Advances in Production Engineering & Management **ISSN 1854-6250**
Volume 11 | Number 4 | December 2016 | pp 311–323 Journal home: apem-journal.org
http://dx.doi.org/10.14743/apem2016.4.229 Original scientific paper

A case-based reasoning approach for non-traditional machining processes selection

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A B S T R A C T

To sustain in the modern era of rapid manufacturing development, it becomes necessary to generate complex shapes on materials which are highly temperature and corrosion resistant, hard to machine, and have high strength-to-weight ratio. Generation of complex shapes on those materials using conventional machining processes ultimately affects surface finish, material removal rate, accuracy, cost, safety etc. Non-traditional machining (NTM) processes have the capability to machine those advanced engineering materials with satisfactory results. But, selection of the most appropriate NTM process for a particular machining application is often a complicated task. Case-based reasoning (CBR), a domain of artificial intelligence, is a paradigm for reasoning new problems from the past experience. In CBR, a memory model is assumed for representing, indexing and organizing past similar cases, and a process model is supposed for retrieving and modifying the past cases and assimilating the new ones. This paper primarily focuses on the application of CBR approach for NTM process selection. Based on different process characteristics and process parameter values, the past similar cases are retrieved and reused to solve a current NTM process selection problem. For this, a software prototype is developed and three real time examples are cited to illustrate the application potentiality of CBR system.

A R T I C L E   I N F O

Keywords:
Non-traditional machining processes
Process selection
Artificial intelligence
Case-based reasoning

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Article history:
Received 7 June 2016
Revised 25 October 2016
Accepted 12 November 2016

1. Introduction

With the development of newer materials having improved thermal, mechanical and chemical properties, it has now become quite difficult to machine those materials using conventional machining processes. These processes, generally based on cutting and abrasion mechanism, incur higher machining cost while generating complex shape features on composites, ceramics and other advanced engineering materials. The achieved surface quality and dimensional accuracy of the machined components are also not satisfactory, and often fail to meet the desired target. In these machining processes, unwanted material from the parent workpiece is generally removed employing mechanical energy. This energy is supplied by means of a cutting tool kept in contact with the workpiece, causing shear deformation along the shear plane, leading to chip formation. New exotic work materials and complex geometrical shapes on those materials have been putting more pressure on the capabilities of the conventional machining processes. This leads to the development and deployment of a new set of machining processes, popularly known as non-traditional machining (NTM) processes. In these processes, unwanted material is removed from the parent workpiece using various forms of energy, like chemical, thermal, mechanical, electrical or combination of those energies. In an NTM process, there is no direct contact between the cutting tool and the workpiece. In abrasive jet machining process, excess material is removed by means of microscopic chips and in electrochemical machining process by electrolytic dissolution. In laser beam machining process, there is even no need of any cutting tool. It is also not necessary that the cutting tool should be harder than the workpiece material in an NTM process. Now-a-days, it has become easier to generate complex shapes on materials, like steel, carbide, titanium and its alloys, ceramics, superalloys (Inconel 718, hastelloy) etc. employing NTM processes [1,2]. Till date, there have been approximately 20 NTM processes developed and applied in modern manufacturing industries. Selection of the best suitable NTM process for a particular work material and shape feature combination is generally made by a domain expert on the basis of various factors, such as workpiece material, shape feature to be generated, material removal rate, surface finish, surface damage, corner radii, tolerance, cost, safety, power requirement etc. Thus, an expert in this domain must have a vast and in-depth knowledge about the characteristics and capabilities of different available NTM processes. But, in the present manufacturing scenario, most of the process engineers lack the requisite domain knowledge and availability of experts is also sometimes constrained.

Usually, a domain expert acquires knowledge from the past experience as well as from other reliable sources. Taking this concept as a plinth, when an expert attempts to select an NTM process for a given machining application, he/she just recalls the similar past situations and their solutions. Thus, based on the similar past problems and their solutions, new NTM process selection cases are solved. This entire cognitive process of a domain expert's thinking has given birth to a new branch of artificial intelligence (AI) technique, known as case-based reasoning (CBR) approach. This CBR approach is applied here for NTM process selection. In this paper, in order to choose the most suitable NTM process for a specific machining application, an exhaustive case-base containing the machining characteristics of various available NTM processes and their pertinent process parameters is first created. These machining characteristics and process parameter data are later used to select the feasible NTM processes according to the end requirements. The selection procedure is based on retrieval of the best matched case from the case-base using the nearest neighbourhood technique, while calculating the similarity score between two cases. The best matched case, which is retrieved from the case-base according to the values of different process characteristics as set by the process engineer/end user, has the similarity score greater than the other cases. To automate and simplify the application of CBR approach in NTM process selection, a software prototype having a graphical user interface (GUI) is designed and developed in Visual Basic 6.0. The developed system simultaneously considers both the user requirements (product characteristics) and technical requirements (process characteristics) for a given NTM process selection problem.

2. Literature review

Using two multi-attribute decision making (MADM) tools, i.e. analytic hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS), Yurdakul and Cçogun [3] attempted to simplify the NTM process selection procedure for the manufacturing personnel. A list of feasible NTM processes satisfying the users' requirements was first generated and those processes were then ranked based on their suitability to meet the desired machining operation. An expert system was developed by Chakraborty and Dey [4] for selecting the best NTM process under constrained material and machining conditions. It would rely on the priority values of different criteria and sub-criteria for a specific NTM process selection problem, and the NTM process with the highest acceptability index was finally identified. Chakraborty and Dey [5] developed a quality function deployment (QFD)-based expert system for NTM process selection. An overall score for each of the NTM processes was estimated using the weights extracted from the house of quality matrix for various process characteristics. The overall scores of some of the NTM processes simultaneously satisfying certain critical criteria requirements were again compared and the NTM process having the maximum score was finally selected as the optimal choice. A web-based knowledge base system was proposed by Edison Chandraseelan et al. [6] for identifying the most suitable NTM process to meet some input parametric requirements, like type of the work material, shape application, process economy, and other process capabilities, like surface finish, corner radii, width of cut, tolerance etc. Sadhu and Chakraborty [7] applied an input minimized Charnes, Cooper and Rhodes (CCR) model of data envelopment analysis for NTM process selection. Employing weighted-overall efficiency ranking method of MADM theory, the efficient NTM processes were ultimately ranked in descending order of their priorities. Temuçin et al. [8] designed a fuzzy decision support model for NTM process selection while assessing the potentials of some distinct NTM processes. Chatterjee and Chakraborty [9] proved the application potentiality of evaluation of mixed data (EVAMIX) method for solving NTM process selection problems using three demonstrative examples. Roy et al. [10] integrated fuzzy AHP and QFD techniques for selection of NTM processes based on some predefined customers' perspectives. Temuçin et al. [11] solved the NTM process selection problem under fuzzy and crisp environment, and proposed a decision support model to guide the process engineers to explore the potentials of some distinct NTM processes. The applicability of the proposed model was also validated. Khandekar and Chakraborty [12] applied fuzzy axiomatic design principles for selection of NTM processes. Madić et al. [13] demonstrated the applicability, suitability and computational procedure of operational competitiveness ratings analysis (OCRA) method for solving NTM process selection problems.

Nowadays, CBR as a part of cognitive science, has been emerged out as an interesting research topic. Amen and Vomacka [14] employed CBR approach as a tool for selection of material and heat treatment process from an exhaustive database to simplify the task of a designer. Khemani et al. [15] applied CBR approach in fused cast refractory manufacturing industry. Fang and Wong [16] applied a hybrid CBR approach in agent-based negotiation for effective supply chain management. Armaghan and Renaud [17] adopted CBR approach to prove the complementary nature of multi-criteria decisions and CBR approach. Although the past researchers applied numerous MADM methods and developed different distinct decision aids for selection of NTM processes for varying machining applications, but till date, no attempt has been put forward on selection of NTM processes using CBR approach. This paper thus proposes development of a decision making model based on CBR approach for selecting the best suited NTM process for a given machining application. It is observed that CBR is the correct and simplest approach in this domain where availability of experts is sometimes constrained. In CBR approach, a set of feasible NTM processes is first retrieved from the case-base satisfying the work material and shape feature combination. Based on the user and technical requirements, it then identifies the best matched NTM process from the stored similar cases. The past cases are just reused here for NTM process selection for providing the optimal solution.

3. CBR approach

Intelligence, being a part of cognitive science, can be defined as the process involving rational and abstract thinking. It is often goal oriented and purposeful. It consists of knowledge and feats, both conscious and unconscious, which are acquired through continuous study and experience. The AI is actually the intelligence in machines. Intelligent system is the basement of knowledge engineering. It involves several tasks, like knowledge acquisition, creation of a knowledge base, knowledge representation and use of the acquired knowledge. The represented knowledge is basically used for reasoning or inference. In AI, knowledge is represented using symbols along with heuristics or rules of thumb. While using these heuristics, one should not have to rethink when a similar problem is encountered. The expert system can be defined as an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough requiring significant human expertise for their solution. Basically in expert system, knowledge is represented using 'if-then' rules.

The CBR approach is a part of AI technique that utilizes information stored in the knowledge base, when similar past problems are encountered again. It provides solution to the present problem that is almost similar to the past. In CBR approach, a problem is represented as an input in the present situation. It just retrieves the most similar case to the new one from its case-base while calculating the similarity score over the defined parameters. It first searches the case history and chooses that case having the closest similarity to the current problem. In CBR system, the case-base is well structured and documented. The case representation may be flat, where all cases are represented at the same level, or it can be hierarchical, expressing relationship between cases and sub-cases.

There are four major steps that constitute a CBR system, i.e. retrieve, reuse, revise and retain. Thus, it is also called as 4-R cycle or CBR cycle, as shown in Fig. 1. When a problem occurs in the current situation, similar past situations are retrieved from the case-base. Reusing the past cases, a predictable solution to the current problem is thus provided. If there is a need of any revision, the retrieved data are revised and retained as a new case in the case-base for future use [18-21].

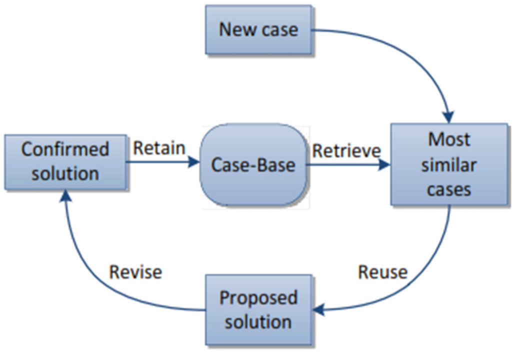

Fig. 1 A CBR cycle or 4-R cycle

Retrieving the most similar case along with the solution is based on some logical expressions. The similarity between two cases is usually measured with respect to each parameter. It also depends on the type of parameter (beneficial or non-beneficial) being used. The followings are the most common methods for calculating similarity between two cases:

a) Numeric:

$$\text{Sim}\ (a,b) = |a - b|/Range \tag{1}$$

where *Range* is the difference between the upper and lower boundaries of a set.

b) Symbolic:

$$\begin{aligned} \text{Sim}(a,b) &= 1 \ \text{ if } a = b \\ &= 0 \ \text{ if } a \neq b \end{aligned} \tag{2}$$

c) Multi-valued:

$$\text{Sim}(a,b) = \frac{Card\ (a)\ \cap\ Card\ (b)}{Card\ (a)\ \cup\ Card\ (b)} \tag{3}$$

where *Card* is the cardinality (size) of a set.

d) Taxonomy:

$$\text{Sim}(a,b) = \frac{h\ (\text{common node}\ (a,b))}{\min(h(a),h(b))} \tag{4}$$

where *h* is the height (number of levels) of the specified taxonomy tree.

The procedural steps of a CBR approach are presented as below:

a) A solution is first defined using several parameters. One of the parameters should be chosen carefully so that it would remain unique throughout the documentation procedure, e.g. case number.

b) A huge set of known solutions is put into the case-base of CBR system. An existing database can also be used for this purpose.

c) The CBR system generally reads the database and organizes a copy of its own.

d) The user generally formulates a query according to the end requirements. All the available variables are first displayed. The user has the option to choose all or few variables based on the problem statement. The query includes those variables as set by the user. The user also has the option to allocate different priority weights to the considered variables.

e) As a result of the user-defined query, CBR system may display a number of cases or the best matched case. It may also be possible that none of the cases would match the query exactly.

Favouring CBR technique as the most efficient tool for NTM process selection is a challenging task, as several other approaches have already been available for the same purpose. It is observed from the available literature that none of the MADM methods, like AHP, EVAMIX, TOPSIS etc. can provide complete solution when the domain is ill-structured and murky. The working principle of CBR is based on some available specific experiences instead of abstracted rules. It is considered as a useful tool if the utilization of prior experience is more vital than to produce a thoroughly optimized solution according to the specifications. The CBR approach has no optimizing potentiality, but it can be used for searching, not for calculations. Its efficiency is determined by fast retrieval of the most similar cases from the case-base. The principle of CBR also states that it can find the similarities between cases but not reasons. So, it is unable to judge how important the encountered departures are that can be determined only by an experienced user.

A comparison between the existing search techniques and the adopted CBR approach is elucidated in Table 1.

Table 1 Comparison between different search techniques and CBR approach

Method	Flexibility	Operational approach	Computational time	Programming complexity	Decision maker's involvement	Type of data
Genetic algorithm	Medium (lack of learning ability)	Population based probabilistic search and optimization technique	High (based on the desired accuracy and termination criterion)	High	High	Numerical
Artificial neural network	High	Mimics the working principle of biological neurons	High	Medium	Medium	Numerical
Simulated annealing	Medium	Cooling process of molten metal is modeled artificially to construct an optimization algorithm	Medium (based on the desired accuracy and termination criterion)	High	High	Numerical
Expert system	Medium	Exact matching of input and stored data producing several 'if-then' rules for inference	Medium	Medium	High	Both numerical and textual
CBR	High	Notion of similarity between present and prior stored cases	Low	Low	Medium	Both numerical and textual

4. CBR-based approach for NTM processes selection

Although CBR approach has already been successfully applied in various fields of mechanical engineering, such as material selection, design selection, parts selection for automobile industries etc., no attempt has still been made for its application in the domain of NTM process selection. The CBR approach has the potential to provide complete information about a case where minimum information is available to the user. It yields the best results when the user provides detailed query information.

While selecting the most suitable NTM process for a particular machining application, the process engineer has to consider several machining characteristics of the available NTM processes. In the developed CBR approach-based decision making model, nine NTM processes, i.e. abrasive jet machining (AJM), abrasive water jet machining (AWJM), electric discharge machining (EDM), laser beam machining (LBM), ultrasonic machining (USM), electrochemical machining (ECM), electrochemical discharge machining (ECDM), plasma arc machining (PAM) and wire electric discharge machining (WEDM) are taken into consideration. As the process characteristics, type of the workpiece material, shape feature to be generated, material removal rate (MRR) (in mg/min), surface roughness (SR) (in μm), surface damage (SD) (in μm), tolerance (Tol) (in mm), overcut (OC) (in mm), corner radii (CR) (in mm), taper (TP) (in mm/mm), cost (C) (in relative (R) priority scale), power (P) (in kW) and safety (S) (in R scale) are considered. For cost, the R scale is set as 1 - lowest, 2 - very low, 3 - low, 4 - medium, 5 - high, 6 - very high and 7 - highest. On the other hand, for safety, the R scale is set as 1 - highly safe, 2 - safe and 3 - attention required. As work materials, a) aluminium, b) aluminium alloys, c) ceramics, d) composites, e) glass, f) steel, g) superalloys and h) titanium are considered in this model. The above-mentioned NTM processes can generate a) hole (precision) (0.03 mm $\leq D < 0.13$ mm), b) hole (standard) ($L/D \leq 20$), c) hole (standard) ($L/D > 20$), d) through cut (shallow) ($t/w \leq 2$), e) through cut (deep) ($t/w > 2$), f) through cavity (standard) ($t/w > 10$), g) through cavity (precision) ($t/w \leq 10$), h) pocket (shallow) ($t \leq 1$ mm), i) pocket (deep) ($t > 1$mm) and j) surface of revolution feature on the work material (where L is the length of the hole, D is the diameter of the hole, t is the thickness and w is the width of the machined feature). The relevant machining characteristics data for different NTM processes are accumulated from experimentations, machining data handbooks and other reliable resources to create the corresponding case-base. The collected data are then organized in a structured manner in MS Access. The step-wise operational procedures of the developed CBR system for selecting the best suited NTM process for a particular machining application are depicted as follows:

Step 1: When the developed CBR system starts to run, the first screen, as shown in Fig. 2, appears to the end user where the type of the work material to be machined and type of the shape feature to be generated can be chosen from the given options as the primary inputs to the system.

Step 2: After clicking 'OK' button, a list of feasible NTM process(es) capable of generating the desired shape on the specified work material is displayed. For this, Eqn. (2) is utilized for filtering and retrieving the data.

Step 3: When the user presses 'Next' button, another screen, as shown in Fig. 3, is displayed to identify the most suitable NTM process from the list of feasible processes while satisfying the set machining requirements.

Step 4: In this screen, the end user has to choose the desired process characteristics based on which the final NTM process selection is made.

Step 5: When 'Enter range' functional key is clicked, the required number of empty cells are automatically generated where the input ranges for the selected NTM process characteristics can be provided.

Step 6: After inputting the desired ranges of values, pressing of 'Best NTM process' button identifies the most suitable NTM process for the specified machining application while satisfying the set criteria values. For retrieving the best NTM process in this step, Eqn. (1) is employed.

Step 7: The actual retrieved values of all the technical characteristics for the best matched NTM process are also displayed.

Step 8: When 'Best NTM process' button is clicked, the technical details (tentative settings of the associated process parameters) of the best matched NTM process are also available, as shown in Fig. 4.

Although in step 5, there is an option for entering ranges of process characteristic values, but if the developed CBR system does not find any data within those ranges from the case-base, it would retrieve the possible data nearest to the query set. For a particular NTM process selection problem, MRR is the sole beneficial attribute where its value is always required to be maximized. On the other hand, SR, SD, Tol, TP, OC, CR, C, P and S are non-beneficial attributes requiring their minimum values. The best matched case should have the highest similarity score, which is calculated with respect to each of the process characteristics. After summing up these similarity scores for the set process characteristics for each case, the NTM process having the highest similarity score is chosen as the most suitable option.

5. Illustrative examples

5.1 Example 1: Standard hole on composite material

In this example, standard holes are to be generated on a composite material. After providing the inputs of composite as the work material and hole (standard) as the shape feature options in the primary selection window of Fig. 2, a set of feasible NTM processes consisting of AJM, AWJM, ECDM, ECM, EDM, LBM and USM is displayed, when 'OK' button is clicked. All the processes can generate standard holes on composite materials. In the next window of Fig. 3, MRR, SR, Tol, OC, CR and C are opted as the most important process characteristics based on which the final NTM process selection is to be made. In this example, the desired input ranges for those process characteristics are set as MRR 100-1000 mg/min, SR 2-12 μm, Tol 0-0.5 mm, OC 0-0.05 mm, CR 0-0.5 mm and C 1-4 (in R scale). Now, when 'Best NTM process' functional button is clicked, LBM process is identified as the best matched case, capable of meeting the set process characteristic values. It is interesting to observe that apart from the set process characteristics, values of the other process characteristics are also available for the best matched NTM process. In this example, the selected LBM process can achieve values of MRR as 286.08 mg/min, SR as 2.63 μm, SD as 102 μm, Tol as 0.02 mm, OC as 0.001 mm, CR as 0.5 mm, TP as 0.05 mm/mm, C as 1 (in R scale), P as 0.23 kW and S as 3 (in R scale).

In Fig. 4, the process engineer can also have an idea about the settings of different machining parameters of LBM process. These are the tentative process parametric settings and for achieving the maximum machining performance, fine-tuning of these settings is often necessary. A real time photograph of LBM process is also available in Fig. 4.

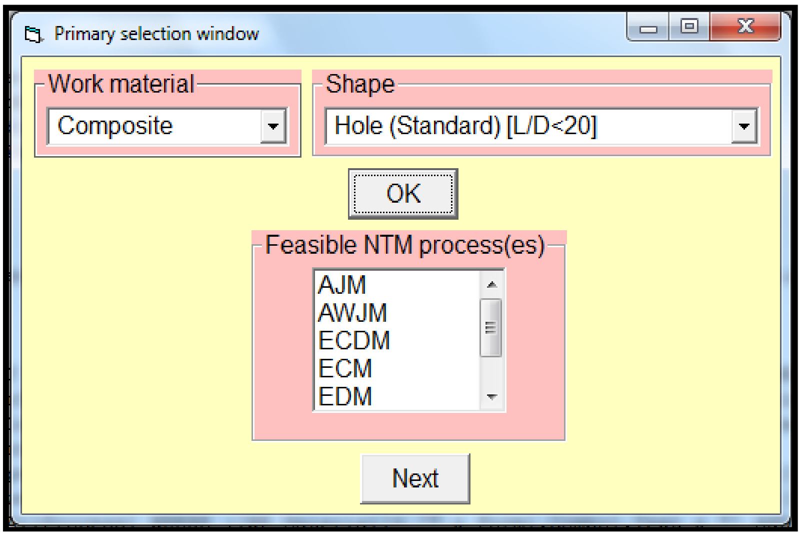

Fig. 2 Primary selection window for Example 1

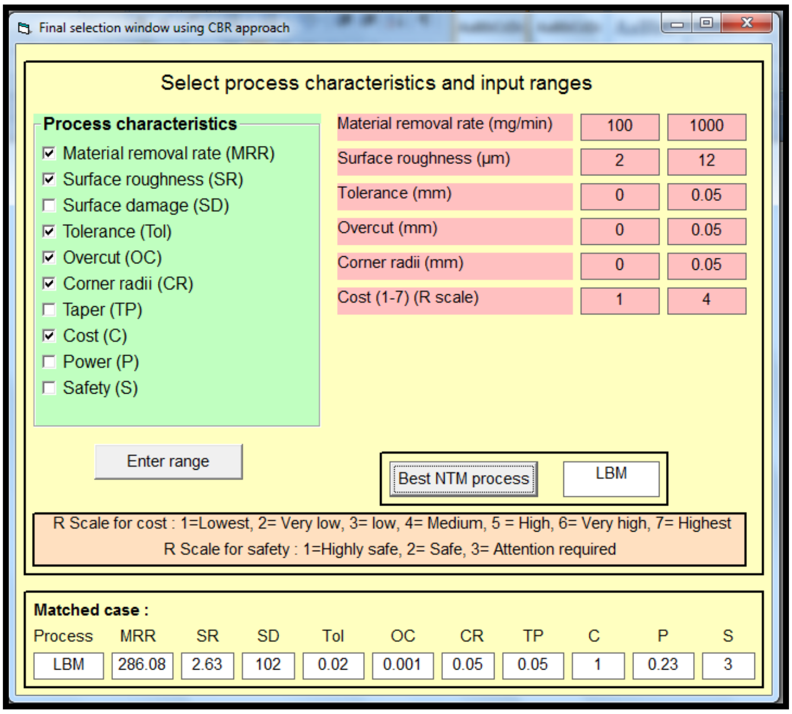

Fig. 3 Best NTM process for Example 1

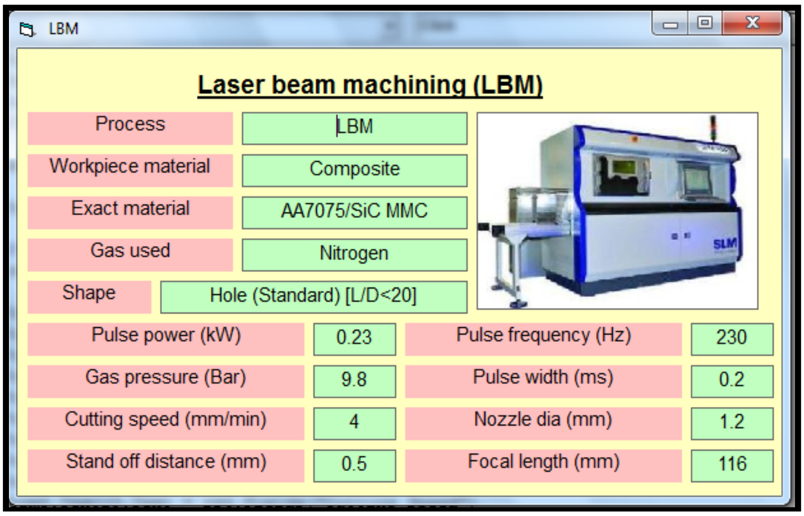

Fig. 4 Details of LBM process

5.2 Example 2: Standard through cavity on ceramics

Here, the process engineer wants to generate a standard through cavity on a ceramic work material. In the primary selection window, as shown in Fig. 5, the developed CBR approach first extracts five NTM processes, i.e. AJM, AWJM, EDM, USM and WEDM as the feasible options satisfying the said work material and shape feature combination requirement.

In Fig. 6, MRR, SR, Tol, OC, CR, C and S are chosen as the most important process characteristics based on which the final NTM process needs to be selected. Based on the ranges of values for these process characteristics, USM process is identified as the best matched case for this machining application. For USM process, the attainable process characteristics are MRR as 131.96 mg/min, SR as 0.66 μm, SD as 25 μm, Tol as 0.014 mm, OC as 0.15 mm, CR as 0.08 mm, TP as 0.005 mm/mm, C as 5 (in R scale), P as 0.4 kW and S as 1 (in R scale).

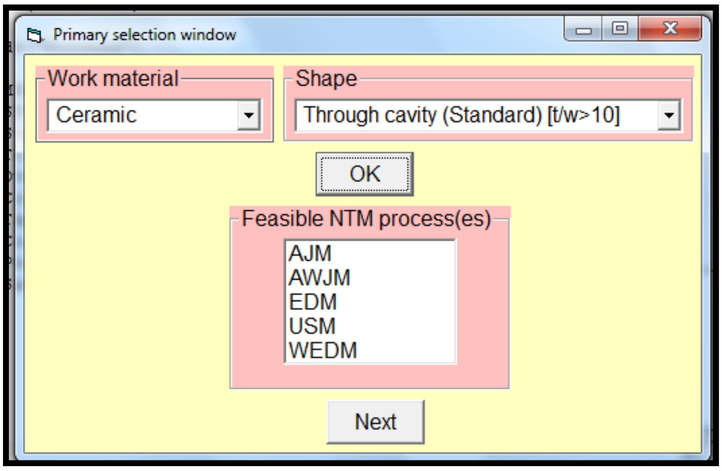

Fig. 5 Primary selection window for Example 2

In Fig. 7, the tentative parametric settings and the technical specifications of USM process along with its actual photograph are displayed to guide the process engineer to achieve the best machining performance.

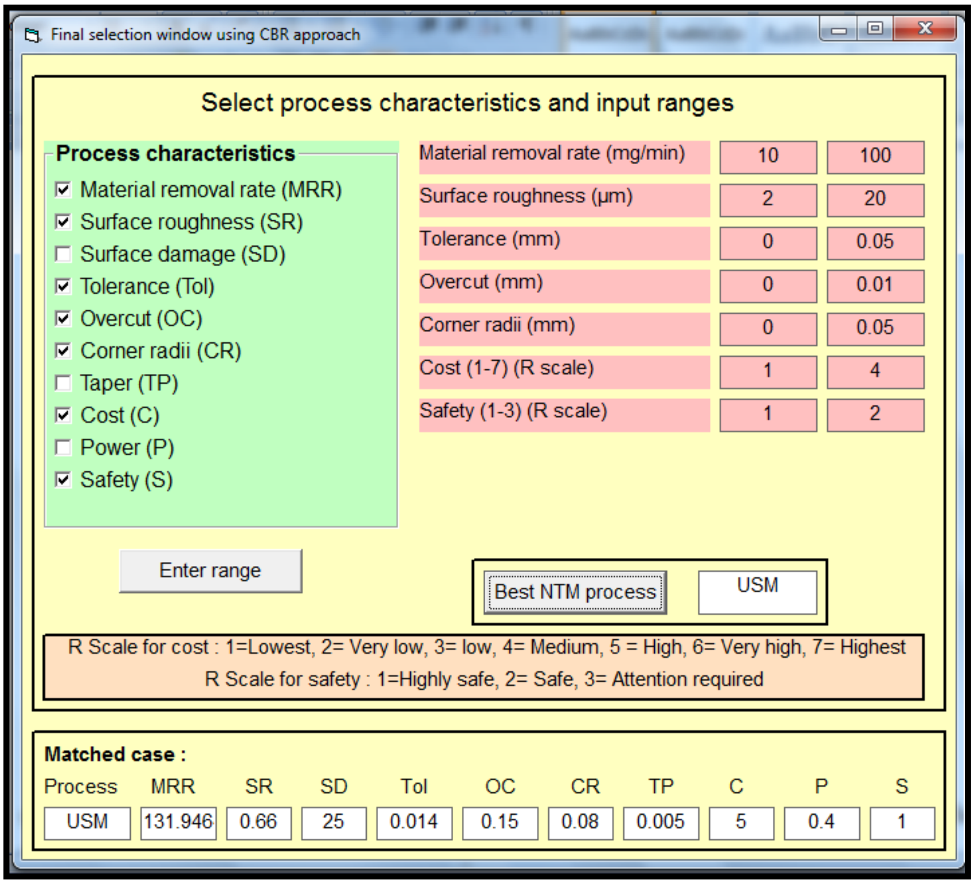

Fig. 6 Best NTM process for Example 2

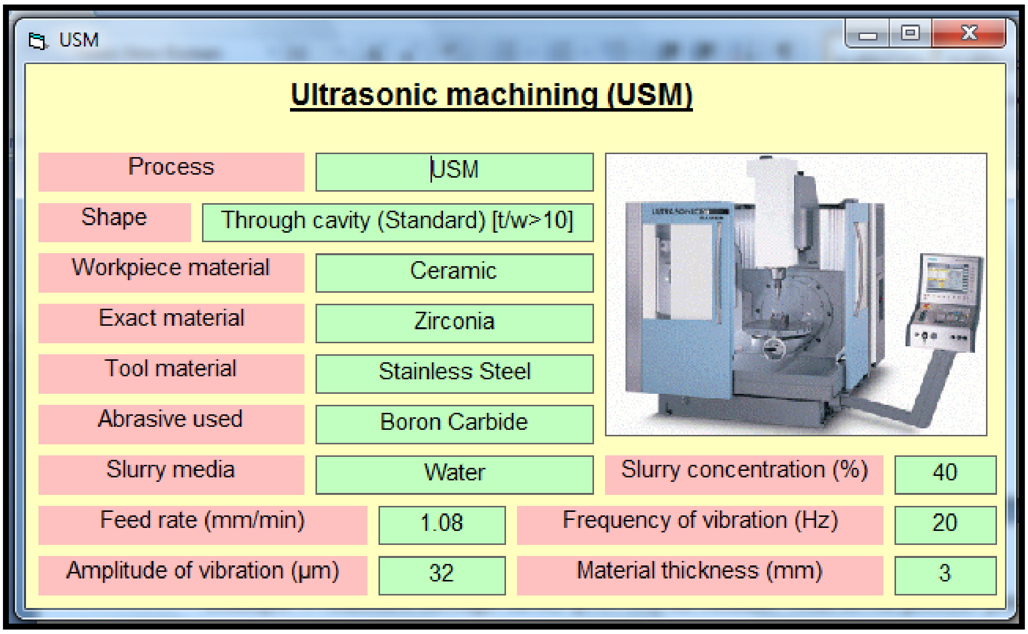

Fig. 7 Details of USM process

5.3 Example 3: Shallow through cutting on steel

In this example, a shallow through cutting operation needs to be performed on a standard steel plate. For this work material and shape feature combination, the CBR system first recognizes AJM, AWJM, ECM, EDM, LBM and PAM as the six feasible NTM processes, as shown in Fig. 8. Then, in Fig. 9, seven process characteristics, i.e. MRR, SR, SD, Tol, OC, CR and C are identified by the process engineer for the final selection of the most suited NTM process for the considered machining application. In this window, the ranges of values of the set process characteristics are also provided.

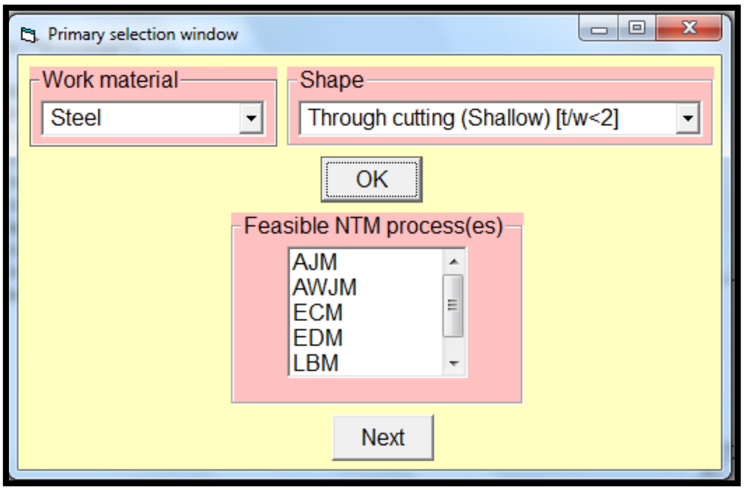

Fig. 8 Primary selection window for Example 3

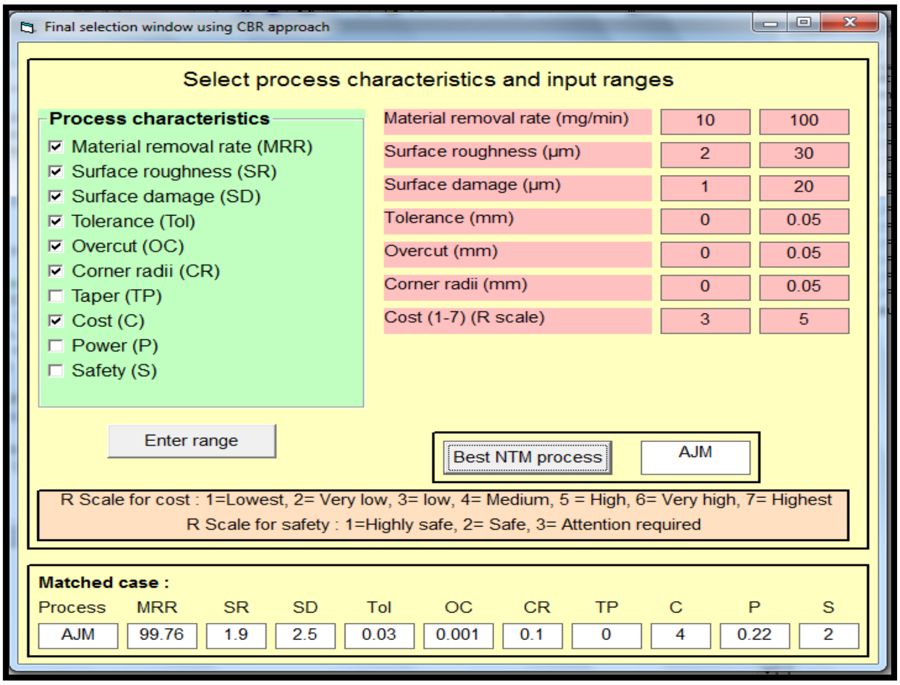

Fig. 9 Best NTM process for Example 3

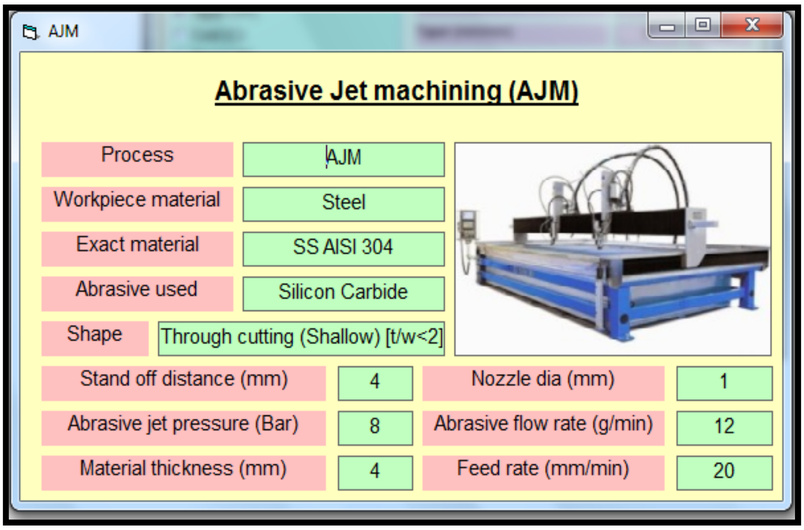

Fig. 10 Details of AJM process

The developed CBR system identifies AJM as the most appropriate NTM process for generating a shallow through cut on steel material. In Fig. 9, values of various process characteristics of AJM process are provided as MRR - 99.76 mg/min, SR - 1.9 µm, SD - 2.5 µm, Tol - 0.03 mm, OC - 0.001 mm, CR - 0.1 mm, TP - 0.005 mm/mm, C - 4 (in R scale), P - 0.22 kW and S - 2 (in R scale). In Fig. 10, this CBR system also guides the process engineer in setting the most desired values of various AJM process parameters for achieving the optimal machining performance. But, depending on the end requirements and availability of the machining setup, those AJM process parameters need to be accurately adjusted.

In CBR approach, all the cases, along with the relevant parameters, are well-structured in the case-base. They are collected from real time experiments, machining handbooks and expert's opinions. Hence, when a case is retrieved by CBR system, it is likely to be closely matched with the expert's opinion. Moreover, CBR is a technique that can provide the closest solution to the input problem. In all these three examples, the final results provided by CBR system are well validated by the experts who have a vast capability of understanding and years of experience.

In CBR approach, as the selection procedure is entirely based on similarity score calculation over several process characteristics for an efficient case retrieval, there is almost negligible probability that two cases have exactly the same similarity score. Moreover, in the developed CBR approach-based software prototype, the data type for the similarity score is considered as 'double'. Thus, two NTM processes may be apparently same from the logical as well as application point of view, but they are always slightly different based on the calculated similarity scores over several process characteristics by CBR system.

6. Conclusion

In this paper, based on CBR approach, a decision making model is developed for selecting the most appropriate NTM process for a given work material and shape feature combination. The functional mechanism of CBR approach is based on retrieving and reusing the past similar cases from the case-base. In the case-base, numerous cases are stored from the real time experimental data which are later utilized to extract the case nearest to the given query set. It is observed that the CBR system can provide a reasonable solution to a given machining problem where there is a lack of expert knowledge. The developed model can be a pathway towards new research in the direction of NTM process selection. Its potentiality and solution accuracy are validated using three real time demonstrative examples. It can also guide a process engineer in setting various NTM process parameters for a specific machining operation, although fine-tuning of those parametric settings may sometimes be required. Its accuracy can further be increased while developing a hybrid CBR system, incorporating more cases in the case-base or providing more options with respect to work material and shape feature choices. A validation of the results derived using the CBR approach against the existing search mechanisms, like genetic algorithm, simulated annealing, artificial neural network etc. may be the future scope of this research paper.

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