MACHINING PROCESSES SELECTION - A CASE-BASED REASONING APPROACH

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(*Soumava Boral*)

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Dedicated to

My Parents

and

My beloved sisters

Mrs Soumita Medda

and

Lt. Sourima Boral

1.0 INTRODUCTION

1.1 An Overview of Machining Processes

People of early civilizations were forced to develop essential things to facilitate their regular habits. They learned to carve wood and stones for hunting and farming purpose. But, most of those essential things were made by hands. Later, these activities were referred as manufacturing, which can be classified technologically as well as economically. Technologically, it is referred as the process to alter the shape, size, properties and appearance of a given raw material to produce a usable finished good. Economically, it is defined as the process by means of which values are imparted to the raw materials through various manufacturing capabilities such as machines, equipments, skills of workers etc. An activity is said to value added if the customers are willing to pay for that. In broader sense, manufacturing is the process of converting raw materials into finished goods that encompasses design of a product, selection of raw materials and the sequence of processes through which the final entity is generated.

In this modern era of global competitiveness, manufacturing companies are compelled to develop innovative ideas during the research and development phase. Manufacturing is considered as the backbone of an industrialized nation. In India, industries account for about 17% of gross domestic products (GDP). Basically, higher the level of manufacturing activity, higher will be the standard of living of its people. The term 'manufacture' was first appeared in 1567, while the term 'manufacturing' was first coined in 1683. It was derived from two Latin words and those were '*manus*' (hand) and '*factus*' (make). In terms of a single sentence, it was defined as *'making things by hand'*. But the powers of hands are limited and hard materials cannot be processed by hands. Manufacturing persisted as a craft until the first industrial revolution towards the end of 18th century with low volumes and single piece productions. Highly skilled craftsman were required to individually produce the pieces and to fit them when the assembly was required. But it was the only mean, which was slow and expensive, in the absence of any machines.

Manufacturing processes may be processing operations or assembly operations. In processing operations shape, size and appearance of the raw materials get converted into practicable goods, using several forms of energies such as thermal, chemical, electro-chemical, mechanical etc. Whereas, in assembly type manufacturing processes two or more primitive parts are joined to generate a new product. The term material removal process is often used interchangeably with the term machining process. Machining is normally the most expensive manufacturing process because more energy is consumed and also, a lot of waste material is generated in this process. Machine tools along with cutting tools are employed during these machining processes to remove the excess materials. In earlier days, machine tools were operated by means of steam engines, but with the advancement of technology, these machine tools are now driven by electric motors using some basic mechanism of belt-pulley, gears etc.

Machining is considered as the most diversified and precise operation among all the manufacturing processes as, several simple and complex part geometries can be generated by it. Parts produced by basic manufacturing processes, such as casting, forging, shaping, have irregular shape, size and dimensions and these parts are often needed to be refined in order to economically produce an acceptable part. Few decades ago, harder cutting tools were considered as a major criterion to conduct machining operations. But, after the emergence of non-traditional machining (NTM) processes, this idea gets changed dramatically. In NTM processes, apart from mechanical energies, thermal, electrical, chemical, electro-chemical energies are also utilized for removing the excess materials. Till now, researches are going on to develop new machining processes of higher capabilities. Machining processes are desirable or even necessary in manufacturing operations for the following reasons:

a) Closer dimensional accuracy may be needed then is available from casting, forming and shaping processes alone.
b) Parts may have some internal and external geometric features, sharp corners and flatness that cannot be produced by forming and shaping processes.
c) Often, some parts are subjected to several heat treatment operations for improved hardness and wear resistance. These parts may undergo surface discoloration or distortion for which some additional finishing operations, such as grinding, honing, lapping are required to obtain the desired final dimension and surface finish.
d) It is often required to produce special surface geometries or surface textures on work surface of a material, which cannot be processed by other means.
e) Machining a part is more economical than to manufacture it by other processes, particularly if the numbers of parts desired is small.

Apart from these advantages, machining processes have certain limitations. They are cited below:

a) Every removal processes usually generate waste materials and require more emery, capital and labour than forming and shaping operations.
b) Unless carried out carefully, machining processes can have adverse effects on surface qualities and properties of the material/product.
c) Removing a volume of material usually takes more time than to shape it by other processes.

It is also said that, machining is not only a single process; it's a family of processes. It is important to view machining and manufacturing operations as a system that consists of workpiece, the cutting tool and the machine. In depth knowledge about the interactions between these elements are necessary to carry out machining processes efficiently and economically. To perform the machining operations, it is desired to have a relative motion between the machine tool and workpiece material that is achieved either by means of formative motions (i.e. cutting motion, feed motion) or by means of auxiliary motions (i.e. indexing motions, additional feed motion, relieving motion). Shape of the cutting tool and its penetration into the workpiece, along with the primary or secondary motions can produce the desired shape features on the workpiece.

1.2 Different Types of Machining Processes

Machining processes are considered as the key element in the field of manufacturing. It is an excellent mean of imparting value to the raw materials and converting them into usable goods. Figure 1.1 gives a pictorial representation of manufacturing engineering, which is often used interchangeably with production engineering.

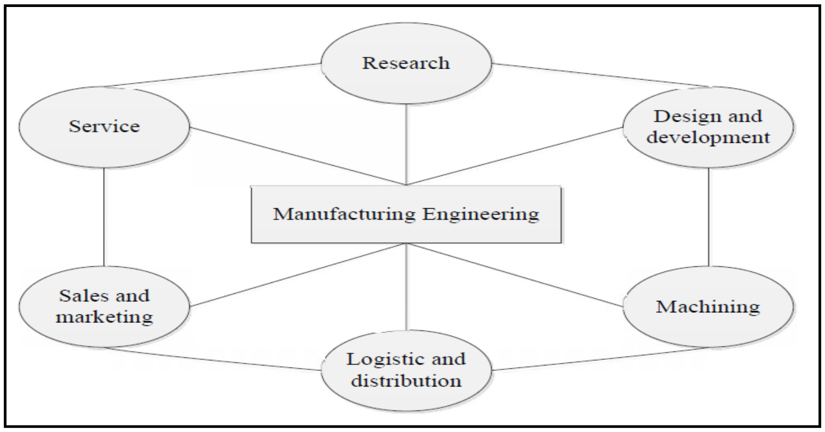


Figure 1.1 Pictorial representation of manufacturing engineering

Figure 1.2 shows the classification of manufacturing processes. In broader sense, machining processes / material removal processes can be classified into three sub-categories: -

a) Conventional machining processes: - The word ‘conventional machining processes’ is often used interchangeably with ‘traditional machining processes’. A cutting tool, harder than the workpiece material is employed during the machining operations. Here, machining operations are generally performed by several traditional machine tools, such as lathe, drilling machines, milling machines etc.

Cutting tool is penetrated in the workpiece material to certain depth and due to the relative motion between the tool and the workpiece material, shearing forces are generated as shown in Figure 1.3. These forces are supplied by the cutting tool. Plastic deformation is induced into the workpiece material. These shear forces lead to shear deformation along the shear plane and produce macroscopic chips.

Conventional machining processes are capable to generate circular shapes as well as other major shapes on the workpiece materials. Turning process generates cylindrical parts, drilling process generates holes of different diameters, milling and shaping generates flat surfaces. Quality of the parts produced by these machining processes is greatly dependent on the condition of the cutting tool.

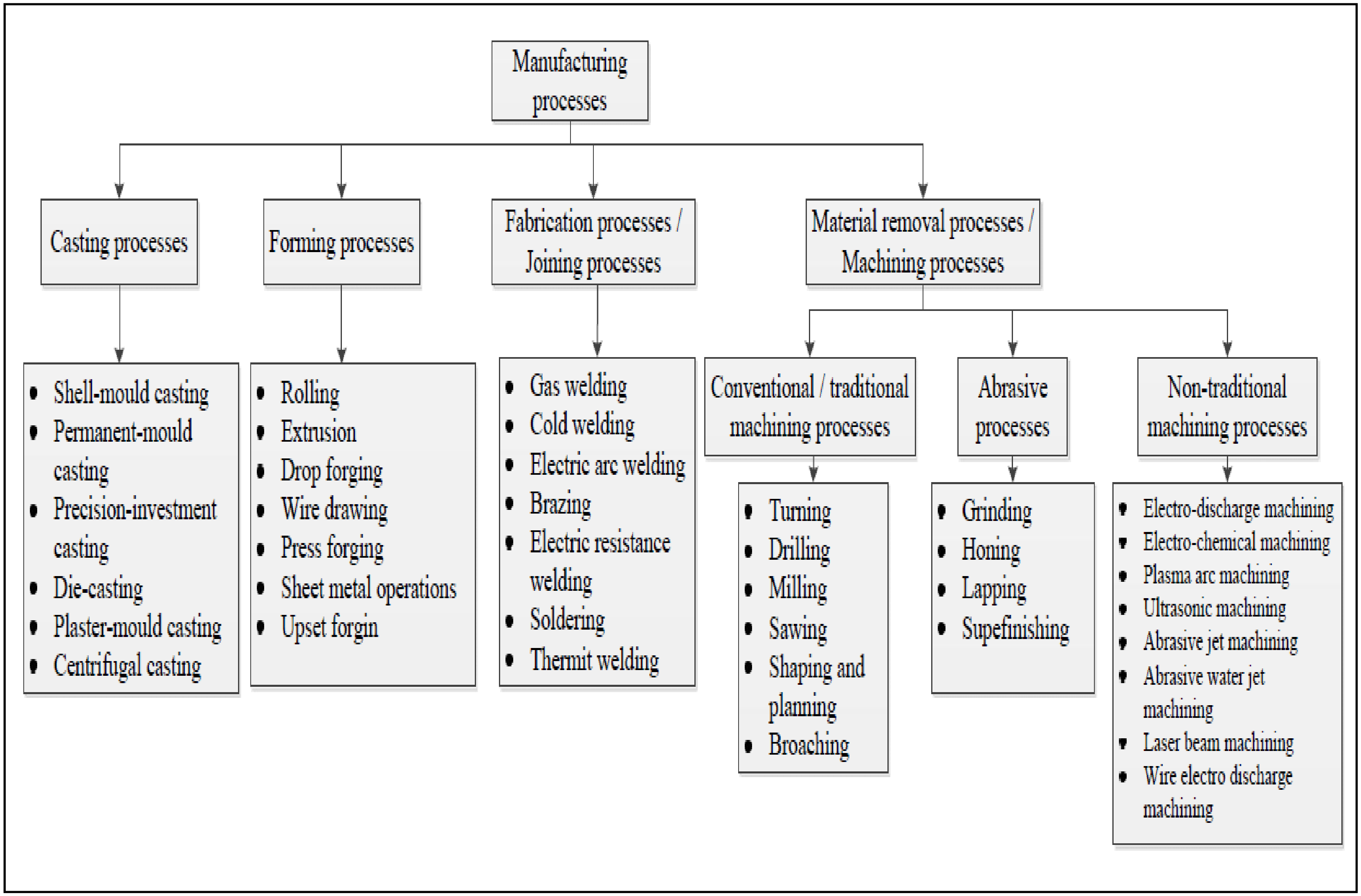


Figure 1.2 Classification of manufacturing processes

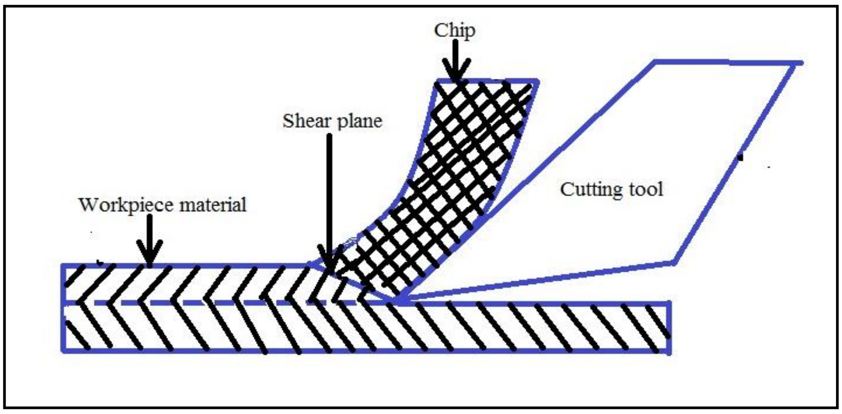


Figure 1.3 Shear deformations in conventional machining process leading to chip formation

Traditional machine tools are required to carry out conventional machining processes. Some popular conventional machining processes are described below: -

i) Turning: - It is the most vital machining process and can produce a wide verity of parts. Primarily, turning is used to produce cylindrical parts by a single point cutting tool on lathes. The cutting tool is fed either in parallel direction or in perpendicular direction to the axis of rotation of the workpiece or along a specified path to produce complex rotational shapes. Two types of motion are present in turning: primary cutting motion of the rotating workpiece and secondary feed motion of the cutting tool. Turning can be further classified as straight turning, taper turning, contour turning, form turning etc. Thread cutting, chamfering, facing operations are also considered as the turning operations. Several types of turning operations are highlighted in Figure 1.4. Turning operation can be carried out in several machine

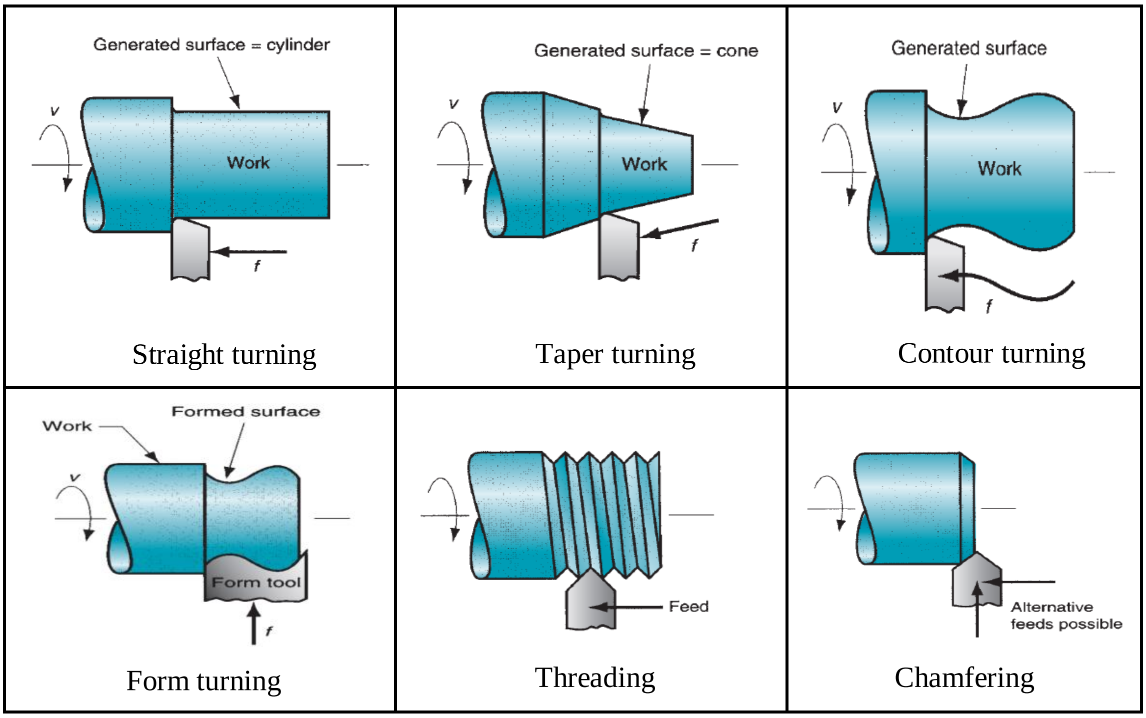


Figure 1.4 Several turning operations [1]

tools such as lathe, conventional milling machine, CNC turning centre (CNC TC), CNC horizontal machining centre (HMC), CNC vertical machining centre (VMC) etc.

ii) Milling: - Milling includes a number of versatile operations capable of producing a variety of shape features by means of multi-tooth cutting tool. The axis of cutting tool is generally perpendicular to the direction of feed, either parallel or perpendicular to the surface of the workpiece. Depending on the orientation and geometry of the cutting tool this machining process is further classified as plain milling, face milling, form milling, surface milling etc., which are shown in Figure 1.5. Several influencing parameters, which are considered during milling operations are material removal rate (MRR), surface roughness(SR), tolerances, production rate, power etc. In this context, it is important to mention that milling operations can be carried out in VMC, HMC, conventional milling machines etc.

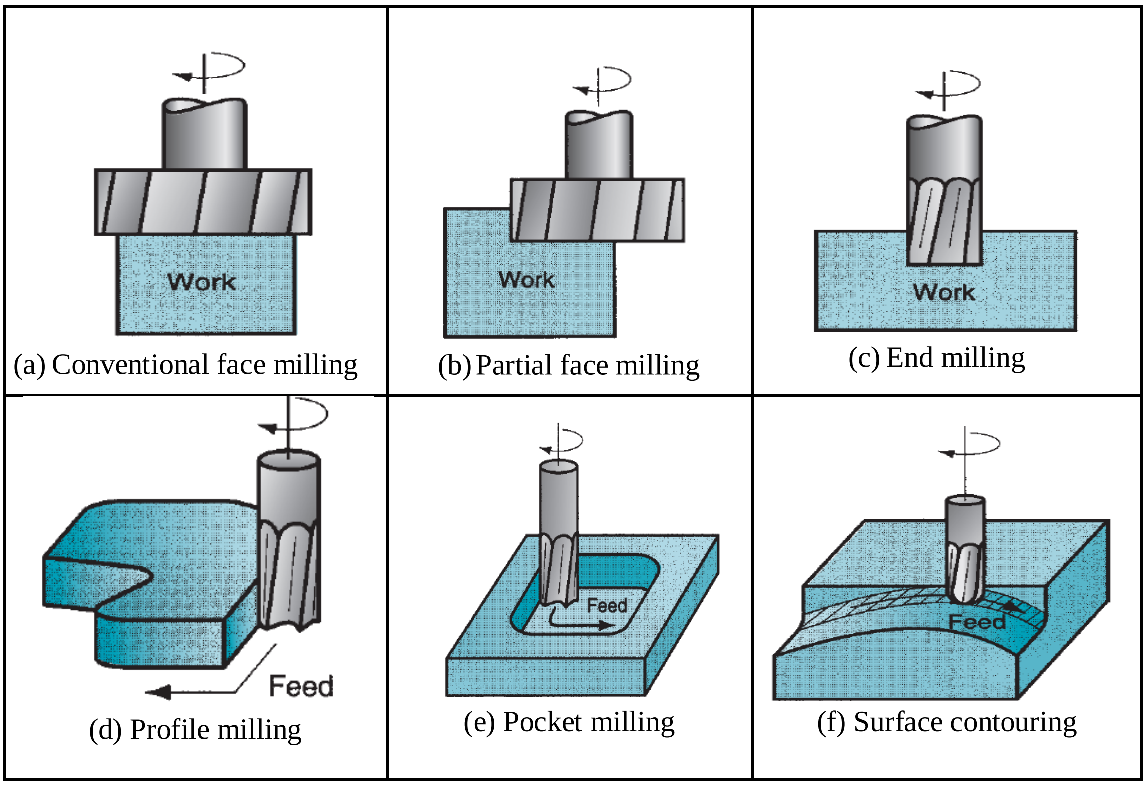


Figure 1.5 Several milling operations [1]

iii) Drilling: - Drilling is a process of producing round holes in a material or enlarging an existing hole, by means of multi-point cutting tools called drills. Drilling process is employed to drill blind holes or through holes. For drilling holes of larger diameters, it is often preferred to use pilot drills. Several operations are related to drilling, such as core drilling, step drilling, counter boring, counter sinking, reaming, center drilling and gun drilling, which are shown in Figure 1.6. Drilling operations can be carried out in conventional drilling machine, CNC drilling machines, conventional lathe, CNC VMC, CNC HMC etc.

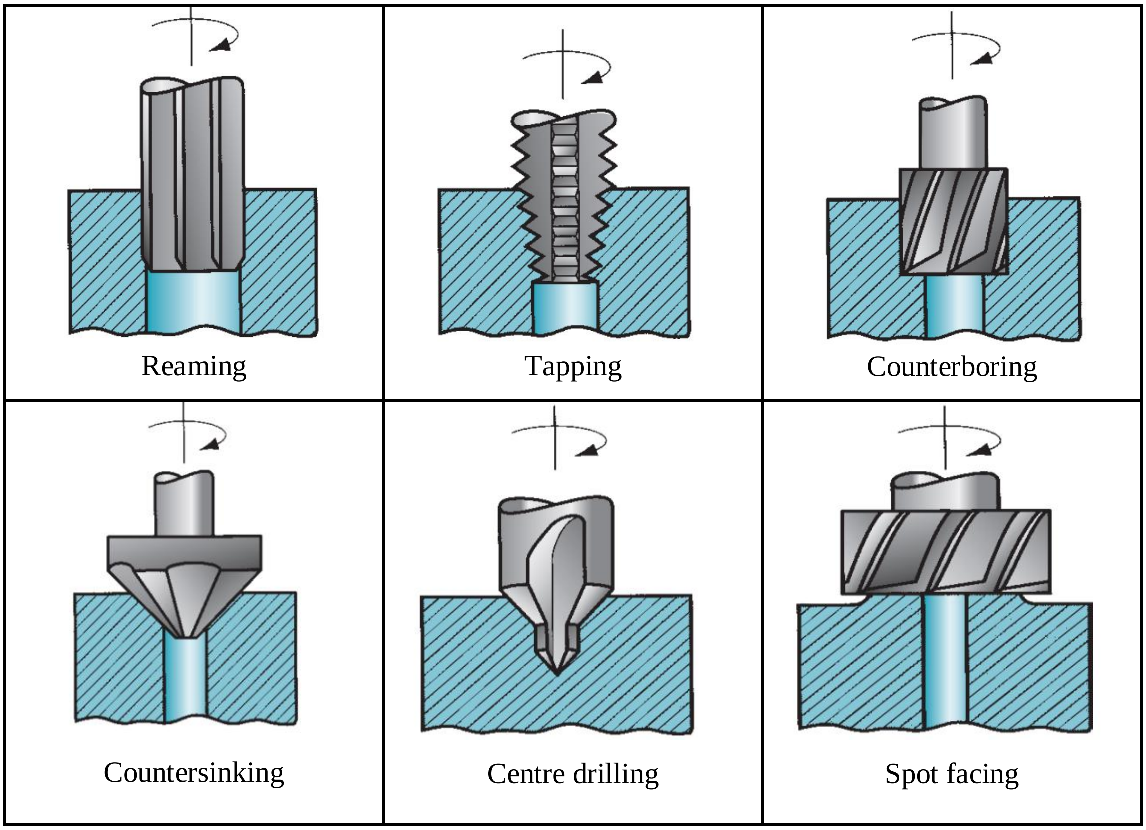


Figure 1.6 Several types of drilling operations [1]

iv) Planing and shaping: - These are almost similar operations, which vary only in the kinematics of the process. Planing operation is performed in planing machine and shaping operation is performed in shaping machine. These machines are shown in Figure 1.7. In planing operation, primary cutting motion is performed by the workpiece and feed motion is imparted by the cutting tool. Whereas, in shaping motion reverse phenomenon is occurred.

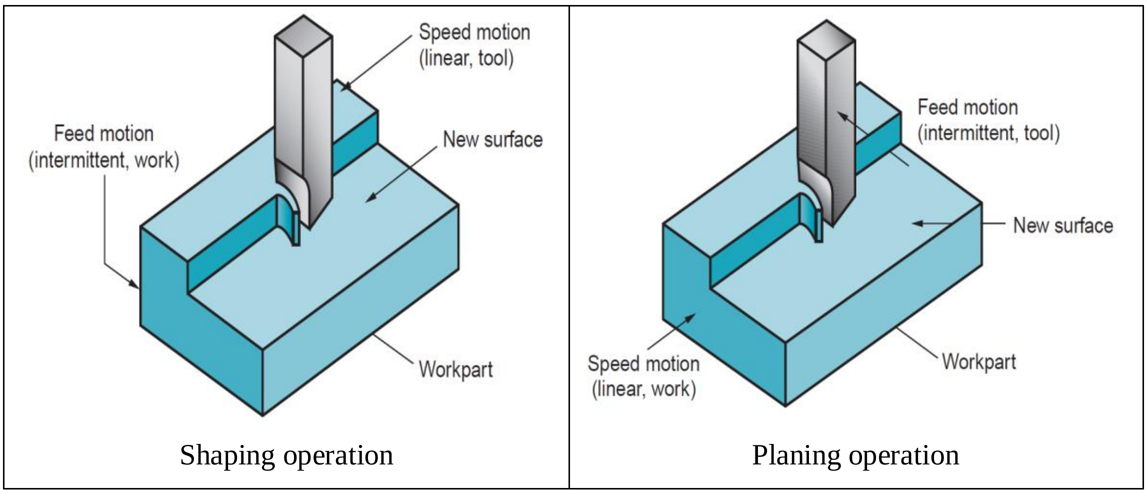


Figure 1.7 Shaping and planing operation [1]

v) Broaching: -Broaching is a machining operation in which a multi-point cutting tool, referred as broach, is feed to the workpiece in the direction of the tool axis. It is a highly productive machining operation and can produce products with high tolerance and surface finish. This machining process is displayed in Figure 1.8.

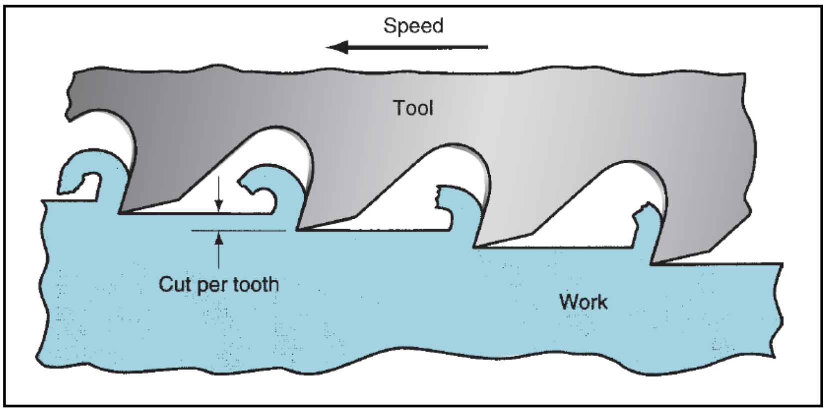


Figure 1.8 Broaching operation [1]

vi) Sawing: - In sawing operation a narrow slit is cut into the workpiece material by a tool consisting of series of closely spaced teeth. It is generally used to separate the workpiece into two components. Sawing operations are carried out by saws. Several types of sawing operations are displayed in Figure 1.9.

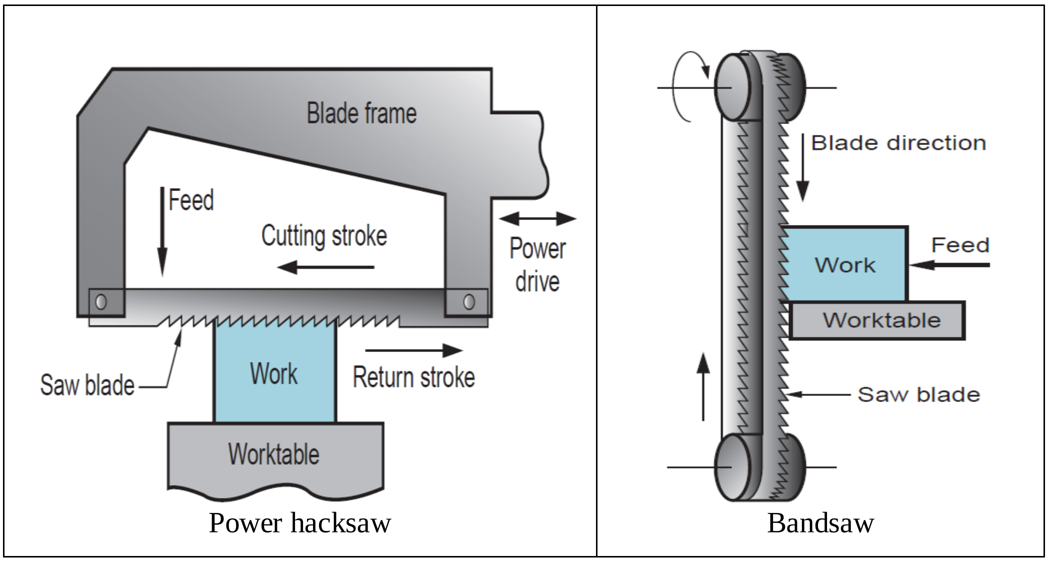
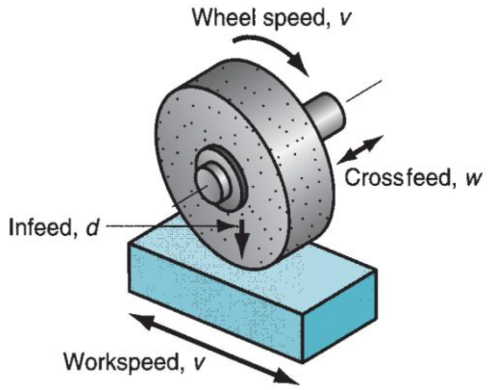
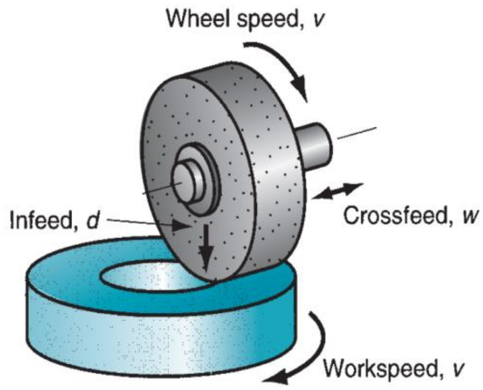


Figure 1.9 Several sawing operations [1]

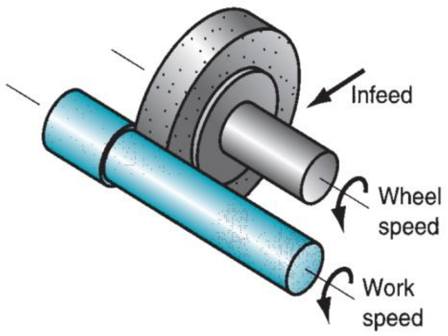
b) Abrasive machining processes: - In this type of machining process excess material gets removed from the parent workpiece by the use of several small abrasive particles known as grits. These abrasive particles are in the form of bonded wheel. Better surface finish and closer dimensional tolerances are generated in this type of machining processes. Materials are removed in the form of minute chips. Examples of abrasive machining processes include grinding, buffing, honing, lapping, super finishing etc. Flat as well as surface of revolutions can be generated by abrasive machining processes. Several types of abrasive machining processes are shown in Figure 1.10 and Figure 1.11.



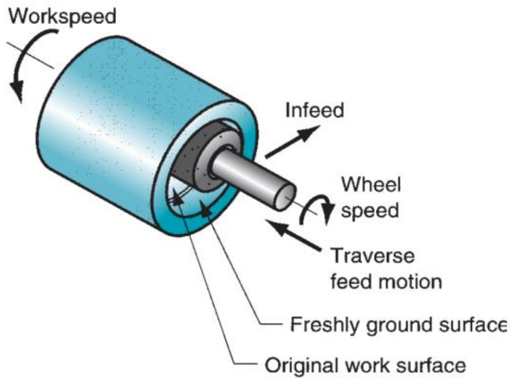
Surface grinding (horizontal spindle with reciprocating worktable)



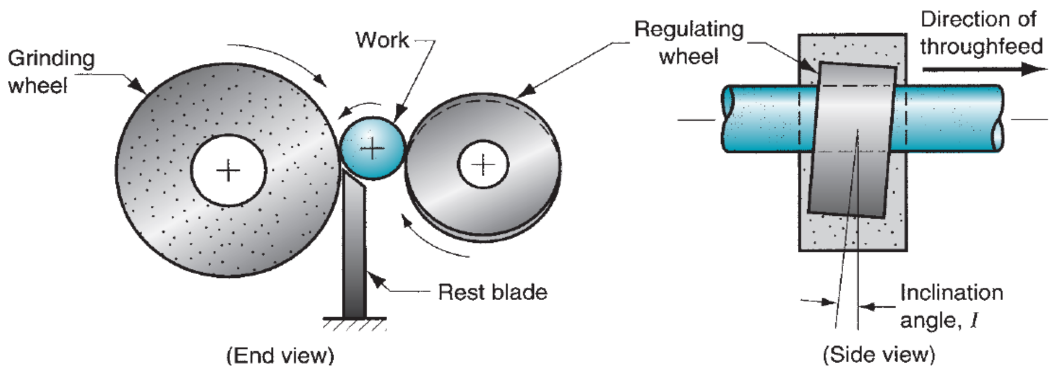
Surface grinding (Horizontal spindle with rotating worktable)



External cylindrical grinding

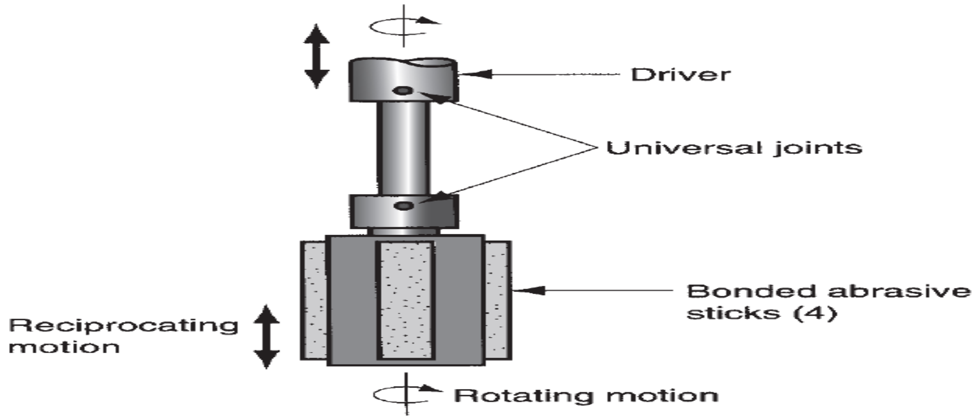


Internal cylindrical grinding

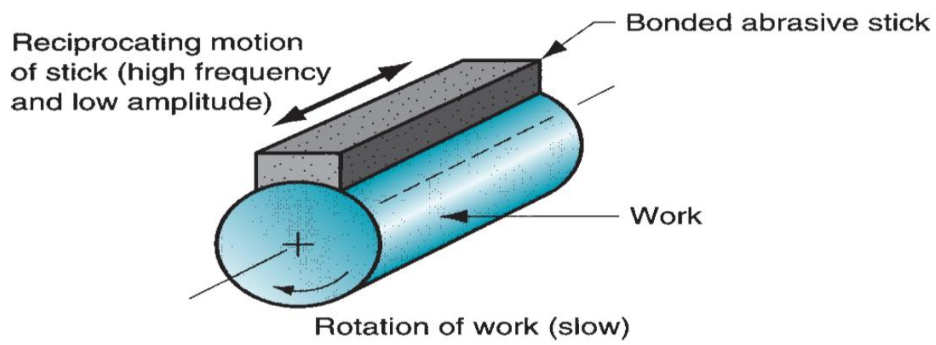


External centreless grinding

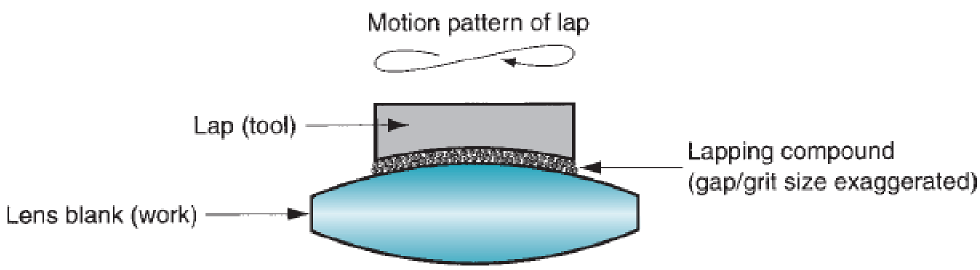
Figure 1.10 Several types of grinding operations [1]



Honing operation



Superfinishing operation



Lapping operation

Figure 1.11 Honing, superfinishing and lapping operation [1]

c) NTM processes: - An idea of machining, combining mechanical and chemical means was first introduced by Gussev towards the end of 1920. Later Burgess, an American scientist, was able to differentiate between the mechanical and electrolytic methods of material removal. In the year of 1942, idea of ultrasonic machining (USM) process was given by Balamuth. An idea of spark erosion machine was proposed by B R Lazarenko and N I Lazarenko in the year of 1943. Idea of laser machining was proposed by Basov, Prokhorov and Fabrikanth in the year of 1950. But, most of the NTM processes were put into action in last few decades. These new machining processes are grasping an ever increasing application in all branches of mechanical engineering.

With the advancement of technology, it is often required to generate intricate and precise shapes on some advanced materials. These advanced materials include hard to machine and high-strength temperature-resistant alloys (e.g. Rene 80, Inconel 718 etc.). Such materials when machined with conventional machining processes incur higher machining costs, and also the surface quality and dimensional accuracy of the machined components are not satisfactory and often fail to meet the desired target.

Roles of NTM processes in modern manufacturing industries are inevitable owing to the following reasons: -

i) Hardness and strength of advanced materials are too high or these materials are too brittle that it cannot be machined by any other machining processes.
ii) Sometimes, workpiece materials are too flexible, slender or delicate to withstand the shear forces generated during cutting operations.
iii) In some cases, it is not possible to hold the workpiece materials in the fixtures for machining operations.
iv) Shapes to be generated on workpiece materials are too complex or too much delicate that it cannot be generated by other machining processes.
v) Dimensional accuracy and tolerance requirements are too much stringent than those obtained by other machining processes.
vi) Temperature rise or residual stresses in the workpiece materials are not desirable.

These requirements had given the birth of NTM processes. Classification of NTM processes based on the nature of energy used is depicted in Figure 1.12: -

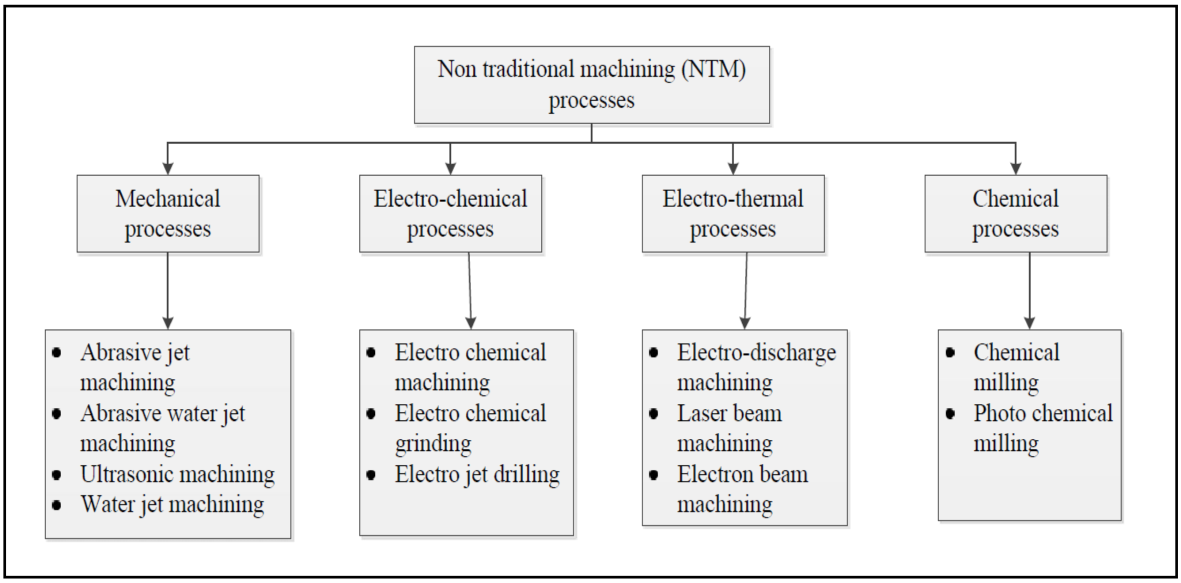


Figure 1.4 Classification of NTM processes based on the energy used

NTM processes can be characterized as follows: -

i) In NTM processes material removal may takes place with or without the chip formation. In abrasive jet machining (AJM) process materials are removed by the impact of high velocity abrasives with the workpiece material. Microscopic chips are formed in this type of machining process. Whereas, in case of electro chemical machining (ECM) process material removal takes place due to electrochemical dissolution at the atomic level.

ii) It is possible that there may not be any physical tool present in NTM process. In laser beam machining (LBM), machining is carried out by the impact of laser beam on the workpiece material. Whereas in case of ECM, physical tool is very much required for carrying out machining operations.

iii) It is not necessary that the tool in NTM processes should be harder than the workpiece material. In electro discharge machining (EDM) process, copper tools are preferred most of the time to machine harder materials.

But still there are some disadvantages of NTM processes and researches are going on to overcome these disadvantages. These disadvantages are described below:

i) High skilled labor is required in NTM processes. Special trainings are required for the labors to operate these machines.

ii) Capital cost and maintenance cost are high in case of NTM processes.

iii) Material removal rate is too small and sometimes generation of a complex feature may take several days.

Several types of NTM processes along with their basic diagrams are depicted herewith: -

i) AJM: - In AJM, a high velocity jet of dry air, nitrogen or carbon di-oxide (CO_2) containing the abrasive particles, is aimed on the workpiece material's surface under controlled conditions. Concentrated forces are developed during the impact of high velocity abrasive particles that causes the removal of materials from the parent workpiece. This process is more suitable when the workpiece is brittle and fragile. This process can perform several operations, like cutting small holes, generating intricate patterns, trimming and bevelling, removing oxide layers from surface, general cleaning of components with irregular shapes etc. Generally aluminium oxide and silicon carbide particles are preferred as abrasive particles. Basic working principle of AJM is shown in Figure 1.13.

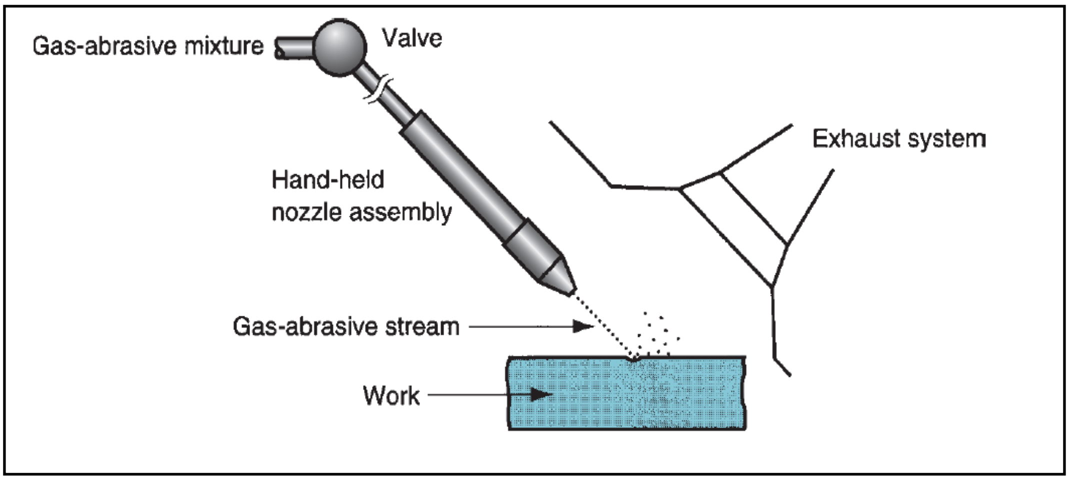


Figure 1.13 Working principle of AJM process [1]

ii) Abrasive water jet machining (AWJM): - AWJM is a technology for removal of material, where abrasive particles are entrained into a jet of water that is accelerated to high velocities on the workpiece surface, by the use of high pressures. This process has complete adaptability to cut any material of any geometry and there is no expensive tooling to be bought owing to fast interchangeability and no set-up costs. Additionally, it can be used to roughly machined parts, which can then be finished on higher-value equipment, thus reducing bottlenecks on these machines and improving productivity. This process is represented schematically in Figure 1.14.

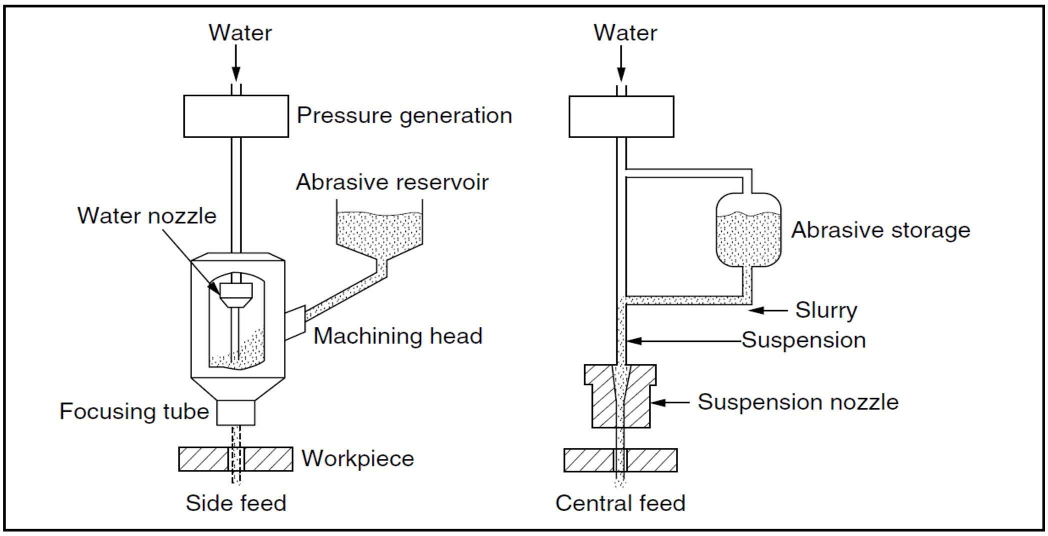


Figure 1.14 Injection and suspension jet in AWJM process [2]

iii) EDM: - It is also called as spark-erosion machining as its principle is based on the erosion of metals by spark discharges. It is well known from the theory of electricity that when two current carrying conductors are allowed to touch each other, a spark is generated and temperature of this spark is very high, which is sufficient to melt a material. Basic EDM system consists of a shaped tool (electrode) and a workpiece, connected to DC power supply and placed in a dielectric fluid. When the potential difference between the tool and workpiece becomes too high, a transient spark discharges through the fluid, removing a very small amount of metal from the workpiece surface. Schematic diagram of EDM is depicted in Figure 1.15.

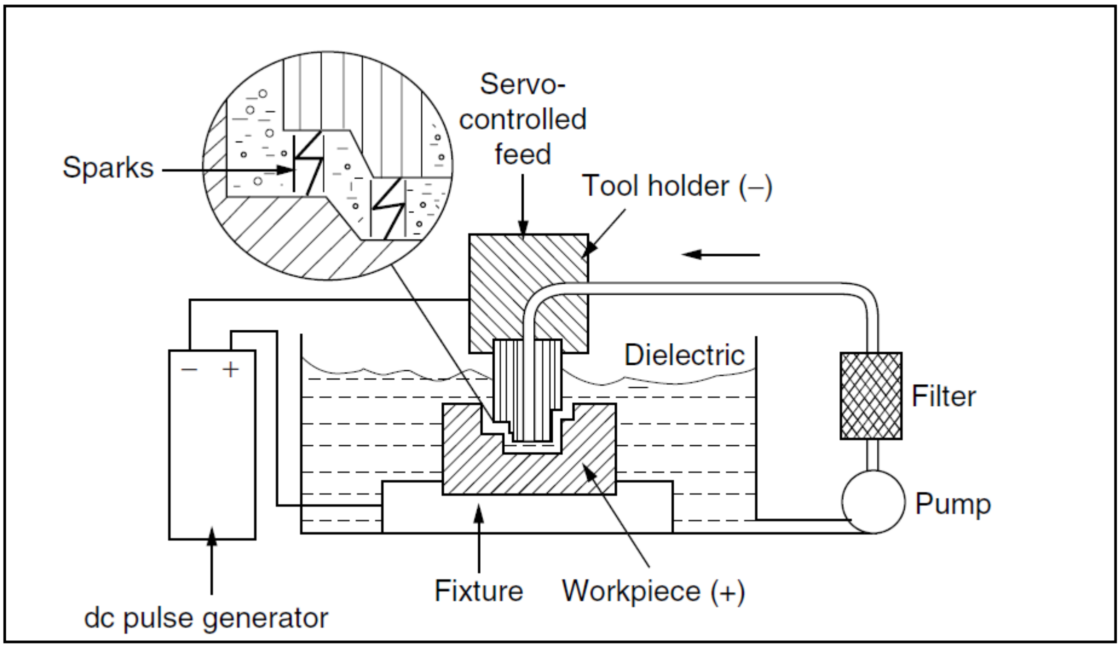


Figure 1.15 Schematic diagram of EDM process [2]

iv) LBM: In this machining process, the source of energy is laser that focuses optical energy on the workpiece surface in a controlled manner. Due to this highly focused and high-density energy, materials generally evaporate from the workpiece. There are several types of lasers used in manufacturing operations such as CO_2 laser, Nd:YAG (neodymium: yttrium-aluminium-garnet) laser, Nd: glass, ruby laser, excimer lasers. The surface produced by LBM process is usually rough and has a heat affected zone (HAZ). Laser beam may be used with gas steam, such as oxygen, nitrogen or argon (laser-beam torch), for cutting thin sheet metals. Schematic diagram of LBM process is given in Figure 1.16.

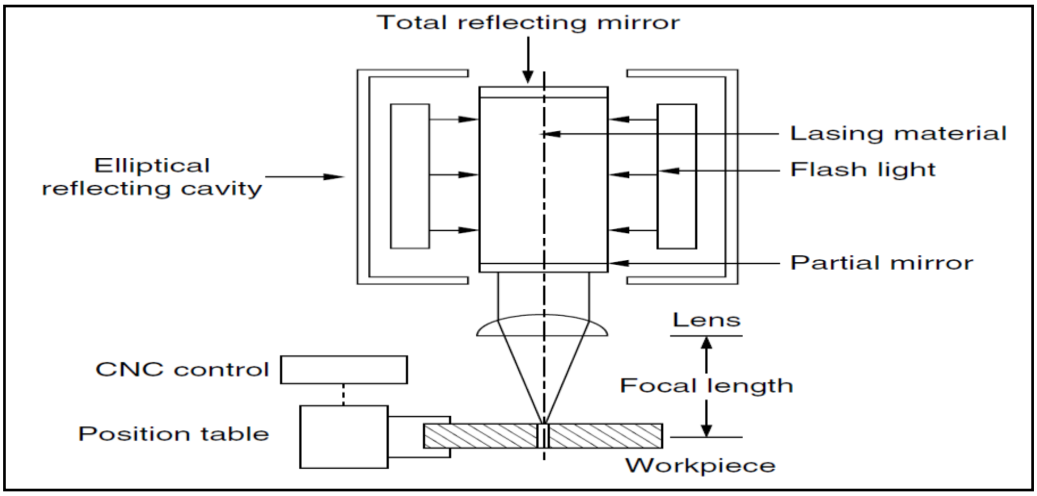


Figure 1.16 Schematic diagram of LBM process [2]

v) USM: The basic process of USM involves a tool, (made of ductile and very tough material) vibrating with a very high frequency and a continuous flow of abrasive slurry is maintained in the small gap between the tool and the workpiece surface. The tool is gradually fed with uniform force. The impact of hard abrasive grains fractures the hard and brittle work surface, resulting in the removal of material from the parent workpiece, in the form of small wear particles, which are carried away by abrasive slurry. Here, the tool material is hard and ductile, thus it has very low wear rate. Basic elements in USM are shown in Figure 1.17.

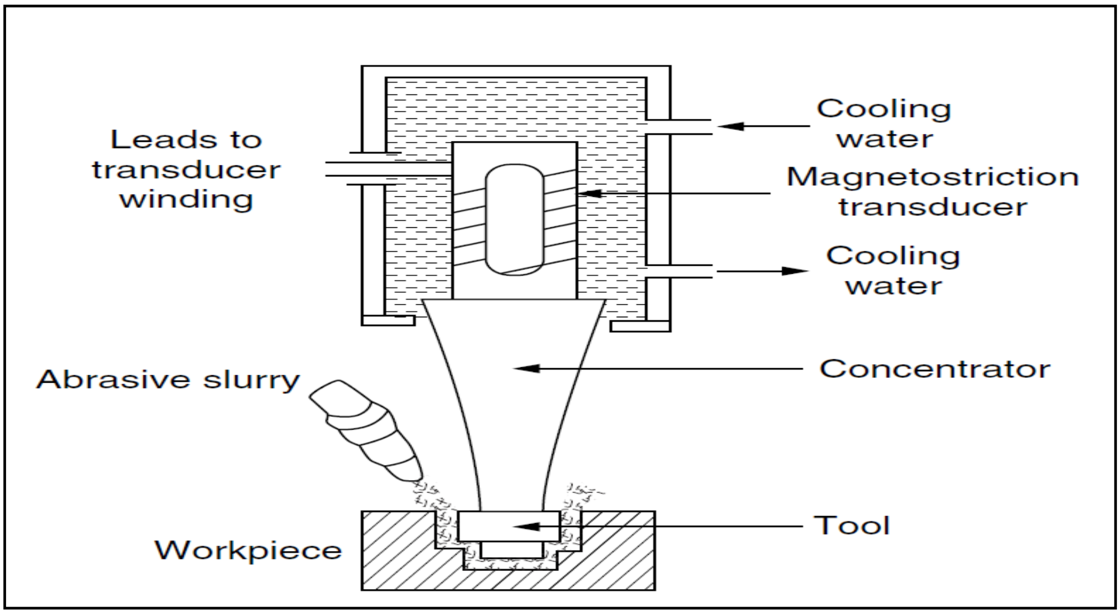


Figure 1.17 Basic elements in USM process [2]

vi) ECM: It is a reverse process of electroplating, where an electrolyte acts as a current carrier and the high rate of electrolyte movement in the tool-workpiece gap washes out the metal ions from the workpiece. Here, workpiece is made cathode and tool is anode. The cavity produced due to removal of materials is the female mating image of the tool. The tool is generally made of brass, copper, bronze or stainless steel. Electrolyte used in this process, is a highly conductive inorganic salt solution, such as sodium chloride mixed in water or in sodium nitrate. This process can produce burr free surfaces. No thermal damage is caused in the workpiece material, and lack of tool forces prevents distortions of the part. Furthermore, as there is no tool wear, and the process is capable to produce highly complex shapes, this process is mostly preferred in modern manufacturing industries. Several elements of ECM are shown in Figure 1.18.

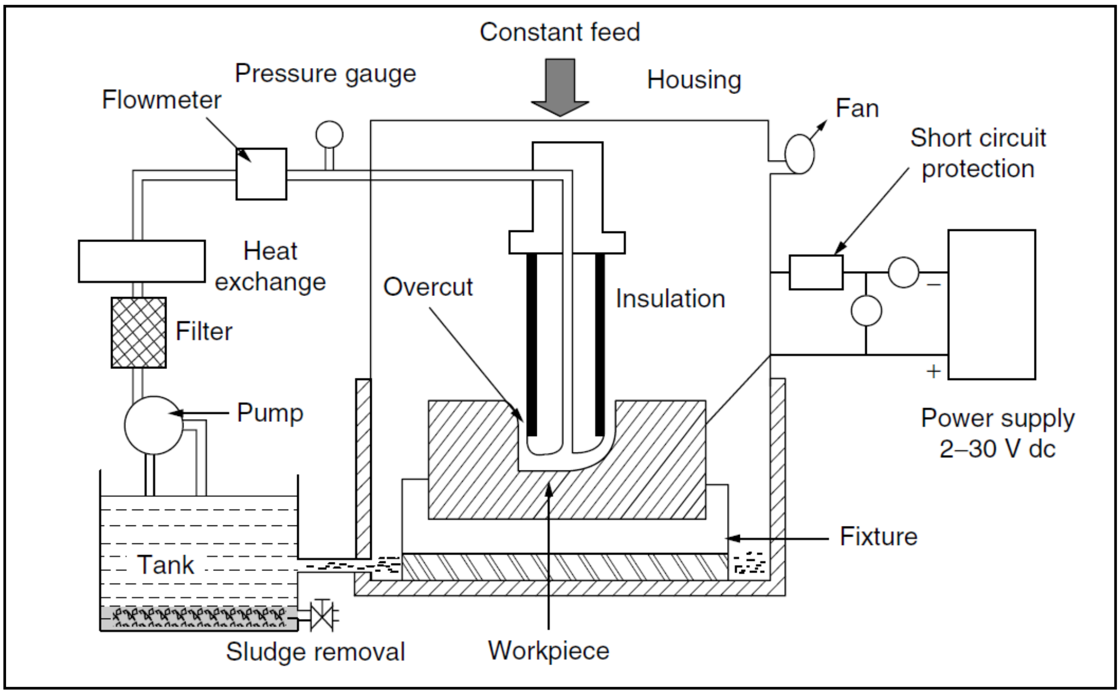


Figure 1.18 Basic elements of ECM process [2]

vii) Electro chemical discharge machining (ECDM): It is a kind of hybrid NTM process that uses the principles of EDM and ECM, leading to much higher MRR. If a beyond critical-voltage is applied in the electrochemical cell, discharge is initiated between one tool of the electrodes and the surrounding electrolytes. This phenomenon is termed as electrochemical discharge. It is a very useful NTM process for developing small diameter holes, intricate shapes on conductive as well as non-conductive materials (e.g. glass). Several components of ECDM process are shown in Figure 1.19.

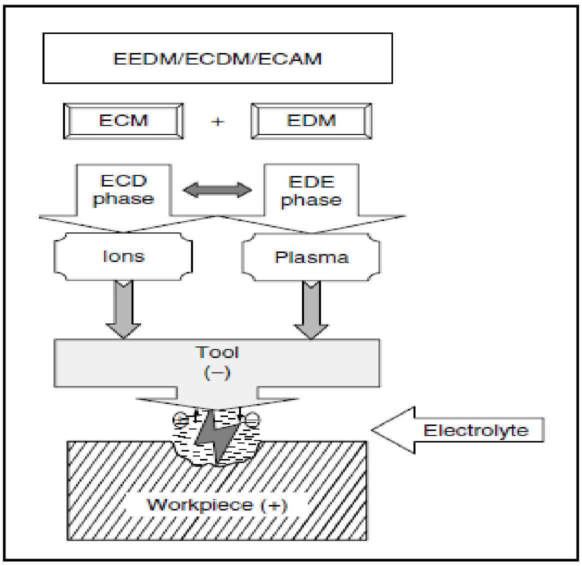


Figure 1.19 Several components of ECDM process [2]

viii) Plasma arc machining (PAM): Plasma is a high temperature ionized gas. PAM is carried out by means of a high speed jet of high temperature plasma and by the impingement of this jet, material is melted readily. PAM can be used on all materials which conduct electricity. This process is extensively used for profile cutting on stainless steel, super alloys and monel metals. Plasma is generated by subjecting a flowing gas to the electron bombardment of the arc. For this, arc is set up between the electrode and the anodic nozzle; the gas is forced to flow through this arc. The mechanism of material removal is based on heating as well as melting and removal of the molten metal by the blasting action of plasma jet. Basic elements of PAM are given in Figure 1.20.

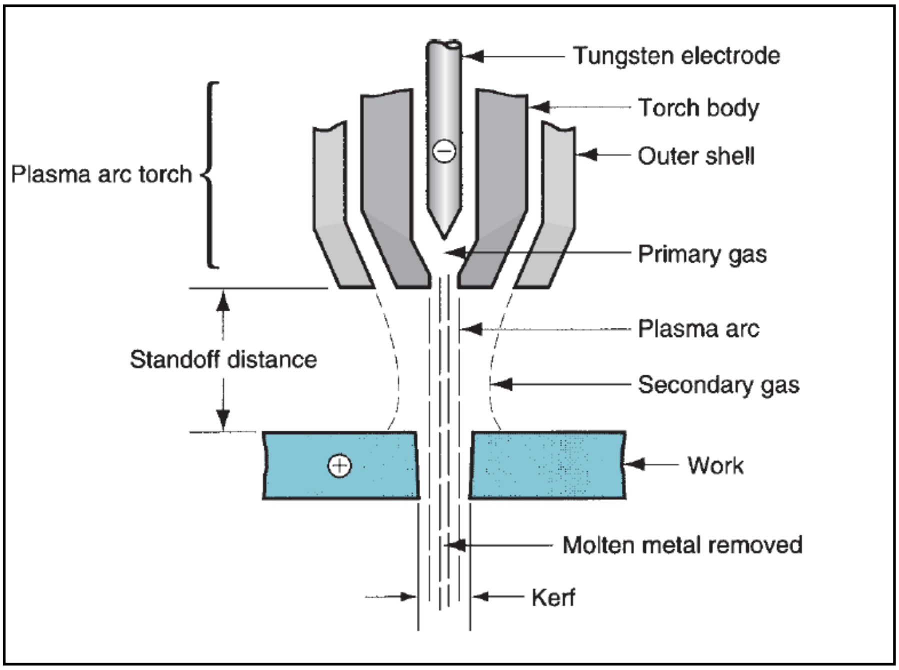


Figure 1.20 Basic elements of PAM process [1]

ix) Wire electro discharge machining (WEDM): This process is similar to contour cutting by band saw. A slowly moving wire travels along a specified path, cutting the workpiece material, with the discharge sparks acting like cutting teeth. This process is generally used to cut plates, as well as for making punches, tools and dies from hard metals. Schematic diagram of WEDM machine is shown in Figure 1.21.

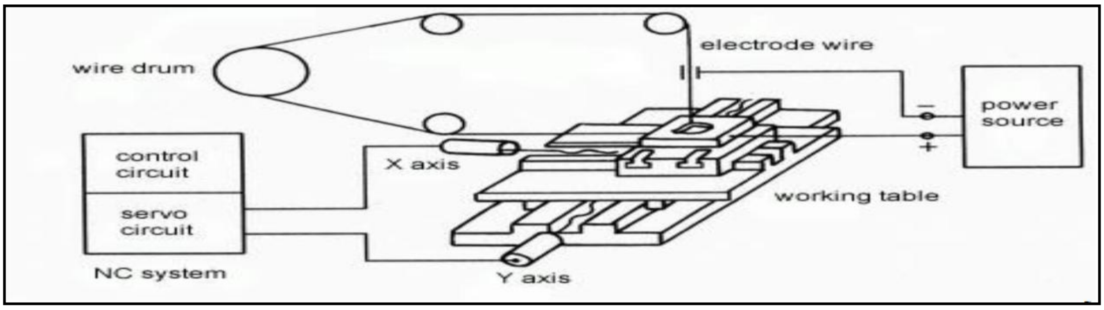


Figure 1.21 Schematic diagram of WEDM machine

1.3 Need for Selection of Machining Processes

Globalization of business, increasing competitiveness in world economy and decrease in product life cycle compelled manufacturing companies to use new equipments that are continuously introduced in the market. Manufacturing process are the steps through which raw materials are converted into finished goods. In subtractive manufacturing processes it is required to remove the excess materials from the parent workpiece to bring it into the desired shape and size. In the era of industrial revolution in Europe, boring machine was first introduced in 1775 for producing bore in the cylinder of a steam engine. Later on 1800, screw cutting lathe was developed. Although, turning of wood was accomplished for many centuries, Maudsley's machine added a mechanized tool carriage by which feeding and threading operations can be performed more precisely. Milling machine was created by Eli Whitney in the year of 1818, in United States. Most of the conventional boring machines, lathes, milling machines, planning machines, shaping machines used today have the same basic designs of the earlier ones. Modern machining centers, which are advanced versions of CNC machine tools were introduced in late 1950s, discovered a new path in the field of machining technology. Productivity as well as precision and accuracy of the machining processes were reached to the pinnacle. But with the elevation of technology, aerospace, mold and die making industries are also forced to develop some advanced materials, which are hard to machine by traditional machining processes. NTM processes have immense potentiality to overcome these problems with satisfactory performance.

From the discussion, made in section 1.2, it is clear that there are a numbers of different machining processes available to meet the desired surface finish, material removal rate, accuracy, precision etc. It is always wanted to accomplish the machining operation effectively, efficiently and economically by removing excess materials smoothly, speedily and easily with lower power consumption, surface irregularities and tool wear. Selection of proper machining operations and machine tools is one of the major considerations during machining. Improper selections of machining processes negatively affect the overall performance of the production system. Production rate, quality and cost of manufacturing is strongly dependent on the type of machining processes used. Selection of new machining processes is tedious and it requires advanced knowledge and experiences. This selection process for a given material, requisite shape, dimensional accuracy and service is too much critical and broadly requires the following steps to follow:

a) Consider all the machining processes as probable candidates: - In this step, all the available machining processes are considered for selection. Conventional machining processes as well as NTM processes are considered depending upon the availability of the machine tools.

b) Screening phase: - In this screening phase, several process characteristics as well as process parameters are considered. Some process parameters are not easily available and have to acquire them from the machine catalogue or from expert's opinion. Also, process capabilities of the available machining processes are considered for selection process. Some major selection criteria are: -

    i) Capability to generate desired shape on the selected material.
    ii) Achievable MRR and SR by the machining processes.
    iii) Accuracy, precision and tolerance achievable by the considered machining processes.
    iv) Overall costs incurred by primarily selected machining processes. Achievable production rate and power consumption during the machining processes are also considered as key factors.
    v) Repeatability and resolution achievable by the machine tools during the machining process is also considered during this screening phase.
    vi) Safety of the operators also kept in mind during the machining process.

    Apart from the depicted factors, there are also some other factors those are also to be considered during this screening phase.

c) Ranking of machining processes and machine tools using the objectives: - In this phase, ranking of the primarily selected machining processes and machine tools are carried out according to criteria. Candidate with highest score is considered as the best one.

d) Seeking for supporting information for the top candidates: - Other relevant information regarding the top scored machining process or machine tool is collected for the ease of machining.

1.4 Literature Review

Myint and Tabucanon [4] proposed a visual interactive decision support framework designed to aid decision makers in selecting the most appropriate machines for a flexible manufacturing system (FMS). The framework could be used in the pre-investment stage of the planning process, after a decision had been made, in principle, to build an FMS. There was two parts in the constructed framework. The first part was called the pre-screening stage, which narrowed down all possible configurations by using analytical hierarchy process (AHP). The second part used a goal programming model to find out the satisfactory candidate from the remaining shortlisted configuration. After that, AHP was again used to carry the sensitivity analysis.

Lin and Yang [5] proposed the use of AHP for evaluating the appropriate machine for machining a certain type of part. Several factors were considered for this selection process, such as lead time, labour cost, operation shifts. Three types of machines were considered for developing the pair wise comparison matrix and those machines were conventional machines, NC machines and flexible manufacturing cell (FMC). An ES for evaluation of machine selection by the AHP method was established and it was recommended that expert experiences must be surveyed to establish a knowledge base of expert opinions.

Atmani and Lashkari [6] described a model for machine tool selection and operation allocation in FMS. A linear, 0-1 integer programming model of the machine-tool assignment, and operation allocation was proposed. It was assumed that there was a set of machines with known processing capabilities. A set of part types with known process plans were selected for manufacturing and each operation of a part type was assigned to various machine using specified tools. The model optimized the optimal plan by minimizing the total operational cost, material handling cost and set-up cost. A numerical example was also provided to demonstrate the potentiality of the model.

Devedžić and Pap [7] proposed a model for linguistic evaluation of machine tools parameters and a procedure for alternatives ranking. Generation of machine tools suitability measure was provided by the linguistic quantification of machine tools' parameters values and their significance for given machining conditions. Ranking of alternatives was done in two stages. First stage ranking was related to selection of linguistic value from pre-defined dictionary according to the generated suitability measure. In the second stage of ranking, evaluation of some additional parameters and experts' subjective belief about their importance for given conditions was carried out. For this purpose Choquet integral and Sugeno's $\mathbf{\Lambda}$ -measure was chosen. Fuzzy sets membership functions of values of appropriate linguistic variables were formed according to the literature, empirical information, data and results of an experiment which was conducted in laboratory and real industry environment.

Wang et al. [8] proposed a fuzzy multi attribute decision making (FMADM) method for selecting the best machine tool in FMC. FMADM approach was used to evaluate and rank alternatives. Proposed approach allowed the decision maker to assign the different importance to the attributes in the rating phase. The four criteria considered during the alternative rating phase were purchasing cost of the machine tool, total machine floor space, total machine number, and the productivity. At first, machine database was screened to choose suitable machine types by inputting the threshold values of key attributes for each machine. Then, alternatives were formed for each machines considered in the first step with their attributes. Fuzzy weight of each attribute was obtained from the user. Then weighted average rating of each alternative was obtained. Finally those alternatives' fuzzy numbers were ranked and suggested the higher rank alternative to the manager.

Rai et al. [9] proposed a fuzzy goal-programming concept to model the problem of machine tool selection and operation allocation with explicit considerations given to objectives of minimizing the total cost of machining operation, material handling and set up. The constraints pertaining to the capacity of machines, tool magazine and tool life were included in the model. A genetic algorithm (GA) based approach was adopted to optimize the fuzzy goal programming model. An illustrative example was also provided along with some results of computational experiments.

Moon et al. [10] proposed an integrated machine tool selection and operation sequencing model with capacity and precedence constraints using GA. The proposed model determined the machine visiting sequence for all part types, such that the total production time for the production order was minimized and workloads among machine tools were balanced. The model was formulated as 0-1 integer programming. A genetic algorithm approach based on a topological sort technique was developed to solve the model. To demonstrate the efficiency of the proposed GA approach on the integrated machine tool selection and sequencing problem, a number of numerical experiments using various size problems were carried out. The numerical experiments showed that the proposed GA approach was efficient to those problems.

Yurdakul [11] proposed AHP as strategic decision-making tool to justify machine tool selection. AHP and analytic network process (ANP) were applied in calculation of the contributions of machine tool alternatives to the manufacturing strategy of a manufacturing organization. Hierarchical decision structures were formed in the application of the AHP and ANP approaches. Ranking scores, which were used to rank the alternatives, were obtained as outcomes of the applications. Application of the ANP approach also enabled the incorporation of interdependencies among the components of decision structures. An illustrative example was also provided to validate the proposed approach.

Çimren et al. [12] proposed a user friendly decision support system (DSS) for machine tool selection. The developed system guided the decision-maker in selecting the available machines through AHP. Cost analysis was also carried out to help the user to evaluate the results, which were based on economical considerations. Also, reliability and precision analysis were included in the evaluation procedure. Sensitivity analysis was also carried out to evaluate the robustness of the selection procedure.

Chan et al. [13] presented a fuzzy goal-programming approach to model the machine tool selection and operation allocation problem of FMS. The objective of the authors was to determine the optimal combination for the machine and tool operations keeping in mind the minimization of various costs, which were machining cost, set-up cost and material handling cost. The constraints taken into consideration were pertaining to tool life, tool magazine capacity and machining time. The solution methodology was based on one of the nature inspired algorithm, namely artificial immune systems.

Ayağ and Özdemir [14] applied a fuzzy AHP (FAHP) approach to evaluate machine tool alternatives. FAHP was introduced in the pair wise comparison of AHP to weight the alternatives under multiple attributes. Benefit/Cost (B/C) ratio analysis was also carried out by using the both FAHP score and procurement cost for each alternative. The alternative with highest B/C ratio was selected as the best machine tool. Also, a case study was presented to make the approach more understandable.

Chan and Swarnkar [15] proposed ant colony optimization approach to a fuzzy goal programming model for a machine tool selection and operation allocation problem in an FMS. Proposed model tried to determine optimal machine tool combination and the assignment of the operation for the given part types to available machines while maintaining the machining cost, material handling cost and set-up cost within certain limits. The constraints included were limited tool magazine capacity, tool life and machine capacity.

Mishra et al. [16] adopted a fuzzy goal-programming model having multiple conflicting objectives and constraints pertaining to the machine tool selection and operation allocation problem. A new random search optimization methodology, termed as quick converging simulated annealing was used to resolve the issue of parameters, which were non-deterministic and imprecise in nature. The main features of the proposed algorithm was that it outperformed genetic algorithm and simulated annealing approaches, as far as convergence to the near optimal solution was concerned. Moreover, it was also capable of eluding local optima. Extensive experiments were performed on a problem involving real-life complexities, and some of the computational results were reported to validate the efficacy of the proposed algorithm.

Ayağ [17] presented a hybrid approach for machine tool selection through AHP and simulation. AHP was used to select all possible machine tool alternatives with higher weights under certain circumstances. Then, a simulation generator was used to automatically model a manufacturing organization and also an initiative was made to try each alternative remaining from AHP as a scenario on the generated model. Finally, the best alternative was selected by using the unit investment cost ratio.

Durán and Aguilo [18] applied fuzzy-AHP approach for computer-aided machine tool selection. The presented approach introduced triangular numbers into traditional AHP method. In order to consider uncertainty and improving imprecision in ranking attributes and/or machine alternatives, FAHP based software for selecting the machine tool was developed in MATLAB. An example of machine tool selection was also described to validate the proposed model.

Önüt et al. [19] described a fuzzy technique of order preference by similarity to ideal solution (FTOPSIS) based methodology for evaluation and selection of vertical CNC machining centres for a manufacturing company. Four different models of CNC VMC of three different manufacturers were considered. Criteria considered for the decision making process were cost, operative flexibility, installation easiness, maintainability and serviceability, productivity, compatibility, safety and user friendliness. FAHP procedure was implemented to determine the importance-weight of the criteria and FTOPSIS method was employed to determine the alternatives of the machine tools according to the selection criteria.

Sun et al. [20] proposed a machine tools selection technology for networked manufacturing. Authors analyzed the art of machine tools selection based on grey relation analysis (GRA) and AHP method. Machine tools selection index according to cost, time and quality was discussed first. Then, machine tools multi-hierarchy grey selection model was put forward for selection evaluation system. Lastly an example was provided to demonstrate the method.

Ayağ and Özdemir [21] applied a fuzzy ANP (FANP) approach for machine tool selection. Fuzzy set theory was designed to model the vagueness or imprecision of human cognitive process. FANP technique was proposed in this particular domain to make up the vagueness and uncertainty existing in the importance attributed to the judgement of the decision-maker. In order to reach the final solution, a preference ration analysis was carried out by using the results of FANP, and investment cost of alternatives.

İç and Yurdakul [22] developed a DSS, namely MACSEL, to help the decision makers in the machining centre selection decisions. Within the developed DSS, to select the feasible set of machining centers, fifteen questions were placed in the elimination (pre-selection) module. FAHP or FTOPSIS was used to rank the feasible machining centers. In the DSS, FAHP was used if a detailed pair-wise weighting of the hierarchically structured criteria was wanted. On the other hand, when a simpler separate weighting of each criterion was considered, FTOPSIS was used.

Yurdakul and İç [23] analyzed the benefit generated by using fuzzy numbers in a TOPSIS model which was developed for machine tool selection problem. Authors identified from literature surveys that fuzzy numbers were used instead of crisp values to deal with the vagueness and imprecision, inherent in the machine tool selection problem. It was initiated by the authors to measure the benefit generated by incorporating fuzziness in the multi criteria decision making (MCDM) models. TOPSIS was used to rank the alternatives. By increasing the fuzziness level steadily in the fuzzy numbers, the obtained machine tool rankings were compared with the ranking obtained by the crisp values. The statistical significance of the difference between the ranks was calculated using Spearman's rank- correlation coefficient. It was observed from the result that as the vagueness and imprecision was increased, fuzzy numbers instead of crisp numbers was used. On the other hand, when there was a low level of fuzziness or the average value of the fuzzy numbers were guessed, crisp number would be more than adequate.

Balaji et al. [24] depicted a case study of machine tool selection for a FMS using elimination and choice translating reliability (ELECTRE). Authors considered several quantitative and qualitative attributes for the selection of machine tools. Maintainability, degree of service available, popularity of the supplier etc were the qualitative attributes, considered during the initial screening phase. Other quantitative attributes considered were maximum swing over bed, spindle motor power, repeatability in various directions etc. Also a sensitivity analysis was carried out by changing the values of input parameters to check the robustness of the proposed method.

Qi [25] proposed a model based on fuzzy MCDM approach for machine tool selection problem. At first, a constructive evaluation model for machine tool selection was made. Then logarithmic least squares method based on fuzzy pair wise comparison matrix was applied for assessment of uncertain weights of selection criteria. The ways to determine performance value of the alternative with respect to qualitative and quantitative criteria were discussed respectively, and fuzzy integral was applied for the aggregation of performance scores of the alternative regarding different criteria. Finally the effectiveness of the method was demonstrated by a real time example.

Tsai et al. [26] proposed an AHP method for the selection of 4-axis CNC machining centres. A method to determine the valuable criteria for selecting CNC machine tools using the vast amount of specifications along with consulting experts was described. AHP method was also described stepwise to select the best CNC machine tool, considering several criteria.

Athawale and Chakraborty [27] developed a TOPSIS method based approach for machine tool selection. Authors presented a logical procedure to evaluate the CNC machines in terms of system specifications and cost by using TOPSIS method. The criteria considered for decision-making problem were capital cost, machining diameter and length, spindle speed, tool capacity, flexibility, safety and compatibility. The priority weights for different criteria were determined using AHP method and subsequently, these weights were used for arriving at the best decision regarding selection of proper CNC machines. An illustrative example was also provided to validate the proposed method.

Alberti et al. [28] designed a DSS for high speed milling machine selection based on machine characteristics and performance test. Profile machining tests were designed and conducted among participating machining centres. The DSS was based on dimensional accuracy, feed rate, interpolation scheme used by CNC and machine characteristics such as machine accuracy and cost. Experimental data for process error and cycle operation time were obtained from profile machining tests with different geometrical feature zones that were often used in manufacturing of discrete parts or die/molds. All those input parameters had direct impact on productivity and manufacturing cost. Artificial neural network (ANN) models were utilized for DSS with reasonable prediction capability.

Samvedi et al. [29] proposed an integrated approach for CNC machining centre selection using FAHP and GRA. FAHP was used to calculate the priority weights of the criteria and GRA was used to rank the alternatives. Eight criteria were considered for the selection process. They were cost, operative flexibility, installation easiness, maintainability and serviceability, productivity, machine tool compatibility, safety and user friendliness. These criteria were considered for four CNC vertical machining centres of different models. Pair wise comparison was made between the criteria and between different alternatives for a given criterion. Delphi technique, a group decision making tool was used by the expert team during the preparation phase of these pair wise comparison matrices. Triangular fuzzy numbers were used to tackle the ambiguities involved in the group decision making process. Chang’s extent analysis was used to convert the fuzzy values of paired comparison to crisp values.

Taha and Rostam [30] proposed a FAHP-ANN based DSS model for machine tool selection in a FMS. A program was developed in the model to find the priority weights of the evaluation criteria and alternative’s ranking called PECAR for FAHP model. ANN was used to verify the results of FAHP and to predict the alternative’s ranking. A feed forward back propagation ANN was designed and trained using the results from the PECAR program. A numerical example to select the most suitable CNC machine based on data collected from a designed questionnaire was given to demonstrate the applicability of the proposed model. The result of neural net simulation was compared with the results from FAHP model. It was concluded that the proposed DSS by combining FAHP and ANN models could be used as a powerful tool to select the most suitable alternative machines to form the structure of a FMC.

Ayağ and Özdemir [31] proposed a method for machine tool selection through modified TOPSIS and alpha-cut based FANP. The ANP method was used to determine the relative weights of a set of the evaluation criteria. Modified TOPSIS method was utilized to rank competing machine tool alternatives in terms of their overall performance. A fuzzy extension of ANP was used to alleviate uncertain human preferences as input information in the decision-making process. Instead of using the classical eigenvector prioritization method in AHP that was only employed in the prioritization stage of ANP, a fuzzy logic method, providing more accuracy on judgments was applied. The resulting FANP method increased the potential of the conventional ANP for dealing with imprecise and uncertain human comparison judgments.

Ic et al. [32] developed a component-based machining centre selection model using AHP. Technical specification values, such as table size, axis movement, power, spindle speed etc are directly taken from machines' catalogue. However specification values such as accuracy, repeatability, and axis velocity were difficult to measure and their values tend to vary under changing conditions. Instead of using specification values, the components, which were the sources of difference in the technical specification values, was evaluated in a multi-criteria machining-centre selection model. The developed AHP model ranked machines according to the component types they possess and also avoided any error or misinformation in the technical specification values provided in machine-tools manufacturers' catalogues. The proposed model was also compared with two other MCDM models that use only technical specifications.

Taha and Rostam [33] proposed a hybrid FAHP- preference ranking organization method for enrichment evaluation (PROMETHEE) DSS for machine tool selection in a FMC. A MATLAB-based FAHP was used to determine the weights of the criteria and it was called as program for priority weights (PWEC) and the PROMETHEE method was applied for the final ranking. A database (DB) of 118 CNC TC was created using Microsoft Excel. DB was incorporated with real-time data from machine tool sales organization. Decision Lb software was utilized for the final raking of the alternatives and analysis. An illustrative example was also provided to show the potentiality of the proposed method.

Aghdaie et al. [34] developed an integrated approach of two MADM model namely step-wise weight assessment ratio analysis (SWARA) and complex proportional assessment of alternatives with grey relations (COPRAS-G), for machine tool evaluation and selection process. Eight criteria for evaluation process including cost, operative flexibility, maintainability and service ability, size and physical, compatibility, safety, precision and productivity were considered for the selection process. SWARA was useful for determining the importance of each criterion and calculating the weight of each criterion. COPRAS-G was useful for evaluating alternatives more precisely than usual crisp COPRAS. It was also used for ranking of machine tool alternatives from the best to the worst one.

Nguyen et al. [35] presented a hybrid approach of FANP and COPRAS-G for fuzzy MADM in evaluating machine tools with consideration of the interactions of the attributes. The FANP was used to handle the imprecise, vague and uncertain information from expert judgments and to model the interaction, feedback relationships and interdependence among the attributes which was used to determine the weights of the attributes. COPRAS-G was employed to present the preference ratio of the alternatives in interval values with respect to each attribute and to calculate the weighted priorities of the machine alternatives. Alternatives were ranked in ascending order by priority. As a demonstration of the proposed model, a numerical example was implemented based on the collected data and the literature. The result was then compared with the rankings provided by other methods such as TOPSIS-Grey, simple additive weighting with grey relations (SAW-G) and GRA.

Prasad and Chakraborty [36] developed a quality function deployment (QFD)-based expert system (ES) for CNC TC selection. Importance to the voice of customer is given by QFD approach. The selection process was carried out for three different production plans namely flexible, mass and tailor made (customer specific). A database containing technical specifications of more than 200 CNC TC was developed in MS Access. A software prototype along with three real-time examples was demonstrated in VISUAL BASIC 6.0, using the collected data.

Sahu et al. [37] proposed that judging of appropriate CNC machine tool among the several choices was a MCDM problem including not only qualitative and quantitative attributes, but also subjective attributes such as productivity, precision and accuracy etc. These attributes were defined imprecisely by the expert panels. VlseKriterijumskaOptimizacijaIKompromisnoResenje (VIKOR) compromise ranking method was introduced for determining a compromise solution for ranking the machine tool from available alternatives in fuzzy MCDM environment. A fuzzy multiple attributes and group decision-making scenario was modelled for the selection of best CNC machine tool among available feasible alternatives. A distance-based (MCDM) method that was interrelated to VIKOR (compromise ranking method) was also presented. A compromise solution, providing a maximum ‘group utility’ for the ‘majority’ and a minimum of an individual regret for the ‘opponent’ was determined by the model.

Wu et al. [38] proposed a multi-criteria group decision making (MCGDM) technique based on fuzzy VIKOR method to solve a CNC machine tool selection problem. Linguistic variables were represented by triangular fuzzy numbers and those were used to reflect decision maker preferences for the criteria importance weights and the performance ratings. After the individual preferences were aggregated of after the separation values were computed, they were then defuzzified. Authors proposed two algorithms based on a fuzzy linguistic approach. Based on those two algorithms and VIKOR method, a general MCGDM framework was proposed. A comparative study of the two algorithms using the above case study information highlighted the need to combine the ranking results, as both algorithms had distinct characteristics.

Cakir [39] proposed an approach consisting of fuzzy simple multi attribute rating technique (SMART) approach and fuzzy weighted axiomatic design (FWAD) approach to determine the optimal continuous fluid bed tea dryer for a privately owned tea plant operating in Turkey. The weights of the evaluation criteria were calculated via fuzzy SMART and then FWAD was utilized to rank competing machine alternatives in terms of their overall performance. In the FWAD application phase, five experts had determined functional requirements (FRs) and had rated alternatives. Therefore, individual fuzzy opinions were required to be aggregated in order to set up a group consensus. A group decision analysis, referred to as the least squares distance method was used to aggregating the ratings of FRs and alternatives. It was concluded that the proposed hybrid methodology was a robust decision support tool for ranking machine alternatives under fuzzy environment and furthermore, it could be exploited for other fuzzy decision making problems.

Karim and Karamker [40] developed a DSS in machine evaluation process. The proposed framework acted as a guide for decision makers to select the suitable machine via an integrated approach of AHP and TOPSIS. In the first step of the proposed method, the criteria of existing were inspected and identified and then the weights of the sector and sub-sector were determined that had come to light by using AHP. In the second step, eligible alternatives were ranked by using TOPSIS. A demonstration of the application of these methodologies in a real life problem was also presented.

Cogun [41] presented a computer-aided selection procedure as a general purpose aid to the designer in making preliminary selections of NTM processes for a given part. The selection procedure used an interactively generated 16-digit classification code to eliminate unsuitable combinations from consideration and ranked the remainder. The coding system, data bases and computer program for the elimination phase of the selection process was developed. In the proposed method, only the work material and some of the process capabilities, namely minimum surface finish, minimum size tolerance, minimum corner radii, minimum taper, minimum hole diameter, maximum hole height to diameter ratio and minimum width of cut, were used to determine best selection among the competitive NTM processes.

Yurdakul and Çoğun [42] presented a multi-attribute selection procedure to help manufacturing personnel in determining suitable NTMPs for given application requirements. The selection procedure first enabled the user to narrow down the list of NTMPs to a short list containing feasible processes. Then, the procedure ranked the feasible NTMPs according to their suitability for the desired application. In ranking the feasible alternatives, the selection procedure used a combination of two MADM tools, namely AHP and TOPSIS. For use in the selection procedure, possible shape applications performed by the processes, process technical capabilities and attributes necessary to measure the performance of processes were developed. Many industrial case studies were introduced to examine the dependability of the developed approach, and successful results were obtained.

Dey and Chakraborty [43] presented a systematic methodology for selecting the best or optimal non-traditional machining process under constrained material and machining conditions. Authors included the design of an AHP based ES with a graphical user interface to ease the decision-making process. The developed ES relied on the priority values for different criteria and sub-criteria, as related to a specific non-traditional machining process selection problem. Proposed method was dependent on the logic table to discover the non-traditional machining processes that lied in the acceptability zone, and then selected the optimal process having the highest acceptability index value. The proposed expert system could automate the selection of a non-traditional machining process and provided artificial intelligence (AI) in the MCDM process.

Dey and Chakraborty [44] presented a quality function deployment (QFD) based methodology to ease out the optimal NTM process selection procedure. It included the design of a QFD-based ES that could automate the decision making process with the help of graphical user interfaces and visual aids. The developed ES employed the use of a house of quality (HOQ) matrix for comparison of the relevant product and process characteristics. The weights obtained for various process characteristics were utilized to estimate an overall score for each of the NTM processes. Finally, if some of the NTM processes satisfied certain critical criteria, they were again compared with each other on the basis of their overall scores and the process having the maximum score was selected as the optimal choice.

Chandraseelan et al. [45] presented a web-based knowledge base system for identifying the most appropriate nontraditional machining process to suit specific circumstances based on the input parameter requirements such as material type, shape applications, process economy and some of the process capabilities namely, surface finish, corner radii, width of cut, length to diameter ratio, tolerance etc. The proposed selection procedure was based on the idea that certain characteristics of a part restrict the choice of certain non-traditional machining processes for it to have a relatively small number of alternatives. Authors proposed that, designers and engineers who are geographically separated but well connected by the Internet and can use this web-based system to realize process selection. The proposed methodology simplified the sharing of process knowledge and provided intelligent decision-making in a collaborative way through the internet. Proposed system employed three-tier web architecture for implementing user module, to do the selection and expert module to update the knowledge base. The web-based non-traditional machining process selection system could cut down the product cost, enhance the product quality, and decrease the product lead-time considerably. A wide range of industrial parts had been evaluated in order to demonstrate the performance of the proposed selection procedure.

Chakladar and Chakraborty [46] proposed a combined method using the TOPSIS and AHP to select the most appropriate NTM process for a specific work material and shape feature combination, while taking into account different attributes affecting the NTM process selection decision. Authors also included the design and development of a TOPSIS-AHP-method-based ES that could automate the decision-making process with the help of a graphical user interface and visual aids. The ES not only segregated the acceptable NTM processes from the list of the available processes, but also ranked them in decreasing order of preference. It also helpd the user as a responsible guide to select the best NTM process by incorporating all the possible error-trapping mechanisms.

Chandraseelan et al. [47] proposed a knowledge-based system developed for identifying the most appropriate NTM processes to suit specific circumstances. 20 NTM processes of industrial importance were incorporated into the system. Only material type and some of the process capabilities namely surface finish, tolerance, surface damage, corner radii, taper, hole diameter, width of cut, depth to diameter ratio(for cylindrical holes),and depth to width ratio(for blind cavities), were used to determine the best selection among competitive NTM processes.

Chakladar et al. [48] presented a digraph-based approach to ease out the appropriate NTM process selection problem. It included the design and development of an expert system that could automate this decision-making process with the help of graphical user interface and visual aids. The proposed approach employed the use of pair-wise comparison matrices to calculate the relative importance of different attributes affecting the NTM process selection decision. Based on the characteristics and capabilities of the available NTM processes to machine the required shape feature on a given work material, the permanent values of the matrices related to those processes were computed. Finally, if some of the NTM processes satisfied a certain threshold value, those were shortlisted as the acceptable processes for the given shape feature and work material combination.

Sugumaran et al [49] presented a general purpose aid to the designer in making preliminary selection of NTM process for a given part. In the proposed procedure, work materials, shape machined, operations capabilities such as minimum tolerance, minimum surface finish, minimum corner radii, minimum hole diameter, maximum depth to diameter ratio and maximum thickness of the work piece were include. Based on the required part characteristics, a neural network (NN) generated a list of NTM processes to produce a particular part. A neural network tool 'Neuralyst' was used for the development of systems for NTM. It used pattern matching/associative memory. The network was trained and parameters were optimized for better results.

Sadhu and Chakraborty [50] developed a two-phase decision model in NTM process selection domain. In the first phase, the most efficient NTM processes were selected for a given shape feature and work material combination having the best combination of performance parameters with the help of input-minimized based Charnes, Cooper and Rhodes (CCR) model of data envelopment analysis (DEA). In the second phase, those efficient NTM processes were ranked in descending order of priority using the weighted-overall efficiency ranking method of multi-attribute decision-making (MADM) theory. Two real-time machining applications were cited which prove the applicability, versatility and adaptability of this two-phase NTM process selection decision-making model. It was showed that, the results were quite consistent with those as derived by the past researches.

Das and Chakraborty [51] proposed an ANP-based approach to select the most appropriate NTM process for a given machining application taking into account the interdependency and feedback relationships among various criteria affecting the NTM process selection decision. To avoid the difficult and time consuming mathematical calculations of the ANP, a computer program was also developed in Visual Basic 6.0 with graphical user interface to automate the entire NTM selection decision process. It simply acted as an ANP solver. Authors also concluded that, observed results from the ANP solver were quite satisfactory and match well with those obtained by the past researchers.

Karande and Chakraborty [52] applied an integrated PROMETHEE and GAIA (geometrical analysis for interactive aid) method to help the process engineers in selecting the most appropriate NTM process for a given work material and shape feature combination. Authors also provided, four real time examples solved by the proposed combined approach and showed that the results exactly matched with those identified by the past researchers and proved the universal acceptability of the proposed method as an efficient visual decision aid.

Choudhury et al. [53] proposed a distance based approach for NTM process selection. Authors focused on selection of NTM processes based on hybridized TOPSIS and an AHP ES in which an AHP matrix was referred. The weights of the AHP matrix were obtained from the process selection criteria. Depending on the weights obtained, relative closeness of the NTM alternatives were evaluated using TOPSIS which showed that ECM and plasma arc machining (PAM) were the best NTM processes and the worst NTM process was EDM.

Chatterjee and Chakraborty [54] proposed evaluation of mixed data (EVAMIX) method for NTM processes selection. The proposed method helped to select the most appropriate NTM process for a given machining application based on some parametric requirements, such as material type, shape feature, process economy and other process capabilities, like MRR, SR, surface damage depth, tolerance, machining medium contamination, efficiency etc. The proposed method had an advantage of treating the quantitative (cardinal) and qualitative (ordinal) criteria separately, which helped the decision makers not to lose information during the decision-making process. Three real-time examples were also given to validate the model.

Roy et al. [55] selected NTM processes using FAHP and QFD techniques. FAHP was used to calculate the relative importance of various NTM processes taking product and process characteristics as the comparison basis. Finally, an overall score of various NTM processes was obtained using QFD methodology based on various shape features and work material combinations. Authors also considered the variations in the process capability features. Analysis made by the authors showed that ECM processes had an edge over the other NTM processes with respect to surface finish, corner radii, minimum surface damage depth, and production time.

Chauhan and Pradhan [56] proposed a combine TOPSIS-AHP approach to select appropriate NTM process among various NTM process for a particular shape feature on a given work material. Proposed MCDM method recognized different NTM process selection attributes and their interrelations for a given NTM process selection problem. This method could simultaneously take a number of quantitative and qualitative NTM process selection attributes. The combined method articulated the information about the condition under which a specific NTM process was not acceptable for a specified machining application. The main advantage of the proposed ES was it did not require any in-depth technological knowledge regarding the applicability of NTM processes. The chances of error in the proposed method were very less and could be applied to real time MCDM problem.

Temuçin et al. [57] provided a distinct systematic approach both in fuzzy and crisp domain to deal with the selection problem of appropriate nontraditional machining process and proposed a decision support model for forth leading decision makers to assess potentials of distinct non-traditional machining processes. The required data for decision matrices was obtained via a questionnaire to specialists as well as deep discussions with experts, making use of past studies, and experimentally. An application of the proposed model was also performed to show the applicability of the model.

Prasad and Chakraborty [58] presented a decision making framework based on QFD principle to aid in identification of the most appropriate NTM process for a specific application. QFD technique was adopted by the authors to take voice of the customers into consideration. A user friendly software prototype in Visual BASIC 6.0 with graphical user interface was designed and developed to automate the NTM process selection procedure.

Sagbas and Capraz [59] incorporated a comparative study by using FAHP and FTOPSIS approaches to aid the decision-makers in selecting the most appropriate NTM process for a given material and shape feature combination. Several process capabilities (e.g. Tolerance, surface quality, processing speed), shape applications (e.g. hole, through cutting etc.) and process economical criteria were considered for this selection process. Real-time examples were also provided to validate the method.

Khandekar and Chakraborty [60] proposed the application of fuzzy axiomatic design principles for selection of the most suitable NYMPs for generating cavities on ceramics and micro-holes on hardened tool steel and titanium materials, based on their practical/industrial importance. It was found that for micro-drilling operation on hardened tool steel, EDM was found to be the best process followed by AJM and ultrasonic machining (USM). On the other hand, for generation of micro-holes on titanium, ECM was the most suitable process. AJM emerged out as the most efficient process for generating blind cavities on ceramics. It was also showed by the authors that results obtained were well in accordance with the expected machining practices and perfectly matched with the decisions of the machining professionals.

Prasad and Chakraborty [61] developed a decision guided framework, based on exhaustive database, in Visual Basic 6.0 to help the process engineers in selecting the most appropriate NTM process for a specific work material and shape feature combination. The proposed model also assisted to identify the ideal process parameter combinations for the most suitable NTM process. Three real-time examples were also provided to validate the proposed model.

Madić et al. [62] introduced the use of operational competitiveness ratings analysis (OCRA) method for solving the NTM process selection problems. Applicability, suitability and computational procedure of OCRA method was demonstrated while solving three case studies dealing with selection of the most suitable NTM processes. In each case study the obtained rankings were compared with those derived by the past researchers using different MCDM methods. Authors also showed that, the results obtained using the OCRA method had good correlation with those derived by the past researchers.

1.5 Object and Scope of the Present Work

With the advancement of technology, more and more problems are faced by the manufacturing organizations. From the above literature survey, it is clearly understood that machine tools are one of the most important parts in manufacturing process that could help manufacturing companies to survive their existence among other competitors. Machining processes are carried out by machine tools and selection of appropriate machine tools and manufacturing processes is considered as a major MCDM problem in modern manufacturing industries. As discussed in previous sections, traditional machining processes as well as NTM processes have equal importance in this modern era of manufacturing development and each machining process has its own capability. While a single manufacturing process can generate different types of shape features on different materials, it becomes quite difficult for the process engineer to select the most suitable machine tool and manufacturing processes.

Today, there is a huge scarcity of experienced personnel/experts in modern manufacturing industries. Often, higher salary is demanded by these experienced personnel that become major expenses for medium and small scale industries. Also, it is not guaranteed that all the decisions taken by experts will be a beneficial one. In this situation, some semi-experienced personnel are hired by the manufacturing companies. These personnel are responsible to take decisions regarding the selection of proper machine tools and manufacturing processes. During this decision making process, it is often desired by these semi-experienced manufacturing personnel, to use the successful past experiences. It is very easy to store all the successful machining process selection cases in a database. But, using the most similar prior experience in solving the new problem is quite difficult.

Based on the aforesaid discussion and requirements, the objectives of the present work are set as follows:

a) To develop a decision making system that is able to retrieve most similar prior case and to help the decision maker in selection of best machine tools and NTM processes. This novel approach of decision making is termed as case-based reasoning (CBR).
b) To identify the basic working principles of a CBR system. Also to provide a clear description of process and memory model of the CBR system.
c) To identify the most relevant parameters in selection of machine tools and NTM processes. An idea about these parameters are generally gathered from manufacturing personnel, machine shop operators, machining handbooks, machine catalogue as well as from past research works.
d) To collect an exhaustive case-base (CB) of successful past cases from the machine shops that will contain all the machining data to alleviate the gap between new case and prior stored cases.

e) To put these exhaustive past cases along with their problem and solution parts in a database system that can be easily retrieved during the decision making process. Here Microsoft Access is used to store these cases.
f) To develop a software prototype in Visual Basic 6.0 to automate the decision making process of the CBR system.
g) To illustrate and validate the developed CBR system by real-time examples of machine tools and machining processes selection problems.

Future scope of this research work includes the following:

a) To include more cases in the CB so that more similar cases are retrieved.
b) To use other complicated case representation, indexing and organizing structures which is capable to deal with more cases efficiently.
c) To use other advanced case retrieval techniques so that retrieval efficiency is increased.
d) To use this CBR methodology in other domains of mechanical engineering such as materials selection, automobile selection etc.

2.0 CASE-BASED REASONING APPROACH

2.1 An Introduction to Case-based Reasoning Approach

"I have but one lamp by which my feet are guided, and that is the lamp of experience. I know no way of judging of the future but by the past"

– Patrick Henry (Speech in Virginia Convention, Richmond. March 23, 1775) [65].

Intelligence, being a part of cognitive science, may 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. AI is concerned with design of intelligence in an artificial artefact or a system. This term 'AI' was first coined by McCarthy in 1956 in famous Dartmouth Conference. AI systems are generally man made systems and intelligence is built into them. So, AI is a thing which is having behaviour like human. But humans are not always completely intelligent. Thus few other scientists define AI as a system that behaves in its best possible manner. Behaviour is referred in two ways. First one is, thinking intelligently and reasoning properly to come up with the solutions (intelligence in thinking). The second is acting or the way a system acts (intelligence in acting). Several approaches to AI are given in the Figure 2.1. Intelligent entities or agents should able to do mundane tasks and expert tasks. These mundane tasks include planning routes and activities, recognizing people or objects through vision, communicating through natural languages etc.

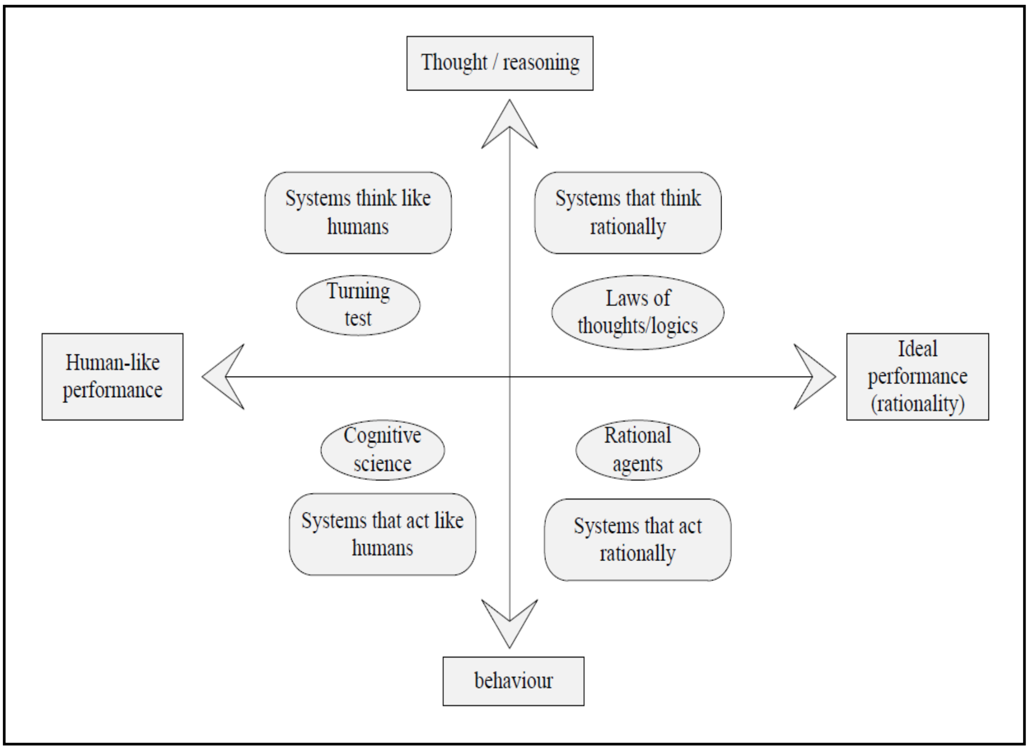


Figure 2.1 Several approaches to AI

Tasks having high level of complexities are considered as expert tasks. It includes medical diagnosis, mathematical problems solving, playing chess, symbolic integrations etc. AI can able to do these expert tasks efficiently. Several AI topics are shown in Figure 2.2.

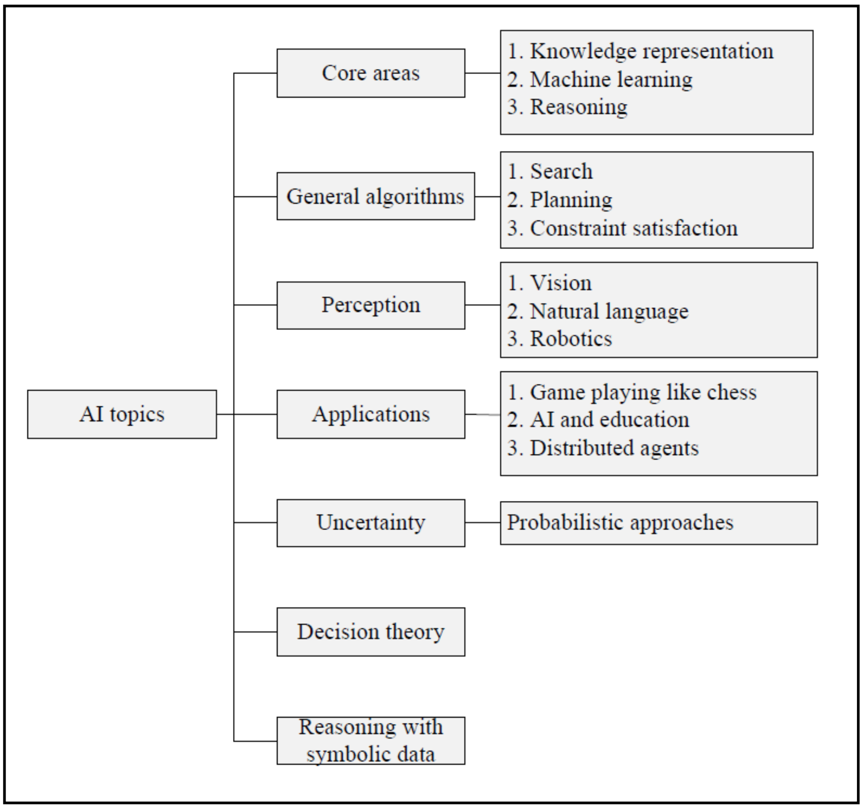


Figure 2.2 AI topics

In 1990's there was major advancement in all the research areas of AI such as machine learning, data mining, CBR, ES, ANN etc.

Researchers are continuously trying to develop a flexible information processing system that can exploit the tolerance for imprecision, uncertainty, approximate reasoning and partial truth to achieve traceability, robustness, low solution cost and close relation to human decision making process.CBR is a recent approach of AI that may be defined as a model of inferring that incorporates problem solving, understanding and learning, and integrates all of them with memory processes. Basically these tasks are accomplished using typical solutions, called cases, already experienced by a system. During past decades soft computing techniques have had a significant impact on CBR. It is one of the emerging paradigms for designing intelligent systems [66]. It imitates human thinking trying to make a decision based on earlier experiences [67]. CBR assumes a memory model for representing, indexing and organizing past similar cases, and a process model for retrieving and modifying the past cases and assimilating the new ones. It is an approach to incremental, sustained learning, since a new experience is retained each time a problem has been solved, making it immediately available for future problems [68]. In CBR terminology, it is made up with three basic terms- ‘case’, ‘based’, and ‘reasoning’. Meaning of these three terms are depicted below:

a) Case: It is a record of contextualized experiences of past problem. The recorded past information depend on the domain of the reasoner and the purpose to which the case will be put. In a problem solving CBR system, the details of a case will include the specification of a problem and the relevant attributes of the environment that are the circumstances of the problem. The other major part of the case is the solution that was adopted in the previous situation. Depending on the reasoning capability of the CBR system, this solution may include only facts of the solution or the steps involved in obtaining the solution. The CB of a CBR system is often compared with the knowledge stored in a model/rule based system. The cases stored in the CB of a CBR system are more specific in nature as compared with knowledge in model/rule based system. Knowledge in model/rule based system has been abstracted so that it can be applied in a widest variety of situations as possible. But the knowledge contained in a CB remains specific to the case in which it is stored.
b) Based: using known theory, knowledge or information.
c) Reasoning: A process of inference using intelligible information.

Four major components of a CBR system are retrieve, reuse, revise and retain, which involve such basic tasks as clustering and classification of cases, case selection and generations, case indexing, case learning, measuring similarity between cases, case retrieval and inference, reasoning, rule adaptation and mining. Several soft computing tools such as fuzzy logic and ANN have immense potentiality to perform these tasks. These tools are generally used to handle ambiguous, vague or ill-structured information and concepts, learning and adaptation of intractable cases, searching for optimal parameters and computing with clumps of similar cases for speedy computation. CBR system generally combines all these characteristics in various combinations for developing efficient methodologies, algorithms and knowledge base networks for various real life decision making applications.

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 CB. It first searches the case history and chooses those cases having the closest similarity to the current problem. In CBR system, the CB 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.

2.2 Architecture of Case-based reasoning approach

CBR has a young birth history, which arouse out of the research in cognitive science and it is considered as a plausible high-level model of cognitive processing. CBR system becomes very much effective and efficient for some problem domains, which have the following properties: -

a) If a domain do not have a underlying model, or have a model that is impossible to understand, then CBR can be applied in that area. Past experiences are enough to develop a CBR model without understanding the underlying mechanism of a problem domain.
b) If a domain does not have novel or exceptional cases then several inductive rules can be developed to build an ES. But, in a situation where new and exceptional cases are encountered frequently, then it is impossible for an ES to maintain the consistency among the rules. CBR can be applied in such domain very easily.
c) If similar past problems are encountered often, then CBR system can work efficiently.

In the basic structure of a CBR system, it has a memory model and a process model. In the field of cognitive science, memory models are thoroughly studied and categorized. An intelligent person requires knowledge about the world. This knowledge is utilized for reasoning or problem solving purposes. Memory is the repository of knowledge. Major types of memory models developed till date are:

a) Semantic network memory model: It generally represents the static facts about the world. Such as tommy is a dog, dog is mammal, mammals have hair etc. This type of knowledge is static over time. But the fact is, knowledge may change over time. Also, this memory model does not explain how knowledge is incorporated into the memory because knowledge is not an innate thing in humans.
b) Episodic memory model: It was proposed by Tulving in the year of 1972 [69]. It is a memory of autobiographical events, associated with emotions, times, place, who, what, when knowledge. So, knowing things are factual or semantic but remembering is a feeling, located in the past (episodic). A person learns today, how to play piano. But after several days person cannot remember when the learning process was happened. Thus, it is concluded that the person has lost episodic memory.
c) Dynamic memory model: It was proposed by Schank in the year of 1982 [70]. It is based on schema-oriented memory models. Dynamic memory utilizes a unit of representation, the memory of pocket (MOP) - a dynamic structure used to represent patterns of situations in memory.
d) Category and exemplar model: In this memory model, cases are referred as exemplars. According to this theory, individuals can make decisions by comparing new examples

with all the examples which are already present in the memory. Here, each case is associated with a category. Instead of relying on a single prototype, categories have many or known exemplars to fit into them. The greater the number of exemplars the new item will match, the better will it adapt against all members of a category. It may possible single exemplar may be selected as prototype.

Basic tasks associated in the memory model of a CBR system are – case representation, case-organizing and case indexing. Case representation process may be defined as the process of enabling the computer to recognize, store and process the past contextualized experiences. Case representation and indexing method should be chosen carefully because it provides the basic structures for which other CBR processes are carried out. Relational database management system (RDBMS) technique is most commonly used for case representation. A relation is a subset of discrete objects of related domains. In RDMS each case is represented by a row and columns are used to represent the attributes of the cases. If cases are broken down into sub cases, a relationship network may be developed. Among the several popular case-organizing methods flat memory, serial search is the simplest one where cases are stored sequentially in a simple list or in a file. No difficult indexing structures are preferred here. Searching is carried out sequentially until full case-library is searched. Indexing is a process of mapping the record key to the storage location. Among the several case indexing methods most popular is traditional indexing method where indexes are referred to the primary or secondary keys of a record.

A process model is defined in terms of processes, methods, products, goals and resources. Till date several process model of CBR have been proposed but among them two popular process models are – R^4 model of CBR proposed by Aamodt and Plaza [68] and Leake's model [71]. These two popular process models basically describe the major stages required for developing CBR system. These major stages are depicted below with the help of Figure 2.3.

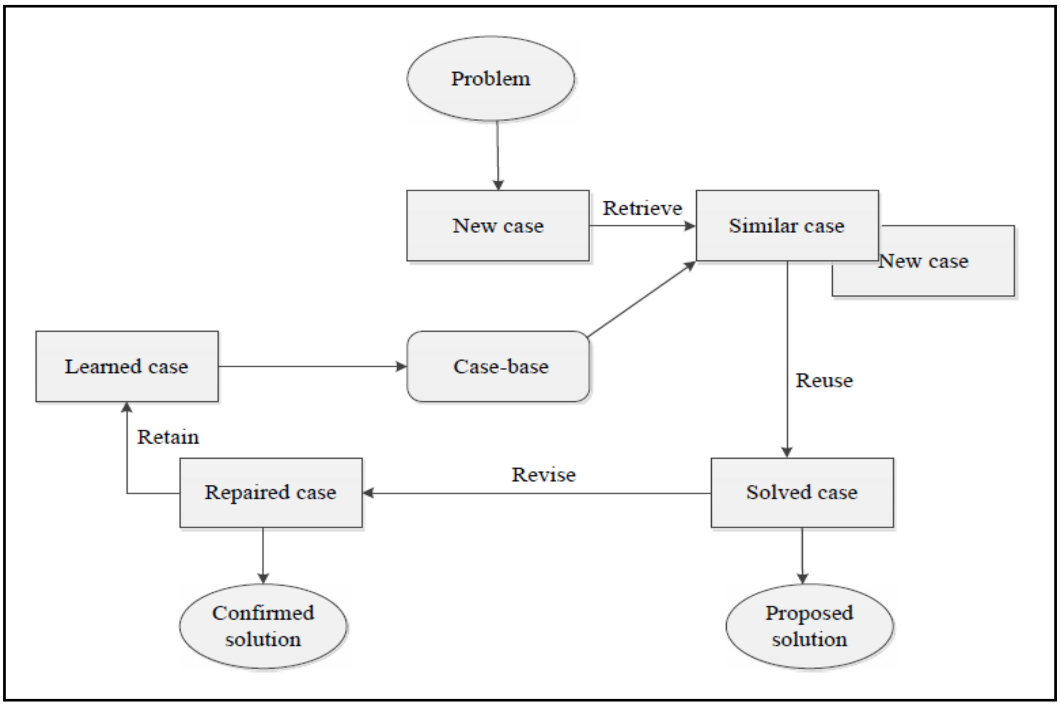


Figure 2.3 CBR cycle or R^4 cycle

a) Retrieve: Case retrieval is the basic and fundamental step in a CBR system. When a new problem is given to the CBR system, based upon the richness of the attributes, several cases are retrieved from the CB. Similarity measure is used to quantify the degree of resemblance between a pair of cases. For this reason, CBR system is sometimes called as '*similarity search technique*'. There are two major case-retrieval approaches used globally:-

i. Distance-based/ computational approach: Distance between a pair of cases is calculated in this method. It also depends upon the richness of attributes. If user provides more precise information to the CBR system, smaller will be the distance between the new case and prior cases stored in CB. So, more accurate results are retrieved from the CB. Similarity score is calculated between pair of cases, over each attribute. Case that has highest similarity is selected as the best case, according to the requirements.

ii. Indexing/representational approach: Cases are coded into the structure of CB itself and they are connected by indexing structures. The indexing structure is traversed to search the similar case. In case of graphical appearance problems, CBR system compares bitmap of design pictures to find the similarity.

Usually CBR system uses the inverse of weighted normalized Euclidian distance or Hamming distance for similarity measurement.

Euclidian distance is represented by: Sim(A,B) = 1 – Dist. (A,B)

$$= 1- \sqrt{\sum_i w_{i^2}\ dist^2(a_i\ , b_i)} \qquad \textbf{Eqn. 2.1}$$

Hamming distance is represented by: Sim(A,B) = 1 – Dist. (A,B)

$$=1 - \sum_i w_i \, dist\,(a_i, b_i) \qquad \textbf{Eqn.2.2}$$

Here w_i = weight for attributes. w_i is also normalized for denoting the importance of i-th attribute, and i=1,2,3,…,n. Here n is the number of attributes in the case.

The normalized distance, dist. (a_i,b_i) is calculated as: dist. $(a_i,b_i) = \dfrac{|a_i - b_i|}{|max_i - min_i|}$. **Eqn. 2.3**

For numerical attributes, max_i and min_i is the maximum and minimum value of the attributes, respectively. For symbolic attributes if $a_i = b_i$, then dist. $(a_i,b_i) = 0$ and it is 1, when $a_i \neq b_i$. So, it is seen from Eqn. 2.1, 2.2 and 2.3 that dist. =0 when the similarity is maximum but when dist. =1 then the similarity is minimum.

For multi-valued parameters cardinality is compared to calculate similarity:

$$\text{Sim(a,b)} = \frac{\text{Card(a)} \cap \text{Card(b)}}{\text{Card(a)} \cup \text{Card(b)}} \qquad \textbf{Eqn. 2.4}$$

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

When elements are in taxonomical form, similarity is calculated by:

$$\text{Sim(a,b)} = \frac{\text{h(commonnode(a,b))}}{\text{min(h(a),h(b))}} \qquad \textbf{Eqn. 2.5}$$

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

CBR commonly uses a k-NN algorithm to retrieve similar past cases from the CB. This algorithm is designed to be used with numeric data that allows a natural distance function to define similarity [72] and it is the simplest algorithm that can compare an input case with all existing cases in the CB. It is a non-parametric method and does not make any assumptions about the probability distributions of the variable being assessed. The best matched case has the closest similarity with the input case, given to the CBR system. Various distance measuring and similarity measuring methods have already discussed in Eqn. 2.1, 2.2 and 2.3, 2.4 and 2.5. So, in nearest neighbor retrieval, the best case is chosen when the weighted sum of its features that match the current case is greater than the other cases in the CB. If all features have weighted equally, a case that matches the present case on n features will be retrieved rather than a case that matches on only k features (k<n). Generally, output of a k-NN classifier is a class membership. An object is classified by a majority vote of its neighbors. K-NN is a type of instance based learning or lazy learning, where the function is only approximated locally and all the assumptions are deferred until classification. It can also assign weights to the neighbors and generally important features/neighbors are assigned with more weights.

b) Reuse: After retrieval of most similar case from the CB, CBR system may copy its solution directly (reuse) or there is a phase of adaption occurs. Usually, past solution needs some adjustments to fit with the new situation. Case adaptation is generally the process of adapting the old solution. The knowledge which is required to carry out the adaption phase is called as adaptation knowledge. There are basically two ways of acquiring adaptation knowledge, which are cited below: -

i) by interviewing domain experts and then coding of task specific adaptation knowledge manually into the CBR system. This knowledge may be represented as decision tables, IF-THEN rules etc,

ii) by using machine learning techniques the knowledge of adaptation can be learned from the cases.

Generally three types of traditional case adaption strategies are basically used in the field of CBR:

i) Reinstantiation: This method involves direct copying and the use of an old solution from the retrieved best matched case. If there is a high similarity between the present and retrieved case, solution of past case is copied and used to solve the new case. This method involves low cost and quick response for the user.
ii) Substitution: This method involves substitution of attributes of old case that contradicts with the new problem requirement.
iii) Transformation: This method is used when there is no proper substitute is available. A newly generated solution is presented to the user based on the constraints and characteristics of the solution required.

Case adaptation is also carried out by several machine learning techniques such as – fuzzy decision trees, back propagation neural network, Bayesian model, support vector machine and genetic algorithm.

c) Revise: If the solution of the new case generated by the reuse phase is not correct then an opportunity for learning from failure arises. This phase is termed as case revision phase which consists of two tasks:

i) Evaluation of case solution which is generated by the case reuse phase. If it is successful then learning from the success is done.
ii) Else case solution is repaired by domain-specific knowledge.

d) Retain: In this phase, CBR system decides what is useful to retain from the new problem solving episode into the existing CB. This phase involves taking a decision regarding, which part of the solution is to be retained and in what form. Also it includes deciding of indexing method for the new experience.

2.3 Application of Case-based Reasoning Approach for Machining Processes Selection

It is seen from the literature review that several decision making approaches are already applied in the field of machining process selection. But, in this research work, for the first time, an endeavor is made to apply CBR technique in machining process selection. Now the reasons for which CBR is applied in this domain are as follows:

a) The manufacturing domain is ill understood and it is not easy to articulate the knowledge in the form of rules [73]. Moreover, knowledge acquisition from a knowledge-rich-sources and its orderly placement in the knowledge base is quite difficult in manufacturing domain.

b) CBR has proved its immense potentiality in the field of help desk and configuration management, where instant solution is needed to real problems. In manufacturing organizations, it is often required to provide the instant solutions to a machining process selection problem, not only to decrease the processing time, but also to improve the accuracy and quality of the produced parts.

c) It is not very much difficult to put all the data in a database, relating to several process parameters and process characteristics of a machining process. But, during the exploitation of this database, traditional database retrieval techniques require precise matching of values, where CBR system uses a notion of similarity that does not require the exact matching of values.

This research work is carried out on two areas, first for the selection of machine tool using CBR approach and second for the selection of NTM process using CBR approach. Procedural steps followed during CBR search is stated below, briefly:-

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 CB 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 along with its complete information. It may also be possible that none of the cases would match the query exactly.

3.0 SELECTION OF MACHINE TOOLS USING CASE-BASED REASONING APPROACH

Machine tools are used to produce desired geometrical shapes on solid bodies (preformed blanks) and for that they are basically comprised of: -

a) Devices for firmly holding the tool and workpiece material.
b) Drives for providing motion and power to the tool and work.
c) Kinematic system to transmit motion and power from the sources to the tool-work.
d) Automation and control systems.
e) Structural body to withstand and accommodate those systems with sufficient strength and rigidity.

Machine tools are key equipments in manufacturing industries. Conventional machining processes are characterized by high MRR, low cost, standard accuracy, precision and surface roughness. As discussed in above sections, selection of best machine tool for a particular application is a difficult decision making problem for the process engineer. In this work, a CBR system is developed in order to select the best machine tool for a particular application. Steps followed during the development process of this CBR system are as follows: -

a) Step-I: - Several machine tools are available for consideration during the development phase of CBR system. Here, nine types of different machines tools of different makers are considered for the development of this CBR system and they are CNC TC, CNC drilling, VMC, HMC, surface grinding, high speed precision lathe, conventional vertical milling, radial drilling and horizontal boring.
b) Step-II: - Several materials can be machined in the machine shop with the help of aforesaid machine tools. Taking all those materials in account generally makes the CBR system complex one. From this huge material list, only those materials are selected, which are frequently used and machined. Materials considered during the development phase of CBR are - Steel, aluminium alloys, aluminium, super alloys, cast iron, titanium alloys, titanium, composites and copper.
c) Step-III: - Various complex shape features can be generated using the aforesaid machine tools, on the materials mentioned in step-II. A single machine tool can generate different kind of shape features using different cutting tools (e.g. CNC TC can produce surface of revolution on cylindrical materials. It can also produce through and blind holes on these cylindrical shaped materials). Some important shape features are identified and grouped for consideration. Shape features considered for this selection process are a. surfacing (surface of revolution), b. surfacing (contour generation), c. pocketing (shallow) [thickness (t) <3mm], d. pocketing (deep) [thickness (t) ≥3mm], e. through hole (standard) [length (L) / diameter (D) < 3], f. through hole (precision) [length (L) / diameter (D) ≥ 3] , g. blind hole (standard)

[length (L) / diameter (D) < 2mm], h. blind hole (precision) [length (L) / diameter (D) ≥ 2].

d) Step-IV: - Selection of proper process machining characteristics for the decision making process is a complex task. At first, as many as process characteristics are considered. The influence of these process characteristics and process parameters on the final product cannot be clearly determined. Experts agree that all the process parameters and process characteristics are important but, selection of most important process parameters and process characteristics is done by consulting with several experts in the industry, as well as from the machining handbooks and past research works. Process characteristics that are considered here for the development of CBR system are described below: -

i) MRR: - It is defined as the rate of removal of excess materials from the parent workpiece by means of some external agencies (e.g. cutting tools). It may be expressed by means of weight of material removed in unit time (MRR_M) or by means of volume of materials removed in unit time (MRR_V). Here, MRR_M is considered for designing the CBR system. It is expressed in terms of grams/min. It is always desired that MRR should be higher but, not compensating with the quality of products manufactured. Values of MRR are directly obtained from the experiments.

ii) SR: - Depending upon the type of production, all surfaces have their own characteristics, which are collectively referred as surface texture. This surface texture can be identified in terms of some well defined and measurable quantities such as – flaws or defects, lay or directionality, roughness and waviness. Roughness is defined as closely spaced, irregular deviations from the flat surface, on a scale much smaller than that of waviness. SR can be measured using two methods - arithmetic mean value (R_a value) and root-mean-square average (R_q value). Here R_a value is considered for measuring the SR. SR is expressed in terms of µm in this developed CBR system. Values of SR are obtained directly from the experiments.

iii) Tolerance (Tol): - Tolerance or dimensional tolerance is defined as the permissible variation in the dimensions of a part. Tolerance are important because of their impact on not only the proper functioning of the product, but the manufacturing costs as well; generally, the smaller the tolerance, the higher the production costs [74]. Tolerance of the manufactured parts should be kept as small as possible, without incurring higher cost and lower production rate. Different machine tools can achieve different values of tolerance.

iv) Positional accuracy (PA): - It is defined as how accurately a machine tool can be positioned in the desired location. Its value should be minimal to get desired accuracy and precision. It is measured in terms of mm. Positional accuracy in CNC machines can be accomplished by direct method (i.e. a sensing device is used to read the graduated scale which is built into the machine) or indirect method (i.e. by means of rotary or optical encoders). This data is collected from machine tool catalogue directly.

v) Repeatability (RP): - Repeatability is defined as the closeness of agreement of repeated position under the same operating conditions [74]. It is also expressed in terms of mm. This data is also collected from machine tool catalogue.

vi) Resolution (RS): - It is defined as the smallest increment of the machine tool. It is expressed in terms of mm. This data is also collected from machine tool catalogue for developing this system.

vii) Cost (C): It includes machine tool procurement cost, approximate labour cost, overhead cost associated with the machine tool. It is expressed in relative (R) priority scale. For cost, R scale is set as 1 = very low, 2 = low, 3 = medium, 4 = high, 5 = very high.

viii) Stiffness of the machine tool (S): Stiffness of the machine tool should be kept as higher as possible. A machine tool with rigid structured is capable to perform heavy duty operations with less vibrations and chattering. Thus quality of manufactured product is also improved. For safety, R scale is set as 1 = poor, 2 = moderate, 3 = high.

ix) Production rate (PR): Production rate is defined as the rate of output produced per unit time. It directly depends on the feed rate and cutting speed. But, it is not possible to increase the feed rate indefinitely because it will call for a higher rigidity of the machine tool and an increase in the cutting forces. This may ultimately result in the failure of cutting tool, poor surface finish and a distorted shape of the workpiece [75]. Production rate (PR) is expressed in relative (R) priority scale. R scale for production rate is set as 1 = very low, 2 = low, 3 = medium, 4 = high and 5 = very high.

x) Power (P): Here, the term ‘power’ means spindle power, which is required for successful and efficient operation of the machine tool and it should be kept at optimal level. But scarcity of desired power may hamper the quality and production rate. It is expressed here in terms of kilo-watt (kW).

d) Step - V: - The most critical and supreme task in developing a CBR system is collection of cases. An exhaustive CB containing all the successful cases is prepared from the real-time experiments that are conducted in machine shop. Some data are easily available from the experiments and machine tools' catalogue while others are collected from the experienced machine shop operators and production engineers. Data regarding cost, stiffness and production rate are collected in its raw form and then they are converted into R scale and are also validated by the production engineers and experts.

e) Step - VI: - In this step, soft computing techniques are utilized to personify the reasoning capability of the CBR system that is developed for machine tools selection problem. Real time data that are collected from the machine shop are indexed and organized in the CB using MS Access along with the theory of RDBMS. In this system, traditional indexing method is chosen and each case is stored against a case-id that is generated automatically as the knowledge acquisition phase progresses. Every case is assigned against each row and their attributes are assigned against each column along with a unique case-id and this standard record schema is referred as flat memory case representation. It is not necessary for a CBR system to retrieve the exactly matched case from the CB when user formulates a query. With partial numbers of attributes, full case which has the closest similarity, along with its problem part and solution part is retrieved. More the number of attributes are provided to the CBR system, more will be refinement and more exact cases are retrieved. In k-NN algorithm, similarity is calculated over each process characteristics and finally summed up to get the best matched case. In this proposed CBR system hamming distance is calculated using equation no 2.3, between the query values and stored values for each process characteristics. Then, all these similarity scores are summed up to get the overall similarity using equation no 2.2.Finally, similarity score is represented by percentage value. Case that has highest similarity percentage is selected as the best matched case. Also, in this proposed CBR system, equal weight is provided to each attribute, as every attribute has same importance in this machine tool selection problem. Finally, the proposed solution is reused by the user to solve present problem. As all the cases that are stored in the CB are accumulated from real time experiments, so the option of revision is not provided in this CBR system.

In this present CBR system, retrieval is done in two stages. At first, an initial matching is done against the work material and shape feature combinations. In the very next stage, an option for providing the ranges of various process characteristics is given to the user. This developed CBR system accepts these ranges intelligently as it is desired that MRR, S and PR of a machine tool should be maximized while SR, Tol, PA, RP, RS, C and P should be minimized. Based upon these attributes that are provided by the user in both first and second screen, case with highest similarity is displayed. Also, if there are some missing attributes that are unknown to the user before generating the query, is also provided by the CBR system. In the third screen, other operational parameters along with specified machine tool, which is used for machining operation, are also presented to the user.

In this context, to validate the acceptability of the proposed CBR model, three real time examples are provided herewith by means of a computer that has an Intel® Core^{TM} 5-2450M CPU @2.50 GHz, 2.00 GB RAM operating platform:

Example 3.1: Surface of revolution on steel

In this example, surfacing operation (surface of revolution) is carried out on cylindrical steel bar. In the primary selection window 'steel' is provided as work material and 'surfacing (surface of revolution)' is provide as the shape feature to be generated. A set of feasible

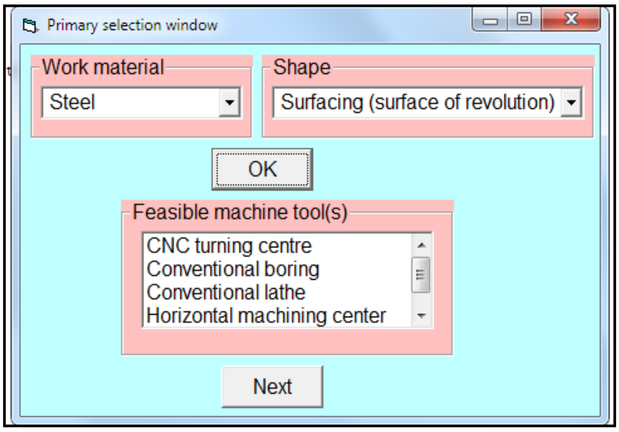


Figure 3.1 Primary selection window for Example 3.1

machine tools is proffered to the user, by this primary selection window, when 'OK' button is clicked. Primarily feasible machine tools those are capable to generate desired shape on steel are CNC TC, conventional boring, conventional lathe, HMC and VMC (Figure 3.1). When 'Next' button is clicked, user is guided to the final selection window, where a list of process characteristics is presented to the user (Figure 3.2). MRR, SR, Tol , RP, C, PR, P is considered as the most pertinent process characteristics by the user. When the 'Enter range' button is clicked, options for providing the ranges of selected process characteristics are catered to the user. Ranges for MRR - 0.10 to 0.18 g/min, SR - 5 to 8 µm, Tol – 0.005 to 0.05 mm, RP - 0.05 mm to 0.08 mm, C - 3 to 4 is R scale, PR - 3 to 5 in R scale and P - 5.5 to 7.5 kW are opted for consideration. When 'Best machine tool' button is pressed, CBR system automatically selects CNC TC as the best feasible machine tool for the desired process parameters and process characteristics. As discussed above, this selected case has the highest similarity among the other primarily matched cases that are contained in the CB. The selected machine tool can achieve values of MRR as 0.18g/min, SR as 5.1µm, Tol as 0.005mm, PA as 0.005mm, RP as 0.05mm, RS as 0.03mm, C as 3 (in R scale), S as 2 (in R scale), PR as 5 (in R scale) and P as 5.5Kw. After clicking on the best machine tool, which is displayed in a text-box just beside the 'Best machine tool' button, user is guided to the next screen as shown in Figure 3.3. Here, several operational parameters along with the name of manufacturer of the machine tool and range of procurement cost of the machine tool in USD are provided to the user.

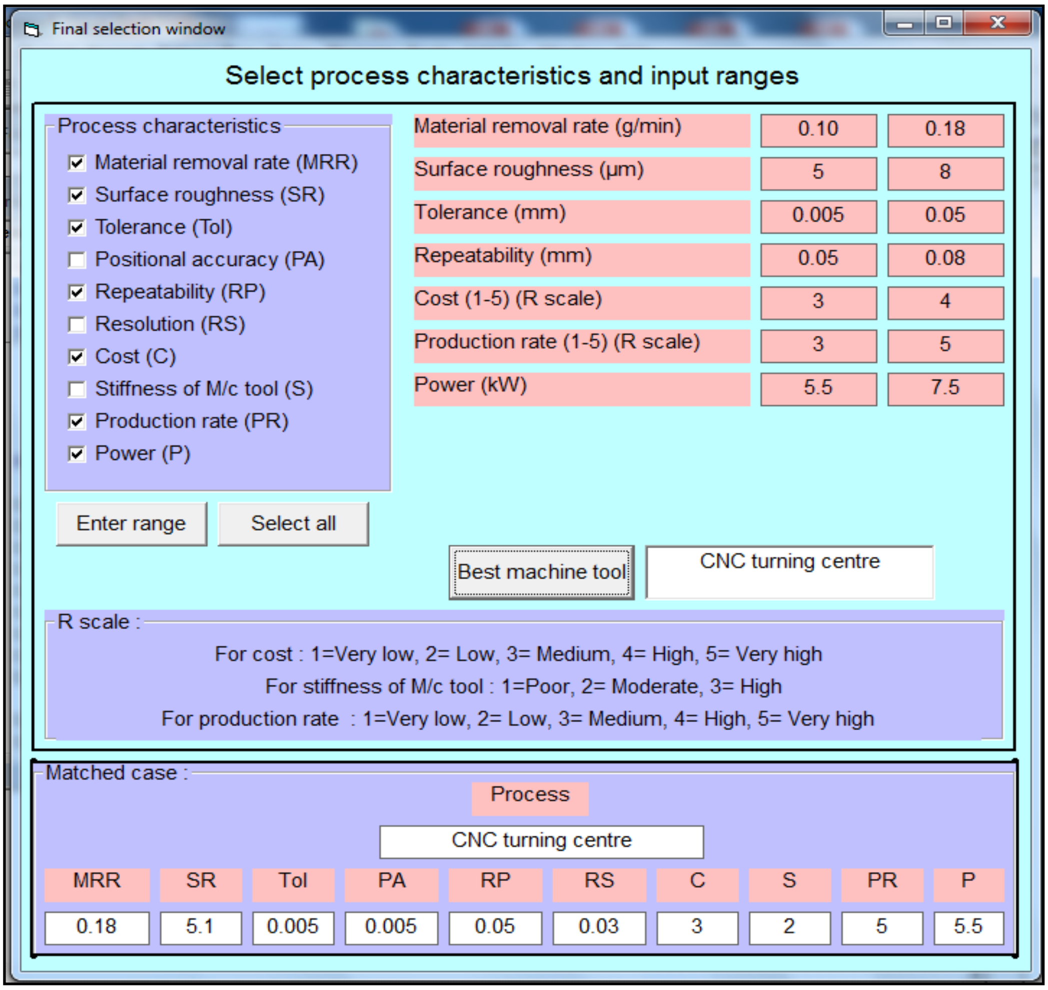


Figure 3.2 Final selection window and best machine tool for Example 3.1

Taking this result as a plinth, user may reconsider the ranges of process characteristics for fine tuning. Values of these parameters are tentative and best machining performance is achieved by using them in the machine shop.

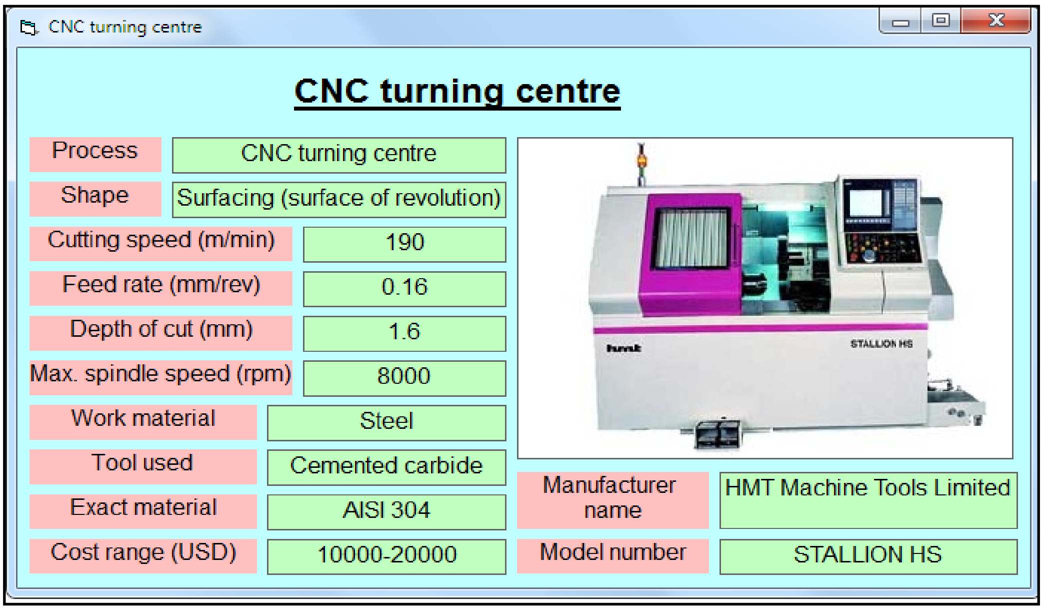


Figure 3.3 Details of operational parameters and machine tool

Example 3.2 Shallow pocketing on aluminium

In this example pocketing operation is performed on rectangular aluminium bar. This pocketing operation is termed as shallow pocketing because the depth of pocket is less than 3mm from the surface of the bar. Primary filtering is carried out when user opted ‘aluminium’ as work material and ‘Pocketing (shallow - t<3mm)’ as shape. Primary selection

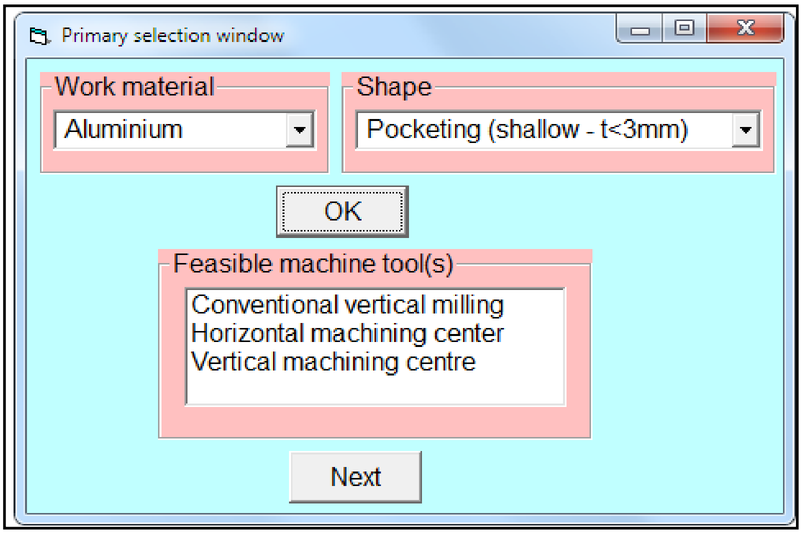


Figure 3.4 Primary selection window for Example 3.2

window is shown in Figure 3.4. After pressing ‘OK’ button, a list of feasible machine tools is catered to the user. These include conventional vertical milling, VMC and HMC. After pressing the ‘Next’ button user is guided to the final selection window as shown in Figure 3.5.

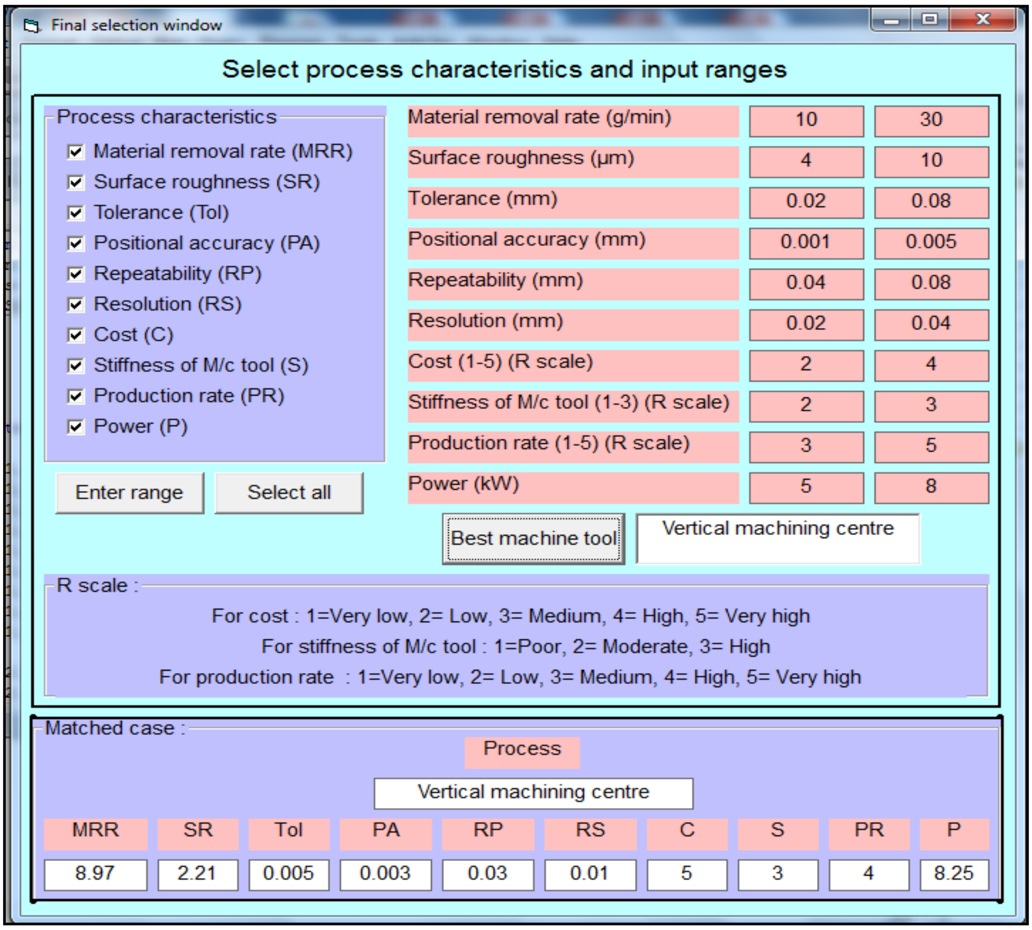


Figure 3.5 Final selection window and best machine tool for Example 3.2

Here, 'Select all' button is pressed to select all the process characteristics for best result. Input ranges of process characteristics are provided in the respective boxes. In this example, ranges given for MRR as 10g/min to 30g/min, SR as 4µm to 10µm, Tol as 0.02mm to 0.08mm, PA as 0.001mm to 0.005mm, RP as 0.04mm to 0.08mm, RS as 0.02mm to 0.04mm, C as 2 to 4 (in R scale), S as 2 to 3 (in R scale), PR as 3 to 5 (in R scale) and P as 5kW to 8kW. After clicking on the 'Best machine tool' button, CBR system automatically selects VMC as the best machine tool for the provided process parameters and process characteristics. The best matched case can attain the value of MRR as 8.97g/min, SR as 2.21µm, Tol as 0.005mm, PA as 0.003mm, RP as 0.03 mm, RS as 0.01mm, C as 5 (in R scale), S as 3 (in R scale), PR as 4 (in R scale), P as 8.25kW. It is seen from Figure 3.5 that there is a mismatch between the ranges provided to the CBR system and the values of process characteristics that are retrieved from the CB of the CBR system. All the values of process characteristics are not in the desired range. When the text-box just beside the 'Best machine tool' button is clicked, user is guided to the next window, shown in Figure 3.6. In this window detailed operational parameters along with machine tool manufacturer's name, model number and photograph of the machine tool is provided to the user. Also, a range of procurement cost in USD is provided to the user. From this window an idea about the operational parameters is obtained by the user. These are the tentative operational parameter settings and for achieving maximum machining performance, fine-tuning of these parameters maybe required.

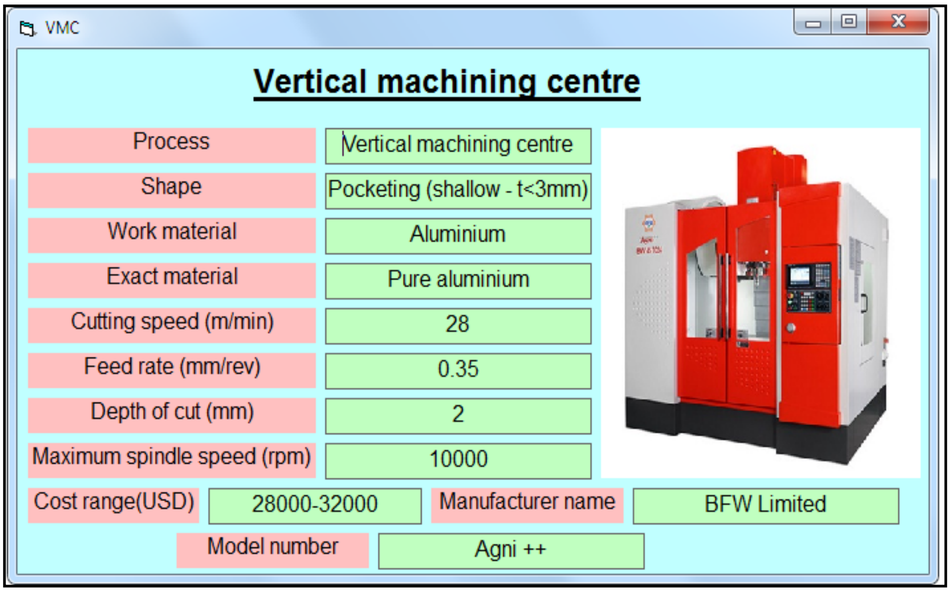


Figure 3.6 Details of operational parameters and machine tool

Example 3.3 Precision through hole on composite material

In this example, through hole (precision - L/D>3) is generated on composite material. In the primary selection window, as shown in Figure 3.7, the developed CBR system first extracts seven feasible machine tools, i.e. CNC drilling, CNC TC, conventional drilling, conventional lathe, conventional vertical milling, VMC and HMC as the feasible options satisfying the said work material and shape feature combination requirement.

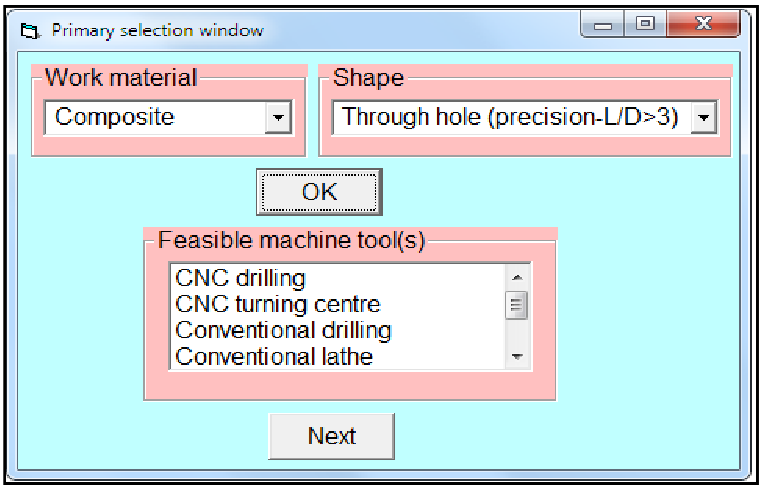


Figure 3.7 Primary selection window for Example 3.3

In Figure 3.8, SR, Tol, C, S, PR and P are chosen as the most important process characteristics based on which final machine tool needs to be selected. Based on the range of values for these process characteristics, CNC drilling is identified as the best matched

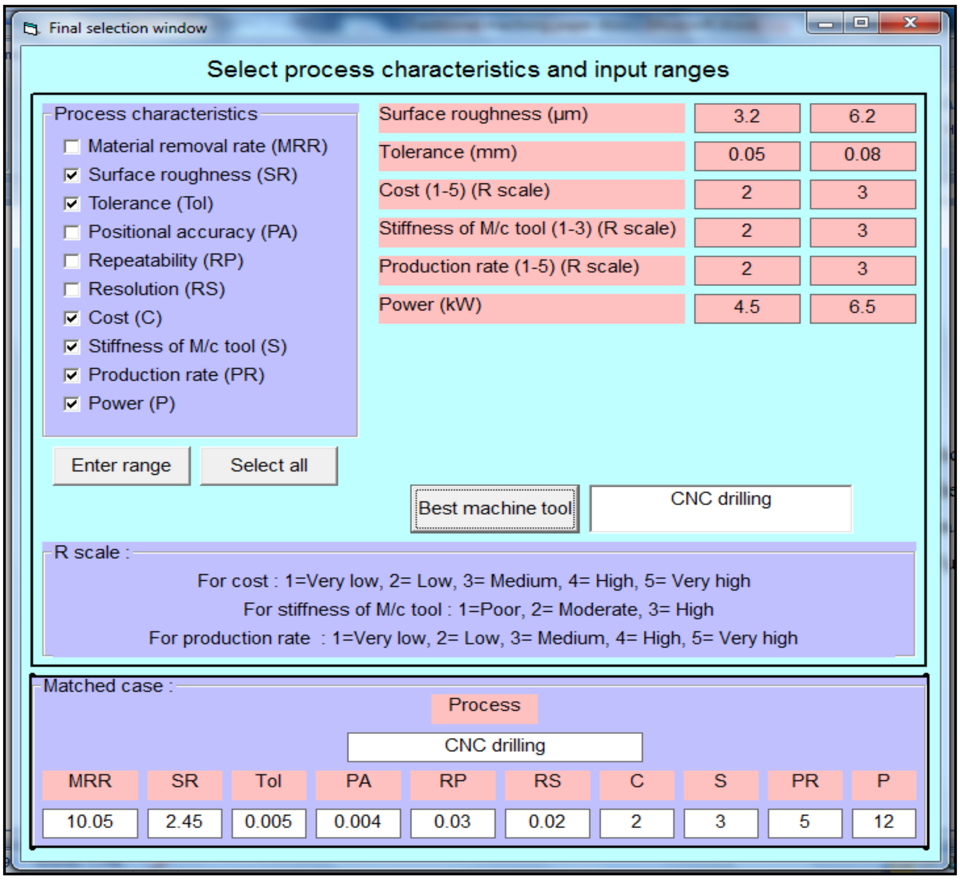


Figure 3.8. Final selection window and best machine tool for Example 3

machine tool for this application. For CNC drilling, the attainable process characteristics are MRR as 10.05g/min, SR as 2.45µm, Tol as 0.005mm, PA as 0.004mm , RP as 0.03mm, RS as 0.02mm, C as 2 (in R scale), S as 3 (in R scale), PR as 5 (in R scale), P as 12kW. In Figure 3.9, the tentative operational parameter settings and the name of the machine tool

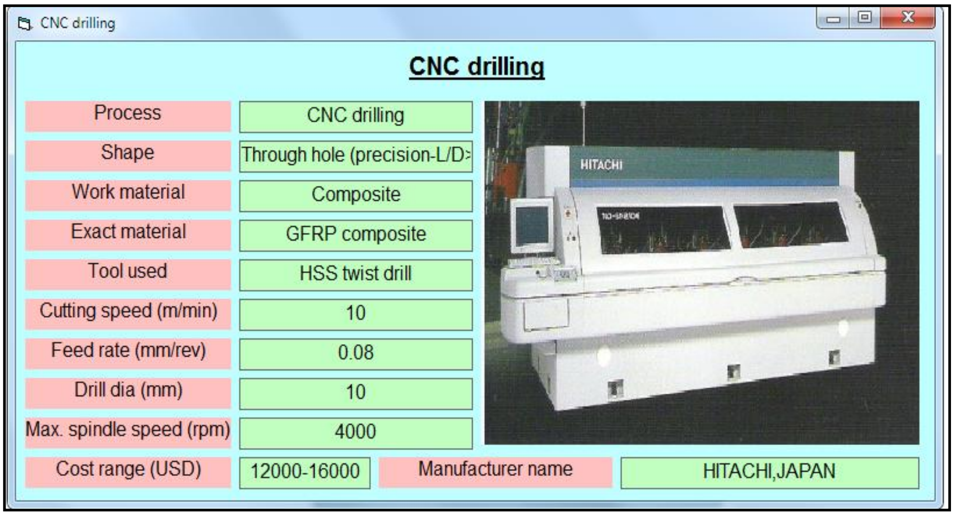


Figure 3.9 Details of operational parameters and machine tool

manufacturer's along with the approximate procurement cost in USD is displayed to the user to achieve the best machining performance.

4.0 NON-TRADITIONAL MACHINING PROCESSES SELECTION USING CASE-BASED REASONING APPROACH

In this section, an attempt is made to select NTM processes for a particular workpiece material and shape feature combination. Till date, approximately 20 NTM processes are already developed and applied in modern manufacturing industries. . In this developed CBR approach-based decision making model, nine NTM processes, i.e. AJM, AWJM, EDM, LBM, USM, ECM, ECDM, PAM and WEDM are taken into consideration. Brief descriptions of the aforesaid NTM processes are already cited in section 1.2.

During the development of this CBR system, several process parameters and process characteristics are taken into considerations, which are cited below: -

a) Type of workpiece material: - Eight types of workpiece materials are considered in this system. They are: i) steel, ii) superalloys, iii) composites, iv) ceramics, v) aluminium alloys, vi) aluminium, vii) glass and vii) titanium.

b) Surface feature to be generated: - Above-mentioned NTM processes are capable to 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).

c) MRR: - It is considered in terms of milligram/minute. In NTM processes, it is always desired to maximize the MRR.

d) SR: - Surfaces generated by NTM process are too smooth. SR is expressed in µm. In NTM processes, it is always desired to minimize the SR.

e) Surface damage (SD): - Due to excessive heat (i.e. in LBM) or due to some mechanical collisions (i.e. in AJM or AWJM), surface of the workpiece material gets damaged upto some thickness. Surface damage is also expressed in terms of µm. In NTM processes SD should be minimized.

f) Tolerance (Tol): - It is expressed in terms of mm. It is always desired to get fine tolerance.

g) Overcut (OC): - This is the gap between tool and the workpiece material. This parameter is too much prominent is EDM, WEDM. It is expressed in terms of mm. In NTM processes, OC is always desired to be minimized.

h) Corner radii (CR): - During the production of a hole or through cutting of a sheet, corners of the hole or sheet are not always sharp. During machining operation, a radius is produced at those corners. This is known as corner radii (CR). In NTM processes, it is always desired to minimize the CR. It is expressed in terms of mm.

i) Taper (TP): - This parameter becomes prominent during the production of hole or during through cutting. The joining line between the upper and lower surface of the workpiece material gets deviated. It is expressed in terms of mm/mm. It is always desired to minimize the TP.

j) Cost (C): - It includes procurement cost, overhead cost and labour cost incurred during machining operation. It is expressed in terms of relative (R) priority scale. 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. It is always desired to minimize the C.

k) Power (P): - It is basically the rated power, required during the machining operation. It is expressed in terms of kW. It is always desired to minimize the P.

l) Safety (S): - Safety is a major criterion during NTM processes. It is also expressed in R scale. For safety, the R scale is set as 1 - highly safe, 2 - safe and 3 - attentions required. It is desired to maximize the S in NTM processes.

Data of relevant machining characteristics for different NTM processes are accumulated from experiments, machining data handbooks and other reliable resources to create the corresponding CB.

Steps followed during the development phase of this CBR system are almost same as the steps followed during the development of CBR system for machine tool selection. The software prototype of the proposed CBR system is also developed in Visual Basic 6.0, in an Intel® Core™ 5-2450M CPU @2.50 GHz, 2.00 GB RAM operating platform. The potentiality of the developed CBR system is cited by means of three real-time examples as below:-

Example 4.1 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 Figure 4.1, a set of feasible NTM processes consisting of AJM, AWJM, ECDM, ECM, EDM, LBM and USM is displayed, when ‘OK’ button is clicked. All these processes can generate standard holes on composite materials. In the next window of Fig. 4.2, 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 0-0.05 mm, OC 0-0.05 mm, CR 0-0.05 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

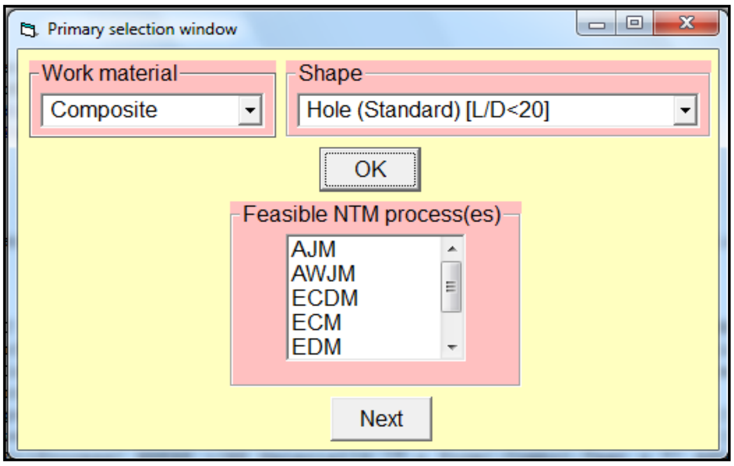


Figure 4.1 Primary selection window for Example 4.1

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 Figure 4.3, 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 Figure 4.3.

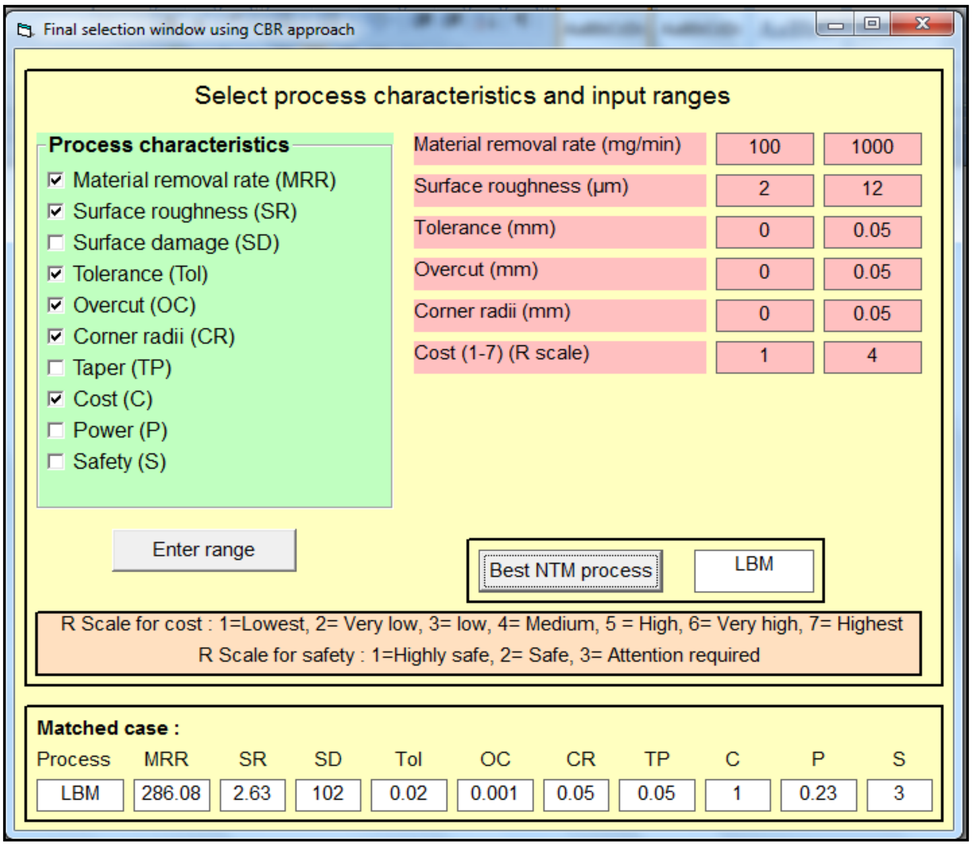


Figure 4.2 Best NTM process for Example 4.1

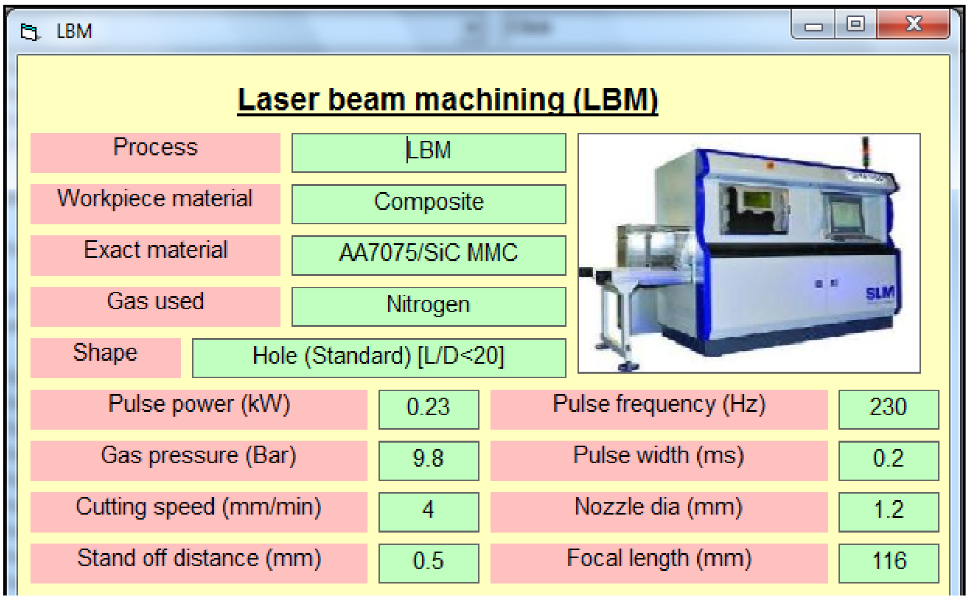


Figure 4.3 Details of LBM process

Example 4.2 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 Figure 4.4, 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.

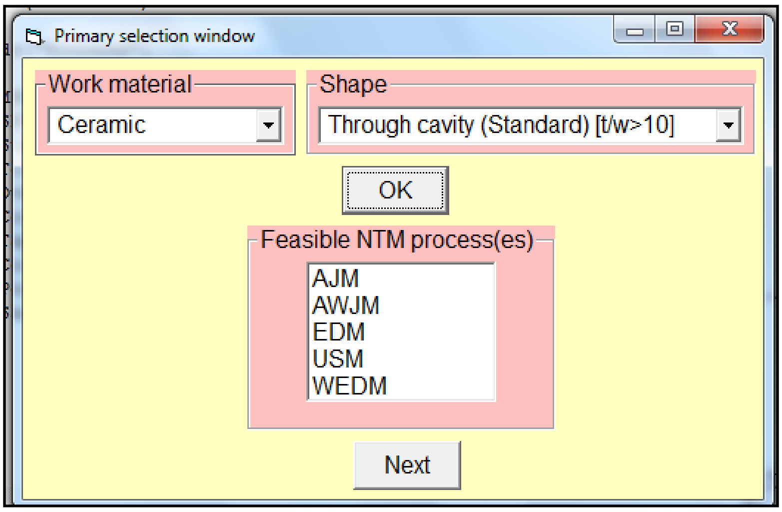


Figure 4.4 Primary selection window for Example 4.2

In Figure 4.5, 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). In Figure 4.6, 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.

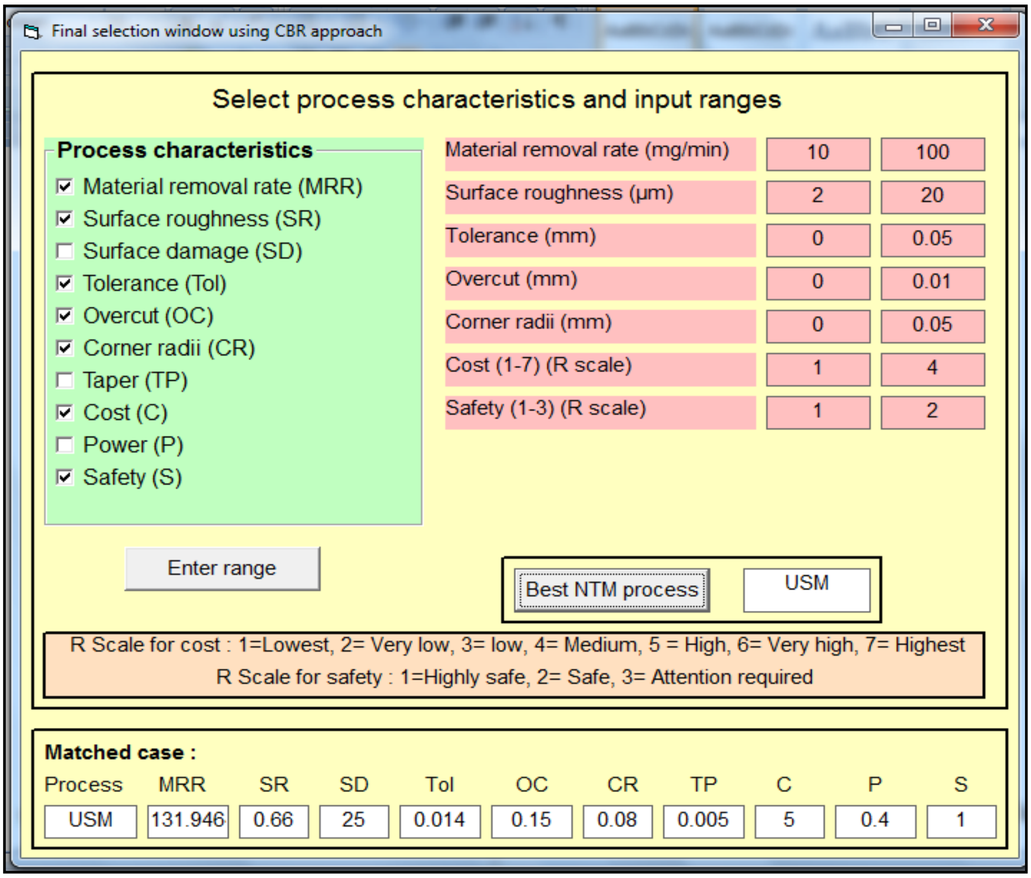


Figure 4.5 Best NTM process for Example 4.2

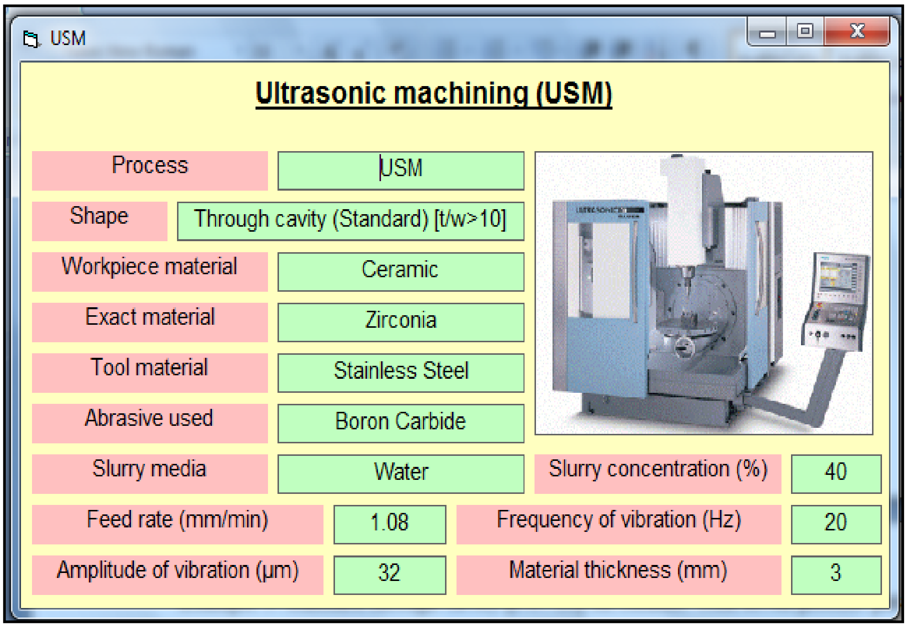


Figure 4.6 Details of USM process

Example 4.3 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 Figure 4.7. Then, in Figure 4.8, 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.

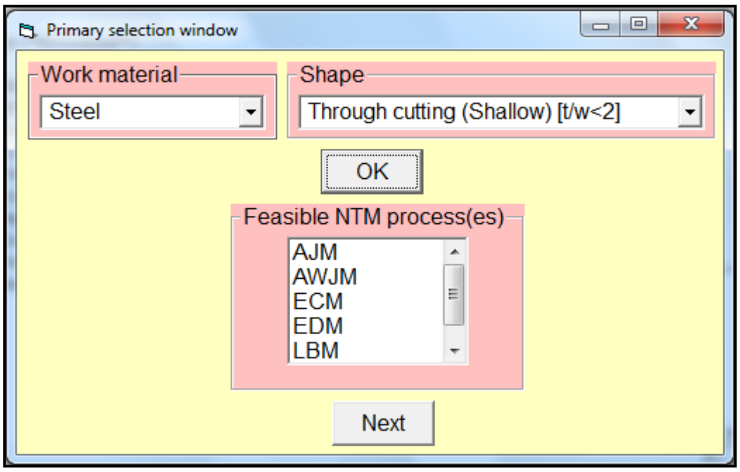


Figure 4.7 Primary selection window for Example 4.3

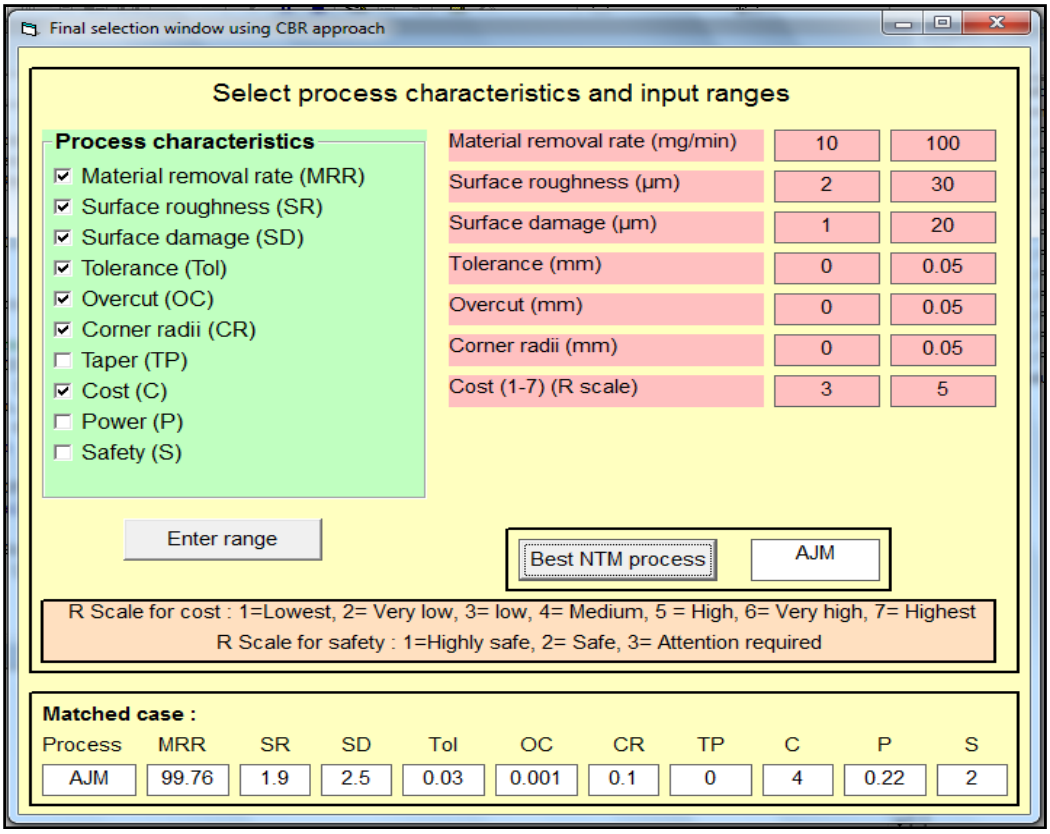


Figure 4.8 Best NTM process for Example 4.3

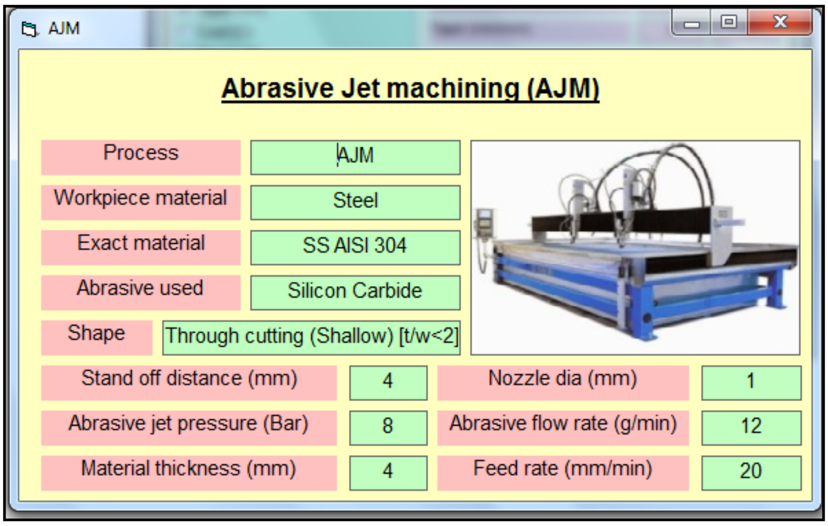


Figure 4.9 Details of AJM process

The developed CBR system identifies AJM as the most appropriate NTM process for generating a shallow through cut on steel material. In Figure 4.8, 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 Figure 4.9, 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.

5.0 CONCLUSIONS

Based on the set objectives and results obtained from the developed CBR system, the following conclusions can be drawn:

a) CBR system can be applied in several domains for decision making purposes, where the availability of knowledge is not adequate. Collection of past cases is easier than to represent the knowledge through formal 'IF-THEN' rules.
b) Several traditional as well as advanced methods for case indexing, case representation, case organizing, case retrieving, reusing of past cases and revision of past cases if necessary, are discussed in this work.
c) Several machine tools as well as non-traditional machining processes are discussed along with their capabilities and working principles.
d) Successful past cases of machine tools selection and machining processes selection are stored in MS Access. A software prototype is developed in Visual Basic 6.0 to automate the CBR system. Visual Basic 6.0 is integrated with structured query language (SQL). Stored cases in MS Access are accesses by SQL statements. An idea about the basic principles of RDBMS is also mentioned for accessing these cases and relating the process characteristics with each others.
e) This proposed CBR model is applied to select most appropriate machine tool and machining process for a particular material and shape feature combinations. Several useful materials and shape features along with some important process characteristics are considered during this selection process.
f) Real-time examples are also provided to validate the proposed CBR model.

Based on the CBR approach, many decision making tasks can be solved very easily. User of the CBR system does not have to think repeatedly past cases. So, time can be saved and concrete solutions can be provided to the present problem instantly.

This work cited the applicability of CBR system in the field of production engineering. This research work may be extended by introducing it in other fields of engineering, such as in automobile engineering, material science, power plant engineering, heat treatment processes etc. Still, researches are going on to improve the learning and reasoning capabilities of the CBR system.

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