INCORPORATING KNOWLEDGE COVERAGE MEASUREMENT INTO KNOWLEDGE TRANSFORMATION FROM DATA FOR KNOWLEDGE ACCUMULATION

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Abstract

The amount and quality of manufacturing knowledge in the knowledge base determine the degree of intelligence in the manufacturing process, and one of the most challenging issues is how to assess knowledge capability in a quantitative manner. From the perspective of manufacturing knowledge function, measurement indicators including verification environment, knowledge coverage and using effect, are conducted to construct an evaluation framework of knowledge capability maturity model. An algorithm model is proposed to calculate knowledge coverage, which is a new concept presented to determine the inventory of available knowledge in the knowledge base. Based on the percentage value of allowance for quality indicators, a novel method is also presented to evaluate using effect in a quantitative way. For measuring knowledge capability, we develop a knowledge capability maturity model with nine stages. Meanwhile, knowledge maturity level transition is presented and some suggestions are given to managers for making decisions. An application example not only adequately validates the effectiveness of the proposed model, but also fully demonstrates its advantages in the quantitative measurement..

Keywords: Knowledge Capability Maturity Model; Knowledge Measurement; Knowledge Coverage; Discretization; Knowledge Maturity Level Transition

1. Introduction

Intelligent manufacturing has become the main current trend in the new generation manufacturing [1]. As one of the most vital resources for sustaining manufacturers' competitive advantage, knowledge plays a central role in realizing manufacturing intelligence[2-4]. In order to make full and effective use of organizational knowledge resources, knowledge should be organized in a standardized way such as knowledge based systems. Meanwhile, in order to maintain a competitive advantage, enterprises should constantly keep acquiring new knowledge to adapt to the rapid changes in the environment [5,6]. In such situations, companies must clearly know what knowledge is available, what knowledge must be acquired or what knowledge needs to be improved and so on. Therefore, it is necessary to develop an assessment model that can be used to accurately evaluate the knowledge in the company's knowledge base[7,8].

When characterizing the development and evaluation of an entity, a maturity model is usually referred and used to describe the varying states of an entity, with the entity being anything that is of interest [9]. In general, maturity models have the following properties [10,11]: i) The development of a single entity is simplified and described with a limited number of maturity levels; ii) Levels are characterized by certain requirements, which the entity has to achieve on that level; iii) Levels are ordered sequentially, from an initial level up to an ending level (the latter is the further improvement of the former); iv) During development, the entity progresses forward from one level to the next. As a natural application of the life-cycle approach, maturity models have been applied in many fields. In the IT field, ‘‘Capability Maturity Model (CMM)" for software development was constructed by the Software Engineering Institute of Carnegie-Mellon University. In addition, a lot of research on maturity models in the field of knowledge management has emerged one after another in recent years.

KPMG defined a maturity model as five stages: knowledge chaotic, knowledge aware, knowledge focused, knowledge managed, and knowledge centric [12]. They also defined the four key criteria as people, process, content and technology. In each area there are certain activities to be done. Firms can be assessed according to how they implement these activities. Infosys Technologies described the five knowledge management maturity (KMM) levels as default, reactive, aware, convinced and sharing [13]. Each maturity level is characterized by certain observable capabilities along each of the three major prongs: people, process and technology. Siemens has constructed a knowledge management maturity model (KMMM) which consists of an analysis model, a development model and a defined assessment process [14]. The analysis model helps the KMMM consultant to take account of all important aspects of knowledge management (KM) and reveals which key areas and topics should be developed in the future. The development model provides information as to how the respective key areas and topics can be best developed to reach the next maturity level. The assessment process structures all relevant steps from assessment definition to result interpretation.

In order to further improve the possibility of success, a variety of knowledge management models have been presented. For example, Teah et al. [15] reviewed, compared, and integrated existing Knowledge Management Maturity Models to propose a General KMMM, which focuses on assessing the maturity of people, process and technology aspects of KM development in organizations. Chen et al. [16] proposed an approach of measuring knowledge management performance from competitive perspective. The approach integrates analytical network process (ANP) with balanced scorecard (BSC) to establish the model of KM performance measurement from four perspectives, including customer perspective, internal business perspective, innovation and learning perspective, and financial perspective. Wen [17] has developed a model to measure the effectiveness of knowledge management activities by using focus groups, analytical hierarchy processes and questionnaire analysis. These qualitative and quantitative methods have been integrated to summarize the experts' opinions, select the measurement indicators, and calculate the weightings of dimensions and items. Hiseh et al. [18] have constructed a knowledge navigator model (KNM) which consists of an evaluation and calculation framework. Furthermore, they defined the KM maturity level into five stages: knowledge chaotic stage, knowledge conscientious stage, KM stage, KM advanced stage, and KM integration stage. The evaluation framework of KNM consists of three aspects: three target management objects (culture, KM process, and information technology), 68 KM activities, and 16 key areas. The calculation framework includes the research methods used in constructing this framework, and the derived results such as the score ranges used to differentiate maturity levels. Measuring various processes of knowledge management, namely, creation, accumulation, sharing, utilization and internalization of knowledge at the firm level have also been descripted by Lee et al. [19]. Through social resources embedded into their structure, a model was presented to optimize their knowledge management maturity [20].

In addition to knowledge management maturity modeling, some people focus more on the knowledge aspect. Schenkl et al. [21] proposed an approach for evaluating the knowledge within a company and to specify the required knowledge for providing a specific product-service system. Through Multiple-Domain Matrix based knowledge maps, the knowledge gap can be derived. Wen et al. [22] have presented a knowledge-based decision support system for measuring enterprise performance, using both neural network forecasting and knowledge reasoning, so that it could help managers better understand current and future situations of the enterprise. Xu and Bernard [23] restricted knowledge to the context of product development, and proposed some effective definitions and measurements of knowledge value. Based on those, the values of both tacit and explicit knowledge can be quantified. In addition, they have proposed an integrated knowledge reference system which could serve as a base to characterize product development and knowledge evolution process [24].

Those ideas and methods introduced by former researchers all have insightful contributions to the modeling and analysis of knowledge management in industrial productions. However, they mainly describe or analyze the knowledge integrated systems in a qualitative way and there is a lack of direct discussions on knowledge capability that could be quantified [25]. Meanwhile, in order to promote the application of assessment model, it should aim to develop means that help identify the level of maturity [26].Therefore, there is a growing need to specify the concrete impact of knowledge on the product development process and also to analyze knowledge capability in a quantitative way.

One of the uses of KM is in the area of decision making and assessment of process. Decision makers can verify the quality of development of their knowledge base in order to move forward to the next step. It could help managers better understand current and future situations of the enterprise knowledge [27,28].

Although there is considerable research in knowledge management performance measurement, there seems to be a lack of quantitative evaluation methods for knowledge capability, and this paper proposes an approach to address this issue. The paper is structured as follows: Section 2 is the characteristic and capability analysis of manufacture process knowledge. Section 3 introduces a knowledge vector, which characterizes knowledge capability in a comprehensive way, and its three elements, i.e., verification environment, knowledge coverage and using effect are analyzed in detail. Moreover, the specific evaluation method for each index is constructed. In Section 4, a knowledge capability maturity model is established to describe knowledge activities, and the knowledge maturity level transition machine is established. In Section 5, a case is studied to illustrate how knowledge capability measurement can be implemented by using the method. Finally, the paper concludes with Section 6.

2. 2 Measurement indicators for manufacturing process knowledge

2.1 The characteristic and capability analysis of manufacturing process knowledge

Through studying the composition and characteristics of manufacturing process knowledge, the factors affecting the maturity of manufacturing knowledge are analyzed, thereby the evaluation indexes of knowledge maturity are determined. As a bridge between design and manufacture, the task of process design is to provide parts processing solutions for the manufacturing stage based on the information received from the design stage. In this process, the actual situation of the enterprise and the functional characteristics of the product should be considered, which determines the complexity and diversity of manufacturing process knowledge.

Manufacturing process knowledge is the cross-integration of multidisciplinary knowledge in machinery, materials and mechanics. Among them, the forming mechanism of many process methods has not been clarified, and this process knowledge comes from a lot of practice in production. Since that, it usually needs to go through research, development, verification and other stages of development before it can be applied. Like a thing, knowledge has a life cycle. New knowledge is born as something fairly nebulous and that it takes shape as it is tested, and matures through application in various settings. That is to say, in different environments or stages, the knowledge system embodies the feasibility, stability, reusability and other performance. Therefore, verification environment is taken as an index to evaluate the capability maturity of the knowledge-based system in this paper.

At the same time, there is a great variety of manufacturing process knowledge. Different manufacturing objects or different processing links need to use different process knowledge, which requires enterprises to have a certain amount of process knowledge reserve to be competent and complete corresponding manufacturing process design tasks. As with other things, the product objects that the system supported by manufacturing process knowledge can solved are also very limited. Thus, this paper proposes a coverage index to assess the range of objects that the knowledge system can solve. In addition, the reliability of process knowledge is directly reflected in production. That is, using effect reflects the effectiveness of manufacturing process knowledge system. Accordingly, this paper takes using effect as another index to evaluate capability maturity of manufacturing process knowledge.

For the operation of the knowledge base system, as shown in Figure 1, the three most concerned aspects are: ① whether the current object can be solved; ② whether the solution process is reliable; ③ whether the results obtained are valid. The three indicators proposed in this paper can also reflect the performance of these three aspects. Through the coverage index, it can know whether the current object can be solved. With verification environment, it can clarify whether knowledge system is reliable. With using effect, it is clear whether it is effective.

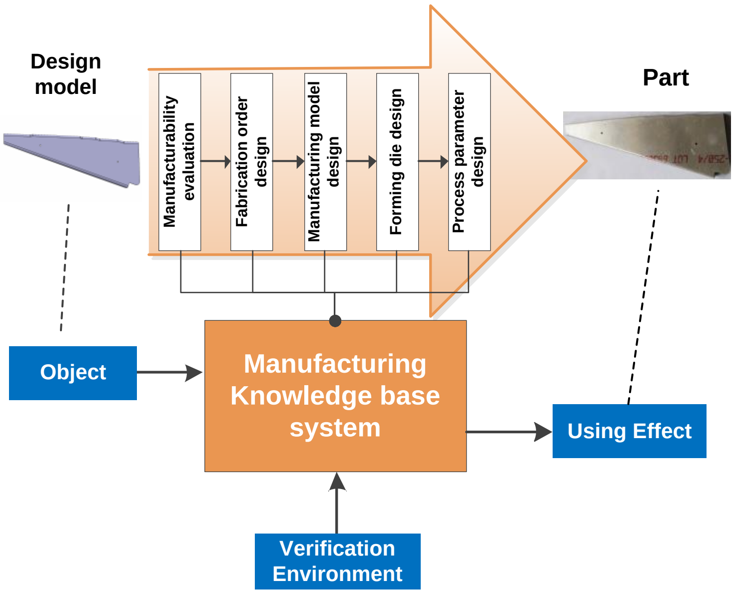

Figure 1 – Operating mechanism for manufacturing knowledge base system

In view of the above analysis, knowledge capability maturity (KCM) is characterized by three main aspects: verification environment (VE), knowledge coverage (KC), and using effect (UE), as shown in Figure 2.

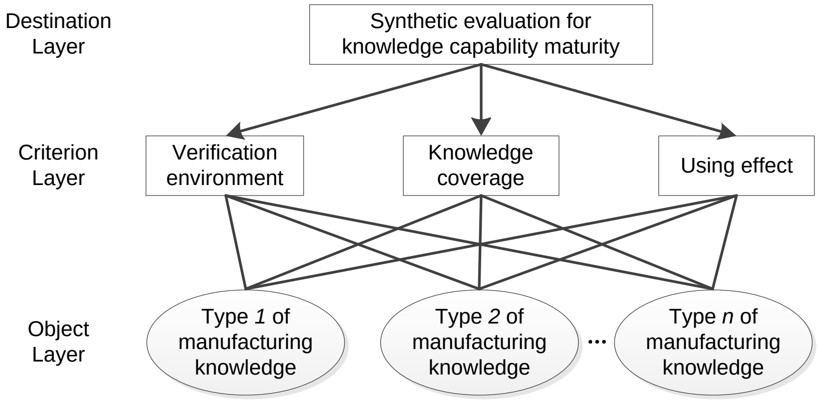

Figure 2 – The evaluation indexes of knowledge capability maturity

2.2 Verification environment

The lifecycle of manufacturing process knowledge is the state sequence of the various stages knowledge application in different environments. From theoretical research to actual mass production application, the development of manufacturing process knowledge usually needs to go through the following stages: theoretical analysis and research, verification of laboratory simulation environment, test verification of manufacturing plant, and batch production of the actual production environment. Among them, the degree of mass production ranges from the initial single-piece trial production to small-scale production, to mass production and finally to lean production. In this process, the capability maturity of manufacturing process knowledge is constantly improved. It can be seen that verification environment refers to the specific conditions and background of manufacturing process knowledge in the mature process of generation, use and optimization.

By referring to verification environment of technology maturity and manufacturing maturity in existing studies, this paper summarizes verification environment of manufacturing process knowledge into four main stages. ① Theoretical research: the technology supported by the knowledge system is in the stage of basic principle and feasibility study; ② Laboratory validation: the technology supported by the knowledge system is in the verification phase of the laboratory simulation operating environment; ③ Manufacturer test verification: the technology supported by the knowledge system is in the verification phase of manufacturing environment; ④ Actual production applications: the technology supported by the knowledge system is applied in actual production.

2.3 Knowledge coverage

With the help of machine equipment, tooling and men as labor, manufacturing is the process of converting raw material into products according to a certain process. In fact, the classification of manufacturing process is derived from the way materials are transformed. Therefore, the classification model for manufacturing process knowledge can be established in accordance with part categories, process methods and manufacturing activities. Firstly, according to the part category, manufacturing process knowledge is classified. Where, parts categories= {frame rib, skin, panel, profile, ..., pipe}. Usually, all kinds of parts can be manufactured by one main forming process at least. Next, manufacturing process knowledge for a certain part can be classified based on process method. Where, process methods= {rubber hydraulic forming, bending forming, shot peening, ..., tube bending}. After determining the main process method used for a certain part, manufacturing process knowledge can be further divided in line with manufacturing activities. Where, manufacturing activities = {manufacturability assessment, fabrication order design, manufacturing model design, ..., forming die design, machining parameters design}.

The core of the knowledge base system is knowledge content itself, and the lack of knowledge cannot provide a reliable decision. Thus, if companies need to make reliable decisions from the knowledge base, they must accurately know the reserves in the knowledge base, that is, which areas have sufficient knowledge, and which areas require more knowledge. This paper presents knowledge coverage to quantitatively assess the knowledge reserves in the current knowledge base, which will be defined from the following two aspects. (1) Granularity. Knowledge granularity embodies the hierarchical situation of knowledge in the entire knowledge organization and is described by a knowledge tree. Knowledge is organized as a tree of several levels, and each knowledge unit at a higher level is comprised of one or several knowledge units of its sublevels. The knowledge unit on the leaf nodes of the tree is regarded as the basic unit of enterprise knowledge. They are introduced to clarify the level number of knowledge units and the integrity of the knowledge types of manufacturing business activities. (2) Quantity. Knowledge quantity is an important aspect of knowledge that should be considered. From the perspective of functional characteristics of knowledge, knowledge quantity can be described by the range of objects that the corresponding knowledge unit can solve.

2.4 Using effect

Using effect describes whether the knowledge can be held in a relatively stable state and its ability to recover from perturbation. The quality of parts is regarded as the outcome of knowledge activities. In order to measure the effect of knowledge in industrial production quantitatively, the score of using effect should be defined in the first place. Since the quality of parts is characterized by multiple indicators, the score can be calculated by means of integrating all those indices. Each index has different unit to measure and different allowance error. As a result, it is reasonable to use a percentage value to quantify using effect. In the real-world application, using this method to assess using effect of knowledge can help people make the appropriate choice among different knowledge resources.

3. Evaluation method for indicators

3.1 Evaluation method for verification environment

For quantification, a 9-level scale is used for verification environment, where 0.1 to 1 corresponds from theoretical research to real production environment, respectively, as shown in Table 1.

Table 1 Rating for verification environment

Grade	Definition	Score
1	Content and rationale study	0.1
2	Feasibility research	0.2
3	It has passed the laboratory environment verification and achieved the required performance indicators.	0.3
4	It has been verified in the laboratory environment for many times and achieved the required performance indicators.	0.4
5	It has passed the factory environment verification and achieved the	0.5

	required performance indicators.	
6	It has been verified in the factory environment for many times and achieved the required performance indicators.	0.6
7	In the actual production environment, the procedure is stable with an element of repeatability.	0.8
8	The standardization of the procedure is realized and applied to mass production.	0.9
9	The prodecure is continuously improved and optimized in actual production.	1.0

3.2 Computing method for knowledge coverage

Knowledge unit is represented as two sets of feature-value pairs that represent the object to be solved and the corresponding solution in this research. Therefore, knowledge coverage is defined as: the ratio of the number of objects that can be solved by the corresponding type of knowledge to the total number of objects that expected to be solved. The object has many different attributes, so it is reasonable and desirable to have it characterized by an n-dimension vector. The vector is introduced to characterize object in knowledge unit.

Let $\left\{O_g^t \middle| O_g^t = \left(\left(f_{g,j}^t\right)_{j=1}^{j=m_t}\right)_{g=1}^{g=k_t}\right\}$ be a finite set of objects can be solved by t type of knowledge in the knowledge base, where O_g^t denotes one object of the set, $f_{g,j}^t$ represents the *jth* feature value of O_g^t, m_t is the total number of features used to represent the object, and k_t is the number of objects.

Likewise, let $\left\{\hat{O}_i^t \middle| \hat{O}_i^t = \left(\left(\hat{f}_{i,j}^t\right)_{j=1}^{j=m_t}\right)_{i=1}^{i=n_t}\right\}$ be a finite set of objects expected to be solved by t type of knowledge, where $\hat{O}_i^t$ denotes one object of the set, $\hat{f}_{i,j}^t$ represents the *jth* feature value of $\hat{O}_i^t$, and n_t is the total number of objects. Ordinarily, there are two kinds of features in view of characteristic value, i.e., feature with discrete value and feature with continuous value. Consequently, $\hat{O}_i^t$ can be expressed as $\hat{O}_i^t = \left(\left(\hat{f}_{i,d}^t\right)_{d=1}^{d=r_t}, \left(\hat{f}_{i,c}^t\right)_{c=1}^{c=s_t}\right)$, where $\hat{f}_{i,d}^t$ denotes the *d*th discrete feature value of $\hat{O}_i^t$, $\hat{f}_{i,c}^t$ denotes the *c*th continuous feature value of $\hat{O}_i^t$, r_i and s_i are the number of feature with discrete value and feature with continuous value, respectively.

Afterwards, the analysis model for knowledge coverage can be built based on the definition of knowledge coverage, as shown in Figure 3. The calculation framework for knowledge coverage consists of two aspects: (1) Range determination. It aims at obtaining the total number of all objects expected to be solved. In accordance with the categorization of characteristic value, the object vector can be divided into three groups. ① $r_i \neq 0$ and $s_i = 0$, Only features with discrete value are contained in the object vector. ② $r_i = 0$ and $s_i \neq 0$, Only features with continuous value are contained in the object vector. ③ $r_i \neq 0$ and $s_i \neq 0$, both two groups of features appeared in the object vector. (2) Cover analysis of objects. The purpose of this step is calculating the number of valid objects included in the knowledge base.

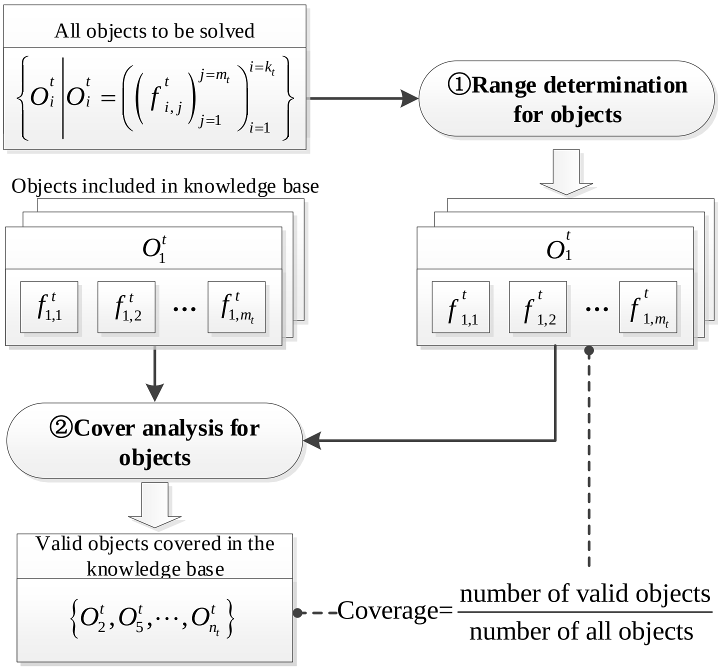

Figure 3 – The analysis model of knowledge coverage

3.2.1 Range determination for objects to be solved

(1) Only features with discrete value are contained in the vector

In this case, the calculation for the range of the solved object is carried out by establishing a classification model of discrete-valued features. A hierarchical tree $T=(V,E,S)$ is defined to express the weights associated with the features in the solved object and relationships between features. $V=\{v_1,v_2,\cdots,v_n\}$ is a finite set of discrete value of features. v_i can be regarded as a node in T and the root node of tree is represented by $root(T)$ to distinguish other nodes. $E=\{(v_p,v_q)|e(v_p,v_q)=1\}$ is a finite set of classification relationships of features, in which $e(v_p,v_q)$ is a Boolean variable that is used to represent the relationship between node v_p and node v_q. $e(v_p,v_q)=1$ indicates that v_q is a direct child of v_p. The set of directed child nodes belonging v_p is denoted by $Sub(v_p)=\{(v_x)|e(v_p,v_x)=1, v_x\in V\}$, and if $Sub(v_p)=\phi$, it means that v_p has no child node, and v_p is defined as the leaf node of tree T. S is a function: S: $V\times E\rightarrow\omega(E)$, which assigns each node a weight to represent its degree of importance to its siblings, thereby satisfying the sum of the weights of all the children of one node is 1. Where, $\omega(E)=\{(\omega_{pq})|e(v_p,v_q)=1\}$.

At this point, a path from $root(T)$ to the leaf node v_l represents a classification feature chain ($l\in\{1,2,\cdots,L\}$, $Sub(v_l)=\phi$). Where, L is the total number of leaf nodes in T. Set n_l as the number of classification feature chains from $root(T)$ to v_l and Let ω_{ij} denote the weight of each node (except the root node) in the i-th classification feature chain ($i\in\{1,2,\cdots,n_l\}$, $j\in\{1,2,\cdots,m_i\}$). m_i is the number of nodes (except the root node) in the i-th classification feature chain. Thus, by aggregating each feature chain's value, an algorithm for knowledge coverage of the solved object with only discrete-valued features is presented as belows.

$$Cov^{\mathrm{D}}=\sum_{l=1}^{L}\left[\sum_{i=1}^{n_l} f(i)\left(\prod_{j=1}^{m_i}\omega_{ij}\right)\right] \tag{1}$$

Where, $f(i)$ is the two-valued function : $f(i)=1$ means that the *i*th classification characteristic chain is contained in the knowledge base; $f(i)=0$ indicates that the *i*th classification characteristic chain doesn't exist in the knowledge base.

(2) Only features with continuous value are contained in the vector

Since the number of objects expected to be solved would be infinite under the circumstances, it can not be determined directly. The discretization of continuous-valued features is carried out to make the number of objects become finite. The discretization process used in this paper includes two steps: Firstly, according to the distribution on the value of feature, the initial range of feature is divided into several sub-intervals, which can be called first-level discrete; Secondly, the sub-interval is further discretized with equal width, that is, take a finite number at equal distance in the subinterval. Thus, each subinterval is reduced to a finite number of discrete values. Through the discretization of the above two steps, the initial continuous-valued range can be converted into a finite number of discrete values. Since the objects are represented by multiple features, the interrelationship between features needs to be considered in the discretization process. If the value of one attribute defines the value range of another attribute, there is an association relationship between them. If the values of two attributes do not have a constraint relationship with each other, they are independent of each other.

In order to illustrate the calculation method for the total number of objects expected to be solved, a tree structure can be extended to build the discretization model $DT=(I,W,P,U)$, in which I is a finite set of discrete intervals, I_{jl} denotes *l*th discrete interval of *j*th feature, $I_{jl}\in I$; J is the total number of features, $j\in\{1,2,\cdots,J\}$; L_j is discrete interval number of *j*th feature, $l\in\{1,2,\cdots,L_j\}$; W is the weight on I where $W_{jl}\in W$ represents the corresponding weight of I_{jl}; P is discrete points on I where $P_{jl}\in P$ represents the corresponding points of I_{jl}; U denotes a finite set of union intervals, U_h is a path from the root to one of leaf nodes, $U_h\in U$, H is the total number of union intervals, $H\le\prod_{j=1}^{J}L_j$, $h\in\{1,2,\cdots,H\}$. When J features characterizing the object are independent of each other, H takes the maximum value. Therefore, the total number of objects that are expected to be solved can be figured out by aggregating the value of discrete points in each union interval.

According to the above definition, a discretization model of the solved object with only continuous-valued is constructed, with taking into consideration relationship between features, as shown in Figure 4. Assume that the solved object is identified by three continuous-valued features. Firstly, sub-intervals are figured out through the first level discretization: $I=\{I_{11},I_{12},I_{13},I_{21},I_{22},I_{23},I_{31},I_{32},I_{33}\}$. Where, I_{31}、I_{32} and I_{33} are leaf nodes, and the union intervals established from root node to leaf nodes include: $U_1(I_{11}-I_{21}-I_{31})$, $U_2(I_{12}-I_{22}-I_{31})$, …, $U_9(I_{13}-I_{23}-I_{33})$. Secondly, assign a weight W_{jl} to the corresponding subinterval I_{jl}. Since there is an association between the first two features, only the sub-intervals of the first feature are given weights. Subsequently, set a discrete spacing d_{jl} for the subinterval I_{jl} to obtain the corresponding discrete points P_{jl}. Let N_h be the value of the discrete point in U_h, which can be calculated based on the above established model. For example, $N_1=\left[W_{11}\cdot(P_{11}\cdot P_{12})\right]\cdot(W_{31}\cdot P_{31})$. Similarly, the value of N_h can be obtained. Therefore, the total number of objects expected to be solved can be further figured out, namely $\sum N_h$.

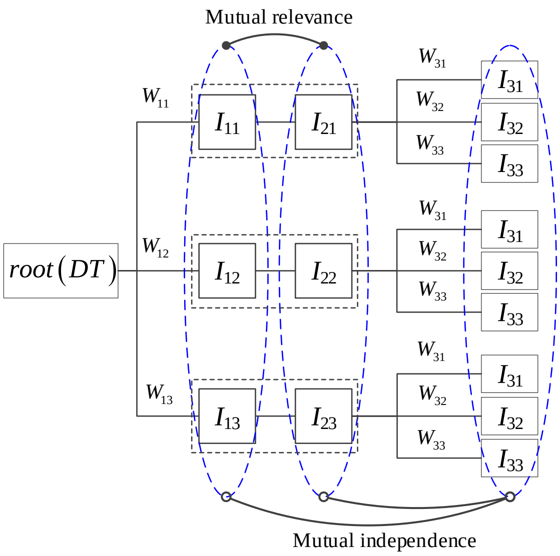

Figure 4 – Discretization model

Let I_{Jl} represent the set of leaf nodes, L_J is the number of leaf nodes, $l \in \{1, 2, \cdots, L_J\}$; Let n_l be the number of paths (union intervals) from the root to leaf node I_{Jl}; In addition, the weight assigned to the *k*-th sub-interval of U_i provided by the experts is W_{ik}, $k \in \{1, 2, \cdots, K_i\}$. Where, K_i is the number of sub-intervals in U_i. While P_{ik} denotes the expected discrete points of *k*-th sub-interval in U_i, P'_{ik} stands for the number of points covered in *k*-th sub-interval of U_i. Thereby the calculation formula of knowledge coverage is given by:

$$Cov^{\mathrm{C}} = \frac{\sum_{l=1}^{L_J}\left[\sum_{i=1}^{n_l}\left(\prod_{k=1}^{K_i} W_{ik} \cdot P'_{ik}\right)\right]}{\sum_{l=1}^{L_J}\left[\sum_{i=1}^{n_l}\left(\prod_{k=1}^{K_i} W_{ik} \cdot P_{ik}\right)\right]} \tag{2}$$

Where, the determination of P_{ik} requires further cover analysis below.

(3) Both two groups of features appeared in the vector

Under this circumstances, the calculation method of knowledge coverage is established by combining the first two calculation models. The method consists of three main steps as shown in Figure 5. Firstly, according to discrete-valued features of the object, a classification relation model is built to obtain the corresponding classification feature chains. Secondly, the discretization of continuous-valued features in each classification feature chain is carried out to further obtain the total number of objects expected to be solved. Then, the number of objects that can be covered in the knowledge base will be determined, by cover analysis between the objects expected to be solved and the objects that the knowledge base can solve. Therefore, based on Equation (1), the following formula is established to calculate knowledge coverage Cov^{H} for the object containing discrete-valued features and continuous-valued features.

$$Cov^{\mathrm{H}} = \sum_{l=1}^{L}\left[\sum_{i=1}^{n_l} Cov_i^{\mathrm{C}}\left(\prod_{j=1}^{m_i}\omega_{ij}\right)\right] \tag{3}$$

Where, Cov_i^{C} represents the coverage of continuous-valued features in the classification feature chain and and can also be regarded as the value of a leaf node in the classification model. According to the result of discretization, Cov_i^{C} can be figured out by Equation (2).

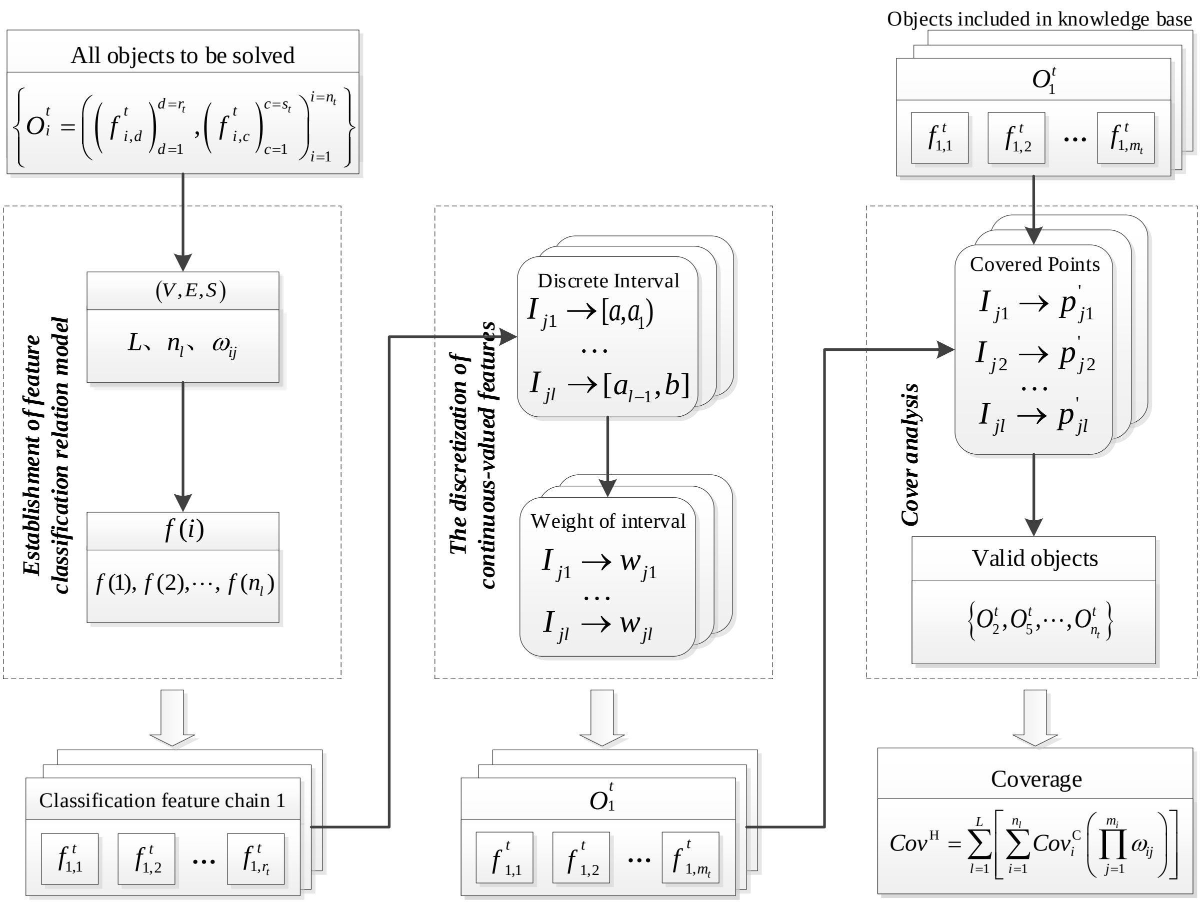

Figure 5 – The calculation framework for knowledge coverage

3.2.2 Cover analysis

For cover analysis, it is essentially a comparison between the objects that can be solved in the knowledge base and the objects that are expected to be solved. By setting the cover condition, it can identify whether the corresponding object is covered or not. The cover condition is defined by the distance between objects, including two aspects: one is the distance between the corresponding features used for comparison in the object, and the other is the distance between two objects. When both two kinds of distances are less than the given threshold, the cover condition is considered to be satisfied. The calculation method for the distance is given as following.

Let $dis(\hat{O}_i^t, O_g^t)$ denote the distance between $\hat{O}_i^t$ and O_g^t. Where, $\hat{O}_i^t$ is the i-th object expected to be solved and O_g^t stands for the g-th object that can be solved in the knowledge base. Then, let $dis(\hat{f}_{i,j}^t, f_{g,j}^t)$ represent the distance on the jth feature between $\hat{O}_i^t$ and O_g^t. The descriptions of the object are often represented by multiple attributes, and the formats of attribute values are various. In reality, the formats of attribute values usually consists of two main categories: numeric and character.

(1) For numerical features, Manhattan distance is employed in this paper to measure them. The measurement will distort the results when the features have different sizes for their domains of definition. Therefore, the Max–Min function is employed to normalize the distance calculation. Finally, the dissimilarity can be calculated from distance, represented as:

$$dis(\hat{f}_{i,j}^t, f_{g,j}^t) = \left| \frac{\hat{f}_{i,j}^t - f_{g,j}^t}{Max_j - Min_j} \right| \tag{4}$$

Where, Max_j and Min_j are the maximum and minimum values of the feature j, respectively. Since the discrete spacing of each feature is different, it is necessary to set cover conditions for each feature: $\left|\hat{f}_{i,j}^t - f_{g,j}^t\right| < d_{jl}$ and $dis(\hat{O}_i^t, O_g^t) < \lambda$. Where, d_{jl} is the corresponding discrete spacing of I_{jl} and λ is the corresponding threshold. When the above conditions are met, it indicates that object O_g^t covers object $\hat{O}_i^t$.

(2) For character features, since the feature values are the kind of enumeration values, there are no quantitative relationships among the feature values. In other words, the specific value of the difference cannot be measured. In this case, the feature similarities between $\hat{f}_{i,j}^{t}$ and $f_{g,j}^{t}$ can be evaluated by judging whether the feature values are equivalent. Then the calculation formula of $dis(\hat{f}_{i,j}^{t}, f_{g,j}^{t})$ is given by:

$$dis(\hat{f}_{i,j}^{t}, f_{g,j}^{t})=\begin{cases}1, & \hat{f}_{i,j}^{t} \neq f_{g,j}^{t} \\ 0, & \hat{f}_{i,j}^{t} = f_{g,j}^{t}\end{cases} \tag{5}$$

Dissimilarity between $\hat{O}_i^t$ and O_g^t can be transferred from transformation indicators using a combiner after values of the indicators of two objects on each feature have been calculated. In this research, the combiner is implemented as follows:

$$dis(\hat{O}_i^t, O_g^t) = \frac{1}{m}\sum_{j=1}^{m} dis(\hat{f}_{i,j}^{t}, f_{g,j}^{t}) \tag{6}$$

Obviously, the greater the distance is, the more dissimilar $\hat{O}_i^t$ and O_g^t will be.

3.3 Measurement for using effect

The forming quality of parts largely depends on the accuracy of forming. The resulting part is allowed to have a certain range of deviation compared with the designed part. The smaller the deviation value, the higher the accuracy is achieved. Therefore, the deviation value is used as an evaluation index of using effect supported by the process knowledge system, and different levels of deviation standards are established. The forming quality can be comprehensively evaluated by counting the percentage of parts that can be formed under various deviation criteria. The established equation is shown below.

$$SR = \sum_{i=1}^{n}\sum_{j=1}^{m} W_i \times G_{ij} \times R_{ij} \tag{7}$$

Where, SR denotes the score of using effect; W_i represents the weight of the ith index; G_{ij} denotes the deviation grade score of the ith index; R_{ij} stands for the percentage value of parts in the jth deviation grade; n is the number of quality indices; m is the number of the deviation grade.

As shown in Figure 6, the process of quality measurement consists of four steps. ① Weight determination: let QI_i denote the ith measurement index of quality, $i = 1, 2, \cdots, n$. The weight of QI_i is often obtained from experts. ② Grade classification: the deviation grade score model of the ith index is established based on the allowance error. ③ Distribution determination: in accordance with the deviation grade score model, the percentage value of parts distributed in each grade need to be determined specifically. ④ Calculation: the final score could be calculated using equation (7).

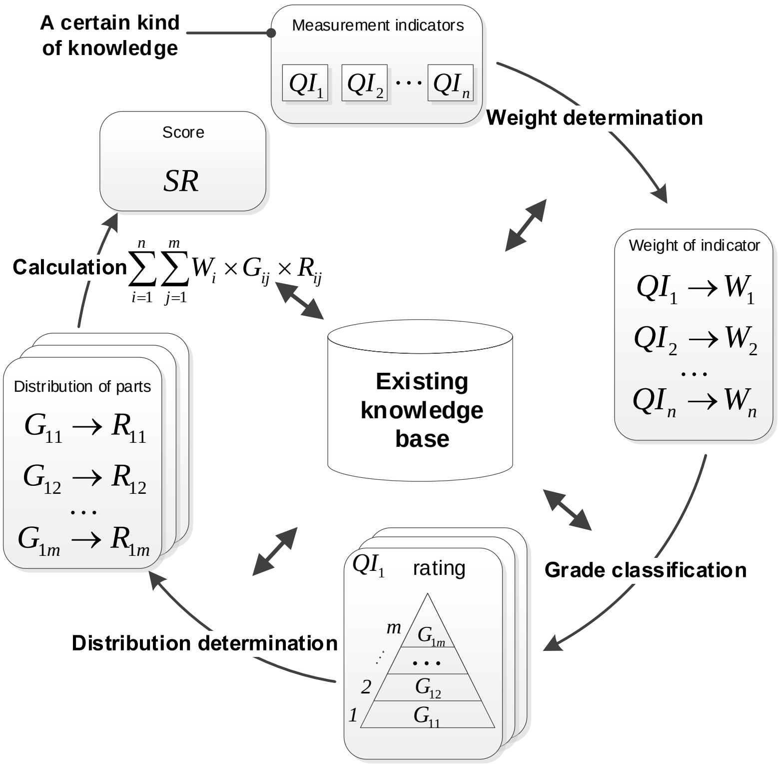

Figure 6 – Evaluation process for quality assessment indicators

4. Capability maturity model for manufacturing process knowledge

4.1 Definition of knowledge capability maturity level

The mature process of manufacturing knowledge is as follows: verification environment gradually gets close to the actual production environment, the types of parts that can be solved gradually expand and the effect of parts gradually close to the precise. Taking verification environment, knowledge coverage, and using effect as three dimensions, the capability maturity model of manufacturing process knowledge is established, which is divided into nine grades, as shown in Table 2. The model provides us with a method to describe the knowledge evolution process in a more comprehensive way.

Table 2 Definition for process knowledge capability maturity

Level	Definition
KCM1	✧ Rationale study
KCM2	✧ Feasibility research
KCM3	✧ Laboratory environment verification ✧ Percent of pass ≥60%，SR≥0.26
KCM4	✧ Multiple validation in the laboratory environment ✧ Percent of pass ≥70%，SR≥0.36
KCM5	✧ Factory environment verification ✧ Knowledge coverage ≥40% ✧ Percent of pass ≥75%，SR ≥0.45
KCM6	✧ Multiple validation in the factory environment ✧ Knowledge coverage ≥60% ✧ Percent of pass ≥80%，SR≥0.55
KCM7	✧ The procedure is stable in real

	production ✧ Knowledge coverage ≥70% ✧ Percent of pass≥85%，SR ≥0.65
KCM8	✧ Standardization of procedure in real production ✧ Knowledge coverage ≥80% ✧ Percent of pass≥90%，SR≥0.75
KCM9	✧ Continually improve in production ✧ Knowledge coverage ≥90% ✧ Percent of pass ≥95%，SR≥0.80

In addition, by using the averaged weighted score, the overall evaluation score of knowledge capability maturity can be obtained as follows:

$$S_{kc} = w_e \bullet ve_i + w_a \bullet kc_j + w_r \bullet ue_k \tag{8}$$

Where, ve_i, kc_j, and ue_k refer to the verification environment, knowledge coverage and using effect, respectively, and w_e, w_a and w_r are their weights, as different situations may emphasize different aspects.

At this point, the current maturity status of knowledge in the knowledge base can be determined through the following two steps, as shown in Figure 7. Firstly, according to the index evaluation method established above, each index value can be figured out respectively. Then, compared with the criteria for knowledge capability maturity level in 0, the current maturity level of knowledge in the knowledge base can be determined.

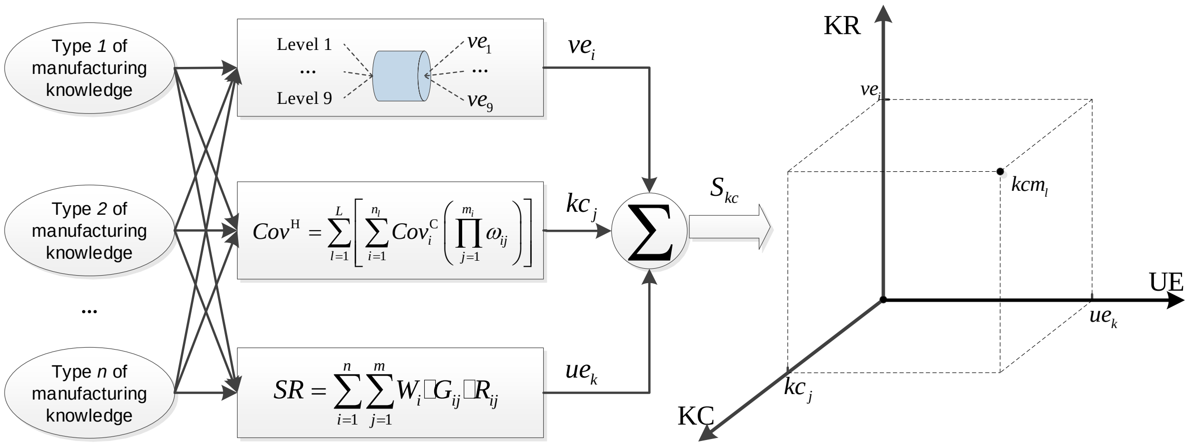

Figure 7 –The measurement process of knowledge capability maturity

4.2 Transition of knowledge capability maturity level

To further improve knowledge capability, companies need to make appropriate strategies in line with the current state, such as set priorities for the implementation of tasks to be solved. Consequently, a new concept knowledge maturity transition machine is proposed and defined to represent the knowledge state in the development. A quintuple $\langle Q, \Delta, K, kcm_i, kcm_{i+1} \rangle$ is employed to construct the knowledge maturity transition machine.

Q is a finite set of knowledge maturity level, $Q = \{kcm_1, kcm_2, \cdots, kcm_9\}$.

K is a finite set of knowledge required to improve the knowledge maturity level, including two subsets: knowledge improved, namely the existing knowledge needs further verification or optimization; knowledge imported, namely the knowledge that needs to be acquired from the outside.

kcm_i is the initial knowledge maturity level, which is an element of Q, $kcm_i = (ve_i, kc_i, ue_i)$.

kcm_{i+1} is the next knowledge maturity level to arrive, which is an element of Q, $kcm_{i+1} = (ve_{i+1}, kc_{i+1}, ue_{i+1})$.

In addition, let $kcm_i^{'}=\left(ve_i^{'},kc_i^{'},ue_i^{'}\right)$ be the current state of knowledge maturity. For quantification, the percentage of the accomplished gap to the supposed gap can be calculated by: $\Delta=\left(w_e\dfrac{ve_i^{'}-ve_i}{ve_{i+1}-ve_i}+w_c\dfrac{kc_i^{'}-kc_i}{kc_{i+1}-kc_i}+w_r\dfrac{ue_i^{'}-ue_i}{ue_{i+1}-ue_i}\right)\times 100\%$. Obviously, if $kcm_i^{'}$ is nearer to kcm_{i+1}, then Δ has a higher value.

In fact, the aim of measurement is to serve as a means for comparison. Therefore, the knowledge maturity transition machine adopts the idea of comparison, and regards knowledge activities as a sequence that starts from the initial knowledge maturity level and finally reaches the final knowledge maturity level.

5. Case study

Taking springback compensation knowledge of frame-rib parts as an example, the assessment process of knowledge capability maturity would be illustrated in detail as below. Springback compensation knowledge of frame-rib parts, that is, springback angle can be obtained by comprehensively considering factors such as material, geometric parameters and so on. Here, the object solved by this type of knowledge is mainly characterized by several features of material grade, flange type, material thickness, bending radius and bending angle. Among them, material grade and flange type are discrete-valued features, while the remaining material thickness, bending radius and bending angle are continuous-valued features.

According to the calculation framework of knowledge capability maturity in Fig.7, it is necessary to figure out three evaluation indexs' values of springback compensation knowledge of frame-rib parts firstly.

(1) For verification environment, this type of knowledge has been applied in actual production. Therefore, according to the definition in Table 1, the verification environment of this kind of knowledge has reached level 7, with a corresponding score of 0.8.

(2) Since the solved object has both discrete-valued features and continuous-valued features, the knowledge coverage can be obtained according to the calculation framework in Fig.5. Firstly, the classification relationship could be established according to the two features of material grade and flange type. Since the material grade includes dozens of 2024-O, 7075-O, 2B06-O, etc., this paper only takes the most commonly used 2024-O frame rib parts as an example. For flange type, there are two types: co-directional flange and opposite directional flange. Thus, the classification feature chains established within discrete-valued features are shown in Fig.8. Where, the weight value of each feature is obtained according to the statistics of the actual number of frame-rib parts in a certain type of aircraft.

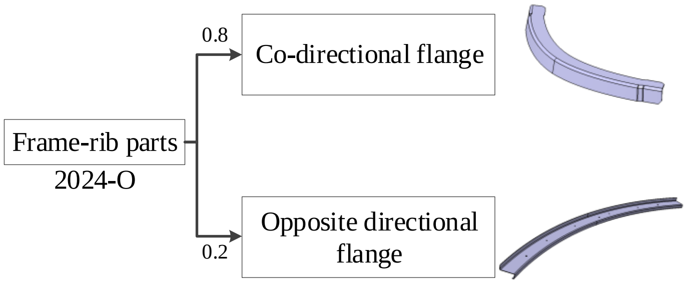

Figure 8 –Classification feature chains of 2024-O frame-rib parts

Secondly, the discretization for features with continuous value would be executed taking the relationship of attributes into account. The calculation process is described by taking the classification feature chain "2024-O & Co-directional flange" as an example. Since material thickness determines the interval of the specific bending radius, material thickness is associated with bending radius. Besides, there is no restriction between material thickness and bending angle. Also bending radius and bending angel are independent each other. Through the two-stage discretization process, the results are shown in Table 3.

Table 3 Discretization for features with continuous value

Material thickness			Bending radius			Weight	Bending angel			Weight	Union interval
discrete interval	spacing	points	discrete interval	spacing	points		discrete interval	spacing	points		
[0.4,0.8]	0.1	5	[0.8,5.6]	0.8	7	0.05	[60°, 65°]	5°	2	0.025	U_1
							[70°, 75°]	5°	2	0.05	U_2
							[80°, 100°]	5°	5	0.85	U_3
							[105°, 110°]	5°	2	0.05	U_4
							[115°, 120°]	5°	2	0.025	U_5
[0.9,2.2]	0.3	5	[2.4,8.0]	0.8	8	0.90	[60°, 65°]	5°	2	0.025	U_6
							[70°, 75°]	5°	2	0.05	U_7
							[80°, 100°]	5°	5	0.85	U_8
							[105°, 110°]	5°	2	0.05	U_9
							[115°, 120°]	5°	2	0.025	U_{10}
[2.3,3.2]	0.4	4	[4.8,10.4]	0.8	8	0.05	[60°, 65°]	5°	2	0.025	U_{11}
							[70°, 75°]	5°	2	0.05	U_{12}
							[80°, 100°]	5°	5	0.85	U_{13}
							[105°, 110°]	5°	2	0.05	U_{14}
							[115°, 120°]	5°	2	0.025	U_{15}

Afterwards, cover analysis of object should be carried out through the distance calculation. Let d_{jl} denote the discrete space of the discrete interval I_{jl}. According to the condition: $\left|\hat{f}_{i,j}^{t} - f_{g,j}^{t}\right| < d_{jl}$, the unsuitable objects would be screened out to reduce the calculation time. As shown in Table 4, only O_1^1, O_2^1 and O_3^1 three objects in the knowledge base need to calculate the distance with $\hat{O}_1^1$ further, for these three objects satisfy the screening conditions: $\left|0.6 - f_{g,2}^{1}\right| < d_{21}$, $\left|1.6 - f_{g,3}^{1}\right| < d_{31}$ and $\left|95^\circ - f_{g,4}^{1}\right| < d_{43}$. Where, d_{21} represents the spacing of the first discrete interval of material thickness, d_{21}=0.1; d_{31} stands for the spacing of the first discrete interval of bending radius, d_{31}=0.8; d_{43} denotes the spacing of the third discrete interval of bending angle, d_{43}=5. The object distance between $\hat{O}_1^1$ and O_1^1 could be calculated using equation (6), that is $dis(\hat{O}_1^1, O_1^1) = \frac{1}{3}\left(\frac{|0.6-0.55|}{3.2-0.4} + \frac{|1.6-1.0|}{10.4-0.8} + \frac{|95^\circ - 92^\circ|}{120^\circ - 60^\circ}\right) = 0.043$. In like manner, the computation results of $dis(\hat{O}_1^1, O_2^1) = 0.01$ and $dis(\hat{O}_1^1, O_3^1) = 0.049$ could be obtained by equation (6). Let λ be the threshold, and set that $\lambda = \frac{1}{4} \times \frac{1}{3}\left(\frac{d_{21}}{3.2-0.4} + \frac{d_{31}}{10.4-0.8} + \frac{d_{43}}{120^\circ - 60^\circ}\right) = 0.017$. Since $dis(\hat{O}_1^1, O_2^1) < \lambda$, O_2^1 is regarded as the object covering the target $\hat{O}_1^1$. The covering situation of rest knowledge unit is obtained as shown in Figure 9. Where, U_1, U_2, $\cdots$, U_{15} correspond to each union interval in Table 3.

Table 4 The distance needs to be calculated respectively

Features of part				VS	The objects satisfying screening conditions			
	Thickness	Radius	Angel		Thickness	Radius	Angel	
$\hat{O}_1^1$	0.6	1.6	95°		0.55	1.0	92°	O_1^1
					0.6	1.6	93°	O_2^1
					0.65	2.2	91°	O_3^1

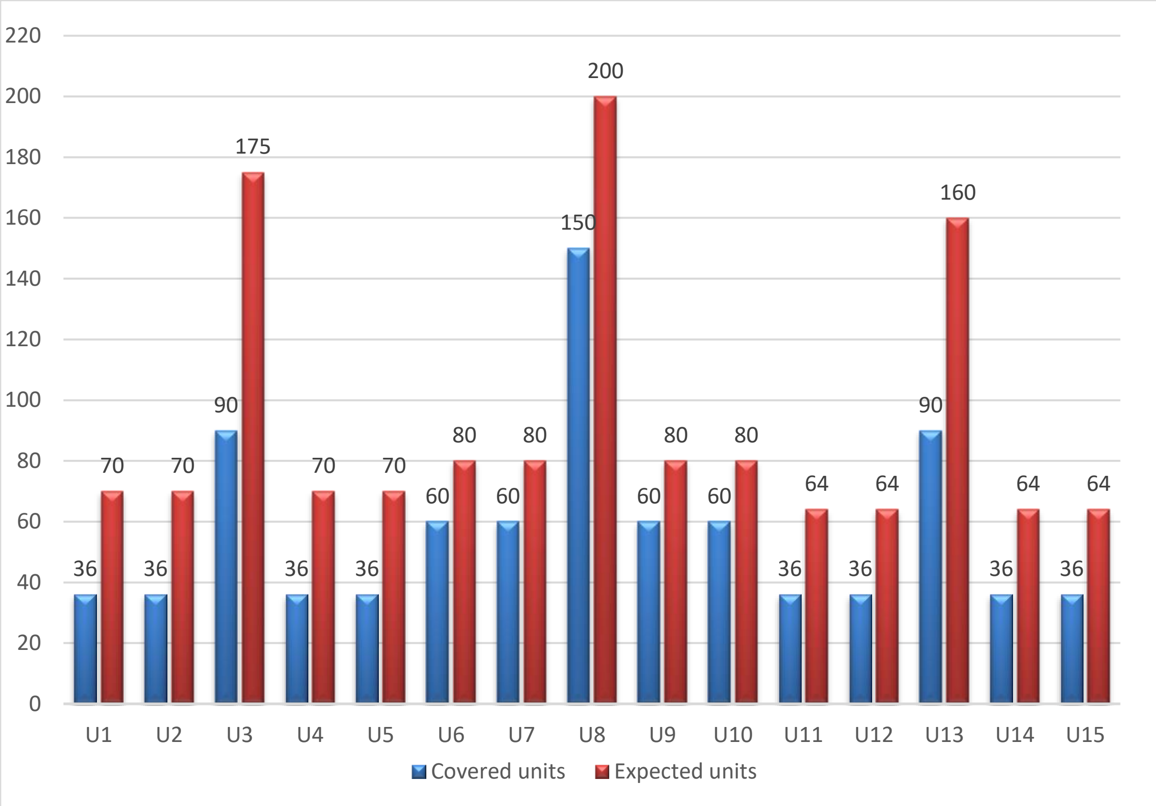

Figure 9 –Covering situation of each union interval

While N_{re} denotes the number of valid objects included in the knowledge base, N_{ex} represents the total number of all objects expected to be solved. They can be calculated using equation (2) as following:

$$
\begin{aligned}
N_{re} &= \sum_{l=1}^{L_J}\left[\sum_{i=1}^{n_l}\left(\prod_{k=1}^{K_i} W_{ik}\cdot P_{ik}^{'}\right)\right] \\
&= \left(0.05\times0.025\times36+0.05\times0.05\times36+0.05\times0.85\times90+0.05\times0.05\times36+0.05\times0.025\times36\right) \\
&\quad+\left(0.90\times0.025\times60+0.90\times0.05\times60+0.90\times0.85\times150+0.90\times0.05\times60+0.90\times0.025\times60\right) \\
&\quad+\left(0.05\times0.025\times36+0.05\times0.05\times36+0.05\times0.85\times90+0.05\times0.05\times36+0.05\times0.025\times36\right) \\
&= 131.04
\end{aligned}
$$

$$
\begin{aligned}
N_{ex} &= \sum_{l=1}^{L_J}\left[\sum_{i=1}^{n_l}\left(\prod_{k=1}^{K_i} W_{ik}\cdot P_{ik}\right)\right] \\
&= \left(0.05\times0.025\times70+0.05\times0.05\times70+0.05\times0.85\times175+0.05\times0.05\times70+0.05\times0.025\times70\right) \\
&\quad+\left(0.90\times0.025\times80+0.90\times0.05\times80+0.90\times0.85\times200+0.90\times0.05\times80+0.90\times0.025\times80\right) \\
&\quad+\left(0.05\times0.025\times64+0.05\times0.05\times64+0.05\times0.85\times160+0.05\times0.05\times64+0.05\times0.025\times64\right) \\
&= 179.0425
\end{aligned}
$$

Obviously, the coverage of flange springback compensation knowledge in rubber pad forming for frame rib parts using 2024-O type material could be computed by $Cov^{C}=\frac{N_{re}}{N_{ex}}$ and the result is 73.19%.

According to the above process, the coverage of another classification feature chain can be obtained, and the results are shown in Table 5.

Table 5 Coverage of each classification feature chain for 2024-O frame-rib parts

Material grade	Flange type	Weight	Coverage(Cov_i^{C})
2024-O	co-directional flange	0.8	73.19%
	opposite directional flange	0.2	69.52%

Then, according to equation (3), the coverage of springback compensation knowledge for 2024-O frame rib parts can be obtained as below.

$$Cov^{\mathrm{H}} = \sum_{l=1}^{L}\left[\sum_{i=1}^{n_l} Cov_i^{\mathrm{C}}\left(\prod_{j=1}^{m_i}\omega_{ij}\right)\right] = 73.19\% \times 0.8 + 69.52\% \times 0.2 = 72.46\%$$

(3) The evaluation of using effect is mainly carried out by two quality evaluation indexes of bending angle deviation and shape deviation. Let $\Delta\phi$ denote bending angle deviation and Δd represent shape deviation. The tolerances for forming quality requirements are $\pm 1.0^{\circ}$ and 0.5 mm respectively. With tolerances as the basic reference, the corresponding deviation grades and corresponding scoring standards are established, as shown in Table 6.

Table 6 The scoring standards of $\Delta\phi$ and Δd

Grade	$\Delta\phi$	Δd	G_{ij}
1	$\Delta\phi > 1.0^{\circ}$	$\Delta d > 0.5$	0
2	$0.9^{\circ} < \lvert\Delta\phi\rvert \le 1.0^{\circ}$	$0.4 < \lvert\Delta d\rvert \le 0.5$	0.6
3	$0.8^{\circ} < \lvert\Delta\phi\rvert \le 0.9^{\circ}$	$0.3 < \lvert\Delta d\rvert \le 0.4$	0.7
4	$0.6^{\circ} < \lvert\Delta\phi\rvert \le 0.8^{\circ}$	$0.2 < \lvert\Delta d\rvert \le 0.3$	0.8
5	$0.5^{\circ} < \lvert\Delta\phi\rvert \le 0.6^{\circ}$	$0.1 < \lvert\Delta d\rvert \le 0.2$	0.9
6	$\lvert\Delta\phi\rvert \le 0.5^{\circ}$	$\lvert\Delta d\rvert \le 0.1$	1

According to the established deviation grade standards, the actual distribution of the formed parts in $\Delta\phi$ and Δd indexes in the knowledge base is statistically analyzed, and the results are shown in Table 7.

Table 7 The distribution of parts at each grade

	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
P_{1j}	10%	10%	40%	20%	10%	10%
P_{2j}	10%	10%	50%	20%	10%	0

At the same time, in line with expert experience, the weights of the two indicators for the forming quality are determined: the weight for bending angle deviation $W_1 = 0.6$, and the weight for shape deviation $W_2 = 0.4$. Then, the using effect score of formed parts supported by the knowledge system of springback compensation can be obtained based on equation (7).

$$\begin{aligned} SR &= \sum_{i=1}^{2}\sum_{j=1}^{6} W_i \times G_{ij} \times P_{ij} \\ &= 0.6 \times (0 \times 10\% + 0.6 \times 10\% + 0.7 \times 40\% + 0.8 \times 20\% + 0.9 \times 10\% + 1 \times 10\%) \\ &\quad + 0.4 \times (0 \times 10\% + 0.6 \times 10\% + 0.7 \times 50\% + 0.8 \times 20\% + 0.9 \times 10\% + 1 \times 0\%) \\ &= 0.678 \end{aligned}$$

According to the analysis of the above case, the current knowledge maturity level belongs to the KML7. Obviously, the initial and next knowledge maturity vector can be obtained based on the definition of knowledge maturity model: $kcm_7 = (0.8, 70\%, 0.65)$, $kcm_8 = (0.9, 80\%, 0.75)$. Since the measurement result of current state is $kcm_7^{'} = (0.8, 72.46\%, 0.678)$, Δ could be calculated by:

$$\begin{aligned} \Delta &= \left(W_e \frac{ke_7^{'} - ke_7}{ke_8 - ke_7} + W_c \frac{kc_7^{'} - kc_7}{kc_8 - kc_7} + W_r \frac{kr_7^{'} - kr_7}{kr_8 - kr_7}\right) \times 100\% \\ &= \left(0.3 \times \frac{0.8 - 0.8}{0.9 - 0.8} + 0.4 \times \frac{72.46\% - 70\%}{80\% - 70\%} + 0.3 \times \frac{0.678 - 0.65}{0.75 - 0.65}\right) \times 100\% \\ &= 18.24\% \end{aligned}$$

In the real application, using Δ to describe the current state in the way to the next target can help decision makers know the progress clearly. Then, K can reflect the rest gap that needs to be completed from current level to the next level of maturity. With the coverage indicator, it can clarify the direction of knowledge imported in K, that is, what knowledge needs to be added. Based on verification environment and using effect, it can determine the direction of knoweldge improved in K.

6. Conclusions

Our research aims to propose a comprehensive evaluation method to quantitatively assess knowledge capability based on maturity model. This paper begins by analyzing the characteristic and capability of manufacturing process knowledge and proposes several new basic notions such as knowledge coverage, and so on. After that, three evaluation indexes of verification environment, knowledge coverage and using effect have been chosen to measure knowledge capability. Likewise, the specific evaluation method of each evaluation index is constructed. Then they are formalized and integrated into a structured and explicit approach to characterize knowledge capability maturity model. One of the uses of knowledge capability maturity model is in the area of decision making and assessment of the current state of knowledge in the base. Decision makers can verify the quality of development of their knowledge base in order to move forward to the next stage. By identifying the gap between the current state and the target state, it will be beneficial to develop the best improvement strategy. Through the assessment of knowledge coverage, it can be clear which knowledge needs to be added and prioritized. With the evaluation of verification environment and using effect, it is possible to clarify which existing knowledge is in urgent need of improvement. The measurement method proposed in this paper will be a useful solution for satisfying the practical requirements. The effectiveness of the method is illustrated by taking the springback compensation knowledge of frame rib in rubber forming.

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8. Copyright Statement

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