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ORIGINAL ARTICLE

# Digital twin-based process reuse and evaluation approach for smart process planning

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**Abstract**

With the advances in new-generation information technologies, smart process planning is becoming the focus for smart process planning with less time and lower cost. Big data-based reusing and evaluating the multi-dimensional process knowledge is widely accepted as an effective strategy for improving competitiveness of enterprises. However, there was little research on how to reuse and evaluate process knowledge with dynamical changing machining status. In this paper, we propose a novel digital twin-based approach for reusing and evaluating process knowledge. First, the digital twin-based process knowledge model which contains the geometric information and real-time process equipment status is introduced to represent the purpose and requirement of machining planning. Second, the process big data is constructed based on the three-layer and its association rules for accumulating process knowledge. Moreover, the similarity calculation algorithm of the scene model is proposed to filter the unmatched process knowledge. For accurately reusing the process knowledge, the process reusability evaluation approach of the candidate knowledge set is presented based on the real-time machining status and the calculated confidence. Finally, the diesel engine parts are applied in the developed prototype module to verify the effectiveness of the proposed method. The proposed method can promote the development and application of the smart process planning.

**Keywords** Digital twin · Process knowledge · Process big data · Feature vector · Reusability evaluation

## 1 Introduction

With the advances in new-generation information technologies, especially big data, cyber-physical systems, cloud computing, and digital twin are considered as the key technologies to achieve smart manufacturing. Especially in process planning, reusing the exiting knowledge is becoming the focus for improving competitiveness of enterprises. According to practical verification, the digital twin's ability to link enormous data to fast simulation also makes it possible to perform evaluation and optimization of manufacturing processes. The digital twin-based process knowledge reuse and evaluation method, which provides a novel enabling tool for evaluating the potential process knowledge, could help a planner efficiently get the accurate process knowledge for machining planning.

The 3D computer-aided process planning systems are widely applied in manufacturing industries, and a vast number of MBD-based process models which consist of a lot of process knowledge are created and stored in their repository. The existing process knowledge (e.g., machining resources, process requirements) are embedded in the machining features. It will be a huge waste if the enterprises' efforts on these machining features could not be well explored and reused. However, there was little research on how to reuse process knowledge for smart process planning. Most existing knowledge reuse methods mainly focus on retrieving the similar parts. However, the embedded process knowledge in the MBD-based process model is generally determined on the feature layer rather than the top part or component layer. Therefore, how to find the similar machining feature effectively and efficiently for the potential process knowledge reuse becomes an urgent problem to be solved.

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Recently, researchers have paid more and more attention on semantics retrieval [1–3] and shape retrieval [4] for process design. However, these methods cannot be directly used in feature-based machining planning. The main reason is that these methods only retrieve the similarity knowledge from the part layer rather than from the machining feature layer. This often leads to the inefficiency of the reused knowledge. It mainly exists the following issues: (1) there is no effective process knowledge reuse method of the feature-based process planning, (2) finer machining features similarity calculation and dynamic process evaluation approach are absent, and (3) the real-time machining status is not considered in the process design.

Based on the above description of the motivations, a novel digital twin-based approach for reusing and evaluating process knowledge is presented. First, the proposed digital twin-based process knowledge model (DT-PKM) which contains the geometric information and process constraints (e.g., process resources, annotation information) is constructed. Here, a feature vector which expresses the machining feature is proposed, and it can be as the basis of similar feature retrieval. Then, the process big data which fuses the real-time machining status and the process knowledge is designed based on the three-layer structure. Finally, the process knowledge filter algorithm is presented to rapidly obtain the candidate process knowledge set. To ensure the accuracy of the matched process knowledge, the priority matching layers and evaluation rules are proposed based on the real-time collected data and the calculated confidence.

The rest of the paper is organized as follows. In Section 2, we give a brief review of related work about process knowledge reuse and evaluation. Section 3 introduces the basic concepts of DT-PKM and overviews our approach. Section 4 gives the construction method of DT-PKM and the process big data. In Section 5, the filter and evaluation algorithm of the process knowledge is given in detail. Section 6 elaborates the study case and analyzes the experimental results. Section 7 concludes the main contribution of the paper and Section 8 discusses research issues in the future.

## 2 Related works

Recently, feature-based CAx (e.g., CAD, CAM, CAE, CAT, CAPP) systems are currently considered as the state-of-the-art technologies for product modeling [5, 6]. Especially, feature-based process planning has been an active research topic and a lot of work has been done in this field. These works are very closely related to our research, and they focus on feature recognition or the knowledge-based system for reusing process knowledge.

### 2.1 Feature-based process planning

Machining feature is a vital link for the effective integration of various modules of computer integrated manufacturing systems (CIMS). The feature-based process planning methods are becoming the main research direction. Li et al. [7] proposed automatic generation of process models based on feature working steps and feature cutter volumes. In turning-milling center, Kumar et al. [8] developed an automatic process planning system based on the machining feature recognition in the complex machining. For prismatic micro parts, Kumar et al. [9] proposed the automatic extraction method of manufacturing information and process parameters based on feature-based model, and then the proposed CAPP system is developed to verify the proposed method. Obviously, machining feature is the basis of the intelligent machine planning. Feature recognition technology has become the key to the 3D-CAPP system. In the domain of feature recognition, researchers have proposed and implemented various algorithms: graph-based algorithms, volumetric decomposition techniques, hint-based geometric reasoning, hybrid approach, etc.

According to the attribute adjacency graph method, Zhu et al. [10] developed an automatic process planning system for milling and turning operation by the predefined feature types; for eliminating manual planning and shortening the planned lead time, Jong et al. [11] applied hybrid recognition technology to integrate the graph-based approach for the mold manufacturing scheduling. For integrating process planning and scheduling, Bensmaine et al. [12] proposed a reconfigurable manufacturing system for different operations with the analyzed graph nodes.

The hint-based geometric reasoning approach is designed and first implemented in object-oriented feature finder. Sormaz et al. [13] recognized the interacting features based on 2D hints, then the extracted information was input to the developed process planning module by using sweep solid modeling operation. The hint-based approach defined geometric reasoning rules, which associates machining information to recognize the isolated and interacting machining features [14].

In order to improve the efficiency of feature recognition, the hybrid approach is widely used. To realize the artificial intelligence planning, Marchetta et al. [15] integrated the hybrid procedural and knowledge-based to address both classic feature interpretation and feature representation problems. Huang et al. [16] proposed a hybrid graph and genetic algorithm approach for process planning problems in a concurrent manner by simultaneously considering the activities. For integrated process planning and scheduling, Yu et al. [17] proposed a new hybrid algorithm to facilitate the integration and optimization of these two systems, and greater performance and higher productivity of manufacturing system can be achieved by using the proposed method.

Most researchers applied the feature recognition technology to create the process planning system. Compared to 2D planning, feature-based process planning can improve the efficiency of planning and accumulate the process knowledge better. However, how to reuse the feature-based process knowledge has not attracted enough attention.

## 2.2 Process knowledge reuse

Reusing the similar process planning could improve the efficiency and quality of process design with less time and lower cost. Substantial research effort has pursued the similarity-based retrieval methods to support process knowledge reuse, and it mainly included text-based [18], content-based [1, 19], shape-based [3], topology-based [20], and feature-based retrieval methods.

Text-based and content-based retrieval are the main methods of knowledge reuse. The semantic text and its connotation are the basis of text-based retrieval, and it is widely used in process knowledge reuse. In text-based retrieval method, for reusing the shop-floor knowledge, Zhang et al. [18] proposed a comprehension reuse method with different manufacturing resources; according to the emerging collaborative technologies, Peng et al. [1] designed and developed a smart collaborative system to streamline the design process as well as to facilitate knowledge capture. Content-based retrieval mainly includes shape-based and annotation-based retrieval methods. Lee et al. [19] described a model for knowledge management and collaboration in engineering change processes and built a prototype system by using the case-based reasoning method. However, text-based and content-based reusing methods cannot fully express the high-dimensional process knowledge.

Under the assumption that "similar structures have similar processes," the similarity between the query model and the process models is compared to reuse the association knowledge. In the domain of machining knowledge reuse, shape-based and topology-based retrieval methods have become the mainstream. To apply machine learning, Ip et al. [21] proposed the core shape matching algorithms to suit different classifications of CAD models. For reusing the NC machining process, Huang et al. [20] proposed a flexible and effective method by retrieving the similar subparts, and the process plan was generated with less time and lower cost. According to the incorporated modeling knowledge, Li et al. [3] presented a novel method to facilitate CAD model retrieval and reuse by the general and partial shapes. For improving the efficiency of process knowledge reuse in decision support systems, Cochrane et al. [22] described a set of modeling guidelines to classify manufacturing knowledge. Marefat et al. [4] developed an indexing scheme to store and speedily retrieve digital part/component by using the features and the spatial relationships.

## 2.3 The digital twin for process planning

Digital twin is an integrated multi-physics, multi-scale, probabilistic simulation of a complex product and it uses the best available physical models, etc., to mirror the life of its corresponding twin [23]. Since the concept of digital twin was proposed, it has been applied in many industrial fields such as designing and multi-objective optimization of hollow glass production line [24], real-time detection in aerospace vehicles [25], and real-time geometry assurance in individualized production [26] and has demonstrated its great potential.

Digital twin, as an effective mean to achieve physical-information fusion, has a significant promotion to realize the smart manufacturing. The innovation and efficiency from product design, production planning, to manufacturing implementation are improved by applying the digital twin [27]. Digital twin technology is getting more and more attention. It serves as a bridge between the physical world and the cyber world, providing the manufacturing enterprises with a new way to carry out smart production and precision management [28]. In a satellite assembly shop-floor, Zhuang et al. [29] proposed digital twin-based framework to fulfill smart production management and control. Tao et al. [30] proposed a digital twin-based shop-floor to realize the interaction and convergence between physical and virtual spaces.

According to the rough annals of digital twin listed above, it is obvious that the efforts have mainly focused on the integration between cyber and physical spaces. However, in most recent past, how to apply digital twin technology to the process design has not gotten enough attention. In ref. [31], digital twin-based process planning is proposed, and the key technologies are explained, but how to reuse and evaluate the process knowledge are not elaborated. In order to improve the effectiveness of process knowledge reuse, we propose a dynamic evaluation method for process knowledge based on the real-time machining status.

In recent years, our team dedicated to create process models and manage process information [32, 33]. Process knowledge reuse has been regarded as an important factor to be considered in order to manufacture high value-added products with the best possible quality and short lead time at a competitive cost [34]. Existing process reuse methods (e.g., semantics-based retrieval, geometry-based retrieval) can solve the diversification knowledge matching although they do not pay more attention to the actual design requirements. Feature-based method also stays passive in the knowledge reuse, and it ignores the process knowledge evaluation which leads to inefficiencies in process reuse. To solve these problems, a new kind of digital twin-based process knowledge model is proposed, combining the process big data and the dynamic reusability evaluation method.

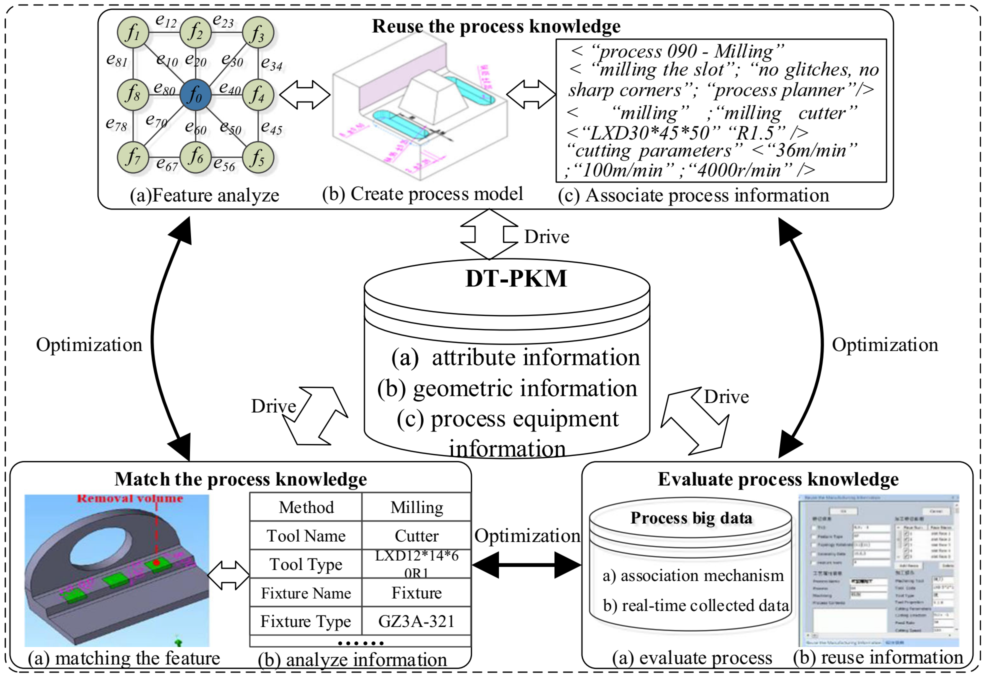



**Fig. 1** The framework of process knowledge reuse and evaluation based on DT-PKM

## 3 Basic concepts and overview of the method

In this section, some basic concepts are defined, and then the proposed method is briefly outlined. In this article, the machining features refer to 2.5D machining feature and the 3D models are represented by the boundary representation (B-rep).

### 3.1 Basic concepts

**Definition 1.** *The digital twin-based process knowledge model (DT-PKM)*. DT-PKM refers to the purpose and requirement of machining process, specifically involves the attribute information which inherits from the design model, the geometric information, and its process constraints.

It can be denoted as follows:

$$\mathrm{DT{-}PKM} = \{\mathrm{PPB}, \mathrm{PPG}, \mathrm{PEI}\} \quad (1)$$

where the PPB refers to the process planning background, e.g., part type, material; the PPG refers to the process planning goals, and it depends on the basic information of the machining feature; the PEI refers to the process equipment information, e.g., machine, tool, fixture.

The DT-PKM is the basis for reusing and evaluating the process knowledge. The framework of reusing and evaluating process knowledge based on the DT-PKM is shown in Fig. 1. The procedure of reusing and evaluating process knowledge can be divided into three steps: first, analyze the process planning intents based on the product model; second, the process knowledge is reused base on the DT-PKM; finally, according to the real-time collected data from the shop-floor, the process knowledge is dynamically evaluated. Process planning intent is responsible for asking questions, and the DT-PKM gives the appropriate solution. Because it determines the kind of process knowledge and its specific content. Therefore, process planning intent is seen as the "question" and DT-PKM is seen as the corresponding "answer." In order to precisely reuse and evaluate the process knowledge, the DT-PKM should be accurately described and expressed.

Recently, feature-based 3D-CAPP has become an active research topic and a huge volume of literatures have been reported on this subject. They have reached a consensus that the in-process modeling is the key technology in process design. Feature-based modeling approaches have played a relevant role in qualitative knowledge specification and integration since the 1970s [35], while these works reveal that the definitions of machining features do not have consensus. Table 1 presents some most recurrent definitions for "machining feature."

**Table 1** Some machining feature definitions used in the literatures

| Definitions of machining feature |
|---|
| "the information-set relative to the manufacturing knowledge, such as machining method and equipment information [36, 37]," |
| "the surface feature of the solid model [38]" |
| "the removed material volume for the formed cave [39]" |
| "geometric shapes with certain engineering semantics [40]" |

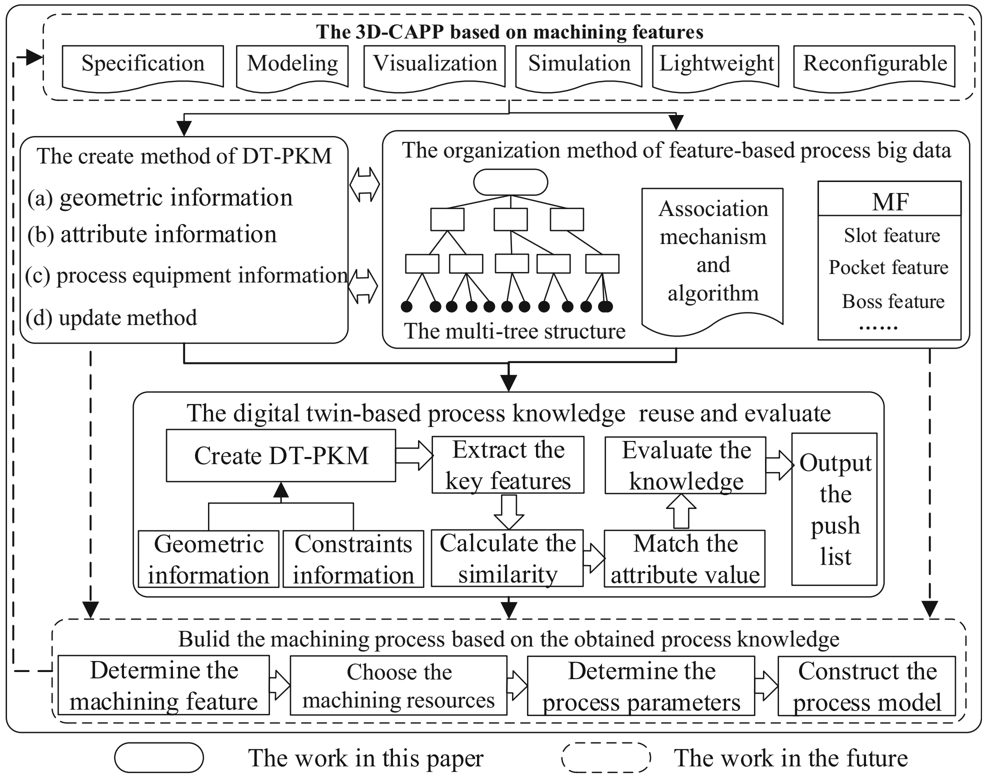



**Fig. 2** A digital twin-based method for reusing and evaluating process knowledge

Based on the above analysis, machining feature remains to be understood differently by different stakeholders.

**Definition 2.** *Machining feature (MF)*. A machining feature is defined as the geometric information (GI) of the set of adjacent faces that can be associated with a set of process constraints (PC) such as process resources and annotation information.

MF can be denoted as follows:

$$\mathrm{MF} = \{\mathrm{GI}, \mathrm{PC}\} \tag{2}$$

$$\mathrm{GI} = \{\mathrm{FA}, \mathrm{TR}, \mathrm{GD}\} \tag{3}$$

$$\mathrm{PC} = \{\mathrm{MI}, \mathrm{SA}, \mathrm{AI}\} \tag{4}$$

where FA refers to the adjacent faces attributes, TR represents the typological relations of the adjacent faces, and GD represents the geometric dimension of the removal volume; MI refers to the basic machining information such as machining methods, processing order, and tooling. SA refers the shape attributes of the machining feature; AI represents the annotation information.

Here, FA is an attributed graph with the nodes of the graph representing the machining feature face, and the edges of the graph representing the intersecting line between two feature faces. The attributes of the node include the face types (such as plane and curved) and the edge types (such as concave edge, convex edge, and hybrid edge). TR describes the space location among the feature faces. And the interrelationship between two faces is represented by parallel, vertical, or angle.

## 3.2 Overview of approach

Most machining features are matched by calculating the similarity, and then the process knowledge are evaluated and reused. This will inevitably increase the efficiency of the process design. In order to achieve this goal, the associated information (e.g., geometric information, topological information, attribute information) of the machining feature should be well organized and managed. The complex and dynamical process knowledge is represented by the multi-tree structure. And they are stored in the process repository. Meanwhile, the vector description method of the machining feature can accelerate filter and match the similar feature accurately. The systematic overview of the proposed approach is shown in Fig. 2. It is seen that the proposed method contains four key parts.

(1) *Analyze the process planning intents*. In order to meet the requirement of reusing the process knowledge accurately, the process intents of machining feature should be analyzed. The proposed feature recognition method [32] can effectively extract the attribute information of the machining features. Based on the obtained machining features and its attribute information, the process intents model is constructed and expressed. In process planning, the create methods of process models and automatically

**Table 2** The expression structure of PPB

| Num. | The elements of the PPB | Contents |
|---|---|---|
| 01 | Family type | Cylinder head, connecting rod, … |
| 02 | Part type | V12 cylinder head, V12 connecting rod, … |
| 03 | Stock type | Forging, casting, stamping,… |
| 04 | Material | Al, 45 steel, GGr15,… |
| 05 | Manufacturing type | Heat treatment NC, general, … |

updating methods are proposed by our completed works [32, 33]. Therefore, the process intents models can be conveniently created.

(2) *Construct the DT-PKM and the process big data*. The DT-PKM is the basis of the proposed systematic method. It contains the basic process requirements and the process equipment information, which make the accurate evaluation based on the machining status. The process big data is made up of real-time collected data, machining features and its associated process knowledge, process equipment, etc. In order to rapidly and accurately reuse the knowledge, the constructed process big data should be automatically updated based on the dynamic machining.

(3) *Filter the unmatched process knowledge*. A rapid filter method is carried out based on the extracted key features and its attribute values. The abundant features that are unable to be matched with the query feature are filtered based on the calculated similarity.

(4) *Reuse and evaluate the process knowledge*. After rapidly and accurately filtering out the unmatched machining features, the candidate process knowledge set of the query feature are obtained. Then, according to the real-time data of the process equipment (e.g., machine failure, tool wear), the reused process knowledge are evaluated and hierarchically reused.

## 4 Construct the DT-PKM and process big data

In the feature-based process planning, it can not only easily recognize the machining feature of the B-rep model but also conveniently obtain the embedded process information. The other advantages are shown as follows: (1) the in-process models can be conveniently created by geometric reasoning methods and (2) downstream detecting and predicting can be supported. Thus, the process planning goals are easily expressed by the predefined machining features. Then, the DT-PKM and the process big data are constructed. In order to better illustrate the method, this paper takes the diesel engine key parts as an example for detailed explanation.

### 4.1 Create the DT-PKM

The DT-PKM includes three parts: process planning background (PPB), process planning goals (PPG), and process equipment information (PEI). The feature-based methods can effectively organize and express the process knowledge. Thus, the DT-PKM is created based on the machining features. The PPB is the basic of the DT-PKM, it mainly includes the part information; the PPG is the carrier of the process knowledge, and it is organized by the geometric information of the machining features. The PPB and PPG are seen as the basis of the candidate process knowledge sets. The PEI is seen as the basic of process evaluation, which mainly includes the real-time status of process equipment.

(1) The process planning background

The parts which have the similar machining processes are called family parts. Thus, the part type is taken as the basic information of the PPB. PPB describes the identical information of the family parts, including family type, part type, stock type, etc. Table 2 illustrates the expression structure of PPB based on the diesel engine parts.

(2) The process planning goals

The machining feature is seen as the carrier of the process knowledge, so the PPG is illustrated based on the machining features. In order to conveniently describe the PPG, a feature vector representation method is developed. The feature vector can be automatically generated by the formed B-Rep model. This helps to build a feature library incrementally to meet the requirements of the machining domain. The PPG is denoted as the following:

$$\mathrm{PPG} = \left\{F_{\mathrm{type}}, D_{\mathrm{tool}}, M_{\mathrm{face}}, M_{\mathrm{adj}}, M_{\mathrm{typo}}, I_{\mathrm{size}}\right\} \tag{5}$$

where the $F_{\mathrm{type}}$ refers to the machining feature type, the $D_{\mathrm{tool}}$ refers to tool access direction, the $M_{\mathrm{face}}$ refers to the machining face matrix, the $M_{\mathrm{adj}}$ refers to the adjacency face graph matrix, the $M_{\mathrm{typo}}$ refers to the typology relation matrix, and the $I_{\mathrm{size}}$ refers to the size information of the removal volume of the machining features.

**Table 3** The machining feature types and their codes

| Num. | Feature types | Code | |
|---|---|---|---|
| 01 | Hole | Milled hole | O |
| 02 | Pocket | Slot | U |
| | | Pocket | P |
| 03 | Open pocket | Groove | G |
| | | Open pocket | C |
| | | Step | T |
| | | Slope | L |
| 04 | Face | Horizontal face | F |
| | | Slope | L |
| | | Freeform surface | S |
| 05 | Boss | Boss | B |

- Machining feature type

The machining features are classified into five categories according to their shapes: holes, pocket, open pocket, boss, and face. The codes of machining feature types are shown in Table 3.

- Tool access direction

Tool access direction (TAD) is defined as the feed direction of the cutter axis in machining. Based on the basic manufacturing knowledge, TAD of the planar is mainly perpendicular or parallel to the machining face and the TAD of the quadric surface is mainly along its axis machining. The same TAD is seen as a necessary condition for similar features. The TAD is expressed by the vector $D_{\mathrm{tool}} = (x, y, z)$.

- Machining face matrix

The $M_{\mathrm{face}}$ expresses the geometric information and connection relationship of the machining features. The face types of the machining feature are divided into six categories: plane, cylinder face, conical face, torus ring, sphere, and chamfer. The face types are attached to the different values as shown in Table 4.

Any two adjacent machining faces can be connected by one edge. For presenting the connection relationships, the intersecting edges are described by shape attribute and geometric attribute. The intersecting edges are divided into three types based on their geometric attribute: concave edge, convex edge, and tangent edge, and their attached values are 0001, 0010, and 0011. Additionally, the edges are divided into three types based on the shape attributes: line, arc, and spline curve, and their attached values are 0001, 0010, and 0011. Therefore, the intersecting edges are expressed and stored by the following mode: concave-line edge, convex-arc edge, convex-spline curve edge, etc. The connected edges can be expressed based on the shape attachment value and the geometric attachment value, for example, the expression of convex-arc edge is 0110.

**Table 4** The machining feature face types and their values

| Num. | Face types | Value |
|---|---|---|
| 01 | Plane | 0001 |
| 02 | Cylinder face | 0010 |
| 03 | Torus ring | 0011 |
| 04 | Conical face | 0100 |
| 05 | Sphere | 0101 |
| 06 | Chamfer | 0110 |

According to the machining face types and their connection relationships, the $M_{\mathrm{face}}$ is formed by the attached values. In matrix, the diagonal elements show the face types, and other elements show the connection relationships.

- Typology relation matrix

$M_{\mathrm{typo}}$ can be formed by the machining face types and their typological relationships. The typological relationships of machining feature faces are determined based on their orientation, positions, and shapes. The relationships are divided into four types: parallel, vertical, not vertical, and tangent, and they are respectively attached to the values 0001, 0010, 0011, and 0100. According to the normal vector of each face, the angle between two faces is calculated, then the typology relations are determined by the obtained angle. The diagonal elements of the $M_{\mathrm{typo}}$ show the face types and other elements show the typology relationships.

- Size information

In order to obtain the size information of the machining feature better, we use the oriented bounding box (OBB) method. $I_{\mathrm{size}}$ contains three elements: length, width, and height, and they are easily obtained based on the OBB of the machining feature volume.

(3) Process equipment information

The execution of machining processes can be affected by disturbances during machining process. The PEI mainly refers to the real-time status of process equipment such as the real-time status of the machine and fixture and the wear state of the tool. With the advance of sensor network, wireless network, automation technology, and analysis technology, a wide range of applications have been achieved in manufacturing shop-floors with perceptual system and multi-agent as a representative of internet of things technology. This meets the needs of the real-time status information of process equipment in manufacturing shop-floors. Based on the distributed numerical control system, the machine status (e.g., work, idle) can be obtained. The wear state of the tool is acquired based on the tool lifecycle management software. In order to better support the process evaluation, we adopt the object-oriented method to organize and manage the real-time data of the machining status.

### 4.2 Organize the feature-based process big data

How to better organize and manage the process knowledge is the basis for constructing the process big data. This has also become a key factor for improving the efficiency of the 3D CAPP. According to the framework of the DT-PKM, feature-based technology can be used to conveniently accumulate the dynamic process knowledge. Therefore, the process big data is easily established based on the machining feature, and the process knowledge are stored and managed by structured hierarchical relationships. The developed organization model is shown in Fig. 3. The process big data is divided into two layers: input layer and output layer. The input layer refers to the machining feature information and the output layer refers to the process information.

(1) The organization model of the process knowledge

Accurate, complete, and efficient organization of machining knowledge is a key basis for constructing the process big data. The management method of the process knowledge directly relates the efficiency and accuracy of filtering and matching.

The multi-tree structure of process knowledge is constructed based on the object-oriented method. The top layer refers to the parts information, and it is called the basic information layer; the middle layer refers to the feature information, and it is called the machining information layer; the bottom layer refers to the additional information, and it is called the quality layer. The organization model of the process knowledge is shown in Fig. 4.

The basic information layer shows the required knowledge of the process planning background, and the contained information is shown in Table 2. The basic information can be represented as Formula (6).

$$I_{\text{basic}} = \sum_{i=1}^{5} I_i (i = 1, 2, 3, 4, 5) \tag{6}$$

The machining information layer shows the required knowledge of the formed features. They are the main content of reusing process knowledge. The machining knowledge is divided into six types and shown in Table 5. They can be represented as Formula (7).

$$I_{\text{mach}} = \sum_{i=1}^{6} I_i (i = 1, 2, 3, 4, 5, 6) \tag{7}$$

The quality layer shows the additional processes after completing the current processes, such as detection information and annotation information. Because the corresponding process equipment of this layer is uncertain, the layer knowledge is not seen as the focus.

(4) The associated rules

The associated rules between the process knowledge and the machining features are divided into two types: multi-dimensional association and single-dimensional association. The associated rules have the following attributes.

**Definition 3.** *Single-dimensional association*. The existing sets $X$ and $Y$, $X = \{X_1, X_2, \ldots, X_n\}$, and $Y = \{Y_1, Y_2, \ldots, Y_n\}$, $\exists\ \forall$ $X_i \rightarrow Y_j$ ($X_i \in X$, $Y_j \in Y$) are one-to-one correspondence, and the association rule of $X_i \rightarrow Y_j$ is called single-dimensional association.

**Definition 4.** *Multi-dimensional association*. The existing sets $X$ and $Y$, $X = \{X_1, X_2, \ldots, X_n\}$, and $Y = \{Y_1, Y_2, \ldots, Y_n\}$, $\exists\ \forall$ $X_i \rightarrow [\ldots, Y_{j-1}, Y_{j+1}, \ldots]$ ($X_i \in X$, $Y_j \in Y$) are one-to-more correspondence, and the association rule of $X_i \rightarrow [\ldots, Y_{j-1}, Y_{j+1}, \ldots]$ is called multi-dimensional association.

In the basic information layer, the part information is determined based on a certain machining part such as the family type and stock type. Therefore, the associated rules, which associate the machining part with the corresponding information in the basic information layer, are seen as single-dimensional association rule. In the machining information layer, the machining information dynamically changes with the uncertain process equipment, such as the groove feature which can be machined by milling or turning. Therefore, the associated rules, which associate with the machining feature and the processing information in the machining information layer, are seen as multi-dimensional association rule.

## 5 Filter and evaluate the process knowledge

In order to improve the efficiency and accuracy of matching process knowledge, the feature-based hierarchical filtering methods and process knowledge evaluation methods are proposed. The procedure of filtering and evaluating process knowledge is shown in Fig. 5. First, the DT-PKM of the case model is constructed by the extracted process requirements. And according to the established process big data, a great deal of process knowledge is filtered or matched. Second, the similar machining features are output based on the proposed matched method. Then, the output process knowledge is evaluated based on the associated rules. Finally, the optimal process knowledge is pushed and reused.

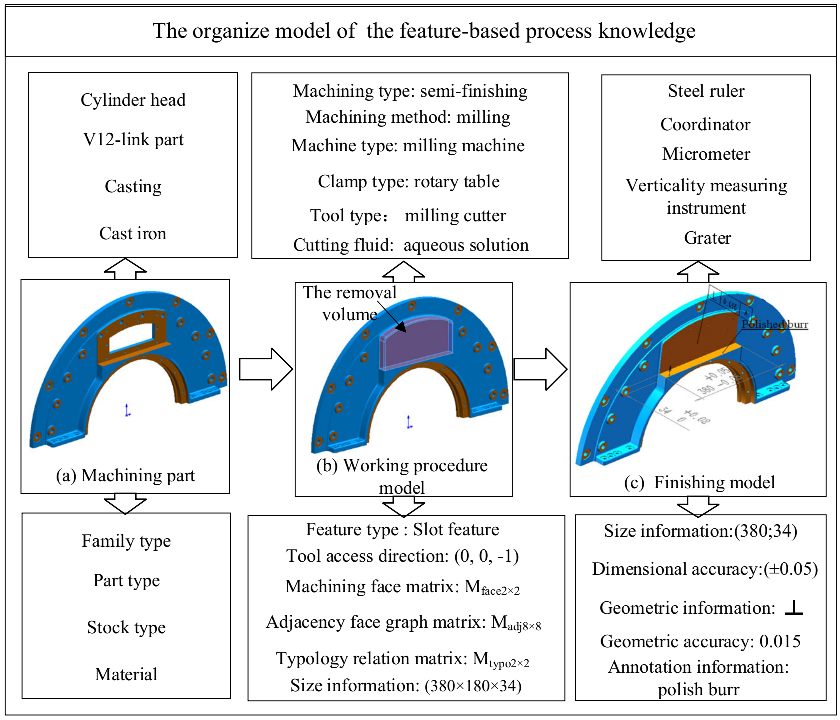



**Fig. 3** The organization mode of the feature-based process knowledge

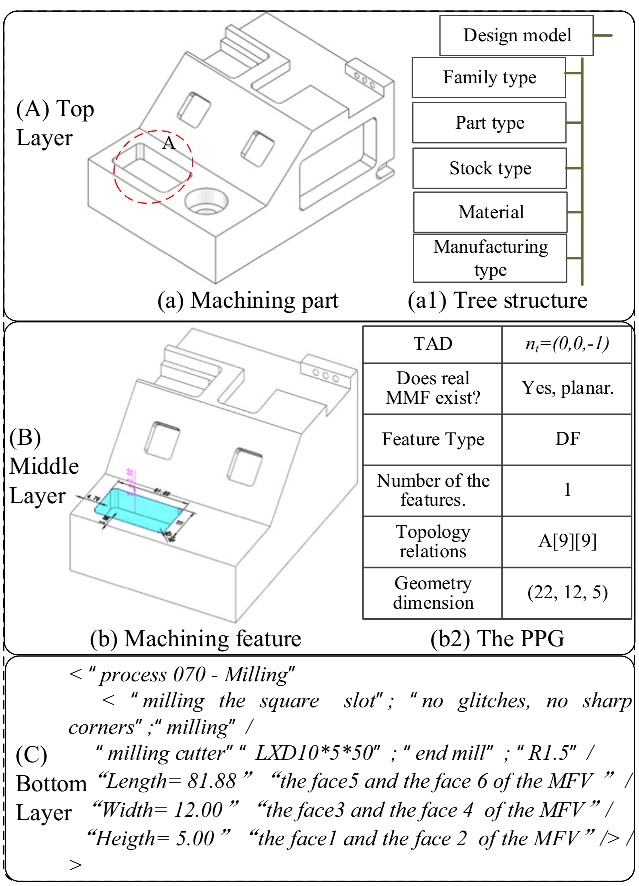



**Fig. 4** **A**–**C** The organization model of the process knowledge

### 5.1 Obtain the candidate process knowledge set

Obtaining the candidate process knowledge set is the prerequisite for evaluating and reusing process knowledge. Creating the DT-PKM of the machining feature is the basis of obtaining the candidate process knowledge set. In this respect, the similarity calculation method of the DT-PKM is proposed and it includes three parts: the basic information matching, the machining feature matching, and the quality information matching. For family parts, the basic information must be exactly matched, yet the similarity of the machining features needs to be calculated. Therefore, the calculation method of the similar features is seen as the focus of this part.

In Section 4.2, the machining information of the machining features is divided into six types to be elaborated. The similarity between two machining features is calculated by Formula (8). The sum of the attributes weight is equal to 1. The expression of attributes may be expressed by vectors, matrices, or numbers. So, the similarity of machining features can be judged by the similarity of their attributes.

$$\omega(F_a, F_b) = \sum_{i=1}^{6} \lambda_i \times \sigma_i \qquad \sum_{i=1}^{6} \lambda_i = 1 \tag{8}$$

(1) The vector match

The similarity between two vectors can be expressed by their angle or distance. The smaller the calculation results,

**Table 5** The types of the machining information

| Num. | The types of machining information | Contents |
|---|---|---|
| 01 | Machining type | Roughing, semi-finishing, finishing··· |
| 02 | Machining method | Milling, turning, boring, fining··· |
| 03 | Machine type | Lathe, milling, grinder, drilling··· |
| 04 | Tool type | Milling cutter, turning tool, broach, drill··· |
| 05 | Clamp type | Chunk, sucker, rotary table, vise··· |
| 06 | Cutting fluid | Aqueous solution, oil solution, mix liquid··· |

the higher similarity between the two attributes. The calculation formula is shown as follows.

$$conine(p,q) = \frac{\sum_{i=1}^{n} p_i q_i}{\sqrt{\sum_{i=1}^{n} p_i^2 \times \sum_{i=1}^{n} q_i^2}} \tag{9}$$

where $cos(p, q)$ indicates the cosine distance, $p_i$ indicates the *ith* variable of the stored vector $p$, and $q_i$ indicates the *ith* variable of the matching vector $q$.

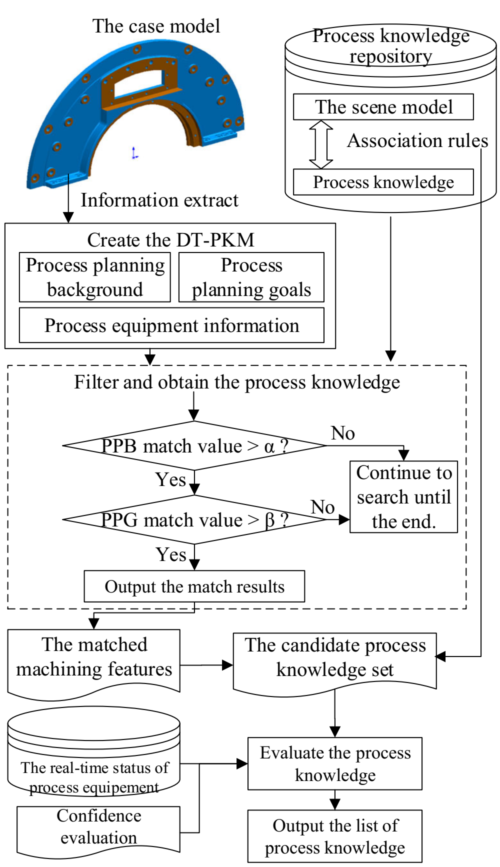



**Fig. 5** The procedure of filtering and evaluating process knowledge

(2) The matrix match

In order to conveniently calculate the similarity between two matrixes, the multi-dimensional matrix needs to be transformed into the form of single-dimensional vector. Then, the matrix is matched by calculating the vector's similarity.

(3) The attributes value match

The similarity between two attributes value can be expressed by their average value and it is calculated by Formula (10). Supposing two values are $a_1$ and $a_2$, the formula of similarity calculation ($S_a(a_1, a_2)$) is shown as follows.

$$S_a(a_1, a_2) = \frac{1}{n}\sum_{i=1}^{n} \frac{||a_{1i}| - |a_{1i} - a_{2i}||}{|a_{1i}|} \tag{10}$$

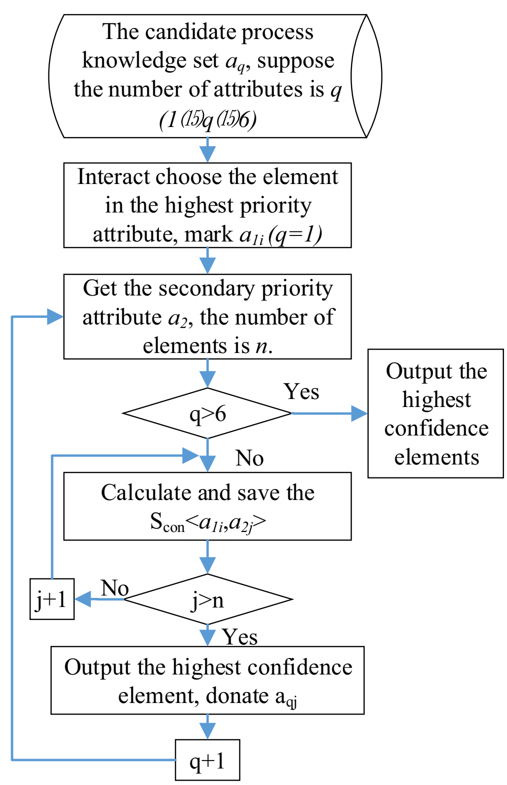



**Fig. 6** The confidence evaluation method of process knowledge

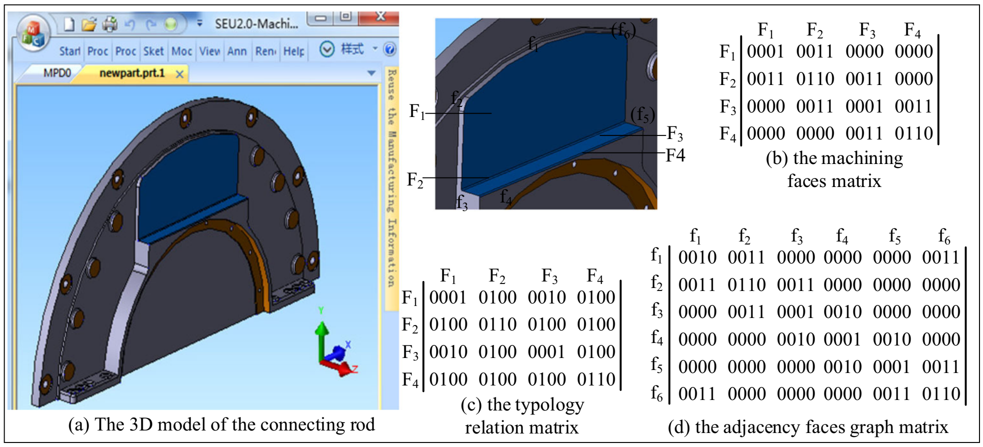



**Fig. 7** The process planning goals of the connecting parts

## 5.2 Evaluate the candidate process knowledge set

According to the matched machining features, the candidate process knowledge set is obtained based on the associated rules. In order to accurately push the reused process knowledge, the candidate process knowledge needs to be evaluated. The evaluation method is divided into two parts: PEI evaluation and confidence evaluation. The execution of process planning can be affected by disturbances (e.g., tool failure, machine failure) during machining process. If the real-time status of process equipment does not match the candidate process knowledge, these process knowledge will be deleted. Then, other process knowledge is evaluated by calculating the confidence.

In Section 4.2, the process knowledge is divided into six parts to be expressed. These parts are interrelated and they possess the priority levels. The machining method is determined by the machining type, so the machining type takes precedence over the machining method. The priority order of these process attributes is shown in Table 5. The reliability of the adjacent process attributes is evaluated by the confidence evaluation method. The confidence is calculated by Formula (11) and the evaluation procedure is shown in Fig. 6. Supposing process knowledge items $p_1$ and $p_2$, the reliability of $p_1$ and $p_2$ is calculated as follows:

$$S_{\mathrm{con}} < p_1, p_2 >= \frac{\mathrm{Preq}(p_1 \cap p_2)}{\mathrm{Preq}(p_1)} \tag{11}$$

where the $\mathrm{Preq}(p_1)$ shows the occurrence number of $p_1$ and the $\mathrm{Preq}(p_1 \cap p_2)$ shows the occurrence number of $p_1$ and $p_2$.

The confidence evaluation method of process knowledge is explained as follows:

Step 1 Get the attribute with high priority in the candidate process knowledge set and determine the optimal elements.

Step 2 Get the attribute with secondary priority and the contained elements.

Step 3 Calculate the confidence between two elements in the evaluated attributes and get the highest evaluated elements in the attribute with secondary priority.

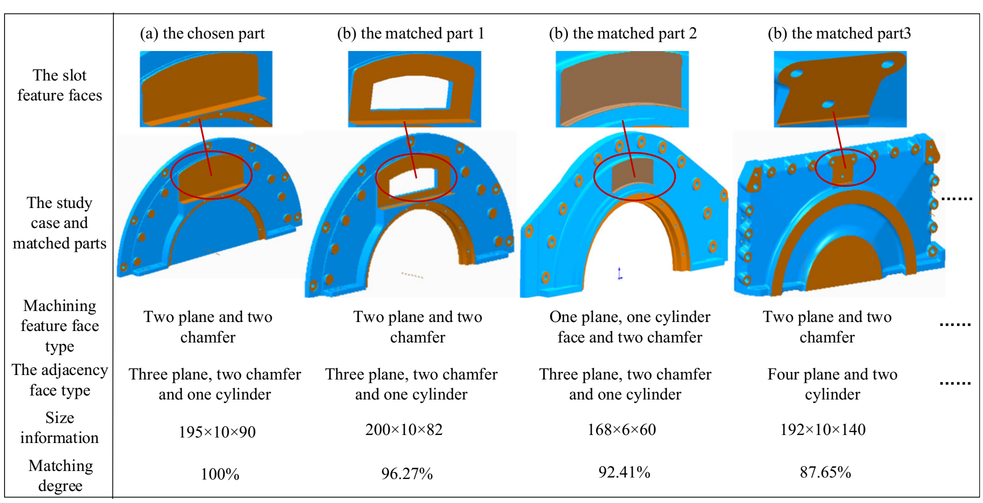



**Fig. 8** The matched results of the slot features

**Table 6** Similarity description of two slot features

| The attributes of PPG | $F_{\text{type}}$ | $D_{\text{tool}}$ | $M_{\text{face}}$ | $M_{\text{typo}}$ | $M_{\text{adj}}$ | $I_{\text{size}}$ |
|---|---|---|---|---|---|---|
| The slot feature ($S_1$) of the query part | Slot feature | (0, − 1, 0) | Fig. 7(b) | Fig. 7(c) | Fig. 7(d) | 195 × 10 × 90 |
| The slot feature ($S_2$) of the matched part 2 | Slot feature | (0, − 1, 0) | $M_{4\times4}$ | $M_{4\times4}$ | $M_{6\times6}$ | 168 × 6 × 60 |
| $\lambda_i$ | 0.1 | 0.1 | 0.3 | 0.2 | 0.1 | 0.2 |
| $\sigma_i$ | 1 | 1 | 0.944 | 0.957 | 0.997 | 0.709 |
| $\omega(s_1, s_2)$ | | | 0.924 | | | |

Step 4 Continue Step 2 until all the attributes are evaluated.
Step 5 Output the highest confidence elements.

## 6 Experiments

According to the developed MPD-processor system [41], the proposed methods and key techniques are integrated in this system. In the marine diesel engine, a large number of machined parts have similar processing. The connecting parts are the key components in marine diesel engines. To demonstrate the digital twin-based method for reusing and evaluating process knowledge, the connecting parts of diesel engine are chosen to be tested and analyzed based on our developed module. The obtained results clearly show the capability of the presented method.

### 6.1 Acquire the candidate process knowledge set

The PPB of the chosen connecting parts of the marine diesel engines is shown in Fig. 7(a). The machining features are easily recognized by our proposed method [32]. Take the slot feature as an example to explain the construction process of

**Table 7** The candidate process knowledge set

| Num. | Machining type | Machining method | Machine type | Clamp type | Tool type | Cutting fluid |
|---|---|---|---|---|---|---|
| 01 | Roughing | Turning | CK5120 | Platen | Turning tool YT6 | Aqueous solution |
| 02 | Roughing | Turning | CK5120 | Platen | Turning tool YG8 | Aqueous solution |
| 03 | Roughing | Turning | CK5120 | Flat | Turning tool YT6 | Oil solution |
| 04 | Roughing | Turning | CK5116 | Flat | Turning tool YG8 | Oil solution |
| 05 | Roughing | Milling | XK5032 | Flat | Cylindrical cutter | Aqueous solution |
| 06 | Roughing | Milling | XK6132 | Platen | Cylindrical cutter | Oil solution |
| 07 | Semi-finishing | Turning | CK5116 | Platen | Turning tool YT6 | Aqueous solution |
| 08 | Semi-finishing | Turning | CK5120 | Platen | Turning tool YG8 | Oil solution |
| 09 | Semi-finishing | Milling | XK5032 | Flat | Cylindrical cutter | Aqueous solution |
| 10 | Semi-finishing | Milling | XK6132 | Platen | Cylindrical cutter | Oil solution |
| 11 | Finishing | Turning | CK5116 | Platen | Turning tool YT6 | Aqueous solution |
| 12 | Finishing | Turning | CK5120 | Platen | Turning tool YG8 | Oil solution |
| 13 | Finishing | Milling | XK5032 | Flat | Cylindrical cutter | Aqueous solution |
| 14 | Finishing | Milling | XK6132 | Platen | Cylindrical cutter | Oil solution |

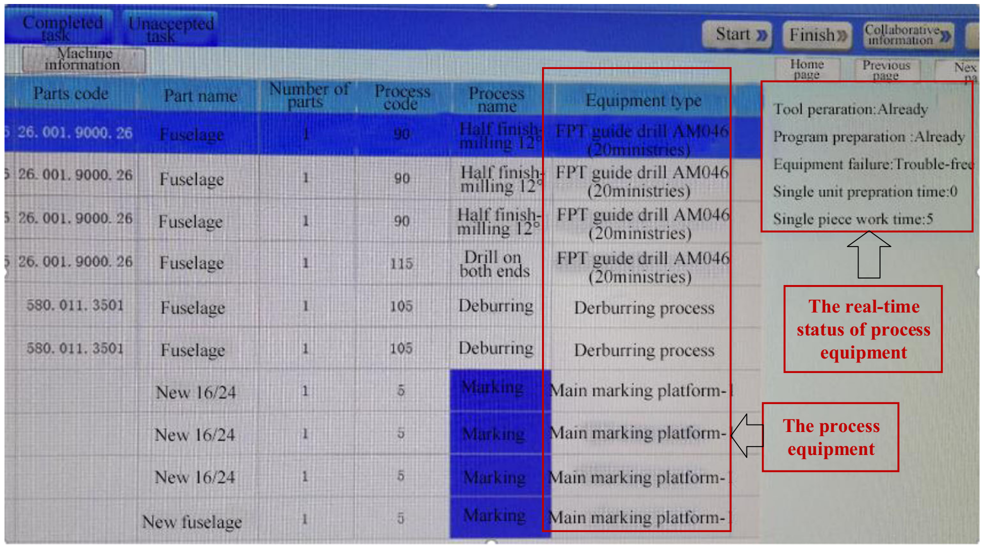



**Fig. 9** Interfaces of the process equipment information management

PPG. The PPG of the connecting parts is shown in Fig. 7(a–d). The tool access direction of the slot feature is expressed as $D_{tool} = (-1, 0, 0)$. Based on our proposed method, the type of machining face can be easily determined: $F_1$ and $F_3$ are the plane; $F_2$ and $F_4$ are the chamfer. Then, the machining face matrix and the adjacency face graph matrix are created based on the predefined codes of the face types as shown in Fig. 7(b, d). Based on the obtained normal vector of each face, the typology relations are determined and the established matrix is shown in Fig. 7(c). The size can be gotten by the oriented bounding box of the removal volume and it is indicated as $195 \times 10 \times 90$.

In order to get the candidate process knowledge set, the similar PPB and PPG should be determined firstly. Based on the proposed matching methods, the process of obtaining the candidate process knowledge set is described as follows. In the family parts, the PPB of the parts is the same. Therefore, matching PPG becomes the focus. In order to obtain more accurate process knowledge, the type of machining feature and the tool access direction should be perfectly matched with the query PPG. Based on the similarity calculation formula, the matched results of the slot features are shown in Fig. 8.

We take the slot feature of the matched part 2 as an example to elaborate the similarity calculation of the PPG. According to the heuristic rule, the weights of the attributes are set to 0.1, 0.1, 0.3, 0.2, 0.1, and 0.2. The calculated results are shown in Table 6.

## 6.2 Evaluate the candidate process knowledge

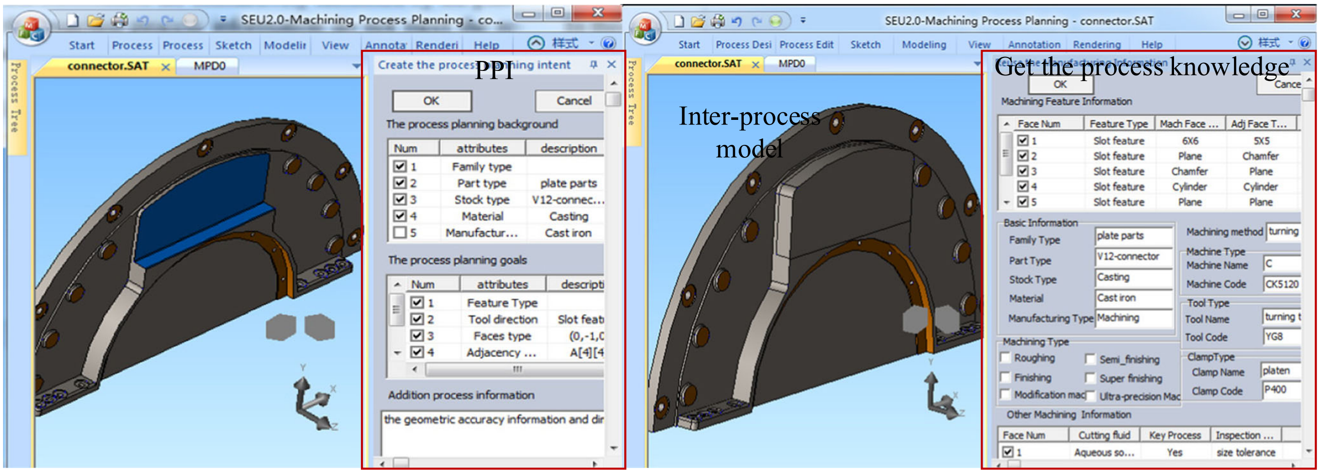
According to the obtained similar PPB and PPG, the candidate process knowledge set is shown in Table 7. The evaluating method is divided into two steps: process equipment evaluation and confidence evaluation.

In order to improve the effectiveness of evaluating process knowledge for machining parts, workshop monitoring system needs to be constructed to realize the real-time data acquisition of process equipment. This shows the real-time status of the manufacturing resource (e.g., tool, machine, fixture, measure tool). Figure 9 shows the real-time data collected of the process equipment for machining connecting parts. Whether the processing equipment is used normally or not is seen as the basis for process evaluation. If the processing equipment is not working properly, the corresponding process knowledge item will be deleted directly. If the processing equipment meets the requirements, the confidence evaluation is needed.

The reliability of the adjacent process attributes is calculated by confidence Formula (11). The chosen type of the machining step of the connecting parts is roughing, then the adjacent process knowledge item is identified by calculating the confidence. When $S_{con} < P_{type}, P_{meth-milling} \geq 0.33$ and $S_{con} < P_{type}, P_{meth-turning} \geq 0.67$, the machining method is determined as turning; When $S_{con} < P_{meth-milling}, P_{mach-CK5120} \geq 0.75$ and $S_{con} < P_{meth-milling}, P_{mach-CK5116} \geq 0.25$, the machine type (CK5120) is determined; When $S_{con} < P_{mach}, P_{clamp-platen} \geq 0.67$ and $S_{con} < P_{mach}, P_{clamp-flat} \geq 0.33$, the clamp type is determined as platen. Finally, the reused process knowledge is determined: roughing-turning-CK5120-platen-YT6/YG8-aqueous solution.

## 6.3 Prototype system

Figure 10 shows the prototype system of reusing and evaluating process knowledge, and the steps of reusing process knowledge for the query machining features are shown as follows. Firstly, a machining feature is seen as the query object, then its DT-PKM is automatically created; secondly, the candidate process knowledge set is shown in the dialog, and the




(a) Create the process planning intent (b) Get and push the process knowledge

**Fig. 10** **a** and **b** Interfaces of the process knowledge reuse and evaluation

corresponding process knowledge is evaluated based on the real-time status of process requirement and the confidence; finally, the reused process knowledge is pushed and the corresponding process model is created. In Fig. 10a, the slot feature faces are recognized and their types are determined. According to the constructed framework of DT-PKM, the matched results are shown in Fig. 10b. The candidate process knowledge which has the highest confidence is pushed and reused.

In order to demonstrate the significant improvement of our approach in efficiency, the comparisons with the interactive programming based on the developed old MPD-processor are listed in Table 8. It can be seen from the table that 32 steps of process knowledge require more than 180 user interactions and 300 s by using the manual programming approach. However, with our proposed approach, 26 steps of process knowledge can be automatically generated which require only 120 user interactions, and the other 6 steps of process knowledge are manually completed which require less than 50 user interactions, and the programming time is about 90 s. The efficiency of the proposed method improves by three times evidently and the reused machining information increases more than 60%.

## 7 Discussion

In this section, we will further discuss the advantages and potential application domains of our proposed approach.

Obviously, the manual method takes three times as much time as the proposed method. There are some reasons to be responsible for this problem: (a) do not evaluate the reused knowledge. This requires the planners to interactively select the process knowledge from the candidate set; (b) do not concern the real-time status of the process equipment. This often causes that the status of process equipment does not meet the process requirements, and the process planning needs to be changed again; (c) do not concern the feature-based process knowledge. This results in the inability to reuse process knowledge. Because the machining feature is seen as the carrier of process knowledge in MBD-based process planning. Therefore, the above reasons lead to a reduction in the efficiency of reuse process knowledge. Comparison with the manual method, our proposed method possesses the following flexibilities: (a) strengthen the user's subjective initiative in the process of reuse knowledge and cater to the users' individual and diversified needs for knowledge based on the

**Table 8** Comparisons of efficiency analysis

| Items for comparison | Manual programming based on the old MPD-processor | Programming with our approach | |
|---|---|---|---|
| | | Automatic programming | Manual programming |
| Number of process knowledge | 32 | 26 | 6 |
| Number of the user interactions | More than 180 | 120 | Less than 50 |
| Creation time(/s) | More than 300 | 20 | Less than 90 |
| Efficiency improvement | More than 60% | | |

confidence; (b) fuse the collected data of processing requirement into the DT-PKM and reduce the number of process changes; (c) create the feature-based process big data based on the three-layer and its association rules and satisfy the family parts for reuse the process knowledge.

Our approach has the potential to create the machining process planning of the query part smartly based on the matched DT-PKM. The vector representation of machining features could help the user effectively locate the similar PPG, retrieve the similar feature which is distributed on multiple feature representation elements in the repository, and then generate the process route of the query part by recombining and optimizing the obtained process knowledge segments of multiple similar PPG. Moreover, although the plate parts of the marine diesel engines are taken as an example to illustrate the principle of process knowledge reuse and evaluate in this paper, the proposed approach is also suitable for other parts such as box and shaft.

## 8 Conclusion and future works

With increasing competitiveness for manufacturing enterprises, engineers are often challenged to design the machining process of the similar parts with less time and lower cost. In order to deal with this challenge, a feasible strategy which reuses the existing process knowledge is paid close attention to. A general approach for reusing and evaluating process knowledge is proposed, which includes the creation of DT-PKM, the establishment of process knowledge big data, and the evaluation method. Moreover, the DT-PKM framework is created to represent the process requirement and the real-time status of process equipment. The process planning goals of the query feature is revealed by the vector representation methods of the machining features. In addition, the priority levels of feature-based process knowledge are explored to evaluate the candidate process knowledge. Finally, the candidate process knowledge is reused and evaluated automatically based on the developed module. The experiments with a prototype system indicate that our approach can support process knowledge reuse effectively and precisely.

In the near future, several issues are worth to be further explored to improve the practicability of the proposed methods: (1) the proposed methods are extended to other domains, e.g., assembly process design, casting process design. (2) combine the real-time evaluation results to optimize the process parameters; and (3) the real-time acquisition and analysis of the machining status data, e.g., the size information, quality information.

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