Hindawi
Mathematical Problems in Engineering
Volume 2018, Article ID 8346859, 14 pages
https://doi.org/10.1155/2018/8346859

Research Article

A New Service Module Partition Approach for Product Service System Based on Fuzzy Graph and Dempster-Shafer Theory of Evidence

Zhen Yin,[1,2] Qi Gao,[1,2] and Xue Ji[1,2]

[1] *School of Mechanical Engineering, Shandong University, Jinan 250061, China*
[2] *Key Laboratory of High Efficiency and Clean Mechanical Manufacture, Shandong University, Jinan 250061, China*

Correspondence should be addressed to Qi Gao; gaoqi@sdu.edu.cn

Received 4 February 2018; Accepted 31 May 2018; Published 27 June 2018

Academic Editor: Peide Liu

Due to the personalized and diverse service needs, service scheme configuration should be more quick and flexible in the process of product service system (PSS) scheme design. Service modularization can effectively improve the service configuration efficiency and modules' reusability. However, compared with the modularity of tangible products, the partition of service modules in the practical context is still a problem to be discussed. In this paper, a service partition approach for PSS based on the fuzzy graph and Dempster-Shafer theory of evidence is presented. Firstly, service activities correlation analysis is carried out, according to which the fuzzy graph is drawn. By setting different thresholds, the fuzzy graph is cut, and different partition results are obtained. Secondly, the evaluation indexes of customization, generalization, and technological evolution are proposed and used as evidence sources of the Dempster-Shafer theory of evidence. Through the synthesis of the evidence sources, the optimal partition scheme is got. Finally, to verify the method, a case study is illustrated through the NC machine tools module partition. And results show that the proposed method can provide specific ideas and concrete guidance of the service module partition.

1. Introduction

The global economy is transitioning from the product economy to the service economy. Service has gradually become the core value of the entire economy. Manufacturing is also undergoing profound changes. Manufacturing companies have begun to change from traditional manufacturing to service-oriented type. Manufacturing enterprises are no longer merely producers of physical products, but also providers of additional services [1]. Instead of selling products, enterprises provide a total solution consisting of both products and services, namely, the product service system (PSS), which provide them with the greatest value. The first definition of PSS combining sustainability was given by Mont [2]: "a system consists of products, services, organizer network and support facilities, designed to be competitive to meet customer needs and reduce the environmental influences compared to traditional business models."

In service-oriented manufacturing mode, customers' needs for product services have become diversified and personalized. The intense market competition drives companies to provide more types of products and services to meet customers' needs [3]. Modular design is a key technology that emerges under this situation. It emphasizes the low correlation between modules, so that the modules can be designed independently. Each module has one or more specific functions and the discrete function modules can be reorganized to provide customers with various functions [4]. Therefore, the reasonable partition of modules is the basis and key to modular design. From the perspective of manufacturing companies, this paper studies the partition of service modules to solve the problems faced by enterprises when they provide product services to customers, with diverse and constantly changing demands.

When addressing the service module partition problem, the goal of manufacturing companies is to provide product services at low cost and high quality to meet the diverse and constantly changing needs of customers. In order to better meet the diversified needs of customers and win praise

from customers, the companies should be able to provide customization services. Besides, in the fierce market competition, manufacturing companies can only survive by providing low-cost product services, which requires the companies to continuously reduce the cost of service configuration and operation. If service modules have certain commonality, the reconfiguration of the modules can be effectively avoided, thereby the service cost can be reduced. In order to ensure that the provided services are difficult to be imitated by competitors, to form technical barriers, and to maintain the competitiveness of enterprises, it is necessary for the companies to maintain advanced product service quality and to upgrade and improve their services constantly. Therefore, for the service module partition problem, this paper puts forward three indexes of customization, generalization, and technological evolution to evaluate the service module partition results.

The main structure of this paper is organized as follows: Section 2 is literature review. Section 3 briefly introduces the service module partition method based on the fuzzy graph. Section 4 explains the suggested scheme evaluation process based on the Dempster-Shafer theory of evidence. Then, Section 5 illustrates the proposed approach by a case study of NC machine tools service modularization. Section 6 shows the results of the methods and discussions of the results. Section 7 concludes the paper and discusses its contributions as well as limitations.

2. Literature Review

Many scholars have conducted a lot of research in the module partition. The heuristic method, structure matrix method, fuzzy clustering method, and other technologies have been applied in module partition process one after another, which promotes the development and application of module partition.

The heuristic method mainly adopts various heuristic algorithms to obtain the optimal or approximate solution of a specific objective function based on some module driving forces. These algorithms include genetic algorithms [6] and group genetic algorithms [7]; Chang et al. [8] applied design structure matrix (DSM) based on the modular concept to group different design parts together to obtain optimized module efficiency. The module partition method based on heuristic algorithm and structure matrix needs quantified information model, which is not applicable to complex service module partition with uncertain information, and there is a problem of excessive calculation with increasing service complexity.

In the fuzzy clustering method research, the fuzzy clustering method mainly uses some standard tools to represent the interdependencies among the components and then divides them by the corresponding clustering method. Aurich et al. [9] gave the modular guidelines for technical product service system and summarized a guide book on modular design and manufacture of product service system; Pekkarinen and Ulkuniemi [10] developed a modular service platform model for business services. They showed how business service providers could draw up and deliver new services cost-effectively and flexibly through modularization; Yu et al. [11] developed a modular design method based on fuzzy graph to achieve environment-oriented design strategies. In the module partition process, multiple objectives within the product life cycle are comprehensively considered; Moon et al. [12] developed a service ontology capture and design knowledge reuse method in service class integration through object-oriented concept and philosophical approach. They built the service process model by using the graphical model to describe the function sequence in bank service. Through the integration of house of quality and modularization logic, Lin, Pekkarinen, and Ulkuniemi [13] developed a design framework based on quality function deployment, which can help enterprises provide high quality and diversified logistic services; Wang et al. [14] studied the relationships between physical product and service. They proposed the PSS module development method by using quality function deployment and group technology; Geum, Kwak, and Park [15] proposed a service modularization framework based on an improved house of quality. They implemented the partition of service modules based on model-driven and interdependent approaches. Li et al. [16] presented the principle of PSS module partition by analyzing the relationship between product and service, product module and service module. They proposed a three-stage module group process, including "top-down" and "bottom-up" service module partition process, "top-down" product module partition method, and modularization method based on quality function deployment and mapping matrix; Carlborg and Kindström [17] introduced service modularization into the development and deployment of services; it can meet the diverse needs of customers; Li et al. [18] made use of the weighted complex network to modularize the products and systems. Song et al. [19] suggested the correlation evaluation indexes between the service components. They used figures to represent the relationship between elements and applied the fuzzy graph to visualize the relationship between service components intuitively.

Although the fuzzy clustering method adapts to the uncertainty of complex service information and can easily establish a corresponding mathematical evaluation model, there are still some shortcomings in dealing with basic problems. Details are as follows: (1) With regard to the determination of the weight of attribute indicators in the process of module partition, most studies lack deep and systematic analysis on the influence of the intrinsic association and coupling between attribute indexes, which leads to the insufficient scientificity and objectivity of the weight determination result. (2) With regard to the model of module partition, the existing research methods mostly adopt the traditional evaluation model, that is, simply weighted adding the evaluation index value, but ignoring the interaction between different indexes such as gain, impairment, and overlap. Therefore, a perfect module partition model should consider the interaction comprehensively. (3) Regarding the integration of decision-making opinions among program evaluation experts, the existing research is mainly to add the evaluation value of each expert linearly after assigning weight to them and then perform optimization based on

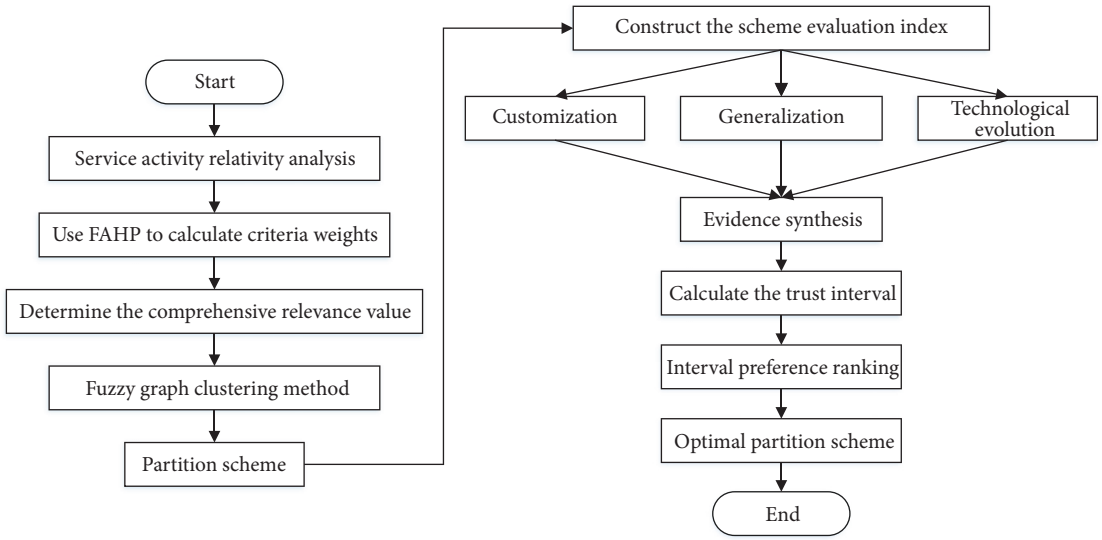

Figure 1: Service module partition process.

the evaluation value of module partition scheme. Due to the differences in background and knowledge level between experts, the traditional decision-making method will lead to difference and conflict of expert opinion and lack the corresponding mediation mechanism, which is contrary to the coordination of group decision-making.

In order to solve the above problems, this paper proposes a service module partition method for product service system based on fuzzy graph and Dempster-Shafer theory of evidence. Firstly, in order to effectively solve the ambiguity and uncertainty existing in the process of determining the attribute index value and its weight, the attribute index is evaluated by using interval-form rough number, and the weight of the attribute index is confirmed by analytic hierarchy process. Secondly, taking into account the nonlinear interaction between the evaluation indexes and the differences of evaluation values given by different experts, the Dempster-Shafer theory of evidence is used to fuse and obtain a coordinated ranking result. Finally, the feasibility and effectiveness of the proposed theory and method are verified by application cases. The whole research idea is illustrated in Figure 1.

3. Module Partition Methodology

3.1. Service Activity Correlation Analysis. Service module is a function-independent abstract entity of tangible or intangible service. It realizes service function through interaction between physical module and service process. The service module is composed of many service activities. The relation between them is complex and will affect the result of service module partition. That is the reason why the interdependence between these service activities needs to be analyzed at first when creating service modules. Therefore, in the process of service module partition in product service system oriented to customer needs, it is necessary to take into account the resource input of the service process and the output of

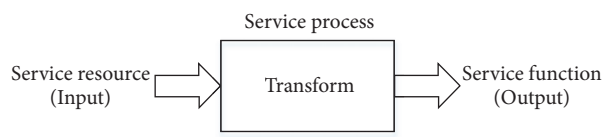

Figure 2: Service implementation process.

service functions in addition to considering the class of service activities. That means the appropriate description of the interaction between service activities requires the comprehensive consideration of the class, process, function, and resource of service activities. The service implementation process is shown in Figure 2.

In the process of service modularization, there must be some particular classification criteria as a guide to divide the related service activities into a service module accurately. We divide the relevance of service activities into function correlation, resource correlation, class correlation, and process correlation and establish an index evaluation system of service activity correlation, which includes function correlation index D_1, resource correlation index D_2, class correlation index D_3, and process correlation index D_4.

3.1.1. Service Activity Function Correlation. In the service modularization process, service activities with similar or related functions are clustered together to form a service module. The functional interdependency of service activities is called functional relevance [19]. The functional relevance indexes are assigned according to the functional relevance of the service activities. Table 1 provides the evaluation criteria of service activity functional relevance. For example, machine fault diagnosis and remote fault diagnosis are two service activities that are essential for implementing the service function of fault diagnosis. Therefore, their functional correlation strength R^f is assigned as 1.

Table 1: Service activity function relevance [5].

Relevant degree	Function relevance description	Assignment R^f
Very strong	The two service activities are indispensable to realize the same function.	1
Strong	The application of one service activity has a strong influence on the implementation of the other service activity.	0.75
Medium	The application of one service activity has an impact on the implementation of the other service activity.	0.5
Weak	The application of one service activity has a weak influence on the implementation of the other service activity.	0.25
None	There is no functional relationship between the two service activities.	0

Table 2: Service activity resource relevance.

Relevant degree	Resource relevance description	Assignment R^r
Very strong	The resource-sharing relationship of the two service activities is very strong.	1
Strong	The resource-sharing relationship of the two service activities is strong.	0.75
Medium	The resource-sharing relationship of the two service activities is medium.	0.5
Weak	The resource-sharing relationship of the two service activities is weak.	0.25
None	The resource-sharing relationship of the two service activities is none.	0

Table 3: Service activity class relevance.

Relevant degree	Class relevance description	Assignment R^c
Very strong	The class-based interdependency of two service activities is very strong.	1
Strong	The class-based interdependency of two service activities is strong.	0.75
Medium	The class-based interdependency of two service activities is medium.	0.5
Weak	The class-based interdependency of two service activities is weak.	0.25
None	The class-based interdependency of two service activities is none.	0

3.1.2. Service Activity Resource Correlation. If two service activities share the same service resource, they are interdependent on resources. For example, service engineers are a kind of human resource shared by product maintenance activities and fault diagnosis activities. Therefore, the relation between product maintenance and fault diagnosis can be regarded as resource-based interdependence. Service resource is the core element of service function implementation. There are three types of service resources: software system (such as machine fault diagnosis system), hardware system (such as error detection tool), and human resources (such as testing engineer) [19]. Table 2 gives the resource relevance evaluation criteria.

3.1.3. Service Activity Class Correlation. Class is an abstract collection of tangible substances or intangible concepts that have the same attributes. Service activity class relevance refers to the same or similar attributes (functions or characteristics) of different service activities. For example, machine tool temperature test and machine vibration and noise test belong to performance testing class, because these two service activities have the property of performance test. Table 3 gives the relevance evaluation criteria. For example, the transmission error detection and the positioning error detection have common features of error detection, so the class relevance assignment of the two service activities is set to 1.

Table 4: Service activity process relevance.

Relevant degree	Process relevant description	Assignment R^p
Very strong	The process-based interdependency of two service activities is very strong.	1
Strong	The process-based interdependency of two service activities is strong.	0.75
Medium	The process-based interdependency of two service activities is medium.	0.5
Weak	The process-based interdependency of two service activities is weak.	0.25
None	The process-based interdependency of two service activities is none.	0

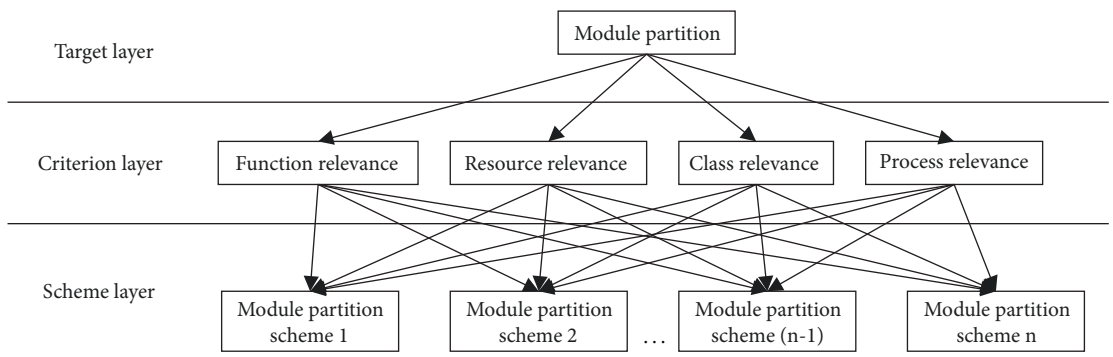

Figure 3: Module partition hierarchical structure model.

3.1.4. Service Activity Process Correlation. In PSS, the interaction of service activities is mainly reflected in the conveying of material and information and the transformation of knowledge or skills between service participants. The conveying of material, information, and knowledge constitutes the service flow of PSS. If the output of one service activity is used as input by another service activity, these two service activities are considered to be interdependence based on service flows [19]. Table 4 gives the process relevance evaluation criteria.

The correlation matrix R is obtained by calculating the correlation between service activities. R_{ij} is the general relevance between service activities and can be calculated by

$$R_{ij} = \begin{cases} w_f R_{ij}^f + w_r R_{ij}^r + w_c R_{ij}^c + w_p R_{ij}^p & i \neq j \\ 1, & i = j \end{cases} \quad (1)$$

where R_{ij}^f, R_{ij}^r, R_{ij}^c, and R_{ij}^p are assignments of function relevance, resource relevance, class relevance, and process relevance, respectively. w_f, w_r, w_c, and w_p are weight coefficients of function, resource, class, and process correlation criteria. i, j are service activity labels. The four weight coefficients satisfy the following equation:

$$w_f + w_r + w_c + w_p = 1 \quad (2)$$

3.2. Criterion Weight Calculation. The weight coefficient reflects the importance of different relevant indicators in the decision-making process. It directly relates to the accuracy of correlation matrix R. The hierarchical analysis method is used to construct the two pairs of corresponding judgment matrix, which eliminates the ambiguity of subjective evaluation. Therefore, the triangular fuzzy number is utilized to improve the fuzzy analytic hierarchy process (FAHP) to obtain the index weights, which are more in line with the expert experience and application background.

Step 1 (create a hierarchical model). The problem of module partition is divided into three layers: the top layer is the target layer, the middle layer is the criterion layer, and the bottom layer is the scheme layer. The module partition hierarchical structure model is shown in Figure 3.

Step 2 (construct the fuzzy judgment matrix). Assume the criterion layer element is $D_1, D_2 \cdots D_n$; $i, j = 1, 2, \ldots, n$. The decision-makers determine which is more important through comparing the two criteria. They get the judgment matrix $A = (a_{ij})_{n\times n}$ through assigning the importance degree to the scale value according to Table 5. a_{ij} represents the importance degree of criterion D_i relative to D_j. The evaluation matrix has the following properties:

(1) $a_{ij} > 0$
(2) $a_{ji} = 1/a_{ij}$
(3) $a_{ii} = 1, a_{jj} = 1$

In the assessment model established by the analytic hierarchy process (AHP), the comparison standard a_{ij} represents the relative importance of i and j in criterion layer. Since the psychological limit of distinguishing differences is 7 ± 2,

Table 5: Comparing scales and their implication.

Scale a_{ij}	Implication
1	Two criteria: a_i and a_j, they are equally important.
3	Two criteria: a_i and a_j, the former is slightly more important than the latter.
5	Two criteria: a_i and a_j, the former is obviously more important than the latter.
7	Two criteria: a_i and a_j, the former is strongly more important than the latter.
9	Two criteria: a_i and a_j, the former is absolutely more important than the latter.
2, 4, 6, 8	Intermediate values of the above adjacent scales.

Table 6: Random consistency index.

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49

experts generally take 1-9 and their reciprocals as the value of a_{ij} when comparing the relative difference between two objects. The median of the above values 2, 4, 6, 8 and their reciprocals can also be taken.

Experts compare and evaluate the four indexes under the principle of module independence according to their experiences. The comparison scale is translated into a triangular fuzzy number M_{ij}, which is expressed as (l_k, m_k, u_k). l_k is the lower bound of the fuzzy number while u_k is the upper bound. m_k is the value of the fuzzy number when the membership degree is 1. i and j are criterion labels. The 4×4 groups of fuzzy numbers are synthesized by using the following equation:

$$\mathrm{M_{ij}} = \left(\frac{\sum_{p=1}^{k} l_p}{k}, \frac{\sum_{p=1}^{k} m_p}{k}, \frac{\sum_{p=1}^{k} u_p}{k} \right) \tag{3}$$

Then, the triangular fuzzy number is translated into a certain value by using the graded mean integration method. It is shown in the following equation:

$$P(M) = \frac{l + 4m + u}{6} \tag{4}$$

Step 3 (check the consistency of the judgment matrix). Because the decision matrix may contain contradiction of critical analysis, the consistency test is carried out to ensure that the inconsistency of evaluation matrix is within an acceptable range. The consistency check formula proposed by Professor Saaty is illustrated with the following equation:

$$\begin{aligned} \lambda_{\max} &\approx \frac{1}{n} \sum_{i=1}^{n} \frac{\sum_{j=1}^{n} a_{ij} W_j}{W_i} \\ CI &= \frac{(\lambda_{\max} - n)}{n} - 1 \\ CR &= \frac{CI}{RI} \end{aligned} \tag{5}$$

where $\lambda_{\max}$ is the maximum eigenvalue of the evaluation matrix and RI is the random consistency index, which depends on the dimension of the judgment matrix and is obtained by Table 6. If $CR \geq 0.1$, the judgment matrix cannot pass the consistency test and the matrix should be improved until $CR < 0.1$.

Step 4 (calculate the weight of each evaluation index). The square root method is utilized to derive the weight coefficient of each index in the judgment matrix that has passed the consistency test. It is shown in the following equation:

$$\begin{aligned} W_i &= \left(\prod_{j=1}^{n} a_{ij} \right)^{1/n} \\ W_i^0 &= \frac{W_i}{\sum_i W_i} \end{aligned} \tag{6}$$

where W_i is the weight vector of evaluation indexes and W_i^0 is the normalized weight vector of the evaluation indexes.

3.3. Module Partition Methods. The fuzzy graph is a weighted graph, proposed by Rosenfeld [21]. It is a mathematical tool that can well represent the binary relationship between various service activities. It consists of fuzzy vertex sets and fuzzy edge sets. Although there are many ways to express the relationship between service activities, the fuzzy tree map can more clearly express service activities than other expressions due to the large number of service activities and the complex relationship between them. Service activities can be represented by fuzzy vertices, and the correlation between service activities can be represented by fuzzy edges. The connected edge of the fuzzy graph is a value within [0, 1], which represents the connectivity of this edge.

Based on fuzzy mathematics theory, the fuzzy graph clustering algorithm can classify things by analyzing the fuzzy similarity relation according to the characteristics, affinity, and the similarity of stuff. It can simplify the complex interactive relationship between service activities effectively. It can also express the relationship between service activities intuitively, which is convenient for designer to gather service activities into the service modules.

The mathematical model of fuzzy tree is $G = (V, R^*)$, and V is the node-set, representing the core service activities. R^* is the fuzzy relation between service activities according to the correlation matrix R. If $E = \{e = v_i v_j \mid R^*(v_i, v_j) > 0; v_i, v_j \in V\}$, $G^* = (V, E)$ is the core diagram of $G = (V, R^*)$. Service activity comprehensive correlation index R_{ij} is assigned to the

corresponding edge of G, respectively, and $w(v_i v_j) = R_{ij}$ $(i \neq j)$.

$$\sum_{e \in E(T')} w(e) \leq \sum_{e \in E(T)} w(e) \tag{7}$$

T is a spanning tree of G. If all spanning trees T' of G satisfy (7), T is the largest spanning tree of G. Through setting a different threshold α, the edges of $w(e) < \alpha$ are truncated, and the partition schemes can be got with the granularity of α. α is the partition coefficient of the correlation between service activities.

The construction and cutting approach of the maximum spanning tree is described as follows.

Step 1. Service activities are taken as the vertices of the graph, and n service activities correspond to n vertices, denoted as A_i $(1 \leq i \leq n)$.

Step 2. The comprehensive relevance R_{ij} between any two service activities A_i and A_j connects the corresponding vertices of A_i and A_j to form an edge $A_i A_j$.

Step 3. The comprehensive relevance value R_{ij} $(1 \leq i, j \leq n)$ is sorted through the largest to the smallest, in which $R_{ij}^1 > R_{ij}^2 > \cdots > R_{ij}^k > \cdots > R_{ij}^h$. R_{ij}^k $(k = 1, 2, \ldots, \mathrm{h})$ is the integrated correlation value of two service activities. h is the number of different integrated correlation values.

Step 4. In the absence of intersection, connect the service nodes with the maximum correlation value R_{ij}, and mark the comprehensive correlation value of the corresponding edge. If a loop can emerge in the process of connecting two service activity nodes, do not connect them.

Step 5. Repeat the previous step for integrated correlation values $R_{ij}^2, R_{ij}^3, \ldots, R_{ij}^h$ until all service activities' nodes are connected, then obtain the maximum spanning tree T.

Step 6. Assign different thresholds α according to the correlation value R_{ij}^k of the edge of the maximum spanning tree T. The edges are cut off where the comprehensive correlation value is less than α. Then, the partition schemes under different threshold levels are obtained.

4. Module Partition Evaluation Methodology

During the cutting process, the threshold α is defined as the module granularity factor ($\alpha \in [\alpha_{\min}, 1]$), which is proportional to the number of modules divided. According to the module granularity factor α, the service activities are divided into the scheme set $B = \{B_k,\ k = 1, 2, \ldots, n\}$. The optimal module partition granularity is obtained through the evaluation of different schemes.

4.1. Scheme Evaluation Indexes. The evaluation indexes of PSS service modularization are set up based on customization, generalization, and technological evolution. These indexes can evaluate the partition schemes from three different aspects, and the optimal partition scheme will satisfy the actual demands.

4.1.1. Customization. Customization is a kind of personalized service, and it can adjust service activities according to the needs of customers. Through the change of service activities' parameters, service activities are rapidly configured in the services to meet the multilevel and multipurpose clients' personalized needs.

4.1.2. Generalization. Generalization is a form that you can choose and determine service activities with functional interchangeability in mutually independent services. The service activities have a standardized form that can be utilized in other service modules. Generalization can maximize the range of application of service activity, thus reducing the overall cost.

4.1.3. Technological Evolution. Technological evolution reflects the technical upgrading of service activities. With the continuous development of technology, the requirement of technical content of service activities is continually improving. The constant technological evolution can improve service quality and better meet the needs of customers.

4.2. Scheme Evaluation Methods. Module partition scheme evaluation is not only a multiattribute index evaluation process, but also a group collaborative decision-making activity. In the evaluation process, it is often difficult for experts to agree on the ranking results of schemes evaluation because the experts have different industry backgrounds and preferences, and their professional capabilities and knowledge levels are also different. The general strategy of the existing research is to give experts the corresponding weight according to their status. The group's evaluation value of a scheme is obtained by summing the products of each expert's evaluation value and the corresponding expert's weight. It can be seen that the traditional weighted summation model is difficult to accurately and vividly portray the divergence of different expert in decision-making.

The Dempster-Shafer theory of evidence was born in the 1960s. Dempster [22] proposed the concept of set-valued mapping and defined the upper and lower probabilities. Subsequently, Shafer [23] reinterpreted the upper and lower probabilities of the reliability function and created the "Mathematical Theory of Evidence." The Dempster-Shafer theory of evidence has a systematic theoretical knowledge. It can eliminate the uncertainty and ambiguity caused by randomness during the decision-making process. It is good at reconciling conflict problems and can gather different evidence harmoniously. It is widely used in decision-making fields for its advantages in dealing with inconsistent and conflicting information because of its better flexibility and harmonization. Therefore, the Dempster-Shafer theory of evidence is used to integrate the evaluation of different experts on module partition scheme, so as to achieve the purpose of promoting group compromise and coordination decision.

Table 7: Fuzzy evaluation matrix.

	D_1	D_2	D_3	D_4
D_1	(1, 1, 1)	(4, 5, 6)	(2.33, 3.33, 4.33)	(2.33, 3.33, 4.33)
D_2	(0.17, 0.21, 0.26)	(1, 1, 1)	(0.22, 0.28, 0.39)	(0.26, 0.36, 0.61)
D_3	(0.25, 0.34, 0.58)	(2.67, 3.67, 4.67)	(1, 1, 1)	(0.53, 0.94, 1.5)
D_4	(0.23, 0.31, 0.44)	(2, 3, 4)	(1.11, 1.83, 2.67)	(1, 1, 1)

It is a recognized evidence synthesis approach, which can be used for the practical synthesis of customization, generalization, and technological evolution. Also, the Dempster-Shafer theory of evidence can deal with uncertain and unknown decision-making problems without prior probabilities. The main steps of applying the Dempster-Shafer theory of evidence are as follows.

Step 1. Transform the evidence sources of each scheme B_k into the fundamental utility preference values under the Dempster-Shafer theory of evidence. All focal values of a decision attribute C_j are B_k ($k = 1, 2, \ldots, \mathrm{t}$, $\mathrm{t} < 2^{\Theta}$), and Θ is the identification framework. The preference degree of all focal values of the attributes $m_j(B_k)$ is expressed as in the following equations:

$$P(B_k) = w_j b_j \tag{8}$$

$$m_j(B_k) = \frac{P(B_k)}{\sum_k P(B_k)} \tag{9}$$

where w_j is the importance weight of the jth evidence source and b_j the quantitative value of the jth evidence.

Step 2 (evidence synthesis). Assume that E_1, E_2, and E_3 are three pieces of evidence under the identification framework Θ, and the corresponding basic probability distribution functions are $m_1(U_h)$, $m_2(V_i)$, and $m_3(W_j)$. m is the orthogonal sum of m_1, m_2, and m_3, denoted as $m_1 \oplus m_2 \oplus m_3$. If the conflict factor $K \geq 1$, the orthogonal sum $m_1 \oplus m_2 \oplus m_3$ does not exist. Its combination rules are presented in the following equation:

$$K = \sum_{U_h \cap V_i \cap W_j = \varnothing} m_1(U_h)\, m_2(V_i)\, m_3(W_j) \tag{10}$$

$$m(B_k) = \begin{cases} \dfrac{\sum_{U_h \cap V_i \cap W_j = B_k} m_1(U_h)\, m_2(V_i)\, m_3(W_j)}{1-K}, & \forall B_k \subset \Theta,\ B_k \neq \varnothing \\ 0, & B_k = \varnothing \end{cases} \tag{11}$$

where $1/(1-K)$ is the regularization factor and U_h, V_i, and W_j are the focal values of m_1, m_2 and m_3, respectively.

Step 3 (interval preference sequence). Decision-making schemes are sorted based on the interval preference sequence method to obtain the optimal granularity of PSS service modules. T is the confidence degree of B_k and $T = B_f(B_k)$; N is the false trust level of B_k and $N = P_f(B_k)$. Thus, the uncertain interval is obtained by using the following equations:

$$B_f(B_k) = \sum_{Y \subseteq B_k} m(Y), \quad \forall B_k, Y \subseteq \Theta \tag{12}$$

$$P_f(B_k) = \sum_{Y \cap B_k \neq \varnothing} m(Y), \quad \forall B_k, Y \subseteq \Theta \tag{13}$$

For the two interval numbers $[a_1, a_2]$ and $[b_1, b_2]$, preference degree for $a > b$ is defined as in the following equation:

$$P(a > b) = \frac{\max(0, a_2 - b_1) - \max(0, a_1 - b_2)}{(a_2 - a_1) + (b_2 - b_1)} \tag{14}$$

If $P(a > b) > 0.5$, interval a is better than interval b. So scheme a is better than scheme b, recorded as $a \succ b$. If $P(a > b) = 0.5$, there is no difference between the intervals a and b, recorded as $a \sim b$. Similarly, if $P(a > b) < 0.5$, interval a is inferior to interval b. So the scheme a is inferior to scheme b, recorded as $a \prec b$.

5. Case Study

For manufacturing industry, NC machine tools are critical. With complicated structures, they need high-quality technical support and professional services during operation and maintenance. Also, different customers have different service requirements. To better provide services and meet different customers' needs, we can provide high-quality service in a modular way [24]. The software MATLAB® 2009a is used to perform the calculations in the process of verification.

5.1. Service Activities Identification. To obtain service activities accurately, we investigated the NC machine tools enterprises. According to the investigation results, we ultimately summarized 29 service activities, numbered by $S_1, S_2, S_3, \ldots, S_{28}, S_{29}$ from top to bottom, as shown in Figure 4.

5.2. Service Module Partition. Elements in one service module are highly interdependent, but different modules have different characteristics. Therefore, the premise of efficient module partition is a clear description of the relationships between service activities. The concrete steps are as follows.

Step 1 (calculate correlation index weights). The comparison of any two indexes is carried out by three experts according to the principle of module independence. Firstly, the values and their corresponding fuzzy upper and lower bounds are confirmed when the membership degree is 1 according to Table 5. Then, the fuzzy evaluation matrix is constructed depending on (3), as shown in Table 7.

Table 8: Relevance matrix **R**.

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	…	S_{24}	S_{25}	S_{26}	S_{27}	S_{28}	S_{29}
S_1	1.000	0.740	0.641	0.601	0	0.212	0.212	…	0	0	0	0	0	0
S_2		1.000	0.740	0.601	0	0.212	0.670	…	0	0	0	0	0	0
S_3			1.000	0.740	0	0.212	0.212	…	0	0	0	0	0	0
S_4				1.000	0.500	0.500	0.212	…	0	0	0	0	0	0
S_5					1.000	0.344	0	…	0	0	0	0	0.429	0.429
S_6						1.000	0.473	…	0.152	0	0	0	0	0
S_7							1.000	…	0	0	0	0	0	0
…								…	…	…	…	…	…	…
S_{24}									1.000	0	0	0	0	0
S_{25}										1.000	0	0	0	0
S_{26}											1.000	0	0.030	0.030
S_{27}												1.000	0.740	0.030
S_{28}													1.000	0.740
S_{29}														1.000

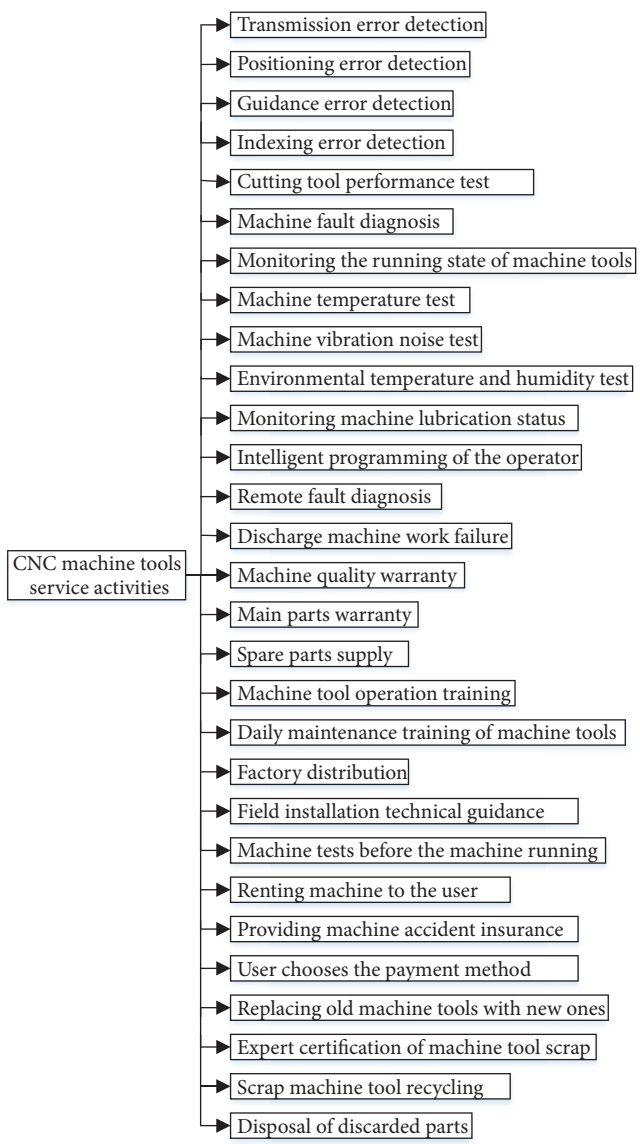

Figure 4: Service activity structure tree.

$\lambda_{\max} = 4.136$, RI = 0.89, CI = 0.045, CR = 0.051 < 0.1, and the fuzzy evaluation matrix passed the consistency check. Finally, the weight vector of indexes was $w_1 = [0.506, 0.202, 0.075, 0.217]$.

Step 2. The correlation between service activities are calculated by (1). The basic service activities correlation matrix is shown in Table 8.

Step 3. The maximum spanning tree of the service activities is constructed according to the fuzzy graph method, as shown in Figure 5.

When α takes different values, the maximum spanning tree is truncated to obtain the module partition scheme set $B = \{B_k,\ k = 1, 2, \ldots, n\}$, as shown in Table 9.

5.3. Partition Scheme Verifications. The hierarchical structure for the schemes evaluation is presented in Figure 6.

The experts use the linguistic variables shown in Table 10 to evaluate the schemes with respect to each index (customization, generalization, and technological evolution) and present them in Table 11.

These linguistic evaluations from experts are converted into triangular fuzzy numbers to construct the fuzzy schemes evaluation matrix shown in Table 12.

The experts convert the fuzzy schemes evaluation matrix into crisp values with (4) and carry out the normalization process shown in Table 13.

The weight vector of customization, generalization, and technological evolution was $w_2 = [0.35, 0.4, 0.25]$ according to the characteristics of machine tools industry and experts' experience. The primary utility distribution value of each focal element is computed using (8) and (9).

$$m_1(B_1) = 0.1735,$$

$$m_1(B_2) = 0.1517,$$

$$m_1(B_3) = 0.1651,$$

$$m_1(B_4) = 0.1800,$$

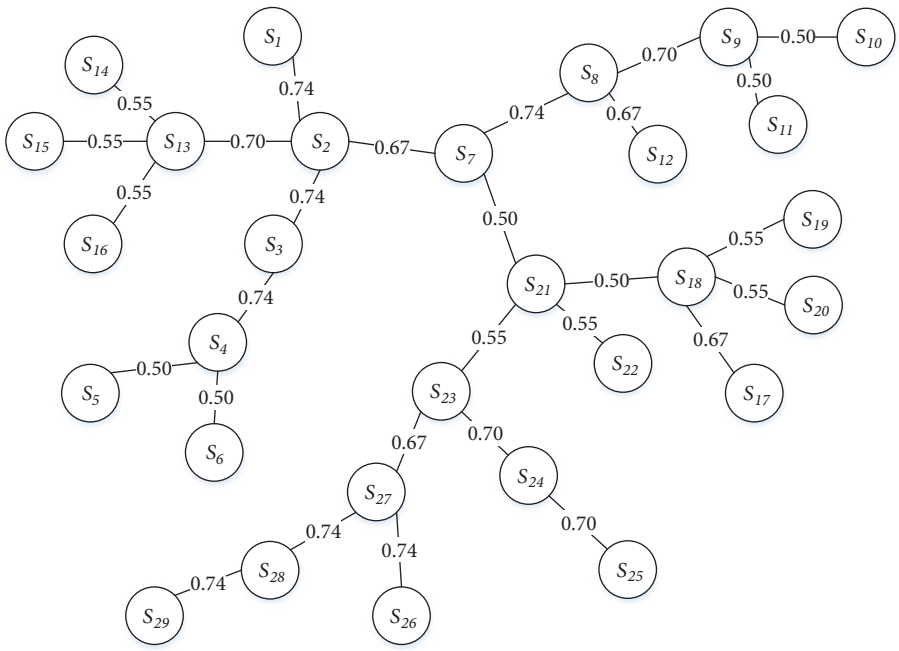

Figure 5: Service activity maximum spanning tree.

Table 9: Service activity partition scheme.

No.	Threshold α	Partition result
Scheme B_1	1	$\{S_1\}$, $\{S_2\}$, $\{S_3\}$, $\{S_4\}$, $\{S_5\}$, $\{S_6\}$, $\{S_7\}$, $\{S_8\}$, $\{S_9\}$, $\{S_{10}\}$, $\{S_{11}\}$, $\{S_{12}\}$, $\{S_{13}\}$, $\{S_{14}\}$, $\{S_{15}\}$, $\{S_{16}\}$, $\{S_{17}\}$, $\{S_{18}\}$, $\{S_{19}\}$, $\{S_{20}\}$, $\{S_{21}\}$, $\{S_{22}\}$, $\{S_{23}\}$, $\{S_{24}\}$, $\{S_{25}\}$, $\{S_{26}\}$, $\{S_{27}\}$, $\{S_{28}\}$, $\{S_{29}\}$
Scheme B_2	0.74	$\{S_1, S_2, S_3, S_4\}$, $\{S_5\}$, $\{S_6\}$, $\{S_7, S_8\}$, $\{S_9\}$, $\{S_{10}\}$, $\{S_{11}\}$, $\{S_{12}\}$, $\{S_{13}\}$, $\{S_{14}\}$, $\{S_{15}\}$, $\{S_{16}\}$, $\{S_{17}\}$, $\{S_{18}\}$, $\{S_{19}\}$, $\{S_{20}\}$, $\{S_{21}\}$, $\{S_{22}\}$, $\{S_{23}\}$, $\{S_{24}\}$, $\{S_{25}\}$, $\{S_{26}, S_{27}, S_{28}, S_{29}\}$
Scheme B_3	0.70	$\{S_1, S_2, S_3, S_4, S_{13}\}$, $\{S_5\}$, $\{S_6\}$, $\{S_7, S_8, S_9\}$, $\{S_{10}\}$, $\{S_{11}\}$, $\{S_{12}\}$, $\{S_{14}\}$, $\{S_{15}\}$, $\{S_{16}\}$, $\{S_{17}\}$, $\{S_{18}\}$, $\{S_{19}\}$, $\{S_{20}\}$, $\{S_{21}\}$, $\{S_{22}\}$, $\{S_{23}, S_{24}, S_{25}\}$, $\{S_{26}, S_{27}, S_{28}, S_{29}\}$
Scheme B_4	0.67	$\{S_1, S_2, S_3, S_4, S_5, S_6, S_{13}, S_{14}, S_{15}, S_{16}\}$, $\{S_7, S_8, S_9, S_{10}, S_{11}\}$, $\{S_{12}\}$, $\{S_{17}\}$, $\{S_{18}, S_{19}, S_{20}, S_{21}, S_{22}, S_{23}, S_{24}, S_{25}\}$, $\{S_{26}, S_{27}, S_{28}, S_{29}\}$
Scheme B_5	0.55	$\{S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, S_9, S_{12}, S_{13}, S_{14}, S_{15}, S_{16}\}$, $\{S_{10}\}$, $\{S_{11}\}$, $\{S_{17}, S_{18}, S_{19}, S_{20}\}$, $\{S_{21}, S_{22}, S_{23}, S_{24}, S_{25}, S_{26}, S_{27}, S_{28}, S_{29}\}$
Scheme B_6	0.50	$\{S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, S_9, S_{10}, S_{11}, S_{12}, S_{13}, S_{14}, S_{15}, S_{16}, S_{17}, S_{18}, S_{19}, S_{20}, S_{21}, S_{22}, S_{23}, S_{24}, S_{25}, S_{26}, S_{27}, S_{28}, S_{29}\}$

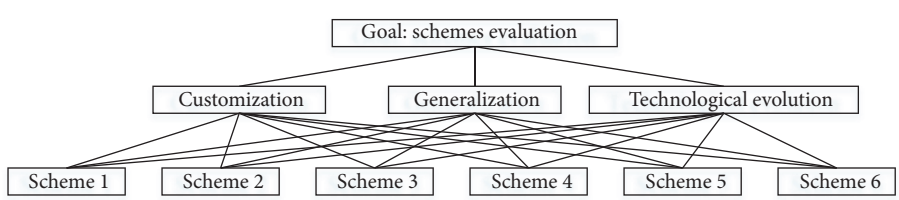

Figure 6: The hierarchical structure for the schemes evaluation.

Table 10: Linguistic variables for schemes evaluation [20].

Linguistic variables	Corresponding value
Very poor (VP)	(0, 0, 1)
Poor (P)	(0, 1, 3)
Medium poor (MP)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Medium good (MG)	(5, 7, 9)
Good (G)	(7, 9, 10)
Very good (VG)	(9, 10, 10)

Table 11: Evaluation of experts in linguistic variables for evaluation indexes.

No.	Customization	Generalization	Technological evolution
Scheme B_1	G,G,MG,F	MG,MG,F,F	VG,G,MG,F
Scheme B_2	MG,MG,G,F	G,G,MG,VG	G,G,MG,MG
Scheme B_3	F,F,MG,G	F,F,MP,P	MG,MG,MG,F
Scheme B_4	F,F,MP,MP	MP,MP,F,F	F,F,MP,MP
Scheme B_5	MP,MP,P,P	MP,MP,P,P	MP,MP,F,F
Scheme B_6	VP,VP,P,P	VP,P,MP,F	MP,P,VP,VP

Table 12: The fuzzy schemes evaluation matrix.

No.	Customization	Generalization	Technological evolution
Scheme B_1	(5.5, 7.5, 9)	(4, 6, 8)	(6, 7.75, 9)
Scheme B_2	(5, 7, 8.75)	(7, 8.75, 9.75)	(6, 8, 9.5)
Scheme B_3	(4.5, 6.5, 8.25)	(1.75, 3.5, 5.5)	(4.5, 6.5, 8.5)
Scheme B_4	(2, 4, 6)	(2, 4, 6)	(2, 4, 6)
Scheme B_5	(0.5, 2, 4)	(0.5, 2, 4)	(2, 4, 6)
Scheme B_6	(0, 0.5, 2)	(1, 2.25, 4)	(0.25, 1, 2.5)

$$\begin{aligned}
&m_1(B_5) = 0.1562,\\
&m_1(B_6) = 0.1735;\\
&m_2(B_1) = 0.1787,\\
&m_2(B_2) = 0.1536,\\
&m_2(B_3) = 0.1655,\\
&m_2(B_4) = 0.1700,\\
&m_2(B_5) = 0.1535,\\
&m_2(B_6) = 0.1787;\\
&m_3(B_1) = 0.1861,\\
&m_3(B_2) = 0.1545,\\
&m_3(B_3) = 0.1745,\\
&m_3(B_4) = 0.1622,\\
&m_3(B_5) = 0.1366,\\
&m_3(B_6) = 0.1861
\end{aligned} \tag{15}$$

The preference information about each scheme for different attributes is synthesized using (11).

$$\begin{aligned}
&m(B_1) = 0.1794,\\
&m(B_2) = 0.1533,\\
&\mathrm{m}(B_3) = 0.1681,\\
&m(B_4) = 0.1705,\\
&m(B_5) = 0.1493,\\
&m(B_6) = 0.1794
\end{aligned} \tag{16}$$

T and N of each decision scheme B_k are determined by (12) and (13). Then, the confidence interval $[T, N]$ of each decision scheme is obtained and sorted based on the preferred sequence of range number. The optimal partition granularity of service activities is got by using (14). The results are as follows:

$$\begin{aligned}
&P(B_1 > B_2) = 0.4608,\\
&P(B_1 > B_3) = 0.4251,
\end{aligned}$$

Table 13: Module partition scheme evaluation value.

No.	Customization	Generalization	Technological evolution
Scheme B_1	0.352	0.284	0.364
Scheme B_2	0.296	0.367	0.337
Scheme B_3	0.392	0.215	0.393
Scheme B_4	0.333	0.333	0.334
Scheme B_5	0.255	0.255	0.490
Scheme B_6	0.162	0.565	0.273

$$\begin{aligned}
&P(B_1 > B_4) = 0.3144,\\
&P(B_1 > B_5) = 0.3755,\\
&P(B_1 > B_6) = 0.5000,\\
&P(B_2 > B_3) = 0.4653,\\
&P(B_2 > B_4) = 0.3524,\\
&P(B_2 > B_5) = 0.4132,\\
&P(B_2 > B_6) = 0.5392,\\
&P(B_3 > B_4) = 0.3856,\\
&P(B_3 > B_5) = 0.4452,\\
&P(B_3 > B_6) = 0.6752,\\
&P(B_4 > B_5) = 0.5246,\\
&P(B_4 > B_6) = 0.6856,\\
&P(B_5 > B_6) = 0.6245
\end{aligned} \tag{17}$$

Finally, the module partition schemes are sorted as $B_4 \succ B_5 \succ B_3 \succ B_2 \succ B_1 \sim B_6$. Therefore, the optimal module partition scheme is B_4. This result is the final compromised conclusion that comes from comprehensive consideration of the interactivity between the evaluation indicators and the coordination of the three evaluation experts' opinions. It is learned from practice that B_4 is the service scheme with the highest degree of customer satisfaction. Therefore, the result of module partition obtained by the method in this paper is consistent with the actual performance of the scheme. The optimal service module result is shown in Figure 7. M_1 is machine monitoring module, which is used to monitor the running state of the engine. M_2 is maintenance and inspection module, mainly for maintenance and inspection of the machine. M_3 is the sales module, including sales, distribution, installation, training, and other activities related to machine transactions. M_4 is the programming module, and it provides exceptional programming service. M_5 is a spare parts module. It mainly offers components. M_6 is the machine recycling module, and it provides related services to the machine recovery.

6. Results and Discussions

The maximum spanning tree is a graphical method that can visualize the interdependence intensity between service activities. In the fuzzy tree diagram, α is introduced to segment the fuzzy tree. It denotes the coefficient of the module partition granularity. Larger α corresponds to finer partition granularity while smaller α corresponds to thicker partition granularity. For instance, when $\alpha = 0.67$, all service activities divide into 6 modules; they are Module 1 $\{S_1, S_2, S_3, S_4, S_5, S_6, S_{13}, S_{14}, S_{15}, S_{16}\}$, Module 2 $\{S_7, S_8, S_9, S_{10}, S_{11}\}$, Module 3 $\{S_{12}\}$, Module 4 $\{S_{17}\}$, Module 5 $\{S_{18}, S_{19}, S_{20}, S_{21}, S_{22}, S_{23}, S_{24}, S_{25}\}$, and Module 6 $\{S_{26}, S_{27}, S_{28}, S_{29}\}$. However, when $\alpha = 1$, all service activities divide into 29 modules. Then, the customization, generalization, and technological evolution are regarded as the evidence sources of Dempster-Shafer theory of evidence. The trust interval of each scheme is obtained through calculation. The optimal partition scheme is also obtained by interval preference sorting method.

In contrast to other methods, we have established indicators of the relationship between service activities, which makes relation description more clearly. Secondly, we proposed the customization, generalization, and technological evolution evaluation indexes to precisely evaluate the service partition schemes. Results demonstrate the effectiveness and feasibility of the method. And it can also be used to guide the actual operation.

7. Conclusions

A module partition method based on fuzzy graph and an evaluation method based on Dempster-Shafer theory of evidence are proposed. The fuzzy graph can represent the association between service activities more intuitively than other clustering algorithms. Meanwhile, the Dempster-Shafer theory of evidence does not need to know the prior probability. It is widely used to deal with uncertainties and can reduce the interference from human factors in the process of service module partition. Firstly, the weight of correlation index is obtained through a fuzzy analytic hierarchy process. On this basis, the fuzzy graph clustering algorithm is used to divide the service activities. The service activities are split into different modules under different granularity. Secondly, the Dempster-Shafer theory of evidence is introduced to synthesize the customization, generalization, and

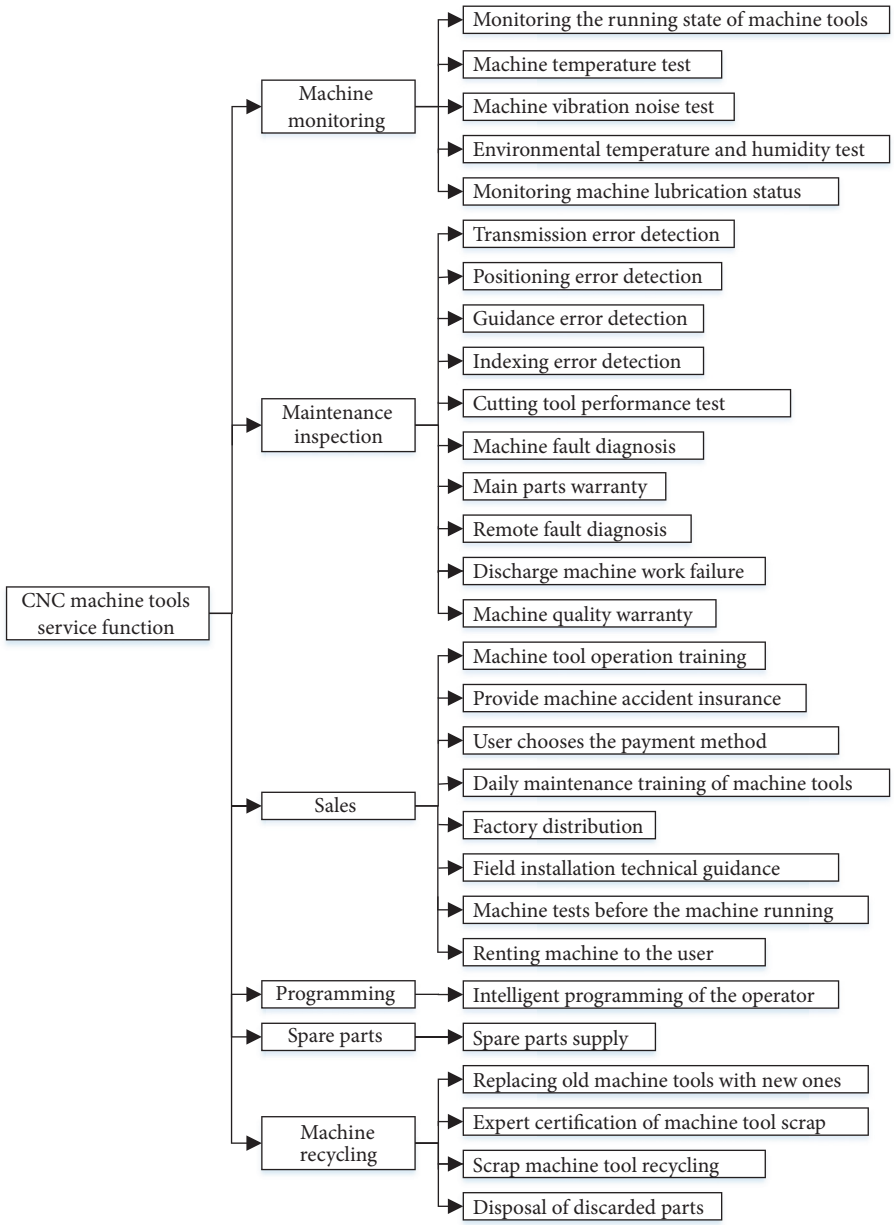

Figure 7: Partition result structure tree.

technological evolution evaluation indexes. The assessment of the module partition scheme is achieved by evidence synthesis and interval preference sequence. Finally, the feasibility and effectiveness of the proposed method are verified through the analysis and application of the module partition process of NC machine service activities.

In conclusion, the combination of fuzzy graph and Dempster-Shafer theory of evidence provides a theoretical basis for the partition of PSS service modules. More specifically, the main contributions of this paper can be summarized as follows: the method used in this paper abandons the weighted average method evaluated by experts in previous studies. We introduce the Dempster-Shafer theory of evidence with simulated negotiation and coordination mechanism, to fuse the inconsistent evaluation opinions of the experts and get the compromise result of schemes ranking, which improves the scientificity and objectivity of the decision-making process. The theoretical methodology proposed in this paper has certain reference value for guiding enterprises to implement service module partition and promote enterprises to service-oriented transformation and upgrading.

In future research, the uncertain information processing methods in artificial intelligence, such as fuzzy set, fuzzy rough set, vague set, and intuitionistic fuzzy set, can be introduced into the framework of this paper.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the National Science-Technology Support Plan Projects of China (no. 2015BAF32B03).

References

[1] F. F. Suarez, M. A. Cusumano, and S. J. Kahl, "Services and the business models of product firms: An empirical analysis of the software industry," *Management Science*, vol. 59, no. 2, pp. 420–435, 2013.

[2] O. K. Mont, "Clarifying the concept of product-service system," *Journal of Cleaner Production*, vol. 10, no. 3, pp. 237–245, 2002.

[3] H.-E. Tseng, C.-C. Chang, and J.-D. Li, "Modular design to support green life-cycle engineering," *Expert Systems with Applications*, vol. 34, no. 4, pp. 2524–2537, 2008.

[4] A. K. Kamrani and R. Gonzalez, "A genetic algorithm-based solution methodology for modular design," *Journal of Intelligent Manufacturing*, vol. 14, no. 6, pp. 599–616, 2003.

[5] Y. Deng, "Fuzzy analytical hierarchy process based on canonical representation on fuzzy numbers," *Journal of Computational Analysis and Applications*, vol. 22, no. 2, pp. 201–228, 2017.

[6] Y. Ji, R. J. Jiao, L. Chen, and C. Wu, "Green modular design for material efficiency: a leader-follower joint optimization model," *Journal of Cleaner Production*, vol. 41, no. 2, pp. 187–201, 2013.

[7] S. Yu, Q. Yang, J. Tao, X. Tian, and F. Yin, "Product modular design incorporating life cycle issues - Group Genetic Algorithm (GGA) based method," *Journal of Cleaner Production*, vol. 19, no. 9-10, pp. 1016–1032, 2011.

[8] T.-R. Chang, C.-S. Wang, and C.-C. Wang, "A systematic approach for green design in modular product development," *The International Journal of Advanced Manufacturing Technology*, vol. 68, no. 9-12, pp. 2729–2741, 2013.

[9] J. C. Aurich, C. Fuchs, and C. Wagenknecht, *Modular design of technical product-service systems*, Springer, Netherlands, 2006.

[10] S. Pekkarinen and P. Ulkuniemi, "Modularity in developing business services by platform approach," *The International Journal of Logistics Management*, vol. 19, no. 1, pp. 84–103, 2008.

[11] J. Li, H.-C. Zhang, M. A. Gonzalez, and S. Yu, "A multi-objective fuzzy graph approach for modular formulation considering end-of-life issues," *International Journal of Production Research*, vol. 46, no. 14, pp. 4011–4033, 2008.

[12] S. K. Moon, T. W. Simpson, S. Jun, and S. R. T. Kumara, "Service representation for capturing and reusing design knowledge in product and service, families using object-oriented concepts and an ontology," *Journal of Engineering Design*, vol. 20, no. 4, pp. 413–431, 2009.

[13] Y. Lin, S. Pekkarinen, and P. Ulkuniemi, "QFD-based modular logistics service design," *Journal of Business & Industrial Marketing*, vol. 26, no. 5, pp. 344–356, 2011.

[14] P. Wang, X. Ming, D. Li, F. Kong, L. Wang, and Z. Wu, "Modular Development of Product Service Systems," *Concurrent Engineering*, vol. 19, no. 1, pp. 85–96, 2011.

[15] Y. Geum, R. Kwak, and Y. Park, "Modularizing services: a modified HoQ approach," *Computers & Industrial Engineering*, vol. 62, no. 2, pp. 579–590, 2012.

[16] H. Li, Y. Ji, X. Gu, G. Qi, and R. Tang, "Module partition process model and method of integrated service product," *Computers in Industry*, vol. 63, no. 4, pp. 298–308, 2012.

[17] P. Carlborg and D. Kindström, "Service process modularization and modular strategies," *Journal of Business and Industrial Marketing*, vol. 29, no. 4, pp. 313–323, 2014.

[18] Y. Li, X. Chu, D. Chu, and Q. Liu, "An integrated module partition approach for complex products and systems based on weighted complex networks," *International Journal of Production Research*, vol. 52, no. 15, pp. 4608–4622, 2014.

[19] W. Song, Z. Wu, X. Li, and Z. Xu, "Modularizing product extension services: an approach based on modified service blueprint and fuzzy graph," *Computers & Industrial Engineering*, vol. 85, pp. 186–195, 2015.

[20] J. Xu, X. Jiang, and Z. Wu, "A Sustainable Performance Assessment Framework for Plastic Film Supply Chain Management from a Chinese Perspective," *Sustainability*, vol. 8, no. 10, 2016.

[21] A. Rosenfeld, "FUZZY GRAPHS," in *Review of Fuzzy Sets & Their Applications to Cognitive & Decision Processes*, pp. 77–95, 1975.

[22] A. P. Dempster, *Upper and Lower Probabilities Induced by a Multivalued Mapping*, Springer, Berlin Heidelberg, 2008.

[23] G. Shafer, *A Mathematical Theory of Evidence*, vol. 42, Princeton university press.

[24] Q. Q. Zhu, P. Y. Jiang, G. Q. Huang, and T. Qu, "Implementing an industrial product-service system for CNC machine tool," *The International Journal of Advanced Manufacturing Technology*, vol. 52, no. 9-12, pp. 1133–1147, 2011.