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AN IDENTICAL HARMONY DEGREE-BASED OPTIMIZATION SELECTION METHOD FOR CLOUD MANUFACTURING SERVICE COMPOSITION

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Abstract— In a cloud manufacturing scenario, the matching degree between manufacturing tasks and cloud services, as well as the synergy degree between multiple selected cloud services are key metrics to measure the benefits of cloud manufacturing service application. However, the latter is often overlooked in the cloud service selection process. In this paper, a matching-synergy analysis-based optimization

method of cloud manufacturing service composition is proposed. Firstly, an evaluation system of cloud service composition quality is established, including service matching degree (SM), service composition synergy (CS), and other metrics, such as service time (T), service cost (C) and reliability (R). Secondly, considering the interests of both service requestors and service resource providers, a two-constraint combination preference model is constructed, and solved by using the improved ant colony algorithm (IACO). Finally, the feasibility and effectiveness of the proposed method are verified with the example of an automobile bumper cloud service.

Keywords: - C**loud manufacturing; service composition; matching degree; synergy degree; improved ant colony algorithm**

1. INTRODUCTION

With the application of cloud computing, Internet of Things, artificial intelligence, and other new generation information technologies in the manufacturing field, manufacturing industries are undergoing significant changes. In the dynamic global environment, manufacturing service, specialization and cooperation are the mainstream trends. In this background, cloud manufacturing has emerged as a new networked manufacturing model, which provides a new solution to solve the problem of personalized product development for manufacturing enterprises, especially the large number of small and medium-sized enterprises, to realize the optimal allocation of manufacturing resources, and then improve the core competitiveness and independent innovation of enterprises. Cloud manufacturing overcomes the limitations of individual manufacturing enterprises, and encapsulates the scattered and diverse manufacturing resources and manufacturing capabilities of different enterprises into the manufacturing cloud services in a cloud pool, and uses cloud computing and intelligent algorithms to intelligently optimize their management and operation according to user needs, maximizing the use of manufacturing resources and capabilities.

Users' manufacturing needs are usually characterized by complexity and diversity, and individual cloud manufacturing services are often difficult to meet the personalized needs of users. For the complex personalized tasks submitted by users, the cloud manufacturing service platform needs to decompose them into fine-grained subtasks, select the services that meet the requirements from the service platform according to user needs and combine them to jointly execute user tasks [7]. As one of the key technologies to improve the utilization of cloud manufacturing resources and realize the value-added of manufacturing resources, cloud manufacturing service combination plays an important role in the implementation and development of cloud manufacturing services. In recent years, scholars at home and abroad have explored and achieved certain research results on the problem of cloud manufacturing service combination. In terms of composition optimization QoS attribute index selection, in addition to the study of time, cost, reliability and other basic attribute indexes [8-12], Zhou J et al [13] considered composability, reputation, ZHANG et al [14] considered delivery time and delay time, Li Yongxiang et al [15] considered manufacturing service provider credibility, Yang Y et al [16] considered service quality and energy consumption from the perspective of sustainable manufacturing perspective considers service quality and energy consumption. Most

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of the above literature is based on the analysis of service composition optimization objectives, constructs the corresponding service composition optimization selection model, and proposes the corresponding solution algorithm, while less consideration is given to the degree of matching between cloud manufacturing services and the assigned manufacturing tasks as well as the degree of collaboration between cloud manufacturing services. However, in the current model of collaborative participation in product customization and development by users and service resource providers, etc., the degree of service matching and service composition synergy have a significant impact on improving the execution efficiency of manufacturing tasks. Therefore, it is important to consider the degree of matching between cloud manufacturing services and the assigned manufacturing tasks as well as the degree of collaboration between cloud manufacturing services in the cloud manufacturing model of providing customized services to users for the smooth execution of the cloud manufacturing service composition. At the same time, most of the above studies have designed service indexes to meet the user's needs as much as possible from the perspective of the interests of the service demander. However, few studies have considered the interest matching problem of service resource provider from the perspective of service resource provider, and solving this problem can help service resource provider to calculate its input-output ratio and think about whether its company input is profitable.

Based on the above analysis, the main contributions of this paper are：

1.1. Limitations

- Depends on the mobile phone camera used by the user (i.e. the better the pixels of the particular mobile phone better the clarity of the picture).
- Can be used only with mobile phones supporting J2ME applications like we can use all the major phone vendors (Nokia, Motorola, Sony-Ericsson, etc), which has OS like Symbian.
- On the server side a static IP address is required to receive pictures from the mobile phone (client) and also to send message to the mobile phone (administrator).

1. A cloud manufacturing service composition quality of service (QoS) evaluation index system including CS (service composition synergy) and SM (service matching degree) indexes is established on the basis of the traditional T (service time), C (service cost) and R (reliability) indexes, and the concepts of service matching degree and service composition synergy degree are proposed.
2. The interests of both the service demander and the service resource provider are considered comprehensively, and a double-constraint composition optimization selection model including the service demander constraint and the service resource provider constraint is established.
3. An improved ant colony algorithm (IACO) for cloud manufacturing service composition is proposed.
4. An application example is given to verify the effectiveness of the proposed preferred model and solution algorithm.

The remainder of this paper is organized as follows. The "Literature review" section introduces the technical background and related work on manufacturing service composition in cloud manufacturing environment. The "Mathematical model of cloud manufacturing service composition " section describes the service composition problem and establishes the mathematical model of cloud manufacturing service composition on this basis. The "Improved ant colony algorithm" section improves the traditional ant colony algorithm to fit the service composition optimization problem in this paper. The "Application case" section verifies the feasibility and effectiveness of the proposed method by comparing an application case with the algorithm. The "Conclusion" section includes a summary of the research content of this paper and the key research directions for future work.

Literature review

The service composition optimization selection problem originated in the field of Web services and cloud computing and aims to improve the efficiency and quality of the service composition by selecting suitable services for composition from many candidate services [17,18], and in cloud manufacturing, various manufacturing services with different QoS are continuously aggregated to form a larger pool of services and a larger search space to find the global optimal solution. Cloud computing services include computing software resources and capability services, and in cloud manufacturing, in addition to these services, various manufacturing capabilities and resources are also provided in the form of services. Therefore, the problem of service composition optimization selection in cloud manufacturing is more complex than that applied in traditional cloud computing environments [19]. The existing approaches on service composition mainly focus on four aspects: business flow-based [20], graph- based

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[21], agent-based [22], and QoS-based service composition methods [23]. QoS- based service composition methods are the research hotspots of all the above service composition methods, and the research on QoS-based service composition methods is divided into the following three main categories.

1.1 Service combination based on heuristic algorithm

Since QoS-based service composition methods are NP-hard problems, a common method to solve this problem is to transform the multi-objective optimization problem of service composition preference into a single-objective optimization problem, and then solve it using mature heuristic algorithms, such as genetic algorithm [24, 25], artificial bee colony algorithm [26], particle swarm optimization algorithm [27], ant colony optimization algorithm [28], chaos algorithm [29], etc., and also scholars use the advantages of each algorithm to design hybrid algorithms to solve the service composition problem, such as Wang et al. [30] proposed a novel hybrid algorithm called Bee-Colony Simplex method hybrid Algorithm (ABCSA), which uses the simplex method and chaotic global optimal guidance strategy. Jin et al. [31] proposed a new hybrid teaching-based optimization algorithm to solve the QoS-MCSC problem, which combines the advantages of uniform mutation, adaptive pollination algorithm and teaching-based optimization algorithm. Gavvala et al. [32] proposed a new Eagle Strategy with Whale Optimization Algorithm (ESWOA) to ensure a proper balance between exploration and development. Zhu et al. [33] proposed and detailed a new optimization method, Improved Hybrid Differential Evolution and Teaching Based Optimization (IHDETBO). Zhang et al. [34] proposed an improved genetic and ant colony algorithm to solve the model. The hybrid algorithm combines the advantages of the local search of the ant colony algorithm and the global search of the genetic algorithm, which can solve the problems of the slow convergence of the ant colony algorithm and the tendency to fall into local optimum, and the poor local search ability of the genetic algorithm and the tendency to converge too early. Bouzary et al. [35] proposed a new hybrid algorithm that combines the newly developed Gray Wolf Optimization (GWO) algorithm with the evolutionary operator of the genetic algorithm, and the embedded crossover and variation operators achieve a dual function.

1.1 Service composition based on Pareto dominance

Some scholars have also directly used multi-objective optimization algorithms for solution, in this class of methods, the concept of Pareto dominance is used to obtain a set of non-dominated solutions that establish different trade-offs between all objectives of the service composition problem. For example, Tao et al. [36] discussed an approach based on PSO and non-dominated ranking techniques to find the Pareto frontier for the problem of associating perceptual manufacturing resource service composition. proposed an improved fast non-dominated ranking genetic algorithm with elite strategy, which uses the optimal decision method combining hierarchical analysis and entropy value method to comprehensively evaluate each equipment resource composition in the resulting Pareto optimal solution set. Chen et al. [8] proposed a fast non-dominated ranking genetic algorithm with elite strategy with inheritance and jump genes to solve the proposed model and find a series of preferred service compositions for the service demander. Chattopadhyay et al. [37] proposed an NSGA-based approach to find the Pareto-optimal solution to the QoS-aware Web service auto-composition problem. However, as the number of objectives increases, the Pareto dominance-based approach may lose its efficiency in finding the optimal solution. Yin et al. [38] proposed a method for optimal selection of cloud manufacturing service composition based on the NSGA-III algorithm, and experiments showed that NSGA-III can better achieve the solution of manufacturing services on high-dimensional objectives compared to NSGA-II. Bi et al. [39] proposed the preference nondominated ranking genetic algorithm III (P-NSGA-III) to solve the service composition optimization selection problem in cloud manufacturing. Compared with the traditional preference-based multi-objective algorithm, the adaptive preference reference point set generation method directly distributes the preference reference points on the hyperplane of NSGA- Ill according to the preference weights of QoS criteria provided by customers, which can guide the search toward the part of interest and greatly improve the search efficiency.

1.2 Other methods

In addition to the above intelligent algorithms, Yuan et al. [11] used an evaluation method based on gray correlation analysis (GRA) for service composition optimization selection. Liang et al. [40] proposed a Deep Reinforcement Learning (DRL) algorithm for the QoS-MCSC problem. Experimental results show that this method outperforms Deep Reinforcement Network (DQN) and Q-Learning algorithms. Liu et al. [41] discussed an adaptive service combination problem solving method based on deep reinforcement learning (DRL). The method

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uses recurrent neural networks (RNN) for prediction of the objective function. Reinforcement learning and deep learning are combined to obtain the service composition solution.The above literature is less likely to consider the degree of matching between cloud manufacturing services and the assigned manufacturing tasks and the degree of synergy between cloud manufacturing services. Meanwhile, most of the above studies start from the perspective of the interests of the service demander and design the service indexes to meet the users' needs as much as possible, while there are fewer studies that consider the matching of the interests of the service resource provider from the perspective of the service resource provider. For this reason, this paper comprehensively considers the interests of both service demander and service resource provider, establishes a two- constraint combined preference model including service demander constraints and service resource provider constraints, and solves it by using the improved ant colony algorithm (IACO).

2 Mathematical model of cloud manufacturing service composition

2.1 Problem description

In the cloud manufacturing environment, the whole process from task submission to task execution is mainly divided into three stages, i.e., manufacturing task decomposition stage, manufacturing subtask matching stage, and Service composition optimization selection stage, as shown in Fig 1. In the manufacturing task decomposition phase, the service demander submits a manufacturing task T to the cloud platform, which analyzes the task requirements and invokes task resolution tools to decompose the task into N manufacturing subtasks according to atomic business for each subtask, there may exist a huge number of candidate services with different QoS attributes that satisfy the same functionality requirement. In this paper, we mainly focus on the effective solution in the service composition optimization stage, and select a service composition with the overall optimal QoS among many service composition solutions under the multiple objectives of various QoS constraints.

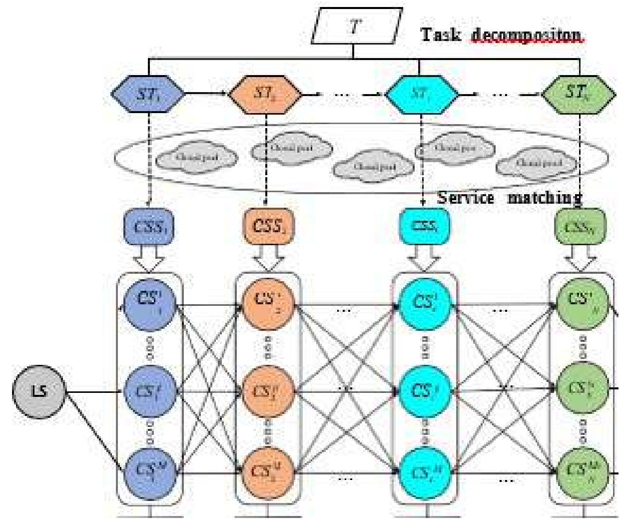

Fig. 1 Schematic diagram of cloud manufacturing service composition

2.2 QoS index system for cloud manufacturing service composition

QoS is an important index to determine the quality of the service composition and an important factor to be considered in the process of service composition. In addition to the traditional cloud manufacturing service composition optimization selection indexes such as time, cost, and reliability, the selection of QoS attribute indexes of cloud manufacturing service composition should fully consider the matching degree between cloud manufacturing services and the assigned manufacturing tasks as well as the degree of synergy between cloud manufacturing services. therefore, based on the operational characteristics of cloud manufacturing services and their supply and demand matching requirements, the QoS index system of cloud manufacturing service composition established in this paper is shown in Fig 2.

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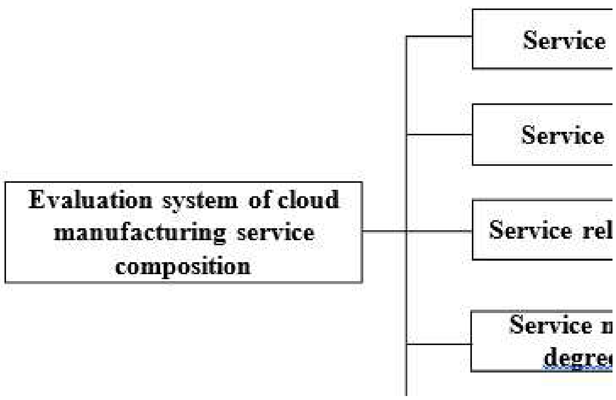

Fig. 2 Evaluation system of cloud manufacturing service composition.

3 *Improved ant colony optimization algorithm*

3.1 The basic ACO algorithm

The ant colony optimization algorithm (ACO) is a new metaheuristic algorithm inspired by the foraging behavior of ant colonies in nature and has been successfully applied to many fields and studies in the literature. Corresponding to the basic ACO algorithm, the information of each parameter in this paper is as follows:

1) N : denotes the number of subtasks.
2) Mi : denotes the number of manufacturing candidate services corresponding to the ith subtask
3) m : denotes the number of ants.
4) (t) : denotes the residual pheromone on the path from city i to city j at time t . The initial time is set as □ij (0) C , and C is the initial pheromone concentration, which is usually a small constant.
5) (t): represents heuristic information, □ij (t) □ 1/ (representing the distance between city i and city j).
6) k : in the process of moving, ant k (k □ 1, 2,3

Strategy 4: Strategy 3 speeds up the convergence speed, but there is a possibility that the algorithm falls into a local optimum. A roulette mechanism can be used so that the ants also have some possibility to go to the next candidate service with small probability, thus allowing the ants to go to the new path and avoiding the probability of the algorithm falling into a local optimum to some extent. The flowchart of the IACO algorithm is shown in Figure 3, and the steps are shown in Table 2. Note that the length of a solution is the sum of the distances of all its line segments, and the optimal solution is the route with the shortest length.

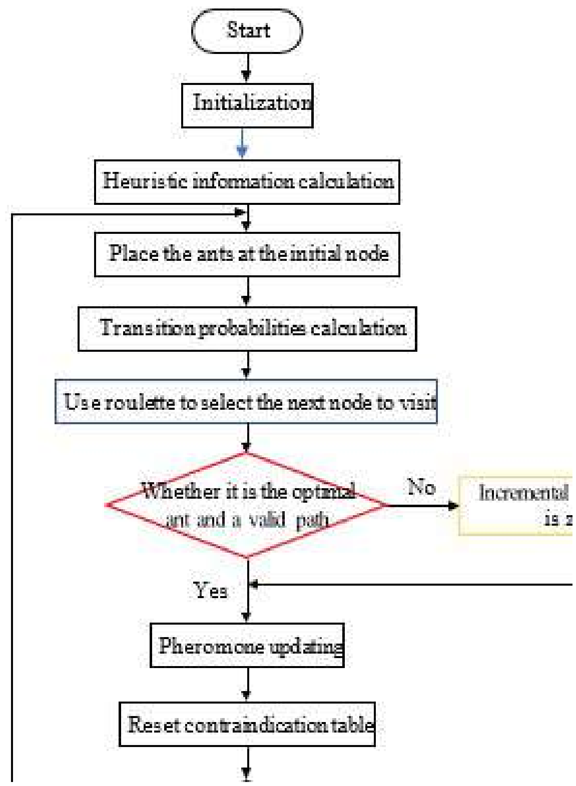

Fig. 3 Flow chart of IACO algorithm

Step 1: Initialize the ACO algorithm parameters. Set the set of paths that ants are allowed to visit and initialize the pheromone concentration.

Step 2: Heuristic information calculation. The data are normalized according to equation and then combined into distance values according to equation.

m) decides which direction to move based on the pheromo

Step 3: Generate m ants. Place each of the m ants randomly on the nodes of the allowed path set.

Step 4: Calculate the state transition probability. Search all the paths connected to this ant node and calculate the state transition probability of the ant to the next node according to equation.

Step 5: Roulette selection. A roulette mechanism is used to select the next node where the ant is going based on the probability calculated in step 4.

Step 6: Determine whether it is the optimal ant and whether the path is a valid path. If the ant is the optimal ant and the path is valid, the pheromone of its access path is updated, otherwise the pheromone increment on its invalid path is set to 0.

Step 7: Pheromone update. Update pheromones and perform contraindication table clearing based on equations.

Step 8: Run the loop. Repeat step 3 to step 7 until the maximum number of iterations, and then output the optimal solution.

4 *Application cases*

4.1 Case model

In order to verify the feasibility and effectiveness of the IACO algorithm and model proposed in this paper in solving the problem of cloud manufacturing service composition optimization selection, the method proposed in this paper is applied to the field of mold manufacturing, and the experiment takes car bumper manufacturing as the background, and 100 car bumper manufacturing tasks are submitted to the cloud manufacturing service platform by the service demander. In this paper, five most representative nodes are selected from product design, manufacturing, testing and packaging, and each subtask is matched to the relevant candidate service resource set through the resource search matching mechanism. The service demander constraint indicators are: service time not more than 30 days, service cost not more than 80,000 yuan, service reliability not less than 0.93, the cloud platform through the evaluation of its historical transaction records, to get the service demander credibility of 0.94, payment speed of 30, the service resource provider of the service demander credibility and payment speed of the constraint information shown in Table 2.The logistics time and logistics cost between the matched to resource providers are shown in Table 3.

5 *Conclusions*

Based on the traditional T(service time), C(service cost) and R(reliability) indexes, the QoS evaluation index system of cloud manufacturing service composition including CS(service composition synergy degree) and SM(service matching degree) was established, and the concepts of service matching degree and service composition synergy degree were proposed. Secondly, considering the interests of both service demanders and service resources, a double constraint combination optimization model including service demander constraints and service resource provider constraints is established, and solved by using the IACO algorithm. Finally, the feasibility and effectiveness of the proposed method are verified by an example of car bumper cloud manufacturing. With the increase of the number of candidate services in the manufacturing service pool, the scale of the service composition increases rapidly. The next step will be to study the intelligent algorithms applicable to large-scale service composition on the basis of the existing research results, and at the same time, since the indicators such as energy consumption and credibility are not considered in this paper, in the future, the service optimization indicators such as energy consumption and credibility will be incorporated into the multi-objective optimization model of cloud manufacturing service composition to enrich the constraint indicators on both sides of the service and make the simulation more appropriate to the actual situation.

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