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Preliminary communication

Development of the Adaptive System for Tool Management

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Abstract: Technological developments in the manufacturing industry have accelerated recently. Although many traditional manufacturing factories had adopted automated production, owing to the inability to control the status of individual tools, it is challenging for manufacturers to accurately track the real time status of production line tools. To bring smart production into existence, a robust database system needs to be ensured. New models of computer numerical control machines are equipped with a built-in tool management system (TMS), but most versions of this system are only able to set a machining time limit or a total number of workpieces limit for each tool to determine tool replacement intervals. Such system could likely cause early tool replacement, resulting in waste and increased tool costs. In order to implement green manufacturing, the prediction of tool wear is essential to reduce wastage of materials. In this study, we developed a TMS that is based on a not only SQL (NoSQL) database, which not only stores several different types of data, but also can store prediction models to make it suitable for the demands of varying enterprise scales. It will be more helpful to ensure processing safety and effectively reduce manufacturing costs.

Keywords: group method of data handling; NoSQL database; polynomial network; tool management system

1 INTRODUCTION

In a machining process, many tools are used and often changed during the process; thus, voluminous tool information changes constantly. A study by Cincinnati Milacron has revealed that a workpiece gets machined only 1.5% of the time it spends on the shop floor. For 3.5% of the time, it is being positioned or gaged. For 95% of the time, it is in transport or the machine is idle because tooling or gaging is not available (Strycula and Vidmar 1986; Carter 1971). Tooling is a major component of the variable costs of automated machining, accounting for 25 - 30% of the manufacturing operating costs [1]. Moreover, statistical results have shown that cutting tools account for approximately 2 - 4% of the production costs, but their management costs account for approximately 15 - 30% of the production costs [1-2]. Ineffective management could adversely affect the production efficiency and manufacturing costs of enterprises. As most of tool managements use relational database management systems (RDBMS), the current framework is no longer able to cope with the massive amount of instant access when more and more information becomes relevant for organizational decisions. NoSQL databases are created in response to the limitations of relational database technology that better satisfies the needs of IoT-related environments. Compared with traditional relational databases, NoSQL databases have the following features and benefits [3]:

- Simple deployment.
- Store unstructured, semi-structured, or structured data.
- Meet the scalability and failover.
- Can be used as a caching layer for storing the transaction data.

Because of the above advantages, document databases are general-purpose databases that can be used in a variety of industries such as manufacturing, logistics, healthcare, and more. The authors demonstrated core concepts of a simple e-commerce application development with MongoDB [4-5]. The research developed a similarity query system for road traffic big data that runs on top of an existing MongoDB document store [6]. Hu et al. constructed a product traceability system by using NoSQL database [7]. [8] proposed a smart healthcare system architecture to collect data about environmental conditions and patients' physiological parameters in real time and store data in a MySQL database named Control DB. A two-layered architecture was designed to aggregate the sensed data into a batch and then reduce the size of each batch by compression [9]. Therefore, the small and medium-sized enterprises can adopt the proposed architecture to store the huge data with low cost and the aid of compression.

In response to the trends in smart manufacturing, it is required to be able to dynamically record tool information during processing and implement tool life cycle management. However, traditional cutting tool management systems mainly focus on warehouse management, the manufacturing, purchasing, maintenance, and status information are neglected [10]. According to our survey, a well-known tool management software in the market, such as Zoller or Gühring, the tool life monitoring module embedded in the system is relied on threshold setting by the operator to remind users to replace the tool. Therefore, the tool cannot be fully utilized for cutting. The remaining useful life (RUL) prediction has received increasing research attention in recent years due to its essential role in improving industrial manufacturing systems productivity and reliability [11]. Generally, the RUL prediction methods are mainly classified into physics-based [12], data-driven [13-14], and hybrid models [15-16]. Since NoSQL allows the flexibility of data inconsistency and the ability to store a large volume of data, this paper is devoted to developing the tool management system using document-based NoSQL. The rest of this paper is organized as follows. Section 2 discusses the system architecture and features of the TMS. In Section 3, we demonstrated how to integrate the corresponding prediction model into the TMS. An insight into the TMS operation through actual case studies is provided in Section 4. The conclusion of this research is presented in Section 5.

2 DATABASE MANAGEMENT SYSTEM OF CUTTING TOOL

The TMS is based on the browser/server network infrastructure, in which users can enter the system operating interface through the RESTful API. Each resource is manipulated through GET, PUT, POST and DELETE data types, which refer to the reading, updating, creating and deleting operations on resources, respectively. The web server receives requests from the client and interacts with the database, which reduces the computer load of the client. It also could reduce the system cost and workload during maintenance and upgrades. Fig. 1 demonstrates the TMS based on the browser/server architecture.

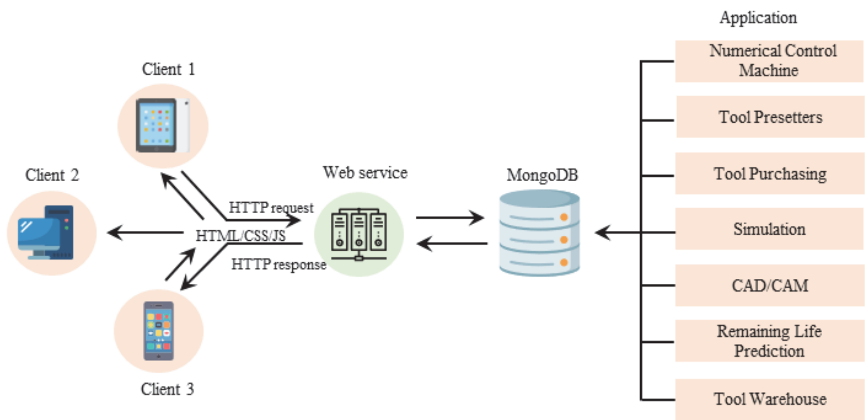


Figure 1 Tool management system based on the browser/server architecture

2.1 System Architecture of Tool Management System

In this paper, the TMS integrates two management modes which are the tool management and engineering development. The ideal candidates for the tool management are the processing staff, purchasing officer, warehouse staff and administrator who can specifically manage the usage records and flow tracking of tools through the query of a single database. In addition to the records of the machine operator's use and return tool, when the tools are lower than the safety stock level, the system will notify the purchasing officer to place an order with the tool supplier to replenish the tool immediately for shortening the production preparation time for tools. The administrator can monitor the tool usage in real time to improve the tool utilization rate and reduce administrative management and production costs. The engineering development is aimed at CAD/CAM manufacturing staff who can query the tool inventory through the TMS to get the required tool in real time. The cutting parameters recommended by the supplier can be substituted into the simulation software to review the RUL of each tool through the life prediction model [17]. The accuracy of tool preparation and tool distribution can be implemented by the production staff through the coded tool list. The measuring staff can also inspect the tool according to the configuration table and update the tool compensation to the TMS synchronously. This system is convenient for machine operators to place the tools in the corresponding number and input the correct compensation value of tools.

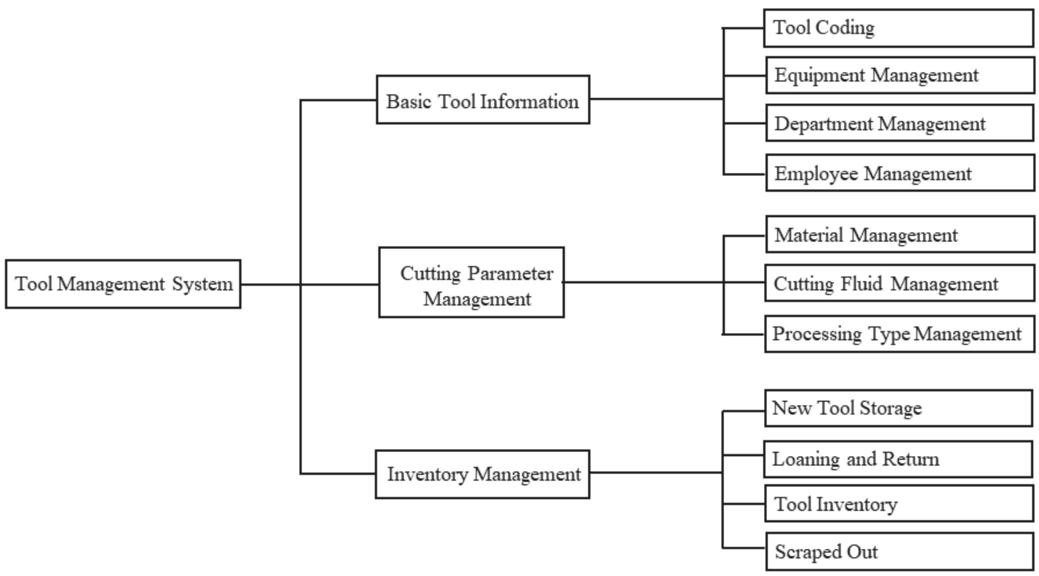


Figure 2 Functional architecture of the tool management system

2.2 Functions Description of Tool Management System

This research uses the Django web framework combined with MongoDB database to enable users to query the same database with different operating systems. The TMS can be categorized into basic tool information, cutting parameter management, and inventory management, as shown in Fig. 2.

2.2.1 Basic Tool Information

Owing to certain needs of production and processing, many tools are exchanged between tool libraries and machines. To have a good knowledge of the tool flow direction and monitor individual tool information effectively and quickly at each stage, each tool must be coded specifically to manage the entire life cycle of the individual tool from purchase till scrapped. To digitize tool information and make it reasonable for the code making and reading later in the tool management system, Li and Yang [18] proposed two types of coding rules, namely, rigid and flexible code structures. The flexible code rule increases tool utilization, reduces the storage times, and improves the information communication and sharing between different departments.

The tool code used in this study is composed of sixteen digits and characters, which consist of five levels, the "-" symbol, and a serial number with four digits. The serial number is used for managing the tools within the same classification group during a process, which prepares for the life-cycle management of tools in the future [18]. The first level is composed of two digits, representing cutting tools, measuring implements or fixture, etc. The second level is composed of two digits, representing the types of cutting tools, such as turning tools, milling tools, drill types, combined tools, etc. The third level is the sub-part of the second level, which is composed of three digits describing tool holders, turning inserts, milling cutter bodies, etc. The fourth level is composed of two digits, which represent the manufacturing methods; and the fifth level is composed of three digits, which describe the structure, such as tool arbor, cutter head, etc.

2.2.2 Cutting Parameter Management

The best cutting tool management approach in mass production is tool wear minimization during sequential machining processes [19]. Proper cutting parameters can reduce the friction coefficient between the tool and workpiece, which can effectively reduce the cutting force and temperature to guarantee continuous machining with minimal tool wear. However, most manufacturers mainly rely on the specialists' experience or query related information for the cutting parameter settings. As a result, providing effective on-the-job training to new employees becomes challenging. Therefore, establishing a sensible cutting parameter database system is crucial to solving these problems; such a system can systematically enable the simulation software to set a tool trajectory plan. It is possible to achieve seamless machining with safe and efficient cutting parameters set in various cutting ranges [19]. To conduct an effective and accurate RUL prediction, the cutting parameters of each tool are stored in the MongoDB. The data are provided by the tool manufacturer, expert knowledge of machining processes, and cutting experiments, etc. Fig. 3 shows the entity relationship diagram of cutting data.

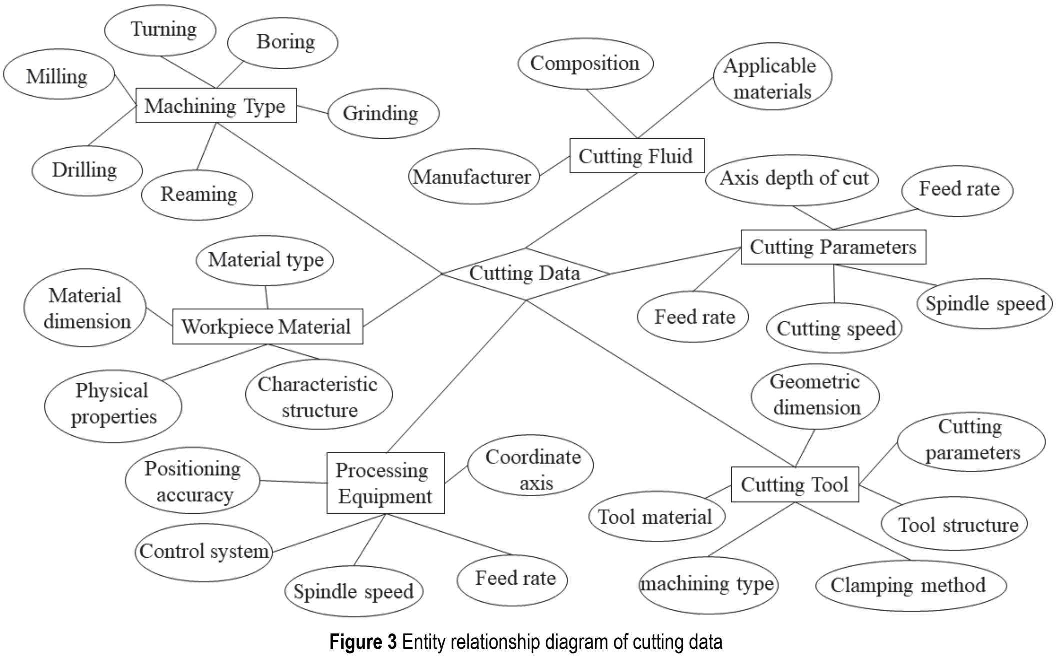


Figure 3 Entity relationship diagram of cutting data

2.2.3 Inventory Management

The TMS generates various operation lists according to the production plan and records each cutting tool status in detail, such as loaned, returned, scrapped, re-sharpening, etc. The available tools in the warehouse are monitored by setting the upper and lower stock limits and displayed by the corresponding colours, as shown in Fig. 4. As the remaining stocks will be lower than the threshold value, the storage warning function notifies the upstream manufacturers to replenish the tools.

3 INTEGRATION OF TOOL LIFE PREDICTION SYSTEM INTO TOOL MANAGEMENT SYSTEM

Due to a sustainable increase in IoT devices and the diversified data formats, the traditional related database will become increasingly overloaded. A robust database system plays an important role to achieve Industry 4.0.

Therefore, the TMS in this research is developed based on NoSQL and integrated with the tool life prediction model, which makes it different from the market.


Inventory

Location: Status: ToolName: ToolBrand:

ToolID	Specification	Storeroom	Quantity of Inventory	Minimum Stock	Maximum Stock
M0301	Endmills with Different Helix	A-1	6	3	20
M1005	ER16 Spring Collets	F-2	5	5	10
M02	Shell end mills	B-1	20	10	50
M1601	four-edged, positive geometry with R0,4	C-3	5	5	50
M1001	CARBIDE BLANK FOR TURNING TOOLS	C-3	15	10	30
M0402	Rhombic Inserts with 7° Clearance for 20 mm	D-1	15	30	50
M0401	91° Lead Angle Lever Lock Boring Bars	D-2	20	20	50
M0501	DIN69871AD+B ABS Adapter	C-2	8	5	15
M1101	Mapal reaming insert HX type	C-3	15	10	20
M0102	50/60 DIN69871A Flange Contact	C-1	5	5	10
M1613	Driven tool holder	B-3	5	3	20

Figure 4 Diagram of inventory management

Cutting tools are important auxiliary tools in the manufacturing industry and are relatively expensive consumables. According to the survey data provided by Walter [20], the tool cost only accounts for approximately 4 - 6% of the total production cost; however, its impact on productivity could reach 20 - 30%. Therefore, replacement of new tool before the damaged can avoid scrapping workpieces and damaging the equipment. This study uses the group method of data handling (GMDH) for predictive modelling to determine RUL of a machining tool.

The GMDH was developed by Ivakhnenko [21] in 1967 based on the principles of heuristic self-organization for identifying nonlinear relations between input and output variables, also known as polynomial neural networks. The system behavioural model can be deduced without presupposing the data type, and optimized high-order nonlinear equations can be used to obtain system characteristics and make predictions. Several studies have been performed to build a mathematical model describing tool wear or tool life in a cutting process. They are briefly reviewed here.

Juan et al. [17] used cutting speed, feed per tooth, and axial depth of cut as the inputs of model prediction with tool life as the model output for a polynomial neural network technology that achieved predictive maintenance. Jiaa and Dornfeld [22] used the GMDH approaches for the recognition and prediction of the tool wear state from a multi-sensor configuration (acoustic emission and cutting force) in a turning operation and showed that the GMDH approach was superior to predictions made with conventional analysis, such as the stepwise regression analysis. The derived model using the GMDH revealed that the prediction of tool flank wear has concerned the cutting parameters: speed, feed and depth of cut [23]. A possible method predicting and detecting cutting tool failure in real-time using the GMDH was reported by Uematsu and Mohri [24]. The work presented by Onwubolu et al. [25] used the e-GMDH algorithm in end milling for modelling the tool wear as a function of the cutting parameters: cutting speed, feed, and depth of cut. All past research related to the use of GMDH in manufacturing showed that this method could effectively monitor tool condition or predict tool life.

3.1 High-Speed Machining (HSM) Experiment and Tool Life Model

Several milling experiments were carried out on a high-speed machine tool (Papars B8) using a four teeth corner radius end mill with 10 mm in diameter and TiAlN coating for machining SKD61 tool steel blocks. The helical angle is 45° and corner radius is 0.5 mm. The high-speed milling process parameters were selected varying the cutting speed in the range 314 - 628 m/min, feed per tooth in the range 0.1 - 0.15 mm/tooth, and the axial depth of cut in the range 0.5 - 1.5 mm. The end mill tool life obtained with a flanked wear threshold of $VB \leq 0.2$ mm is used as the base criterion (ISO 3002/1) to assess the tool health. The features of the flank wear land on the end mill were measured by an Olympus tool microscope, as shown in Fig. 5.

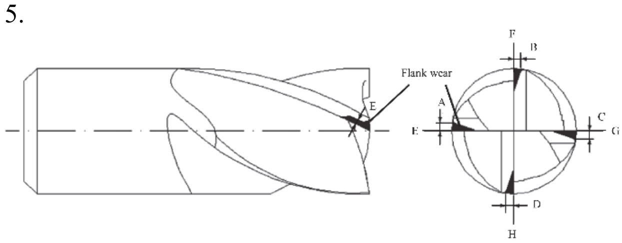


Figure 5 Features of the flank wear land on the end mill

Fig. 6 shows the developed polynomial neural network for predicting tool life. The error between the predicted and measured tool life in the experimental verification of the polynomial network is less than 10%. Therefore, the developed network has a reasonable accuracy for the modelling of HSM operations.

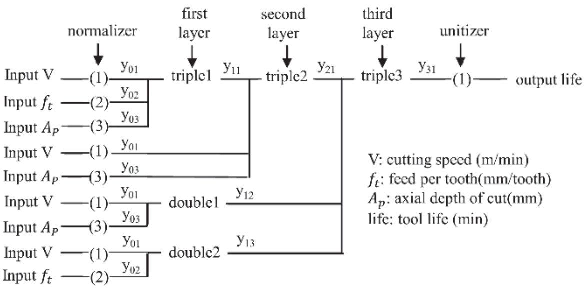


Figure 6 Structure of the polynomial neural network for predicting HSM tool life

3.2 Integration of Tool Management System and Tool Life Prediction System

The polynomial neural network is mainly used to learn the hidden relationship between data parameters and target values through historical data; it searches for the best model that provides the most accurate prediction capability. Different tool and workpiece materials, cutting conditions, machining methods, and machine characteristics have varying degree of influence on tool life. Here, we stored a machining model trained by Juan et al. [17] into the database using the PUT method of MongoDB's GridFS API. A machining model data is stored in the data field in the chunks collection in binary form, as shown in Fig.7 and Fig. 8. GridFS API makes use of two collections chunks and files to store model files. The user can obtain the RUL based on the cutting conditions by calling the corresponding prediction model and applying the GET method.

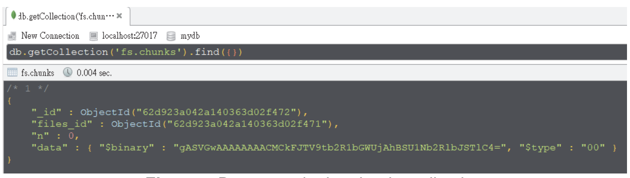

```
db.getCollection('fs.chunks').find({})
fs.chunks 0.004 sec.
/* 1 */
{
    "_id" : ObjectId("62d923a042a140363d02f472"),
    "files_id" : ObjectId("62d923a042a140363d02f471"),
    "n" : 0,
    "data" : { "$binary" : "gASVGwAAAAAAAACMCkFJTV9tb2R1bGWUjAhBSU1Nb2R1bJSTlC4=", "$type" : "00" }
}
```

Figure 7 Document in the chunks collection

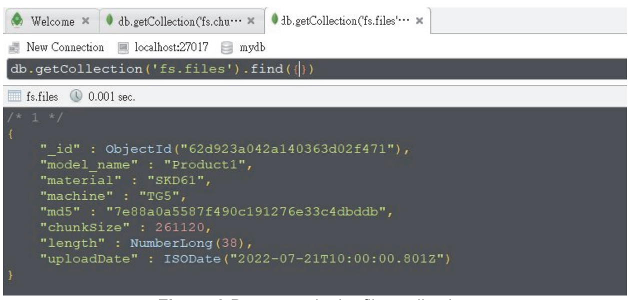

```
db.getCollection('fs.files').find({})
fs.files 0.001 sec.
/* 1 */
{
    "_id" : ObjectId("62d923a042a140363d02f471"),
    "model_name" : "Product1",
    "material" : "SKD61",
    "machine" : "TG5",
    "md5" : "7e88a0a5587f490c191276e33c4dbddb",
    "chunkSize" : 261120,
    "length" : NumberLong(38),
    "uploadDate" : ISODate("2022-07-21T10:00:00.801Z")
}
```

Figure 8 Document in the files collection

4 INTEGRATED SYSTEM PERFORMANCE VERIFICATION

The purpose of the tool management system is to enable different departments to transfer tool data and control the tool usage to arrange the appropriate machining processes. We used a 10 mm diameter, 2-flute end mill for the high-speed milling of the workpiece, as shown in Fig. 9, with a hardness of HRC40 to illustrate how the pre-processing was performed using the TMS.

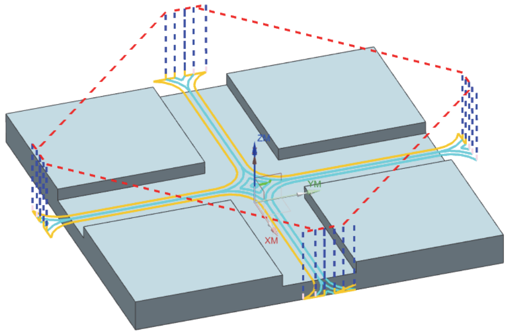
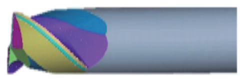


Figure 9 Geometrical solid model of the part

Step 1: The engineering staff reviews the inventory list and RUL of each part through the TMS after receiving the production plan, as shown in Fig. 10. If the part stock is insufficient or the tool life is near termination, which results in the tool not being able to meet the production demand, a purchase list is proposed to the purchasing department.

Cutting-tool ID	Cutting-tool Name	Cutting-tool Type	Tool room storage	Remaining useful life(min)	Status	ToolLife Prediction
T-085200105-0001	Double Turbo milling cutters	Holder	A-1-15.2	344	Borrowing	Update
T-085200203-0001	ZOMX16	Inserts	A-2-15.1	144	Borrowing	Update
T-085200203-0002	ZOMX16.1	Inserts	A-2-15.1	144	Borrowing	Update
T-085200203-0003	ZOMX16.2	Inserts	A-2-15.1	144	Borrowing	Update
T-085200301-0001	JS564F2C	Cutting-tool	A-3-1.1	235	Borrowing	Update
T-085200304-0001	2-Flute ball end mill	Cutting-tool	A-3-1.2	300	Borrowing	Update
T-085200301-0002	D10-C-16L	Cutting-tool	B-1-2.1	323	Borrowing	Update



T-085200401-0001	BT30-10-25L	Holder	B-1-2.2	472	Borrowing	Update

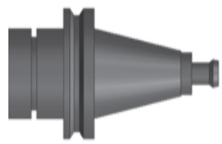
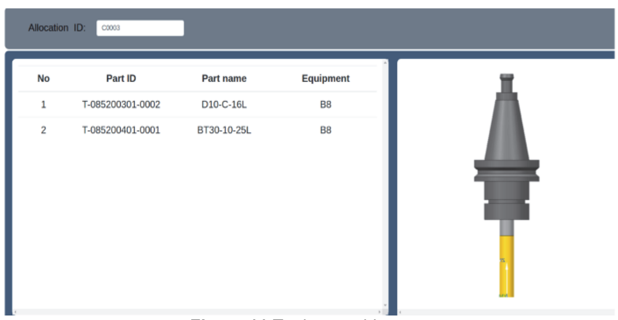


Figure 10 Retrieving tool inventory

Step 2: Select ID number T-085200401-0001 BT30 tool holder and T-085200301-0002 10 mm diameter end mill, and enter the assembly page for part assembly, as shown in Fig. 11. The tool life prediction system can calculate the RUL using the selected cutting conditions, as shown in Fig. 12. The cutting parameters can be substituted into a CAM software for simulation tests.


Allocation ID: C0003

No	Part ID	Part name	Equipment
1	T-085200301-0002	D10-C-16L	B8
2	T-085200401-0001	BT30-10-25L	B8

Figure 11 Tool assembly page

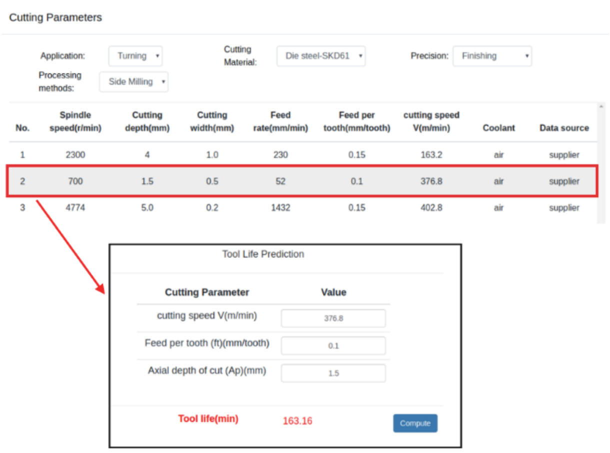


Figure 12 Cutting conditions selection page and tool life prediction

Step 3: The production staff logs into the TMS for loaning according to the parts list compiled by the engineering staff, as shown in Fig. 13.

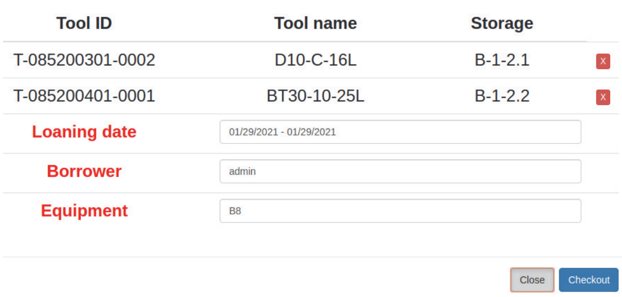


Figure 13 Tool loaning page

Step 4: The combined tool is delivered to the measurement room for measurement and inspection. In this paper, we used the Zoller genius 3 to obtain the tool compensation value and transmit the measurement results to the TMS through RESTful API, as shown in Fig. 14.

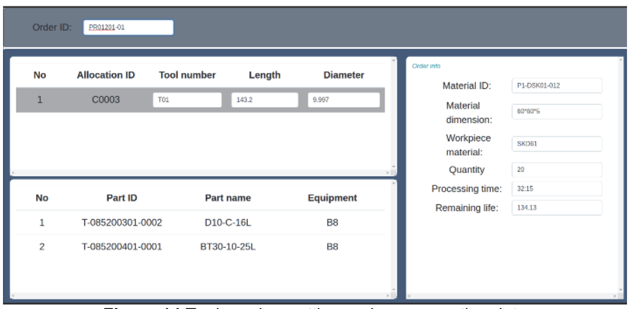


Figure 14 Tool number setting and compensation data

Step 5: The production staff loads the tools one by one to the machine according to the setting sequence of the TMS and the tool compensation value which can be transferred to the CNC control system by communication protocol for machining. After the machining is completed, the TMS automatically updates the remaining cutting time by subtracting the actual cutting time of the controller via TCP/IP from the tool life.

5 CONCLUSION

The TMS plays a crucial role in the manufacturing industry. It strictly controls the usage of tools in the production process and enables each workstation on the production line to connect to the central database. Under certain processing conditions, the maximum utilization rate of the tool can be further improved to reduce material waste and enhance sustainability. The simulation and experimental results indicate that the prediction model can be invoked through RESTful API. We will continuously develop and integrate the corresponding prediction models for different materials into the TMS, which will be applied to related machine tool application industries such as metal processing and manufacturing. Our proposed TMS has the following advantages over traditional management systems:

1. As the NoSQL database design does not require a predefined schema, it provides flexibility for the traditional enterprise to integrate the big data and flexibly integrates and analyses with other systems without rebuilding the database.
2. The tool life prediction algorithm integrated into the TMS. According to our experience, as long as the error of the tool geometric angle (helix angle, relief angle, rake angle) is within 5 %, the tool life value can be obtained under different cutting conditions. It is different from setting the threshold value of tool failure.
3. The TMS can provide CAD/CAM/CAPP assistance for tool query and selection. All information about the tool, matching shank, tool holder or insert can be retrieved using the TMS.

Acknowledgement

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