Development of a Knowledge Warehouse for Grinding

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ABSTRACT

Successful of grinding in practice is highly depending on the level of expertise of the machinist and engineer. Knowledge Management might offer a strategy to keep the valuable knowledge. The main objective of Knowledge Management (KM) is to manage knowledge process, the knowledge itself could not be managed, what can be managed is the knowledge gathering, storing and organizing, retrieving, and sharing. The organization should have an effective and efficient information system to facilitate knowledge management process. This paper presents the current development of a Grinding Knowledge Warehouse (GKW) which facilitates and supports knowledge management process for grinding technology and provides a guidance to select the required grinding conditions or parameters for a given grinding operation taking account of the lessons learned from previous cases.

Keywords knowledge management, grinding, missing data,

1 INTRODUCTION

Grinding is basically a chip-removal process in which the cutting tool is an individual abrasive grain in a grinding wheel (Kalpaakijian, 1991). Successful application of grinding technology relies on the understanding of the complex relationships between quality variables and process control conditions as well as operator's skills and experience ((Rowe et al, 1994), (Van de Spek et al, 1997), (Peter et al, 1976), (Rowe et al, 1987)). Therefore this knowledge should be well managed for effective production.

Rowe (1994) summarized the application of Artificial Intelligence (AI) that used in grinding technology: knowledge based expert systems, fuzzy logic, neural networks, genetic algorithms and adaptive control for optimization. The existing techniques for selection of grinding variables are data retrieval methods, empirical methods, and AI. Different techniques have been implemented to select grinding conditions using Case-Based Reasoning (CBR), Rule-Based Reasoning (RBR), and Hybrid approach ((Rowe et al, 1999), (Watson, 1995), (Rowe et al, 1988), (Santosus, 2001)). Although these techniques have been investigated by many researchers and some initial experiments completed, it has not been implemented in the industry fully. Different Knowledge-based on expert systems in grinding were developed for example , Gupta et al (2001), Midha et al (1991), Billatos et al (1993) and Morgan et al (2007). These approaches use human experts and production rules, and they provide a solution through an inference procedure, e.g. on desirable grinding conditions for a given grinding situation or on selection of a grinding wheel or grinding conditions. Different types of knowledge, which are available in the form of mathematical equations and experimental data, cannot be easily incorporated into the existing approaches.

Shin et al (2008) developed generalized grinding process models for surface roughness and grinding power. These models depend on coefficients that could be determined through a number of designed experiments. In the first phase of the application, model form is formulated, through a combination of a systematic study, an extensive survey of existing specific models, experiments and knowledge from experts. Then models coefficients for different workpiece and wheels are determined by experiments. These models can be used for designing process operating conditions or process optimization with experimental efforts and the extensive coefficient calculations that could be considered as a drawback.

From the above literature review of knowledge based system in grinding, none of these models or system addressed the missing or incomplete data. The causes of missing data may be different, some due to design, and some due to chance. Most grinding cases found in publications do not provide complete information. It could possibly be because investigators were concerned with a specific aspect of the process rather than the whole grinding problem. Some variables may not be collected from all investigations. During data collection, researches might collect data from their experiments ignoring some data that were not important for them or simply designed experiments according to their own criteria without considering completeness of records. Such incomplete data set could have serious effects on a case based reasoning, because it requires a complete case data set to support.

This paper presents the current development of Grinding Knowledge Warehouse (GKW) which facilitates and supports knowledge management process for grinding technology. On the other hand, the GKW provides a guidance to select the required grinding conditions or parameters for a given grinding operation taking into accounts the lessons learned from previous cases. The database and problem-solving modules are explained including rule based and case based reasoning. Finally, missing data issue is introduced and discussed.

2 GRINDING KNOWLEDGE WAREHOUSE

The GKW is designed to facilitate and support knowledge management process for grinding technology. The GKW includes six modules as shown in (figure 1).

Data Input Module, the main task of this component is data preparation. It collects data through the data collection interface from grinding database and CoP's members interaction. This component is not only to extract, load and integrate the data into database facility, but also to periodically refresh the database to reflect updates at the data from user-system interaction.

Database Module is created to store, retrieve and share data in various forms. These data are transformed to the problem-solving module and then the learning knowledge discovery, which provides the user, by guidance to select the right conditions for manufacturing operation (for example, variables for grinding). The database module is based on relational database management system by using MySQL.

Knowledge Acquisition Module facilitates knowledge conversion from tacit knowledge to explicit knowledge, for an instance, it directly acquires tacit knowledge from knowledge engineers or Community of Practices (CoPs).

The core of *Problem-Solving Knowledge Discovery Module* is CBR, RBR, and Model Base Reasoning (MBR). This module includes data transformation, knowledge inference engine and knowledge representation. The RBR and CBR are used to provide the engineers and workers a guidance to select the required grinding conditions or parameters for a given grinding operation taking into accounts the lessons learned from previous cases. The GKW provides a problem-solving module, which enables the user to find solutions for different grinding problems. The user can further browse different cases regarding different application criteria. The CBR and RBR in this research are based on the system proposed by Chen (1998) and Li (1996) 'Intelligent Selection of Grinding Conditions'.
CBR is an approach that seeks to identify a close match between a new operation to be performed and the characteristics of previously successful case stored in a case base. The process of the CBS developed is to:

- assign an index to each of the key features of the case specification;
- retrieve past cases with similar indexes to the case specification in memory;
- adapt the case from the memory to match the new case specification;
- test the new case.

If the test is successful the output will be stored. If unsuccessful, the case is further modified and loop repeated till success or case exhausted.

Selection of an appropriate case is achieved when the user input specification index is matched with a case in the case base. The user inputs the part number, grinding type, work material (material group, material, hardness), workpiece initial and finish diameter, workpiece requirements (roughness, contact width, workpiece width) and wheel type (bond, grit size, etc.). The system identifies the primary indexes which are grinding type, work material, hardness and wheel type. The primary indexes are used to determine a set of applicable cases. If there is a mismatch in this category a case is rejected. If the match were successful for one or more cases, a set of applicable cases would be located. If not, the reasoning process had failed and the executer would quit and apply the RBR.
The secondary indexes are used to choose the nearest case from those applicable cases determined by the very important indexes. If there is a mismatch of this category the case could be modified to fit the problem. The secondary indexes include individual material, roughness value, work diameter, wheel speed, and wheel diameter. In most situations, the case retrieved would not exactly fit the case specification definition. The case has to be modified to conform to the new requirements. The minimum data required for the CBR system to run are material, material group, hardness, roughness, and start diameter. If any of these data is missing the cased based system won't be able to run.

The rule based system is automatically activated when the system failed to find matched case using CBR. The minimum parameters are roughness, hardness, material and start diameter. If any of these data is missing, the system won't be activated. A rule in the RBS is a conditional statement that specifies an action that is supposed to take place under certain set of conditions. The set of rules is usually in the form of
IF
<some conditions are met>
THEN
<execute some actions>.

It is useful to structure problem-solving system in a way that facilitates a description of a search process. In the grinding parameters selection, the rule based system plays mainly the role of an assistant. The recommendations for cylindrical grinding with conventional wheels are sorted into tables. The rules are applied for selective material, which are tool steel, cast iron, and super alloys. The data in the table can be encoded into rules (Li, 1996).

The inference engine interprets the knowledge in the knowledge base and performs logical deduction and contains knowledge base modifications. The inference engine provides the reasoning strategy for searching the knowledge base to determine which rules apply to the situation and makes the appropriate decision (Chen,1998), (Li, 1996). Inference engines are forward chaining (data driven or antecedent reasoning) and/or backward chaining (goal driven or consequent making). Forward chaining also called data driven inference mechanism. It starts with the available information as it is received and is trying to draw conclusions which are appropriate to the set goals. Conclusions are reached on the basis of the rules which are true, and the search continues until a solution or set of solutions found. The most serious limitation of rule-based system is inability to learn from operation experience and the inability to take account of developing technology.

The approach adopted for selection of grinding conditions using RBR and CBR is the forward chaining reasoning. The basic reasoning method is a pattern-matching algorithm. In a predetermined order, the condition portion of rule is compared with the current state of facts. When all the conditions of a rule are satisfied, then that rule becomes eligible for execution.

The Learning Knowledge Discovery Module extracts implicit, previous unknown and potential useful rules and patterns, modifies and updates the existing rules and patterns. This module provides engineers with guidance to select the right conditions for a specific grinding operation. *Knowledge Warehouse Module* supports efficient explicit knowledge storage and retrieval in various forms based on the analysis task. The knowledge warehouse manages the integration of a wide variety of knowledge, such as rules in rule base, cases in case base, models in model base etc., into a functioning entity. The knowledge includes various types of knowledge such as numerical data, text streams, validated models, and movie clips, as well as the algorithm used for manipulating them. Finally, the *Knowledge Analysis Management Module* manages various analysis tasks and provides effective management of technologies such decision support system, statistical analysis, query, and reporting.

3 MISSING DATA CONSIDERATION

A combination of CBR and RBR is employed to select grinding condition and update the knowledge base of the warehouse. A fundamentals characteristic of the CBR system is the requirement for sufficient cases to be saved in the database to cover the target specification. Grinding cases are collected from different articles (Shin et al, 2008), (Li, 1996), (Shin et al, 2003) and thesis (Chen, 1998), (Ebbrel, 2002) for cylindrical and surface grinding. For a successful search, if insufficient cases are available, the system will default to RBR procedures.

In the CBR, the main input parameters should be entered by users are material group, material, wheel name, diameter, material hardness, wheel diameter, wheel speed, workpiece speed and roughness. While the retrieved cases should have the same data available otherwise the case based system won't be very effective. The very important indexes are needed for identifying the applicable cases in CBR. The system can efficiently utilize CBR and RBR, if the work material, wheel parameters, hardness, roughness, work speed, work diameter, wheel speed, wheel diameter, dressing lead, dressing depth and feed rate value are all available in the saved case. If at least one of these parameters is incomplete the case-based system will fail to find the matched applicable cases or the rule-based system will be activated. In order to avoid this situation, the GKW will have a strategy to try to complete the missing/incomplete data.

From the collected cases, the roughness value and material group were often to be incomplete and missing. The material group could be identified if the work material is known. Since, the surface roughness is an important performance measurement for grinding as well as it is an important grinding variable in selecting grinding conditions from the CBR and RBR in GKW. Ideally, the roughness value may be calculated using a generic roughness model that proposed by Lindsey (1973). The general roughness model for surface grinding proposed by Lindsey (1973) is shown in equation

$$T_{av} = 12.5\times 10^{3} \frac{d_g^{16/27} a^{19/27}}{D_e^{8/27}} (1+\frac{a_d}{s_d}) s_d^{16/27} (\frac{v_w}{v_s})^{16/27} \quad (1)$$

$$R_a = 0.487\, T_{av}^{0.30} \text{ for } 0 < T_{av} < 0.254$$

$$R_a = 0.7866\, T_{av}^{0.72} \text{ for } 0.254 < T_{av} < 2.54$$

where T_{av} , a, a_d, d_g, s_d, v_w, v_s, D_{eq}, R_a ,average chip removal thickness (in micron), depth of cut, dressing depth, grain size, dressing lead, wheel speed, work speed, equivalent diameter, and surface roughness respectively. For cylindrical grinding the above equation could be simplified as shown in equation (2):

$$T_{av} = \frac{3.653\{(1+\frac{a_d}{s_d})(d_g \times s_d)^{16/27} (\frac{v_s}{v_w})^{3/27} (\frac{Z_w}{v_s})^{19/27}\}}{D_{eq}^{8/27}} \quad (2)$$

$$R_a = 0.487\, T_{av}^{0.30} \text{ for } 0 < T_{av} < 0.254$$

$$R_a = 0.7866\, T_{av}^{0.72} \text{ for } 0.254 < T_{av} < 2.54$$

where Z_w average chip removal, The average chip removal van be calculated using equation (3), work diameter and feed rate, v_f , d_w

$$Z_w = \pi d_w v_f \quad (3)$$

The work material, roughness, work diameter, wheel diameter and wheel speed are considered to be the important indexes. These are required to calculate the similarity value from the applicable cases so the recommended case can be selected. From the collected cases, these parameters are complete. Dressing lead, feed rate and work speed are modified to match the specifications for the new case. So the feed rate, roughness, dressing lead, work speed, wheel speed, workpiece diameter, wheel diameter for the recommended case should be available to modify for the required values.

In order to increase the flexibility and the efficiency of the CBR, workgroup, work material, wheel, hardness, roughness, feed rate, roughness, dressing lead, work speed, wheel speed, workpiece diameter, and wheel diameter should be complete. If one of these parameters is missing CBR may not be activated or the result could be poor. Some of these parameters could be calculated using mathematical model, such as roughness value, or known if they are missing. CBR would be more efficient if the very important and important indexes are complete. Roughness value is critical parameter to calculate similarity and select applicable case in a CBR. In order to tackle this problem, the system should be able to complete the missing data as soon as the case is saved. First, the system will remind the user that important parameters are incomplete and encourage him/her to complete the record. If the user is happy with the case or s/he cannot complete the case and saves the record with missing parameters, the system will try to complete the case filling missed parameters and will display it for the user to agree and save the modified case. The system will complete missing data by using mathematical models or if-then rules. For roughness value, the models are discussed above. Mathematical equations are available to calculate some parameters in grinding for example using equation (3) to calculate the average chip removal.

If the missed parameter is not key parameter then the grinding model could be used with relatively low errors. Now the difficulty is that when a key parameter in a model is missed from a database, the model will not work in general. Considering the application of empirical model, normally one empirical model will be applicable in a certain range. For different application ranges, it may require different constants for a model with the same or different structures. In the scenario where the individual range of each model may have an overlap range. Certainly, both models are applicable in the overlap range. To extend such case, an assumption could be made as it is possible to find a model to give a best fit to both ranges. For the new model, the data missing will not be a problem. For example, surface grinding and cylindrical grinding are different type of grinding. The control parameters are different. However, they both can have some common parameters such equivalent diameter, depth of cut, cutting speed, etc. By using the combination of these common parameters, a model could be established for both type of grinding. Genetic Programming (GP) might be a tool to identify such model.

4 CONCLUSIONS

A simple and easy to use GKW, that support decision making process for selecting grinding condition using case based and rule based reasoning, have been developed and presented in this paper. The developed GKW facilitates transferring tacit knowledge into explicit knowledge by assisting the decision making processes for selecting grinding conditions and updating the knowledgebase warehouse with grinding cases. Since, a fundamentals characteristic of the CBR system is the requirement for sufficient cases to be saved in the database to cover the target specification, a methodology for dealing with missing data is proposed. If insufficient cases are available for a successful search, the system will default to RBR procedures. For different sets of grinding data, there are different roughness models available. But they cannot be applied to other cases. It is a critical issue to find the best way in dealing with the missing or incomplete data. Further work is needed to combine different models into a model that is applicable for all conditions with minimum error.

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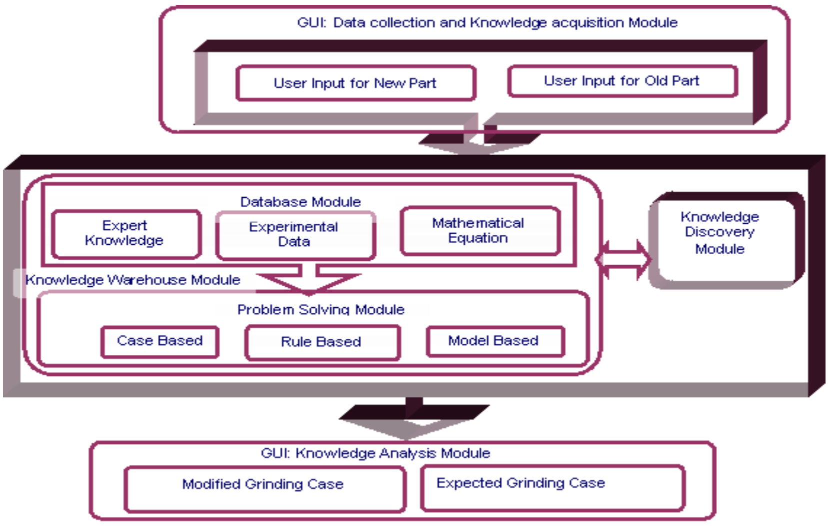

Figure 1: GKW Structure