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A Multidimensional Information Fusion-Based Matching Decision Method for Manufacturing Service Resource

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ABSTRACT With the development of specialization, coordination and intelligence in the manufacturing service process, the issue of how to quickly extract potential resources or capabilities for distributed manufacturing service requirements, and how to carry out resource matching for manufacturing service requirements with correlated mapping characteristics, have become the critical issues to be addressed in the cloud manufacturing environment. Through the combination of the characteristics of relevance, synergy and diversity of manufacturing service tasks on the intelligent cloud platform, a matching decision method for manufacturing service resources is proposed in this paper based on multidimensional information fusion. On the basis of integrating multidimensional information data in cloud manufacturing resource, the information entropy and rough set theory are applied to classify the importance of manufacturing service tasks, while the matching capability are analyzed by using a hybrid collaborative filtering (HCF) algorithm. Then, the information of function attribute, reliability and preference is employed to match and push manufacturing service resources or capabilities actively, so as to realize the matching decision of manufacturing service resources with precise quality, stable service and maximum efficiency. At last, a case study of resources matching decision for body & chassis manufacturing service in a new energy automobile enterprise is presented, in which the experimental results show that the proposed approach is more accuracy and effective compared with other different recommendation algorithms.

INDEX TERMS Manufacturing service, information fusion, hybrid collaborative filtering, resource matching.

I. INTRODUCTION

With the development of cloud computing, big data, ''Internet +'', Internet of things, artificial intelligence and other emerging technologies, the manufacturing industry has also changed from the previous single production model to a service-oriented, collaborative and intelligent cloud manufacturing model [1]. Based on big data, cloud manufacturing will not only improve production efficiency, but also generate new product and service models in addition to traditional products, open up new growth space, and redefine the operation mode and competitiveness of manufacturing industry [2].

Cloud manufacturing is a new model of networked and agile manufacturing based on knowledge, which supports customers to acquire resources and capability of manufacturing services in real time, and increases or decreases manufacturing resources dynamically and nimbly, then completes all kinds of process throughout the manufacturing life cycle intelligently [3]. For manufacturing applications and business operations on the virtual cloud manufacturing systems, the resources and capabilities required by customers come from the large scale manufacturing cloud pool. The manufacturing resources and capability are integrated by cloud

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manufacturing, and virtualized to customers in the form of services. In particular, on-requirement matching is the basic link to achieve the goal of cloud manufacturing services. That is, the resources and capability on the cloud manufacturing platform is searched and selected according to customer requirements. Therefore, how to select the most suitable resources from the cloud manufacturing service resource pool and match them to customers in an appropriate form to satisfy various requirements is a key issue in the research field of cloud manufacturing service [4].

From the previous research, the research on the cloud manufacturing service resource selection and optimal matching has made some achievements. However, there are two major challenges to be solved. One is the analysis of influencing factors for resource selection and matching, the other is resource matching methods of manufacturing service.

On one hand, analysis of influencing factors in the search and matching for manufacturing service resources, has evolved from a single item to multiple indicators gradually. Those influencing factors include product function, manufacturing and service quality, and so on. But most of them only consider single environment or element in the resource selection and optimization [5]. Zhang *et al.* proposed a Bayesian method based on time perception in a distributed manufacturing environment, for better recommendation effect of manufacturing service resources [6]. According to the importance of each part in collaborative assembly, Fei *et al.* presented a matching scheme through genetic optimization algorithm, which has a good effect on reducing the remaining number of parts [7]. Raj *et al.* applied an ant colony algorithm for selection and matching of products and services, and examples showed that using lower precision parts can obtain higher precision assemblies [8]. Based on service quality attributes, Yahyaoui *et al.* established a classification plan, using rough set theory to match the best Web service to users [9]. In order to solve the problem of on-requirement mutual selection of service providers and tasks in cloud manufacturing environment, Zhao *et al.* Established a task-resource bilateral matching model based on quality of service (QoS), and adopted cloud model and variable fuzzy recognition method for quantitative analysis and calculation [10]. Tursi *et al.* established an ontology-based service resource information system with product performance as the core, and a resource model with the service information system [11].

In order to obtain better resource matching effect, multiple influencing factors is analyzed and studied. For example, to reduce the information loss of function indicators, increase the controllable range of data measurement, and analyze the conditions that require interval fuzzy preference for resource decision, Bentkowsk *et al.* introduced interval numbers instead of real numbers for function indicators of resource requirement (power, size, etc.) [12]. Considering the ambiguity of qualitative indicators in the decision-making process for cloud resource selection and the difficulty of function indicators represented by interval measures, Liu *et al.* suggested a hybrid multi-index method of resource matching decision for cloud manufacturing based on OWA operator in uncertain environment [13], and proposed a QoS matching method of personalized clustering and reliable trust perception for resource recommendation in cloud manufacturing environment for personalized requirements [14]. The above results show that the influencing factors of cloud manufacturing resource matching are mainly distributed in unilateral aspects such as function, reliability. However, there are few studies that comprehensively consider these multiple influencing factors.

On the other hand, there is still the need for a detailed mapping relationship between manufacturing service resources and task requirement implementation in cloud environment. And the research mainly focuses on resource selection based on task characteristics at first [15], [16]. Jones presented an analysis method based on customer requirements for product services, and assisted designers in the design and improvement of service products by mining service product task characteristics [17]. Kotekar *et al.* proposed a clustering method for Web services based on task / function similarity using cat swarm optimization algorithm [18]. Shen *et al.* studied the agglomeration mechanism of cloud manufacturing resources and used the weight-based intuitionistic trapezoid fuzzy method to achieve the matching of required tasks and services [19]. According to the new characteristics of the relevance of manufacturing tasks and service synergy on cloud platform, Ren *et al.* proposed a two-side matching decision method for manufacturing tasks which takes into account learning and synergy, by using the expected utility theory and social network theory [20].

Subsequently, in order to improve the efficiency and effectiveness of matching, quick search method for manufacturing service resources is studied extensively. Schaefer et al proposed a keyword-based Web service matching method, and designed a binary algorithm solution model for maximum similarity [21]; Strunk *et al.* used semantic matching and genetic algorithms to find services that satisfy requirements [22]. Argoneto *et al.* adopted the cooperative game algorithm based on GaleShapley model and the fuzzy engine in resources searching, and verified the high efficiency of the matching method for cloud manufacturing capabilities. [23]. In addition, Armstrong *et al.* analyzed user task differences through K-means algorithm, determined the number of clusters within a certain range, and used evaluation criteria to obtain the optimal fast clustering results [24]. Yuan *et al.* proposed a recommendation method based on VSM and Bisecting K-means clustering in order to improve the uses personalized experience [25].

At the same time, the research of rapid resource matching by task ordering is also carried out gradually [26], [27]. PageRank et al proposed an importance ranking method that considers the efficiency relation between tasks and resource nodes [28], and the LeaderRank algorithm also considered the ordering correlation between tasks/resource nodes, so it is more suitable for fast matching [29].

In the above researches, most of them focus on the direct matching and selection of manufacturing service requirement and related resources under single influence factors or environmental conditions. Moreover, in the cloud manufacturing environment, research on the matching decision of manufacturing service resources and task sequencing simultaneously, is still rare [30]. In order to improve the matching decision accuracy between manufacturing service resources and tasks in the cloud environment, this paper takes into account the multiple influence factors in resource matching and constructs a multi-source information fusion model. And rough sets are proposed to sort the importance of manufacturing service task requirements for the rapid effectiveness of resource matching. On this basis, through the hybrid collaborative filtering method, reasonable matching and push of manufacturing service resources are achieved, and the results of other recommendation methods are compared and evaluated. In this paper, the importance of task identification of manufacturing service requirement is sorted, and the requirements of manufacturing service with functional characteristics, reliability, preference similarity and other influencing factors can be accurately matched, to push the potential resources of manufacturing service. Therefore, it has certain theoretical and practical significance to realize the accurate, rapid and effective matching decision of manufacturing service resources and task requirements in cloud environment.

The remainder of this paper is organized as follows: Section 2 presents a resource matching decision architecture of cloud manufacturing services based on multidimensional information fusion. Section 3 proposes a hybrid collaborative filtering algorithm based on rough sets to match and push the manufacturing service resources, and Section 4 presents the experiments and results based on the proposed approach. Finally, some conclusions of this paper and future work are drawn in Section 5.

II. THE RESOURCE MATCHING ARCHITECTURE OF MANUFACTURING SERVICES

In order to satisfy the initiative, timeliness and collaboration requirements of manufacturing services in the cloud environment, based on the description of cloud manufacturing service data, a manufacturing services resource matching architecture oriented multi-dimensional information fusion is proposed, so as to realize the use of resource library in cloud manufacturing environment. As a concrete form of manufacturing service resource matching decision, information fusion can accelerate the mining and utilization of resources in the cloud environment to realize the new cloud manufacturing service pattern.

A. MAIN COMPONENTS IN THE RESOURCES MATCHING ARCHITECTURE

In the decision-making process of manufacturing service resource matching in the cloud environment, the main goal of the proposed architecture is to analyze, divide and map task modules according to the manufacturing service requirements, select appropriate task resources and capabilities, match and push them to the manufacturing service customer requirement proactively. As manufacturing services are restricted by many requirements, the whole process of manufacturing service resource matching is a process of completing the expected tasks continuously. The decision process of manufacturing resource matching based on multidimensional information fusion can be defined as: a manufacturing service requirement or target is decomposed into specific tasks, and the matching and push of manufacturing service resources are realized by combining the information about the relationship between tasks and requirements. According to the matching results of manufacturing service tasks and resources, the corresponding manufacturing service activities are implemented. When a corresponding task changes, it is necessary to further select the collaborative resources, until a manufacturing service activities is completed. The resources matching architecture of the manufacturing service in the cloud manufacturing environment mainly consists of three parts: matching decision process, collaborative manufacturing service activities, application support modules (protocol library, algorithm library, database). The details of each part can be showed in Figure 1.

Figure 1 presents that the expected target of manufacturing service is decomposed into a series of manufacturing service subtasks according to the task decomposition rules in the protocol library. Using the matching decision algorithm in the algorithm library and multidimensional information such as task content and resource characteristics in the database, the matching manufacturing service resource is obtained. Then the manufacturing service resources receive subtasks and process collaboratively until the manufacturing service activity is completed.

B. MULTI-DIMENSIONAL INFORMATION IN CLOUD MANUFACTURING

The resources matching of cloud manufacturing service is to push the corresponding resource information from the resource database to the corresponding customers according to the task conditions defined in the initial stage. Prior to the decision-making of resources matching, those related multi-dimensional information is classified and explained.

(1) Requirements information of manufacturing services

The requirements information of manufacturing services are comprehensive details of manufacturing service resources and capabilities, considering the customer requirements of market forecasting, personalized customization, mass production, and other factors that affect the technical parameters of manufacturing services.

The requirements information for manufacturing service is comprehensive requirements detail of resources and capabilities, which is put forward by considering the customer requirements for market prediction, personalized customization, mass production, etc., and combining with various influencing factors such as manufacturing service technical

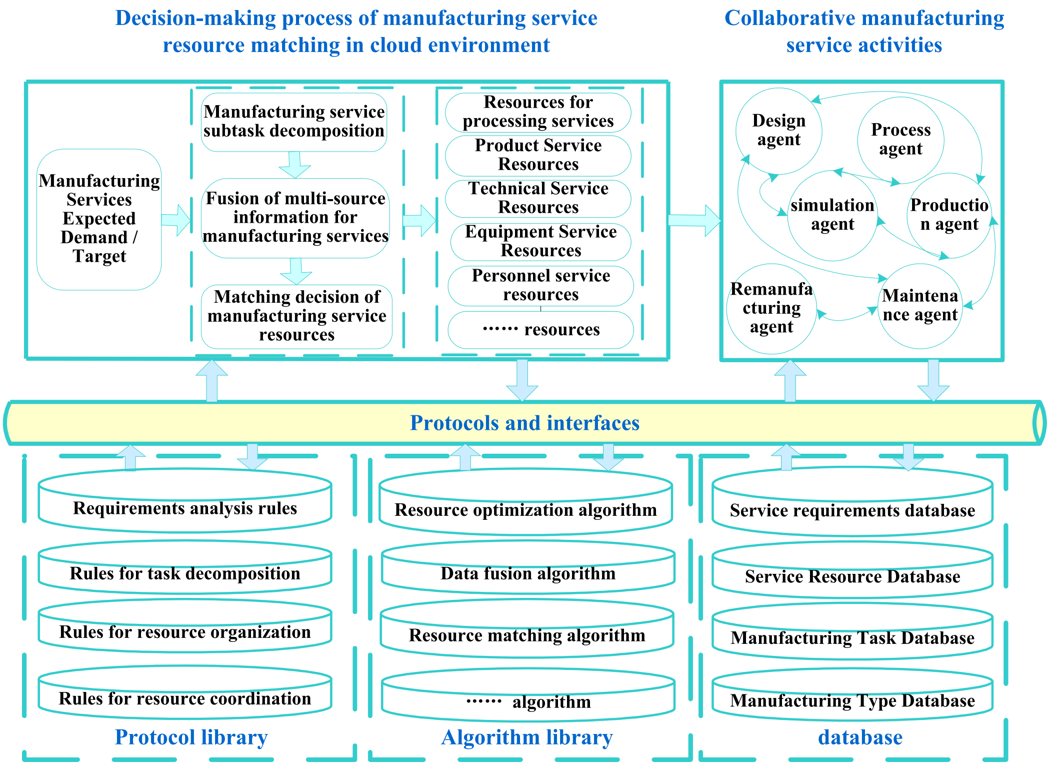

FIGURE 1. Resource matching architecture oriented multi-dimensional information fusion.

parameters. Its information structure can be described as follows:

CS = (CSI, CSB, CSD, CSN) is defined as requirement information of manufacturing service. Where CSI represents the identification number of the requirement, CSB is the product and service module to which the requirement belongs. CSD denotes domain knowledge, that is, information about the manufacturing services domain related to requirements. CSN describes specific manufacturing service requirements, such as manufacturing requirement content, service time requirements, manufacturing service conditions, and customer requirement preferences and so on.

(2) Task information of manufacturing services

Manufacturing service tasks, that is, in the initial phase of collaborative work, manufacturing service requirements or objectives are broken down into specific tasks or subtasks. According to the specific manufacturing service tasks, the requirements can be clearly defined. Meanwhile, task information of manufacturing service will be provided to the corresponding resources and capabilities.

PST = (PSTI, PSTC, PSTO, PSTD, PSTA) is defined as task information of manufacturing service. Where PSTI represents the identification number of the manufacturing service task, PSTC is the importance of the task (weight), PSTO denotes the manufacturing service object and the category to which it belongs, and the PSTD is the specific description of manufacturing service tasks. The PSTA describes ancillary conditions for the completion of manufacturing service tasks, such as task time constraints, workflow order, and so on.

(3) Resources information of manufacturing services

Manufacturing service resources are the collection of resources and capabilities in the cloud environment. According to the basic rules of requirement satisfaction and task ordering, resource or capability information is actively pushed to the manufacturing service customer requirement. Resource information of manufacturing service can be extracted from data such as capability qualifications, process parameters, design templates, and product examples.

PSR = (PSRI, PSRB, PSRS, PSRA, PSRD) is defined as resource information of manufacturing service. Where, PSRI represents the identification number of manufacturing service resource. PSRB describes the service category of manufacturing service resource, such as requirement analysis, planning and design, process structure, simulation and trial-production, production and manufacturing, logistics and warehousing, operation and maintenance, remanufacturing. PSRS is the description object of manufacturing service resource, that is, the resource information to solve a manufacturing service problem. PSRA describes the stored information of manufacturing service resources, including the ownership of resource. And PSRD is specific service content description, which can be design scheme, product parameters, production process, operation and maintenance methods, etc., or successful case of manufacturing service resources. Through the objective description of the resources information, the conflicts or constraints that may occur in manufacturing service could be solved.

(4) Characteristic information of manufacturing services

The characteristic information of manufacturing service is the collection of active factors that directly participates in the resource matching decision and the main basis for pushing matched resources to the manufacturing service requirement. The characteristics information of manufacturing services can be described in multiple dimensions such as QOS, operational effects, process, etc.

PSC = (PSCI, PSCB, PSCD) is defined as characteristic information of manufacturing service. Where PSRI represents the identification number of manufacturing service characteristic, PSRB describes the manufacture service type to which the resource belongs. PSRD is a specific description of the characteristics of manufacturing services, such as QOS, collaboration or coordination, efficiency, energy consumption and stability in operation; materials, time, cost and quality in the process, flexibility in production, environment, and so on.

(5) Professional information of manufacturing services

Professional information of manufacturing services is a data collection created by industry definitions or standards, which includes the division information of parts, assemblies, components, parts and assemblies, and information on general, specialized, intelligent devices by industry or size, information of general parts and special parts according to the production or processing standard division.

PSP = (PSPI, PSPB, PSPS, PSPD) is defined as professional information of manufacturing services. Where PSPI is the identification number of manufacturing service industry, PSPB refers to the category of manufacturing service industry, PSPS are subclasses of industry. For example, the industries belonging to the middle category in the special equipment include: mining and metallurgy, electronics and electrical machinery, and so on. And PSPD is a specific description of professional information for the manufacturing services.

In the cloud manufacturing environment, multi-dimensional information of manufacturing service resources is collected, analyzed, and pushed to obtain the matching of resources and tasks. Subsequently, the cloud manufacturing service tasks are completed together, based on actual experience. Through the analysis of multidimensional information for manufacturing services, an information fusion process of resources matching in cloud manufacturing environment is introduced.

C. INFORMATION FUSION PROCESS OF MANUFACTURING SERVICE IN CLOUD ENVIRONMENT

The multi-dimensional information fusion process, in which manufacturing service resources utilize available services and capabilities such as processing, product, technology and personnel to satisfy customer requirements continuously, is formulated as follow.

$$R_m = i \leftarrow \Theta\{T, I, S, N, E\} \tag{1}$$

where, R_m is defined as the manufacturing service requirement, and the target example of manufacturing service can be obtained from the customer requirement. i is an instance of manufacturing service resource. Θ refers to a process of matching decision-making for manufacturing service resources, T describes the manufacturing service target. I is the collaborative information, which is mainly composed of multidimensional information for manufacturing services. S denotes the condition that the constraint satisfies in the manufacturing service, N is the number of manufacturing services, and E represents the manufacturing service experience.

Based on the multi-dimensional information fusion model, the system actively matches and pushes manufacturing service resources, so as to reduce the difficulty and time for customers to obtain manufacturing services as much as possible, and to improve efficiency and effectiveness of manufacturing service resources in collaborative work.

III. RESOURCES MATCHING OF MANUFACTURING SERVICE

The processing and searching of a large number of multidimensional data presents challenges in cloud environment [31]. The Collaborative filtering is an important method to avoid invalid data search and obtain effective data in big data platform [32]. So the manufacturing service resources is matched and pushed by a hybrid collaborative filtering algorithm in this paper. In the context of rapid changes in personalized demand, the capabilities and quality requirements of cloud manufacturing service resources have also changed accordingly. Therefore, based on multidimensional information and characteristics of the manufacturing service resources in cloud, the matching influencing factors are divided into three aspects: functional domain, reliability, preference, so as to complete the comprehensive matching estimation of manufacturing service resources [6], [33].

A. MATCHING OF FUNCTION ATTRIBUTES

Assume there are n field concepts $\{r_j|1 \le j \le n\}$ of functional attribute for manufacturing services. And the associated set of manufacturing service resources u_a is expressed as $\{u_i|1 \le i \le l, a \notin [1, l]\}$, $s_{i,j}$ is represented as the matching degree between resource u_i and the field concepts r_j of functional attribute for manufacturing service. While I_i is described as a field concepts set of functional attribute for manufacturing service in known matching degree of u_i currently. At the same time I_a is the field concepts set of functional attribute in known matching degree of u_a. Then the matching degree $s_{a,j}$ of manufacturing service resource u_a and functional attribute r_j is given as follows:

$$s_{a,j} = \bar{s}_a + \sum_{i=1, r_j \in I_i}^{l} w(a, i)(s_{i,j} - \bar{s}_i) / \sum_{i=1}^{l} w(a, i) \tag{2}$$

where, $\bar{s}_i$ is the average value of the matching degree between the defined manufacturing service resources u_i and functional attributes.

$$\bar{s}_i = \sum_{r_j \in I_i} s_{i,j} / |I_i| \tag{3}$$

In the same way, $\bar{s}_a$ is the average value of the matching degree between the defined manufacturing service resources u_a and functional attributes. Meanwhile, $w(a, i)$ is the similarity between manufacturing service resources u_a and u_i which satisfy customer requirements in terms of functional attributes. $w(a, i)$ can be expressed as follow:

$$w(a, i) = \frac{\sum_{r_j \in I_a} (s_{a,j} - \bar{s}_a)(s_{i,j} - \bar{s}_i)}{\sqrt{\sum_{r_j \in I_a} (s_{a,j} - \bar{s}_a)^2 \sum_{r_j \in I_a} (s_{i,j} - \bar{s}_i)^2}} \tag{4}$$

If multiple functional attribute vectors need to be matched at the same time, the similarity $w_F(i, j)$ can be calculated using linear weighting. According to the difference between $w_F(i, j)$ and the actual data, whether to adjust the similarity weight is determined.

B. RELIABILITY MATCHING

During the reliability matching of manufacturing service resources, characteristic information of manufacturing service is mainly involved, which include the process credibility, the reliability of product or service quality, the timeliness of delivery and other factors. The calculation equation of similarity is consistent with the equation (4) in function attribute matching. So the reliability similarity $w_R(i, j)$ of the manufacturing service resources u_i and u_j to customer requirements is showed as follow.

$$w_R(i, j) = \alpha_1 w_{r1}(i, j) + \alpha_2 w_{r2}(i, j) + \alpha_3 w_{r3}(i, j) \tag{5}$$

where, α_1, α_2 and α_3 are the reliability regulation coefficients, and $\sum_{i=1}^{3} \alpha_i = 1$.

C. PREFERENCE SIMILARITY MATCHING

As the customer requirement include the preferences in innovation, cost control, energy conservation, emission reduction, efficiency optimization and so on, and the feature vector of preferences can be composed of 0 and 1. Jaccard is used to obtain the preferences similarity $w_p(i, j)$ of manufacturing service resources.

$$w_p(i, j) = Jaccard(g_i, g_j) = \frac{|g_i \cap g_j|}{||g_i \cup g_j||} \tag{6}$$

So the similarity matching between manufacturing service resources and customer preferences is showed as follow.

$$\begin{aligned} w_P(i, j) = {} & \beta_1 w_{p1}(i, j) \\ & + \beta_2 w_{p2}(i, j) + \beta_3 w_{p3}(i, j) + \beta_4 w_{p4}(i_i, j) \end{aligned} \tag{7}$$

where, β_i is the adjustment coefficient of preference similarity, and $\sum_{i=1}^{4} \beta_i = 1$.

D. COMPREHENSIVE SIMILARITY MATCHING

Similarly, a linear weighting function $w_C(i, j)$ is used to calculate the comprehensive similarity of manufacturing service resources in adjacent sets.

$$w_C(i, j) = \gamma_1 w_F(i, j) + \gamma_2 w_R(i, j) + \gamma_3 w_P(i, j) \tag{8}$$

where, γ_k is the adjustment coefficient of comprehensive similarity and $k \in 1, 2, 3$. The value of γ_k will affect the integrated similarity between manufacturing service resources. By adjusting the value of γ_k to observe the change in the integrated matching effect, the appropriate γ_k can be obtained when the matching effect is the best.

And the formula of selection and matching for manufacturing service resource is shown as follows.

$$P_{im} = \frac{\sum_{u_j \in U_i} w_C(i, j) \times P_{jm}}{\sum_{u_j \in U_i} w_C(i, j)} = \frac{\sum_{u_j \in U_i} \sum_{k=1}^{3} \gamma_k w_k(i, j) \times P_{jm}}{\sum_{u_j \in U_i} \sum_{k=1}^{3} \gamma_k w_k(i, j)} \tag{9}$$

The adjacent resources set of the manufacturing service resource u_i is expressed as $\{u_j | u_j \in U_i\}$, P_{jm} represents the result of resource u_j being selected by m-th customer. If u_j has been selected, P_{jm} is 1, otherwise is 0.

Through the integration of multi-dimensional information, such as function attribute, process credibility and service preference in matching decision of manufacturing service resource, the hybrid collaborative filtering algorithm is used for data analysis of manufacturing service resources. Then, the selection and matching of manufacturing service resources can be obtained by combining the customer's intention to the adjacent resources selection.

E. TASK IMPORTANCE-ORIENTED RESOURCE MATCHING DECISION OF MANUFACTURING SERVICE

In order to further improve the processing efficiency of multidimensional information, the order of manufacturing service tasks should be determined in advance on the basis of resource matching using collaborative filtering algorithm. Allow for rough set theory is a useful tool for dealing with uncertainty and ambiguity, which start from the description of a given problem, the inner law of the problem can be obtained through the approximation domain of the indistinguishable relation of the given problem. Meanwhile the defect can be overcome that the traditional methods of processing uncertain information often need prior knowledge or additional data [34]. The rough sets are used to rank the importance of manufacturing service subtasks, which can deal with the complexity of collaborative manufacturing service environment and the uncertainty of task information more effectively than the traditional methods such as genetic algorithm, analytic hierarchy process and fuzzy evaluation [35], [36].

Definition 1: A quad $S = (U, A, V, f)$ is an information system, of which $U \neq \phi$ is known as domain; A represents a Non-empty finite set of all attributes, using $V = \bigcup_{a \in A} V_a$; V_a

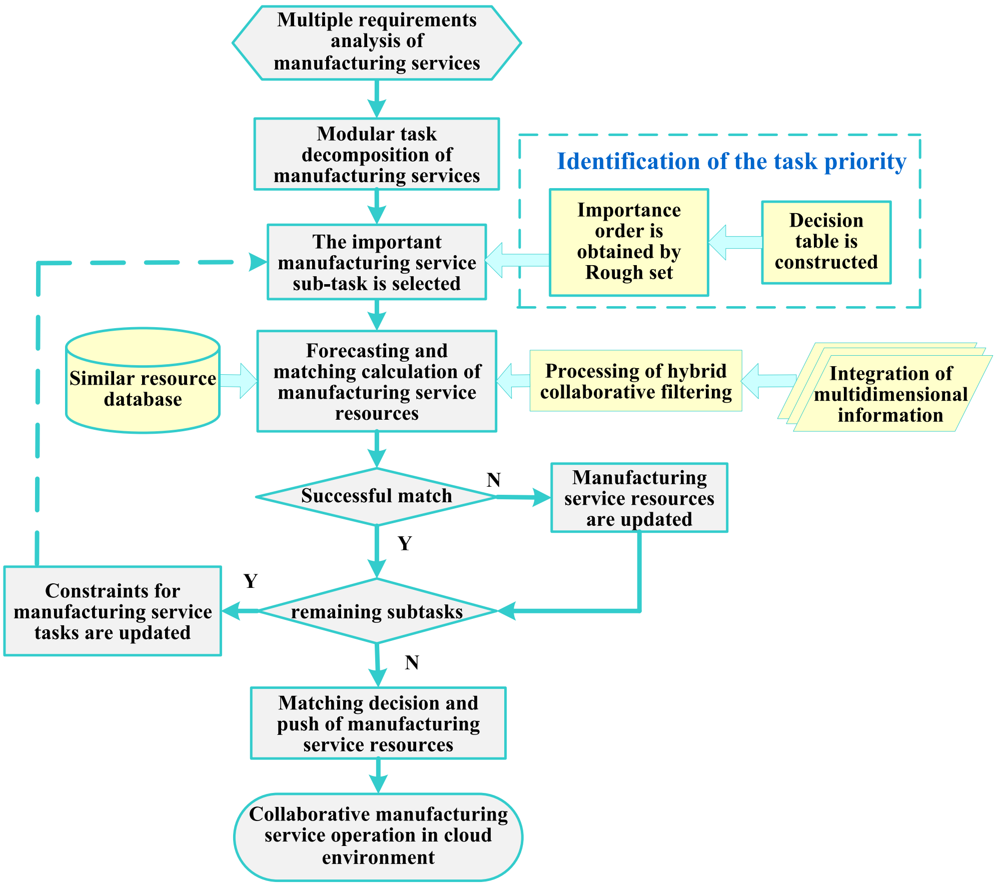

FIGURE 2. Task importance-oriented manufacturing service resource matching decision.

is range of attribute a; f represents an information function of $U \times A \to V$, which assigns an information value to each attribute of each object.

Definition 2: A binary equivalence relation $IND(B)$ is determined by each attribute subset $B \subseteq A$:

$$IND(B) = \{(x, y) \subset U \times U | \forall a \in A, f(x, a) = f(y, a)\} \quad (10)$$

Definition 3: Equivalence relation $IND(B)$ constitutes a division of U, while $B \subseteq A$, expressed by $U/IND(B) = \{X_1, X_2, \ldots, X_n\}$. Where, X_i represent different equivalence classes, which form an equivalence class with all indistinguishable objects in case of $IND(B)$, denoted as $[x]_{IND(B)}$.

Definition 4: If $a \in A$, and $IND(B) \neq IND(A - \{a\})$, a is necessary in A; otherwise a is redundant.

Definition 5: $H(P)$ is the information entropy of attribute subset $P \subseteq A$, which can be obtained by the following function:

$$P(X_i) = \frac{|X_i|}{|U|}, \quad i = 1, 2, \ldots, m \quad (11)$$

$$H(P) = -\sum_{i=1}^{m} P(X_i) InP(X_i) \quad (12)$$

In which, $U/IND(P) = \{X_1, X_2, \ldots, X_m\}$ and $P(X_i) = \frac{|X_i|}{|U|}$, $i = 1, 2, \ldots, m$.

Definition 6: $S_A(a)$ is used to express the important of attribute which in $a \in A$, given as follows:

$$S_A(a) = |H(A) - H(A - \{a\})| \quad (13)$$

If $S_A(a) > 0$, then $a \in A$ is necessary in A. If $S_A(a) = 0$, then a is redundant.

Then the process of resource matching decision and collaborative data push based on manufacturing service task importance is shown in figure 2, which mainly includes the following six steps:

Step 1: On the basis of the previous multidimensional data collection and analysis, the information fusion is applied to identify and determine the influence degree of each task on the whole manufacturing service.

Step 2: Through the analysis of customer‘s requirements, the manufacturing service requirements are decomposed into each subtask by combining with the multiple manufacturing service objectives. Subtasks should have an appropriate granularity, which can be decomposed from the product level, component level, part level and process level layer by layer [37].

Step 3: Using the calculation of rough set theory, the priority of importance is obtained. Then the subtask of manufacturing service with large influence degree is selected, and the

TABLE 1. Attribute table of resource matching decision based on multidimensional information fusion.

	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}	E_{11}	E_{12}	E_{13}	…	E_{27}	E_{28}
C_1	1	1	2	1	3	3	2	1	1	2	1	1	1	…	1	1
C_2	1	1	1	1	1	1	1	2	2	1	2	2	1	…	2	2
C_3	2	1	1	2	2	1	1	1	1	1	2	2	1	…	2	2
C_4	1	1	1	1	1	1	2	2	2	2	1	1	2	…	2	1
C_5	2	2	1	2	2	2	2	2	2	2	2	2	1	…	2	1
C_6	1	1	1	2	2	1	3	3	2	3	2	2	1	…	3	1
C_7	1	1	1	2	2	1	3	3	2	3	2	2	1	…	3	1
C_8	1	1	1	1	2	1	2	2	2	1	1	2	1	…	2	1
D	1	1	2	1	3	3	2	1	1	2	2	1	2	…	2	1

multivariate matching decision or push is implemented based on the data of the manufacturing service resource base.

Step 4: Whether a matching decision succeeds is judged. If it is successful, turn to (5), and then make the matching decision between the next task and the resource. Otherwise, the manufacturing service resources are updated, and matching decisions of manufacturing service subtasks in this round is made. Meantime the matching data of manufacturing service resources is supplemented, and the multivariate matching decision and push are re-conducted, and then turned (5).

Step 5: Whether there are any remaining tasks to be judged. If so, combined with the requirement conditions of multivariate matching decision mentioned above, the constraint conditions of the existing task are updated turning to (3). Otherwise turn (6).

Step 6: Then the matching decisions and active push of manufacturing service resources are obtained, and manufacturing service tasks are completed to satisfy customers' multiple requirements for manufacturing services in the cloud environment.

IV. CASE STUDY AND RESULTS ANALYSIS

In this section, a matching decision of manufacturing service resource in a new energy automobile was toke as a case. Considering the new energy automobile enterprise has mastered one of the core technologies for new energy: vehicle controller technology, which needs to form a cooperative relationship with a number of resources in the cloud manufacturing platform to cooperatively complete the multiple tasks such as vehicle manufacturing and service of a new car at the same time.

A. PRIORITY RANKING OF MANUFACTURING SERVICE TASKS

According to the specific manufacturing service tasks proposed by new energy automobile enterprises, the order of task importance was obtained using rough set theory, which could accelerate manufacturing service activities in the cloud environment. In this case, using the actual business data of the enterprise, the manufacturing service requirements are decomposed into 8 subtasks according to the product level: battery research and development, car chassis manufacturing services, products and services of motor drive systems, braking energy recovery system (BER), anti-lock braking system (ABS), products and services of both inside and outside decoration, electronic stability program (ESP), vehicle intelligent information processing system, etc., which denoted as $C_1, C_2, C_3 \cdots C_8$, respectively.

For discussing importance of each subtask, the definitions are given as below.

A quad $S = (U, A, V, f)$ is defined as a decision information system in manufacturing service tasks. Where, $E \neq \phi$ is domain, and A is a nonempty finite set for decision attributes identification. In a general way, $A = C \cup D$, $C \cap D = \phi$, where C is called a conditional attribute, and D is decision attribute.

Meanwhile the task descriptions in the solutions provided by the previous 28 resources of cloud manufacturing service are selected and denoted as $E_1, E_2, E_3 \cdots E_{28}$ to calculate the importance of manufacturing service subtasks. And the manufacturing services effect of each solution is divided into very consistent, consistent, non-compliant, with described as $D = (D_1, D_2, D_3)$. Where, $D_1 = 3, D_2 = 2, D_3 = 1$.

In combination with the multidimensional information set of manufacturing service, the conditional attribute indexes are R&D period, service quality, manufacturing cost, production quality, functional attribute, preference satisfaction, reliability, credibility, etc. All conditional attribute values are discretized. According to the certain discrete rules, the conditional attribute values are converted into graded values, which are classified into three levels, and the three levels correspond to 3, 2, 1. Thus, the values of the conditional attribute and the decision attribute in 28 solutions are obtained, as shown in table 1.

TABLE 2. Importance degree of conditional attributes in matching decisions for manufacturing service resources.

Conditional Attribute	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
Importance Degree	0.107	0.071	---	0.071	---	---	---	0.036

Based on the table 1, the dependence of decision attribute D to condition attribute C can is defined, represented by $\gamma C_i(D)$. There is dependence between D and C, and the dependency indicates the proportion of equivalence instance to all instances in the decision system, which can be correctly divided into equivalence classes about C, using information of condition attribute C. And the dependence is expressed as a coefficient $\gamma C_i(D)$:

$$\gamma C_i(D) = \frac{card(posC_i(D))}{card(E)} \tag{14}$$

where, the cardinality of set is represented by $card(\cdot)$.

And the importance degree of attribute C is solved. The importance degree of conditional attribute $C_i(C_i \in C)$ can be understood as the matching degree of change in decision making, removing attribute C_i from the conditional attributes. The greater the change, the more important the attribute is. The calculation equation for importance degree of the attribute C is:

$$Sig(C_i = \gamma C(D) - \gamma(C - C_i)(D) \tag{15}$$

Then the importance degree is normalized. The importance factor is obtained by normalizing the importance degree of attributes. ω_i is the importance degree of the i-th condition attribute, show as below:

$$\omega_i = \frac{Sig(C_i)}{\sum_{i=1}^{n} Sig(C_i)} \tag{16}$$

So the operation results can be awarded using equation (14-16), which include:

$$card(E) = 28,$$
$$card(posC(D)) = 28,$$
$$\gamma C(D) = \frac{card(posC(D))}{card(E)} = \frac{28}{28} = 1.$$

While the importance degree of each attribute is shown in table 2:

After the above calculation, the importance degree of 8 subtasks in the matching decision of manufacturing service resources was obtained. Among them, battery R&D and manufacturing, body and chassis manufacturing services, braking energy recovery system are more important, and motor drive system and other tasks are second. According to the importance of subtasks and specific requirements of subtasks, such as functional attribute requirements, cost information, system maintenance services, and so on, the matching and push of resources in cloud manufacturing services could be implemented.

B. MATCHING AND PUSH OF CLOUD MANUFACTURING SERVICE RESOURCES

Considering the greater importance of body and chassis, suitable vehicle chassis resources of the manufacturing service is matched and pushed, using historical data such as the cooperation effect and evaluation of previous manufacturing service resources. Relevant data were collected on the website of "Cloud Service Innovation Platform for High-end Equipment Manufacturing". The hybrid filtering algorithm and multi-dimensional information of manufacturing service resources proposed in this paper was used in related operations, among which the similarity calculation is a key step of hybrid collaborative filtering. In the similarity calculation, the subtasks of the body and chassis are broken down into modules such as the frame, suspension, transmission, steering system, brake at the component level. And the similarity calculation is carried out from three aspects of multi-dimensional information: functional attributes, reliability, and preference matching. Moreover, the classification and utility information of each resource are shown in table 3:

In the selecting and matching of resources, website related data were used, and positive feedback behavior and weighting rules were adopted: inquiry = 1, negotiation = 1, purchase = 4. At the same time, the collected data were denoised and normalized to obtain behavior statistics of requirement & resource. During the similarity degree matching, the information weight of basic function, reliability, cost was assigned to 0.5 according to the customer experience, and the other matching weights of the same kind were equally distributed. Then the each weight of comprehensive similarity degree matching was the same and recorded as $\gamma_1 = \gamma_2 = \gamma_3 = 0.33$. Using the hybrid collaborative filtering algorithm, the results of comprehensive similarity degree matching are obtained and shown as "$\surd$" in table 4.

In order to verify the effectiveness of the proposed matching and recommendation method, the data set of the existing manufacturing service platform was used to compare with other recommended methods. Typically, the indicator such as *f*-measure is used to judge the matching effect, which is determined by both precision rate and recall rate. Among them, the precision rate indicates the accuracy, and the high precision rate shows the high accuracy of the matched objects. And the recall rate is based on the coverage of recommended results. A large recall rate indicates a high coverage ratio of the matched objects. The matching effect degree is comprehensively expressed by *f*-measure. The larger F value is, the better the comprehensive matching effect will be. The

TABLE 3. The classification and utility information of manufacturing service resource.

	Functional Attributes			Information Of Cost (Yuan)			Preference Of Risk (Point)			Reliability (%)		
	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
Frame	Side Rail Type	Side Rail Type	Side Rail Type	26000	28000	27000	1200	1280	1250	72%	71%	70%
	Backbone Type	Backbone Type	Backbone Type	30100	29000	29500	1230	1100	1260	73%	69%	70%
Suspension	Leaf Spring Type	Leaf Spring Type	Leaf Spring Type	11000	11500	12200	780	790	785	90%	88%	86%
	Gas Spring Type	Gas Spring Type	Gas Spring Type	10500	11800	10000	775	795	770	91%	93%	86%
Transmission	Drive	Drive	Drive	4370	4830	4800	480	500	495	99%	97%	96%
	Single Speed	Single Speed	Single Speed	4500	4790	4400	485	490	470	98%	99%	95%
Steering System	Electronic Type	Electronic Type	Electronic Type	9400	9300	9490	720	710	725	79%	78%	70%
	Electrodynamic Type	Electrodynamic Type	Electrodynamic Type	9640	9500	9520	750	740	735	76%	77%	77%
Brake	Disc	Disc	Disc	1150	1138	1145	95	95	95	98%	99%	99%
	Drum	Drum	Drum	1100	1260	1370	85	100	108	99%	99%	98%

TABLE 4. Matching and predicting of manufacturing service resources.

	Frame		Suspension		Transmission		Steering System		Brake	
	Side Rail Type	Backbone Type	Leaf Spring Type	Gas Spring Type	Drive	Single Speed	Electronic Type	Electrodynamic Type	Disc	Drum
R1	√		√	√			√		√	
R2		√			√					
R3						√		√		√

equation for F is showed as follow [38].

$$Precision = \frac{1}{m} \times \sum_{i=1}^{m} \frac{|R_i \cap L_i|}{|L_i|} \tag{17}$$

$$Recall = \frac{1}{m} \times \sum_{i=1}^{m} \frac{|R_i \cap L_i|}{|R_i|} \tag{18}$$

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{19}$$

Among them, $|R_i \cap L_i|$ means the number of tasks that resource u_i is recommended to customer C_i and that customer C_i does use resource u_i to accomplish. $|L_i|$ represents the number of tasks for recommendation resources u_i, $|R_i|$ is the number of tasks that the customer actually adopts the resources, m is the resources number of recommendation. Then the values comparison of P and R in different algorithms are shown in figure 3 and figure 4 separately. The different algorithms included: Item CF, User CF, Vector Space Model(VSM) K-means clustering, VSM and Bisecting K-means clustering, Cosine- CF, Pearson Correlation Coefficient –CF, Adjusted Cosine-CF, Rough Set-CF and so on. As shown in Figure 3 and 4, our approach achieves P value of higher accuracy and R value of higher coverage compare with other matching and recommendation methods. Meanwhile, in Figure 5, we can find that the F value of comprehensive matching effect is relatively high in the approach.

In the case, the adjustment coefficients are selected with an interval of 0.2 and gradually increased from 0 to 1. The length N of tasks recommended list is gradually increased from 10 to 30 at intervals of 5. As can be seen from figure 5, the effectiveness range of the optimal recommendation is basically the same as that of other current recommendation methods [39]–[41].

Using F values, the hybrid-CF based on RS (RS-CF) method was compared with other recommendation algorithms, such as traditional text-based collaborative filtering, user-based collaborative filtering and so on. Figure 3 shows

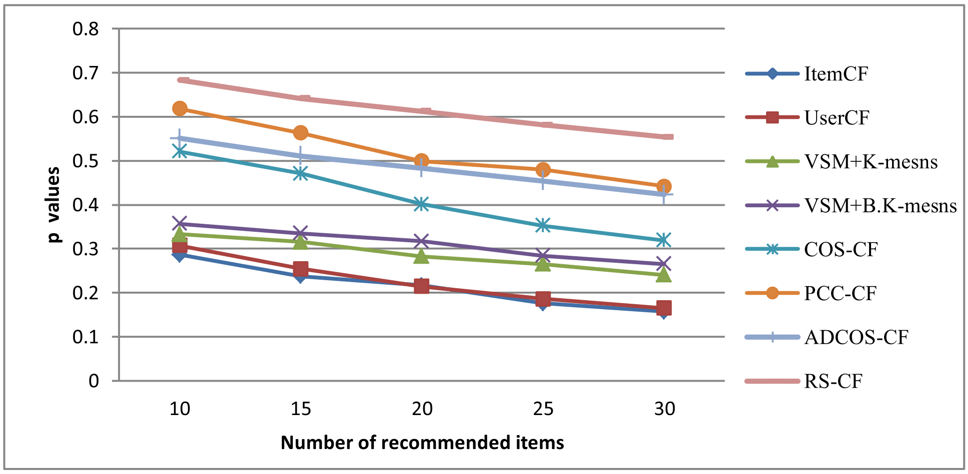

FIGURE 3. Comparison of *P* values for different recommendation algorithms.

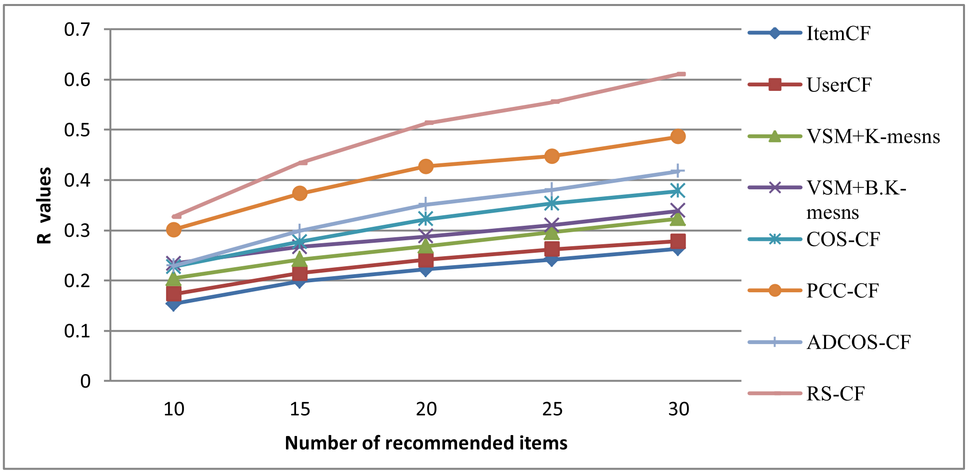

FIGURE 4. Comparison of *R* values for different recommendation algorithms.

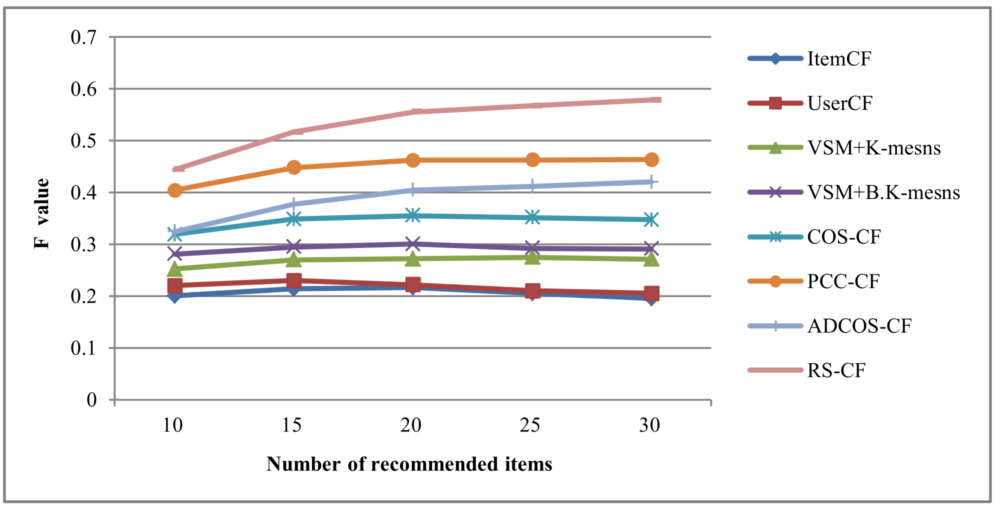

FIGURE 5. Comparison of *F* values for different recommendation algorithms.

the comparison results. It can be seen that the F value of the hybrid collaborative filtering algorithm proposed in this paper increases faster, indicating that the matching effect of this method is better, which is more conducive to the rapid identification and push of manufacturing service resources reasonably and effectively.

V. CONCLUSION

In this paper, the resource matching decision framework is constructed in the cloud manufacturing environment, and the multivariate information of manufacturing service tasks, requirements, resources, characteristics, specialties, etc., is analyzed. Then a manufacturing service resource matching decision method based on multidimensional information fusion is proposed, which includes: the rough set theory is used for dynamic analysis and the importance ranking of manufacturing service tasks. Taking advantage of the similarity degree of manufacturing service resources, the hybrid collaborative filtering algorithm is used to recommend and push manufacturing service resources, so as to complete the matching decision task of manufacturing service resources. Subsequently, the rationality and effectiveness of the proposed method are verified, by analyzing a case of matching decision of body and chassis manufacturing service resources in a new energy automobile enterprise. At the same time, compared with other recommendation algorithms, the matching effect of this method is proved to be superior. In the future work, the different effects of multidimensional information on resource matching decision in collaborative manufacturing service are further analyzed. In addition, the selection and optimization of different adjustment coefficients in the hybrid collaborative filtering algorithm, as well as the influence and correlation of the matching results, which is generated by the number of recommended projects and the number of adjacent similar projects, are also deeply studied.

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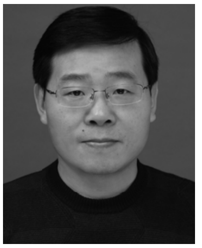

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