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RESEARCH ARTICLE

Multi-Agent Interests Service Composition Optimization in Cloud Manufacturing Environment

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ABSTRACT In order to solve the problems such as the dynamic change of historical attribute service evaluation indicators, the lack of comprehensive consideration of the interest needs of all cloud manufacturing participants, and the strong subjectivity of the composition optimization results in the process of cloud manufacturing service composition. Taking the demands of service demanders, platform operators and service providers as constraints, this paper constructs a multi-objective optimization model of cloud manufacturing service composition that comprehensively considers multi-agent interests, and introduces the time decay function to deal with the service evaluation indicators with historical attributes, which reduces the impact of the dynamic changes of service evaluation indicators. Secondly, this paper adopts the NSGA-II with the elite selection strategy to solve the cloud manufacturing service composition optimization (SCO) model, and uses the grey target decision-making method to select the optimal solution from the Pareto solutions obtained by the NSGA-II, which avoids the problem of strong subjectivity in service composition decision-making. Finally, through case analysis, it was found that the bull's-eye distance of the optimal solution obtained by the NSGA-II was reduced by at least 34.95% compared to the genetic algorithm, verifying the feasibility of the optimization model and the effectiveness of the algorithm.

INDEX TERMS Cloud manufacturing, service composition optimization, multi-agent, grey target decision-making, NSGA-II.

I. INTRODUCTION

With a new round of changes in the global manufacturing industry, the division of labor in the manufacturing industry is becoming more and more refined and specialized. A single manufacturing service can no longer meet the diversity of user needs. At the same time, due to the shortage of tasks or unreasonable arrangements, service providers with core technologies and equipment also have idle resources. Therefore, the manufacturing industry urgently needs to change from the production-oriented mode to the service-oriented mode to meet the diverse needs of users and realize the rational utilization of manufacturing resources [1].

Based on the above background, new concepts such as cloud manufacturing and agile manufacturing are emerging [2]. Cloud manufacturing refers to the combination of existing advanced manufacturing technologies with emerging technologies such as cloud computing and intelligent science [3]. It is a service-oriented networked intelligent manufacturing mode. There are three main participants in the cloud manufacturing process: service demander, platform operator and service provider. The service provider

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services and virtualizes the manufacturing resources, and then encapsulates them as cloud services; the service demander publishes manufacturing requirements to the cloud platform, that is, submits manufacturing tasks to the platform operator; The platform operator is mainly responsible for the maintenance of the platform operation, the management of manufacturing services and manufacturing tasks, etc. After receiving the manufacturing demand, the platform operator will select the appropriate manufacturing service to perform the task [4]. This emerging manufacturing model can make full use of a great quantity of widely distributed manufacturing resources, realize the optimal combination and allocation of manufacturing resources and manufacturing demand, and promote the transformation and development of manufacturing. SCO is not only one of the key links in the whole cloud manufacturing system, but also a key way for cloud manufacturing to realize on-demand distribution and avoid manufacturing resource waste and idleness [5].

The SCO problem has the characteristics of composition explosion and is defined as NP-hard problem [6]. The cloud manufacturing SCO process involves multi-agent participating together. In addition to meeting the requirements of service demanders, the interests of other subjects are also the key points of service composition research. Therefore, under the condition of considering the interests of multi-agent, how to efficiently select the optimal service composition is the most essential requirement of service system, and it is also a key step for the transformation and development of manufacturing industry in the cloud manufacturing environment.

Aiming at the optimization problem of cloud manufacturing service composition, this paper not only considers the timeliness impact of historical attribute evaluation indicators of service resources on service resources, but also comprehensively considers the interests of the three main participants. Then, this paper constructs a three-objective cloud manufacturing SCO model, and solves the cloud manufacturing SCO model considering multi-agent interests by using the non-dominated sorting genetic algorithm (NSGA-II) and grey target decision-making method.

The contributions of this paper are as follows: (1) In order to reduce the impact of the timeliness of evaluation indicators, this paper introduces a time decay function to process historical data and weights, reducing the impact of dynamic changes in service evaluation indicators. (2) In order to comprehensively consider the interests of the three main participants, this paper constructs a three objective cloud manufacturing SCO model. (3) The NSGA-II and grey target decision-making method are proposed to solve the combinatorial optimization model of cloud manufacturing services considering the interests of multi-agent. The grey target decision-making method reduces the negative impact of subjectivity.

This paper is organized as follows. Section II mainly summarizes the literature on cloud manufacturing SCO. Section III constructs the cloud manufacturing SCO model that considers multi-agent interests. Section IV designs the NSGA-II to solve the cloud manufacturing SCO model. Section V conducts the case analysis. Section VI summarizes this paper and discusses future research directions.

II. RELATED WORK

At present, scholars continue to explore the problem of cloud manufacturing SCO, and have achieved certain research results [7], [8]. Cloud manufacturing SCO is a multivariable and uncertain decision-making problem. Scholars' research on cloud manufacturing SCO mainly focuses on three aspects: service resource evaluation indicators, SCO model construction, and SCO methods [9], [10], [11].

A. CLOUD MANUFACTURING SERVICE RESOURCE EVALUATION INDEX

In terms of the selection of evaluation indicators for cloud manufacturing service resources, Que et al. selected four basic indicators such as time and cost to construct the problem model, and proposed a new model from service providers to users [12]. Yang et al. selected evaluation indicators such as time, cost, and energy consumption from the perspective of sustainable development, and constructed a multi-objective SCO model [13]. In response to the different needs of multiple users, Yuan et al. established a service quality index system, which mainly includes six important indicators such as time, cost, availability, and composability [14]. In addition to the research on basic attribute indicators such as time, cost, and availability, Mubarok et al. proposed a multi-level reliability evaluation model [15]. Similarly, using the multi-level modeling method of manufacturing services, Ding et al. constructed a cloud manufacturing service portfolio optimization model based on three different levels of time, cost and reputation evaluation indicators [16]. Aiming at the uncertainty of reality, Gao et al. established the SCO model based on quality of service and robustness [17]. When studying the trust relationship between the manufacturing supplier and the demander, Yang et al. established an evaluation index system for cloud manufacturing service satisfaction [18].

When studying the evaluation indicators of cloud manufacturing service resources, most scholars ignore the timeliness of historical attribute evaluation indicators such as reliability and availability [19]. For manufacturing service satisfaction, Yang et al. used a decay function to describe the change in service satisfaction [18]. However, only the historical attributes of service satisfaction are considered, and the dynamic changes and timeliness of indicators such as the sustainability of service resources are not considered.

B. CONSTRUCTION OF CLOUD MANUFACTURING SERVICE COMPOSITION OPTIMIZATION MODEL

In terms of cloud manufacturing SCO model construction, Seghir and Khababa constructed a QoS-aware cloud SCO model from the perspective of service demanders [20]. Also focusing on meeting the requirements of service demanders, Bouzary and Chen proposed a grey wolf algorithm based on a new evolutionary operator to solve the large-scale SCO problem [21]. In order to reduce the operating cost and time of service providers, Aghamohammadzadeh et al. constructed a SCO model based on logistics planning and manufacturing operations [22]. Cloud manufacturing SCO is jointly participated by multiple agents, and the relationship between multi-agent is also the research focus of scholars. Wu et al. considered service quality optimization from the perspectives of platform operators and service demanders, and established a multi-objective integer bilevel multi-follower planning model to meet the needs of platform operators and service demanders [23]. Considering the interests of the service demander and the service provider, Guan et al. constructed a mutual selection model of cloud manufacturing service composition based on the interests of both the demander and the provider [24]. To solve the problem of SCO in case of service exceptions, Wang et al. took business exceptions, quality of service, etc. as constraints and established the service composition reconfiguration model based on actual constraints [25].

The whole process of cloud manufacturing service portfolio optimization mainly involves three subjects: service demander, platform operator and service provider [26]. Wang et al. constructed an evolutionary game model of "service demander-service provider-platform operator," and studied the trust relationship among the three subjects in the cloud manufacturing environment [27]. In order to meet and balance the long-term and short-term utility of each participant, Zhang et al. established the SCO model that considers the short-term utility of the service demander and the long-term utility of the service provider [28]. When constructing the service resource composition optimization model, most scholars only consider the needs and interests of one or two parties, and rarely consider the interests of three subjects at the same time. Without considering the integrity of the whole SCO process, the SCO model is not perfect.

C. CLOUD MANUFACTURING SERVICE COMPOSITION OPTIMIZATION METHOD

In the aspect of cloud manufacturing SCO method, Akbaripour and Houshmand combined the local search algorithm with the imperialist competition algorithm, and proposed a new hybrid algorithm to solve the SCO problem with sequential composition structure [29]. Yang et al. proposed a guided artificial bee colony-grey wolf algorithm to solve a robust SCO model for cloud manufacturing [30]. In order to maintain the balance between algorithm exploration and development, Gavvala et al. proposed a whale optimization algorithm based on the new eagle strategy [31]. At the same time, in order to improve the search efficiency of the algorithm, Gao et al. proposed a hybrid genetic algorithm based on a novel roulette selection operator to solve the problem [17]. Feng et al. introduced local search strategies of other algorithms on the basis of the NSGA-II, and used the improved NSGA-II to solve the SCO problem [32]. To cope with the complexity of manufacturing requirements, Wu et al. proposed a novel optimal service composition path algorithm based on dual heuristic functions [33]. Xie et al. proposed a two-stage method consisting of K-means clustering and the improved PSO algorithm to improve the efficiency of solving SCO problems [34]. In order to better balance local and global search capabilities, Jin et al. utilized the uniform mutation method for global search and proposed an improved whale optimization algorithm to quickly obtain the optimal solution [35].

Most of the current researches transform multi-objective optimization problems into single objective optimization problems through linear weighting, which makes the final solution more subjective and affects the final solution quality to a certain extent [36]. For the complex multi-objective SCO problem, Zhou et al. integrated the differential evolution operator into the artificial bee colony equation and proposed an improved ABC algorithm [37]. Zhang and Zhao constructed a two-level programming model and used the NSGA-II to solve the multi-objective SCO problem [38]. When solving two-dimensional and three-dimensional objective optimization problems, NSGA-II algorithm better maintains the diversity of populations and solves the problem faster than other multi-objective evolutionary algorithms, and has achieved good results [39], [40].

The above related work has made many contributions to the cloud manufacturing SCO, and have also achieved many research results [41], [42]. However, there are still some issues with the cloud manufacturing SCO. Firstly, when studying the evaluation indicators of cloud manufacturing service resources, scholars have established the system of service quality indicators and continuously improved it. However, some scholars have overlooked the timeliness of historical attribute evaluation indicators such as reliability and availability. Secondly, from the perspective of constructing SCO models, most scholars consider the needs and interests of one or both parties, but rarely consider the interests of the three parties simultaneously. Third, from the perspective of SCO methods, scholars use different intelligent algorithms to solve the SCO problem and improve the quality of service composition. However, some scholars have transformed multi-objective problems into single objective problems, which makes the final solution subjective and to some extent affects the quality of the final solution.

The problem of cloud manufacturing SCO needs further research. Therefore, on the basis of existing literature research, when solving the problem of cloud manufacturing SCO, this paper first considers the timeliness of the historical attribute evaluation index of service resources, and introduces a time attenuation function to avoid the impact of the time dynamic change of the historical index. Secondly, this paper also comprehensively considers the interests of the three main participants. Taking the needs of the service demander, platform operator and service provider as constraints, this paper constructs a three objective cloud manufacturing SCO model, and uses NSGA-II algorithm and grey target decision-making to solve the cloud manufacturing SCO model considering the interests of multi-agent.

TABLE 1. Cloud manufacturing service resource evaluation index system.

Primary index	Secondary index	Related description	Type
Quality of Service indicators	Service time	Service production time and operation time	Cost type
	Service cost	Service production cost and operation cost	Cost type
Sustainability indicators	Historical service reliability	Ratio of service successful completion times to total service operation times	Benefit type
	Historical service security	The ratio of the number of times that the service has no abnormal production to the total number of services	Benefit type
	Historical service satisfaction	Evaluation results of users and platforms on service resources	Benefit type
Financial performance indicators	Financial profit rate	Ratio of financial net profit of services to total service cost	Benefit type
	Service idle rate	Ratio of services idle to total services	Benefit type

III. CONSTRUCTION OF CLOUD MANUFACTURING SERVICE COMPOSITION OPTIMIZATION MODEL CONSIDERING MULTI-AGENT INTERESTS

A. SELECT SERVICE EVALUATION INDICATORS

The selection of cloud manufacturing service evaluation indicators should fully consider the service quality requirements and the comprehensiveness of indicator selection. This paper comprehensively considers the needs of the three participants in the process of manufacturing service composition and the relevant characteristics of manufacturing resources. The evaluation index system of the optimization model is shown in Table 1. The whole evaluation system is divided into three parts: quality of service indicators (QoS), sustainability indicators (SuS) and financial performance indicators (FP). Among them, quality of service indicators are oriented to the service demander, including the service time and service cost in the process of task completion, which are mainly used to measure the status of service execution; Sustainability indicators are oriented to platform operators, including historical service reliability and historical service satisfaction, which are mainly used to measure the sustainable development of the platform itself; Financial performance indicators are oriented to service providers, including financial profit rate and service idle rate, which are mainly used to measure the financial performance of enterprises.

B. PROBLEM DESCRIPTION AND ASSUMPTIONS

Manufacturing is a multi-agent collaborative manufacturing service network, which is mainly composed of three parts: service demander, service provider and platform operator, as shown in Figure 1. During the manufacturing process, the service demander is responsible for releasing production tasks and personalized requirements to the cloud platform; The service provider is responsible for encapsulating manufacturing resources and related information as services and sending them to the cloud platform; The platform operator is responsible for decomposing tasks into manufacturing subtasks and selecting appropriate service combinations to undertake each manufacturing subtask. Cloud manufacturing service composition refers to selecting the best service that meets the constraints from a large number of candidate service collections according to the four task execution structures of series, parallel, selection and cycle to complete the tasks provided by the service demander. In the process of cloud manufacturing SCO, the service paths of parallel, selective and circular structures can be transformed into serial structures. Therefore, it is assumed that the relationships among the decomposed subtasks are in series.

In the entire manufacturing service portfolio optimization process, the complex manufacturing task CMT initiated by the service demander needs to be decomposed into n manufacturing sub-tasks $CMST_i$ according to the functional characteristics and resource types of the task, that is, $CMT = \{CMST_i \mid i = 1, 2, \cdots, n\}$. Each subtask $CMST_i$ corresponds to a candidate service set $CMSG_i$, and $CMSG_i$ contains several candidate services CMS_{ij}, that is, $CMSG_i = \{CMS_{ij} \mid j = 1, 2, \cdots, m_i\}$. Among them, CMS_{ij} indicates that the subtask $CMST_i$ is completed by the jth candidate service in $CMSG_i$, and m_i indicates the number of candidate services in $CMSG_i$. When all the subtasks $CMST_i$ get the corresponding CMS_{ij} through combination optimization, a service composition $CMSL$ is formed at this time, that is, $CMSL = \{CMS_{1j}, CMS_{2j}, \cdots, CMS_{nj}\}$. Different service composition schemes have different time, cost and service quality to complete the manufacturing task, so it is necessary to select the optimal service composition to complete the complex manufacturing task in order to maximize the benefits.

C. BUILDING A MULTI-OBJECTIVE SERVICE COMPOSITION OPTIMIZATION MODEL

1) OBJECTIVE FUNCTION

First define the decision variable x_{ij}:

$$x_{ij} = \begin{cases} 1, & \text{Candidate services } CMS_{ij} \\ & \text{execution task } CMST_i \\ 0, & \text{Candidate services } CMS_{ij} \\ & \text{does not execution task } CMST_i \end{cases} \tag{1}$$

$$s.t. \sum_{j=1}^{m_i} x_{ij} = 1, \quad i = (1, 2, \ldots n) \tag{2}$$

Equation (2) indicates that each manufacturing resource can only provide services for one manufacturing subtask at a time, which is the constraint condition of the decision variable.

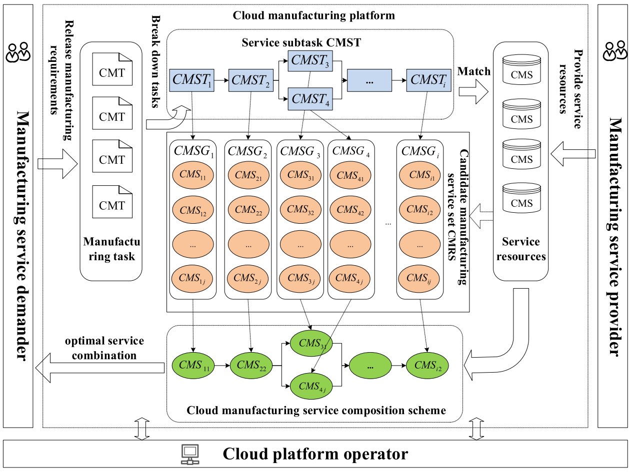

FIGURE 1. Cloud manufacturing service composition process.

a: QoS OPTIMIZATION OBJECTIVES OF SERVICE DEMANDER

i) MINIMUM SERVICE TIME

The optimization objective of manufacturing service time refers to the minimum total service time of the whole service composition process in cloud manufacturing. The objective function is shown in Equations (3) - (5):

$$min\,T = \min(T_m + T_l) \tag{3}$$

$$T_m = \sum_{i=1}^{n}\sum_{j=1}^{m_i} x_{ij} * T_m^{ij} \tag{4}$$

$$T_l = \sum_{i=1}^{n}\sum_{j=1}^{m_i}\sum_{j^*}^{m_{(i+1)}} x_{ij}x_{(i+1)j^*} * T_l^{(ij,(i+1)j^*)} \tag{5}$$

where, T_m represents the total processing time of the service composition, T_m^{ij} represents the processing time of the service CMS_{ij} to complete the task $CMST_i$. T_l represents the total operation time between services in the service composition, $T_l^{(ij,(i+1)j^*)}$ represents the logistics operation time from service CMS_{ij} to service CMS_{i+1j^*}.

ii) MINIMUM SERVICE COST

The optimization objective of manufacturing service cost refers to the minimum total service cost of the whole service composition process of cloud manufacturing. The objective function is shown in Equations (6)-(8):

$$min\,C = \min(C_m + C_l) \tag{6}$$

$$C_m = \sum_{i=1}^{n}\sum_{j=1}^{m_i} x_{ij} * C_m^{ij} \tag{7}$$

$$C_l = \sum_{i=1}^{n}\sum_{j=1}^{m_i}\sum_{j}^{*m_{(i+1)}} x_{ij}x_{(i+1)j^*} * C_l^{(ij,(i+1)j^*)} \tag{8}$$

where, C_m represents the total processing cost of the service composition, C_m^{ij} represents the processing cost of the service CMS_{ij} to complete the task $CMST_i$. C_l represents the total operating cost of services in the service composition,

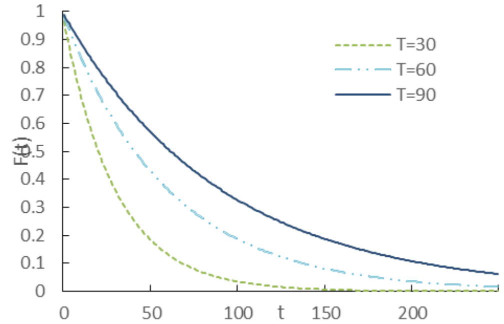

FIGURE 2. Decay trend of the time decay function.

$C_l^{(ij,(i+1)j^*)}$ represents the logistics operating cost from service CMS_{ij} j to service CMS_{i+1j^*}.

b: SuS OPTIMIZATION OBJECTIVES OF PLATFORM OPERATOR

The manufacturing service cloud platform needs long-term development and planning. In this paper, the success rate, security and satisfaction of service resources are taken as the sustainable development indicators of platform operators. Sustainable development indicators are subjective evaluation indicators with historical attributes. The previous evaluation methods give the same weight to the historical service evaluation indicators in different time periods, ignoring the dynamic and timeliness of the historical evaluation data. In order to reduce the impact of timeliness of historical attribute evaluation indicators, a time decay function will be introduced to process historical data and weights, as shown in Equations (9) - (10):

$$f(t) = e^{-\lambda t} \tag{9}$$

$$\lambda = 1/T_0 \tag{10}$$

In the above Equation, T_0 represents the time interval that determines the size of the parameter λ. Time t is an independent variable, and the value range of function $f(t)$ is [0, 1]. In Equation (9), the time t is negatively correlated with the time effect function. When the value of t is larger, the value of $f(t)$ is smaller, which means that the longer the historical evaluation time is, the smaller the weight of the historical evaluation function is, and the smaller the impact on the existing service combination effect is. The parameter λ is related to the decay rate of the time effect function. When the time interval T_0 is shorter, the time effect function decays faster, as shown in Figure 2.

Combined with the characteristics of time effect function, this paper takes the cooperation time of cloud manufacturing entities as the total time, divides the total time evenly into multiple time windows, and calculates the weight of historical evaluation function in different time periods. The specific Equation is as follows:

$$W_l = \frac{\int_{t_1}^{t_2} e^{-\lambda \Delta t_l} dt}{\Delta t_l} \tag{11}$$

In Equation (11), t_1 and t_2 represent two time points of the time interval, Δt_l represents the l-th time window, W_l represents the historical evaluation function weight of the l-th time window, that is, the average weighted value of the time effect function the l-th time window.

i) HIGHEST HISTORICAL SERVICE RELIABILITY

The optimization objective of manufacturing service reliability refers to the highest successful execution rate of the whole service composition process of cloud manufacturing. The objective function is shown in Equations (12) - (13):

$$max\ HR = (\sum_{i=1}^{n}\sum_{j=1}^{m_i} R_{ij} * x_{ij})/n \tag{12}$$

$$R_{ij} = \frac{\sum_{l=1}^{L} R_l^{ij} * W_l}{\sum_{l=1}^{L} W_l} \tag{13}$$

where, R_l^{ij} represents the service reliability of the service CMS_{ij} in the l-th time window, R_{ij} represents the service reliability of the service CMS_{ij} in the total time.

ii) HIGHEST HISTORICAL SERVICE SECURITY

The optimization objective of manufacturing service security refers to the highest probability that task execution will not be disturbed by impact during the whole service composition process of cloud manufacturing. The objective function is shown in Equations (14) - (15):

$$max\ HS = (\sum_{i=1}^{n}\sum_{j=1}^{m_i} S_{ij} * x_{ij})/n \tag{14}$$

$$S_{ij} = \frac{\sum_{l=1}^{L} S_l^{ij} * W_l}{\sum_{l=1}^{L} W_l} \tag{15}$$

where, S_l^{ij} represents the service security of the service CMS_{ij} in the l-th time window, S_{ij} represents the service security of the service CMS_{ij} in the total time.

iii) MAXIMUM HISTORICAL SERVICE SATISFACTION

The optimization objective of manufacturing service satisfaction refers to the maximum satisfaction of the whole service composition process of cloud manufacturing. The objective function is shown in Equations (16) - (17):

$$max\ HSA = (\sum_{i=1}^{n}\sum_{j=1}^{m_i} SA_{ij} * x_{ij})/n \tag{16}$$

$$SA_{ij} = \frac{\sum_{l=1}^{L} SA_l^{ij} * W_l}{\sum_{l=1}^{L} W_l} \tag{17}$$

where, SA_l^{ij} represents the service satisfaction of the service CMS_{ij} in the l-th time window, and SA_{ij} represents the service satisfaction of the service CMS_{ij} in the total time.

c: FP OPTIMIZATION OBJECTIVES OF SERVICE PROVIDER

i) HIGHEST FINANCIAL PROFIT MARGIN

The optimization objective of the financial performance of manufacturing services means that the financial profit margin of the whole service composition of cloud manufacturing is the highest. The objective function is shown in Equation (18):

$$max\ Fp = (\sum_{i=1}^{n}\sum_{j=1}^{m_i} Fp_{ij} * x_{ij})/n \tag{18}$$

where, Fp_{ij} represents the profit brought by the service CMS_{ij} to the service provider.

ii) HIGHEST RESOURCE PERFORMANCE

In the process of service composition, services with a high idle rate should be selected to ensure that the system configuration is reasonable and to avoid congestion of individual services. The optimization objective of manufacturing service resource performance means that the service idle rate of the whole service composition of cloud manufacturing is the highest. The objective function is shown in Equation (19):

$$max\ SI = (\sum_{i=1}^{n}\sum_{j=1}^{m_i} SI_{ij} * x_{ij})/n \tag{19}$$

where, SI_{ij} represents the idle rate of service CMS_{ij}.

2) OVERALL MODEL

The model of cloud manufacturing SCO is as follows:

$$F = (min\ Qos, min\ SuS, min\ FP) \tag{20}$$

$$min\ Qos = w_1 * T + w_2 * C \tag{21}$$

$$min\ SuS = 1 - (\beta_1 * HR + \beta_2 * HS + \beta_3 * HSA) \tag{22}$$

$$min\ FP = 1 - (\alpha_1 * Fp + \alpha_2 * SI) \tag{23}$$

Equation (21) - (23) represent three expressions for primary indicators, where the values of primary indicators are obtained from the weighted sum of secondary indicators. The weights in the above equations are obtained based on user preferences. w_1, w_2 are the weights of the secondary indicators of the service demander; $\beta_1, \beta_2, \beta_3$ are the weights of the secondary indicators of the platform operator; α_1, α_2 are the weights of the secondary indicators of the service provider.

The constraints of the SCO model considering multi-agent interests are as follows:

$$\text{s.t.} \begin{cases} T \le T_{max} \\ C \le C_{max} \\ HR \ge HR_{min} \\ HS \ge HS_{min} \\ HSA \ge HSA_{min} \\ Fp \ge Fp_{min} \\ SI \ge SI_{min} \end{cases} \tag{24}$$

where, T_{max} is the maximum service time acceptable to the service demander, and C_{max} is the maximum service cost

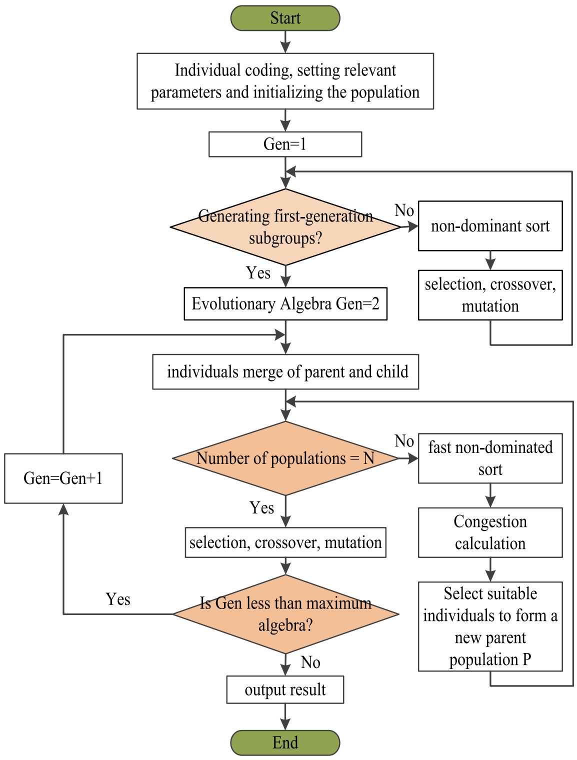

FIGURE 3. Basic process of NSGA-II.

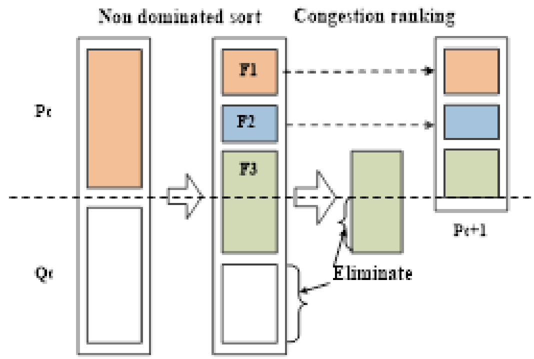

FIGURE 4. Elite selection strategy.

acceptable to the service demander. HR_{min} is the minimum service reliability acceptable to the platform operator, HS_{min} is the minimum service security acceptable to the platform operator, and HSA_{min} is the minimum service satisfaction acceptable to the platform operator. Fp_{min} is the minimum financial profit margin acceptable to the service provider, and SI_{min} is the minimum resource idle rate acceptable to the service provider.

IV. SOLVING THE OPTIMIZATION MODEL OF CLOUD MANUFACTURING SERVICE COMPOSITION CONSIDERING MULTI-AGENT INTERESTS

The cloud manufacturing SCO problem considering multi-agent interests is a NP-Hard problem. Heuristic approach are often used to solve NP-Hard problems, which is one of the most suitable methods to solve this problem. At the same time, considering multi-agent interests means considering multiple objective functions. NSGA-II is one of the more popular multi-objective algorithms. It reduces the complexity of genetic algorithm (GA), has the advantages of fast running speed and good convergence, and is also the benchmark for the performance of other multi-objective optimization algorithms. Therefore, this paper adopts an improved NSGA-II to solve the cloud manufacturing SCO problem considering the interests of multi-agent.

A. BASIC PROCESS OF NSGA-II

The basic process of NSGA-II is shown in Figure 3:

The steps of NSGA-II are described as follows:

Step 1: set the population size, crossover, mutation and other relevant algorithm parameters according to the solution problem, and select an appropriate coding rule to convert the solution space of the problem into the coding space.

Step 2: Randomly select N individuals in the above coding space to generate an initial population P_1 with a population size of N.

Step 3: Perform non-dominated sorting on the initial population, and divide the non-dominated level of the individual. On this basis, crossover, mutation and other operations are performed on individuals to generate a new offspring population P_2.

Step 4: Merge the parent and child populations into a new population P_3, and the number of individuals in this population is 2N. Perform fast non-dominated sorting on the new population and calculate the crowding degree of individuals at each level. According to the size of the non-dominated level and the crowding degree, the N individuals with the best fitness value are selected to form a new population P_4, as shown in Figure 4. The population P_4 performs operations such as mutation again to generate new offspring.

Step 5: Determine whether the algorithm has reached the maximum number of iterations. If the termination condition of the algorithm is satisfied, output the Pareto solution set, and select the optimal solution through the grey target decision method; If the algorithm termination condition is not satisfied, repeat the above steps 3, 4 and 5.

B. ALGORITHM DESIGN OF NSGA-II

1) ENCODING

According to the characteristics of cloud manufacturing SCO, this paper uses integer coding to encode chromosomes, and establishes the mapping relationship between chromosome genes and service resources, as shown in Figure 5. The cloud manufacturing platform decomposes complex manufacturing tasks into n manufacturing subtasks. Each manufacturing subtask corresponds to a separate service candidate set, and each service candidate set has m candidate services. In the above-mentioned service candidate set, n candidate service resources matching subtasks are selected and combined into a service solution. At the same time, each chromosome represents a service combination scheme, and the number of genes in the chromosome represents the number of subtasks.

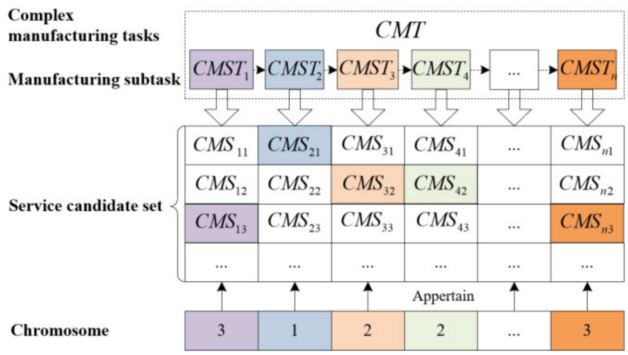

FIGURE 5. **Mapping relationship between service composition and chromosomes.**

2) SELECTION OPERATOR

The selection operation of NSGA-II algorithm aims to select individuals with better performance in the population and continuously optimize the population. The selection operation of NSGA-II algorithm aims to select individuals with better performance in the population and continuously optimize the population. Compared with roulette and other selection methods, tournament selection method is not only easy to implement, avoiding the sorting steps of fitness values, but also superior to other selection methods in solving speed and accuracy. According to the characteristics of cloud manufacturing SCO problem, this paper adopts the binary tournament selection method, and makes the selection according to the non-dominated sort ranking level and crowding degree of individual population.

3) CROSSOVER OPERATOR

NSGA-II algorithm generates new individuals through crossover operations to maintain the diversity of the population. The crossover operation simulates the reproduction process in nature. The chromosomes of the parent exchange some genes according to the rules of the crossover operator, thereby forming two new individuals. For different optimization problems, the algorithm chooses different crossover operators. In this paper, k-point crossover is selected as the crossover operator according to the integer coding method and the repeatability of chromosome genes. Determine k intersection points in the parent generation, and then perform the intersection operation on the fragments between the intersections of the two parents. In the meantime, the crossover probability of crossover operation is very important. If the crossover probability is too high, excellent genes will be lost. If the crossover probability is too low, the diversity of the population will be reduced, thus reducing the global optimization ability of the algorithm. Therefore, the value range of the crossover probability of the crossover operation is generally reasonable in the range of [0.4, 0.9].

4) MUTATION OPERATOR

NSGA-II algorithm uses mutation operation to avoid the algorithm falling into local optimization quickly and improve the global search ability. At the same time, the mutation operation also increased the population diversity and promoted the continuous optimization of the population. For different optimization problems, the mutation operator selected by the algorithm is different. For example, bit flip mutation is suitable for binary encoding. According to the integer coding method and the repeatable characteristics of chromosome genes, the reverse mutation method is selected as the mutation operator in this paper. The reverse mutation operator first randomly selects a gene sequence, then reverses the gene sequence in the sequence, and finally reinserts the gene into the chromosome to generate a new chromosome. In addition, the mutation probability of the mutation operation is important to the operation of the algorithm. Unreasonable mutation probability will affect the running time and results of the algorithm, and too high mutation probability will turn the NSGA-II algorithm into a random search mode. Therefore, the value of the crossover probability of the crossover operation is generally [0.005, 0.1].

5) TERMINATION CONDITIONS

In order to prevent the algorithm from entering the loop solution, NSGA-II algorithm must set some termination conditions to end the operation of the algorithm. The selection of termination conditions is also crucial, because we need to ensure that the algorithm has completed the operation of the problem model. There are two main methods of termination conditions: the first method is to set the target value in advance, and when the algorithm reaches this value, the algorithm ends. This method must know the target value in advance, which is not suitable for the model constructed in this paper. The second method is to set the number of iterations in advance, and when the algorithm runs to a predetermined number of iterations, the algorithm ends. The second method not only conforms to the model constructed in this paper, but also controls the running time of the algorithm. Therefore, this paper adopts the above-mentioned second termination method to terminate the operation of the algorithm.

C. MULTI-OBJECTIVE GREY TARGET DECISION-MAKING METHOD

The multi-objective optimization problems balance multiple objectives based on the objective situation of the problem and the subjective consciousness of the user, and find the best solution within a certain range. The grey target decision-making method is suitable for solving multi-objective optimization problems and making decisions for comprehensive evaluation. In the grey target decision-making method, events (satisfactory solutions) that meet user requirements form a grey target range. Within the range of grey targets mentioned above, the grey target decision-making method first calculates the effectiveness sample matrix of each objective, and then assigns weights to each objective function based on objective data and calculates the bull's-eye distance, reducing the negative impact of subjectivity. Therefore, grey target decision based on entropy is selected as the decision method of service composition in this paper, and the optimal service composition scheme is selected from the Pareto optimal solution set obtained by NSGA-II algorithm. This method selects the optimal scheme by calculating the bull's-eye distance of each scheme. The specific process is as follows:

Step 1: Design the effect sample matrix X. The effect sample matrix is composed of the effect sample values of the optimization objectives of the decision plan, as shown in Equation (25):

$$X = (x_{ij})_{n\times m} \tag{25}$$

where, n is the total number of decision-making schemes; m is the total number of optimization objectives constructed by the model; x_{ij} is the effect sample value, which is expressed as the effect sample value of the j-th optimization objective of the i-th scheme.

Step 2: Calculate the decision matrix R. The decision matrix is composed of the effect measure value r_{ij}, as shown in Equations (26) - (27):

$$R = (r_{ij})_{n\times m} \tag{26}$$

$$r_{ij} = \frac{Z_j - x_{ij}}{max\left\{\underset{1\le i\le n}{max}\{x_{ij}\} - Z_j, Z_j - \underset{1\le i\le n}{min}\{x_{ij}\}\right\}}, \quad j = 1, 2, \ldots, m \tag{27}$$

where, Z_j is the operator of rewarding the good and punishing the bad, which is as follows:

$$Z_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij}, \quad j = 1, 2, \ldots, m \tag{28}$$

Step 3: Calculate the weight w_j of the optimization objective. The weight of the optimization objective is obtained according to the entropy value E_j of the optimization objective. The specific Equation is as follows:

$$w_j = \frac{(1 - E_j)}{\sum_{j=1}^{m}(1 - E_j)} \tag{29}$$

$$E_j = -\frac{1}{ln\, n}\sum_{i=1}^{n} y_{ij}\, ln\, y_{ij} \tag{30}$$

where, E_j is the entropy of the optimization objective, and the value range is $E_j > 0$; y_{ij} represents the proportion of the optimization objective value of each scheme, and the proportion is as follows:

$$y_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{31}$$

Step 4: Calculate bull's-eye distance d_i of the optimization objective. The bull's-eye distance represents the advantages and disadvantages of the selected scheme, so an optimal scheme is selected from the Pareto solution set. The specific Equation is as follows:

$$d_i = \sqrt{\sum_{j=1}^{m} w_j\left(r_{ij} - r_j^0\right)^2} \tag{32}$$

TABLE 2. Partial evaluation index value of cloud manufacturing service resources.

Serial number	T_m/ min	C_m/yuan	Fp/ %	SI/%	…	HR/%	HSA/%
CMS_{11}	113	33	11	30	…	87/81/ 87/81	78/91/ 73/73
CMS_{12}	110	49	12	25	…	80/89/ 82/79	84/78/ 78/79
CMS_{13}	119	48	13	28	…	81/88/ 91/93	73/89/ 89/89
CMS_{14}	105	35	15	39	…	89/86/ 89/88	69/73/ 83/83
CMS_{15}	116	38	11	40	…	86/79/ 92/87	76/69/ 91/87
CMS_{21}	113	33	15	34	…	88/82/ 88/84	73/78/ 78/81
CMS_{22}	111	33	13	39	…	83/91/ 81/92	78/91/ 91/78
…	…	…	…	…	…	…	…
CMS_{62}	101	48	16	25	…	83/84/ 89/81	92/89/ 84/89
CMS_{63}	99	51	15	23	…	80/88/ 91/91	88/76/ 83/79
CMS_{64}	103	49	14	31	…	86/76/ 90/86	88/83/ 89/84
CMS_{65}	98	53	13	27	…	88/87/ 87/89	85/72/ 87/86

V. CASE VERIFICATION AND ANALYSIS

A. CASE DATA

Taking the gear manufacturing process of a bearing manufacturing company in China as an example, the manufacturing process of cycloid gear is selected as a complex manufacturing task. The manufacturing service demander releases manufacturing requirements on the cloud platform, and the platform operator decomposes the complex manufacturing task into six serial subtasks through task decomposition. After the supply and demand matching of cloud manufacturing services, the non-functional parameters of the service resources corresponding to each subtask are shown in Table 2, and the operation cost and operation time of the service resource candidate set are shown in Table 3.

According to the requirements of the service demander, platform operator and service provider for the SCO process, the constraint parameters required by the cycloidal gear manufacturing SCO model in the cloud manufacturing environment are as follows: $T_{max} = 550$, $C_{max} = 780$, $HR_{min} = 75\%$, $HS_{min} = 75\%$, $HSA_{min} = 75\%$, $Fp_{min} = 10\%$, $SI_{min} = 23\%$. The weight values in the overall model are obtained based on user preferences. According to the user preferences of the bearing manufacturing company, the weight values of the secondary indicators are: 0.31/0.69, 0.3/0.4/0.3, 0.59/0.41. The bearing manufacturing company makes a major adjustment every year. Therefore, 12 months were selected as the total time in this experiment, and each quarter was set as a time interval, for a total of four time intervals. According to Equations (9) -(11), the historical weights with time effect are obtained as: 0.644, 0.237, 0.087,

TABLE 3. Operation time and operation cost of service resources.

Service resource operation route	service resources operation time(min)/operation cost(yuan)				
	1	2	3	4	5
$CMS_{11}-CMS_{2i}$	19/38	17/34	18/36	16/32	17/34
$CMS_{12}-CMS_{2i}$	17/34	14/28	13/26	14/28	16/32
$CMS_{13}-CMS_{2i}$	18/36	16/32	12/24	15/30	15/30
$CMS_{14}-CMS_{2i}$	13/26	14/28	10/20	9/18	12/24
$CMS_{15}-CMS_{2i}$	15/30	11/22	13/26	14/28	16/32
$CMS_{21}-CMS_{3i}$	16/32	11/22	10/20	14/28	13/26
$CMS_{22}-CMS_{3i}$	8/16	7/14	5/10	8/16	9/18
$CMS_{23}-CMS_{3i}$	12/24	9/18	7/14	10/20	6/12
$CMS_{24}-CMS_{3i}$	15/30	10/20	13/26	13/26	11/22
$CMS_{25}-CMS_{3i}$	9/18	6/12	8/16	10/20	13/26
…	…	…	…	…	…
$CMS_{51}-CMS_{6i}$	15/30	17/34	12/24	13/26	16/32
$CMS_{52}-CMS_{6i}$	9/18	12/24	11/22	14/28	10/20
$CMS_{53}-CMS_{6i}$	9/18	6/12	7/14	10/20	8/16
$CMS_{54}-CMS_{6i}$	8/16	7/14	12/24	11/22	9/18
$CMS_{55}-CMS_{6i}$	24/48	19/38	23/46	22/44	20/40

TABLE 4. Service composition scheme based on Pareto solution set.

Serial number	Objective function value F_1	F_2	F_3	Bull's-eye distance	Sort
1	450.24	0.1273	0.7671	0.549016	3
2	449.07	0.1313	0.7680	0.558725	5
3	467.52	0.1352	0.7571	0.786182	6
4	472.66	0.1277	0.7600	0.796691	7
5	426.65	0.1309	0.7752	0.364683	1
6	423.27	0.1342	0.7699	0.383768	2
7	501.94	0.1276	0.7588	1.14336	9
8	445.69	0.1345	0.7627	0.556127	4
9	470.90	0.1320	0.7624	0.797649	8

0.032. After the above constraint parameters are brought into the model, the NSGA-II and the grey target decision-making method are used to solve the SCO model.

B. CASE SOLVING AND ANALYSIS

Under the above parameter settings, the NSGA-II is operated by python programming. The experimental environment of this paper is PyCharm 2021.3.2, windows 10, 2.40GHz CPU. The parameters of NSGA-II are set by consulting relevant literature and the characteristics of cloud manufacturing SCO problem. Among them, the initial population size of the algorithm is 100, the number of iterations is 300, the mutation probability is 0.1 and the crossover probability is 0.9.

After 300 iterations, the average fitness change trend of the cloud manufacturing SCO model is shown in Figure 6. Figure 6 (a) shows the iterative trend of QoS fitness value of the service demander, Figure 6 (b) shows the iterative trend of SUS fitness value of the platform operator, and Figure 6(c) shows the iterative trend of FP fitness value of the service provider. It can be seen from Figure 6 that after 20 iterations of the NSGA-II, the fitness values of the three objective functions have converged and are in a stable state.

The Pareto front obtained by NSGA-II is indicated in Figure 7, where F1 indicates the QoS value, F2 indicates the SUS value, F3 indicates the FP value of the service provider, and the points in the figure represent a service composition scheme. The Pareto front is uniformly distributed in the solution space and forms a hypersurface, which proves the diversity of solutions from the side.

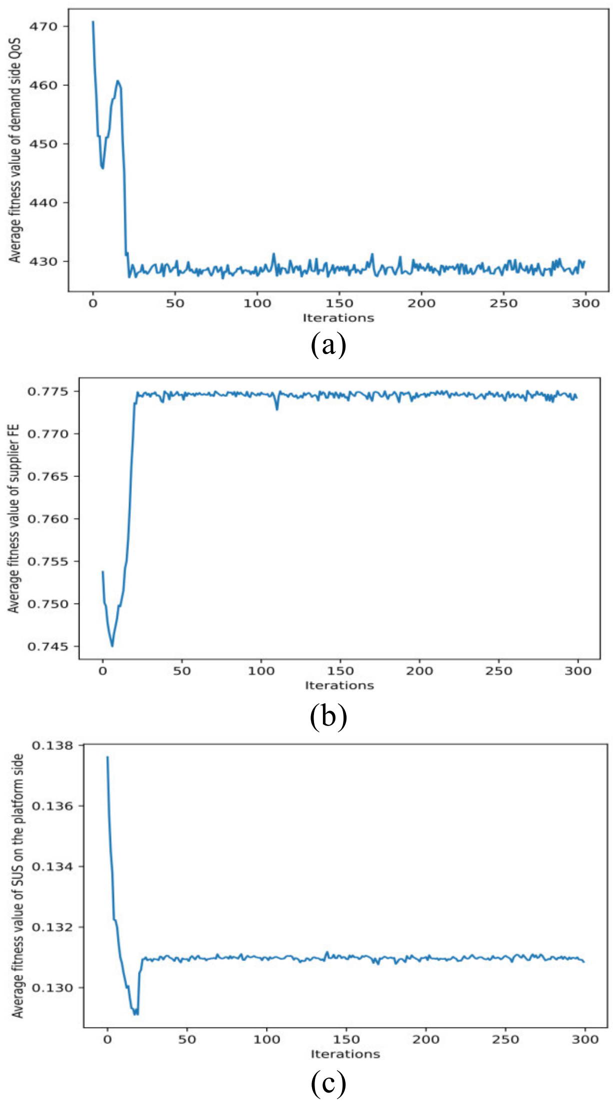

FIGURE 6. Fitness change trend of three objective functions based on multi-agent interests.

On the basis of the Pareto optimal set solved by NSGA-II and considering the interests of multiple agents, this paper uses the grey target decision-making method to select the optimal cycloidal gear manufacturing service composition scheme. The specific calculation results are indicated in Table 4. The optimal cycloidal gear manufacturing service composition scheme is [2, 3, 2, 5, 3, 2], that is, [CMS_{12}, CMS_{23}, CMS_{32}, CMS_{45}, CMS_{53}, CMS_{62}].

To verify the validity of the algorithm, this paper takes three agents as optimization objectives, and uses GA to solve the SCO problem. Then, compare and make decisions between the three results and the scheme obtained

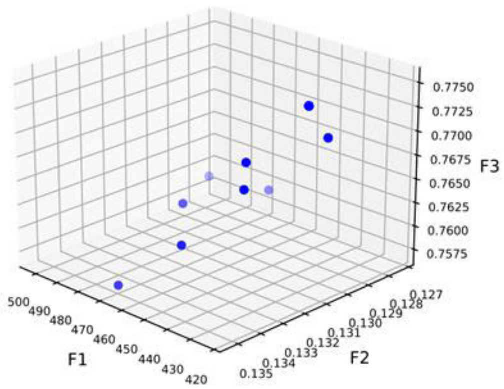

FIGURE 7. Pareto front diagram of NSGA-II algorithm.

TABLE 5. Comparison and analysis of algorithm results.

Method		Objective function value F_1	F_2	F_3	Bull's-eye distance	Sort
GA	QoS	408.62	0.1428	0.7469	0.560657	2
	SuS	480.11	0.1270	0.7644	0.889092	4
	FP	447.83	0.1379	0.7226	0.607560	3
NSGA-II		426.65	0.1309	0.7752	0.364684	1

by the above NSGA-II. The operation results are shown in Table 5.

From the point of view of the optimization objective, the scheme with QoS of service demander as the optimization objective is better than the scheme required by the NSGA-II in terms of objective function values F_1 and F_3. However, the scheme obtained by the NSGA-II is better on the objective function value F_2. The scheme with SuS of platform operator as the optimization objective is better than the scheme required by the NSGA-II in terms of objective function values F_2 and F_3. However, the scheme obtained by the NSGA-II is better on the objective function value F_1. The scheme with FP of service provider as the optimization objective is better than the scheme required by the NSGA-II in terms of objective function values F_3. However, the scheme obtained by the NSGA-II is better on the objective function value F_1 and F_2. Because when GA algorithm optimizes a single target, it will optimize it to the extreme, and when optimizing multiple targets at the same time, it is a trade-off between multiple targets, and the resulting solution is a compromise solution. At this time, the four schemes are in a non-dominated state, and the grey target method is used for decision-making. Through case analysis, it was found that the bull's-eye distance of the optimal solution obtained by the NSGA-II was shortened by 34.95%, 39.97%, and 58.98% compared to the genetic algorithm. The bulls-eye distance of the scheme obtained by the NSGA-II is smaller and better than the other three schemes. The above results prove the feasibility of the SCO model considering multi-agent interests and the effectiveness of NSGA-II and realize the management and effective utilization of service intelligent resources.

VI. CONCLUSION

Aiming at the cloud manufacturing SCO problem, this paper comprehensively considers the interests of cloud manufacturing multi-agent, and builds a multi-objective service composition model. In this model, the time decay function is introduced to avoid the influence of time dynamic changes of historical indicators of service resources. On this basis, this paper adopts the NSGA-II and the grey target decision-making method to solve the SCO model considering multi-agent interests. Finally, through case analysis, it was found that the bull's-eye distance of the optimal solution obtained by the NSGA-II was reduced by at least 34.95% compared to the genetic algorithm, verifying the feasibility of the optimization model and the effectiveness of the algorithm. In order to facilitate the establishment and solution of the SCO model, this paper makes some assumptions, which is somewhat different from the actual situation. In the next step, we will conduct in-depth and comprehensive research on the model to make it more relevant to the needs of actual service composition. At the same time, deep learning, machine learning and other methods will be integrated into the research of cloud manufacturing SCO to provide better service solutions for multi-agent in the cloud manufacturing environment.

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