].

IV. EVALUATION INDEX USED IN THE CME

Cooperation among the agents in the CME is a dynamic game process that will be affected by the agents' own utility and different matching strategies. Under different SDM strategies, the development status of the agents in the CME and the whole ecosystem will be different. As the leader of the CMfg platform, PO mainly focuses on the development of the CME at the macro level. Resources utilization, ecosystem development and services transaction are the main aspects of concern. Its main responsibility is to ensure the rapid growth and sustainable development of CME through reasonable transaction mechanism design and effective operation and maintenance strategies to obtain considerable profits. Therefore, evaluating the effectiveness of the SDM strategy lies in whether it can promote the healthy development of the CME. In natural ecosystems, the evaluation indicators of ecosystem health include vitality, resilience, organizational structure and other aspects. Among them, ecosystem vitality refers to all the energy and individual activities in the ecosystem, which can be quantified by the input materials in the system or by using the method of network analysis. Organizational structure refers to the complexity of the interaction between the ecosystem structure and individuals (cooperation and competition, etc.), and the relevant indicators for measuring the structure include diversity index. Resilience refers to the ability of the system to recover gradually after the external interference. This paper does not involve the interference of the physical environment on the system, so it does not consider the relevant indicators to evaluate the resilience of the system. In the CME, the interaction between market entities is very similar to the relationship between species in nature. Drawing lessons from the health evaluation methods of natural ecosystems, this paper evaluates the evolution process of CME from three aspects: the overall utilization rate of SPs, which describes the resource utilizing status, the diversity of CME, which describes the development of CME, and the total output of CME, which depicts the transaction status of CMEs.

A. THE OVERALL UTILIZATION RATE OF SP

The overall business situation of SPs can reflect the development of the system to a certain extent in the CME. The overall utilization rate of SPs is used to analyze the business situation of SPs in CMEs. The specific formula is as follows:

$$R_P = \frac{p^{success}(t)}{p^{total}(t)} \tag{21}$$

where $p^{success}(t)$ represents the total number of SPs that have been successfully traded at time t and $p^{total}(t)$ is the total number of SPs in the CME at time t.

B. THE DIVERSITY OF CMEs

CMfg platforms have significant ecological characteristics [28]. Ecosystem diversity is an important theory to study the degree of natural ecological diversity. This paper introduces the theory of ecosystem species diversity and defines the diversity of a CME as follows:

Definition 1: The diversity of a CME refers to the degree of diversity in the attributes of the SPs (QoS, service category, etc.) participating in transaction activities.

The species diversity of ecosystems is usually measured by the species richness index, dominance index and information index (Shannon-Wiener index). The Shannon-Wiener index is randomly sampled in an infinite community and the sample contains all species in the community. The greater the diversity of the ecosystem, the greater the index value. Taking QoS as an example for analysis. Based on the Shannon-Wiener index formula, the diversity of a CME is defined as follows.

$$B_m = -\sum_{n=1}^{N} (p_{mn})(\ln p_{mn}) \tag{22}$$

where B_m represents the diversity of QoS, p_{mn} represents the proportion of the number of SPs with QoS in the *n-th* class to the total number of SPs, and N is the number of QoS class categories. For SPs, the more QoS levels are distributed, the more uniform the number of levels, and the greater the diversity of CMEs. Similarly, the more diverse the CME, the more service levels the ecosystem can provide, and thus the CME can better adapt to the needs of different types of SD.

C. TOTAL OUTPUT OF CMEs

Drawing lessons from Ulanowicz's method [29] of calculating the total output of the ecosystem, the CME is regarded as a material exchange network. Suppose the material and energy exchange matrix between m SPs and n SDs is as follows:

$$T = \begin{bmatrix} t(SP_1, SD_1)t(SP_1, SD_2)\cdots\ t(SP_1, SD_n) \\ t(SP_2, SD_1)t(SP_2, SD_2)\cdots\ t(SP_2, SD_n) \\ \vdots \\ t(SP_m, SD_1)t(SP_m, SD_2)\cdots\ t(SP_m, SD_n) \end{bmatrix} \tag{23}$$

To simplify the calculation, the elements in the material exchange matrix between service provider SP_i and demander SD_j are replaced by the cumulative number of transactions between them, where $t(SP_i, SD_j)$ represents the accumulative number of transactions between service provider SP_i and demander SD_j, and $t(SP_i, SD_j)$=0 indicates that there is no transaction between service provider SP_i and demander SD_j. The total output of a CME is the sum of the elements in the material and energy exchange matrix T between m SPs and n SDs, and the formula is as follows:

$$TST = \sum_{i=1}^{m}\sum_{j=1}^{n} t(SP_i, SD_j) \tag{24}$$

V. SIMULATION RESULTS AND ANALYSIS

This paper establishes a joint simulation platform based on NetLogo 6.0.4 and MATLAB R2016b. NetLogo is responsible for providing a multiagent simulation operating environment for the interaction between SDs, SPs and PO, and MATLAB is responsible for calculating the matching degree of supply and demand. The two exchange data through NetLogo-MATLAB Extension.

A. SIMULATION PARAMETERS SETTING

To improve the efficiency of the simulation process without losing generality, this paper makes the following assumptions about the evolution of CME: (1) there is only one PO in the CMfg platform, which adopts the assigned transaction mode. (2) The agents in the experiment only belong to a certain type of SD, SP and PO, and will not be both SD and SP. Each SP only provides a certain type of service. The relevant simulation parameters of the matching model described in Sections III and IV are shown in Table 1.

B. EXPERIMENTAL RESULTS AND ANALYSIS

Figure 4 shows that when the PO adopts one-way and two-way SDM strategies, the development trends of SD demand

TABLE 1. The main parameter settings of the CMS evolution model under one-way and two-way SDM strategies.

Symbol	Description	Initialization	Range of values
ρ	Sensitivity of an SP to trading activity	0.15	(0, 1)
δ	Sensitivity of an SP to its own business situation	2.5	—
k	Sensitivity of an SD to the number of SPs in the system that can provide the required services	0.05	(0, 1)
ξ	Matching threshold	0.6	(0, 1]
K	Adjustment coefficient	0.1	—
Q	Upper limit of SPs in the system	600	$(0, +\infty)$
N	Number of QoS classes	5	—
θ	Normal replacement rate during the protection period	0.1	—
λ	Steepness factor	10	—
r_i	Rejection rate of SP_i	Rand[0, 0.3]	[0, 1.0]
SP_QoS	Integrated service quality of SPi	Rand(0, 5.0]	[0, 5.0]
SD_l_Credit	Reliability of SD_l	Rand(0, 5.0]	[0, 5.0]
P_Price	Price of SP_i	Rand(0, 0.1]	(0, 1.0]

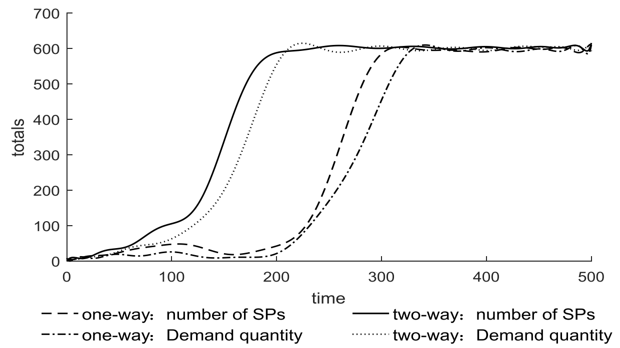


FIGURE 4. The overall evolution of the CME under the one-way and two-way SDM strategies.

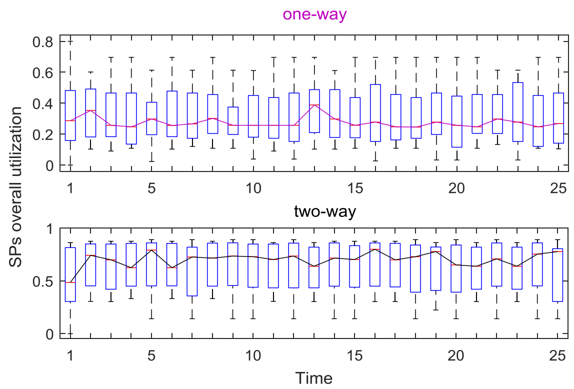


FIGURE 5. The overall utilization rate of SPs under the two strategies.

and the number of SPs in the CME are significantly different. When the two-way SDM strategy is adopted, the time for the CME to reach ecological equilibrium is approximately 33% faster than when the one-way SDM strategy is adopted, which can improve the evolution efficiency of the CME and save marketing costs.

1) THE OVERALL UTILIZATION RATE OF SP

As shown in Figure 5, when the one-way SDM strategy is adopted, the PO always matches the SPs with the best service quality to the SDs, while the SPs with relatively poor service quality are rarely matched with SDs, unless the service capacity of similar SPs with high service quality has reached the upper limit, resulting in a lower overall utilization rate of the SPs. The overall utilization rate of SPs is roughly distributed between 0.2 and 0.4. When adopting the two-way SDM strategy, the PO comprehensively considers the attributes and demand preferences of both the SPs and SDs, and the service that is the best match for both parties does not necessarily have the best service quality. Therefore, the different levels and scope of the SP might find a match with an SD, ensuring that the interests of both the SD and SP, and the overall utilization rate of SPs are roughly distributed between 0.5 and 0.8. The results show that the overall utilization rate of the two-way SDM strategy is approximately 98.7% higher than that of the one-way strategy.

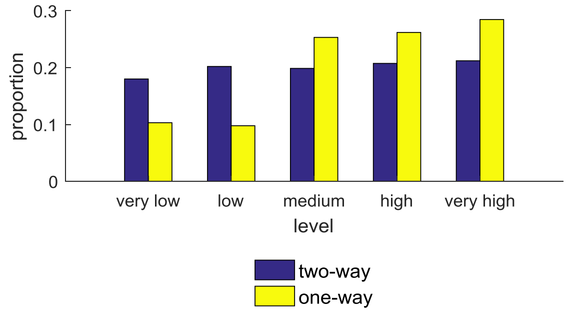


FIGURE 6. Distribution of the QoS level under one-way and two-way SDM strategies.

2) THE DIVERSITY OF CME

The distribution of the QoS levels of SPs in the late evolution period of CMEs under different SDM strategies is shown in Figure 6. When the PO adopts the one-way SDM strategy, SPs with high service quality will frequently be selected, while SPs with lower service quality will be less likely to be selected, or even not selected at all. The distribution of the QoS levels of SPs increases from the lowest level to the highest level and is unevenly distributed. The diversity of CME $B_1 = 1.5176$. When PO adopts the two-way SDM strategy, all SPs may be candidates to respond to SD demand due to the difference in demand categories and preferences. The distribution of the QoS levels of SPs is relatively uniform in the late evolution stages of CME and the diversity of CME $B_2 = 1.6079$. The results show that the two-way SDM strategy is approximately 6% higher than the one-way SDM strategy, which can effectively improve the diversity of CME.

3) THE TOTAL OUTPUT OF CME

As shown in Figure 7, when POs adopt the one-way SDM strategy, the number of transactions slowly increases, the overall utilization rate of SPs is low, the manufacturing resources are idle, and the SPs that have not reached a transaction for a long time will choose to quit the system temporarily or permanently. At the same time, the decrease in SPs will reduce the willingness of SDs to release demand in the platform, which makes the total output of CME increase slowly, and the total number of transactions in the evolution process is 618. When POs adopt the two-way SDM strategy, the number of transactions increases rapidly, the overall utilization rate of SPs is high, and new SPs are very willing to enter the platform. This increase in SPs attracts more SDs to seek services on the platform, the total output of CME will increase, and the total number of transactions in the same time evolution process is 1181. The results show that the total output of the two-way SDM strategy is approximately 91% more than that of the one-way SDM strategy. In addition, the growth rate of transactions with the two-way SDM strategy is significantly greater than that of the one-way SDM strategy, and the two-way SDM strategy is more conducive to the healthy development of CME.

In summary, 50 simulation experiments were carried out on the two groups of matching strategies.

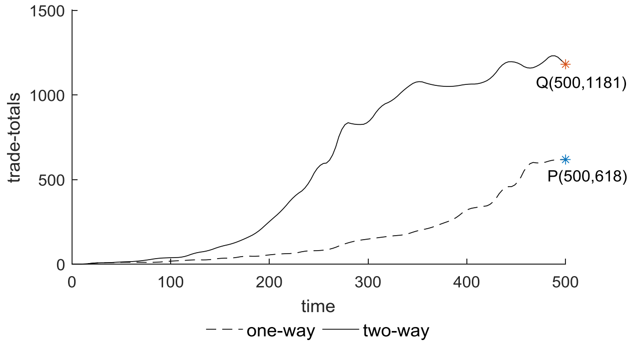


FIGURE 7. Total output of CMEs under one-way and two-way SDM strategies.

To verify whether the two-way SDM strategy is better than the one-way SDM strategy, the independent sample t-test was used to compare the differences of evolution index values between CME adopting one-way SDM strategy and CME using two-way SDM strategy. All statistical procedures were performed in Excel Version 2016, the level of significance was set at 0.05. The statistical analysis results are shown in Table 2.

TABLE 2. Evolution index comparison table.

Index	Mean ± *SD*		*p*-value
	One-way SDM strategy	Two-way SDM strategy	
The time for the CME to reach ecological equilibrium	209.11 ± 13.38	316.11 ± 12.94	0.000
The overall utilization rate of SPs	0.32 ± 0.02	0.64 ± 0.02	0.011
The diversity of CME	1.50 ± 0.02	1.61 ± 0.01	0.003
The total output of CME	612.11 ± 10.95	1203.78 ± 15.94	0.000

Significant differences were observed between one-way SDM strategy and two-way SDM strategy. The mean values of CME using two-way SDM is significantly higher than CME adopting one-way SDM strategy, which means that two-way SDM strategy is more conducive to the healthy development of CMEs.

VI. DISCUSSION

This paper analyzes the impact of one-way and two-way SDM strategies on the evolution trend of CMEs through multiagent simulation. However, it is difficult to collect data from a real CMfg platform to verify the findings of this paper as the industrialized CMfg platform that adopts an assigned transaction mode is still under exploration at this stage. In the following, we will elaborate the basis of simulation parameter setting and present selected scenarios where the findings can be most impactful and value-adding.

A. BASIS OF SIMULATION PARAMETERS SETTING

Part of the simulation parameters of the matching model described in Table 1 are derived from real scenes. We investigated the ZBJ Network (www.zbj.com), which is a famous cloud service trading platform in China. A total of 252 typical participants in the ZBJ Network were chosen, and their online behavioral data were collected. Three linear regression equations were built on the basis of real data, and the values of ρ, δ and k were derived from regression coefficients.

The matching threshold ξ, the upper limit of SPs in the system Q, the number of QoS classes N, the adjustment coefficient K and the normal replacement rate during the protection period θ were set according to a designed scheme.

B. APPLYING IN CME REGULATION

SDM strategies proposed by current studies focus on satisfying SDs' demands, which is the core of a one-way SDM strategy. According to our findings, adopting a two-way SDM strategy can achieve better results in many ways. By considering SPs' service preference for SDs, higher satisfaction will be obtained in SPs, which in turn will motivate them to improve the QoS, thus forming a virtuous circle in CME. To the best of our knowledge, some similar cloud service platforms with matchmaking or bidding transaction modes, such as MFG (https://www.mfg.com/), ZBJ Network and HOPE (hope.haier.com), have adopted the two-way SDM strategy and achieved great success.

C. APPLYING IN OTHER CLOUD SERVICE PLATFORMS

In China, terrific amounts of online car-hailing [30] and takeaway [31] services rely on POs' scheduling. The key in service scheduling is the matching strategy. Applying the two-way SDM strategy in online car-hailing and takeaway platforms will improve the scheduling quality of service, and in the end the overall cloud service platforms' outcomes (e.g., diversity, resource utilization) can be improved. For instance, the drivers' preference for place is considered in DiDi-Chuxing's matching strategy [30], and the usage of drivers and cars is dramatically improved. Predictably, many other cloud service platforms will benefit from the two-way SDM strategy if both demanders' and suppliers' preferences are considered.

VII. CONCLUSION

Aiming at the selection of SDM strategies in CMfg platforms, this paper establishes behavior models of three types of market entities, SP, SD, and PO, and designs multiagent behavior simulation experiments. By introducing evaluation indexes such as the overall utilization rate of SPs, the diversity of CMEs and the total output of CMEs, the influence of one-way and two-way SDM strategies on the evolution trend of CMEs was analyzed from the perspectives of POs. The simulation results show that the two-way SDM strategy considering the preferences of SDs and SPs is more conducive to the sustainable development of CMEs. This paper appropriately abstracts and simplifies the measurement of SP service capabilities, but without loss of generality. In the future, quantitative evaluations and the measurement of the dynamic availability of SPs can be carried out based on the proposed multiagent simulation framework, and a multiagent cooperative game mechanism can be added to improve the accuracy of the simulation model and its ability to reflect reality. This study lays the foundation for the design and dynamic regulation of the transaction rules employed by CMEs.

REFERENCES

[1] L. Zhang, Y. Luo, F. Tao, B. H. Li, L. Ren, X. Zhang, H. Guo, Y. Cheng, A. Hu, and Y. Liu, ''Cloud manufacturing: A new manufacturing paradigm,'' *Enterprise Inf. Syst.*, vol. 8, no. 2, pp. 167–187, Mar. 2014, doi: 10.1080/17517575.2012.683812.

[2] L. Ren, L. Zhang, F. Tao, C. Zhao, X. Chai, and X. Zhao, ''Cloud manufacturing: From concept to practice,'' *Enterprise Inf. Syst.*, vol. 9, no. 2, pp. 186–209, Feb. 2015, doi: 10.1080/17517575.2013.839055.

[3] P. Argoneto and P. Renna, ''Capacity sharing in a network of enterprises using the Gale–Shapley model,'' *Int. J. Adv. Manuf. Technol.*, vol. 69, nos. 5–8, pp. 1907–1916, Nov. 2013, doi: 10.1007/s00170-013-5155-y.

[4] D. Z. Zhao and R. Li, ''Two-sided matching mechanism with agents' expectation for cloud manufacturing resource,'' *Control Decis.*, vol. 32, no. 5, pp. 871–878, Mar. 2017, doi: 10.13195/j.kzyjc.2016.0518.

[5] J. H. Zhao and X. H. Wang, ''Bidirectional matching model of cloud manufacturing service based on service quality,'' *Comput. Integr. Manuf. Syst.*, vol. 22, no. 1, pp. 104–112, Jan. 2016, doi: 10.13196/j.cims.2016.01.010.

[6] X. X. Bi, Y. Dong, H. Yi, and J. S. Liu, ''A resource storage model and supply-demand matching method based on cloud manufacturing,'' in *Proc. 12th Int. Conf. Intell. Comput. Technol. Automat. (ICICTA)*, Xiangtan, China, Oct. 2019, pp. 626–632, doi: 10.1109/ICICTA49267.2019.00139.

[7] H. F. Li, X. Dong, and C. G. Song, ''Intelligent searching and matching approach for cloud manufacturing service,'' *Comput. Integr. Manuf. Syst.*, vol. 18, no. 7, pp. 1485–1493, Jul. 2012, doi: 10.13196/j.cims.2012.07.144.lihf.018.

[8] X. Xue, S. F. Wang, L. J. Zhang, and Z. Y. Feng, ''Evaluating of dynamic service matching strategy for social manufacturing in cloud environment,'' *Future Gener. Comput. Syst.*, vol. 91, pp. 211–326, Feb. 2019, doi: 10.1016/j.future.2018.08.028.

[9] X. Xia, S. F. Wang, L. J. Zhang, and C. Z. Qin, ''Complexity analysis of manufacturing service ecosystem: A mapping-based computational experiment approach,'' *Int. J. Prod. Res.*, vol. 57, no. 2, pp. 357–378, Jan. 2019, doi: 10.1080/00207543.2018.1430906.

[10] J. Thekinen and J. H. Panchal, ''Resource allocation in cloud-based design and manufacturing: A mechanism design approach,'' *J. Manuf. Syst.*, vol. 43, pp. 327–338, Apr. 2017, doi: 10.1016/j.jmsy.2016.08.005.

[11] H. Zheng, Y. Feng, and J. Tan, ''A hybrid energy-aware resource allocation approach in cloud manufacturing environment,'' *IEEE Access*, vol. 5, pp. 12648–12656, Jun. 2017, doi: 10.1109/ACCESS.2017.2715829.

[12] Z. Liu and Z. Wang, ''A novel truthful and fair resource bidding mechanism for cloud manufacturing,'' *IEEE Access*, vol. 8, pp. 28888–28901, Dec. 2020, doi: 10.1109/ACCESS.2019.2962093.

[13] M. Li, X. Jin, C. Guo, J. Liu, G. H. Cui, and T. Qiu, ''RIMNet: Recommendation incentive mechanism based on evolutionary game dynamics in peer-to-peer service networks,'' *Knowl.-Based Syst.*, vol. 166, pp. 156–169, Feb. 2019, doi: 10.1016/j.knosys.2018.12.024.

[14] P. Renna and P. Argoneto, ''Capacity sharing in a network of independent factories: A cooperative game theory approach,'' *Robot. Comput.-Integr. Manuf.*, vol. 27, no. 2, pp. 405–417, Apr. 2011, doi: 10.1016/j.rcim.2010.08.009.

[15] X. Zheng, P. Martin, K. Brohman, and L. D. Xu, ''Cloud service negotiation in Internet of Things environment: A mixed approach,'' *IEEE Trans. Ind. Informat.*, vol. 10, no. 2, pp. 1506–1515, May 2014, doi: 10.1109/TII.2014.2305641.

[16] T. Baarslag, M. J. C. Hendrikx, K. V. Hindriks, and C. M. Jonker, ''Learning about the opponent in automated bilateral negotiation: A comprehensive survey of opponent modeling techniques,'' *Auto. Agents Multi-Agent Syst.*, vol. 30, no. 5, pp. 849–898, Sep. 2015, doi: 10.1007/s10458-015-9309-1.

[17] R. Rajavel and M. Thangarathanam, ''Adaptive probabilistic behavioural learning system for the effective behavioural decision in cloud trading negotiation market,'' *Future Gener. Comput. Syst.*, vol. 58, pp. 29–41, May 2016, doi: 10.1016/j.future.2015.12.007.

[18] R. Rajavel and M. Thangarathanam, ''Agent-based automated dynamic SLA negotiation framework in the cloud using the stochastic optimization approach,'' *Appl. Soft Comput.*, vol. 101, Mar. 2021, Art. no. 107040, doi: 10.1016/j.asoc.2020.107040.

[19] G. Chao, Q. U. Shiyou, X. Yingying, W. Mei, S. H. Guoqiang, L. I. Tingyu, X. U. Junjie, and J. I. Zhengxuan, ''Diffusion mechanism simulation of cloud manufacturing complex network based on cooperative game theory,'' *J. Syst. Eng. Electron.*, vol. 29, no. 2, pp. 321–335, May 2018, doi: 10.21629/JSEE.2018.02.13.

[20] W. Peng, W. Guo, N. Zhao, and L. Wang, ''A niche based evolutionary model of competition and cooperation among the main players of cloud manufacturing ecosystem,'' *Comput. Integr. Manuf. Syst.*, vol. 21, no. 3, pp. 840–847, Mar. 2015, doi: 10.13196/j.cims.2015.03.029.

[21] W. Zhang, Y. Shi, M. Yang, X. Gu, R. Tang, and X. Pan, ''Ecosystem evolution mechanism of manufacturing service system driven by service providers,'' *Int. J. Prod. Res.*, vol. 55, no. 12, pp. 3542–3558, Jun. 2017, doi: 10.1080/00207543.2017.1305131.

[22] Z. He, Z. Z. Zhang, and B. Li, ''Evolution game model of knowledge transfer incentive in cloud manufacturing supply chains,'' *China Mech. Eng.*, vol. 31, no. 6, pp. 695–705, Mar. 2020, doi: 10.3969/j.issn.1004-132X.2020.06.009.

[23] T. Wang, C. Li, and P. Zhang, ''A system dynamics model for the diffusion of cloud manufacturing mode with evolutionary game theory,'' *IEEE Access*, vol. 9, pp. 1428–1438, Dec. 2021, doi: 10.1109/ACCESS.2020.3043833.

[24] J. Zhang, Q. Hu, S. Tan, and X. Wang, ''Entering, exiting and enterprise survival—Based on the data from China's manufacturing enterprises,'' *Sci. Manage. Res.*, vol. 11, pp. 103–110, 143, doi: 10.16304/j.cnki.11-3952/f.2013.11.014.

[25] Y. F. Dong, Z. J. Wu, X. Du, J. Zha, and Q. S. Yuan, ''Meta-activity model driven grain layered service encapsulation and retrieval for multi-domain manufacturing resources,'' *China Mech. Eng.*, vol. 29, no. 12, pp. 1475–1484. Jun. 2018, doi: 10.3969/j.issn.1004-132X.2018.12.014.

[26] Y. Feng and B. Q. Huang, ''Hierarchical and configurable trust evaluation model of cloud manufacturing services,'' *Comput. Integr. Manuf. Syst.*, vol. 23, no. 10, pp. 2291–2303, Oct. 2017, doi: 10.13196/j.cims.2017.10.023.

[27] Y. Hu and G. Guo, ''Two-sided matching model of requirements-service based on comprehensive fuzzy similarity in cloud manufacturing,'' *Comput. Appl. Softw.*, vol. 34, no. 11, pp. 26–33, Nov. 2017, doi: 10.3969/j.issn.1000-386x.2017.11.005.

[28] K. K. Bi, ''The research of key factors of development and evolution of cloud manufacturing ecosystem in perspective of individual,'' Ph.D. dissertation, College Manage. Econ., Tianjing Univ., Tianjing, China, 2015.

[29] R. E. Ulanowicz, *Growth and Developent: Ecosystem Phenomenology*. New York, NY, USA: Springer-Verlag, 1986.

[30] J. J. Yun, X. Zhao, J. Wu, J. C. Yi, K. Park, and W. Jung, ''Business model, open innovation, and sustainability in car sharing industry—Comparing three economies,'' *Sustainability*, vol. 12, no. 5, pp. 1–27, Mar. 2020, doi: 10.3390/su12051883.

[31] D. Liang, Z. Dai, and M. Wang, ''Assessing customer satisfaction of O2O takeaway based on online reviews by integrating fuzzy comprehensive evaluation with AHP and probabilistic linguistic term sets,'' *Appl. Soft Comput.*, vol. 98, pp. 1–14, Jan. 2021, doi: 10.1016/j.asoc.2020.106847.

YUANFA DONG received the Ph.D. degree in mechanical engineering from Chongqing University, Chongqing, China, in 2013. From 2014 to 2017, he was a Lecturer with the College of Mechanical and Power Engineering, China Three Gorges University, where he has been an Associate Professor, since 2017. From 2016 to 2017, he was a Visiting Research Fellow with WMG, University of Warwick. He holds two patents and has authored or coauthored more than 20 papers in refereed international journals and conferences. His research interests include intelligent manufacturing and human–machine integration.

LEI WANG received the B.Eng. degree in engineering management from the College of Science and Technology, China Three Gorges University, Yichang, China, in 2017, where she is currently pursuing the master's degree in mechanical engineering. Her research interests include cloud manufacturing and intelligent optimization.

WEI PENG received the Ph.D. degree in mechanical engineering from Tianjing University, Tianjing, China, in 2017. Since 2017, he has been a Lecturer with the College of Mechanical and Power Engineering, China Three Gorges University. He has authored or coauthored more than ten papers in refereed international journals and conferences. His research interests include intelligent manufacturing and crowdsourcing design.

RONGHUA MENG received the Ph.D. degree in mechanical engineering from the Huazhong University of Science and Technology, Wuhan, China, in 2019. Since 2019, she has been a Lecturer with the College of Mechanical and Power Engineering, China Three Gorges University. She has authored or coauthored more than six papers in refereed international journals and conferences. Her research interests include intelligent scheduling and path planning.

ZHENGJIA WU received the Ph.D. degree in system analysis and integration from the Huazhong University of Science and Technology, Wuhan, China, in 2008. From 2000 to 2008, he was an Associate Professor with the College of Mechanical and Materials, China Three Gorges University. Since 2008, he has been a Professor. He has authored or coauthored more than 60 papers in refereed international journals and conferences. His research interests include production scheduling and system integration.