Postprint: A Computational Experimental Comparative Study of Service Matching Strategies for Cluster Collaborative Manufacturing

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Abstract

To address the issue of how to accurately evaluate various service matching strategies and select the optimal service strategy to achieve supply-demand matching of services in dynamic environments during cluster collaborative manufacturing processes, a computational experimental method for cluster collaborative manufacturing service matching strategies is proposed. This method conducts in-depth research on cluster collaborative manufacturing service matching strategies from three aspects, including the design of service matching strategies (service matching strategies that consider only changes in QoS (quality of service) attributes of service resources, service matching strategies that consider only changes in customer requirements, and service matching strategies that comprehensively consider both changes in QoS attributes of service resources and changes in customer requirements), the construction of cluster collaborative manufacturing experimental system models, and the analysis and evaluation of service matching strategies. Experimental results demonstrate that under both stable and fluctuating supply-demand market environments, the service matching strategy that comprehensively considers changes in QoS attributes of service resources and changes in customer requirements performs optimally and can effectively achieve supply-demand matching of manufacturing services in dynamic environments.

Full Text

Preamble

Comparative Research on Computational Experiment of Service Matching Strategy in Cluster Collaborative Manufacturing

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Abstract: To accurately evaluate various service matching strategies and select the optimal strategy for achieving supply-demand matching in the dynamic environment of cluster collaborative manufacturing, this paper proposes a computational experiment method for service matching strategies in cluster collaborative manufacturing. The method investigates service matching strategies from three perspectives: (1) strategy design—including strategies that consider only QoS attribute changes of service resources, only customer demand changes, and both QoS attribute changes and customer demand changes; (2) construction of an experimental system model for cluster collaborative manufacturing; and (3) analysis and evaluation of service matching strategies. Experimental results demonstrate that under both stable and volatile market conditions, the strategy considering both QoS attribute changes and customer demand changes performs optimally, effectively achieving manufacturing service supply-demand matching in dynamic environments.

Keywords: cluster supply chain; collaborative manufacturing; service matching strategy; customer demand; QoS attribute; computational experiment

0 Introduction

Cluster supply chain represents the coupling of industrial clusters and supply chains, with its service system defined as "a method for achieving enterprise objectives that supports cluster supply chain operations through information technology, facilitates collaboration among enterprises within or between supply chains, and provides various business support for such collaboration." As the core platform of cluster supply chain management, the service system's primary function is to match services based on customer requirements. Since service matching strategies occupy a central position in service systems and directly determine system performance, selecting appropriate matching strategies is crucial.

In real-world environments, service supply-demand matching in cluster collaborative manufacturing exhibits inherent complexity. First, candidate services continuously change. These services are provided by enterprises within or outside the cluster, and due to their growth and autonomy, service QoS information —such as business types, capabilities, and other attributes—constantly evolves. The open nature of cluster supply chains also enables enterprises to join or exit freely, causing the number of available services to fluctuate dynamically. Additionally, certain QoS attributes like response time vary with current workload. Second, customer demands change. Due to limited customer samples and ambiguous requirements, determining accurate attribute weights is challenging. Most existing studies rely on expert experience or customer feedback to assign fixed weights. However, in cluster supply chains, different customers have vastly different preferences—some prioritize specific metrics like price, quality, or cost, while others seek balanced comprehensive indicators—and these preference weights change over time. These dynamic factors directly affect service matching effectiveness. Therefore, service systems must possess self-adjustment and autonomous evolution capabilities to dynamically construct, adjust, and optimize matching schemes on demand, thereby effectively supporting collaboration among cluster manufacturing enterprises.

Current research on cluster collaborative manufacturing primarily approaches the topic from two angles: business operations (economics, management, sociology) and service support (service encapsulation, composition, systems), with limited holistic evaluation of service matching strategies. Existing evaluation studies focus on summarizing implementation results in specific environments, using performance indicators such as customer satisfaction and provider satisfaction over certain time periods. However, cluster collaborative manufacturing service systems are typical complex dynamic systems with substantial uncertainty in both evolution conditions and outcomes, making unpredictable emergencies difficult to replicate in real environments. Consequently, comprehensive testing and evaluation of service strategies in actual settings is impractical. Most existing methods analyze historical data but cannot comprehensively evaluate strategies or predict future scenarios. Thus, how to thoroughly assess the effectiveness of service matching strategies has become an urgent problem in this field.

With the continuous development of complex systems research, computational experiments have emerged as a novel methodology. Characterized by precise controllability, ease of operation, and reproducibility, computational experiments are particularly suitable for studying systems where risks are high, costs are substantial, or direct experimentation is impossible, including transportation systems, socio-economic systems, and supply chain management systems. By combining the target features of cluster collaborative manufacturing with computational experiments, we can design various experimental scenarios that simulate complex multi-entity game situations, conduct extensive repeated experiments under different conditions, and provide decision-making support for service matching strategy evaluation. This paper therefore proposes a computational experiment method for service matching strategies in cluster collaborative manufacturing, comprising three main components: (a) service matching strategy design based on dynamic evolution behavior of supply-demand matching; (b) experimental system construction using computational experiments to simulate different market supply-demand environments; and (c) service matching strategy evaluation through effective performance analysis across different environments to identify the optimal strategy.

1 Computational Experiment Method for Service Matching Strategy in Cluster Collaborative Manufacturing

The proposed computational experiment method is illustrated in [Figure 1: see original paper]. This section provides a detailed introduction to the approach.

1.1 Service Matching Strategy Design

Existing research on manufacturing service supply-demand matching has produced numerous solution methods, including template/ontology and keyword-based approaches, process-driven methods, artificial intelligence and planning-based methods, and service composition techniques. Most of these studies address static matching problems at specific moments, assuming fixed customer demands and candidate services. However, in cluster collaborative manufacturing, enterprise services exhibit social characteristics that intensify diversity, uncertainty, and dynamism in service supply. Moreover, during enterprise collaboration, services dynamically join and exit, while service status, quality, QoS attributes, and inter-service relationships change randomly. Similarly, demand submission and cancellation, functional requirements, process requirements, and relationships among sub-tasks for complex demands also evolve randomly. Therefore, solving real-time matching problems in such complex dynamic environments is key to successful cluster collaborative manufacturing service system operation.

To address these challenges, we designed three service matching strategies: (a) a strategy considering only QoS attribute changes of service resources (Supply-SM), which incorporates QoS attribute update mechanisms into the service system to ensure candidate service QoS attributes remain valid; (b) a strategy considering only customer demand changes (Dem-SM), which establishes a feedback loop between service system matching and customer evaluations, using machine learning evolution algorithms (specifically BP neural networks in this paper) to learn from customer feedback and adjust QoS demand model parameters, eliminating deviations between the system' s assumed QoS demand model and actual customer requirements; and (c) a strategy considering both QoS attribute changes and customer demand changes (SuppDem-SM). Detailed descriptions of these three strategies are provided in Section 2.

1.2 Experimental System Construction

Cluster collaborative manufacturing is a complex network with self-organization and co-evolution characteristics, where disorder or delays at any node may trigger changes across the entire ecosystem, causing established operational strategies to fail. Due to substantial uncertainty in initial conditions, external environments, and internal elements of cluster collaborative manufacturing ecosystem evolution, and the difficulty of replicating extreme or emergency situations, studying service matching strategies in real environments is challenging. To enable quantitative analysis of these strategies, new experimental validation methods are needed—methods that can simulate ecosystem evolution under different scenarios and strategies, provide comprehensive and accurate quantitative analysis of matching strategies, and offer technical means for controllable evolution research in cluster collaborative manufacturing. Therefore, this paper adopts computational experiments to construct the experimental system.

The computational experiment model employs Multi-Agent modeling, abstracting the real system from both supply and demand perspectives. Multi-Agent modeling is an Agent-based approach that "top-down" abstracts real systems into systems composed of multiple Agent entities, where each Agent is an independent entity capable of autonomous decision-making and interaction with other Agents, thereby forming a complex system organically. In real systems, customers select services based on their preferences. Therefore, in our theoretical model, we abstract the main entities directly involved in transactions into two types of Agent: Service Provider Agent and Customer Agent, corresponding to service suppliers and demanders in the real system. Specific modeling details are provided in Section 3.

1.3 Service Matching Strategy Evaluation

We use computational experiments to comprehensively evaluate the designed service matching strategies and identify the optimal one. To assess strategy performance using experimental data, quantitative evaluation is necessary. Common evaluation metrics include customer satisfaction and average capital of all service providers.

Customer satisfaction S evaluates whether the service system' s matched solutions can properly serve customers, where A represents the number of customers satisfied with system-matched services and B represents the total number of customers:

$$S = \frac{A}{B}$$

Average capital of all service providers ($AverageCapital$) reflects the impact of service matching strategies on resource utilization. Effective strategies give all service providers a chance to be selected, resulting in higher resource utilization, while poor strategies cause high-quality providers to be neglected, leading to resource idleness and capital stagnation. Here, K represents the sum of all service providers' capital values and M represents the number of service providers:

$$AverageCapital = \frac{K}{M}$$

2 Service Matching Strategy Design

To concretely elaborate customer requirements and enterprise services, we formalize their descriptions as follows:

2.1 Supply-SM Strategy: Considering Only QoS Attribute Changes

The Supply-SM strategy (Service Resource QoS Attribute Change-Only Service Matching) operates on the principle that the service system must update internal enterprise service QoS attribute information before matching services to customer demands, thereby ensuring timely and effective matched solutions. Based on characteristics of enterprise service resource QoS attributes, we categorize them into state attributes and feature attributes.

State attributes are directly related to the current operational status of enterprise services and directly affect subsequent matching. These include service price, enterprise capital value, and maximum production capacity. The service system must continuously monitor these attributes for changes, and when changes occur, trigger corresponding service components to notify the system for updates in preparation for subsequent matching. The service state update rules are shown in .

Feature attributes are not directly related to current operational status and change primarily due to enterprise internal changes at relatively low frequencies. These include product quality, cost-effectiveness, and enterprise reputation.

The Supply-SM strategy implementation process is as follows:

Input: Demand queue N
Output: Service matching solution for each demand

1. Analyze current demands based on computational experiment initial parameters and construct the customer' s QoS demand model.
2. Perform functional matching upon receiving each service demand, including service category, name, description, and input-output matching.
3. Update candidate service state attributes periodically.
4. Match services according to the customer' s QoS demand model by searching for optimal candidate service paths and selecting the top N solutions with highest QoS values as the matching list.
5. Loop to process the next demand by repeating steps 1-4.

2.2 Dem-SM and SuppDem-SM Strategies: Considering Customer Demand Changes

In real market environments, customer preferences for QoS attributes (e.g., product quality, price) change over time—a common phenomenon. To ensure effective service matching, service systems must continuously adjust their QoS demand models based on customer preferences to obtain better feedback. This section presents strategies that consider customer demand changes, establishing a feedback loop between service system matching and customer evaluations. Customer evaluations serve as training data for the system' s feedback learning, employing BP neural network technology to eliminate deviations between the system' s assumed demand model $f_{system}(QoS)$ and actual customer requirements $f_{user}(QoS)$, enabling the system to adjust its demand model in real-time based on feedback.

We further divide "customer demand change consideration strategies" into two types: (a) Dem-SM, which considers only customer demand changes, and (b)

SuppDem-SM, which considers both customer demand changes and service resource QoS attribute changes. The implementation processes for Dem-SM and SuppDem-SM are illustrated in [Figure 2: see original paper].

The detailed steps are:

Input: Demand queue N
Output: Service matching solution for each demand

1. Analyze current demands based on computational experiment initial parameters and construct the customer' s QoS demand model.
2. Perform functional matching upon receiving each service demand.
3. Update candidate service state attributes periodically (for SuppDem-SM only).
4. Match services according to the customer' s QoS demand model, selecting the top N solutions.
5. Customers evaluate matched services. If customer satisfaction falls below a preset threshold (0.9 in this paper) within a fixed period (12 cycles), proceed to step 6; otherwise, go to step 7.
6. Convert the matching list and corresponding customer feedback ratings into new historical records, represented as one-dimensional vectors $[q_1, q_2, ..., q_m : E]$, where $q_1, q_2, ..., q_m$ are service QoS attribute values and E is the customer evaluation. Use BP neural network to train on this new sample set, using QoS attribute values as input and customer evaluations as output. Update the system' s QoS demand model parameters after training and match services using the new model.
7. Loop to process the next demand by repeating steps 1-6.

3 Experimental System Construction

3.1 Platform Model

The experiment was built on the RePast Simphony simulation platform—a complex systems modeling software developed by the University of Chicago' s Social Science Computational Research Laboratory for Java-based Agent modeling [22]. The computational experiment system operation process is shown in [Figure 3: see original paper].

We assume each customer demand requires services from three types of service providers to complete, represented as stages 1, 2, and 3 in [Figure 3: see original paper]. Blue squares represent Customer Agents, while three different red shapes represent three types of Service Provider Agents offering different services, each with its own production capacity and state attributes. The interaction process is: (1) Customer Agent searches for a stage-1 Service Provider Agent based on its demand and moves to its location; (2) After stage-1 service completion, the stage-1 provider generates a secondary order, prompting the Customer Agent to search for stage-2 services; (3) After stage-2 completion, the stage-2 provider generates another secondary order for stage-3 services; (4)

Upon stage-3 completion, the current Customer Agent disappears and the system generates a new Customer Agent representing new demand.

Two demand scenarios are established: stable demand and fluctuating demand, determined by normal distribution functions to facilitate comprehensive strategy evaluation.

3.2 Service Provider Agent Model

The Service Provider Agent structure is described by Equation (5) with time-dependent attributes including feature attributes F, state attributes S_t, perceived events E_t, behavior set V_t, and decision mechanism Y_t.

Feature attributes F are not directly related to current operational status and change infrequently due to enterprise internal changes. The main feature attributes are shown in .

State attributes S_t continuously change during operation, reflecting the current Agent state. The main state attributes are shown in .

Perceived events E_t are external events that stimulate Agent states and behaviors. Service Provider Agent perceived events are shown in .

Behavior set V_t includes all behaviors spontaneously taken or stimulated by external events based on attributes, accessible resources, and local environment. The main behavior set is shown in .

Decision mechanism Y_t guides subsequent actions based on environmental changes and internal conditions. The decision mechanism is shown in .

3.3 Customer Agent Model

As market participants and service beneficiaries, customers play a decisive role in service selection. The Customer Agent model also uses the structure from Equation (5) but adapted to customer characteristics.

Influencing **feature attributes** F include economic strength and industry. **State attributes** S_t include personal preferences and order quantity. Based on perceived information, customer attributes, attribute changes, and external environment, Customer Agents make decisions: selecting services according to preferences and providing evaluations.

The **behavior set** V_t includes all behaviors spontaneously taken or stimulated by external events. The main Customer Agent behaviors are shown in .

4 Experimental Evaluation

4.1 Computational Experiment Environment and Parameter Settings

To ensure reference value, experimental parameters are based on China' s 2016 Manufacturing Producer Price Index, Purchase Price Index, and Retail Price

Index [23], creating a realistic cluster collaborative manufacturing environment. Specific parameters are shown in .

Customer demand preferences change every 32 cycles. For research convenience, during the first 32 cycles, all three strategies produce completely satisfactory matches. The total experiment duration is 128 cycles. Two demand scenarios are evaluated: stable demand and fluctuating demand, with fluctuation variance $\sigma^2 = 5$ for stable scenarios and $\sigma^2 = 15$ for fluctuating scenarios.

The customer evaluation formula is:

$$Rating = w_1 \times price + w_2 \times reputation$$

where $w_1 + w_2 = 1$. We assume customers are only interested in price and reputation. w_1 values are randomly assigned as 0.3 or 0.7 initially, changing every 32 cycles. When $w_1 = 0.3$, customers prefer reputation; when $w_1 = 0.7$, they prefer price. Specific evaluation rules are:

For price-preferring customers: - If $price \leq price_{11}$: $Rating = [7.6, 8.9]$ with probability 0.8 - If $price_{11} < price \leq price_{12}$: $Rating = [8.3, 9.6]$ with probability 0.5 - If $price_{12} < price \leq price_{13}$: $Rating = [9, 10.3]$ with probability 0.3 - Otherwise: $Rating = 10$

For reputation-preferring customers: - If $reputation = 4$: $Rating = [5.8, 7.3]$ with probability 0.8 - If $reputation = 3$: $Rating = [5.1, 6.6]$ with probability 0.5 - If $reputation = 2$: $Rating = [4.4, 5.9]$ with probability 0.3 - Otherwise: $Rating = 1$

The BP neural network settings are: input layer with 3 nodes (price, reputation, maximum capacity), output layer with 1 node (customer evaluation), hidden layer with 10 nodes, learning rate 0.25, and training target of 7000 iterations.

4.2 Experimental Results and Comparative Analysis

The experimental results under both demand scenarios are shown in [Figure 4: see original paper], [Figure 5: see original paper], and [Figure 6: see original paper]. The left column shows stable demand scenario results, while the right column shows fluctuating demand scenario results.

Conclusions from [Figure 6: see original paper]:

a) **Average service provider capital:** As shown in [FIGURE:6a-2] and [FIGURE:6b-2], with increasing processed customer demands, SuppDem-SM's average provider capital significantly outperforms both Dem-SM and Supply-SM under both demand scenarios. This indicates SuppDem-SM achieves higher resource utilization and better supports enterprise scale development.

b) **Customer satisfaction:** As shown in [FIGURE:6a-3] and [FIGURE:6b-3], as customer preferences and provider attributes change simultaneously, satisfaction ratios fluctuate across all three strategies. However, SuppDem-SM' s overall customer satisfaction ratio is slightly superior to Dem-SM and Supply-SM.

c) **Overall performance:** SuppDem-SM demonstrates superior service matching effectiveness compared to the other two strategies.

[Figure 4: see original paper] and [Figure 5: see original paper] visually demonstrate that as experiment cycles increase and customer preferences change, service provider capital values evolve across all strategies. However, SuppDem-SM consistently achieves significantly higher average provider capital than Dem-SM and Supply-SM in both stable and fluctuating demand scenarios.

5 Conclusion

To better achieve manufacturing service supply-demand matching in dynamic environments, this paper proposes a computational experiment method for service matching strategies in cluster collaborative manufacturing, comprising three components: (a) strategy design—including Supply-SM, Dem-SM, and SuppDem-SM; (b) experimental system construction using computational experiments to simulate different market supply-demand environments; and (c) strategy evaluation through effective performance analysis under stable and volatile market conditions to support strategy selection.

Experimental results show that under both stable and fluctuating supply-demand conditions, the strategy considering both QoS attribute changes and customer demand changes (SuppDem-SM) performs optimally, effectively achieving dynamic manufacturing service supply-demand matching. Compared with traditional evaluation methods, the proposed computational experiment approach enables more comprehensive strategy assessment, benefiting both service providers and customers.

Research on cluster collaborative manufacturing service matching strategies is highly complex, and current comparative studies have limitations. Future research will focus on the impact of inter-enterprise collaboration patterns on service matching strategies, aiming to identify optimal strategies by adjusting collaboration modes according to customer demands, thereby maintaining healthy cluster manufacturing development.

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Note: Figure translations are in progress. See original paper for figures.