A Knowledge Based Machine Tool Maintenance Planning System Using Case-based Reasoning Techniques

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Abstract

In advanced manufacturing systems,Computer Numerical Control (CNC) machine tools are importantequipment to manufacture product components of high precision, whilst from equipment maintenance point of view, they areregarded as the 'products' provided by machine tool manufacturers. Therefore, the reliability of CNC machine tools affects not only the quality of the componentsthey manufacture, but also the reputation and profits of equipment suppliers. This paper presents a novel knowledge based maintenance planning system to facilitate information and knowledge sharing between all stakeholders including machine tool manufacturers, users (manufacturing systems), maintenanceservice providers and part suppliers (for machine tools), in the emerging 'Product-Service' business model.Case Based Reasoning principles have been implementedto improve the efficiency of maintenance planning. Ontologieswere adopted to represent field knowledge using adaptation guided retrievalsbased on semantic similarity and correlation. The adaption algorithm has been developed based on the Casual Theory and the dependence relationship to generate the solution forrequiredmaintenance problems. The proposedsystem was implemented using Content Management technologies, which proved to have advantages over traditional database systems in managing engineering knowledge, andhas been verified using an example CNC machine tool. The results were commented by industrial collaborators as very promising and further exploitation in industry was recommended.

Keywords

Manufacturing system;CNC machine tool; Maintenance; Knowledge management; Case-based Reasoning.

1 Introduction

Computer Numerical Control (CNC) machine tools play important roles in advanced manufacturing systems with automatic control and intelligent manufacturing capabilities. It is important to ensure their operating performance since they are high value and have long life cycles. For machine tool maintenance service providers, quick response tomachine tool users' requirements would improve their benefit and reputation. For machine tool users, the loss of productquality and production throughput because of machine tool breakdowns could be reduced if they can receive quick and accurate maintenance services.For machine tool manufacturers, more benefits would be obtained if they can provide more reliable products and key services as well.Maintenance servicepracticeshave changed a lot in the past: from corrective maintenance to preventive, predictive and design maintenance, and most recently Product-Service Systems (PSS)in which product manufacturers provide not only the products, but also a whole service programfor the entire lifecycle of their products[1], Fig. 1 shows the changes of maintenancepractices over time.

There was significant research effort devoted tothe maintenance of CNC machine tools. For example,Zhang et al [2] and Liu et al [3]reported research in themaintenance process and maintenance methods of machine tool components. A data model for representing machine tool health based on capability profiles was proposed[4]. Met et al [5] presented product service configurations. Zhu et al [6] proposed a PSS based on requirement analysis and knowledge management for aircraftmaintenance. However, few previous researchers regarded machine tools as "products" in the context of the emergingProduct-Service business model. They mainly regarded machine tool maintenance in the context of manufacturing system maintenance for operation and quality control.This research considers CNC machine tools as 'products' in the Product-ServiceSystem context and also as 'equipment' in manufacturing systems to manufacture other products, thus all stakeholders' requirements and their knowledge are incorporated in the proposed method.

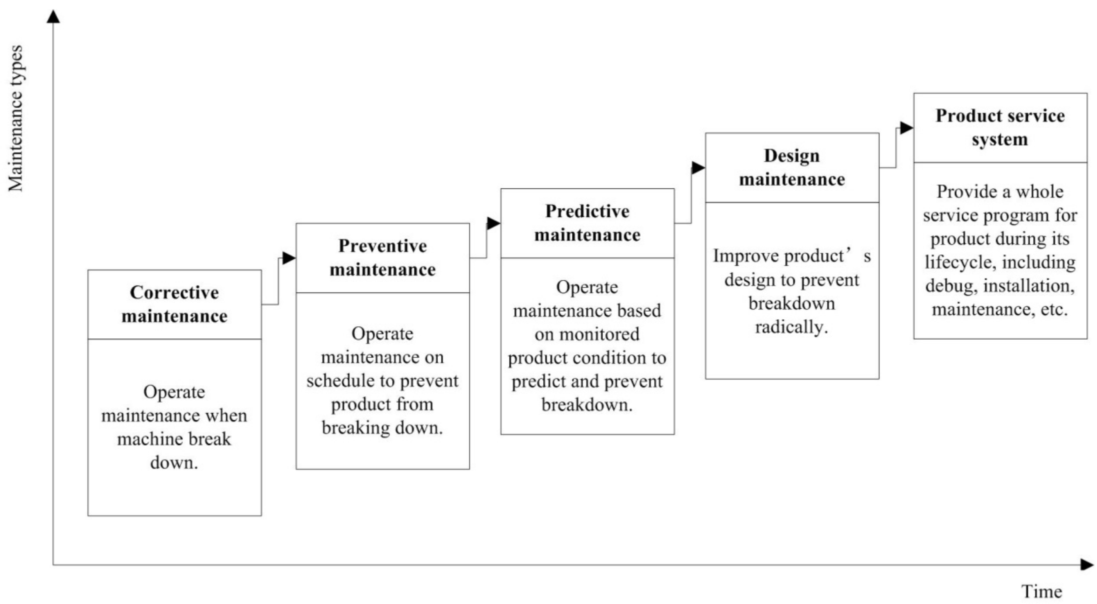

Fig. 1 Changes in maintenance practices [1]

Stakeholders (including machine tool manufacturers, service providers, machine tool users and machine tool part providers) of machine tool maintenance are usually geographically dispersed, which makes the execution of maintenance and service work complicated and very challenging. How to make use of current and historical knowledge and share knowledge between the stakeholders effectivelyis the key to improvingthe efficiency and effectiveness of machine tool maintenance. Maintenance engineers possess abundantinformation and knowledge from their working experiences. To acquire, store and share their knowledge during practice is an important issue in maintenance planning. The application of advanced Information and Communication Technologies (ICT) in maintenance servicesmakes it easier for experts to share their experiences,whilst usingdifferent knowledge management tools still have problems in collaboration or system interoperability due to knowledge incompatibility and mismatching. Semantic Web technology has the potential to support knowledge interoperability, allowingdifferent resources of knowledge shared, and providing the foundation of knowledge aggregation to generate new knowledge [7].

Currently, there are mainly three types of methods for semantic similarity calculation: Content Information method, Context Vector method and Path method [8, 9]. From industrial application point of view, Path method is easy to use, as it only calculates geometric model of ontology, and no pre-calculation or preprocessing is required, which ensures calculation efficiency. However, the simplicity may lead to low reliability as it cannot capture enough semantic evidences to assess similarity. Content Information method and Context Vector method need extra field knowledge to achieve assessing effectiveness. On one hand, preprocessinginformation in the Corpus may lead to high calculation load; on the other hand, the Corpus validity needs to be evaluated. Thus, Corpus method does not have much advantage in real life applications. Moreover, the similarity between different concepts is normally divided into semantic similarity and semantic relevancy[8].Current similarity calculations consider semantic similarity purely, ignoring the semantic relevancy calculations[10, 11], which do not represent the actual relationshipsbetween different concepts.

Maintenance for CNC machine tools is a process of solving new problems using previous knowledge. Based on the idea of problem solving process,Case-Based Reasoning (CBR) had been appliedtofault diagnosis during maintenance by previous researchers[12].However, through the years, CBR had been adopted under 'similarity assumption' that the most similar case was also the most relevant to the new problem to be solved [13], which, however, was not always valid in practice, since the retrieved most similar Case was not always easy to be modified to fit the new Case. It is the adaptation knowledge that matters, thus the Adaptation-Guided Retrieval (AGR) method was firstly proposed in [13]. AGR took the retrieved similar Case which had highest adaptation degree as the basis to generate maintenance solution for the new maintenance requirement.

Based on the problems described above that are encountered in the maintenance for CNC machine tools, this paper presents a Knowledge based Machine Tool Maintenance planningSystem(K-MTMS), which regards CNC machine tool as a "product"– the object of maintenance service, and structuresknowledge transformation process of product in use phase,and connects different stakeholders through the whole product lifecycle. Using ontology to represent maintenance knowledge, both semantic similarity and semantic relevancy are calculated to form similarity degree between two concepts based on multiple inheritances. This wouldreduce calculation complexity and improve the calculation accuracy of semantic similarity degree. This researchadopts Adaptation-Guided Retrieval to support knowledge retrieving during knowledge reasoning phase in maintenance process, which, on one hand, fills up the gap of "similarity assumption" in practice, and on the other hand, improves the effectiveness of maintenance plan using the most adaptive case. The proposed system was developed using a Content Management System (CMS)to manage maintenance knowledge, which makes up the gap that CMS are not being applied in engineering fields although CMS have been widely applied in managing information in business, government and social media. The research proved that CMS have advantages in managing engineering knowledge over traditional database and product lifecycle management systems.

2 The Proposed Knowledge Based Machine Tool Maintenance Planning System

Based on the requirements described above, a Knowledge based Machine Tool Maintenance planning System (K-MTMS) was proposed in the emerging Product-Service business context. K-MTMS can be divided into three layers:Business process layer, Model layer and Application layer (see Fig. 2). The three-layer frameworkprovides stakeholders of machine tool maintenanceto communicate and share information and knowledge, and allows them to collaborate with each other in making maintenanceplans, diagnosing machine tool performance status, allocating resources, reserving and distributing spare parts and executing maintenance plans. The data and knowledge generated during maintenance processes will be captured, structured and stored in the knowledge base, which can be accessed at different levels of stakeholder authorities.

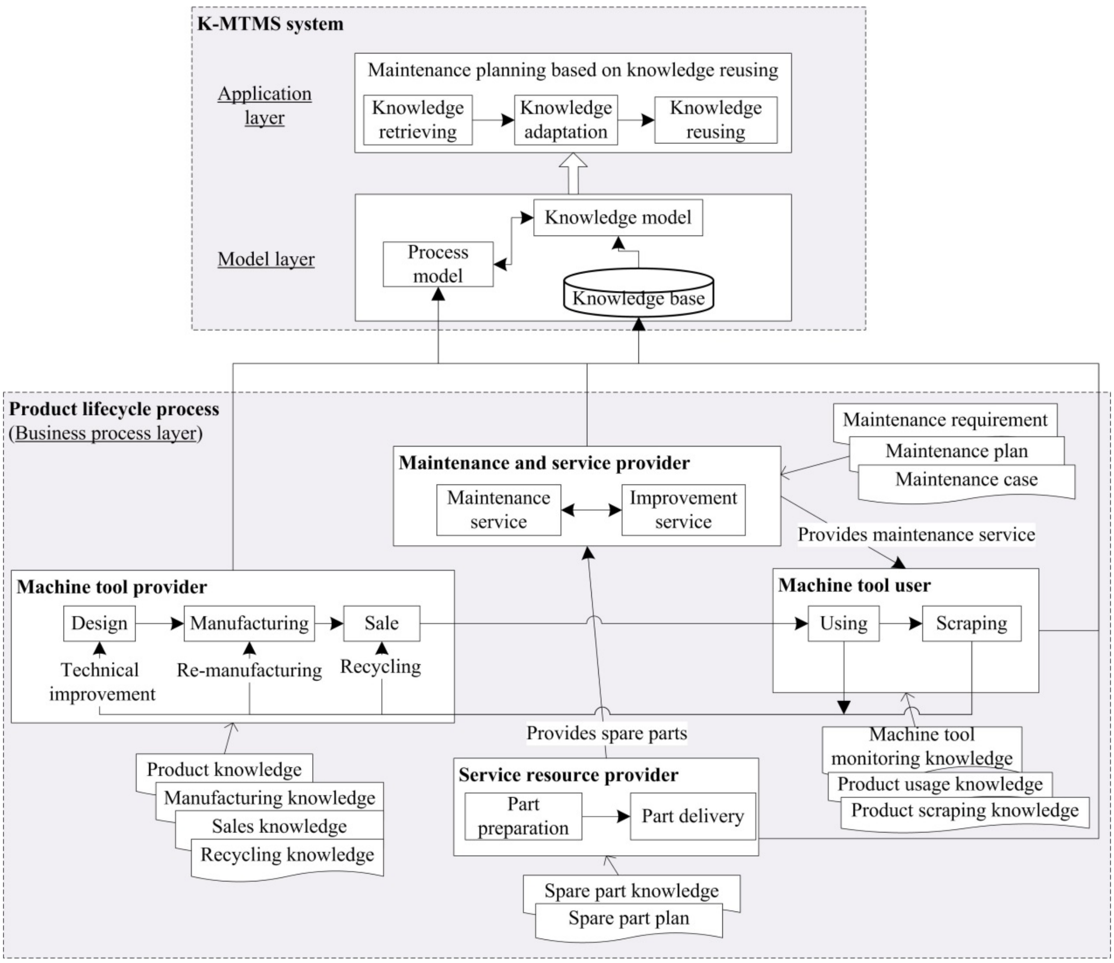

Fig. 2 K-MTMS system structure

At the top of Fig. 2 is the **Application layer**. Maintenance plan will be generated based on the process model and knowledge model (at the **Model Layer**). The idea of knowledge reuse is achieved by Case-based Reasoning (CBR) techniques consisting of

Case retrieval, adaptation degree calculation and Case adaptation.The **Model layer**includes the process model and knowledge model based on business process and related knowledge. Process model includes collaborative maintenance process, scheduled and predictive maintenanceprocesses. Knowledge model includes product knowledge model, process knowledge model, Case knowledge model and knowledge meta space model. Knowledge will be stored into knowledge base that has standard structure for sharing and can be called by different application programs. The data and knowledge in this research were captured from different stages of product life and stored into knowledge base.The **Business process layer**representsthe business process, activities and relationships between all stakeholders in a machine tool's lifecycle, including different knowledge types that support each activity. Machine tool providers not only design, manufacture and sale of machine tools, but are also responsible for product recycling and remanufacturing, and have close relationship with machine tool users (manufacturing systems). Service providers provide specialised maintenance service for machine tool users and also havemachine tools' health status data.Service resource providers provide spare parts and tools for service providers.

The proposed system aims to promote enterprise cooperation and improve the maintenance efficiency of high value machine tools. First of all, when a machine tool userrequestsa maintenance service throughK-MTMS, the machine tool provider and service provider can use the previous information and knowledgein the system to make decisions, so that the difficulties and problems of knowledge management and sharing ability in current enterprise applications can be offset. Secondly, by using this system, different stakeholders' progress can be tracked by others and the maintenanceplans can be timely executedand monitored.Furthermore, the stakeholders that come from different organisations can be gathered together by this system, so that theenterprise cooperationcan be enhanced.

3 The Maintenance Planning Methodology

This research adopts Case-based Reasoning (CBR) techniques to make maintenance plans based onhistorical maintenanceknowledge. Maintenance plans can be made by learning from previous experiences [14]. Its advantage is that it can retrieve historical knowledge stored as Cases, based on the similarity between a new problem and stored historical Cases and the adaptability of retrieved Cases, and reuses the knowledge in the selected similar Case for the planning of a new problem, thus improves the efficiency of solving the new problem. A typical CBR process includes five basic steps (as illustrated in Fig. 3), i.e., (1) Elaborate the new problem semantically, called Current Case (CC); (2) Retrieve previous similar maintenance Cases that their similarities are higher than the set threshold from the knowledge base according to CC; (3) Select the solution of the most adaptive Case to be adjusted as the proposed maintenance solution for CC, called adjusted Case (AC); (4) Revise the solution of AC according to actual maintenancepractices, and generate the revised Case (RC); and (5) Retain AC, RC as well as CC and take them as one of the Cases to be considered for solving future problems in the same way.

Fig. 4 illustrates the details of each step of Case-based reasoning. Through knowledge representation, Case retrieving, Case adaptation and Case revising, new knowledge will be stored as Cases in the knowledge base.

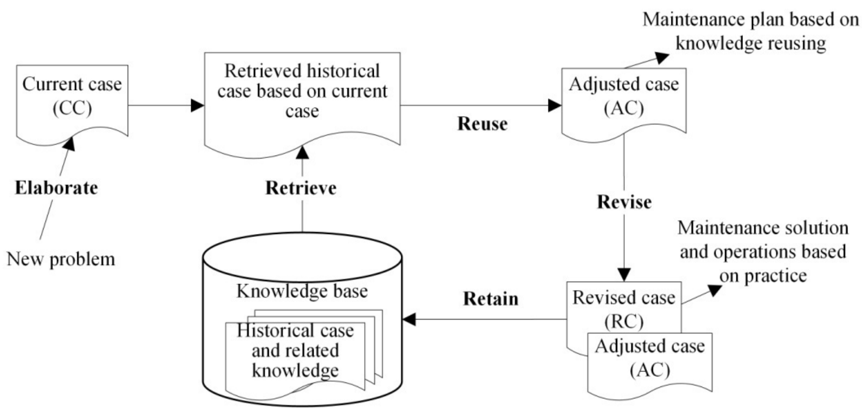

Fig. 3 Machine tool maintenance planning process based on CBR

3.1 Definition and classification of maintenance knowledge

The definition of knowledge is normally bonded with data and information [15, 16]. Data, information, knowledge and intelligence are regarded as Pyramid of Knowledge [1]. Pure words or numbers are called data. Meaningful data is called information. Information that illuminates how to be used forms knowledge. Part of knowledge is learned by people as intelligence. Data, information, knowledge and intelligence are gradually refined and progressive by layers, according to which knowledge discovery technology is used to discover knowledge [17, 18]. In other words, knowledge is the cognition and experience during human activities, which includes the understanding of phenomena, attributes and state of things, and the summary of methods of solving problems. Knowledge can exist in people's memory, manual records or computerised programs, such as machine tool operators and numerical machining systems.

Knowledge in industrial applications is also known as 'executable knowledge', which means that it can be interpreted by people or other media and can influence decisions and behaviours[1]. In the product maintenance and service field, knowledge is some information that is beneficial for failure diagnosis and solutions after being handled [19]. During the process of solving customer problems, maintenance field knowledge is obtained after related information is selected and converted [20]. Thus, knowledge releases its value by being used, and maintenance service field knowledge reflects its characteristics of supporting a specific field.

Based on the above understanding of knowledge, the maintenance knowledge in this paper is defined as all the information and resources that are beneficial for maintenance engineers to make maintenance planning decisions, including the knowledge of design, manufacturing and historical maintenance of parts, sub-systems or the whole product (machine tool), as well as the diagnosis rules, maintenance operations, procedures, required skills and task allocation methods in the maintenance process. This knowledge may exist in paper or electronic documents, computerised programs or people' mind.

In the maintenance field, knowledge has been normally classified from single perspectives, which cannot reflect the characteristics, purpose and manifestation [21, 22], as knowledge eventually relies on knowledge carriers, and is transmitted in different ways explicitly or implicitly. According to the form of knowledge carriers, knowledge can be classified as image, symbol, algorithm, text, tables, video and so on[23]. This paper adopts a two-dimension classification method to classify knowledge that supports maintenance planning according to the process of maintenance knowledge and the form of knowledge carriers, as presented in Table 1.

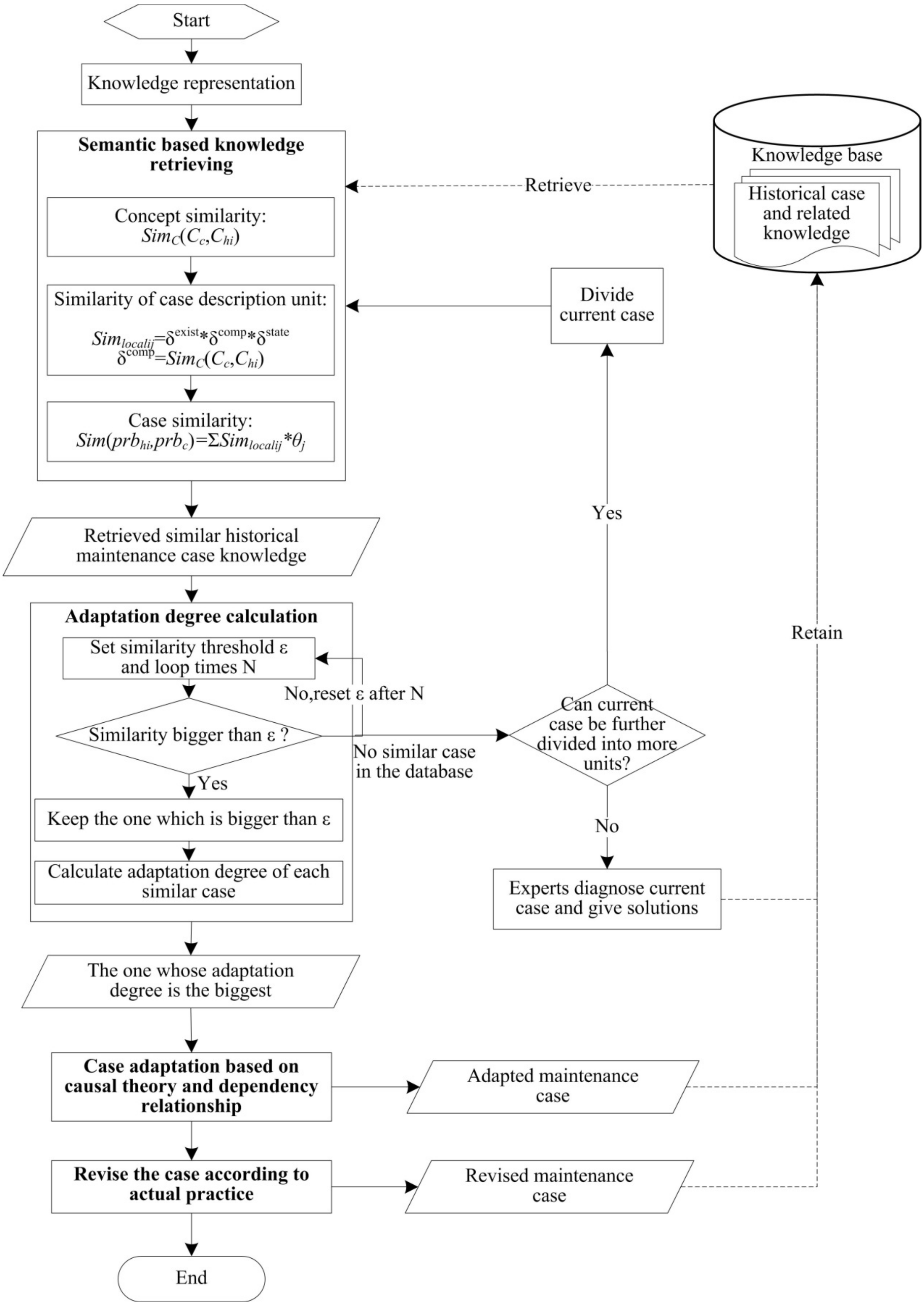

Fig. 4 Knowledge reusing process based on CBR

The key business objectives in maintenance planning are to confirm maintenance objects and machine state, set maintenance strategy, give maintenance solutions, make maintenance work orders, and allocate maintenance resources. Thus, the corresponding knowledge of each business process are called Maintenance Object Knowledge, Failure Diagnosis Knowledge, Maintenance Policy Knowledge, Maintenance Solution Knowledge, Maintenance Procedure Knowledge, and Maintenance Resource Knowledge, respectively. The relationship between the two perspectives of maintenance knowledge and maintenance planning is shown in Fig. 5. For each item of maintenance knowledge, the corresponding business process stage and the knowledge carriers can be found, which provides different ways of knowledge identification and reuse.

Table 1

The two-dimension classification for maintenance knowledge

Form of knowledge carriers / Maint. Service knowledge	Explicit	Implicit	Image(I)	Symbol(S)	Text(Txt)	Tables(Tbl)	Algorithm(A)	Video(V)
Maintenance Object Knowledge	(dis-)assembly specification	Assembly sketch map	√		√			
Failure Diagnosis Knowledge		Decision table, fishbone diagram	√	√		√		
Maintenance Policy Knowledge	Policy rules	Administrativemech anism			√		√	
MaintenanceSolution Knowledge		Maintenance experience						√
Maintenance Procedure Knowledge	Maintenance instructions	Maintenance process	√		√	√		√
Maintenance Resource Knowledge	Instructions for spare parts		√			√		

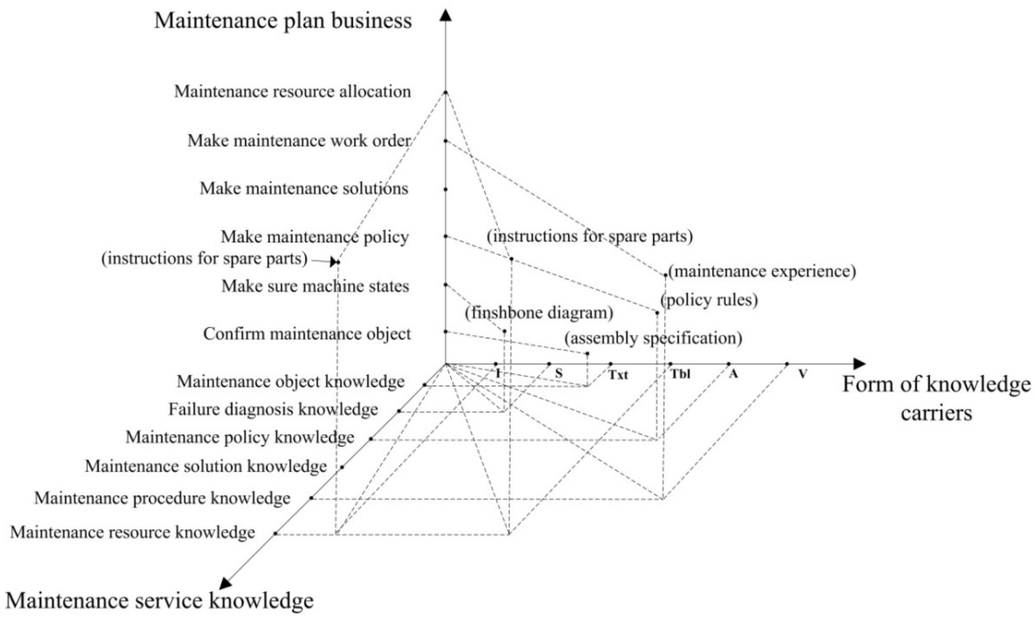

Fig. 5 The relationship of maintenance knowledge and planning

Compared with tangible resources such as equipment, materials, labour and capital, knowledge as the most important production resource has special characteristics. Based on the definition and classification, knowledge is closely connected to business processes, and supports decision making in all processes. Knowledge is usually generated and used along with business process. From failure diagnosis, maintenance policy making to maintenance planning, past knowledge will be used and new knowledge will be generated.Knowledge is also diverse– itcan not only be stored into documents, rules and tables, but also be hidden in maintenance experiences. It is the shareability that makes knowledge more valuable -people could enhance their ability from others' experiences.Knowledge is non-deteriorating. It can be reused time and time again. Itsvalue does not deteriorate by sharing, and the value depends on how it is used. Actually, knowledge can be enriched with usage and shared to better support decision making during process.

3.2 Ontology model for maintenance knowledge

Open Semantic Framework (OSF) was adopted as the ontology implementation tool, as it is a semantic technology based software stack for knowledge management, and includes an ontology editor[24]. It forms a hierarchical structure by integrating with other Open Access software and components so that it can support a whole Web application framework. OSF is a platform-independent web service framework used for acquiring and publishing structured, semi-structured and unstructured data using ontologies. OSF structure is based on RESTful (Representational State Transfer) web service, which makes most modules replaceable without affecting the whole stack. The core organisation of OSF are datasets, which include any records of OSF instances. The field ontology is used by OSF instance to define data and the structural relationship between concepts and properties.OSF provides a module, called OSF for the Content Management System Drupalwhich makes it possible for OSF to be integrated with Drupal system and helps to manage knowledge in Drupal system[25]. Fig. 6 shows the ontology editing and managementinterface using OSF for Drupal.

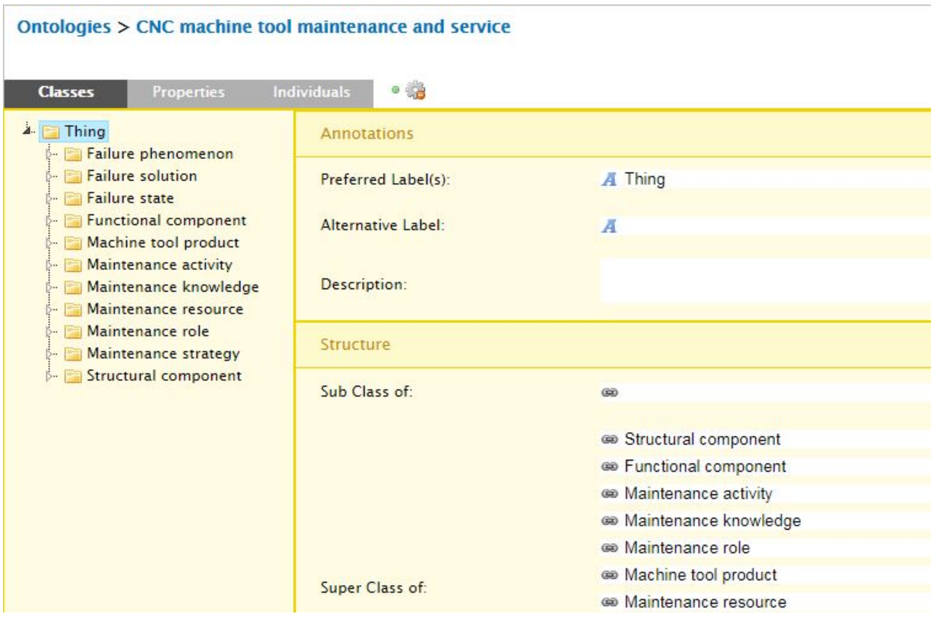

Fig. 6 Ontology editing and management interface by OSF for Drupal

Fig. 7 shows the top Concept-Relation diagram of Ontology for Machine Tool

Maintenance and Service, including business concepts such as machine tool product, failure phenomenon, failure state, maintenance activities, maintenance resources, maintenance roles and maintenance policy, and Case ontology concepts such as context, analysis and solution, as well as the relations between concepts. Table 2 explains the relationships between concepts of the top ontology.

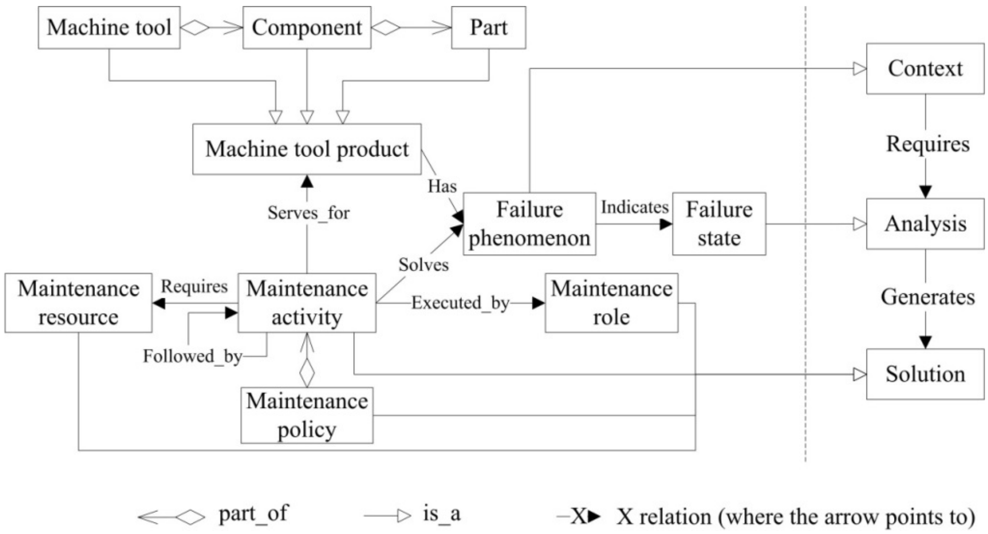

Fig. 7 The top Concept Relation diagramof ontology for machine tool maintenance

Table 2

Illustration of part relations between concepts of ontology for machine tool maintenance

Symbol	Implication	Examples
Serve_for	CR(C_1,C_2)=serve_for, concept C_1serves for concept C_2 .	The maintenance activity "add lubrication oil"serves for machine tool product.
Require	CR(C_1,C_2)=require, concept C_1requires resource and knowledge about concept C_2.	"Adding lubrication oil" requires resource of "lubrication oil".
Is_a	CR(C_1,C_2)=is_a, concept $C_1$is a subclass of concept C_2 .	The allocated maintenance resource "wrench" is a subclass of solution "Tighten the nut".
Followed_by	CR(C_1,C_2)=followed_by, in a process,conceptC_1 is prior than concept C_2.	The maintenance activity "Check lubrication oil level" is followed by another maintenance activity"Adding lubrication oil".
Part_of	CR(C_1,C_2)=part_of, concept $C_1$is a part of C_2 .	The Part "lead screw" is a part of Component "Spindle Unit".
Has	CR(C_1,C_2)=has, concept C_1 has concept C_2 .	"Ball screw pair" may have the failure phenomenon of "vibration".
Solve	CR(C_1,C_2)=solve, concept C_1cansolve the problem that concept C_2 represents.	The maintenance activity "locking bolt of nut pair"solves the failure phenomenon"stick slip"
Executed_by	CR(C_1,C_2)=executed_by, task concept C_1 can be executed by concept C_2 .	Maintenance activities are executed by maintenance engineers.
Generates	CR(C_1,C_2)=generates, from reasoning point, concept C_1 can generate the solution of concept C_2 .	By analyzing the failure of ball screw pair, the solution "wash nut inverter" is generated.

3.3 Mathematical representation for maintenance Cases

Case knowledge needs to be represented in order to be retrieved for calculation. ACase is normally divided into three parts: Problem,Solution and Operation Guide. This project not only provides solutions to certain problems, but also provides Operation Guide, including allocating maintenance resources and describing maintenance activities, providing maintenance engineers with convenience of maintenance work according to job instructions and improving maintenance efficiency. The Caseknowledge in this paper is denoted as *Case*=(*prb*, *sol*(*prb*), *oper_guide*(*prb*)). *HistoricalCase*that is stored in knowledge base used for solving a new problem, is denoted as $Case_{historical}=(prb_h, sol(prb_h), oper\_guide(prb_h))$. The *current Case* being developed to solve a new problemisdenoted as $Case_{current}=(prb_c, sol(prb_c), oper\_guide(prb_c))$. The Case knowledge can be represented by description units, thus the Problem, Solution and Operation Guide can be represented respectively as the followings:

$prb_h=\{u_1^h,u_2^h,...,u_n^h\}$, u_i^h is the description unit for the Problem of historical Case, $i=1,2,...,n$;

$sol(prb_h)=\{U_1^h,U_2^h,...,U_m^h\}$, U_j^h is the description unit for the Solution of historical Case, $j=1,2,...,m$;

$oper\_guide(prb_h)=\{OG_1^h,OG_2^h,...,OG_g^h\}$, OG_e^h is the description unit for the Operation Guide of historical Case, $e=1,2,...,g$;

$prb_c=\{u_1^c,u_2^c,...,u_p^c\}$, u_l^c is the description unit for the Problem of the current Case, $l=1,2,...,p$;

$sol(prb_c)=\{U_1^c,U_2^c,...,U_q^c\}$, U_k^c is the description unit for the Solution of the current Case, $k=1,2,...,q$;

$oper\_guide(prb_c)=\{OG_1^c,OG_2^c,...,OG_r^c\}$, OG_b^c is the description unit for the Operation Guide of the current Case, $b=1,2,...,r$.

To better understand the reasoning process, the number of description units of each part is the same for the corresponding historical Case and the current Case, i.e.,*n=p, m=q, g=r*. The Case description units are composed of concepts, and concepts can be represented by ontology, thus the similarity between Cases is to be calculated by the similarity between description units that can be further calculated through concepts.

4 Adaptation based knowledge retrieval

4.1 Similarity calculation

According to the multiple inheritance relationships between ontologies, a semantic relation calculation method was proposed by Batet et al [8] based on similarity and relevancy. Some of the definitions are as following:

Definition 1: The concept classification of an ontology is a transferable "is-a" relation.

Definition 2: In a structure of ontology concept classification, the super-concept of a concept node means all theother nodes on the path from the root node to this concept node, and is denoted as SC.

Definition 3: In order to comprehensively record semantic information,given *C* as the set of all ontology concepts. If *SC* is the super-concept of C_i, then the union set of C_i and the super-concept of C_i are expressed as:

$$T(C_i)=\{SC\in C, SC\ is\ the\ super-concept\ of\ C_i\}\cup\{C_i\}$$

Definition 4: According to whether concept C_i and C_j are sharing knowledge or not, a Disimilarity Degree is represented as:

$$DD\left(C_i,C_j\right)=\frac{\left|T\left(C_i\right)\cup T\left(C_j\right)\right|-\left|T\left(C_i\right)\cap T\left(C_j\right)\right|}{\left|T\left(C_i\right)\cup T\left(C_j\right)\right|} \tag{1}$$

Where the numeratoris all the non-sharing super-concepts of C_i and C_j and both of themselves.The denominatoris all the super-concepts of C_i and C_j and both of themselves, obviously, $DD(C_i, C_j) \in [0,1]$. This Disimilarity Degree can help to consider all the classification relations between C_i, C_j rather than the ones on the shortest path. At the same time, the Disimilarity Degree reflects the depth and structure of these two concepts, and is inversely proportional to similarity. For transforming it to similarity and linearization, minus logarithmic function was introduced by Batet et al [8], and the similarity becomes:

$$Sim_{log}\left(C_i,C_j\right)=-\boldsymbol{log}_2 DD \tag{2}$$

While this similarity does not belong to [0,1], according to Jabrouni et al [26], it can be normalised as following:

$$Sim_{Nom}\left(C_i,C_j\right)=\begin{cases}1, & C_i=C_j\\ \dfrac{Sim_{log}\left(C_i,C_j\right)}{\boldsymbol{log}_2\left(H+2\right)}, & C_i\neq C_j\end{cases} \tag{3}$$

Where H is the height of ontology, the number of edges of the longest routes from root node to the lowest node.However, only the similarity of classification relations in ontology can be estimated by the above equations. There are still other non-classification relations, which are Data-type relations and Object-type relations.The corresponding attribute value of Data-type relation is data type, and the corresponding attribute value of Object-type relation is class. Specifically, in the maintenance field, it isthe relevancy between one failure and another failure that needs to be paid attention during the retrieval of similar Cases, and it is more about knowledge (or concept) relations. Here only the calculation method of the similarity of Object-type relations is given, and only the failure state of product component is considered in the Data-type relations, which can be reflected during the Casesimilarity calculation. Hu and Zheng[27]established the relation similarity calculation method of these two attributes.

Definition 5: Given that Ob_i, Ob_j are two Object-type relations in maintenance field ontology, the attribute values are C_p, C_k, then the attribute similarity between them can be represented as:

$$Sim_R\left(Ob_i,Ob_j\right)=\begin{cases}Sim_{Nom}\left(C_p,C_k\right), & Ob_i=Ob_j\\ 0, & Ob_i\neq Ob_j\end{cases} \tag{4}$$

Definition 6: The semantic relevancy $Sim_R(C_i,C_j)$ between concept C_i and C_j can be represented as:

$$Sim_R\left(C_i,C_j\right)=\frac{\sum \varphi^{presence} * Sim_R\left(Ob_i,Ob_j\right)}{n} \tag{5}$$

Where n is the absolute value of the attribute union of both concept C_i and C_j, $\varphi^{presence}$ is introduced to represent the presence of the same attributes between the two concepts, $Sim_R(C_i,C_j)\in[0,1]$.

Definition 7: The semantic similarity degree $Sim_*(C_i,C_j)$ between the two concepts C_i and C_j can be represented as:

$$Sim_*\left(C_i,C_j\right)=\lambda_1\times Sim_{Nom}\left(C_i,C_j\right)+\lambda_2\times Sim_R\left(C_i,C_j\right) \tag{6}$$

Where $\lambda_1+\lambda_2=1$. Obviously, $Sim_*(C_i,C_j)\in[0,1]$.

4.2 Similarity calculation between description units

According to the above Case representation by description units, similarity between Case description units needs to be calculated before calculating the overall similarity of the two Cases.The similarity between description units is called local similarity (Sim_{local}). According to Haouchine et al[10], there are two kinds of description units, which are General description unit representing fault information (*u1*), and Description unit representingfailure mode (*u2* ~ *u6*). As Table 3 shows, failure state includes functional mode (*FM*) and failure level (*level*)corresponding to different description units. The one without value indicates that no faults or no abnormity are detected. Similarly, the solution of a Case is described as three units (*U1, U2, U3*) to represent the key words of solution descriptions, where *U1* is failure reason, *U2* is failure component and *U3* is a maintenance operations that is extracted from detailed maintenance solutions to simplify the representation of decision attributes in the following introduction. *U3* is normally described by a verb whose object is *U2*. Take the 2ndCase in Table 3 as example, the machine tool has failure phenomenon "invalid order", and its Solution is (Drive disturbance, Magnetic valve, Replacement), which means "The phenomenon invalid order is led by the failure of magnetic valve, caused by drive disturbance, thus the magnetic valve needs to be replaced".

The maintenance operation *U3* is divided into 4 Description units (*OG1, OG2, OG3，OG4*), meaning (People, Tools, Parts, Activities). For example, the maintenance operation for Case 4 in Table 3 is (Peter, Torque wrench, None, (check the reverse clearance compensation data PRM1851 of Z axisball screw and confirm nothing is changed; check the joint betweenball screwand pedestal, find all 4 hexagon bolts are loose, tighten the hexagon bolt and the stick slip phenomenon disappears.)). As this maintenance operation is not used to be retrieved, but to solve the current problem after retrieving similar historical Cases, only Case Problem and Case Solutions are shown in Table 3. Maintenance operations will be described in detail in the following Sections.

Table 3

Example maintenance Cases of CNC machine tools

CaseNo.	Problem part												Solution part		
	u1		*u2*		*u3*		*u4*		*u5*		*u6*		*U1*	*U2*	*U3*
	Failure Phenomenon	*Level*	Mechanical component	*FM*	Hydraulic component	*FM*	Pneumatic component	*FM*	Electric component	*FM*	Electronic component	*FM*	Cause	Failure component	Maintenance operation
1	Vibration	Higher	Feed unit	Degrade					Feed motor	Degrade			Overheat	Rotor and stator	Reinforce seal
2	Invalid order	Medium	Framework	Degrade			Pneumatic valve	Nominal	Button	Failed			Drive disturbance	Magnetic valve	Replacement
3	Abnormal speed	Higher	Fixture	Failed					Feed motor	Degrade			Damaged	Fixture	Replacement
4	Stick slip	Higher	Z axis screw nut	Degrade					Motor	Nominal			Loose	Nut bolt	Tighten
5	Vibration	Higher	Ball screw pair	Degrade					Motor	Nominal	Speed controller	Nominal	Dirty	Nut inverter	Clean and wash
6	Hydraulic alarm	Higher			Filter	Degrade							Dirty	Filter net	Clean and wash
7	Cutter released slowly by spindle	Higher							Air cylinder	Degrade			Air leak	Air cylinder	Replacement
8	Switchboard unlocked	Higher					Cylinder seal ring	Failed					Air leak	Air cylinder	Replacement

The Problem part of a Case has two types of unit values: failure object and failure state, which are denoted as $u=(u^{comp}, u^{state})$. Local Case similarity is the spot multiplication between the i^{th} Description unit of current Case and the j^{th} Description units of historical Case (denoted as δ_{ij}). In order to keep the correspondence between Cases, $\delta_{ij}^{existence}$ was introduced. The local similarity of a Case can be represented as:

$$Sim_{local_{ij}} = \delta_{ij}^{existence} * \delta_{ij}^{comp} * \delta_{ij}^{state} \quad (7)$$

where δ_{ij}^{state} can be divided into Functional Mode and Failure Level.It can be calculated in different situations:

$$\delta_{ij}^{existence} = \begin{cases} 1, \text{ the } j^{th} \text{ description unit exist within } case_{cur} \text{ and } case_{his} \text{ at the same time} \\ 0, \text{ the } j^{th} \text{ description unit doen't exist at the same time} \end{cases}$$

$$\delta_{ij}^{comp} = \begin{cases} 1, \text{ the corresponding description unit is the same between } case_{cur} \text{ and } case_{his_i} \\ Sim_*\left(C_t, C_{si}\right), \text{ the corresponding description unit is different between } case_{cur} \text{ and } case_{his_i} \end{cases}$$

$$\delta_{ij}^{FM} = \begin{cases} 1, \text{ the functional mode of corresponding description unit is the same between } case_{cur} \text{ and } case_{his_i} \\ 0.8, \text{ the functional mode of corresponding description unit is Failure and Degraded} \\ 0.2, \text{ the functional mode of corresponding description unit is Degrade and Nominal} \\ 0, \text{ the functional mode of corresponding description unit is Failure and Normimal} \end{cases}$$

$$\delta_{ij}^{level} = \begin{cases} 1, \text{ the failure level is the same} \\ 0.5, \text{ the failure level belongs to higher and normal, or lower and normal} \\ 0.2, \text{ the failure level belongs to higher and lower} \end{cases}$$

Thus, the overall Case similarity between the current Case and the historical Case is the weighted sum of all local similarities. Weight indicates different influences of each Description unit of Case context on Case Solutions:

$$Sim\left(prb_{hi}, prb_c\right) = \sum_{j=1}^{n} Sim_{local_{ij}} * \theta_j \quad (8)$$

Where, n is the number of Case Description units; i is the number of historical Cases; and$j$is the sequence of description units. $Sim_{local_{ij}}$ is the local similarity of the j^{th} Description unit between the i^{th} historical Case(prb_h) and the current Case(prb_c).

θ_j is the weight of Case description unit j, where $0 \le \theta_j \le 1$ and $\sum_{j=1}^{n} \theta_j = 1$.

Rough Set Theory (RS theory) was used to determine the value of θ_j to avoid the subjectivity, one-sidednessand instability of weight determination. Commonly used methods for determining weights such as expert rating, fuzzy statistics and binary comparison, cannot reflect the actual situations because of different experiences from different experts, while the RS theorydoes not need to be provided with any prior information other than the data set that the problem needs to deal with, which can fully reflect the objectivity of the data. It is simple and easy to be calculated and has been widely used in weight calculation [28, 29].

Since the historical Case included fault diagnosis results and maintenance operations generated from different values of Case Description units,the rough set theory was used here to calculate the weight of the Case unit in fault diagnosis.The basic idea is to examine how the classification changes after the absence of an attribute by removing it from the decision table.If the classificationchanges accordingly, then the importance of this attribute is high, otherwise the importance of this attribute is low.The calculation of attribute weights is generally represented by the proportion of the attribute'simportance to all attributes' importance[30, 31], that is:

$$w(C_i)=\frac{\gamma_C(D)-\gamma_{C-C_i}(D)}{\sum_{i=1}^{n}\left(\gamma_C(D)-\gamma_{C-C_i}(D)\right)} \tag{9}$$

Where $C_i \subseteq C$ is the subset of condition attributes in decision table $T=(U, A, C, D)$, while $\gamma_C(D)=|pos_C(D)|/|U|$ is called the relative dependency of knowledge D on C in information system $S=(U, A, V, f)$, $pos_C(D)=pos_{ind}(C)(ind(D))$ is the C positive domain of D in information system S, and $Sig_{(C|D)}(C_i)=\gamma_C(D)-\gamma_{C-Ci}(D)$ is the relative importance of C_i.

4.3 Adaptation calculation

As discussed in the Introduction Section, the most similar Cases retrieved are not necessarily easy to be adapted to the current Case. It is necessary to choose from similar Cases of higher adaptability than the threshold (ε), that is, in the similar Cases, the most adaptable is to be modified to get the solution for the currentCase. ε can be set according to actual retrieving requirement and experts' experiences. According to Haouchine et al [10], the adaptability iscalculated as:

$$D_{Adpt}=\frac{\sum_{i=1}^{n}\delta_i^{Class}\cdot\lambda_i}{\sum_{i=1}^{n}\left(\delta_i^{FM}+\delta_i^{level}\right)\cdot\delta_i^{comp}} \tag{1}$$

Where δ_i^{Class} is related to the ontology structure, which is the structural similarity of the concept in the ontology, and does not include the attribute similarity; λ_i is the relative weight determined according to the functional model between the retrieved Case and the current Case (See Fig. 8). If FM = nominal/nominal, then $\lambda_i=2^0$; If FM=nominal/degradation, then $\lambda_i=2^1$; If FM=nominal/failure, then $\lambda_i=2^2$; If FM=degradation/degradation, then $\lambda_i=2^3$; If FM=degradation/failure, then $\lambda_i=2^4$; If FM=failure/failure, then $\lambda_i=2^5$. The retrieved Cases with the most adaptability will be used for further consideration in the next step.

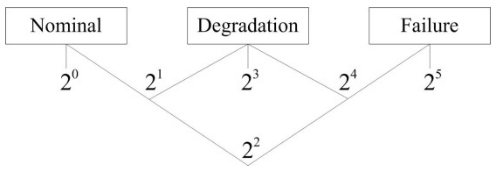

Fig. 8 The value determination of λ

4.4 Case adaptation based on dependency relationships

According to the causal model used by Yang [32], assuming that the Problem T of the current Case has n attributes $T=\{t_1,t_2,\ldots,t_n\}$, and the Problem P of the historical Case H_i has k attributes $P_i=\{p_{i1},p_{i2},\ldots,p_{ik}\}$, then the attribute compatibility number between T of the current Caseand P of the historical CaseH_i is $\{x|\ x\in(T\cap P_i)\}$. The number of matching attributes between T and the historical CaseH_i is n_{2i}: $\{x|\ x\in(T\cap P_i)\cap(valT(x)=valP_i(x))\}$, where $valT$(x) is the value of the attribute x in the attribute set T; $valP_i$(x) is the value of attribute x in the attribute set P_i. According to the relationship between the attributes number n of Problem T and the compatibility number n_{1i} as well as the matching number n_{2i} with Case H_i, the following three situations can be defined:

(1) $n_{1i}=n$ and $n_{2i}=n_{1i}$ (similarity = 1), indicating that the retrieved historical Case

completely matches the current Case, then the Solution and the maintenance Operation Guide in the H_i Case can be reused to the current Case without any adjustment.

(2) n_{1i}=0 and n_{2i}=0 (similarity = 0), indicating that the retrieved historical Casedoes not match the current Case at all, hence the historical Case H_i is irrelevant to the current Case. If for any historical Case {Hi, i∈[1, m], where m is the total number of Cases in the Case base}, they do not match current Case at all, then there are no Cases relevant to the currentCase in the knowledge base. Experts need to analyse the current Case as a special Caseto give solutions or decompose problems in the current Case and recalculate them.

(3) $0<n_{1i}<n$and $n_{2i}\leq n_{1i}$, indicating that not all the retrieved historical Cases match the current Case, thus the similar historical Cases with similarities higher than the preset threshold will be selected. Then the most adaptive historical Case will be analysed and adjusted according to the dependency relationship (DR) between Solution Description unit and Problem Description unit, and then the solution for the current Case will be generated.

The dependency relationship between the Case Description unit and the Problem Description unit is a triple, namely (u_i,U_j,DR_{ij}). DR_{ij} is divided into three types: None, Weak, and Strong. If the Problemdescriptions for two different conclusionsare completely different, then the Problem Description unit u_i is very relevant to the conclusion description unit U_j, and the dependency relationship DR_{ij}=Strong; If the conclusion description unit and the problem description unit can be connected throughcontext, which is causal correlated, then DR_{ij} = Weak; If the problem description unit and the conclusion description unit are independent, then DR_{ij} = None. By making use of the above dependencies, the adjustment algorithm is adopted, and the algorithm steps are as follows:

The Input is the retrieved historical Case $\left(u_{hi}^{ret},U_{hj}^{ret}\right)$, and the output is the conclusion description unit U_{cj} for the current Case:

Step 1: Calculate the DR_{ij} value for each retrieved historical Case $\left(u_{hi}^{ret},U_{hj}^{ret}\right)$, and compose a binary group (DR_{ij}, U_{hj}^{ret}) with the corresponding solution description unit;

Step 2: For any binary group (DR_{ij}, U_{hj}^{ret}), adjust them according to the following DR_{ij} value:

Step 2-1: If DR_{ij}=Strong, the problem description value of the current Case after generalization or specialisation can replace the retrieved Case, and the Solution description corresponding to this Problem description will be changed accordingly;

Step 2-2: If DR_{ij}=Weak, under the same ontology class, find the Problem Description unit of the retrieved Case that related to the Problem Description unit of the current Case, as the replacement of the Solution Description unit of the retrieved Case;

Step 2-3: If DR_{ij}=None, nothing needs to be changed.

Step 3: Finally, the obtained solution value is to be assigned to the current Case.

Since the classes here are in Ontology models, which meet the model for similarity calculations in the previous Sections, this method is beneficial to Case adjustment calculations.

5 System developmentand verification with an example

Diagnosing faults and providing maintenance services for CNC machines in a timely manner will increase the production efficiency of manufacturing companies and reduce cost due to preventing machine tool failures. A CNC machining centre CH7520C which provides integrated drilling, milling and tapping functions and plays an important role inintelligent manufacturing systems, was taken as an example to verify the methods and maintenance planning system developed in this research.

5.1 Ontology representation

Web Ontology Language (OWL) is a standard framework proposed by W3C for dealing with Web information representation [33]. It is designed for information explanation for computers rather than human beings by defining Web information precisely. It includes three sub-languages OWL Lite, OWL DL (including OWL Lite) and OWL Full (including OWL Lite). OWL Lite is used for taxonomy hierarchy that has only one classification level and simple constraints. OWL DL can support reasoning system that needs stronger representation ability to ensure computational completeness and decidability, while OWL Full cannot ensure computational completeness.

For this research, good description logic, computability and decidability are required, thusa maintenance service knowledge model of CNC machine tool was established based on OWL DL.Fig. 9shows part of the ontology concept classes of CNC machine tool maintenance service knowledge, which includes CNC machine tool classifications according to their functions (including CNC machining centres); machine tool component classifications: mechanical components, pneumatic components, hydraulic components, electrical components, electronic components; other aspects including failure phenomenon, fault states, and fault solutions to restore the machine to normal operation, including design improvements, process improvements, maintenance operation improvements, and personnel training. Each class corresponds to the description unit of the maintenanceCases. The actual technical diagnosis based on the Casecontext, fault analysis and fault solution will be used for verification. The ontology modeling method is used to compare the semantic features of concepts in domain ontology.Maintenance context is composed of maintenance objects, failure types, failure phenomenon and potential fault components.

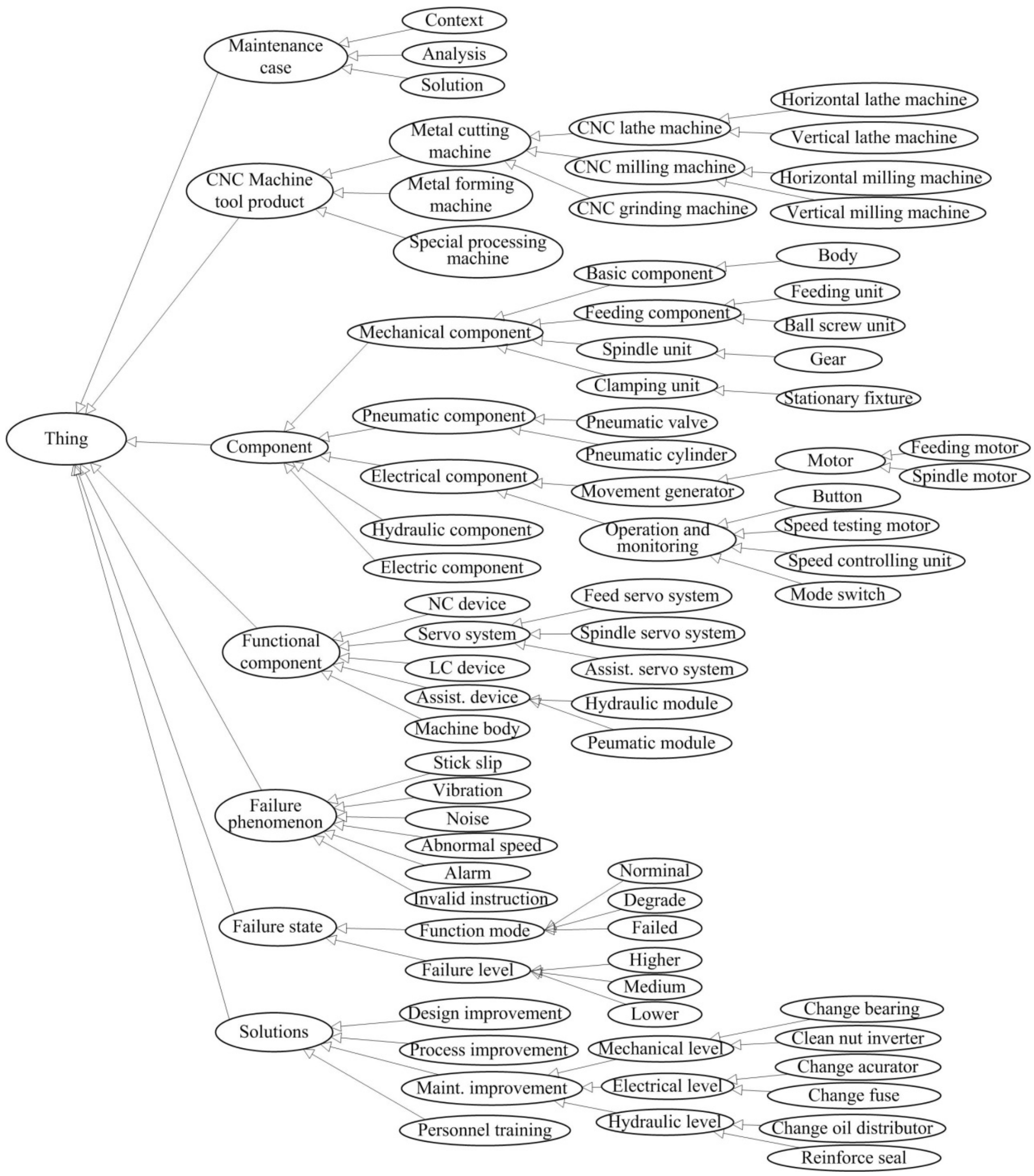

Fig. 9 The concept classification of CNC maintenance service knowledge

For this application, the lightweight ontology is similar to an order-relation-only concept classification. This type of relationship can be a structural tree to describe the semantic connections between concepts in the field of study. In general, the ontology includes axioms, rules and constraints to accurately describe the application domain ontology. The classes in an ontology that includes multiple types of relations are richer than those containing only "class-subclass" relations. Relations in OWL are represented as object properties. Fig. 10 shows the classification of relation types associated with the maintenance system. In order to better represent the relations of object properties between ontology concepts, Fig. 11 gives a partial maintenance concept-relation diagram. Faults are related to the failure of certain components. Thus, the relation property “concern” is used to connect fault phenomenon and components. However, one machine tool component is not only a subclass of another component, but also a part of a certain function component, thus the "belongs to" relation property can define the relationships between componentsmore clearly.

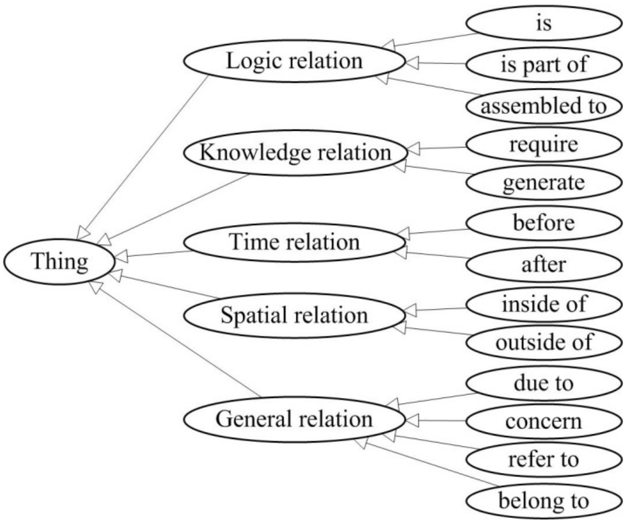

Fig. 10 The classification of relation types

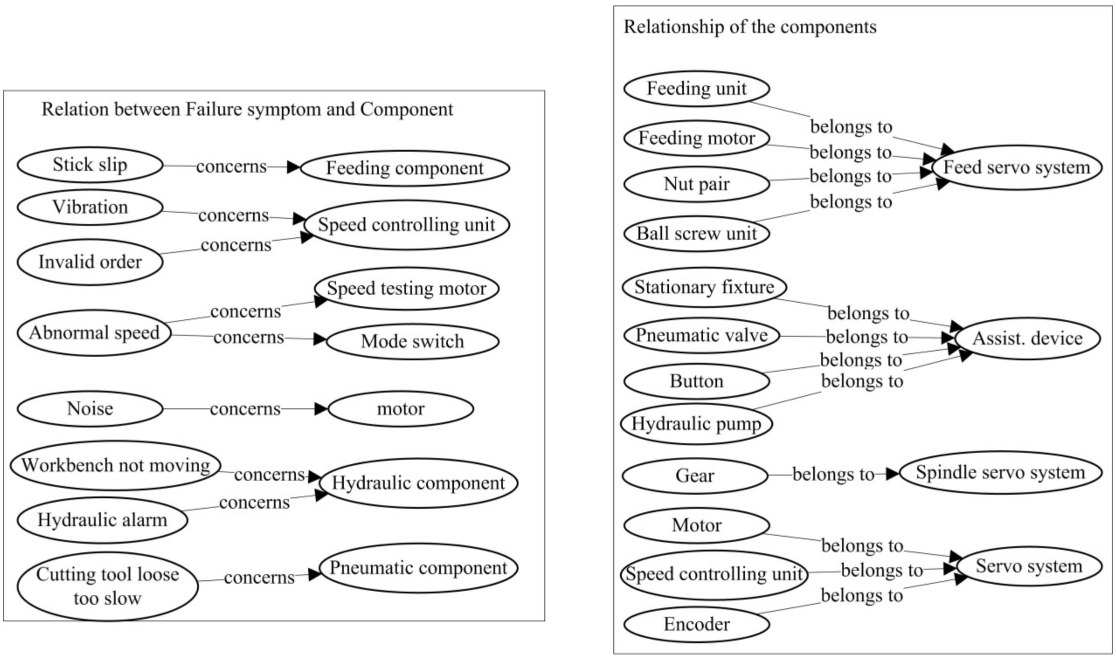

Fig. 11Partial maintenance concept-relationof the example machine tool

5.2 Case retrieval

For the historical Cases given in Table 3,in order to implement Case retrieving process, the current Case to be resolved is elaborated by Description units by ontology concepts during the 1st step of CBR (as shown in Table 4).Thus, the Problems of both current Case and historical Cases are represented by Description Units. Then the similarity calculation method proposed in this paper was used to retrieve historical Cases that are similar to the current Case from the knowledge base. The column *u1~u6* in Table 5 shows the Case local similarities between the current case and each historical Case (six of the historical Cases are compared with the current Case). If there is no Description value forboth the Description Units ofthe historical Cases and the current Case, it means that the component of the Description Unit runs normally, and then the similarity of the Description Unit is 1.

Table 4

Current Cases to be resolved

CaseNo.	The problems											
	u1		*u2*		*u3*		*u4*		*u5*		*u6*	
	Failure phenomenon	Level	Mechanical component	FM	Hydraulic component	FM	Pneumatic component	FM	Electrical component	FM	Electric component	FM
Current Case	Stick slip	Higher	X axle nut pair	Degrade					Feeding motor	Norminal	Encoder	Norminal

Table 5

Local similaritiesbetween the current Case and somehistorical Cases in the knowledge base

Local similarity	*u1*	*u2*	*u3*	*u4*	*u5*	*u6*
source1/target	0.3195	0.6517	1	1	0.2	1
source2/target	0.1598	0.2826	1	1	0	1
source3/target	0.3195	0.2261	1	1	0.2	1
source4/target	1	0.9366	1	1	1	1
source5/target	0.3195	0.6516	1	1	1	1
source6/target	0.3375	0	0	1	1	1

By taking the first Description Unit "fault phenomenon"of the first historical Case as matching example, and based on formula (7), the calculation process can be described below (according to the proportion of concept similarity and attribute similarity, set λ_1=0.8, λ_2=0.2).

$$\delta_{1.1}^{existence} = 1$$

$$\delta_{1.1}^{comp} = \lambda_1 \times Sim_{JKG}\left(Stickslip, Vibration\right) + \lambda_2 \times Sim_R\left(concern, concern\right)$$

$$Sim_{JKG}\left(Stickslip, Vibration\right) = \frac{-\boldsymbol{log}_2 \dfrac{\left|T\left(Stickslip\right) \cup T\left(Vibration\right)\right| - \left|T\left(Stickslip\right) \cap T\left(Vibration\right)\right|}{\left|T\left(Stickslip\right) \cup T\left(Vibration\right)\right|}}{\boldsymbol{log}_2\left(H+2\right)}$$

$$= \frac{-\boldsymbol{log}_2 \dfrac{\left|\left\{Thing, Failure\,phenomenon, Stickslip, Vibration\right\}\right| - \left|\left\{Thing, Failure\,phenomenon,\right\}\right|}{\left|\left\{Thing, Failure\,phenomenon, Stickslip, Vibration\right\}\right|}}{\boldsymbol{log}_2\left(H+2\right)}$$

$$= \frac{-\boldsymbol{log}_2 \dfrac{4-2}{4}}{\boldsymbol{log}_2\left(5+2\right)} = 0.3562$$

$$Sim_R\left(concern,concern\right)=Sim_{JKG}\left(Feeding\ component,Speed\ controlling\ unit\right)$$

$$=\frac{-\boldsymbol{log}_2\frac{\left|T\left(Feeding\ component\right)\cup T\left(Speed\ controlling\ unit\right)\right|-\left|T\left(Feeding\ component\right)\cap T\left(Speed\ controlling\ unit\right)\right|}{\left|T\left(Feeding\ component\right)\cup T\left(Speed\ controlling\ unit\right)\right|}}{\boldsymbol{log}_2\left(H+2\right)}$$

$$=\frac{-\boldsymbol{log}_2\frac{7-2}{7}}{\boldsymbol{log}_2\left(5+2\right)}=0.1729$$

$$\delta_{1.1}^{comp}=0.3562\times0.8+0.1729\times0.2=0.3195$$

$$\delta_{1.1}^{level}=1$$

$$Sim_{local_{1,1}}=\delta_{1.1}^{existence}\times\delta_{1.1}^{comp}\times\delta_{1.1}^{level}=1\times0.3195\times1=0.3195$$

5.2.1 The weight of local similarity

After local similarity has been calculated in Table 5, the weight of each Unit is to be confirmed.Firstly, based on the Rough Set theory, a decision table has been created (as shown in Table 6) which includes two parts: the discrete value of Description Units as the Condition Attribute (corresponding to column *a* ~ *f*), and the value of failure causes as the Decision Attribute (corresponding to column *M1*). U represents Case numbersthat are determined according to the types of machine faults in the knowledge base. Thus the knowledge set *T=(U,A,C,D)* has been formed.The discrete values of each Unit are coded as follows:

$$\text{Failure phenomenon } a\begin{cases}0 & \text{Stick slip} \qquad\qquad 5 \quad \text{Hydraulic alarm}\\ 1 & \text{Vibration} \qquad\qquad 6 \quad \text{Sluggish to loose knife of the spindle}\\ 2 & \text{Noise} \qquad\qquad\quad 7 \quad \text{The switchboard can't lock}\\ 3 & \text{Invalid instruction} \quad 8 \quad \text{The arm is not lifted}\\ 4 & \text{The worktable is not rotated} \ 9 \quad \text{Crash}\end{cases}$$

$$\text{Failure phenomenon } b\begin{cases}0 & \text{No fault component}\\ 1 & \text{Feeding unit}\\ 2 & \text{Ball screw unit}\\ 3 & \text{Nut pair}\\ 4 & \text{Body}\end{cases}$$

$$\text{Electrical failure component } e\begin{cases}0 & \text{No fault component}\\ 1 & \text{Servo motor}\\ 2 & \text{Button}\\ 3 & \text{Solenoid valve}\end{cases}$$

$$\text{Electric failure component } f\begin{cases}0 & \text{No fault component}\\ 1 & \text{Speed controlling unit}\\ 2 & \text{Encoder}\\ 3 & \text{Electrolytic capacitor}\end{cases}$$

$$\text{Hydraulic failure component } c\begin{cases}0 & \text{No fault component}\\ 1 & \text{Hydraulic valve}\\ 2 & \text{Hydraulic pump}\\ 3 & \text{Hydraulic piston}\\ 4 & \text{Filter}\end{cases}$$

$$\text{Cause of failure } M1\begin{cases}0 \quad \text{Overheated} & 4 \quad \text{Abrasion}\\ 1 \quad \text{Interference} & 5 \quad \text{Poor sealing}\\ 2 \quad \text{Damage} & 6 \quad \text{Loosening}\\ 3 \quad \text{Unclean} & \end{cases}$$

$$\text{Pneumatic failure component } d\begin{cases}0 & \text{No fault component}\\ 1 & \text{Pneumatic valve}\\ 2 & \text{Pneumatic cylinder}\end{cases}$$

According to the weight formula (9), the calculation of each weight can be divided into the following steps, and the weight can be obtained in Table 7.

(1) Calculate the division of decision attribute D to conditional attribute set C and each conditional attribute subset C_i, $U/ind(C)$, $U/ind(C_i)$, $U/ind(C\text{-}C_i)$;

(2) Calculate the positive domain C of D in the information system$S$: $pos_C(\mathrm{D})=pos_{ind(C)}(ind(D))$, and remove the positive domain of each attribute subset Ci: $pos_{C\text{-}Ci}(D)=pos_{ind(C\text{-}Ci)}(ind(D))$;

(3) Calculate the dependence of the decision attribute D on the attribute set C:$\gamma_C(D)=|pos_C(D)|/|U|$, and the dependence

after removing each attribute subset Ci:$\gamma_{C\text{-}Ci}(D)$=|$pos_{C\text{-}Ci}(D)$|/|U|(as is shown in the 1st row of Table 7);

(4) Calculate the relative importance of the conditional attribute subset Ci: $Sig_{(C|D)}(C_i)=\gamma_C(D)$- $\gamma_{C\text{-}Ci}(D)$(as is shown in the 2nd row of Table 7);

(5) Calculate the weight of the conditional attribute subset Ci: $w(C_i)$(as shown in the 3rd row of Table 7);

Based on local similarities between the current Case and each historical Cases from Table 5, and the weight of each Description Units, the weighted similarity between the current Case and historicalCases can be calculated in Table 8 (as viewed in the last column) based on formula (8).

Table 6

The decision matrix of Unit weight in the Case

U	a	b	c	d	e	f	$M1$
x_1	1	1	0	0	1	0	0
x_2	3	4	0	0	2	0	1
x_3	1	1	0	0	1	0	2
x_4	2	2	0	0	0	0	2
x_5	9	0	0	0	0	3	3
x_6	4	0	2	0	0	0	4
x_7	5	0	2	0	0	0	3
x_8	0	3	0	0	0	0	6
x_9	7	0	0	2	0	0	5
x_{10}	8	0	0	0	3	0	2
x_{11}	1	2	0	0	0	0	3
x_{12}	6	0	0	2	0	0	5

Table 7

The weight of the Description Unit of each Case

C_i	a	b	c	d	e	f
$\gamma_{C\text{-}Ci}(D)$=|$pos_{C\text{-}Ci}(D)$|/|U|	0.25	0.75	0.75	0.75	0.75	0.8333
$Sig(Ci)= \gamma_C(D)- \gamma_{C\text{-}Ci}(D)$	0.75	0.25	0.25	0.25	0.25	0.1667
$w(Ci)= Sig(Ci)/ \Sigma Sig(Ci)$	0.39	0.13	0.13	0.13	0.13	0.09

Table 8

The local similarity and weighted similarities between the current Case and historicalCases

Local similarity	*u1*	*u2*	*u3*	*u4*	*u5*	*u6*	Weighted similarity
w_j	0.39	0.13	0.13	0.13	0.13	0.09	1
source1/target	0.3195	0.6517	1	1	0.2	1	0.58
source2/target	0.1598	0.2826	1	1	0	1	0.45
source3/target	0.3195	0.2261	1	1	0.2	1	0.53
source4/target	1	0.9366	1	1	1	1	**0.99**
source5/target	0.3195	0.6516	1	1	1	1	**0.69**
source6/target	0.3375	0	0	1	1	1	0.48

5.2.2Adaptation of retrieved Cases

A threshold of 60% was initially set

for retrieved Cases, andthe historical Cases with a similarity greater than 0.6 were selected for adaptation calculation.Note that the setting of the threshold value was based on experience and can be changed according to the number of similar Cases returned from the knowledge base. For the value of 60%, historical Cases 4 and 5 in Table 3 were selected here. According to formula (10), the different descriptor between the retrieved historical Case 4 and the current Case is “u3”, where $\lambda_3=2^3$, and the different descriptors between historical Case 5 and the current Case are “*u2,u3*”, where $\lambda_2=2^3, \lambda_3=2^3$. Therefore, the adaptation values of historical Cases 4 and 5 for the current Case are:

$$D_{adpt4} = \frac{0.9208 \times 2^3}{1 \times 0.9366} = 7.87$$

$$D_{adpt5} = \frac{0.5645 \times 2^3}{1 \times 0.6516} = 6.93$$

According to the adaptation value, historical Case 4 not only has high global similarity to the current Case, but also has a high adaptation value. Therefore, it is more suitable for adjusting historical Case 4 to adapt to the current Case.The dependency of historical Case 4 can be represented as follows:

U2: Nut bolt=F^t(*u1*: Stick slip = high);

U1: Loose of nut bolt =F^t(*u2*: Z-axis nut pair = degrade, DR_{21}=Strong; *u5*: Motor = nominal,DR_{51}=Weak);

Where the DR value of (*u2,U1*) pair is DR_{21}=Strong, and the Description Unit u_{h2}“Z-axis nut pair” in the historical Case and theu_{c2}“X-axis nut pair” in the current Case is under the same ontology class, thus the adjustment can be worked out as follows:

- Replace u_{h2} with u_{c2}="X-axis nut pair" in the current Case;
- The new u_{h2} will affect the U_{h1} Description Unit value, so the U_{h1} value will become "X-axis nut sub bolt loose";
- Assign the new value of U_{h1} to the solutionU_{c1} of the current Case.

By adaptation calculation, the Solution for the current Caseis as follows:Because of the loosening of the X-axis nut bolts, the‘tighten’ operation should be carried out, and the Solutionof the current Case is shown in Table 9.

Table 9

The Solution of the current Case

Case No.	Problem part												Solution part		
	u1		*u2*		*u3*		*u4*		*u5*		*u6*		*U1*	*U2*	*U3*
	Failure phenomenon	Level	Mechanical component	FM	Hydraulic component	FM	Pneumatic component	FM	Electrical component	FM	Electric component	FM	Cause	Failed parts	Solution
4	Stick slip	Higher	Z axis screw nut	Degrade					Motor	Nominal			Loose	Nut bolt	Tighten
Current Case	Stick slip	Higher	X axis nut pair	Degrade					Feeding motor	Norminal	Encoder	Norminal			

In addition, as the maintenance Solution is only the beginning of the maintenance plan, ultimately, the maintenance steps need to be planned for maintenance personnel. The maintenance operation for Case 4 is (John, Torque wrench, none,(Check the Z-axis ball screw backlash compensation machine data PRM1851, and confirm it is normal and not changed; Check the connection of the Z-axis ball screw and find that the four hexagon bolts of nut pair at the joint position between ball screw and column have been loosened. After locking the four bolts, the crawling phenomenon is eliminated.)). Since the X-axis and Z-axis are different in the Description Unit of the current maintenance Problem, and the involved machine components are also different, the operation description in the Solution needs to be adjusted: (Leo, (Torque wrench, Allen wrench), none, (Check that four hexagon socket screws of the joint positon between X-axis ball screw nut and the table are loose, after locking the four screws, the machine tool is restored normal)), as shown in Table 10.

Table 10

The current Case maintenance instructions

Case No.	Operation guide part			
	OG1	*OG2*	*OG3*	*OG4*
	personnel	Tool	spare parts	Maintenance activities
4	John	Torque wrench	None	Check the Z-axis ball screw backlash compensation machine data PRM1851, and confirm it is normal and not changed; Check the connection of the Z-axis ball screw and find that the four hexagon bolts of nut pair at the joint position between ball screw and column have been loosened. After locking the four bolts, the crawling phenomenon is eliminated.
CurrentCase	Leo	Torque Wrench, Allen Wrench	None	Check that four hexagon socket screws of the joint positon between X-axis ball screw nut and the table are loose, after locking the four screws, the machine tool is restored normal

5.3 System development

K-MTMS was developed based on real industrial needs. The development was achieved usingan Open Source Content Management System (CMS) –Drupal [25].Content Management Systems allow the application of management principles to contents [34]. As one of the three most popular systems (the other two are Wordpress and Joomla), Drupal integrates both content management systemsand frameworks and thus overcomes the shortcomings of them, allowing non-technical users to solve content management related issues easily and flexibly [35]. As an Open Source CMS, Drupal consists of multiple modules that contributed by the community. Different modules are responsible for different functions which can be divided into five types: modules for data and content collecting, modules allowing the collected contents to be displayed in different format, modules for the output data to be displayed into blocks and menus, modules for user permissions, and modules for system theme template. Information flows between these modules.Drupal is normally implemented in business, finance and social media, but not much in managing engineering knowledge.Under the development environment of Virtual Linux operating system Ubuntu14.04, as well as PHP5.6, MySQL database and other extensions, the modules developed in this research are Stakeholders, Product knowledge, Corrective Maintenance, Scheduled Maintenance, Predictive Maintenance, Maintenance Case Knowledge, Lessons Learnt and ontology, as shown at the top of the system interface in Fig. 12.

The system has a view page showing historical Cases, the Problems of maintenance Cases (the page is similar to Table 3). The Solution and Operation Guide can be viewed through the "view" link (see Fig. 13). When typing search conditions in the text box according to the current Case and click "Apply", the system will retrieve similar historical Cases and adapt them based on their adaptation degrees. Then the final selected Case will be shown(see Fig. 13).Then the maintenance plan for the current Case can be made based on this Solution.

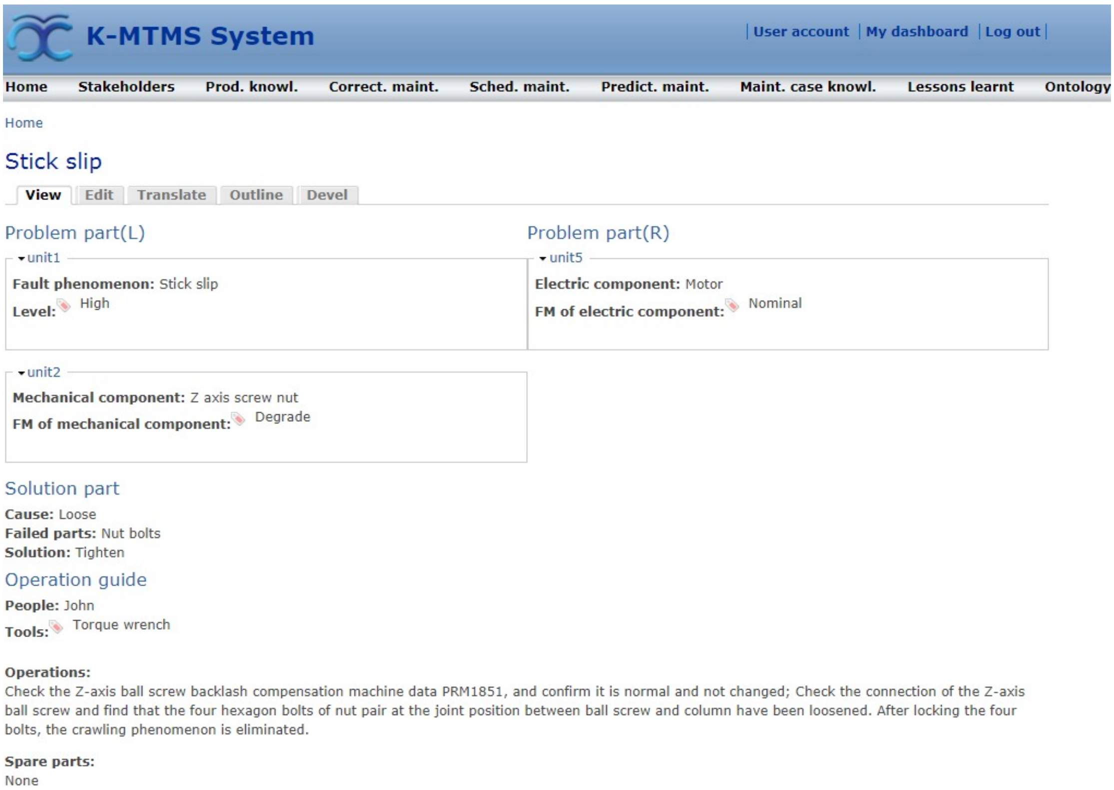

Fig. 12 The maintenance Case details of "stick slip"

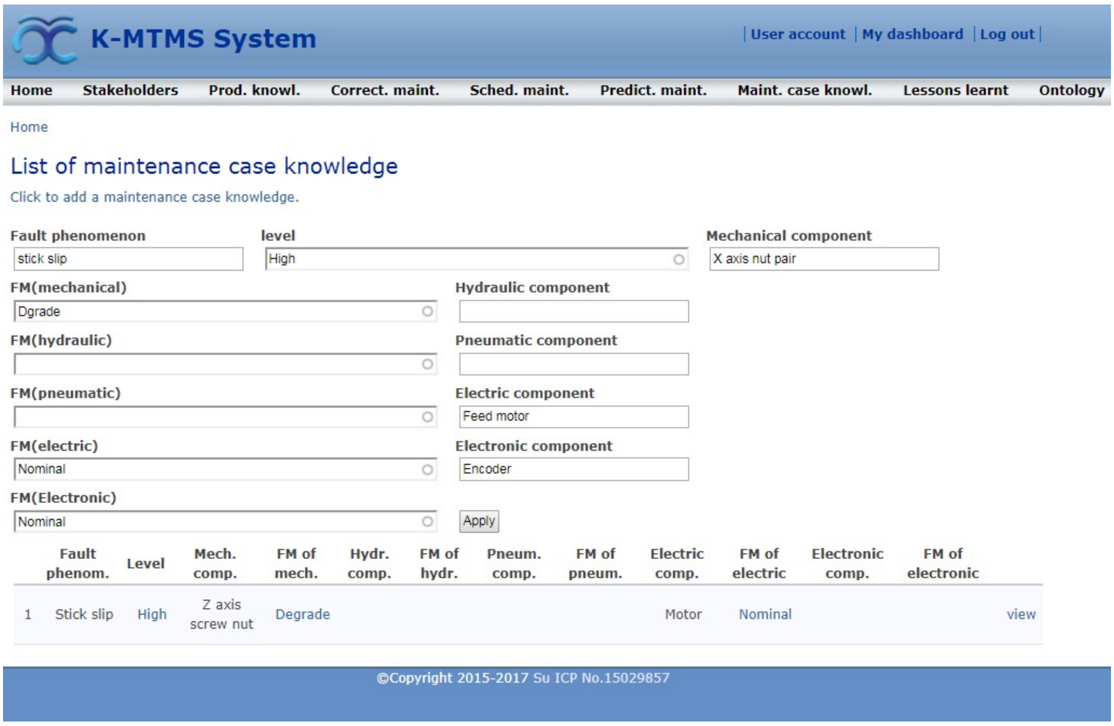

Fig. 13Final selected similar Case

6 Conclusions and further work

CNC machine tools as complex and intelligent manufacturing equipment play important role in advanced manufacturing systems. It is of great significance to improve maintenanceefficiency and effectiveness for CNC machine tools as their working status and operating performance directly affect the quality and costs of manufactured parts and the overall production.Previous research in machine tool maintenance regarded machine tools as manufacturing equipment while this research considered machine tools as'products' in the new Product-Service System context, as well as manufacturing equipment for machine tool users. Therefore, maintenance service is related to many stakeholders during its lifecycle.Based on the knowledge intensive characteristics of maintenance planning, a novel knowledge based maintenance planning system (K-MTMS) has been developed, providing all stakeholders of machine tool maintenance a platform to communicate,share information and knowledge, and make maintenance plans using previous knowledge.

The field maintenanceknowledge model for CNC machine tools has been defined and established using ontology to ensure semantic consistency during maintenanceplanning.In order to better reuse previous knowledge, this paper presenteda knowledge reasoning method using Case-based Reasoning (CBR) and Adaptation-Guided Retrieval (AGR), whichimproved the effectiveness of maintenance planning by choosing the most adaptive cases. Furthermore, in the knowledge retrieving phase of knowledge reasoning, previous researchers preferredto take semantic similarity as the final knowledge similarity, while this research consideredboth semantic similarity and semantic relevancy, whichsignificantly reducedcalculation complexity and improved the calculation accuracy of semantic similarity degree.

In addition, as a pilot implementation,

this research explored Content Management technologies to manage maintenance knowledge in engineering applications, which proved advantages in managing structured and unstructured knowledge over traditional engineering data management systems. CMS have been widely applied in managing information in the fields of business, government and social media, but not much in managing engineering knowledge.

The proposed method was verified by the actual needs and business processes of industry, and can satisfy companies' actual working logic, i.e., firstly looking for past experienceswhen encountering a new problem.If there exist similar experiences, then get the solution for the current problem, otherwise, formulate a new solution that can also be used for future similar problems. Based on the historical knowledge, the efficiency of maintenance planning can be improved.The developed K-MTMS system can avoid the misunderstanding between different application systems, because the representation of knowledge is consistent due to the use of ontology-based Case Description Units.

Yet, this research currently has some limitations. For example, the proposed knowledge reasoning methodology is suitable for knowledge that is already represented in Description Units through ontology, while for those that are not or cannot be represented in this format, this methodology cannot achieve the same effect. Furthermore, the workload of representing maintenance case knowledge into Description Units can be is very high. Therefore, further research will be devoted to overcoming or improving the above limitations.

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