



International Journal of Data Mining and Bioinformatics

ISSN online: 1748-5681 - ISSN print: 1748-5673

<https://www.inderscience.com/ijdmb>

**Resource collaboration-aware service composition optimisation
for cloud manufacturing**

Jianjia He, Jiaqi Zhou, Xi Cheng, Zhuoyu Zhang

DOI: [10.1504/IJDMB.2026.10078708](https://doi.org/10.1504/IJDMB.2026.10078708)

Article History:

Received:	27 January 2026
Last revised:	04 May 2026
Accepted:	06 May 2026
Published online:	13 July 2026

Resource collaboration-aware service composition optimisation for cloud manufacturing

Jianjia He*

Business School,
University of Shanghai for Science and Technology,
Shanghai, 200093, China

and

School of Intelligent Emergency Management,
University of Shanghai for Science and Technology,
Shanghai, 200093, China

and

Center for Super Networks Research (China),
University of Shanghai for Science and Technology,
Shanghai, 200093, China

Email: hejianjia@usst.edu.cn

*Corresponding author

Jiaqi Zhou, Xi Cheng and Zhuoyu Zhang

Business School,
University of Shanghai for Science and Technology,
Shanghai, 200093, China

Email: 232481151@st.usst.edu.cn

Email: 242010947@st.usst.edu.cn

Email: 243573586@st.usst.edu.cn

Abstract: Within cloud manufacturing environments, service composition decisions are affected not only by service functionality and performance, but also by state changes and interactions among underlying manufacturing resources. However, implicit and dynamic resource collaboration relationships are difficult to characterise and incorporate into service composition, which may cause collaboration misalignment during scheme execution. To address this issue, a resource-collaboration-aware cloud manufacturing service composition optimisation method is proposed. Service associations induced by resource interactions are modelled as a service collaboration graph, and a graph attention network is used to learn collaboration embeddings that capture collaboration strength and structural heterogeneity. The embeddings are further mapped into a computable collaboration-degree metric and integrated with service quality and robustness in a multi-objective optimisation model. An improved GAT-NSGA-II algorithm is then designed to guide composition optimisation. Simulation results show that the proposed method improves the collaboration consistency and execution stability of service composition schemes.

Keywords: resource collaboration awareness; service composition optimisation; SCO; graph attention network; cloud manufacturing.

Reference to this paper should be made as follows: He, J., Zhou, J., Cheng, X. and Zhang, Z. (2026) 'Resource collaboration-aware service composition optimisation for cloud manufacturing', *Int. J. Data Mining and Bioinformatics*, Vol. 30, No. 7, pp.84–107.

Biographical notes: Jianjia He received his PhD in Management, a Professor and Doctoral Supervisor of University of Shanghai for Science and Technology. His current research focus is on industrial interconnection, machine learning and artificial intelligence, enterprise management and innovation, smart logistics and supply chain. He has actively presided over and participated in numerous important scientific research projects, achieving fruitful outcomes. His research publications have appeared in journals such as *Technological Forecasting and Social Change*, *Transportation Science*, *Applied Intelligence*, *Energy* and other.

Jiaqi Zhou is a post-graduate, Business School, University of Shanghai for Science and Technology. Her research field is industrial interconnection and smart manufacturing.

Xi Cheng is a post-graduate, Business School, University of Shanghai for Science and Technology. His research field is industrial interconnection and smart manufacturing.

Zhuoyu Zhang is a post-graduate, Business School, University of Shanghai for Science and Technology. Her research field is industrial interconnection and emergency management.

1 Introduction

In cloud manufacturing environments, cloud platforms enable the collaborative execution of complex manufacturing tasks across geographically distributed and heterogeneous entities through the selection and composition of distributed manufacturing services (Haghnegahdar et al., 2022; He et al., 2025; Lim et al., 2025). Consequently, cloud service composition optimisation (SCO) has emerged as a key approach for improving manufacturing resource utilisation efficiency and system responsiveness (Mahroo et al., 2026). Studies generally abstract manufacturing capabilities as a set of composable service units, and construct composition optimisation models based on service quality [quality of service (QoS)] and robustness indicators (Vallidevi et al., 2023; Zhang et al., 2024). The objective is jointly considering cost, time, and reliability. This modelling paradigm preserves service independence and composition feasibility, providing a practical foundation for addressing large-scale service composition problems.

However, in practical execution, service delivery relies on the joint support of underlying manufacturing resources. Thus, a composition scheme's logical feasibility does not necessarily translate into stable performance at the execution level. Particularly in complex manufacturing scenarios, a service composition chain's continuous execution is often affected by fluctuations in resource states and task handoff constraints; specifically, an optimal composition solely derived from individual-service QoS and robustness attributes may still suffer from scheduling conflicts, reduced efficiency, or unstable performance during execution (Pang et al., 2023; Zhang et al., 2025). This

creates a key issue: A non-negligible discrepancy remains between service-layer composition decisions and the actual operational performance observed during execution.

To address this, some studies have incorporated service association information into service composition processes. They characterise relationships among services based on process dependencies (Yue et al., 2025), functional similarity (Hu et al., 2023), or historical invocation patterns (Zeng and Paik, 2024; Zhang et al., 2025), and incorporate such information as auxiliary inputs for composition decisions. Such methods can, to some extent, improve the interpretability and consistency of service selection. However, their association modelling is still largely confined to the service level and does not adequately capture resource constraints and interaction characteristics at the execution stage. Consequently, they cannot provide effective constraints or guide decision-making in cases where a composition scheme is logically feasible yet performs poorly during execution. From an execution perspective, services do not inherently possess direct collaboration mechanisms. Instead, the collaborative or conflicting behaviours exhibited during their combined execution stem from the interactions and coupling relationships among the manufacturing resources underpinning service operations (Wang et al., 2022a). When such interactions accumulate and interplay along a sequential task chain, they engender a resource collaboration state with distinctive structural characteristics. If the decision-making process cannot perceive and differentiate this state, candidate paths with similar service-level attributes may still exhibit pronounced disparities in execution-level performance. Therefore, decision criteria that reflect differences in resource collaboration states need to be introduced while preserving service independence and composability. Accordingly, this study frames cloud manufacturing SCO at the resource layer and introduces a research perspective centred on resource collaborative awareness. This approach characterises variations in collaborative strength among manufacturing resources as they evolve and interact, revealing the underlying dynamics of service provision. Identifying, quantifying, and modelling resource collaboration states and mapping them into the service composition decision process can help improve the overall consistency of composed solutions at the execution level while preserving service independence.

In recent years, artificial intelligence methods have been applied across diverse complex contexts, including image recognition, time-series forecasting, manufacturing analytics, user behaviour understanding, and intelligent educational and organisational systems (Lu, 2025; Luo et al., 2024; Rizvi and Khalid, 2025; Shu, 2025; Wu, 2025; Wu et al., 2024). This demonstrates the broader potential of learning-based modelling for representing complex relationships and supporting system-level analysis. Studies show that graph-structured modelling and representation learning provide effective tools for characterising complex interactions. These have strong applicability in manufacturing structure representation (Alenezi et al., 2025), service association mining (Li et al., 2023; Liu et al., 2025), and scheduling decision-making (Wang et al., 2022b). However, in cloud manufacturing service composition, resource collaboration's influence depends not only on whether such relationships exist, but also is closely tied to variations in collaboration strength and heterogeneity in structural characteristics. These latent features are often difficult to translate, via conventional modelling, into quantitative information that can directly participate in composition optimisation decisions. For collaboration characterisation, research has largely relied on two approaches:

- 1 static collaboration scoring based on rules or prior weights (Evangelou et al., 2021), which depends on expert experience, and exhibits limited transferability across different task scales and heterogeneous resource settings
- 2 structural characterisation methods represented by traditional graph metrics (e.g., degree and centrality) or graph convolutions with homogeneous aggregation (Zhou et al., 2020).

While such methods can incorporate graph-structural information, they typically employ fixed aggregation weights. This makes it difficult to achieve adaptive differentiation when collaboration strengths are heterogeneous and neighbourhood influences substantially differ. Consequently, if static or homogeneous modelling schemes are still adopted, collaboration information can hardly enter the service composition decision process in a learnable, updatable, and comparable form. This can constrain the effective guidance of collaboration differences in selecting composition paths. Therefore, to express differences in collaboration strength and structural heterogeneity in a learnable and updatable manner, resource interaction information can be mapped to the service layer for modelling. Candidate services are treated as nodes. Further, the interaction strength between their dependent resource sets is aggregated into edge weights. Through this, a service collaboration graph induced by resource interactions is constructed. And a graph attention network (GAT) with the adaptive allocation of attention weights can be introduced as the representation tool (Chatzianastasis et al., 2023). By following related application paradigms (Fomin et al., 2024; Hussong et al., 2025) and leveraging its capability to differentiate the importance of neighbouring nodes, GAT facilitates more precise perception of resource collaboration strength. Nevertheless, after obtaining an initial collaboration representation, we lack a unified modelling framework and mathematical formulation on how it can be systematically transformed into objective functions that can drive composition search and incorporate it into the service composition decision workflow.

In summary, on the issue of cloud manufacturing service composition where a composition scheme can be logically feasible yet degrade during execution, the core contradiction is in the difficulty of using existing composition optimisation models to effectively characterise and incorporate execution-stage resource collaboration relationships. This creates a disconnect between the decision and execution layers. To address this issue, this study proposes a service composition decision-making method oriented toward resource collaborative awareness. Specifically, we first introduce the implicit impacts of resource collaboration in the execution stage into the composition decision process. This engenders a unified consideration of resource-layer collaboration information and service-layer composition scheme selection. Second, considering the differences in resource collaboration strength and structural heterogeneity, we construct a resource-interaction-induced service collaboration graph is constructed. Further, the collaboration embeddings of service nodes are learned via GAT's adaptive weighting mechanism to characterise the structured differences across varying collaboration strengths. Third, building on this, the learned collaboration representations are mapped into a computable collaboration-degree metric at the service level. Further, a multi-objective composition optimisation model integrating QoS, robustness, and resource collaboration degree is developed. This allows the quantitative integration of collaboration information in scheme comparison and multi-objective trade-offs. Together,

this can help guide decision-making to move beyond service-attribute screening, and attend to the collaboration states induced by resource sharing and coupling, thereby improving the overall consistency and stability of composition schemes at the execution level.

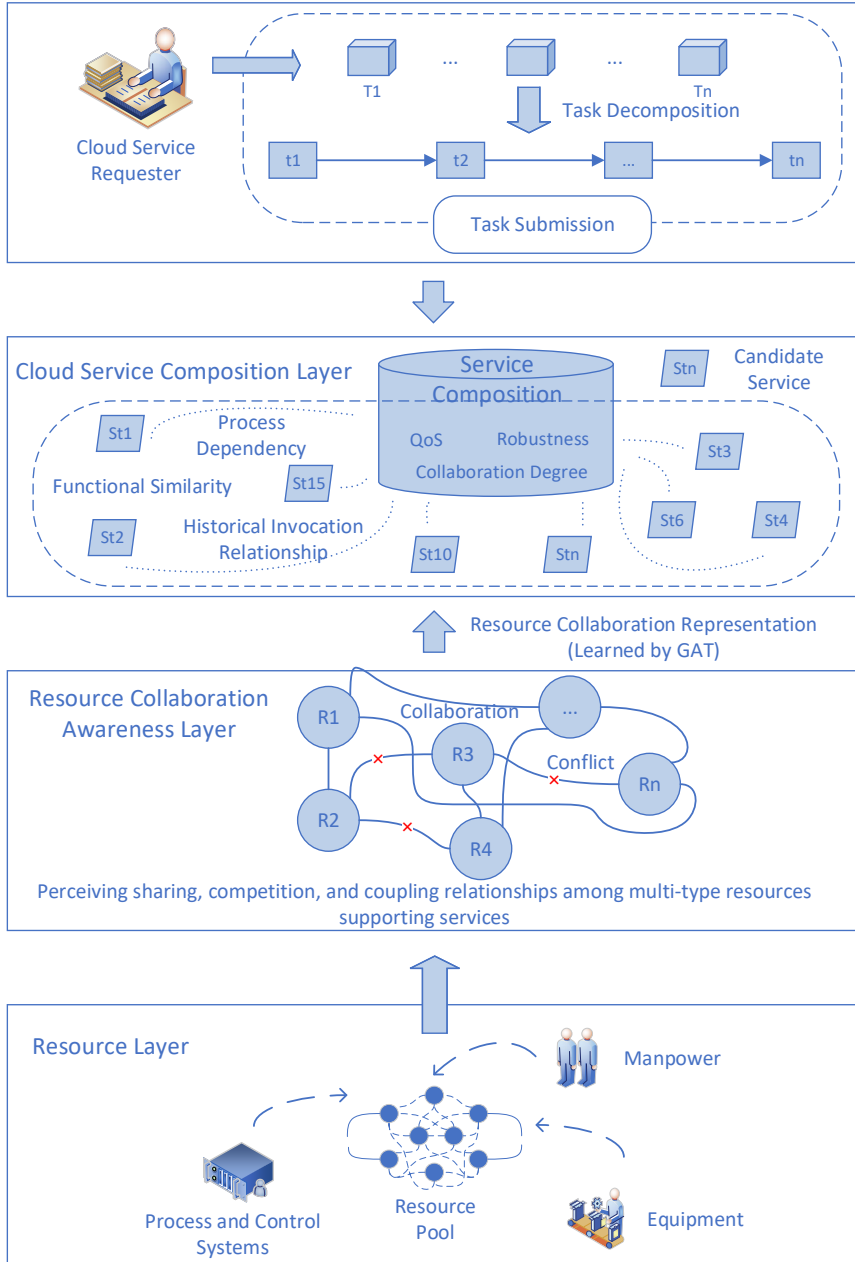
2 Problem description and modelling

2.1 Problem description

In cloud manufacturing environments, complex manufacturing tasks are typically decomposed into sequential subtask sequences subject to process constraints. The cloud platform is required to select services from the candidate set for each subtask and compose them into an end-to-end service chain. Most SCO approaches primarily rely on service-layer attributes such as QoS and robustness as decision criteria. This can ensure that a composition scheme satisfies functional and performance constraints at the logical level. However, they often overlook the collaboration conditions of underlying manufacturing resources, creating a phenomenon whereby a composition is logically feasible yet exhibits degraded performance during execution. To mitigate this issue, a unified characterisation and modelling of resource collaboration states need to be incorporated into the service composition decision process so that the selected composition scheme can better adapt to the actual operational conditions at the execution level. Based on this, a resource-collaboration-aware cloud SCO framework is established, as shown in Figure 1. It can be organised into four layers as follows:

- 1 Cloud service demand layer: task decomposition and submission: The requester submits a manufacturing demand, and the platform decomposes it into a sequence of subtasks $T = \{t_1, t_2, \dots, t_n\}$ with process dependencies, forming a task chain and determining the candidate service set for each subtask.
- 2 Resource layer: resource pool and sources of execution constraints: The underlying resource pool comprises entities such as machines, personnel, and process/control systems, whose states and interaction relationships vary with time and workload. As an encapsulation of resource capabilities, a service's quality and executability depend not only on intrinsic service attributes, but are also influenced by resource conflicts, competition, and collaborative coupling, thereby serving as implicit constraints for composition decisions.
- 3 Resource collaboration perception layer: explicit modelling and learning of collaboration relationships: To address the limitation that the composition layer cannot perceive resource collaboration relationships, a resource collaboration perception layer is introduced to explicitly represent collaboration among resources and transform it into information that can be incorporated into composition decision-making.
- 4 Cloud service composition layer: candidate services and composition decisions: On the basis of satisfying functional feasibility and constraint conditions, the platform performs service selection and composition optimisation. Here, QoS and robustness characterise service quality and stability, while collaboration information reflects the collaboration feasibility of a composition scheme in terms of resource-level collaboration, ultimately producing a set of feasible service composition candidates.

Figure 1 Cloud SCO process with a resource collaboration-aware layer (see online version for colours)



Formally, given a task chain consisting of m sequential subtasks and the candidate service set for each subtask, the decision is to select a service s for each subtask t , where a binary variable $x_{t,s} \in (0, 1)$ denotes the selection relationship; accordingly, a sequential service composition scheme is obtained as $CMS = \{s_1, s_2, \dots, s_m\}$. The objective is to

optimise the QoS, robustness, and resource collaboration degree of the composition scheme while satisfying functional feasibility as well as cost/time and other constraints, so that the comparison and selection of composition schemes can explicitly account for resource-level collaboration relationships among adjacent services, thereby producing a set of service composition decisions that meet the constraints and exhibit a higher collaboration degree.

2.2 Notations

For clarity, the main symbols and variables used in this study are summarised in Table 1.

Table 1 Notations

<i>Symbol</i>	<i>Definition</i>
T	Set of manufacturing tasks
m	Number of sequential subtasks in a task T
t	Subtask index, $t = 1, 2, \dots, m$
s	Index of candidate manufacturing services
s_t	Service selected for subtask t
G	Collaboration-aware service graph
V	Set of nodes in the collaboration graph
ϵ	Set of edges representing potential resource-level collaboration
z_{s_t}	Resource collaboration-aware embedding of service s
CMS	Service composition scheme
$q_{t,s}^k$	Normalised value of service s on QoS dimension k
ω_k	Weight of the k^{th} QoS indicator
$p_{t,s}$	Failure probability of service s
$r_{t,s}$	Average recovery time of service s
$x_{t,s}$	Decision variable: 1 if subtask t selects service s , otherwise 0
$C_{t,s}$	Execution cost of service s for subtask t
$d_{t,s}$	Execution time of service s for subtask t
$C_{\max}$	Maximum allowable total cost
$D_{\max}$	Maximum allowable total execution time
δ	Minimum acceptable resource collaboration threshold
k	QoS metric dimension index, $k \in K$
K	Total number of QoS metric dimensions

2.3 Formal definition of the collaboration-aware service graph

To uniformly characterise resource interaction relationships implicit in service execution processes, the service composition problem is abstracted into a service collaboration graph induced by resource interaction relationships, which serves as a service-level representation of resource collaboration information.

$$G = (V, \epsilon) \quad (1)$$

where each node v_i in the node set $V = \{v_1, v_2, \dots, v_i\}$ represents a candidate manufacturing service, and $\varepsilon \subseteq V \times V$ denotes the set of association edges between services that reflect potential resource collaboration or coupling during execution. Based on this graph structure, representation learning is conducted to model the collaboration states of service nodes, mapping the resource interaction relationships underlying services into low-dimensional collaborative embedding vectors. Thus, a resource collaborative semantic space is constructed. In this space, geometric relationships among service nodes reflect the similarity of their underlying manufacturing resources in terms of collaboration states, providing a foundation for quantitative modelling and resource collaboration optimisation in service composition. To maintain a clear model structure, the collaboration graph is constructed in a static manner within a given task horizon; its edges capture the resource interaction characteristics during that horizon are used as a unified input to subsequent collaboration representation learning and composition decision-making.

2.4 Modelling resource collaboration degree based on collaboration embeddings

In the previous subsection, multi-resource interaction relationships underlying services are mapped into a continuous collaboration embedding space, where each service node corresponds to an embedding vector reflecting its resource collaboration state. These embeddings capture the operational attributes of individual services and their relative positions and roles within the manufacturing resource collaboration structure. Therefore, the geometric relationships between service nodes within the collaborative embedding space can be utilised to characterise the degree of consistency in the collaborative states of the underlying manufacturing resources.

During cloud manufacturing service composition execution, the actual performance of a composition scheme frequently depends on the alignment and collaboration among services at the resource level. For manufacturing processes comprising multiple sequential subtasks, the degree of resource matching between services selected for adjacent subtasks directly affects resource switching efficiency, scheduling conflict risk, and overall execution-level consistency. Accordingly, quantitatively modelling the continuity of resource collaboration across services throughout the composition process is necessary. Suppose the manufacturing process comprises m sequential subtasks. Let the service selected for the t^{th} subtask be s_t , where the selection is determined by decision variables in the subsequent composition optimisation. On the service collaboration graph, the GAT outputs the collaboration embedding vector of each service node, denoted as z_{s_t} . Within the collaborative embedding space, services exhibiting strong resource-level alignment are expected to have highly consistent embedded representations, whereas services associated with resource conflicts or scheduling relationships will exhibit greater divergence. Based on the aforementioned characterisation assumptions, cosine similarity is employed to quantify the degree of resource collaboration between services selected for adjacent subtasks, defined as follows:

$$\text{Collab}(s_t, s_{t+1}) = \frac{1}{2} \left(1 + \frac{z_{s_t}^T z_{s_{t+1}}}{\|z_{s_t}\| \cdot \|z_{s_{t+1}}\|} \right) \quad (2)$$

With the above normalisation, the collaboration degree is bounded in $[0, 1]$, where a larger value indicates a higher level of resource collaboration match. This metric captures directional consistency between two services in the collaborative semantic space and effectively reflects the matching degree of their underlying resources in terms of collaboration states. Since the collaboration embedding vectors are learned from the collaboration-aware service graph, the resulting collaboration degree can adaptively capture different levels of resource collaboration strength under a given graph structure and training data. When resource states or interaction conditions change, the embeddings can be recomputed using the corresponding data to reflect scenario-specific resource collaboration characteristics.

For a service composition scheme $CMS = \{s_1, s_2, \dots, s_m\}$, given the sequential execution of the manufacturing process and the fact that resource conflicts mainly arise at handoffs between adjacent tasks, its overall resource collaboration property is reflected in the continuity of collaboration states between adjacent services. Since adjacent handoffs constitute the primary source of conflicts, the overall resource collaboration degree of a service composition scheme can be expressed, based on the definition of adjacent collaboration degree, as the average of the collaboration degrees between adjacent services:

$$Q(CMS) = \frac{1}{m-1} \sum_{t=1}^{m-1} \text{Collab}(s_t, s_{t+1}) \quad (3)$$

This indicator evaluates collaboration from the composition-path perspective and distinguishes resource collaboration structures among composition paths with similar QoS and robustness performance. Higher collaboration levels imply lower risks of resource switching and resource conflicts during the execution of the service composition solution. Consequently, the implementation process exhibits greater consistency and stability at the system level.

Through the aforementioned modelling approach, the collaborative state implicitly embedded within the interaction process of manufacturing resources is mapped into measurable and optimisable mathematical metrics. This enables resource collaboration perception to move beyond mere representational learning and serve as structural information that directly informs subsequent SCO decisions. After defining the collaboration-degree metric, it is necessary to clarify its relationship with QoS and robustness, to justify its inclusion in the objective formulation as an independent optimisation dimension.

2.5 Resource collaboration-aware multi-objective SCO model

In cloud manufacturing SCO, traditional models primarily focus on QoS and system robustness objectives, which mainly constrain the feasibility and performance levels of individual services. Consequently, they struggle to characterise the differences in resource collaboration structures induced by different services within composed paths. Even when QoS indicators are similar or constraints are satisfied, different service composition schemes may exhibit significantly different execution performance due to frequent resource switching or insufficient collaboration alignment.

Building upon the aforementioned resource collaboration perception modelling, differences in service composition schemes at the resource level are mapped as

measurable collaboration-state continuity. This provides a new evaluative dimension for distinguishing between composition paths exhibiting similar QoS performance yet different collaboration structures. Resource collaboration characterises the execution-level resource interaction structure and the degree of cross-service handoff matching, and thus constitutes a relational attribute. In contrast, QoS and robustness evaluate, respectively, the performance attributes of individual services and their ability to maintain performance under disturbances; neither explicitly represents differences in resource interaction structures.

Based on the aforementioned considerations, while retaining the classical optimisation objectives of QoS and robustness, resource collaboration is introduced as a third optimisation objective. This guides the optimisation process to prioritise service composition schemes that exhibit higher resource-level collaboration, provided that service functional requirements and performance constraints are satisfied. Through multi-objective collaborative optimisation, service composition decisions focus on the optimal performance of individual services and the rationality of the composition path within the resource collaboration structure. Consequently, the overall consistency and adaptability of service composition schemes during practical execution are enhanced.

2.5.1 Objective function formulation

For ease of presentation, consider a manufacturing process consisting of a sequence of subtasks indexed by $t = 1, \dots, m$. Define the following binary decision variable:

$$x_{t,s} = \begin{cases} 1, & \text{if subtask } t \text{ selects candidate services } s \in s_t \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

Objective 1: Maximisation of weighted quality of service (QoS).

QoS is a fundamental indicator for evaluating the feasibility of cloud manufacturing service composition, reflecting the overall performance of services in terms of time, cost, reputation, and availability. This objective constrains the overall performance level of the service composition under functional feasibility, ensuring that selected services satisfy user requirements at the individual service level. Let the normalised value of service performance on the k^{th} QoS dimension be denoted as $q_{t,s}^k$. Subsequently, the weighted QoS objective can be expressed as follows:

$$\max f_1 = \sum_{t=1}^m \sum_{k=1}^K \omega_k q_{t,s}^k \quad (5)$$

Here, ω_k represents the relative importance of different QoS indicators in the decision-making process.

Objective 2: Maximisation of robustness.

During the execution of cloud manufacturing service compositions, services exhibit uncertainties in terms of failure probability and recovery time. To prevent stability degradation caused by high-risk services during execution, a robustness indicator is introduced to constrain failure probability and recovery cost jointly. This indicator complements the QoS objective by capturing execution risks, and the system-level robustness objective is formulated as follows:

$$\max f_2 = - \sum_{t=1}^m \sum_{s \in s_t} x_{t,s} (p_{t,s} \cdot r_{t,s}) \quad (6)$$

This objective penalises composition paths with high failure probabilities and recovery costs, guiding the optimisation process toward more stable and disturbance-resilient service composition schemes at the execution level.

Objective 3: Maximisation of resource collaboration degree (core objective).

Based on the resource collaboration-aware modelling, collaboration states among services have been mapped into a collaboration embedding space. To incorporate this structural information into the optimisation process, resource collaboration degree is introduced as an independent objective to characterise the collaboration consistency of service composition paths at the resource level.

$$\max f_3 = Q(\text{CMS}) \quad (7)$$

This objective guides the optimisation process to prioritise service composition paths with higher compatibility in the resource collaboration semantic space, reducing the risk of resource conflicts during execution. Consequently, resource collaboration awareness is extended from representation learning to participate directly as auxiliary structural information in SCO decisions.

2.5.2 Constraints

Service selection constraint: each subtask must select exactly one service.

$$\sum_{s \in s_t} x_{t,s} = 1, \quad \forall t = 1, 2, \dots, m \quad (8)$$

Cost constraint: the total cost of the service composition must not exceed the predefined upper bound $C_{\max}$.

$$\sum_{t=1}^m \sum_{s \in s_t} x_{t,s} \cdot C_{t,s} \leq C_{\max} \quad (9)$$

Time constraint: the total execution time of the manufacturing process must not exceed the upper bound $D_{\max}$.

$$\sum_{t=1}^m \sum_{s \in s_t} x_{t,s} \cdot d_{t,s} \leq D_{\max} \quad (10)$$

Collaboration feasibility constraint: to prevent service composition schemes with insufficient resource collaboration and elevated execution risk, a lower bound constraint is imposed on the collaboration degree of the composition. δ denotes the minimum acceptable level of resource collaboration. Since the collaboration degree is constructed based on the normalised cosine similarity [see equation (2)], its value is bounded within the interval $[0, 1]$:

$$Q(\text{CMS}) \geq \delta \quad (11)$$

3 Algorithm design

The previous section established a multi-objective cloud manufacturing SCO model that integrates service quality, robustness, and resource collaboration degree based on GAT embeddings. The resource collaboration degree characterises the structural consistency of service composition paths at the resource level, which fundamentally differs from traditional performance-oriented objectives dominated by QoS. Therefore, the resulting optimisation problem is characterised by multiple objectives, strong structural coupling among objectives, and uneven distributions of feasible solutions. In particular, solutions with high resource collaboration degrees tend to be concentrated within localised regions of the composition space. To address these characteristics, the derived resource collaboration embeddings are introduced as structured guidance information within the traditional NSGA-II framework. This approach explicitly integrates the resource collaboration degree, QoS metrics, and constraint conditions defined within the model into critical algorithmic stages, initialisation, mutation, and feasibility repair, constructing an enhanced NSGA-II algorithm tailored for resource collaboration perception models.

3.1 Probability-guided initialisation based on resource collaboration embeddings

Resource collaboration degree reflects the continuity of service composition paths in the resource collaboration semantic space and directly affects the structural rationality of composed solutions during execution. Under random initialisation, composition paths with high collaboration potential are usually underrepresented in the initial population, which makes the collaboration objective difficult to explore during the early stages of evolution. Therefore, a probability-guided initialisation mechanism based on resource collaboration embeddings is introduced to improve the reachability of high-collaboration solutions within the initial population.

This mechanism utilises the service co-occurrence embeddings learned within the model. By characterising the relative positional relationships of candidate services within the co-occurrence semantic space, it constructs a probability distribution for service selection. This approach enhances the probability of high-co-occurrence combination paths appearing within the initial population while preserving population diversity.

$$p(s_j|t) = \frac{\exp(\text{sim}(s_j, \hat{s}_t))}{\sum_k \exp(\text{sim}(s_k, \hat{s}_t))} \quad (12)$$

Among these, $p(s_j|t)$ represents the probability that task t selects service j during the generation of the initial population. Furthermore, $\text{sim}(\cdot)$ is a similarity metric based on the collaborative embedding of resources within the model, and $\hat{s}_t$ serves as a reference collaborative embedding to guide initialisation, with its value determined by the collaborative embedding results of previously selected services from adjacent subtasks.

3.2 Embedding-guided neighbourhood mutation operator

During the evolutionary process, mutation operators primarily act upon the local structure of service composition pathways, thereby influencing the effectiveness of resource

collaboration maintenance throughout the evolution. Whilst entirely random mutation operations may enhance solution diversity, they readily disrupt existing high-coherence structures between adjacent subtasks, resulting in discontinuities within the combinatorial paths of the resource collaboration semantic space. To mitigate such disruption, an embedding-guided neighbourhood mutation operator is introduced. When replacing the service assigned to a subtask, this operator prioritises candidate services whose embeddings are proximal to the original service in the resource collaboration semantic space. This strategy preserves necessary search perturbations while effectively reducing adverse impacts on collaboration continuity among adjacent services.

Algorithm 1 Resource-collaboration-aware NSGA-II for cloud service composition

Input: Subtask set $T = \{1, \dots, m\}$;
Candidate service set $\mathcal{S}_t$ for each subtask t ;
Resource collaboration embeddings $\{\mathbf{z}_j\}$ learned by GAT;
Initial crossover probability $P_c^{(0)}$;
Initial mutation probability $P_m^{(0)}$;
Population size N ;
Maximum number of generations $G_{\max}$.
Output: Final non-dominated solution set $\mathcal{P}^*$.

- 1: Initialize population $\mathcal{P}^{(0)} \leftarrow \emptyset$
- 2: **for** $i = 1$ to N **do**
- 3: **for** each subtask $t \in T$ **do**
- 4: Compute collaboration-guided service selection probability:
$$p(s_j|t) = \frac{\exp(\text{sim}(\mathbf{z}_j, \hat{\mathbf{s}}_t))}{\sum_k \exp(\text{sim}(\mathbf{z}_k, \hat{\mathbf{s}}_t))}$$
- 5: Sample service s_j according to $p(s_j|t)$
- 6: **end for**
- 7: Add individual to $\mathcal{P}^{(0)}$
- 8: **end for**
- 9: Evaluate objectives f_1 (QoS), f_2 (robustness), and f_3 (resource collaboration degree)
- 10: Perform non-dominated sorting and crowding-distance calculation
- 11: **for** $g = 1$ to $G_{\max}$ **do**
- 12: Compute population diversity indicator $\delta^{(g)}$
- 13: Update crossover and mutation probabilities:
$$P_c^{(g)} = P_c^{(0)}(1 - \delta^{(g)}), \quad P_m^{(g)} = P_m^{(0)}(1 + \delta^{(g)})$$
- 14: Select parent individuals by tournament selection
- 15: Apply crossover with probability $P_c^{(g)}$
- 16: **for** each offspring individual **do**
- 17: **for** each subtask $t \in T$ **do**
- 18: Identify collaboration-guided neighbor service:
$$s^* = \arg \max_j \text{sim}(\mathbf{z}_{s_t}, \mathbf{z}_j)$$
- 19: Replace s_t with s^* with probability $P_m^{(g)}$
- 20: **end for**
- 21: **end for**
- 22: **for** each infeasible offspring **do**
- 23: **while** constraints are violated **do**
- 24: Repair by cost-benefit replacement:
$$s_t \leftarrow \arg \min_j \frac{C_{t,j}}{R_{t,j}}$$
- 25: **end while**
- 26: **end for**
- 27: Merge parent and offspring populations
- 28: Perform non-dominated sorting and crowding-distance sorting
- 29: Select top N individuals to form $\mathcal{P}^{(g+1)}$
- 30: **end for**
- 31: **return** $\mathcal{P}^*$

3.3 Adaptive crossover and mutation probability adjustment

In multi-objective cloud manufacturing SCO, different objectives exhibit heterogeneous response characteristics during evolution. Numerical objectives such as QoS and robustness fluctuate widely across the solution space, whereas variations in resource collaboration degree are typically concentrated in local high-collaboration regions. Fixed crossover and mutation intensities may lead to imbalanced objective responses across evolutionary stages.

To coordinate exploration capability and convergence stability during the search process, an adaptive crossover and mutation probability adjustment mechanism is introduced to modify the crossover and mutation probabilities dynamically. Let the crossover probability and mutation probability at generation g be denoted as $P_c^{(g)}$ and $P_m^{(g)}$, respectively. The update rules are defined as follows:

$$P_c^{(g)} = P_c^{(0)} (1 - \delta^{(g)}) \quad (13)$$

$$P_m^{(g)} = P_m^{(0)} (1 + \delta^{(g)}) \quad (14)$$

Here, $\delta^{(g)}$ represents the diversity metric for the g^{th} generation. When population diversity declines, early convergence is avoided by enhancing search perturbations through a reduced crossover probability and an increased mutation probability. Conversely, when population diversity is high, crossover operations are appropriately intensified to accelerate convergence.

3.4 Cost-ratio-based feasibility repair operator

Owing to QoS constraints and lower-bound collaboration constraints, some solutions generated in the evolutionary process may violate feasibility requirements. A cost-ratio-based feasibility repair operator is designed. When an individual violates the total execution cost or total execution time constraints, priority is given to replacing the original service with a candidate service exhibiting lower execution cost $C_{t,s}$ or shorter processing time $d_{t,s}$, provided that such replacement does not significantly degrade service quality. This strategy progressively eliminates constraint violations. When an individual satisfies cost and time constraints but exhibits overall resource collaboration below the model-defined collaboration threshold, the remediation process shifts its focus to the structural level of the combined path. The repair operator is defined as follows:

$$s_t \leftarrow \arg \min_j \frac{C_{t,j}}{Re_{t,j}} \quad (15)$$

This repair strategy minimises disruption to the original resource collaboration structure while ensuring solution feasibility. The enhanced GAT-NSGA-II algorithm leverages resource collaboration embeddings as a structured search guide, explicitly enforces model constraint satisfaction through a feasibility repair operator, and maintains population diversity via adaptive crossover and mutation regulation mechanisms. Within a multi-objective collaborative optimisation framework, this algorithm reliably guides the search process through complex manufacturing-service composition spaces. It enhances the discovery efficiency of highly collaborative feasible solutions while maintaining

stable convergence behaviour and execution-level resilience under dynamic resource state conditions.

The pseudocode for GAT-NSGA-II is in Algorithm 1.

4 Experiments and analysis

4.1 Experimental settings and parameter configuration

To simulate cloud manufacturing service composition scenarios, a synthetic dataset was constructed based on data ranges commonly used in related studies. The dataset contains a candidate service pool comprising 20 heterogeneous manufacturing services. Service performance and reliability are characterised using multidimensional attributes, with their corresponding value ranges listed in Table 2. A total of 20 tasks were considered in the experiments. Each task comprises 5–10 sequential subtasks, and 5–10 executable candidate services are predefined. Accordingly, discrete time steps are introduced to characterise task execution and service states dynamically, constructing service composition scenarios with time-varying characteristics. This experimental setup is designed to create scenarios in which explicit differences in service collaboration exist and collaboration relationships affect the rationality of composition decisions, validating the role of resource collaboration-aware mechanisms in SCO. Collaboration strength is not introduced into the optimisation as a direct prior attribute of services; rather, it is treated as a latent generative factor underlying resource interaction relationships behind services, and is used to construct resource interaction scenarios with structural differences. In the actual optimisation process, the service collaboration degree is adaptively learned by a graph attention network on the service collaboration graph, instead of being directly derived from pre-specified collaboration values.

Table 2 Value ranges of service attributes and collaboration relationships

<i>Parameter</i>	<i>Value range</i>
Execution cost	[8, 16]
Execution time	[7, 9]
Availability	[0.89, 1.00]
Reputation	[0.86, 0.96]
Failure probability	[0.11, 0.20]
Recovery time	[3, 5]
Collaboration strength	[0, 1]

Table 3 Weights of QoS indicators

<i>Indicator</i>	<i>Weight</i>
Execution cost	0.3
Execution time	0.3
Availability	0.2
Reputation	0.2

For the multi-objective optimisation process, all comparative algorithms are executed under the same objective function definitions and evaluation metrics. The weights of QoS indicators are identical and normalised to eliminate the influence of scale differences on the search process. The specific weight settings are presented in Table 3.

During the resource collaborative perception phase, GAT employs a multi-layer structure to perform embedding learning on the service collaboration graph. Parameter settings were selected to obtain stable service synergistic embedding representations, with relevant parameters maintained consistently across all experiments to prevent variations in synergistic characterisation from interfering with service composition decision outcomes. As shown in Tables 4 and 5.

Table 4 GAT structure parameters

<i>Parameter</i>	<i>Value</i>
Number of GAT layers	2
Number of attention heads	4
Node embedding dimension	64
Edge feature dimension	1

Table 5 GAT training parameters

<i>Parameter</i>	<i>Value</i>
Learning rate	0.001
Number of epochs	200
Temperature coefficient	0.1

To ensure fairness in comparative experiments, all NSGA-II-based algorithms are executed under identical parameter settings, as listed in Table 6.

Table 6 Parameters of the improved NSGA-II algorithm

<i>Parameter</i>	<i>Value</i>
Population size	100
Maximum number of iterations	200
Initial crossover probability	0.9
Initial mutation probability	0.1
Neighbourhood candidate size K	3
Maximum repair times	5

4.2 Algorithm performance comparison

To examine how incorporating collaboration information into search process affects composition decision behaviour, three algorithms are selected for comparison: the classic ranking-based search NSGA-II without collaboration information, the decomposition-based search MOEA/D that adopts a decomposition strategy but does not explicitly use collaboration information, and the proposed GAT-NSGA-II, which introduces collaboration representations and incorporates collaboration degree into search process. All three algorithms are applied to the same problem instance with identical objective

functions and evaluation metrics, to analyse the structural differences in composition results before and after introducing the collaboration-aware mechanism.

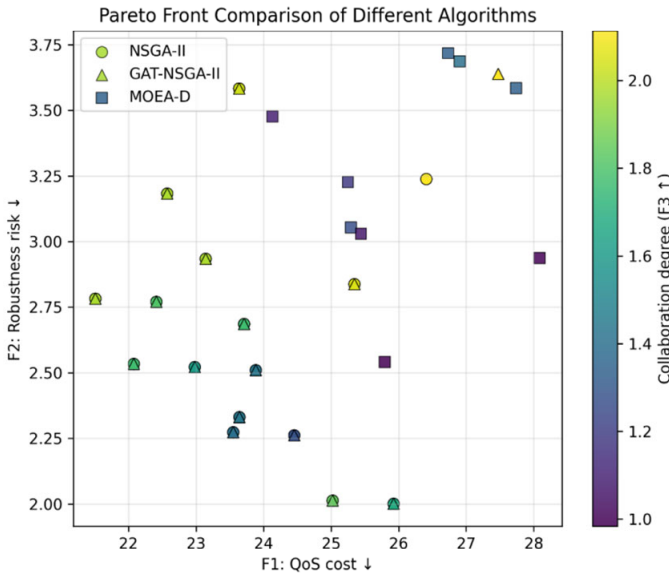
To evaluate algorithmic performance comprehensively, hypervolume (HV), inverted generational distance (IGD), and spacing (SP) are selected as evaluation metrics. HV measures the coverage and overall quality of the solution set in the objective space. Larger HV values indicate better overall performance in terms of convergence and diversity. IGD describes the average distance between the obtained solution set and the reference Pareto front. Smaller IGD values indicate closer proximity to the ideal front. SP characterises the uniformity of the distribution of non-dominated solutions in the objective space. Smaller SP values indicate more evenly distributed solutions.

Under identical parameter configurations and problem instances, each algorithm is independently executed 20 times to reduce the influence of randomness on experimental results. The experimental results are statistically analysed and reported as mean $\pm$ standard deviation. The results are shown in Table 7.

Table 7 Performance comparison of three algorithms

Algorithm	HV	IGD	SP
MOEA/D	5.8808 $\pm$ 2.1014	1.2745 $\pm$ 0.2584	0.3991 $\pm$ 0.4032
NSGA-II	22.5033 $\pm$ 0.9572	0.0965 $\pm$ 0.0644	0.0006 $\pm$ 0.0025
GAT-NSGA-II	23.1499 $\pm$ 0.0880	0.0526 $\pm$ 0.0147	0.0000 $\pm$ 0.0000

Figure 2 Comparison of Pareto fronts obtained by different algorithms for the cloud manufacturing service composition problem (see online version for colours)

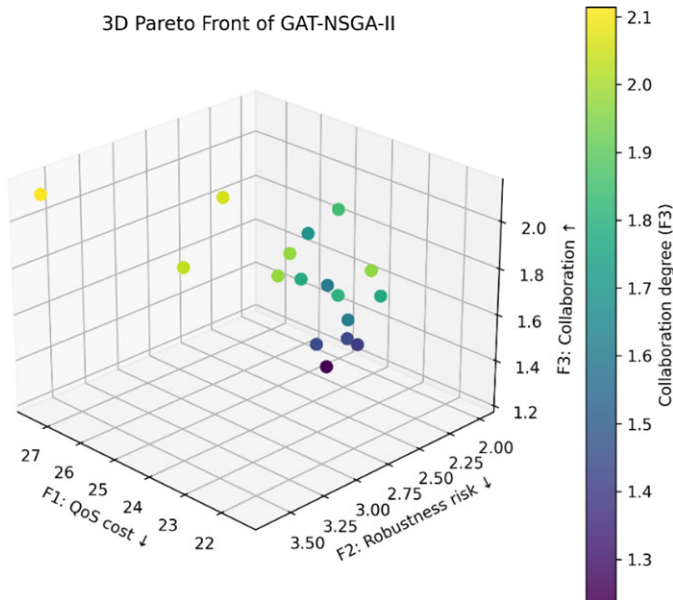


Notes: The horizontal axis represents QoS cost (F1), the vertical axis represents robustness risk (F2), and the colour mapping indicates the collaboration degree (F3).

Under a unified objective formulation and consistent evaluation metrics, the differences in algorithm performance can be attributed to whether collaboration information is explicitly represented and incorporated into the search process. This allows the

subsequent analysis to focus on how the collaboration-aware mechanism influences preference patterns in composition path selection. The results indicate that MOEA/D exhibits large variability in HV and IGD metrics, reflecting limited solution coverage and stability. This suggests that search strategies relying solely on weight decomposition show insufficient adaptability to service composition problems with discrete combinatorial structures and complex collaboration constraints. Conversely, NSGA-II significantly outperforms MOEA/D across all three metrics, demonstrating the robustness of non-dominated sorting-based evolutionary strategies for this class of problems. Furthermore, the proposed GAT-NSGA-II achieves optimal results on HV and IGD metrics, demonstrating smaller performance fluctuations across multiple independent runs. The introduction of resource-aware perception mechanisms has altered the distribution characteristics of non-dominated solutions obtained by the algorithm within the objective space. Compared to algorithms solely based on performance metric search, GAT-NSGA-II exhibits a greater tendency to generate solutions with higher levels of resource collaboration under similar conditions of QoS and robustness. Thus, the collaboration-aware mechanism does not merely pursue optimal values of numerical metrics but enforces constraints on the structural consistency of service composition paths.

Figure 3 Three-objective Pareto front distribution obtained by the GAT-NSGA-II algorithm, with axes corresponding to QoS cost (F1, minimised), robustness risk (F2, minimised), and collaboration degree (F3, maximised) (see online version for colours)



The distribution of the Pareto in Figures 2 and 3 frontier further elucidates the quantitative findings discussed above. Compared to MOEA/D, the non-dominated solution sets obtained by NSGA-II and GAT-NSGA-II exhibit a more concentrated overall distribution, with superior coverage in regions characterised by lower QoS costs and lower robustness risks. Notably, the Pareto solutions obtained by GAT-NSGA-II often correspond to higher levels of synergy (F3) while maintaining relatively low values

of F1 and F2. Thus, the introduction of the graph attention mechanism enables the algorithm to perceive synergistic relationships among resources effectively, guiding the search process to focus on regions with potentially high-quality solutions. Therefore, without explicitly modelling resource collaboration relationships, even when service composition schemes with similar performance are obtained, differences in their collaboration characteristics may be overlooked. The collaboration-aware mechanism can distinguish such differences during the decision-making phase.

Based on the comprehensive quantitative metrics and the Pareto frontier diagram, it can be concluded that GAT-NSGA-II significantly enhances the overall quality and convergence performance of the solution set in complex cloud manufacturing SCO problems, but also demonstrates superior robustness in terms of multi-objective trade-offs and solution set stability. This result validates the effectiveness of the proposed collaborative perception-based optimisation method.

4.3 Ablation study

To verify the necessity of each key module in the proposed method for cloud SCO, a series of ablation experiments are designed and conducted. By sequentially removing or simplifying different components of the model, multiple comparative schemes are constructed and evaluated under identical experimental environments and parameter settings. The specific ablation schemes are described as follows.

- Scheme A0: The graph neural network and the resource collaboration awareness mechanism are removed. Only the traditional NSGA-II algorithm is used for multi-objective SCO, without considering either structural relationships or collaborative characteristics among services.
- Scheme A1: Ablate the collaboration-optimisation objective by retaining the collaboration graph and GAT-based representation learning, while removing the collaboration-degree objective and the lower-bound collaboration constraint; optimisation is performed only with respect to QoS and robustness objectives.
- Scheme A2: The complete proposed model is adopted. A GAT is used for service representation learning, and a resource collaboration-aware multi-objective optimisation model is constructed simultaneously. The experimental results for the three approaches are shown in Table 8.

Table 8 Performance results of different ablation schemes

<i>Scheme</i>	<i>ND</i>	<i>HV</i>	<i>IGD</i>
A0	42	54.1287	0.9138
A1	45	59.8897	0.1720
A2	48	61.3653	0.0552

As shown in Table 8, the inclusion of different modules has a significant impact on the search behaviour of the algorithm and the structure of the obtained solution sets. A comparison of A0 and A1 reveals that introducing the graph attention mechanism leads to clear improvements in solution set coverage and approximation quality – graph-structured feature modelling enhances the capability of the multi-objective search process to identify potential high-quality solution regions. Building on these results, the

full model A2 achieves the best results across all three metrics, indicating that when resource collaboration degree is introduced as both an optimisation objective and a feasibility constraint, the search process can more effectively steer the solution set toward composition paths with higher resource-level collaboration consistency while preserving the advantages in performance and stability. These results suggest that the collaboration-aware mechanism not only improves search quality, but also enhances the overall resource-level consistency of the solution set by guiding the structure of composition paths, thereby offering a more reliable basis for resource handoff and risk control in subsequent execution stages.

The ablation experiment results validate the complementary roles of graph structure modelling and collaboration objective design in optimising cloud service composition, enabling the proposed method to effectively perceive and select feasible collaborative solutions within complex service networks.

4.4 Simulation experiments

To verify the effectiveness of the proposed resource collaboration-aware service composition method in terms of structural learning and decision guidance, analyses are conducted at multiple analytical levels using the simulation dataset to examine how GAT learns collaborative relationships and how these relationships influence service composition decisions.

Figure 4 Schematic comparison between the global service collaboration structure and service composition solutions (see online version for colours)

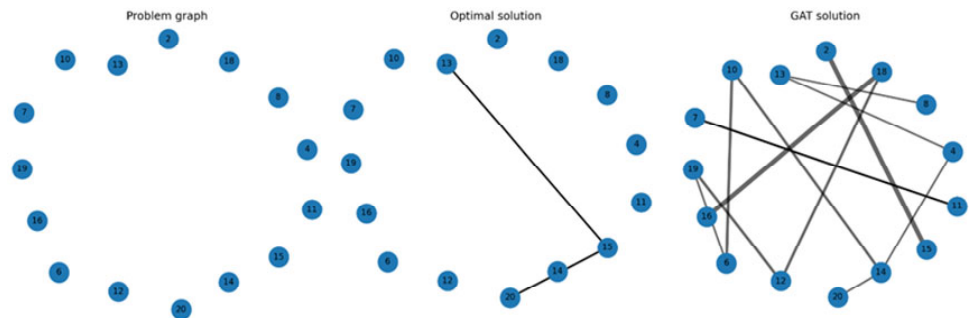
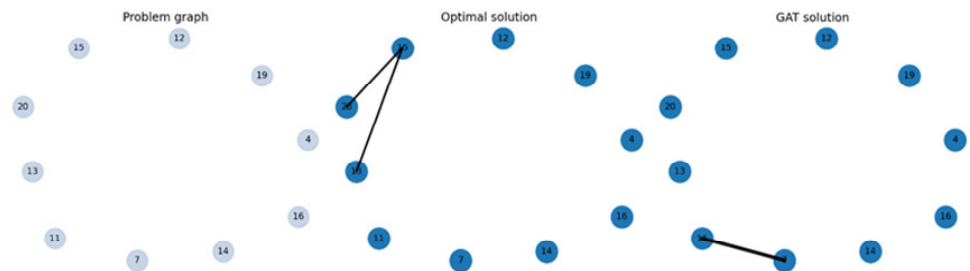


Figure 5 Local interpretation of key collaborative relationships (see online version for colours)



As illustrated in Figure 4, the problem graph, the exact optimal solution of the baseline model, and the collaborative structure representations learned by GAT are jointly presented for a given service relationship graph. Here, Optimal solution denotes the globally optimal path obtained via an exact optimisation method under the given simulation dataset for the baseline model that excludes collaboration objectives and constraints. It serves as a structural reference benchmark and is used to compare preference differences in structural identification arising from collaboration-structure learning. In contrast, the collaboration structure learned by GAT does not correspond to a single path solution; rather, it characterises key structural relationships in the service network that exhibit potential collaboration advantages, providing structured prior information for subsequent SCO. The overall results reveal that the high-weight structural relationships learned by GAT exhibit significant correlation with the optimal solution at the structural level. However, the output does not represent a single pathway but denotes a set of synergistic connections with varying degrees of importance.

Based on Figure 4, Figure 5 provides a local interpretation of key collaborative relationships, where representative collaborative relationships are selected from the global structural representation for detailed local analysis. Notably, although the global optimal path for this dataset is $13 \rightarrow 15 \rightarrow 20$, the key collaborative relationships identified by GAT are concentrated on service pairs such as $7 \rightarrow 11$. Thus, GAT does not learn the optimal path but captures the key structural relationships within the graph that possess high collaborative potential. These relationships act as informative references for subsequent service composition decisions, providing the composition process with additional feasible decision alternatives beyond a single optimal path.

Figure 6 Illustration of collaboration-aware service composition decision-making (see online version for colours)



Building upon the holistic characterisation and localised interpretation of the collaborative structure learning results presented in Figures 4 and 5, Figure 6 provides a structured visualisation of the learned collaborative structure at the service composition level. This visualisation illustrates how resource collaboration perception information is embedded within the service composition process and how it contributes to decision-making. Notably, when service composition decisions rely solely on individual service QoS indicators, the composition path appears as a simple linear service chain based on performance priority— $S13 \rightarrow S15 \rightarrow S20$. When the collaborative structure information learned by GAT is explicitly incorporated into the composition decision process, the service selection process prioritises key service relationships with high collaboration potential, such as $S7 \rightarrow S11$. These results demonstrate the role of the resource collaboration awareness mechanism at the service composition decision level – the collaborative structures learned by GAT can participate in and actively guide service composition decisions, providing additional decision support for service composition under complex constraints. At the decision-making level, this outcome indicates that collaborative resource perception does not serve as a substitute for a performance metric. Rather, it guides service composition toward paths exhibiting greater collaborative coherence among candidates with comparable performance, mitigating the mismatch between composition decisions and execution performance arising from decisions based solely on QoS and robustness.

5 Conclusions

This study addressed the challenge that collaboration relationships among manufacturing resources underlying services are difficult to characterise in cloud manufacturing service composition – causing a mismatch between composition decisions and execution-stage resource interactions. To this end, it proposes a resource collaboration-aware cloud manufacturing SCO method. By mapping resource collaboration information underlying services to the service layer, a collaboration graph is constructed, and introducing a GAT to model collaboration strength and structural heterogeneity among resources, collaboration relationships that were previously implicit in execution processes are made explicitly representable. Accordingly, the learned collaboration embeddings are incorporated as structured information into the service composition decision process. A multi-objective SCO framework integrating service quality, robustness, and resource collaboration degree is established, and a collaboration-embedding-guided, improved NSGA-II algorithm is developed to enable collaboration-aware composition decisions.

Simulation results demonstrate that, after introducing resource collaboration awareness, service composition schemes exhibit significant changes in structural distribution and collaboration characteristics while maintaining the same experimental settings and comparison baselines. Rather than merely pursuing numerical optimality, the collaboration-aware mechanism introduces a structural preference for composition paths with potential collaboration advantages at the decision stage, improving execution-level stability and consistency in composed solutions. Further structural analysis and ablation studies indicate that the GAT is effective in identifying key collaboration relationships, and the resulting collaboration embeddings provide reliable structured priors for the multi-objective optimisation process. This mechanism enables the search process to avoid

excessive reliance on a single optimal path under complex constraints, yielding more flexible and robust service composition solutions. From the perspective of incorporating resource interaction structures into the decision stage, the above results indicate that the collaboration-aware mechanism can proactively mitigate potential conflict risks induced by resource sharing or coupling during the composition stage, thereby reducing the mismatch between composition decisions and execution performance.

From a resource collaboration-aware perspective, this study extends cloud manufacturing SCO by elevating collaboration relationships from empirical rules or static similarity measures to learnable and optimisable structural information, providing a feasible approach to alleviating mismatches between composition decisions and resource execution states. Future work will leverage real industrial data to calibrate the edge weight formulation in the collaboration graph and the collaboration metrics, and will further extend the framework to dynamic collaboration graphs that account for variations in workload and time windows, to examine the applicability and scalability of the collaboration-aware mechanism under more realistic operating conditions.

Declarations

We all declare that we have no conflict of interest in this paper.

References

- Alenezi, D.F., Shi, J., Li, J. et al. (2025) ‘Graph-based variation propagation network for modeling and prediction of hybrid multi-stage manufacturing systems’, *IEEE Transactions on Automation Science and Engineering*, Vol. 22, pp.14317–14331.
- Chatzianastasis, M., Nikolentzos, G. and Vazirgiannis, M. (2023) ‘Supervised attention using homophily in graph neural networks’, *Artificial Neural Networks and Machine Learning – ICANN 2023, Lecture Notes in Computer Science*, Springer, Vol. 14257, pp.576–586.
- Evangelou, G., Dimitropoulos, N., Michalos, G. et al. (2021) ‘An approach for task and action planning in human-robot collaborative cells using AI’, *Procedia CIRP*, Vol. 97, pp.476–481.
- Fomin, D., Makarov, I., Voronina, M. et al. (2024) ‘Heterogeneous graph attention networks for scheduling in cloud manufacturing and logistics’, *IEEE Access*, Vol. 12, pp.196195–196206.
- Haghnegahdar, L., Joshi, S.S. and Dahotre, N.B. (2022) ‘From IoT-based cloud manufacturing approach to intelligent additive manufacturing: industrial internet of things – an overview’, *The International Journal of Advanced Manufacturing Technology*, Vol. 119, Nos. 3–4, pp.1461–1478.
- He, J., Wu, J., Ni, J. et al. (2025) ‘Real-time task scheduling strategy for 3D printing cloud platforms in health scenes’, *Applied Intelligence*, Vol. 55, No. 15, p.1002.
- Hu, Q., Qi, H.Q., Huang, W. et al. (2023) ‘A method to recommend cloud manufacturing service based on the spectral clustering and improved slope one algorithm’, *Journal of Cloud Computing*, Vol. 12, No. 1, p.115.
- Hussong, M., Ruediger-Flore, P., Klar, M. et al. (2025) ‘Selection of manufacturing processes using graph neural networks’, *Journal of Manufacturing Systems*, Vol. 80, pp.176–193.
- Li, M., Shi, X., Shi, Y. et al. (2023) ‘Research on cloud manufacturing service recommendation based on graph neural networks’, *PLoS One*, Vol. 18, No. 9, p.e0291721.
- Lim, J.M., Song, W., Lee, J.S. et al. (2025) ‘Recent advances in CNC technology: toward autonomous and sustainable manufacturing’, *International Journal of Precision Engineering and Manufacturing*, Vol. 26, No. 9, pp.2311–2344.

- Liu, Z., Zhang, Z., Luo, X. et al. (2025) 'An adaptive recognition method for reliable collaboration of manufacturing services based on edge-aggregated graph convolutional network', *International Journal of Production Research*, pp.1–28.
- Lu, K.T. (2025) 'User acceptance behavior analysis of multimodal generative AI', *Journal of Information and Computing*, Vol. 3, No. 2, pp.23–40.
- Luo, Z., Shao, X. and Ma, X. (2024) 'Enhancing learners' performance in contest through knowledge mapping algorithm: the roles of artificial intelligence and blockchain in scoring and data integrity', *Journal of Organizational and End User Computing*, Vol. 36, No. 1, pp.1–21.
- Mahroo, F., Moradi, N., Aftabi, N. et al. (2026) 'A novel integer linear model for reliability-centric service composition in cloud manufacturing', *Computers & Industrial Engineering*, Vol. 211, p.111603.
- Pang, S., Guo, S., Wang, X.V. et al. (2023) 'Dual-dimensional manufacturing service collaboration optimization toward industrial internet platforms', *Engineering*, Vol. 22, pp.34–48.
- Rizvi, R.A. and Khalid, W. (2025) 'Unlocking innovation in manufacturing: the impact of data analytics maturity and knowledge-oriented leadership', *Journal of Management Science and Operations*, Vol. 3, No. 2, pp.17–43.
- Shu, M. (2025) 'Utilizing transfer learning for deep learning based image classification', *Journal of Intelligence Technology and Innovation*, Vol. 3, No. 1, pp.58–73.
- Vallidevi, K., Jothi, S. and Karuppiah, S.V. (2023) 'HO-DQLN: hybrid optimization-based deep Q-learning network for optimizing QoS requirements in service-oriented models', *Expert Systems with Applications*, Vol. 227, p.120188.
- Wang, X., Zhang, L., Liu, Y. et al. (2022a) 'Solving task scheduling problems in cloud manufacturing via attention mechanism and deep reinforcement learning', *Journal of Manufacturing Systems*, Vol. 65, pp.452–468.
- Wang, X.H., Zhang, L., Liu, Y.K. et al. (2022b) 'Dynamic scheduling of tasks in cloud manufacturing with multi-agent reinforcement learning', *Journal of Manufacturing Systems*, Vol. 65, pp.130–145.
- Wu, C.H. (2025) 'Eco-economic predictions: applying QPSO-BiLSTM and attention mechanisms for accurate renewable energy forecasting', *Journal of Management Science and Operations*, Vol. 2, No. 4, pp.28–47.
- Wu, H.T., Li, J.X. and Chen, M.Y. (2024) 'Building a sustainable development education system for large organizations based on artificial intelligence of things', *Journal of Organizational and End User Computing*, Vol. 36, No. 1, pp.1–19.
- Yue, H., Wu, Y.T., Wang, M. et al. (2025) 'Multi-service collaboration and composition of cloud manufacturing customized production based on problem decomposition', *The International Journal of Advanced Manufacturing Technology*, Vol. 138, Nos. 5–6, pp.2157–2171.
- Zeng, K. and Paik, I. (2024) 'Web service embedding: representing the invocation association between services with practical-valued vectors', *Expert Systems with Applications*, Vol. 238, p.122196.
- Zhang, C., Wang, L. and He, K. (2025) 'Cloud service composition optimization based on service association impact and an improved NSGA-II algorithm', *Scientific Reports*, Vol. 15, No. 1, p.26001.
- Zhang, Q., Li, S., Pu, R. et al. (2024) 'An adaptive robust service composition and optimal selection method for cloud manufacturing based on the enhanced multi-objective artificial hummingbird algorithm', *Expert Systems with Applications*, Vol. 244, p.122823.
- Zhou, C.P., Shi, B.Y., Qiu, H.J. et al. (2020) 'Graph convolutional architectures via arbitrary order of information aggregation', *IEEE Access*, Vol. 8, pp.92802–92813.