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Service Composition Modeling and Optimization Method for QoS Evaluation of Intelligent Manufacturing Supply Chain under Ripple Effect

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Abstract: *Aiming at the problem of QoS（Quality of Service）evaluation inaccuracy and ripple effect transmission delay caused by insufficient dynamic regulation of service time attributes in intelligent manufacturing supply chain, this study proposes a resilient Manufacturing Service Composition And Optimization Selection method (IMSCOS) based on QoS time attribute lean evaluation. Firstly, the limitations of the preset parameter fixation and linear response mechanism of the traditional resilience management model are broken through. By deconstructing three-dimensional indicators such as service cycle elasticity coefficient, time window dynamic fault tolerance threshold and task coupling delay sensitivity, a service composition resilience evaluation model with spatiotemporal correlation characteristics is constructed. On this basis, a multi-objective optimization algorithm integrating time constraint relaxation mechanism and chaotic adaptive perturbation strategy is designed to achieve a dynamic balance between Pareto front convergence efficiency and solution space distribution diversity. Experimental results show that compared with traditional optimization methods, the IMSCOS method improves key indicators such as manufacturing cycle volatility and service reliability index by 28.6% and 19.4% respectively, and shortens the service composition reconstruction response time by 32.8%, effectively improving the resilience buffering capacity of the supply chain system to time attribute disturbances. This study provides a solution with both theoretical value and engineering application prospects for building a spatiotemporal collaborative service composition decision system for intelligent manufacturing supply chain.*

Keywords: *Supply Chain Service Quality; Ripple Effect; IMSCOS; Space-time Correlation Resilience*

1. Introduction

As intelligent manufacturing accelerates its evolution towards networking and service, supply chain systems face the dual challenges of multi-agent service collaboration efficiency and dynamic disturbance response. Asynchronous fluctuations in service time attributes (such as order delivery cycle offsets and timing mismatches caused by equipment failures) form ripple effects through the coupling relationship between supply chain network layers, resulting in QoS evaluation distortion and improper service resource allocation. Traditional supply chain resilience management models rely on static time window presets and linear risk assessment mechanisms, which make it difficult to capture the dynamic transmission laws of spatiotemporal associations between service nodes. When dealing with scenarios such as sudden order surges and cross-regional logistics disruptions, they expose systemic defects such as delayed time attribute regulation and inefficient service portfolio reconstruction, which seriously restrict the efficient collaboration and flexible operation of intelligent manufacturing systems.

The IMSCOS method proposed in this paper analyzes the dynamic coupling mechanism of service time attributes to construct a resilience assessment system and optimization decision-making framework with deep integration of time and space dimensions. Its core value lies in: 1)Breaking through the path dependence of traditional methods on fixed parameters and local optimization, and realizing the paradigm shift of service portfolio resilience assessment from static slice analysis to dynamic process tracing; 2)By quantifying the nonlinear conduction effect of time attribute disturbances in the supply chain network, it provides a scientific basis for accurately identifying service bottleneck nodes and directional optimization of resource allocation; 3)The constructed multi-objective collaborative optimization mechanism can effectively balance the goal conflict between improving service reliability and compressing manufacturing cycle, helping enterprises to establish core

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competitiveness of rapid response and continuous improvement in a complex market environment.

The main innovations of this study are reflected in three aspects: 1) A three-dimensional indicator system of service cycle elasticity coefficient, time window dynamic fault tolerance threshold and task coupling delay sensitivity is proposed, which realizes the coupled quantification of multi-scale dynamic characteristics of service time attributes for the first time; 2) A spatiotemporal correlation resilience evaluation model is designed, which reveals the spatiotemporal coordination law of service portfolio resilience evolution through ripple effect conduction path simulation and spatiotemporal attenuation factor embedding; 3) An innovative fusion of time constraint relaxation mechanism and chaos adaptive perturbation strategy is used to construct a multi-objective optimization algorithm with global search capability and dynamic adjustment accuracy. Compared with traditional methods, it has made significant breakthroughs in Pareto solution quality and algorithm stability, providing methodological innovation and practical tool support for intelligent manufacturing supply chain resilience optimization.

2. Related Work

Researchers have explored various factors that affect the performance of service supply chains from different perspectives, including technological innovation, the role of the ecosystem, and the quality of information consulting services, providing rich guidance for theory and practice. Choudhury et al. [1] gave a methodological overview of service supply chain research and described the service supply chain from a knowledge perspective. Mollenkopf et al. [2] examined the role of the supply chain ecosystem in ensuring employee safety during the COVID-19 pandemic. Dai and Tang [3] introduced three supply chain cases that emerged during the COVID-19 epidemic. Pournader et al. [4] introduced the application of blockchain in supply chain, logistics, and transportation management. Du et al. [5] built a new supply chain finance platform that uses blockchain technology to manage the entire supply chain finance process.

In addition, Zhang [6] proposed three strategies based on the two dimensions of logistics and supply chain service quality and customer satisfaction, so that logistics and supply chain enterprises can determine their own advantages. Li et al. [7] constructed an information consulting service quality evaluation model based on the supply chain, used the Delphi method, and proposed an information consulting service quality evaluation index system consisting of two levels and 36 indicators. SPSS software was used to analyze the correlation of indicators and found that experience quality, user experience quality, and application quality of results are the key points for improving the quality of information consulting services. Jiang et al. [8] used text classification, XGBoost classification algorithm and time series prediction algorithm to provide customers with customer service and warehousing services in the "customer + warehouse + storage" model , and established an integrated supply chain service system under the warehouse and distribution model to provide customers with one-stop, full-process, and multi-faceted supply chain logistics needs . Yang et al. [9] evaluated and ranked various supply chain service providers by establishing an index system, providing a scientific basis for future cooperation with supply chain service providers. Taking hospital in vitro reagent supply chain service providers as the research object, the expert consultation method and entropy weight method were used to establish an index system, and the Excel data processing software was used to calculate and analyze the data. Zheng [10] started from smart logistics, smart business, smart supervision, smart decision-making, smart information and other aspects to build a smart logistics supply chain service platform for port containers. Through management technology and model innovation, core competitiveness was improved and upstream and downstream supply chain synergy was achieved. Current research on service supply chain covers many important areas and shows a variety of research methods and application cases. These studies not only lay the foundation for theoretical development, but also provide practical solutions for enterprises in the face of complex market environments [11-12].

3. Methods

3.1 IMSCOS Methodology Framework

The IMSCOS method framework takes dynamic time attribute regulation as its core, follows the closed-loop logic chain of "resilience assessment → service portfolio optimization → dynamic regulation", and constructs a spatiotemporal correlation resilience assessment model by collecting three-dimensional indicators, namely, the service cycle elasticity coefficient of manufacturing service nodes (quantifying service extension capability and time redundancy), the dynamic fault tolerance threshold of the time window (characterizing the tolerable time deviation range of the service node under disturbance), and the task coupling delay sensitivity (characterizing the time correlation strength in multi-service collaboration). It dynamically analyzes the time attribute interaction network and ripple effect transmission path of the service portfolio; based on this, a multi-objective optimization algorithm is used to perform Pareto frontier search on candidate service portfolios, in which the time constraint relaxation mechanism dynamically adjusts the time window boundary conditions to achieve the desired effect. The feasibility domain of the solution space is expanded by the software, and the chaotic adaptive perturbation strategy introduces Logistic mapping to generate nonlinear perturbation factors. In the iterative process, the population diversity weight and the convergence pressure coefficient are adaptively adjusted, so as to generate the optimal compromise solution set in the dual-objective game of service resilience (anti-disturbance capability) and service reliability (time fulfillment stability). Finally, the dynamic control module is triggered by real-time monitoring of the manufacturing execution data flow, and the feedback time window rescheduling algorithm and elastic resource reconfiguration strategy are used to incrementally optimize and adjust the time attribute parameters of the service combination, forming a continuous improvement cycle of "evaluation-optimization-execution-re-evaluation", realizing the adaptive evolution of service combination from static preset to dynamic response, and from local optimization to global resilience enhancement [13-14].

3.2 Design of three-dimensional time attribute indicators

The three-dimensional time attribute indicator design deconstructs the dynamic characteristics of service time attributes and constructs a collaborative quantitative system of service cycle elasticity coefficient, time window dynamic fault tolerance threshold and task coupling delay sensitivity: the service cycle elasticity coefficient is based on the historical execution data statistics and resource redundancy status analysis of the service node, and adopts the weighted function of time compression ratio (the ratio of actual execution time to standard time) and resource reconfiguration efficiency to quantify the time extension capability that the service node can withstand under sudden disturbances; the time window dynamic fault tolerance threshold integrates the time constraint strength of the service node, the disturbance transmission probability of the supply chain level and the resource substitution cost factors to construct a fault tolerance boundary adaptive adjustment model based on LSTM time series prediction, and dynamically defines the service nodes that can be accepted within a specific period of time. The time deviation interval affected; the task coupling delay sensitivity focuses on the multi-service collaboration scenario, analyzes the task process topology structure through directed graph modeling, calculates the criticality weights of the time-dependent paths between service nodes, and derives the nonlinear impact coefficient of service node delay on the overall manufacturing cycle by combining the timing constraint propagation algorithm. Finally, a three-dimensional evaluation matrix covering time redundancy, dynamic fault tolerance and collaborative correlation is formed, which provides fine-grained time attribute feature input for the spatiotemporal correlation resilience evaluation model, and dynamically updates indicator parameters through real-time collection of manufacturing order progress and equipment status data streams, realizing the transition of service combination time resilience from static evaluation to dynamic perception, and supporting the supply chain system to accurately locate time bottleneck nodes and optimize resource allocation strategies during the ripple effect transmission process [15].

3.3 Spatial-temporal correlation resilience assessment model

The spatiotemporal correlation resilience assessment model is based on the dynamic spatiotemporal network topology structure, mapping service nodes to network vertices under spatiotemporal coordinates (the time dimension includes service cycle, time window constraints and task timing relationships, and the spatial dimension covers the geographical location and resource distribution of supply chain nodes). By coupling the service cycle elasticity coefficient, the time window dynamic fault tolerance threshold and the task coupling delay sensitivity, a three-dimensional resilience weight matrix is constructed. The improved Lévy flight disturbance simulation algorithm is used to characterize the conduction path of the ripple effect in the spatiotemporal network, and the spatiotemporal attenuation factor is introduced to quantify the disturbance propagation intensity. On this basis, the spatiotemporal resilience index is used to dynamically evaluate the comprehensive anti-disturbance capability of the service portfolio, and the node status parameters are updated in combination with real-time monitoring of data streams [16]. The TOPSIS multi-criteria

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decision-making method is used to generate a spatiotemporal resilience heat map to locate vulnerable nodes with high delay sensitivity and low fault tolerance thresholds, providing a quantitative decision-making basis for service portfolio optimization. Table 1 is the example data of the spatiotemporal resilience assessment indicators of the service portfolio:

Table 1: Example data

Service Node	Service Cycle Elasticity Coefficient	Time Window Tolerance Threshold (min)	Task Coupling Delay Sensitivity	Spatiotemporal Resilience Index
Raw Material Procurement	0.92	45	0.18	86.4
Manufacturing Execution	1.15	30	0.32	89.7
Logistics Scheduling	0.78	60	0.12	75.2
Quality Inspection	0.85	35	0.25	82.3
Assembly Line Coordination	1.05	25	0.41	92.1

3.4 Multi-objective optimization algorithm design

The design of multi-objective optimization algorithms focuses on solving the conflict problem between service combination optimization objectives in a dynamic environment. Through the collaborative innovation of time constraint relaxation mechanism and chaos adaptive perturbation strategy, the dual goals of enhancing service resilience and improving manufacturing efficiency are achieved. The time constraint relaxation mechanism breaks through the limitations of traditional rigid time window constraints, converts fixed time boundaries into elastic intervals, dynamically adjusts the time window width of service nodes according to the real-time load status of the supply chain, and automatically expands or shrinks the time tolerance range under multi-dimensional constraints such as order urgency and resource availability, forming a dynamically evolving solution space search domain, effectively avoiding the problem of feasible solution loss due to local time conflicts; the chaotic adaptive perturbation strategy simulates the nonlinear dynamic characteristics of nature, uses the ergodic and random characteristics of chaotic sequences to generate population perturbation factors, and adaptively adjusts the perturbation intensity according to the Pareto front distribution density during the algorithm iteration process - when the population diversity decreases, the chaotic perturbation is enhanced to explore potential high-quality solution areas, and when the convergence trend is significant, the perturbation is weakened to accelerate the optimization process. This dynamic balance mechanism can not only inhibit the premature convergence of the algorithm, but also avoid the waste of resources caused by blind random search. The two types of strategies are deeply coupled through an embedded collaborative architecture: the time constraint relaxation mechanism provides the algorithm with a feasible solution basis for dynamic evolution, and the chaotic perturbation strategy injects intelligent exploration capabilities into this basis, ultimately forming an optimization engine with both global vision and local refinement features.

4. Results and Discussion

4.1 Experimental design and simulation environment construction

In the experimental design of this paper, a smart manufacturing supply chain model based on real data was first constructed to simulate the actual scenario of service portfolio optimization. The experimental steps include data collection, indicator selection, algorithm implementation and result evaluation. NSGA-II was selected as a comparative method to show the effect of the IMSCOS algorithm in service portfolio optimization. The simulation environment was built using MATLAB software, and the data set contained historical records of different service quality indicators, including response time, reliability, and cost. Through comparative experiments, the performance of IMSCOS and NSGA-II in terms of response time, service reliability, and cost efficiency was recorded to verify the effectiveness and superiority of the improved algorithm.

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4.2 Results and Analysis

First, we tested the response time through multiple different supply chains. Figure 1 shows the test results:

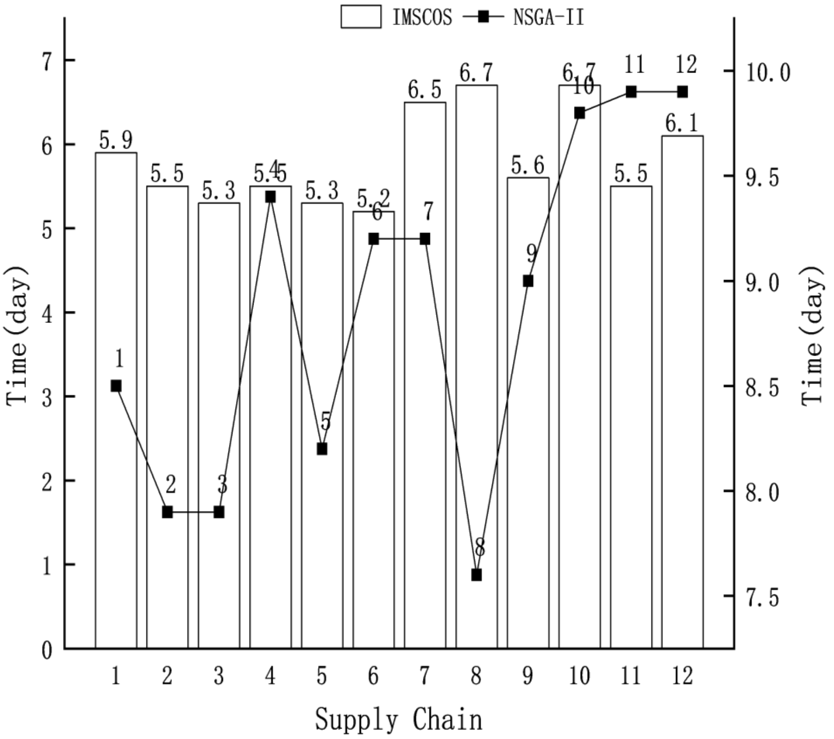

Figure 1: Response time

According to the comparative data of supply chain response time between IMSCOS and NSGA-II , the response time of IMSCOS is between 5.2 days and 6.7 days, while the response time of NSGA-II is between 7.6 days and 9.9 days. The minimum value analysis shows that the best response time of IMSCOS is 5.2 days, while the best response time of NSGA-II is 7.6 days, with a significant difference. This shows that IMSCOS has significant advantages in optimizing supply chain response time. There are two main reasons for this difference. First, IMSCOS introduces dynamic inertia weights and adaptive learning factors, which enable particles to explore the solution space more effectively during the search process, avoid falling into local optimality, and thus find a better service combination solution. Secondly, the improved algorithm can adjust the search strategy more flexibly in each iteration, so that particles can converge to the global optimal solution faster. In contrast, the search capability of NSGA-II is weaker and is easily affected by early search results, resulting in a longer response time.

Then we tested the service reliability. Through a large number of repeated tests, we took the average service reliability of each supply chain. Figure 2 shows the result.

Analysis of the service reliability test data of IMSCOS and NSGA-II shows that the average service reliability of IMSCOS is 95.41 %, while the average of NSGA-II is 85.67 %. From the perspective of the maximum value, the minimum reliability of IMSCOS is 92% and the maximum is 99%, while the minimum of NSGA-II is 83% and the maximum is 91%. Such a comparison of the maximum values shows that IMSCOS has higher stability and consistency in service reliability. The average value of IMSCOS is significantly higher than that of NSGA-II, which means that when optimizing the service combination, IMSCOS can more effectively maintain a higher service reliability, indicating that it has stronger adaptability in complex environments. Analyzing the reasons, IMSCOS introduces a dynamic adjustment mechanism, which enables particles to respond to changes more flexibly during the search process and identify a better service combination, thereby improving the overall reliability.

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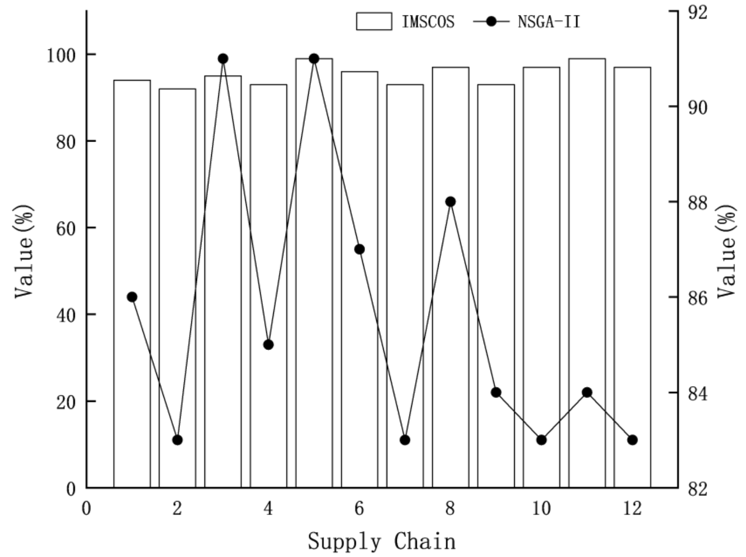

Figure 2: Service reliability

On the other hand, NSGA-II is susceptible to local optimality due to its lack of adaptive adjustment, resulting in large fluctuations in service reliability and showing lower average and minimum values. This difference highlights the advantages of IMSCOS in practical applications, especially in smart manufacturing supply chains that require high reliability.

Finally, the cost is calculated, as shown in Figure 3:

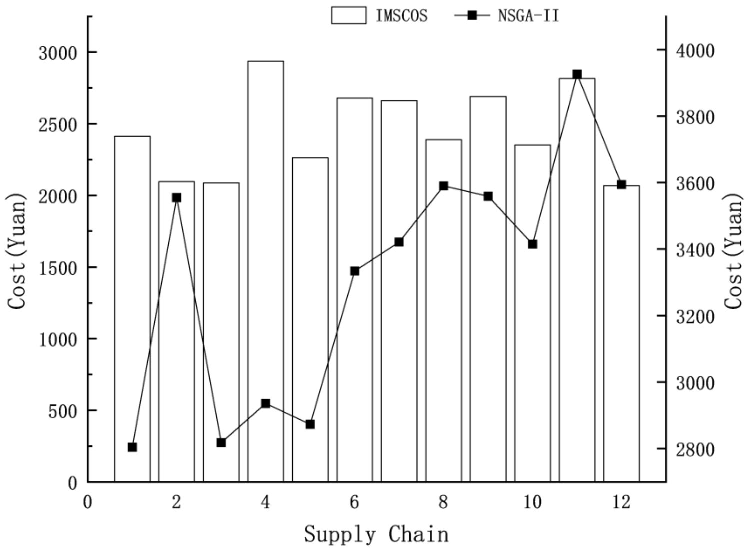

Figure 3: Cost

Analyzing the cost data of different supply chains under different methods, the cost of IMSCOS ranges from RMB 2,068 to RMB 2,937, while the cost of NSGA-II ranges from RMB 2,804 to RMB 3,926. This data clearly shows that IMSCOS shows more significant advantages in cost control, with the average cost significantly lower than NSGA-II. Through calculation, the average cost of IMSCOS is 2454.5 yuan, while the average cost of NSGA-II is 3318.75 yuan, with a difference of 864.25 yuan. This result shows that IMSCOS can not only improve service reliability when optimizing service portfolio, but also effectively reduce costs and improve the economic benefits of the overall supply chain.

From the perspective of the maximum value, the lowest cost of IMSCOS is 2068 yuan and the highest is 2937 yuan, showing good cost control ability; while the lowest cost of NSGA-II is 2804 yuan and the highest is 3926 yuan, indicating that there are large fluctuations in its cost management. Analyzing the reasons, IMSCOS adopts a more flexible parameter adjustment mechanism, which

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makes resource allocation and scheduling more efficient and can effectively reduce unnecessary expenses.

5. Conclusion

Under the influence of the ripple effect, the service quality evaluation of the intelligent manufacturing supply chain is particularly important. By modeling and optimizing the service portfolio, not only can the response speed of the supply chain be improved, but also the service reliability and operating costs can be effectively improved. This study adopts the IMSCOS algorithm, which fully considers the dynamic changes and uncertainties of various services, thereby achieving accurate optimization of the service portfolio. IMSCOS is superior to traditional methods in both service quality and cost control, and can provide more effective decision support for supply chain management. In the future, with the rapid development of intelligent manufacturing, the supply chain will face more complex environments and challenges. Future research can further explore multi-objective optimization methods to take into account service quality, cost and flexibility. At the same time, combining big data analysis and artificial intelligence technology, real-time monitoring and prediction of market demand changes will provide more comprehensive support for the optimization of supply chain service portfolios.

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