APPLICATIONS OF DATA MINING TOOLS IN MACHINING PROCESSES

By

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1.0 INTRODUCTION

1.1 An Introduction to Machining Processes

Machining is any of various processes in which a piece of raw material is cut into desired shape and size by a controlled material removal process. It is the term used to define the combination of all the process that involved in removal of material of any workpiece [1]. Survey indicate that 15 % of all mechanical components value, manufactured in the world, comes from machining. Machining is a type of manufacturing process which is not only applicable for metals but it is used on ceramics, wood, plastics and composites as well.

The precise meaning of the term machining has evolved over the past one and a half centuries as technology has advanced. In the 18th century, the word machinist simply meant a person who built or repaired machines. This person's work was done mostly by hand, using processes such as the carving of wood and the hand-forging and hand-filing of metal. At the time, millwrights and builders of new kinds of engines (meaning, more or less, machines of any kind), such as James Watt or John Wilkinson, would fit the definition. The noun machine tool and the verb to machine (machined, machining) did not yet exist. Around the middle of the 19th century, the latter words were coined as the concepts that they described evolved into widespread existence. Therefore, during the Machine Age, machining referred to the "traditional" machining processes, such as turning, boring, drilling, milling, broaching, sawing, shaping, planing, reaming, and tapping. In these "traditional" or "conventional" machining processes, machine tools, such as lathes, milling machines, drill presses, or others, are used with a sharp cutting tool to remove material to achieve a desired geometry [2].

Since the advent of new technologies in the post–World War II era, such as electrical discharge machining, electrochemical machining, electron beam machining, photochemical machining, and ultrasonic machining, the retronym "conventional machining" can be used to differentiate those classic technologies from the newer ones. In current usage, the term "machining" without qualification usually implies the traditional machining processes. There are two types of machining processes:

a) Conventional or traditional machining process
b) Non-traditional machining process.

1.2 Traditional machining process

Traditional or conventional machining processes can be defined as a process using mechanical energy to remove the material from the workpiece to develop the desired product. Traditional machining requires a tool that is harder than the workpiece that is to be machined.

This tool penetrates into the workpiece for a certain depth of cut. A relative motion between the tool and the workpiece is responsible for form and generation cutting to produce the required shapes, dimensions and surface quality. Such a machining arrangement includes all machining by cutting and mechanical abrasion processes [1, 2]. Machining processes which include cutting or grinding is desirable for the following basic reasons:

a) Closer dimensional tolerances, surface roughness, or surface-finish characteristics may be required than are available by casting, forming, powder metallurgy, and other shaping processes; and
b) Part geometries may be too complex or too expensive to be manufactured by other processes.

However, machining processes inevitably waste material in the form of chips, production rates may be low, and unless carried out properly, the processes can have detrimental effects on the surface properties and performance of parts.

Traditional machining processes consist of turning, boring, drilling, reaming, threading, milling, shaping, planing, and broaching, as well as abrasive processes such as grinding, lapping, and honing. Usually there is a direct contact between the tool and raw material. The classification of conventional machining process is shown in Figure 1.1. Some of the above mentioned machining processes are described in the next section. These machining processes use tools, such as lathes, milling machines, boring machines, drill presses, or others, with a sharp cutting tool for material removal to achieve the desired geometry.

A cutting tool has one or more sharp cutting edges and is made of a material that is harder than the work material. The cutting edge serves to separate chip from the parent work material. Connected to the cutting edge are the two surfaces of the tool: The rake face and the flank. The rake face which directs the flow of newly formed chip, is oriented at a certain angle is called the rake angle "α". It is measured relative to the plane perpendicular to the work surface. The rake angle can be positive or negative. The flank of the tool provides a clearance between the tool and the newly formed work surface, thus protecting the surface from abrasion, which would degrade the finish. This angle between the work surface and the flank surface is called the relief angle.

There are two basic types of cutting tools, namely single point tool and multiple-cutting-edge tool. A single point tool has one cutting edge and is used for turning, boring and planing. During machining, the point of the tool penetrates below the original work surface of the workpiece. The point is sometimes rounded to a certain radius, called the nose radius. Multiple-cutting-edge tools have more than one cutting edge and usually achieve their motion relative to the workpiece by rotating. Drilling and milling uses rotating multiple-cutting-edge tools. Although the shapes of these tools are different from a single-point tool, many elements of tool geometry are similar.

For abrasive cutting of the workpiece generally grinding process is preferred where the grinding wheel embedded with the abrasive particles, generally harder than the workpiece, is used to grind or abrade the unwanted material from the workpiece and generates a glossy surface finish product.

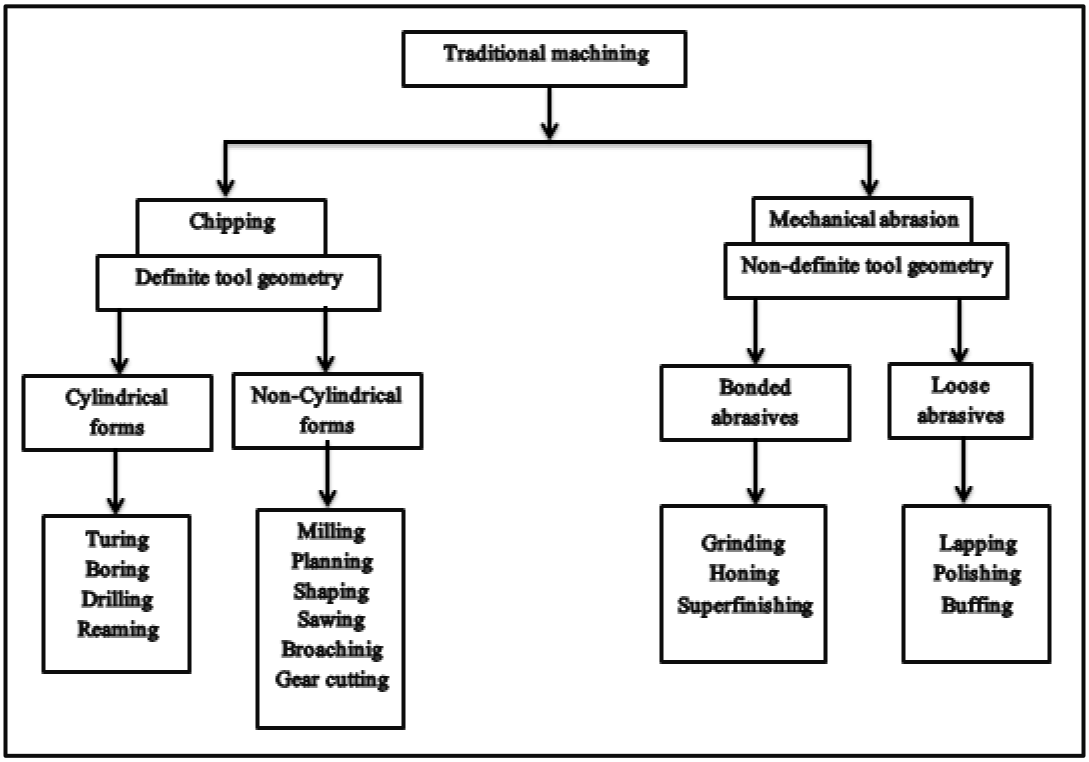

Figure 1.1 Classification of conventional machining process

The advantages of Conventional machining processes are as follows:

a) A high surface finish can be obtained.
b) Machining is not only performed on the metal but it also performs on wood, plastic, composites, and ceramics.
c) Variety of geometry features are possible, such a screw threads, very straight edges, accurate round holes etc.
d) Good dimensional accuracy.

The limitations of the conventional machining process are descried below:

a) The accuracy of the components produce is dependent on the efficiency of the operator.
b) The consistency in manufacturing is not present. Hence 100% inspection of the component is required.
c) The personal needs of the operator are reducing the production rates.
d) Because of a large amount of Manpower involved, the labor problem will also be high.
e) The complex shapes like parabolic curvature components, cubicle curvature components are difficult to manufacture.
f) Frequent design changes in the component cannot be incorporated into the existing layout.

1.2.1 Grinding

Grinding is the most common form of abrasive machining. It is a material cutting process that engages an abrasive tool whose cutting elements are grains of abrasive material known as grit [3]. These grits are characterized by sharp cutting points, high hot hardness, chemical stability and wear resistance. The grits are held together by a suitable bonding material to give shape of an abrasive tool. Grinding machine is employed to obtain high accuracy along with very high class of surface finish on the work piece. However, advent of new generation of grinding wheels and grinding machines, characterized by their rigidity, power and speed enables one to go for high efficiency deep grinding (often called as abrasive milling) of not only hardened material but also ductile materials. Grinding wheel is best described by its grain size and bonding materials.

Compared to the normal cutting tool, the abrasive used in grinding wheels are relatively small. The size of an abrasive grain or more generally called grit is identified by a number which is based on the sieve size used. This would vary from a very coarse size of 6 to 8 to a super fine size of 500 or 600. Sieve number is specified in terms of the number of opening per square inch. The surface finish generated would depend upon grain size used. The fine grain will take a very small depth of cut and hence a better surface finish is produced. Fine grains generate less heat are good for faster material removal. Fine grains are used for making the form grinding wheels. Coarse grains are good for higher material removal rates. These have better friability and as a result are not good for intermittent where they are likely to chip easily. The bonded abrasives can be a composite of the abrasive powder and a matrix and of glass, resin, or rubber. The abrasives can be embedded in solid discs or bonded to paper/cloth which is then stuck to a backing disc. The most commonly used bond materials are vitrified, silicate, synthetic resin, rubber, shellac and metal.

Centre-less grinding is used to grind cylindrical work-piece without actually fixing the work-piece using centers or a chuck, due to which the work rotation is not provided separately. This consists of wheel, one large grinding wheel and another smaller regulating wheel. The work-piece is supported by the rest blade and held against the regulating wheel by the grinding force which is mounted at an angle to the plane of grinding wheel. The regulating wheel is generally a rubber or resinoid bonded wheel with wide face. The axial feed of the work-piece is controlled by the angle of tilt of the regulating wheel. Typical work speeds are about 10 to 50 m/mm. There are three types of centre-less grinding operations possible. They are:

a) Through feed centre-less grinding.
b) In feed centre-less, the grinding is done by plunge feeding so that any form surface can be produced. This is useful if the work-piece has an obstruction which will not allow it to be traversed past the grinding wheel. The obstruction could be a shoulder, head, round form, etc.
c) End feed centre-less grinding, where tapered work-piece can be machined.

Conventional grinding machines can be broadly classified as:

a) Surface grinding machine
b) Cylindrical grinding machine
c) Internal grinding machine
d) Tool and cutter grinding machine

There are several advantages of the grinding process. A grinding wheel requires two types of specification- dimensional accuracy and good surface finish. It has an excellent good form and location accuracy. It is applicable to both hardened and unhardened material. Grinding has innumerable applications. Some of the applications are described below:

a) Surface finishing
b) Slitting and parting
c) Descaling and deburring
d) Stock removal (abrasive milling) finishing of flat as well as cylindrical surface
e) Grinding of tools and cutters and re sharpening of the same.

Conventionally grinding is characterized as low material removal process capable of providing both high accuracy and high finish. However, advent of advanced grinding machines and grinding wheels has elevated the status of grinding to abrasive machining where high accuracy and surface finish as well as high material removal rate can be achieved even on an unhardened material.

1.2.2 Turning

Turning is a form of machining, a material removal process, which is used to create rotational parts by cutting away unwanted material. The turning process requires a turning machine or lathe, workpiece, fixture, and cutting tool. The workpiece is a piece of pre-shaped material that is secured to the fixture, which itself is attached to the turning machine, and allowed to rotate at high speeds. The cutter is typically a single-point cutting tool that is also secured in the machine, although some operations make use of multi-point tools. The cutting tool feeds into the rotating workpiece and cuts away material in the form of small chips to create the desired shape. Turning can be performed on a variety of materials including aluminum, brass, magnesium, nickel, steel, thermoset plastics, titanium and zinc [4].

Turning machine, also referred as lathes, can be found in a variety of sizes and designs. A manual lathe requires the operator to control the motion of the cutting tool during the turning operation. Turning machines are also able to be computer controlled, in which case they are referred to as a computer numerical control (CNC) lathe. CNC lathes rotate the workpiece and move the cutting tool based on commands that are preprogrammed and offer very high precision [5]. In this variety of turning machines, the main components that enable the workpiece to be rotated and the cutting tool to be fed into the workpiece remain the same.

The tooling that is required in turning is typically a sharp single-point cutting tool that is either a single piece of metal or a long rectangular tool shank with a sharp insert attached to the end. These inserts can vary in size and shape, but are typically a square, triangle or diamond shaped piece. These cutting tools are inserted into the turret or a tool holder and fed into the rotating workpiece to cut away material. The most common tool materials are high speed steel, carbide, carbon steel and cobalt high speed steel. The tools that are used in turning are determined through tool properties include the tool’s hardness, toughness and resistance to wear. In turning, the speed and motion of the cutting tool is specified through several parameters like cutting feed, cutting speed, spindle speed, feed rate, axial depth of cut, radial depth of cut. These parameters are selected for each operation based upon the workpiece material, tool material, tool size and more.

Turning can produce a variety of revolved shapes. The typical cutting operations on a lathe are turning, taper, profile cut, groove cut, cut-off, thread cut, facing, face grooving, boring and internal grooving, drilling and knurling. Among these operations, only drilling requires the tool to be fed by moving the tailstock along the slide. In all other processes, the bar stock is held in a fixture at the spindle, with opposite planar.

Turning has a number of advantages. Some of them are stated below as:

a) Easy to perform the operation.
b) Person with little skill set can perform the operation.
c) Material removal rate is flexible.
d) Close tolerance parts can be obtained.
e) Multiple operations can be performed with same tool or same job position.
f) Surface finish of desired accuracy can be obtained to extent.

Turning is used to produce rotational, typically axis-symmetric, parts that have many features, such as holes, grooves, threads, tapers, various diameter steps, and even contoured surfaces. Parts that are fabricated completely through turning often include components that are used in limited quantities, perhaps for prototypes, such as custom designed shafts, engine components and fasteners. Turning is also commonly used as a secondary process to add or refine features on parts that were manufactured using a different process. Due to the high tolerances and surface finishes that turning can offer, it is ideal for adding precision rotational features to a part whose basic shape has already been formed.

1.3 Non-traditional machining process (NTM)

In the early days, tools were made from stone or tree barks. These types of tools were very rough and easily got blunt. With the advent of time the knowledge of the usage of hard and tough material, e .g. ceramics, alloy steel, diamond etc., came into picture. After this they were seeking for a machining operation to make a sharp edge and to give desired shapes and sizes. The conventional machining mainly rely on the electrical energy, gravity and hydraulic energy and the harder material than the workpiece to perform several operations like turning, drilling etc.

With the advent of time, the more challenging problems were faced by the researchers. There increased the demand for the higher production rate, new material with less machinability and high dimensional accuracy and to generate complex geometry like generating turbine blades, blind or through hole in jet nozzle, etc. Again the nano and the micro fabrication were very difficult for the traditional type of machining. To overcome the above problems two suggestions were proposed either to upgrade the current traditional machining process or to propose a completely new process. There came the non-traditional machining process.

Non-traditional machining process is the type of machining process where the materials are removed with the help of mechanical, thermal, electrical or chemical energy or the combination of these energies without the involvement of sharp cutting edge tool alike that of traditional machining process. The non-traditional machining can easily process the hard and brittle materials with high feasibility ratio and very economically. It can overcome various traditional machining challenges like very fragile materials are difficult to clamp for traditional machining operation, difficult to machine when the desired shape are too complex or the workpiece is too flexible or slender [7].

The characteristics of Non-traditional machining process are as follows:

a) In NTM, the physical touching of tool may not be present. For example in laser or hydro jet machining there is no physical touching of the tool but in case of USM physical tool of touching may be there may not be. In laser or plasma etc. there is no physical tool present into system. But in case of ECM or EDM the electrode acts as a tool for the system. Due to no physical touching action, there very less to zero tool wear in the operation.
b) In NTM there is no restriction for the use of material of the tool. For e.g. In EDM, copper can be used as a tool material for the machining of hardened steel.
c) In NTM, the material may not be necessarily removed in the form of chips. For e.g. in AJM chips are in micro-size, in case of LBM no chips are formed (the formed chips are evaporated), in case of ECM the material removal the material removal occur because of electrochemical dissolution.
d) In NTM, all form of energy can be utilized to remove the material out from the workpiece, for example LBM utilized Laser/photons energy, USM uses the vibration energy, ECM uses the electrical energy etc.

The necessity for the NTM processes are describes below:

a) Micro machining and nano fabrication is very difficult in case of the traditional machining. But the NTM process can generate micro and nano feature with ease.
b) Producing complex geometry is very difficult and very time consuming in case of traditional machining. But NTM process can generate complex geometry with ease.

c) Several materials like Ti-alloys, ceramics, carbides, stellites etc. are very difficult to machine in case of traditional machining process but these type of material can be easily machined by NTM processes.

d) Machining of composites is very difficult in case of traditional one but it can be easily machined by NTM process.

e) Traditional machining produces poor quality workpiece with poor surface finish (if the workpiece is made of hard and brittle material). High surface quality can be easily generated with NTM process.

The selection for the best machining process can be based on following aspects:

a) Process parameters.
b) Process capabilities
c) Desired shape and size of the final product.
d) Economics of the operation.

The classification of the NTM process can be best described by Figure 1.2. NTM machining process has a huge number of applications in various domains. NTM is used to shape the ultra-hard alloys used in heavy industry and in aerospace applications and to shape the ultrathin materials used in such electronic devices as microprocessors. It has innumerable number of applications in medical field as well.

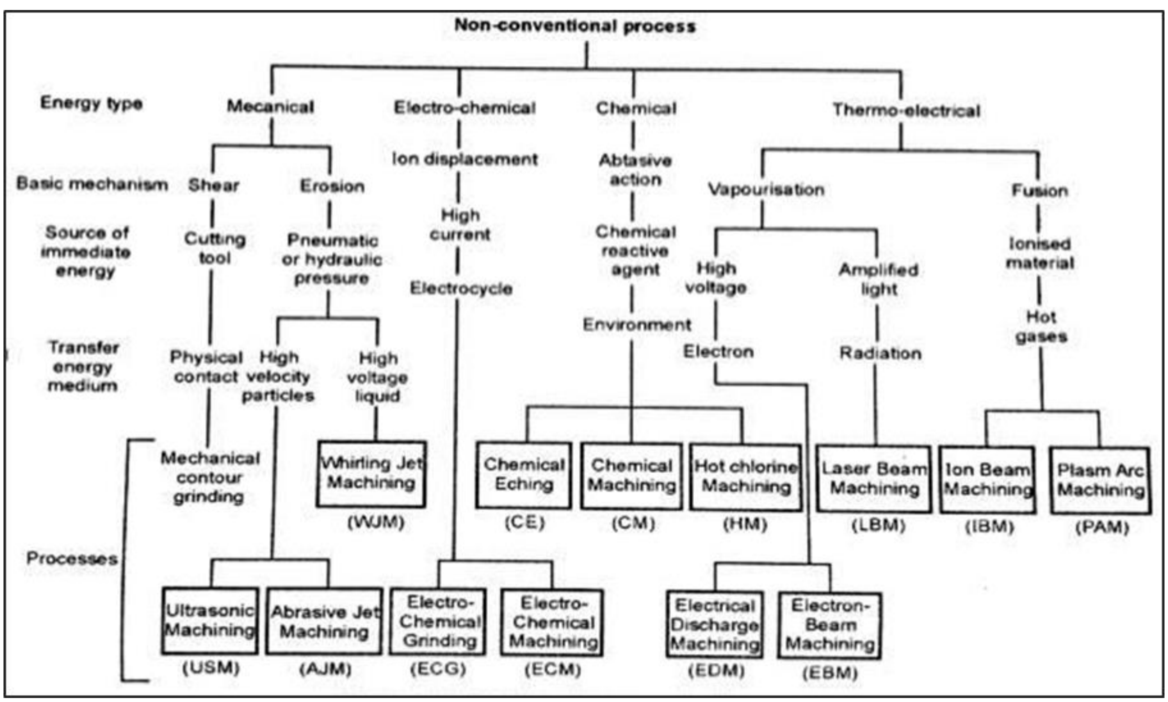

Figure 1.2 Classification of non-conventional machining process

1.3.1 Electrochemical process

Electrochemical process (ECM) is the machining process where the material is removed by anodic dissolution of electrolyte following the principal of Faraday law of electrolysis. It involves two electrodes which are connected to the high voltage power supply. A very small gap is maintained between the electrodes separated by an electrolyte for efficient exchange of ion and thus removal of material from the workpiece is done.

In ECM, the tool is connected to the negative terminal of battery whereas the workpiece to be machined is connected to the positive terminal of the battery. The main machine component of the ECM process is power supply, electrolyte filtration and delivery system, tool feed system and working tank. This power system provides very high ampere of direct current (e.g. 40,000A) and very low potential difference (2-35V). Electrolyte filtration and delivery system consists of piping system, storage tank, pump, control valve, pressure gauge, heating or cooling coil etc. This is mainly used to remove the dissolved sludge from the machining area and to provide the conductive medium for the flow of positive ions. Tool feeding system is used to linearly feed the tool on to the machining area to maintain the constant gap between the electrodes.

The working process of ECM can be summarized as [6, 7]:

a) The workpiece and the tool is assigned into the setups by maintaining the desired gap between the electrodes and the electrolyte filtration system is adjusted to provide the adequate flow of electrolyte in between the electrodes.
b) The second step is to attach the workpiece to the positive terminal of the battery while the tool is attached to the negative terminal of the battery and thus the current flow through the electrolyte.
c) With the advent of current into the system the removal of material from the workpiece starts. The feeding system starts working in order to maintain the gap between the electrodes.
d) The material from the cathode as the positive ion attracted towards tool via electrolyte and amalgamated with the ion present in the electrolyte and precipitate as sludge. This sludge is then removed from the machining area by the continuous supply of electrolytic solutions by pumping it at high pressure of around 10-15kg/cm2.
e) Here no spark is generated and hence the temperature is quite low and there is no direct contact between the tool and workpiece hence no wear and tear and no thermal damage is induced in the system.

f) The extraction of the metals from the workpiece takes place at atomic level, so it provides an excellent surface finish.
g) Finally the precipitate is separated from the electrolyte solution and the filtered electrolyte is again transported to the working area.

ECM has innumerable number of applications e.g. machining disk or turbine rotor blade, generating internal profile of internal cam, production of satellite rings and connecting rods, machining of gears etc.

1.3.2 Ultrasonic Machining

Ultrasonic machining is a machining process in which the material is removed from the workpiece with the help of high frequency vibrating tool in the presence of abrasive slurry. The ultrasonic machining is mainly performed in brittle material or the material with high hardness. The slurry is formed by mixing fine abrasives with water. The tool is mainly vibrating vertically or sometimes orthogonal to the surface of the workpiece to be machined.

The high frequency power source helps to vibrate the tool with low amplitude inside the slurry medium which contains fine abrasive particles. When the tool presses against the workpiece, the slurry abrades off the material from the workpiece.

The main components of ultrasonic machine are sonotrode, transducer and control unit. The control unit contains electronic oscillator which helps to generate very high frequency alternating current. The transducer converts electrical energy of the control unit into mechanical energy. This mechanical energy is transmitted to sonotrode which then vibrates the tool. The working of USM is described below [6, 7]:

a) In the initial stage transducer and sonotrode are connected to the control unit.
b) The electronic oscillator inside the control unit generates an alternating current with high ultrasonic frequency.
c) This high frequency alternating current is transmitted to transducer which converts electrical energy into mechanical energy and this mechanical energy is transmitted to the sonotrode.
d) This high frequency sonotrode hit the surface of the workpiece. This creates the pressure onto the slurry which contains abrasives particles to abrade off the material off from the surface of the workpiece.
e) In USM, a part of the erosion happens from the tool as well. So the tool needs to change after performing some experimental run.

f) As the slurry is present in between the workpiece and tool, so a large porting of heat as well as eroded by-products is carried away from the machining area by the flowing slurry. So the thermal failure does not happen here.

USM is applicable to both metals and non-metals. USM is the most reliable machining process for the brittle material e.g. glass, ceramics, hardened steel, carbides etc. It is used to manufacture the wire drawing dies of tungsten carbide and can also use to machine silicon quartz and synthetic ruby etc. In today's world it has a huge application on manufacturing micro-structured glass wafers.

1.3.3 Electrical discharge machining (EDM)

It is the process of removal of material from workpiece with the help of electrical discharges (sparks) in the presence of a dielectric medium. It is used to machine the material which is very difficult to machine or the material having high strength temperature resistant. It is only applicable for the electrically conductive type of material. Here the workpiece and the tool are connected to the very high voltage power supply and the dielectric fluid separates the electrodes while flowing in between.

EDM process works on the principle of spark generation and spark erosion on the workpiece material. A high potential difference is created between the workpiece and tool and a very small gap is maintained between them. Within the gap the dielectric medium (generally deionized water or kerosene) is allowed to flow. The workpiece is connected to the positive potential while the tool is connected to the negative potential, when the potential is applied the electrons from the tool moves towards the workpiece and while moving it collide with the dielectric medium molecules and ionized them. These accumulations of ions generate the path of current flowing in the form of sparks. Due to generation of spark, the heat is produced which helps to erode off and melt workpiece material to generate the desired cavities or features. After spark erosion, the gap is enlarged this caused the potential difference disbalancement and thus spark break down. The dielectric medium then flushed the eroded material from the machining zone and thus debris is created [6, 7].

The main component for the EDM is the power supply, dielectric fluid supply and the flushing system, tool and work piece holding devices. The high frequency current power supply is used to generate spark emission. The dielectric medium is used to create the sparking action and the flushing system is used to extract the machined material out from the machining zone. The dielectric medium also acts as a cooling medium to lower down the temperature of the machining zone. Tool and workpiece holding device is used to clamp the workpiece and tool to remain steady while machining and also feeding the tool material towards the workpiece to maintain the constant gap between them.

EDM is used to machine the conducting material only. The working of the EDM is described below:-

a) The tool and the workpiece are clamped by the tool and workpiece holding devices and to maintain the desired gap for the EDM to perform. Then the dielectric supply and flushing system incorporate the dielectric fluid into the system which helps to control the arc discharge and flushed out eroded workpiece out to the filtration unit.
b) A feeding servomechanism maintains the gap between the electrodes.
c) The tool is designed opposite in shape to the workpiece.
d) The high frequency power supply produce high potential difference between the two electrodes and due to this the spark is produces which erode off and melt the workpiece material to produce desired debris.
e) The eroded material is then removed from the machining zone by the dielectric fluid in order to prevent the bridging between the electrodes and thus prevent the short circuiting in the setup.

EDM is widely used to make burr free intricate shapes, sharp, small and narrow holes or slots and blind cavities. Dies sinking, plastic molding, die casting compacting, cold heading, extrusion, press tools, wire drawings are some of the application of EDM. It can be used to make the exact replica of the shapes present in the tool but in opposite sense. It has intense application in aircraft industries for manufacturing aircraft engines, diesel fuel injection nozzles and brake valves etc.

1.4 Objective of the Present Research Work

Many difficult and complicated decisions need to be taken in manufacturing industries which selecting an optimal setting for the machining parameter so as to obtain the customized output. The complex interrelationship among various influencing factors, availability of a large number of alternatives and complex mathematical calculations involved in the process make the decision making more time and money consuming for the decision makers. Hence there is a need for development of a systematic and logical approach which helps the experts to select the best settings among the wide range of alternatives and also to predict the outcome for customized setting without performing an actual experiment. Based on the aforesaid discussion and requirements, the objective of the present research works are set as follows:

a) To carry out detailed literature survey about the various machining processes and to study the Design of Experiments (DOE) and its implementation in experimentations.

b) To identify various non-traditional and traditional machining process for parametric analysis and optimization of multiple responses.

c) To carry out detailed literature survey about the various types of data mining processes and their application in solving real time problems.

d) To collect various data (control and output parameters) of the selected machining process.

e) Selection of appropriate data mining algorithm based on the desired knowledge to be discovered from the quality data.

f) To develop input-output parameter relationship modeling by applying various statistical techniques like association rule making technique, SVM technique etc.

g) Apply different data mining tools through different data analyzing software to extract valid, novel and ultimately understandable patterns for developing the relationship between parameters and responses in machining process and determine the optimal solution within the variable bounds.

h) To make a comparative analysis of the performances of various data mining algorithm.

i) To examine the results of applications of various data mining tools.

2.0 DATA MINING

2.1 What is data mining?

Many organizations have based their aggressive strategies around automation and new production technology by adopting different applicable tools. Amongst these tools is Data Mining. The advancement in the computing technologies has made owning and running knowledge management systems and data warehouses or data marts easier and more cost efficient than it has ever been. This is particularly desired in order to keep pace with the changing customer's and business's needs. Managers are required to identify that the workforce knowledge and know-how collection must be strategically positioned to progress. An organization must have the ability to perform daily operations and continuous improvements. Different technologies can be used to track and monitor the organization's performance along several dimensions to ensure that the trends and values are on track.

Data mining is the process of sorting through huge data sets and analyzing the concealed patterns and establishes relationships to solve real time problems by converting them into useful information. The information is then collected and stored in the data warehouse for efficient analysis through various data mining algorithm, facilitating business decision making and other information requirements which allows enterprises to predict future trend. Data mining processes are used to build machine learning models that power applications including the market analysis, fraud detection, customer retention, production control and science exploration [8].

The data mining process works on five main steps which includes identifying the source information and then picking the data points that need to be analyzed and load it into their data warehouses. The data is then stored and managed either on in house server or the cloud. Then the experts especially the business analysts, management teams and information technology professionals edit the data and schematize it. At the last stage data mining software sorts the data based on the user defined data mining algorithm and finally the data is structured into easy to share and understandable format like graphs or tables. The data mining algorithm analyze the data and establish the relationships and patterns in the input data and thus create a model as per the user desire. For illustration, a company uses the data mining application in order to classify the data into similar cluster in order to create the associativity and sequential patterns to draw the conclusions about the trend in customer behavior and thus optimize its inventory. The process of data mining is well defined in Figure 2.1.

Data mining deals with the kind of patterns that can be mined. On the basis of the kind of data to be mined, there are two categories of functions involved in Data Mining, they are descriptive function and classification and prediction function [9]. The descriptive function deals with the general properties of data in the database. Here is the list of descriptive functions comprises of class/concept description, mining of frequent patterns, mining of associations, mining of correlations, mining of clusters class/concept description class/concept refers to the data to be associated with the classes or concepts. It can be derived by data characterization which can be refers to summarizing data of a class under study called the target class and data discrimination which can be refers to the mapping or classification of a class with some predefined group or class. Mining of frequent patterns frequent patterns are those patterns that occur frequently in transactional data. Some of the frequent patterns include frequent item set which is refers to a set of items that frequently appear together, for example, milk and bread and the another one is frequent subsequence that implies a sequence of patterns that occur frequently such as purchasing a camera is followed by memory card and the most important type is frequent sub structure which refers to different structural forms, such as graphs, trees, or lattices, which may be combined with item-sets or subsequences. Mining of association are used in retail sales to identify patterns that are frequently purchased together. This process refers to the process of uncovering the relationship among data and determining association rules. Mining of correlations is a kind of additional analysis performed to uncover interesting statistical correlations between associated-attribute-value pairs or between two item sets to analyze that if they have positive, negative or no effect on each other and mining of clusters analysis refers to forming group of objects that are very similar to each other but are highly different from the objects in other clusters.

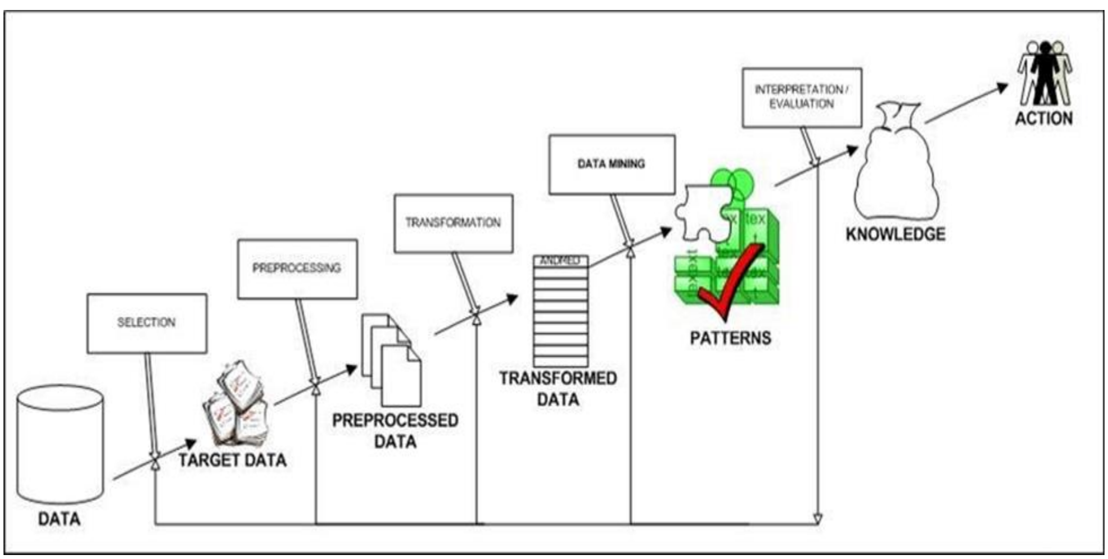

Figure 2.1 Process flow of data mining

Classification is the process of finding a model that describes the data classes or concepts. The purpose is to be able to use this model to predict the class of objects whose class label is unknown. This derived model is based on the analysis of sets of training data. The derived model can be presented as Classification (IF-THEN) Rules, Decision Trees, Mathematical Formulae and Neural Networks. The lists of functions involved in these processes are Classification which predicts the class of objects whose class label is unknown. Its objective is to find a derived model that describes and distinguishes data classes or concepts. The derived model is based on the analysis set of training data i.e. the data object whose class label is well known. Another one is Prediction which is used to predict missing or unavailable numerical data values rather than class labels. Regression analysis is generally used for prediction. Prediction can also be used for identification of distribution trends based on available data. The third one is outlier analysis. Outliers may be defined as the data objects that do not comply with the general behavior or model of the data available and the last one is Evolution analysis which refers to the description and model regularities or trends for objects whose behavior changes over time.

The tasks of data mining are twofold: one is to create predictive power using features to predict unknown or future values of the same or other feature and another one is to create a descriptive power which find interesting, human-interpretable patterns that describe the data. These data mining technique helps to enhance the knowledge discovery and has an innumerable illustration in manufacturing domain as well. Some of the manufacturing domains are discussed below.

a) Data Mining in quality
b) Data Mining in product design
c) Data Mining in manufacturing lead time estimation
d) Data Mining in supply chain management
e) Data Mining in Just-In-Time manufacturing environment.

The detailed descriptions of various data mining technique are present in the upcoming context.

2.2. Regression analysis

Regression analysis is a data mining technique used to predict a range of numeric values (also called continuous values), given a particular dataset. For example, regression analysis might be used to predict the cost of a product or service or to predict the future trend, given other variables. Regression is used across multiple industries for business and marketing planning, financial forecasting, environmental modeling and analysis of trends.

Regression algorithm falls under the family of supervised machine learning algorithm which is a subset of machine learning algorithm. One of the main features of supervised learning algorithm is that they model dependencies and relationships between the target output and input features to predict the value for new data. Regression algorithm predicts the output values based on input features from the data fed in the system. The go-to methodology is the algorithm builds a model on the features of training data and using the model to predict value for new data.

Today, regression models have many applications, particularly in financial forecasting, trend analysis, marketing, time series prediction and even drug response modeling. Some of the popular types of regression algorithm are linear regression, regression trees, lasso regression, logistic regression and multivariate regression [10].

Simple linear regression is a statistical method that enables users to summarize and study relationships between two continuous (quantitative) variables. Linear regression is a linear model wherein a model that assumes a linear relationship between the input variables (x) and the single output variable (y). Here the y can be calculated from a linear combination of the input variables (x). When there is a single input variable (x), the method is called a simple linear regression. When there are multiple input variables, the procedure is referred as multiple linear regression. Some of the most popular applications of Linear regression algorithm are in financial portfolio prediction, salary forecasting, real estate predictions and in traffic in arriving at expected time of arrivals.

LASSO stands for Least Absolute Selection Shrinkage Operator wherein shrinkage is defined as a constraint on parameters. The goal of lasso regression is to obtain the subset of predictors that minimize prediction error for a quantitative response variable. The algorithm operates by imposing a constraint on the model parameters that causes regression coefficients for some variables to shrink toward a zero. Variables with a regression coefficient equal to zero after the shrinkage process are excluded from the model. Variables with non-zero regression coefficients variables are most strongly associated with the response variable. Explanatory variables can be either quantitative, categorical or both. This lasso regression analysis is basically a shrinkage and variable selection method and it helps analysts to determine which of the predictors are most important. Lasso regression algorithm have been widely used in financial networks and economics. In finance, its application is seen in forecasting probabilities of default and Lasso-based forecasting models are used in assessing enterprise wide risk framework. Lasso-type regressions are also used to perform stress test platforms to analyze multiple stress scenarios.

Logistic regression is one of the most commonly used regression techniques in the industry which is extensively applied across fraud detection, credit card scoring and clinical trials, wherever the response is binary has a major advantage. One of the major upsides is of this popular algorithm is that one can include more than one dependent variable which can be continuous or dichotomous. The other major advantage of this supervised machine learning algorithm is that it provides a quantified value to measure the strength of association according to the rest of variables. Despite its popularity, researchers have drawn out its limitations, citing a lack of robust technique and also a great model dependency. Today enterprises deploy Logistic regression to predict house values in real estate business, customer lifetime value in the insurance sector and are leveraged to produce a continuous outcome such as whether a customer can buy/will buy scenario.

Multivariate regression algorithm is used when there is more than one predictor variable in a multivariate regression model. Termed as one of the simplest supervised machine learning algorithm by researchers, this regression algorithm is used to predict the response variable for a set of explanatory variables. This regression technique can be implemented efficiently with the help of matrix operations Industry application of Multivariate Regression algorithm is seen heavily in the retail sector where customers make a choice on a number of variables such as brand, price and product. The multivariate analysis helps decision makers to find the best combination of factors to increase footfalls in the store. Multiple Regression algorithm has several applications across the industry for product pricing, real estate pricing, marketing departments to find out the impact of campaigns. Unlike linear regression technique, multiple regression, is a broader class of regressions that encompasses linear and nonlinear regressions with multiple explanatory variables. Some of the business applications of multiple regression algorithm in the industry are in social science research, behavioral analysis and even in the insurance industry to determine claim worthiness.

2.3 Clustering

Cluster is a group of objects that belongs to the same class. In other words, similar objects are grouped in one cluster and dissimilar objects are grouped in another cluster. Clustering is the process of making a group of abstract objects into classes of similar objects. A cluster of data objects can be treated as one group. While doing cluster analysis, we first partition the set of data into groups based on data similarity and then assign the labels to the groups. The main advantage of clustering over classification is that, it is adaptable to changes and helps single out useful features that distinguish different groups [11].

Clustering analysis is broadly used in many applications such as market research, pattern recognition, data analysis, and image processing. Clustering can also help marketers discover distinct groups in their customer base. And they can characterize their customer groups based on the purchasing patterns. In the field of biology, it can be used to derive plant and animal taxonomies, categorize genes with similar functionalities and gain insight into structures inherent to populations. Clustering also helps in identification of areas of similar land use in an earth observation database. It also helps in the identification of groups of houses in a city according to house type, value, and geographic location. Clustering also helps in classifying documents on the web for information discovery. Clustering is also used in outlier detection applications such as detection of credit card fraud.

In data mining there are agglomeration of huge data as we need a technique to scale them using highly scalable clustering algorithm. Clustering is applicable for all type of data set like numerical data, categorical data and binary data. Clustering can easily deal with low dimension data as well as high dimensional data. It has the ability to deal with noisy, missing or erroneous data with ease.

Clustering can be classified into various categories including partitioning method, hierarchical method, density based method, grid based method, model based method, and constraint based method [12]. Suppose we are given a database of 'n' objects and the partitioning method constructs 'k' partition of data. Each partition will represent a cluster and $k \leq n$. It means that it will classify the data into k groups, which follows conditions like each group contains at least one object and each object must belong to exactly one group. This is called partitioning based method. Hierarchical method creates a hierarchical decomposition of the given set of data objects. We can classify hierarchical methods on the basis of how the hierarchical decomposition is formed. Density-based Method is based on the notion of density. The basic idea is to continue growing the given cluster as long as the density in the neighborhood exceeds some threshold, i.e., for each data point within a given cluster, the radius of a given cluster has to contain at least a minimum number of points. In Grid-based Method, the objects together form a grid. The object space is quantized into finite number of cells that form a grid structure. It has the fast processing time. In Model-based methods, a model is hypothesized for each cluster to find the best fit of data for a given model. This method locates the clusters by clustering the density function. It reflects spatial distribution of the data points. This method also provides a way to automatically determine the number of clusters based on standard statistics, taking outlier or noise into account. It therefore yields robust clustering methods. In Constraint-based Method, the clustering is performed by the incorporation of user or application-oriented constraints. A constraint refers to the user expectation or the properties of desired clustering results. Constraints provide us with an interactive way of communication with the clustering process. Constraints can be specified by the user or the application requirement.

As a data mining function, cluster analysis serves as a tool to gain insight into the distribution of data to observe characteristics of each cluster.

2.3.1 K-means clustering

K-means clustering is a simple unsupervised learning algorithm that is used to solve clustering problems. It follows a simple procedure of classifying a given data set into a number of clusters, defined by the letter "k," which is fixed beforehand. The clusters are then positioned as points and all observations or data points are associated with the nearest cluster, computed, adjusted and then the process starts over using the new adjustments until a desired result is reached.

Algorithm for K-means clustering:

Let $X = \{x_1, x_2, .., x_n\}$ be the set of data points and $V = \{v_1, v_2, .., v_n\}$ be the set of centers. The steps are mentioned below [13]:

a) Randomly select ‘c’ cluster centers.
b) Calculate the distance between each data points and cluster centers using Euclidean distance formulae.

$$Dist_{XY} = \sqrt{\sum_{k=1}^{n} (X_{ik} - X_{jk})^2} \tag{2.1}$$

c) Assign the data point to the cluster center whose distance from the cluster is minimum of all the cluster centers.
d) Recalculate the new cluster using:

$$v_i = (1/c_i) \sum_{j=1}^{c_i} x_i \tag{2.2}$$

where c_i represents the number of data points in the i^{th} cluster.

e) Recalculate the distance between each data points and obtain new cluster centers.
f) If no data was reassigned then stop, otherwise repeat from step 3.

K-means clustering is rather easy to apply to even large data sets, particularly when using heuristics such as Lloyd's algorithm. It has been successfully used in market segmentation, computer vision, and astronomy among many other domains. It often is used as a preprocessing step for other algorithm, for example to find a starting configuration.

2.4 Machine Learning

Machine learning (ML) is a category of algorithm that allows software applications to become more accurate in predicting outcomes without being explicitly programmed. The basic premise of machine learning is to build algorithm that can receive input data and use statistical analysis to predict an output while updating outputs as new data becomes available.

The processes involved in machine learning are similar to that of predictive modeling. Both require searching through data to look for patterns and adjusting program actions accordingly. Many people are familiar with machine learning from shopping on the internet and being served ads related to their purchase. Beyond personalized marketing, other common machine learning use cases include fraud detection, spam filtering, network security threat detection, predictive maintenance and building news feeds [14].

Machine learning algorithms are often categorized as supervised or unsupervised. Supervised algorithms require a data scientist or data analyst with machine learning skills to provide both input and desired output, in addition to furnishing feedback about the accuracy of predictions during algorithm training. Data scientists determine which variables, or features, the model should analyze and use to develop predictions. Once training is complete, the algorithm will apply what was learned to new data.

Unsupervised algorithms do not need to be trained with desired outcome data. Instead, they use an iterative approach called deep learning to review data and arrive at conclusions. Once trained, the algorithm can use its bank of associations to interpret new data. These algorithms have only become feasible in the age of big data, as they require massive amounts of training data.

Machine learning is being used in a wide range of applications today. Some of the areas of applications are:

a) Customer relationship management (CRM) systems
b) Business intelligence (BI) and analytics vendors
c) Human resource (HR) systems
d) Self-driving cars
e) Virtual assistant technology

Just as there are nearly limitless uses of machine learning, there is no shortage of machine learning algorithms. They range from the fairly simple to the highly complex. Here are a few of the most commonly used models are described in the upcoming sections.

2.4.1 Association rule discovery

Association rules are if-then statements that help to show the probability of relationships between data items within large data sets in various types of databases. Association rule mining has a number of applications and is widely used to help discover sales correlations in transactional data or in medical data sets. Association rule mining, at a basic level, involves the use of machine learning models to analyze data for patterns, or co-occurrence, in a database. It identifies frequent if-then associations, which are called association rules [15].

An association rule has two parts: an antecedent (if) and a consequent (then). An antecedent is an item found within the data. A consequent is an item found in combination with the antecedent.

Association rules are created by searching data for frequent if-then patterns and using the criteria support and confidence to identify the most important relationships. Support is an indication of how frequently the items appear in the data. Confidence indicates the number of times the if-then statements are found true. A third metric, called lift, can be used to compare confidence with expected confidence.

While the concepts behind association rules can be traced back earlier, association rule mining was defined in the 1990s, when computer scientists Rakesh Agrawal, Tomasz Imieliński and Arun Swami developed an algorithm-based way to find relationships between items using point-of-sale (POS) systems. Applying the algorithms to supermarkets, the scientists were able to discover links between different items purchased, called association rules, and ultimately use that information to predict the likelihood of different products being purchased together.

Association rules are calculated from item sets, which are made up of two or more items. If rules are built from analyzing all the possible item sets, there could be so many rules that the rules hold little meaning. With that, association rules are typically created from rules well-represented in data. Popular algorithms that use association rules include AIS, SETM, *apriori* and variations of the latter.

With the AIS algorithm, item sets are generated and counted as it scans the data. In transaction data, the AIS algorithm determines which large item sets contained a transaction, and new candidate item sets are created by extending the large item sets with other items in the transaction data. The SETM algorithm also generates candidate item sets as it scans a database, but this algorithm accounts for the item sets at the end of its scan. New candidate item sets are generated the same way as with the AIS algorithm, but the transaction ID of the generating transaction is saved with the candidate item set in a sequential structure. At the end of the pass, the support count of candidate item sets is created by aggregating the sequential structure. The downside of both the AIS and SETM algorithms is that each one can generate and count many small candidate item sets, according to published materials from Dr. Saed Sayad, author of Real Time Data Mining.

With the *apriori* algorithm, candidate item sets are generated using only the large item sets of the previous pass. The large item set of the previous pass is joined with itself to generate all item sets with a size that's larger by one. Each generated item set with a subset that is not large is then deleted. The remaining item sets are the candidates. The *apriori* algorithm considers any subset of a frequent item set to also be a frequent item set. With this approach, the algorithm reduces the number of candidates being considered by only exploring the item sets whose support count is greater than the minimum support count.

In data mining, association rules are useful for analyzing and predicting customer behavior. They play an important part in customer analytics, market basket analysis, product clustering, catalog design and store layout. Programmers use association rules to build programs capable of machine learning. Machine learning is a type of artificial intelligence (AI) that seeks to build programs with the ability to become more efficient without being explicitly programmed [16].

2.4.1.1 Mathematical modeling of Association rule with illustration

In order to demonstrate the generation of association rules, the simple dataset of Table 2.1 is considered here. In this process with five experimental runs, there are three input parameters (a_1, a_2 and a_3), each with three different operating levels (1, 2 and 3). On the other hand, there are four outputs (responses), each having three varying levels (low, medium and high). Thus, the first row of Table 1 signifies that when all the three input parameters are set at ‘1’ level, ‘low’ values for the four responses are observed. It has been often observed that a given dataset may contain duplicate parameters and responses which make it bulky and different to interpret. Thus, it becomes compulsory to minimize the numbers of parameters and responses in the original dataset from efficient framing of association rules. The dataset can be reduced while estimating the values of dependency index between pairs of parameters and responses. The attributes or responses with higher dependency indices with respect to a predefined threshold value are usually removed from the original dataset, without losing any valuable information. The dependency index can be estimated as follows [17]:

$$K(a_i, a_j) = \sum_{L \in a_j^*} \frac{\left|\underline{a_i}(L)\right|}{N} \tag{2.3}$$

$$\underline{a_i}(L) = \cup \left\{ Y \in a_i^* \middle| Y \subseteq L \right\} \tag{2.4}$$

where $a_i^* \text{and} a_j^*$ are the equivalence classes of attributes a_i and a_j respectively (the equivalence class is the set of objects having the same value for attributes a_i and a_j), L is the equivalence class of a_j, Y is the equivalence class of a_i, N is the total number of objects in the dataset, $|\bullet|$ is the cardinality of a set (number of elements in the set) and $\underline{a_i}(L)$ is the lower approximation of set L over attribute a_i.

Table 2.1 Illustrative machining dataset

Exp. run	Input parameter			Response			
	a_1	a_2	a_3	a_4	a_5	a_6	a_7
1	1	1	1	Low	Low	Low	Low
2	1	2	2	Low	Low	Low	Low
3	2	1	1	Medium	Medium	High	Medium
4	3	1	2	Medium	High	Medium	Medium
5	3	3	3	High	Medium	Medium	High

While reducing the dataset, a dependency index of $K(a_i,a_j) = 0$ denotes the interdependency between two parameters (attributes) a_i and a_j, whereas, $K(a_i,a_j) = 100$ signifies their entire dependency. For a given threshold value (which is usually assumed as 85-90%), it is required to determine both the dependency indexes, i.e. $K(a_i,a_j)$ and $K(a_j,a_i)$. Elimination of one of the attributes can only be possible if $\min\{K(a_i,a_j),K(a_j,a_i)\}$ is greater than the threshold value. When the threshold value is high, more number of incompetent attributes remains in the dataset, which make generation of the association rules more complicated. Similarly, its lower value causes many useful attributes getting eliminated from the original dataset with loss of valuable information. Thus, setting of the threshold value plays a major role in development of the subsequent association rules. Now, using Eqs. (1)-(2), the related matrix showing the values of dependency index for the considered machining attributes is developed, as provided in Table 2.2. In this table, as $K(a_4,a_7) = K(a_7,a_4) = 100$, there are strong dependencies between the two responses, i.e. a_4 and a_7, and any of them can be eliminated from the initial dataset for a threshold value of 90%. Here, response a_7 is discarded from further consideration and the reduced dataset is shown in Table 2.3. It can also be observed from this table that the values of the dependency index for $K(a_1,a_6)$ and $K(a_6,a_1)$ are also 100%. But, neither of them can be eliminated because they belong to different attributes, i.e. a_1 is an input parameter and a_6 is a response.

Table 2.2 Dependency indexes between the attributes

Attribute	a_1	a_2	a_3	a_4	a_5	a_6	a_7
a_1	-	40	20	60	60	100	60
a_2	20	-	60	60	20	20	60
a_3	20	40	-	20	20	20	20
a_4	60	40	20	-	60	60	100
a_5	60	40	20	60	-	60	60
a_6	100	40	20	60	60	-	60
a_7	60	40	20	100	60	60	-

Table 2.3 Reduced dataset

Exp. run	a_1	a_2	a_3	a_4	a_5	a_6
1	1	1	1	Low	Low	Low
2	1	2	2	Low	Low	Low
3	2	1	1	Medium	Medium	High
4	3	1	2	Medium	High	Medium
5	3	3	3	High	Medium	Medium

Based on the reduced dataset and *k*-means algorithm, the considered attributes sometimes need to be organizing themselves into different clusters for effective generation of the corresponding association rules. Now, an association rule generation algorithm is adopted to form "If-Then" rules from the reduced dataset with the attributes classified into appropriate number of clusters. This rule generation algorithm is presented as below [17]:

Step 1: Initialize: $D = \{d_1,d_2,\ldots,d_n\}$; $R = \{r_1,r_2,\ldots,r_m\}$

Step 2: Evaluate $X_{ij} = D_i \cap R_j$ for $i = 1,2,\ldots,p$; $j = 1,2,\ldots,q$

Step 3: For each $X_{ij} \neq \varnothing$, a rule is generated as follows:

If $d_1 = V(D_i,d_1)$ and...and $d_n = V(D_i,d_n)$ Then $r_1 = V(R_j,r_1)$ and...and $r_m = V(R_j,r_m)$

[P, Q, C, QTY] [T]

where $P = \frac{|X_{ij}|}{|D_i|}$; $Q = \frac{|X_{ij}|}{|R_j|}$; $C = \frac{|X_{ij}|}{N}$; $QTY = |X_{ij}|$; $T = P + Q + C$

where $D = \{d_1, d_2, ..., d_n\}$ is the set of condition attributes, $R = \{r_1, r_2, \ldots, r_m\}$ is the set of decision attributes, D_i is i^{th} equivalence classes of D ($i = 1,2,\ldots,p$), R_j is j^{th} equivalence class of R ($j = 1,2,\ldots,q$), $V(D_i, d_k)$ are the values of the attributes in equivalence classes of D_i, $V(R_i, r_l)$ are the values of the responses in equivalence classes of R_j, X_{ij} is the intersection of D_i and R_j, P is the percentage of objects in a current equivalence class of condition attribute set that correspond to a rule (a measure of rule confidence), Q is the percentage of objects in current equivalence class of decision attribute set that correspond to a rule, C is the percentage of objects that correspond to a rule (a measure of rule support) and QTY is the quantity of objects corresponding to a rule. In the above algorithm, T represents the total strength (relative importance) of a rule. Higher value of T signifies more strength of a particular association rule for effective decision making. To demonstrate the rule generation algorithm, using the reduced dataset of Table 2.3, in step 1, sets $D = \{a_1\}$ and $R = \{a_4\}$ are initialized. The equivalence classes are now evaluated:

$D_1= \{1, 2\}$, $D_2= \{3\}$, $D_3= \{4, 5\}$, $R_1= \{1, 2\}$, $R_2= \{3, 4\}$, $R_3= \{5\}$

$V(D_1,d_1) = 1$, $V(D_2,d_2) = 2$, $V(D_3,d_3) = 3$, $V(R_1,r_1) = \text{Low}$, $V(R_2,r_2) = \text{Medium}$, $V(R_3,r_3) = \text{High}$

In step 2, the intersections are determined:

$X_{11}= D_1 \cap R_1= \{1, 2\}$, $X_{12}= D_1 \cap R_2=\emptyset$, $X_{13}= D_1 \cap R_3= \emptyset$, $X_{21}= D_2 \cap R_1= \emptyset$, $X_{22}= D_2 \cap R_2= \{3\}$, $X_{23}= D_2 \cap R_3= \emptyset$, $X_{31}= D_3 \cap R_1= \emptyset$, $X_{32}= D_3 \cap R_2= \{4\}$, $X_{33}= D_3 \cap R_3= \{5\}$.

In step 3, the 'If-Then' rules showing the relationships between a_1 as the input parameter and a_4 as the response are generated:

Rule 1: If $a_1= 1$ Then a_4 is Low [P = 100, Q = 100, C = 40, QTY = 2][T = 240]

Rule 2: If $a_1= 2$ Then a_4 is Medium [P = 100, Q = 100, C = 20, QTY = 1][T = 220]

Rule 3: If $a_1= 3$ Then a_4 is Medium [P = 100, Q = 100, C = 20, QTY = 1][T = 220]

Rule 4: If $a_1= 3$ Then a_4 is High [P = 100, Q = 100, C = 20, QTY = 1][T = 220]

In the above-developed rules, rules 3 and 4 would produce confusions among the decision makers because as the input parameter setting of $a_1= 3$, the response (a_4) is both 'Medium' and 'High' which is almost impossible to occur. To avoid this problem, it is always advised to generate association rules while taking into consideration all the input parameters. Now, the following rules are developed for the considerer three responses incorporating all the input parameters.

Rules for a_4:

Rule 1: If $a_1= 1$ Then a_4 is Low [P = 100, Q = 100, C = 40, QTY = 2][T = 240]

Rule 2: If $a_2= 1$ Then a_4 is Medium [P = 66.66, Q = 100, C = 40, QTY = 2][T = 206.66]

Rule 3: If a_1= 3 and a_2= 3 and a_3= 3 Then a_4 is High [P = 100, Q = 100, C = 20, QTY = 1][T = 220]

Rules for a_5:

Rule 1: If a_1= 1 Then a_5 is Low [P = 100, Q = 100, C = 40, QTY = 2][T = 240]

Rule 2: If a_1= 2 and a_2= 1 and a_3= 1 Then a_5 is Medium [P = 100, Q = 50, C = 20, QTY = 1] [T = 170]

Rule 3: If a_1= 3 and a_2= 3 and a_3= 3 Then a_5 is Medium [P = 100, Q = 50, C = 20, QTY = 1] [T = 170]

Rule 4: If a_1= 3 and a_2= 1 and a_3= 2 Then a_5 is High [P = 100, Q = 100, C = 20, QTY = 1] [T = 220]

Rules for a_6:

Rule 1: If a_1= 1 Then a_6 is Low [P = 100, Q = 100, C = 40, QTY = 2] [T = 240]

Rule 2: If a_1= 3 Then a_6 is Medium [P = 100, Q = 100, C = 40, QTY = 2] [T = 240]

Rule 3: If a_1= 2 and a_2= 1 and a_3= 1 Then a_6 is High [P = 100, Q = 100, C = 20, QTY = 1] [T = 220]

Rules for all the responses:

Rule 1: If a_1= 1 Then a_4 is Low and a_5 is Low and a_6 is Low [P =100, Q=100, C=40, QTY=2] [T=240]

Rule 2: If a_1=2 and a_2=1 and a_3=1 Then a_4 is Medium and a_5 is Medium and a_6 is High [P=100, Q=100, C=20, QTY=1] [T=220]

Rule 3: If a_1=3 and a_2=1 and a_3=2 Then a_4 is Medium and a_5 is High and a_6 is Medium [P=100, Q=100, C=20, QTY=1][T=220]

Rule 4: If a_1=3 and a_2=3 and a_3=3 Then a_4 is High and a_5 is Medium and a_6 is Medium [P=100, Q=100, C=20, QTY=1] [T=220]

The rules developed incorporating all the responses are supposed to be more useful for simultaneous optimization of the considered process. Thus, it can be observed that at setting a_1= 1, ‘Low’ values of all the responses are concurrently achieved, with the maximum rule strength of T = 240.

2.4.2 Classification Algorithm

Classification is technique to categorize our data into a desired and distinct number of classes where we can assign label to each class. The applications of Classification are: speech recognition, handwriting recognition, biometric identification, document classification etc.

Classifiers can be: Binary classifiers: Classification with only 2 distinct classes or with 2 possible outcomes and Multi-Class classifiers: Classification with more than two distinct classes. There are various types of classification algorithm. Some of them are described below.

2.4.2.1 Naive Bayes (Classifier)

Naive Bayes is a probabilistic classifier inspired by the Bayes theorem. Under a simple assumption which is the attributes are conditionally independent. The classification is conducted by deriving the maximum posterior by applying to Bayes theorem. This assumption greatly reduces the computational cost by only counting the class distribution. Even though the assumption is not valid in most cases since the attributes are dependent, surprisingly Naive Bayes has able to perform impressively. Naive Bayes is a very simple algorithm to implement and good results have obtained in most cases. It can be easily scalable to larger datasets since it takes linear time, rather than by expensive iterative approximation as used for many other types of classifiers [9].

Advantages: This algorithm requires a small amount of training data to estimate the necessary parameters. Naive Bayes classifiers are extremely fast compared to more sophisticated methods.

Disadvantages: Naive Bayes is known to be a bad estimator.

a) Steps for Implementation:
b) Initialise the classifier to be used.
c) Train the classifier: All classifiers in scikit-learn uses a fit(X, y) method to fit the model(training) for the given train data X and train label y.
d) Predict the target: Given an non-label observation X, the predict(X) returns the predicted label y.
e) Evaluate the classifier model

2.4.2.2 Support Vector Machine

Support vector machine is a representation of the training data as points in space separated into categories by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

Support Vector Machine (SVM) is one of the most powerful algorithm with strong theoretical foundations based on the Vapnik-Chervonenkis theory [18]. This supervised machine learning algorithm has strong regularization and can be leveraged both for classification or regression challenges. They are characterized by usage of kernels, the sparseness of the solution and the capacity control gained by acting on the margin, or on number of support vectors, etc. The capacity of the system is controlled by parameters that do not depend on the dimensionality of feature space. Since the SVM algorithm operates natively on numeric attributes, it uses a z-score normalization on numeric attributes. In regression, Support Vector Machines algorithms use epsilon-insensitivity (margin of tolerance) loss function to solve regression problems. A support vector machines regression algorithm has found several applications in the oil and gas industry, classification of images and text and hypertext categorization.

Advantages: Effective in high dimensional spaces and uses a subset of training points in the decision function so it is also memory efficient.

Disadvantages: The algorithm does not directly provide probability estimates, these are calculated using an expensive k-fold cross-validation.

2.4.2.3 Decision Tree

Decision tree is one of the most commonly used classification algorithm. Given a data of attributes together with its classes, a decision tree produces a sequence of rules that can be used to classify the data. Decision Tree, as it name says, makes decision with tree-like model. It splits the sample into two or more homogeneous sets (leaves) based on the most significant differentiators in your input variables. To choose a differentiator (predictor), the algorithm considers all features and does a binary split on them (for categorical data, split by cat; for continuous, pick a cut-off threshold). It will then choose the one with the least cost (i.e. highest accuracy), and repeats recursively, until it successfully splits the data in all leaves (or reaches the maximum depth) [9, 19].

Advantages: Decision Tree is simple to understand and visualize, requires little data preparation, and can handle both numerical and categorical data.

Disadvantages: Decision tree can create complex trees that do not generalize well, and decision trees can be unstable because small variations in the data might result in a completely different tree being generated.

2.4.2.4 Random Forest (RF)

Random forest is an ensemble model that grows multiple trees and classify objects based on the "votes" of all the trees, i.e. An object is assigned to a class that has most votes from all the trees. Random forest classifier is a meta-estimator that fits a number of decision trees on various sub-samples of datasets and uses average to improve the predictive accuracy of the model and controls over-fitting. The sub-sample size is always the same as the original input sample size but the samples are drawn with replacement [8].

Advantages: Reduction in over-fitting and random forest classifier is more accurate than decision trees in most cases.

Disadvantages: Slow real time prediction, difficult to implement, and complex algorithm.

2.5 Artificial Neural Network

A neural network is a system of hardware and/or software patterned after the operation of neurons in the human brain. Neural networks -- also called artificial neural networks -- are a variety of deep learning technology, which also falls under the umbrella of artificial intelligence, or AI. Commercial applications of these technologies generally focus on solving complex signal processing or pattern recognition problems. Examples of significant commercial applications since 2000 include handwriting recognition for check processing, speech-to-text transcription, oil-exploration data analysis, weather prediction and facial recognition [8].

A neural network usually involves a large number of processors operating in parallel and arranged in tiers. The first tier receives the raw input information -- analogous to optic nerves in human visual processing. Each successive tier receives the output from the tier preceding it, rather than from the raw input -- in the same way neurons further from the optic nerve receive signals from those closer to it. The last tier produces the output of the system.

Each processing node has its own small sphere of knowledge, including what it has seen and any rules it was originally programmed with or developed for itself. The tiers are highly interconnected, which means each node in tier n will be connected to many nodes in tier n-1 -- its inputs -- and in tier n+1, which provides input for those nodes. There may be one or multiple nodes in the output layer, from which the answer it produces can be read.

Neural networks are notable for being adaptive, which means they modify themselves as they learn from initial training and subsequent runs provide more information about the world. The most basic learning model is centered on weighting the input streams, which is how each node weights the importance of input from each of its predecessors. Inputs that contribute to getting right answers are weighted higher.

Typically, a neural network is initially trained or fed large amounts of data. Training consists of providing input and telling the network what the output should be. Each input is accompanied by the matching identification. Providing the answers allows the model to adjust its internal weightings to learn how to do its job better. In defining the rules and making determinations -- that is, each node decides what to send on to the next tier based on its own inputs from the previous tier -- neural networks use several principles. These include gradient-based training, fuzzy logic, genetic algorithms and Bayesian methods. They may be given some basic rules about object relationships in the space being modeled. Preloading rules can make training faster and make the model more powerful sooner. But it also builds in assumptions about the nature of the problem space, which may prove to be either irrelevant and unhelpful or incorrect and counterproductive, making the decision about what, if any, rules to build in very important.

Neural networks are sometimes described in terms of their depth, including how many layers they have between input and output, or the model's so-called hidden layers. This is why the term neural network is used almost synonymously with deep learning. They can also be described by the number of hidden nodes the model has or in terms of how many inputs and outputs each node has. Variations on the classic neural network design allow various forms of forward and backward propagation of information among tiers [20]. The simplest variant is the feed-forward neural network. It passes information straight through from input to processing nodes to outputs. It may or may not have hidden node layers, making their functioning more interpretable. More complex are recurrent neural networks. These deep learning algorithms save the output of processing nodes and feed the result back into the model. This is how the model is said to learn. Convolutional neural networks are popular today, particularly in the realm of image recognition. It has been used in many of the most advanced applications of AI including facial recognition, text digitization and natural language processing.

There are several applications of ANN. Image recognition was one of the first areas to which neural networks were successfully applied, but the technology uses have expanded to many more areas, including:

a) Chatbots
b) Natural language processing, translation and language generation
c) Stock market prediction
d) Delivery driver route planning and optimization
e) Drug discovery and development

These are just a few specific areas to which neural networks are being applied today. Prime uses involve any process that operates according to strict rules or patterns and has large amounts of data. If the data involved is too large for a human to make sense of in a reasonable amount of time, the process is likely a prime candidate for automation through artificial neural networks.

3.0 RULE BASED PARAMETRIC ANALYSIS OF MACHINING PROCESSES

3.1 Need for rule based parametric analysis

With the rapid advancements of various data analysis tools and network technology, data mining has now become an emerging area in computational intelligence which offers new concepts and methods to analyze voluminous data. Availability of large volume of data in different forms has significantly accelerated the applications of data mining. Data mining deals with the application of various competent tools and techniques to refine the extracted knowledge from a large database so as to envisage, categorize and characterize the mined data [9, 21]. It can identify interesting patterns in data to aid in valuable decision making where the applications of the popular statistical and predictive models fail. Understanding the patterns inherent in the data sometimes becomes important when the data sources are heterogeneous and differently distributed. Data mining mainly consists of the applications of various mathematical tools for machine learning, cluster analysis, regression analysis and neural networks. Using a predetermined set of features and a training dataset, regression analysis and neural networks develop a single model. On the other hand, a machine learning algorithm develops a number of models in the form of decision rules while providing the interrelationships between various input features and the final decision. Cluster analysis can also create the same decision rules when the set of features included in each rule is independent from all other rules. The rules developed by the data mining tools are always to be explicit [22, 23].

Rough sets theory (RST), developed by Pawlak in 1982 [24], falls under the broad category of machine learning. Based on the extraction of knowledge from the datasets, it can also provide valuable tools for data analysis and generation of independent decision rules for effective data classification. Having a strong mathematical foundation, it is well suited to efficiently solve various decision making problems. Its main advantage is that it does not require any additional information about the dataset to be mined, like probability theory in statistical approaches, membership functions in fuzzy set theory etc. As a non-statistical approach in data analysis, it thus classifies and analyses imprecise, uncertain or incomplete information and knowledge to generate minimal and non-redundant rule sets [25-27].

3.2 Literature review for the rule based parametric analysis of machining processes

Shen et al. [28] proposed a new method, Rough set theory, to diagnose the valve fault for a multi-cylinder diesel engine. The decision table was established and then the attributed field was specified according to collected signals. After that a discretization method was incorporated into system to transform the continuous values attributes to discrete ones and then the rough sets theory was used to get the final reducts and to extract rules which is then used to distinguish the fault type or to inspect the dynamic characteristic of the machinery.

Tseng et al. [29] adopted a novel approach to solve the quality assurance problem in predicting the acceptance of computer numerical control machined parts. Rough set theory was applied to derive rules for the process variables that contributed to the surface roughness. The proposed rule- composing algorithm and rule validation procedure had been tested with the historical data the company had collected over the years. The results indicated that a higher accuracy over the statistical approaches in terms of predicting acceptance level of surface roughness.

Chen et al. [30] defined the root–cause machineset identification problem of analyzing correlations between combinations of machines and the defective products. Then the proposed root-cause machine identifier method using the technique of association rule mining to solve the problem efficiently and effectively. The experimental results of real datasets showed that the actual root-cause machinesets was almost ranked within the top tenth model.

Vani [15] studied the performance of various algorithms and compared those algorithms based on execution time using various datasets and support values. That paper also compared the merits and demerits of ARM algorithms. A comparison framework had been made using various datasets like adult, census, letter recognition and mushroom. The datasets compared those classical frequent item sets mining algorithms and finally presented the best algorithm suited for proposed datasets.

Kusiak [31] introduced the basic concepts of rough set theory and other aspects of data mining. The rough set offered a viable approach for extraction of decision rules from datasets. The extracted rules from the rough set theory could be used for making predictions in the semiconductor industry and other application and the results was compared well with other contrasting approaches like regression analysis and neural network . That paper stated that the power, generality, accuracy, and longevity of decision rules could be increased by the application of concepts from systems engineering and evolutionary computation.

Hou and Huang [32] showed the application of fuzzy set theory with the fuzzy variable precision rough set approach for mining the casual relationship rules from the database of a remote monitoring manufacturing process. Here fuzzy set theory was used to transfer the data entries into fuzzy sets and the fuzzy variables precession rough set approach was applies to extract rules from the fuzzy sets. The induced rules were identical to practical knowledge and fault diagnosis thinking of human operators. The induced rules were compared with the rules induced by the original rough set approach and stated that the fuzzy rough set were evaluated well by plausibility and future effectiveness measures and was less sensitive to noisy data and induced better rules than original rough set approach.

Lim and Lee [33] integrated decision support system and online analytical processing into existing business performance measurements and hoped to improve the accuracy of analysis and provide in-depth, multi-angle view of data. Weighted and Layered workflow evaluation extended to incorporate business intelligence using C4.5 and association rule algorithms. C4.5 produced more comprehensible decision trees by showing only important attributes whereas association rules described in-rules of multiple granularities. Sorting rules based on rules' complexities permitted online analytical processing to navigate through layers of complexities to extract rules of relevant sizes and to view data from multidimensional perspectives in each layer.

Chao et al. [34] presented an intelligent system which assisted the layout designer in producing associatively data as input to an automated layout generation tool by combining various techniques based on expert systems, object-based data structures and cluster analysis on the petrochemical industry. The system eliminated manual input for the associativity data and assured data consistency. The cluster analysis determined the strength of relationship between any two pieces of equipment. The expert system provided guidance for the subjective part of the layout design. This results in automation of associativity data generation, an improved user interface, and consistency and accuracy of data.

Buddhakulsomsiri et al. [35] presented for mining automotive warranty data. The algorithm used elementary set concept and database manipulation techniques to develop useful relationships between product attributes and causes of failure and represented using IF–THEN association rules. After association rules were developed, the algorithm applied a statistical analysis technique to evaluate the significance of each rule. Application of the association rule-generation algorithm was presented with a data-mining case study from the automotive industry and the rules extracted were used to identify root causes of particular warranty data.

Jiao et al. [16] applied an association rule mining technique to deal with product and process variety mapping. The mapping relationships were embodied in association rules, which could be deployed to support production planning of product families within existing production processes. A case study of mass customization of vibration motors was presented to demonstrate how the association rules mining mechanism helps maintain the coherence between product and process variety. The performance of the association rule mining approach was further evaluated through sensitivity analysis.

Chen [36] developed a cell-formation approach based on association rule induction to find the effective configurations for cellular manufacturing systems. To gain the benefits of flexibility and efficiency, the manufacturing system was decomposed into several manageable subsystems by categorizing similar parts into part families and disparate machines into cells. Seventeen data sets of various size and complexity were used to evaluate the effectiveness of the proposed cell-formation algorithm based on association rule induction. The performance of the proposed approach was compared with several existing techniques and the proposed approach shows its ability to find quality solutions.

Agrawal et al. [37] proposed an efficient algorithm that generated all significant association rules between items in the database of customer item purchased transactions. The proposed algorithm incorporated buffer management and novel estimation and pruning techniques and also contained the results of applying the algorithm to sales data obtained from a large retailing company to validate the effectiveness of the algorithm.

Pasek [38] explored used of a classifier based on rough sets theory and showed the performance of the proposed algorithm over several criteria in a cutting tool wear monitoring application. The proposed algorithm provided solid classification ability with relatively low potential for misclassification errors. That paper stated that the proposed method could be used only for off-line processing and was inadequate for on-line applications until the incorporation of corresponding recursive algorithms.

Bayardo Jr. and Agrawal [39] showed the best rule according to variety of metrics including confidence, support, gain, chi-squared value, gini, entropy gain, laplace, lift, and conviction along a support/confidence border. That paper also showed how that concept could be generalized to mine all rules that were best according to any of these criteria with respect to an arbitrary subset of the population of interest and further argued that by returning a broader set of rules than previous algorithms, that techniques allowed for improved insight into the data and support more user-interaction in the optimized rule-mining process.

Shahbaz et al. [40] examined the application of association rules to manufacturing databases to extract useful information about a manufacturing system's capabilities and its constraints. The quality of each identified rule was tested and, from numerous rules, only those that were statistically very strong and contain substantial design information were selected. The final set of extracted rules contained very interesting information relating to the geometry of the product and also indicated where limitations existed for improvement of the manufacturing processes involved in the production of complex geometric shapes.

Whitehall et al. [41] explained how continuous AQ combined continuous and discrete values and showed that handling continuous attributes as real number instead of forcing them into a discrete representation lead to more efficient concept formation. Here data from a turning process simulator used in support of machine operation planning in manufacturing were used to demonstrate the new algorithm.

Kriegel et al. [42] surveyed major challenges for data mining in the years ahead. Firstly types of patterns in data were studied and secondly the data extractions from various sources were studied and finally proposed the need of user friendly data mining tool with transparent or even reduced parameterization and also gave a scope to discover new type of pattern interpret tools for the complex input data.

Koonce et al. [43] described a software tool, DBMine , which was developed to assist industrial engineers in data mining. The tool implemented three common data mining methodologies, namely Bacon's algorithm, Decision Trees and DB-Learn. The tool was implemented in Microsoft Visual Basic 3.0 and could be utilized data in Microsoft Access 2.0 and in Watcom SQL databases. An example session in which job shop sequences produced by a Genetic Algorithm was also presented.

Haris et al. [44] described the usefulness of data mining tool to predict future trends and performance, allowing decision maker to make forecasting on the data gathered and discussed the integration between optimization and DM for decision making to enhance the quality of decision making process. The paper also proposed that the management in the creation of decision making process derived from datasets should use different strategies to accelerate the transformation of information in different stages.

Harding et al [45] reviewed the applications of data mining in manufacturing engineering, in particular production processes, operations, fault detection, maintenance, decision support, product quality improvement, customer relationship management, information integration aspects, and standardization. This review revealed progressive applications in addition to existing gaps and less considered areas such as manufacturing planning and shop floor control.

Chen et al. [46] incorporated a non-parametric approach, Data Envelopment Analysis (DEA), to estimate and rank the efficiency of association rules with multiple criteria, including subjective domain related measures where the measured based on support and confidence. An example of market basket analysis was applied to illustrate the DEA based methodology for measuring the efficiency of association rules with multiple criteria. The proposed approach provided more insights into the rules discovered and could assist rule evaluation and selection.

Wang et al. [47] analyzed the reasons for the limitation of data mining application in manufacturing industry and focused on reviewing the state-of-the-art of the applications of data mining in product design and manufacturing. That paper proposed that the data mining techniques could find useful patterns to support decision and were much easier for humans to understand than the rough data since the rules were extracted from large datasets and the decisions based upon the extracted rules were more reliable.

3.3 Applications of rule based Parametric Analysis on Conventional machining

In the present day automated manufacturing industries, huge volume of data related to product design, bill of materials, production planning and control, production processes and systems, monitoring and diagnosis etc. are being regularly captured and stored using various data acquisition tools. Valuable information in the form of rules, patterns, clusters, associations and dependencies are always expected to be hidden in the collected dataset of the manufacturing organizations. Thus, it becomes the responsibility of the production engineers to augment effective data mining tools to analyze this huge manufacturing-related dataset to identify potential patterns in various input parameters that control a manufacturing process or quality of the output products. It is observed that RST has already been successfully applied in various domains of engineering and management decision making, like manufacturing process control, fault diagnosis, semiconductor manufacturing, quality assurance, supplier selection, automotive warranty data analysis etc. In this context, a maiden endeavor is put forward to apply the concepts of RST in various conventional machining process, e.g. grinding process and CNC turning process, so as study the effects of various process parameters on different measured responses and predict the optimal settings of those parameters.

3.3.1 Literature review on the Conventional machining processes

Lee et al. [48] studied on the improved differential evolution approach for optimization of surface grinding process. The grinding variables such as wheel speed, workpiece speed, depth of dressing and lead of dressing using a multi-objective function model with a weighted approach were optimized via subjected to a comprehensive set of process constraints. A powerful global numerical optimization method, TSBDEA, combined the different evolution algorithm, DEA, with the Taguchi-sliding-level-method. The illustrative cases of both rough-grinding and finish-grinding were given to demonstrate the applicability of the proposed TSBDEA, and the computational results showed that the proposed TSBDEA could obtain better results than the other methods.

Pai et al. [49] optimized the grinding process during grinding of Al6061-SiC composites. Three grinding variables were studied for simultaneous optimization of material removal rate and surface roughness. Initially, the response surface models for grinding process parameters were developed using response surface methodology. The developed models were optimized using enhanced elitist non-dominated sorting genetic algorithm (enhanced NSGA-II), a time saving algorithm in comparison to conventional NSGA-II. Finally the confirmation tests were performed to validate the results obtained from response surface methodology and enhanced NSGA-II and thus developed algorithm could effectively be used for optimization of grinding process.

Winter et al. [50] presented an approach to identify the process parameters that leads to Pareto-optimal solutions for advancing the eco-efficiency of grinding operations. An internal cylindrical grinding process was selected to demonstrate this approach. Both single-objective and multi-objective optimizations were carried out, where geometric programming and a weighted max-min model were used respectively. Finally sensitivity analysis was presented to reveal the trends of each process parameter in relation to the preference of technological, economic and environmental objectives.

Khan et al. [51] demonstrated an effective approach for the optimization of an in-feed centreless cylindrical grinding of EN52 austenitic grade steel with multiple performance characteristics based on the grey relational analysis. Nine experimental runs, based on the Taguchi method of L9 orthogonal arrays, were performed to determine the best factor level condition. The in-feed centreless cylindrical grinding process parameters, such as dressing feed, grinding feed, dwell time and cycle time, were optimized by taking into consideration the multiple-performance characteristics like surface roughness and out of cylindricity and observed that dressing feed, grinding feed and cycle time had significant effect on the responses.

Çaydaş and Çelik [52] focused on the optimization of process parameters in cylindrical surface grinding process of AISI 1050 steel with grooved wheels. To optimize the process parameters, response surface methodology and genetic algorithm technique were merged together. The revolution speed of workpiece, depth of cut and number of grooves on the wheel were changed to explore their experimental effects on the surface roughness of machined bars. Response surface methodology was used to develop a mathematical model between the input variable and responses and the genetic algorithm was used to optimize the proposed model.

Gadekula et al. [53] examined the parametric optimization of High Carbon High Chromium Steel (HCHCR) material by using the results after experimenting in CNC turning machine. The process variables considered for optimization such as spindle speed, rate of feed and depth of cut (DOC) in dry turning operation. Taguchi technique was used for optimization. These were analyzed effectively to predict the Ra and MRR using signal to noise ratio, equation of Regression and Variance analysis. An orthogonal array, L9 Taguchi technique was applied to identify the performance characteristic affecting surface roughness in turning process. Regression models were developed and validated to predict the surface roughness and AE Signal value.

Kumar et al. [54] performed machining of EN 19 stainless steel material by using CNC Turning operation and investigated the affecting parameters, surface roughness and MRR. The CNC Turning process parameters were feed rate, depth of cut and spindle speed/ rotational speed, lubricant, had been analyzed on MRR and Surface roughness. Carbide tip tool used as a cutting tool for the experiments. Taguchi's L18 mixed type orthogonal array experimental design had been selected for investigation, and optimization was done through Taguchi's approach, and also the analysis of variance (ANOVA) was applied to know the significance of process parameters on response variable.

Nataraj et al. [55] investigated the influence of turning process parameters on the machinability of hybrid metal matrix composite comprising alumina (Al_2O_3) and molybdenum disulphide (MoS_2) particulates dispersed on aluminum casting alloy LM6 in turning process. Here, cutting speed, feed and depth of cut were considered as input process parameters and the resultant force of cutting forces in three directions, Specific Cutting Pressure (SCP) and surface roughness Ra were considered as responses. Statistical analyses were carried out to estimate the performance of machining parameters. The influence of input parameters on machining-force, SCP and the surface roughness Ra were analyzed using surface response graphs. The experimental study revealed that cutting speed and feed were the most influencing parameter that affects the machining force and SCP.

Gupta et al. [56] proposed heuristic approach, namely Genetic algorithm, to find optimum minimum cylindricity form tolerance parameter. The objective function for cylindricity had been statistically modeled using face centered central composite design which works based on response surface methodology. Each term used in model was highly significant with 95% of confidence interval. The analysis showed cylindricity was highly affected by feed rate with 14% contribution followed by depth of cut 6% and tool nose radius 3.5%. There were significant interact of cutting speed with depth of cut, and feed rate with depth of cut and tool nose radius.

Dave et al. [57] presented experimental investigation of the machining characteristics of different grades of EN materials in CNC turning process using TiN coated cutting tools. In machining operation, the quality of surface finish is an important requirement for many turned work pieces. That paper was focused on the analysis of optimum cutting conditions to get the lowest surface roughness and maximum material removal rate in CNC turning of different grades of EN materials by Taguchi method. The orthogonal array, signal to noise ratio and analysis of variance were employed to study the performance characteristics in dry turning operation.

3.3.2 Applications of rule based Parametric Analysis on Grinding Process

Grinding is a machining process where high volume of unwanted material is rapidly removed from the workpiece surface with the help of abrasive grinding wheel or grinder used as a cutting tool [58].

Keeping in mind the large applicability of grinding operations, nine experiments have been conducted on low alloy steel workpiece samples (60 × 40 × 8 mm size) using a vitrified bonded alumina grinding wheel with specification as AA 46/54 K5 V8. Spindle speed (SS) (in rpm), depth of cut (DOC) (in mm) and type of the cutting fluid (TCF) have been considered as the input grinding parameters. On the other hand, SR (Ra) (in µm), amplitude of vibration (V) (in µm) and grinding ratio (G-ratio) have been treated as the process outputs (responses). For each of the grinding parameters, three different operating levels have been considered. The detailed experimental plan along with the measured values of the three responses is provided in Table 3.1. In this table, the numbers enclosed inside the parentheses show the respective operating levels of the considered grinding parameters. Now, this experimental dataset for the grinding operation is analyzed using the principle of RST so as to identify those input parameters which are responsible for controlling the output characteristics of the machined parts/components. At first, data preprocessing in the form of attribute reduction and clustering of the considered attributes are performed. Table 3.2 exhibits the dependency indices as computed for each pair of the attributes and smaller values of those indices (all the values are less than the threshold limit of 85%) prove the independency of all the attributes as considered for this grinding process. It is worthwhile to mention that in Table 3.2, the values of two dependency indices *R*(SS, G-ratio) and *R*(G-ratio, SS) are obtained as 33.33% and 100% respectively. But, as the minimum of them, i.e. 33.33% is less than the predetermined threshold value of 85%, both of them can be treated as entirely independent attributes. Along with the data reduction, the measured responses are also grouped into appropriate number of clusters using *k*-means algorithm to convert the continuous values into separate distinguishable ranges. The clustering and the dependency index help to reduce the number of attributes and number of experiments respectively.

Table 3.1 Experimental dataset for the grinding process

Experiment No.	Grinding parameter			Response		
	SS	DOC	TCF	Ra	V	G-ratio
1	2430 (1)	0.02 (1)	Coolant (1)	0.48	18.22	0.0253
2	2430 (1)	0.03 (2)	Water (2)	0.56	21.32	0.0262
3	2430 (1)	0.04 (3)	Coolant + Water (3)	0.57	26.23	0.0232
4	2560 (2)	0.02 (1)	Water (2)	0.61	22.32	0.0356
5	2560 (2)	0.03 (2)	Coolant + Water (3)	0.65	31.22	0.0323
6	2560 (2)	0.04 (3)	Coolant (1)	0.77	29.57	0.0476
7	2850 (3)	0.02 (1)	Coolant + Water (3)	0.72	26.45	0.0643
8	2850 (3)	0.03 (2)	Coolant (1)	0.8	31.56	0.0656
9	2850 (3)	0.04 (3)	Water (2)	0.65	34.78	0.0781

Table 3.2 Dependency indices for various grinding attributes

Attribute	SS	DOC	TCF	Ra	V	G-ratio
SS	-	0	0	0	0	33.33
DOC	0	-	0	0	0	0
TCF	0	0	-	0	0	0
Ra	66.67	0	0	-	33.33	33.33
V	33.33	33.33	33.33	55.56	-	33.33
G-ratio	100	0	0	44.44	33.33	-

In Figure 3.1, all the considered responses for the grinding process are clustered into two separate groups in each of the cases. For Ra and amplitude of vibration (both are non-beneficial properties requiring their lower values), the formed two clusters for them are respectively designated as ‘Low’ and ‘High’. Here, low values of Ra and amplitude of vibration are always preferred. On the other, for G-ratio (being a beneficial property requiring only higher values), the corresponding clusters are respectively termed as ‘Low’ and ‘High’. For G-ratio, high values are always desired. The number of classes in which the responses are to be segregated also plays an important role in subsequent generation of decision rules. If the number of clusters is high, each generated rule would encompass a small number of elements. On the other hand, when the number of clusters is too small, the interpretation of the rules then becomes complicated. Thus, it is always recommended that the number of clusters would be equal to the number of attributes considered. The details of the cluster analysis results for the three responses of the grinding process are provided in Table 3.3. In this table, the third and fourth columns respectively denote the mean and range values for each of the clusters formed for the considered responses. On the other hand, the fifth column represents the specific objects (experimental run) and column six denotes the total number of objects in each of the formed clusters.

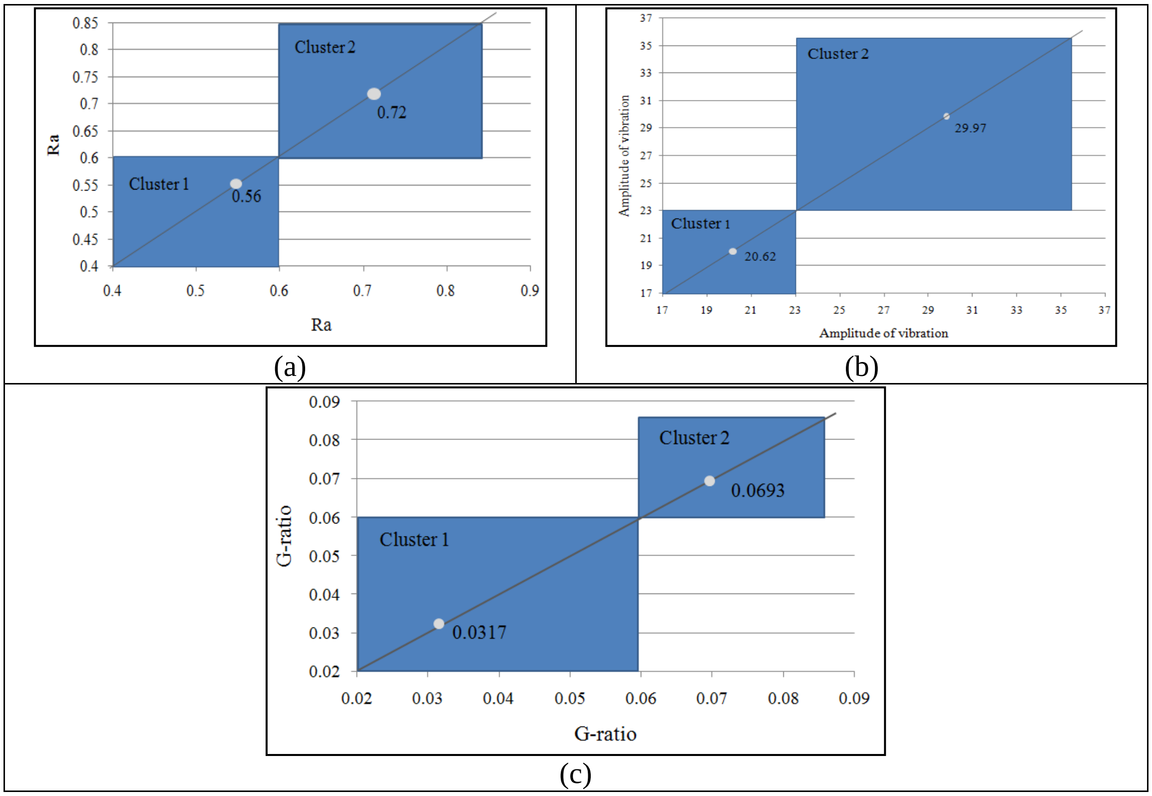

Figure 3.1 Clustering of the considered responses

Table 3.3 Details of the formed clusters for the responses

Response	Cluster number	Mean	Range of each cluster	Objects in each cluster	Total number of objects in each cluster
Ra	Cluster 1	0.56	0.40-0.60	1,2,3,4	4
	Cluster 2	0.72	0.60-0.85	5,6,7,8,9	5
Amplitude of vibration	Cluster 1	20.62	17.00-23.00	1,2,4	3
	Cluster 2	29.97	23.00-35.50	3,5,6,7,8,9	6
G-ratio	Cluster 1	0.0317	0.02-0.06	1,2,3,4,5,6	6
	Cluster 2	0.0693	0.06-0.085	7,8,9	3

Now, after perfuming all the required data preprocessing and clustering tasks, the decision rule generation algorithm is adopted to explore valuable information from the experimental dataset in the form of developed rules. These rules simply depict the relationships between various grinding parameters and responses to effectively control the said grinding operation. The first three sets of rules relate one or more grinding parameters to a single response. In contrast, the last set of rules relates multiple grinding parameters to all the three responses.

Rules for Ra:

Rule 1: If SS = 2430 Then Ra is 0.56 [0.40-0.60].

[P = 100%, Q = 75%, C = 33.33%, QTY = 3] [T = 208.33]

Rule 2: If SS = 2560 and DOC = 0.2 Then Ra is 0.56 [0.40-0.60].

[P = 100%, Q = 25.00%, C = 11.11%, QTY = 1] [T = 136.11]

Rule 3: If SS = 2850 Then Ra is 0.72 [0.60-0.85].

[P = 100%, Q = 60.00%, C = 33.33%, QTY = 3] [T = 193.33]

Rule 4: If SS = 2560 and DOC = 0.3 Then Ra is 0.72 [0.60-0.85].

[P = 100%, Q = 20.00%, C = 11.11%, QTY = 1] [T = 131.11]

Rule 5: If SS = 2560 and DOC = 0.4 Then Ra is 0.72 [0.60-0.85].

[P = 100%, Q = 20.00%, C = 11.11%, QTY = 1] [T = 131.11]

Rules for amplitude of vibration (V):

Rule 1: If SS = 2430 and DOC = 0.2 Then V is 20.62 [17.00-23.00].

[P = 100%, Q = 33.33%, C = 11.11%, QTY = 1] [T = 144.44]

Rule 2: If SS = 2430 and TCF = Water Then V is 20.62 [17.00-23.00].

[P = 100%, Q = 33.33%, C = 11.11%, QTY = 1] [T = 144.44]

Rule 3: If SS = 2560 and DOC = 0.2 Then V is 20.62 [17.00-23.00].

[P = 100%, Q = 33.33%, C = 11.11%, QTY = 1] [T = 144.44]

Rule 4: If SS = 2850 Then V is 29.97 [23.00-35.50].

[P = 100%, Q = 50.00%, C = 33.33%, QTY= 3] [T = 183.33]

Rule 5: If DOC = 0.4 Then V is 29.97 [23.00-35.50].

[P = 100%, Q = 50.00%, C = 33.33%, QTY = 3] [T = 183.33]

Rule 6: If SS = 2560 and DOC = 0.3 Then V is 29.97 [23.00-35.50].

[P = 100%, Q = 16.67%, C = 11.11%, QTY = 1] [T = 127.78]

Rule for G-ratio:

Rule 1: If SS = 2430 Then G-ratio is 0.0317 [0.02-0.06].

[P = 100%, Q = 50.00%, C = 33.33%, QTY = 3] [T = 183.33]

Rule 2: If SS = 2560 Then G-ratio is 0.0317 [0.02-0.06].

[P = 100%, Q = 50.00%, C = 33.33%, QTY = 3] [T = 183.33].

Rule 3: If SS = 2850 Then G-ratio is 0.0693 [0.06-0.085].

[P = 100%, Q = 100.00%, C = 33.33%, QTY = 3] [T = 233.33]

Rules for three responses:

Rule 1: If SS = 2850 Then Ra is 0.72 [0.60-0.85] and V is 29.97 [23.00-35.50] and G-ratio is 0.0693 [0.06-0.085].

[P = 100.00%, Q = 100.00%, C = 33.33%, QTY = 3] [T = 233.33]

Rule 2: If SS = 2430 Then Ra is 0.56 [0.40-0.60] and V is 20.62 [17.00-23.00] and G-ratio is 0.0317 [0.02-0.06].

[P = 66.67%, Q = 66.67%, C = 22.22%, QTY = 2] [T = 155.56]

Rule 3: If SS = 2560 Then Ra is 0.72 [0.60-0.85] and V is 29.97 [23.00-35.50] and G-ratio is 0.0317 [0.02-0.06].

[P = 66.67%, Q = 100.00%, C = 22.22%, QTY = 2] [T = 188.89]

Rule 4: If SS = 2430 and DOC = 0.04 and TCF = Coolant + Water Then Ra is 0.56 [0.40-0.60] and V is 29.97 [23.00-35.50] and G-ratio is 0.0317 [0.02-0.06].

[P = 100.00%, Q = 100.00%, C = 11.11%, QTY = 1] [T = 211.11]

Rule 5: If SS = 2560 and DOC = 0.02 and TCF = Water Then Ra is 0.56 [0.40-0.60] and V is 20.62 [17.00-23.00] and G-ratio is 0.0317 [0.02-0.06].

[P = 100.00%, Q = 33.33%, C = 11.11%, QTY = 1] [T = 144.44]

From the developed rules, it can be propounded that for response Ra (a smaller-the-type of quality characteristic), Rule 1 emerges out as the strongest rule with a T value of 208.33%. Based on this rule, it can be concluded that when the spindle speed is 2430 rpm, all the measured Ra values are expected to be 'Low' laying within the range of 0.40-0.60 µm with a rule confidence P = 100%. Similarly, 75% of all the trials (Q = 75%) having Ra values between 0.40 µm and 0.60 µm have been experimented while setting the corresponding spindle speed at 2430 rpm, and 33.33% of the experimental trials (C = 33.33%) are covered by this rule (i.e. three trials have Ra value between 0.40 µm and 0.60 µm). Amongst all the nine experimental trials, there are three runs that satisfy this rule (QTY = 3). Similarly, for Rule 3, when the spindle speed is 2850 rpm, the measured Ra values are expected to be 'High' falling within the range of 0.60-0.85 µm. For Ra response, all the remaining rules have less strength having not so much importance in this grinding process. Rules 4 and 5 showing the influences of two separate grinding parameters on Ra appear to be interesting to the production engineers, but they have also low total strength. Spindle speed appears in all the developed rules signifying its maximum importance in this grinding operation, followed by depth of cut. It is quite interesting to notice that type of the cutting fluid does not appear in any of the generated rules, signifying that fact that it has no role in controlling the surface characteristics of the ground workpiece samples.

For amplitude of vibration, six rules are similarly generated. Among them, Rules 4 and 5 are observed to be the most decisive ones with the total strength of 183.33%. They signify that when spindle speed is 2850 rpm or depth of cut is 0.04 mm, amplitude of vibration is also high, falling within the range of 23.00-35.50 µm. The developed rules also exhibit the influences of two grinding parameters on amplitude of vibration, but, all of them have low strength. It can also be revealed that all the three considered grinding parameters have also the same effect on amplitude of vibration. Similarly, for G-ratio, three decision rules are formulated. Spindle speed only appears in all these rules. It can be thus stated that when the spindle speed is below 2560 rpm, the corresponding values of G-ratio are low, falling in between 0.02 and 0.06. In Rule 3, having strength of 233.33%, a spindle speed value of 2850 rpm leads to high G-ratio, in the range of 0.06-0.085.

When all the three grinding responses are taken into consideration while formulating the corresponding decision rules, they become more complicated. Amongst the five rules, Rule 1 has the maximum strength of 233.33%, followed by Rule 4 (211.11%). It states that when rotational speed of the grinding wheel is set at its highest operating level of 3 (i.e. 2850 rpm), higher values for all the considered responses are achieved. High grinding wheel speed thus leads to poor machined surface with high Ra values, high amplitudes of vibration and higher G-ratios. But, Rule 4 with moderate strength is supposed to be the most interesting one for the concerned production engineers, because it encompasses all the grinding parameters and responses. Based on these rule, it can be concluded that when the spindle speed is 2430 rpm, depth of cut is 0.04 mm, and a mixture of coolant and water is applied as the cutting fluid, low values of Ra and G-ratio along with high value of amplitude of vibration are observed. Spindle speed plays the most significant role in controlling all the quality characteristics of the considered grinding process, followed by depth of cut and type of the cutting fluid.

Based on the generated rules, the effects of three grinding parameters, i.e. spindle speed, depth of cut and type of the cutting fluid on three different responses, i.e. average surface roughness value, amplitude of vibration and grinding ratio are studied. It is observed from the decision rules developed for average surface roughness that low spindle speed leads to better surface roughness of the ground work samples. On the contrary, high spindle speed or higher depth of cut causes increased amplitude of vibration. Similarly, high spindle speed leads to higher grinding ratio (grinding efficiency). The rules formulated while taking all the three responses into consideration demonstrate that at higher rotational speed of the grinding wheel, higher values for all the considered responses are achieved.

3.3.3 Applications of rule based Parametric Analysis on CNC turning process

Turning is a machining process where the material is removed from the workpiece with the help of single point cutting tool by the process of machining by cutting action in CNC lathe.

Varghese et al. [59] conducted an experiment to investigate the influence of the machining parameters on the responses during the dry turning operation of 11SMn30, free cutting steel with the help of WIDIA CNMG 120408-49-TN 2000 tool. The three parameters selected were spindle speed, Feed rate and depth of cut. The experimental work was carried out on CNC Turning Center STALLION 200. The main drive power was 0.5 KW and the speed range was in the range 80-240 rpm. Rapid traverse-cross/longitudinal were 15/20 m/min, an alloy of mild steel and magnesium rod (22Ǿ x 150mm), 11SMn30 as a workpiece was used for the experiment having constituents as 0.08%C, 0.04%Si, 1.10%Mn, 0.07%P, 0.30%S. Tensile Strength of the material was 395N/mm2 and hardness of 159 HB. The material was mainly applied in the form of free cutting steel and was used in bulk applications for joining. The input parameters consist of three levels as shown in Table 3.4. The detailed experimental dataset are shown in Table 3.5. Now, this experimental dataset for the turning operation is analyzed using the principle of RST so as to identify those input parameters which are responsible for controlling the output characteristics of the machined parts/components. At first, data preprocessing in the form of attribute reduction and clustering of the considered attributes are performed. Table 3.6 exhibits the dependency indices as computed for each pair of the attributes and smaller values of those indices (all the values are less than the threshold limit of 85%) prove the independency of all the attributes as considered for this grinding process. It is worthwhile to mention that in Table 3.6, the values of two dependency indices R(Ra, Rz) and R(Rz, Ra) are obtained as 55.55% and 62.96% respectively. But, as the minimum of them, i.e. 55.55% is less than the predetermined threshold value of 85%, both of them can be treated as entirely independent attributes. Along with the data reduction, the measured responses are also grouped into appropriate number of clusters using k-means algorithm to convert the continuous values into separate distinguishable ranges.

Table 3.4 Cutting parameters and their levels

Cutting Parameters	Level 1	Level 2	Level 3
Speed (m/min)	80	160	240
Feed (mm/rev)	0.1	0.2	0.4
Depth (mm)	0.5	1	1.5

The output responses are clustered in three separate groups as shown in Figure 3.2. For MRR, being a beneficial property, the three clusters are respectively designated as ‘Low’, ‘Medium’ and ‘High’ where as Ra and Rz being the non-beneficial properties, the three clusters are respectively designated as ‘Low’, ‘Medium’ and ‘High’. The details of the clusters of the cluster analysis results for the three responses of the grinding process are provided in Table 3.7. In this table, the third and fourth columns respectively denote the mean and range values for each of the clusters formed for the considered responses. On the other hand, the

Table 3.5 Experimental dataset for CNC turning process

Experiment Number	Turning Parameters			Responses		
	Speed	Feed	Depth	(Ra) (μm)	(Rz) (μm)	MRR (mm^3/min)
1	80	0.1	0.5	3	11.55	3534.2888
2	80	0.1	1	2.8	10.78	7382.7365
3	80	0.1	1.5	2.7	10.395	10720.676
4	80	0.2	0.5	3.2	12.32	7068.5775
5	80	0.2	1	3.1	11.935	14765.473
6	80	0.2	1.5	2.9	11.165	21441.352
7	80	0.4	0.5	3.6	14.076	14137.155
8	80	0.4	1	3.5	13.685	29530.946
9	80	0.4	1.5	3.4	13.294	42882.704
10	160	0.1	0.5	2.8	10.948	7068.5775
11	160	0.1	1	2.7	10.557	14765.473
12	160	0.1	1.5	2.5	9.775	21441.352
13	160	0.2	0.5	3.1	12.121	14137.155
14	160	0.2	1	3	11.73	29530.946
15	160	0.2	1.5	2.8	10.948	42882.704
16	160	0.4	0.5	3.5	13.58	28274.31
17	160	0.4	1	3.3	12.804	59061.892
18	160	0.4	1.5	3.2	12.416	85765.407
19	240	0.1	0.5	2.1	8.148	10602.866
20	240	0.1	1	2	7.76	22148.21
21	240	0.1	1.5	1.9	7.372	32162.028
22	240	0.2	0.5	2.5	9.8	21205.733
23	240	0.2	1	2.4	9.408	44296.419
24	240	0.2	1.5	2.3	9.016	64324.055
25	240	0.4	0.5	3.2	12.544	42411.465
26	240	0.4	1	3	11.76	88592.838
27	240	0.4	1.5	2.9	11.368	128648.11

Table 3.6 Dependency indices for various turning attributes

Attributes	Speed	Feed	Depth	MRR	Ra	Rz
Speed	-	0	0	0	0	0
Feed	0	-	0	11.11	0	0
Depth	0	0	-	0	0	0
MRR	0	0	0	-	0	0
Ra	0	0	0	0	-	55.55
Rz	0	0	0	0	62.96	-

fifth column represents the specific objects (experimental run) and column six denotes the total number of objects in each of the formed clusters.

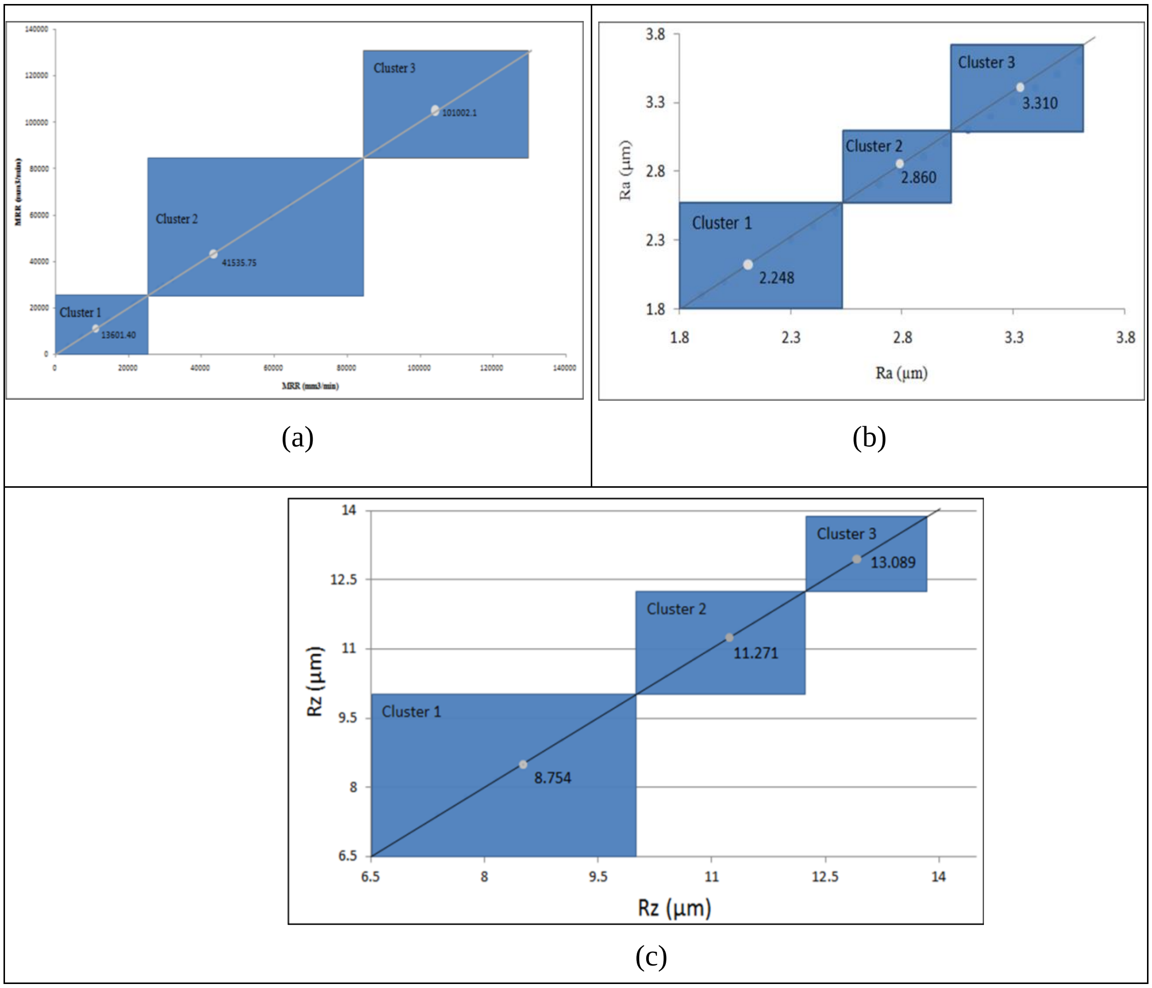

Figure 3.2 Clustering of the considered responses

Now, after data preprocessing and clustering tasks, the decision rule generation algorithm is incorporated into the system from the experimental dataset in the form of developed rules. These rules simply depict the relationships between various turning parameters and responses to effectively control the cutting operation. The first three sets of rules relate one or more turning parameters to a single response. In contrast, the last set of rules relates multiple turning parameters to all the three responses.

Rules for MRR:

Rule 1: If Speed = 80 and feed=0.4 and depth =1.0 Then MRR is 13601.40 [0-22200].

[P = 100%, Q = 10%, C = 3.70%, QTY =1] [T = 113.7]

Rule 2: If Speed = 160 and feed=0.4 and depth =1.0 Then MRR is 13601.40 [0-22200].

[P = 100%, Q = 10%, C = 3.70%, QTY =1] [T = 113.7]

Table 3.7 Details of the formed clusters for the responses

Response	Cluster number	Mean	Range of each cluster	Objects in each cluster	Total number of objects in each cluster
MRR	Cluster 1	13601.40	0-22200	1,2,3,4,5,6,7,10,11,12,13,19,20,22	14
	Cluster 2	41535.75	22200-85700	8,9,14,15,16,17,21,23,24,25	10
	Cluster 3	101002.1	85700-130000	18,26,27	3
Ra	Cluster 1	2.248	0-2.55	12,19,20,21,22,23,24	7
	Cluster 2	2.860	2.55-3.05	1,2,3,6,10,11,14,15,26,27	10
	Cluster 3	3.310	3.05-3.7	4,5,7,8,9,13,16,17,18,25	10
Rz	Cluster 1	8.754	6.5-10	12,19,20,21,22,23,24	7
	Cluster 2	11.271	10-12.20	1,2,3,5,6,10,11,13,14,15,26,27	12
	Cluster 3	13.089	12.20-14.20	4,7,8,9,16,17,18,25	8

Rule 3: If Speed = 240 and feed=0.2 and depth =1.0 Then MRR is 13601.40 [0-22200].

[P = 100%, Q = 10%, C = 3.70%, QTY =1] [T = 113.7]

Rule 4: If Speed = 240 and feed=0.2 and depth =1.5 Then MRR is 13601.40 [0-22200].

[P = 100%, Q = 10%, C = 3.70%, QTY =1] [T = 113.7]

Rule 5: If Speed = 160 and feed=0.2 and depth =1.0 Then MRR is 13601.40 [0-22200].

[P = 100%, Q = 10%, C = 3.70%, QTY =1] [T = 113.7]

Rule 6: If Speed = 160 and feed=0.4 and depth =0.5 Then MRR is 13601.40 [0-22200].

[P = 100%, Q = 10%, C = 3.70%, QTY =1] [T = 113.7]

Rule 7: If Speed = 80 and feed=0.4 and depth =1.5 Then MRR is 13601.40 [0-22200].

[P = 100%, Q = 10%, C = 3.70%, QTY =1] [T = 113.7]

Rule 8: If Speed = 240 and feed=0.4 and depth =0.5 Then MRR is 13601.40 [0-22200].

[P = 100%, Q = 10%, C = 3.70%, QTY =1] [T = 113.7]

Rule 9: If Speed = 160 and feed=0.2 and depth =1.5 Then MRR is 13601.40 [0-22200].

[P = 100%, Q = 10%, C = 3.70%, QTY =1] [T = 113.7]

Rule 10: If Speed = 240 and feed=0.1 and depth =1.5 Then MRR is 13601.40 [0-22200].

[P = 100%, Q = 10%, C = 3.70%, QTY =1] [T = 113.7]

Rule 11: If Speed = 80 and feed=0.1Then MRR is 41535.75 [22200-85700].

[P = 100%, Q = 21.43%, C = 11.11%, QTY =3] [T = 132.54]

Rule 12: If feed=0.2 and depth=0.5 Then MRR is 41535.75 [22200-85700].

[P = 100%, Q = 21.43%, C = 11.11%, QTY =3] [T = 132.54]

Rule 13: If Speed = 160 and feed=0.1Then MRR is 41535.75 [22200-85700].

[P = 100%, Q = 21.43%, C = 11.11%, QTY =3] [T = 132.54]

Rule 14: If Speed = 80 and feed=0.2 Then MRR is 41535.75 [22200-85700].

[P = 100%, Q = 21.43%, C = 11.11%, QTY =3] [T = 132.54]

Rule 15: If feed=0.1 and depth = 0.5 Then MRR is 41535.75 [22200-85700].

[P = 100%, Q = 21.43%, C = 11.11%, QTY =3] [T = 132.54]

Rule 16: If speed = 80 and depth = 0.5 Then MRR is 41535.75 [22200-85700].

[P = 100%, Q = 21.43%, C = 11.11%, QTY =3] [T = 132.54]

Rule 17: If feed=0.1 and depth = 1.0 Then MRR is 41535.75 [22200-85700].

[P = 100%, Q = 21.43%, C = 11.11%, QTY =3] [T = 132.54]

Rule 18: If Speed = 240 and feed=0.4 and depth =1.5 Then MRR is 101002.1 [85700-130000].

[P = 100%, Q = 33.33%, C = 3.70%, QTY =1] [T = 137.03]

Rule 19: If Speed = 160 and feed=0.4 and depth =1.5 Then MRR is 101002.1 [85700-130000].

[P = 100%, Q = 33.33%, C = 3.70%, QTY =1] [T = 137.03]

Rule 20: If Speed = 240 and feed=0.4 and depth =1.0 Then MRR is 101002.1 [85700-130000].

[P = 100%, Q = 33.33%, C = 3.70%, QTY =1] [T = 137.03]

Rules for Ra:

Rule 1: If speed=80 and feed = 0.4 Then Ra is 2.248 [0-2.55].

[P = 100%, Q = 30.0%, C = 11.11%, QTY =3] [T = 141.11]

Rule 2: If speed=160 and feed = 0.4 Then Ra is 2.248 [0-2.55].

[P = 100%, Q = 30.0%, C = 11.11%, QTY =3] [T = 141.11]

Rule 3: If speed=80 and feed = 0.2 and depth =0.5 Then Ra is 2.248 [0-2.55].

[P = 100%, Q = 10.0%, C = 3.70%, QTY =1] [T = 113.70]

Rule 4: If speed=80 and feed = 0.2 and depth =1.0 Then Ra is 2.248 [0-2.55].

[P = 100%, Q = 10.0%, C = 3.70%, QTY =1] [T = 113.70]

Rule 5: If speed=160 and feed = 0.2 and depth =0.5 Then Ra is 2.248 [0-2.55].

[P = 100%, Q = 10.0%, C = 3.70%, QTY =1] [T = 113.70]

Rule 6: If feed = 0.4 and depth =0.5 Then Ra is 2.248 [0-2.55].

[P = 100%, Q = 30.0%, C = 11.11%, QTY =3] [T = 141.11]

Rule 7: If speed=80 and feed = 0.1 Then Ra is 2.860 [2.55-3.05].

[P = 100%, Q = 30.0%, C = 11.11%, QTY =3] [T = 141.11]

Rule 8: If speed=160 and feed = 0.1 and depth = 0.5 Then Ra is 2.860 [2.55-3.05].

[P = 100%, Q = 10.0%, C = 3.70%, QTY =1] [T = 113.70]

Rule 9: If speed=160 and feed = 0.2 and depth = 1.0 Then Ra is 2.860 [2.55-3.05].

[P = 100%, Q = 10.0%, C = 3.70%, QTY =1] [T = 113.70]

Rule 10: If speed=80 and feed = 0.2 and depth = 1.5 Then Ra is 2.860 [2.55-3.05].

[P = 100%, Q = 10.0%, C = 3.70%, QTY =1] [T = 113.70]

Rule 11: If speed=160 and feed = 0.1 and depth = 1.0 Then Ra is 2.860 [2.55-3.05].

[P = 100%, Q = 10.0%, C = 3.70%, QTY =1] [T = 113.70]

Rule 12: If speed=240 and feed = 0.4 and depth = 1.0 Then Ra is 2.860 [2.55-3.05].

[P = 100%, Q = 10.0%, C = 3.70%, QTY =1] [T = 113.70]

Rule 13: If speed=160 and feed = 0.2 and depth = 1.5 Then Ra is 2.860 [2.55-3.05].

[P = 100%, Q = 10.0%, C = 3.70%, QTY =1] [T = 113.70]

Rule 14: If speed=240 and feed = 0.4 and depth = 1.5 Then Ra is 2.860 [2.55-3.05].

[P = 100%, Q = 10.0%, C = 3.70%, QTY =1] [T = 113.70]

Rule 15: If speed=240 and feed = 0.1 Then Ra is 3.310 [3.05-3.7].

[P = 100%, Q = 42.86%, C = 11.11%, QTY =3] [T = 153.97]

Rule 16: If speed=240 and feed = 0.2 Then Ra is 3.310 [3.05-3.7].

[P = 100%, Q = 42.86%, C = 11.11%, QTY =3] [T = 153.97]

Rule 17: If speed=160 and feed = 0.1 and depth = 1.5 Then Ra is 3.310 [3.05-3.7].

[P = 100%, Q = 14.29%, C = 3.70%, QTY =1] [T = 117.99]

Rules for Rz:

Rule 1: If speed=80 and feed = 0.4 Then Rz is 8.754 [6.5-10].

[P = 100%, Q = 33.33%, C = 11.11%, QTY =3] [T = 144.44]

Rule 2: If speed=160 and feed = 0.4 Then Rz is 8.754 [6.5-10].

[P = 100%, Q = 33.33%, C = 11.11%, QTY =3] [T = 144.44]

Rule 3: If speed=80 and feed = 0.2 and depth = 0.5 Then Rz is 8.754 [6.5-10].

[P = 100%, Q = 11.11%, C = 3.70%, QTY =1] [T = 114.81]

Rule 4: If speed=160 and feed = 0.2 and depth = 0.5 Then Rz is 8.754 [6.5-10].

[P = 100%, Q = 11.11%, C = 3.70%, QTY =1] [T = 114.81]

Rule 5: If feed = 0.4 and depth = 0.5 Then Rz is 8.754 [6.5-10].

[P = 100%, Q = 33.33%, C = 11.11%, QTY =3] [T = 144.44]

Rule 6: If speed = 80 and feed =0.1 Then Rz is 11.271 [10-12.20].

[P = 100%, Q = 27.27%, C = 11.11%, QTY =3] [T = 138.38]

Rule 7: If speed = 160 and feed=0.1 and depth =0.5 Then Rz is 11.271 [10-12.20].

[P = 100%, Q = 9.09%, C = 3.70%, QTY =1] [T = 112.79]

Rule 8: If speed = 80 and feed=0.2 and depth =1.0 Then Rz is 11.271 [10-12.20].

[P = 100%, Q = 9.09%, C = 3.70%, QTY =1] [T = 112.79]

Rule 9: If speed = 160 and feed=0.2 and depth =1.0 Then Rz is 11.271 [10-12.20].

[P = 100%, Q = 9.09%, C = 3.70%, QTY =1] [T = 112.79]

Rule 10: If speed = 80 and feed=0.2 and depth =1.5 Then Rz is 11.271 [10-12.20].

[P = 100%, Q = 9.09%, C = 3.70%, QTY =1] [T = 112.79]

Rule 11: If speed = 160 and feed=0.1 and depth =1.0 Then Rz is 11.271 [10-12.20].

[P = 100%, Q = 9.09%, C = 3.70%, QTY =1] [T = 112.79]

Rule 12: If speed = 240 and feed=0.4 and depth =1.0 Then Rz is 11.271 [10-12.20].

[P = 100%, Q = 9.09%, C = 3.70%, QTY =1] [T = 112.79]

Rule 13: If speed = 160 and feed=0.2 and depth =1.5 Then Rz is 11.271 [10-12.20].

[P = 100%, Q = 9.09%, C = 3.70%, QTY =1] [T = 112.79]

Rule 14: If speed = 240 and feed=0.4 and depth =1.5 Then Rz is 11.271 [10-12.20].

[P = 100%, Q = 9.09%, C = 3.70%, QTY =1] [T = 112.79]

Rule 15: If speed = 240 and feed=0.1 Then Rz is 13.089 [12.20-14.20].

[P = 100%, Q = 42.86%, C = 11.11%, QTY =3] [T = 153.97]

Rule 16: If speed = 240 and feed=0.2 Then Rz is 13.089 [12.20-14.20].

[P = 100%, Q = 42.86%, C = 11.11%, QTY =3] [T = 153.97]

Rule 17: If speed = 160 and feed=0.1 and depth = 0.4Then Rz is 13.089 [12.20-14.20].

[P = 100%, Q = 14.29%, C = 3.70%, QTY =1] [T =117.99]

Rules for three responses:

Rule 1: If feed=0.4 Then MRR is 13601.40[0-22200] and Ra is 2.248[0-2.55] and Rz is 8.754[6.5-10].

[P = 55.56%, Q = 100.0%, C = 18.52%, QTY =5] [T =174.08]

Rule 2: If speed=160 and feed=0.2 Then MRR is 13601.40[0-22200] and Ra is 2.860[2.55-3.05] and Rz is 11.271[10-12.20].

[P = 66.67%, Q = 100.0%, C = 7.41%, QTY =2] [T =174.08]

Rule 3: If speed=80 Then MRR is 41535.75[22200-85700] and Ra is 2.248[0-2.55] and Rz is 8.754[6.5-10] or 11.271[10-12.20].

[P = 33.33%, Q = 75.0%, C = 11.11%, QTY =3] [T =119.44]

Rule 4: If feed=0.1 Then MRR is 41535.75[22200-85700] and Ra is 2.860[2.55-3.05] and Rz is 11.271 [10-12.20].

[P = 55.56%, Q = 83.33%, C = 18.52%, QTY =5] [T =157.41]

Rule 5: If speed=240 and feed = 0.1 Then MRR is 41535.75[22200-85700] and Ra is 3.310[3.05-3.7] and Rz is 13.089 [12.20-14.20].

[P = 66.67%, Q = 50.0%, C = 7.4%, QTY =2] [T =124.074]

Rule 6: If speed=160 and feed = 0.4 and depth=1.5 Then MRR is 101002.1[85700-130000] and Ra is 2.248[0-2.55] and Rz is 8.754[6.5-10]

[P = 100%, Q = 100%, C = 3.71%, QTY =1] [T =203.71]

Rule 7: If speed=240 and feed = 0.4 Then MRR is 101002.1[85700-130000] and Ra is 2.860[2.55-3.05] and Rz is 11.271[10-12.20].

[P = 66.67%, Q = 100%, C = 7.41%, QTY =2] [T =174.07]

Rule 8: If speed=80 and feed = 0.2 and depth=1.5 Then MRR is 41535.75[22200-85700] and Ra is 2.860[2.55-3.05] and Rz is 11.271[10-12.20].

[P = 100%, Q = 16.67%, C = 3.70%, QTY =1] [T =120.37]

Rule 9: If speed=160 and feed = 0.2 and depth=0.5 Then MRR is 41535.75[22200-85700] and Ra is 2.248[0-2.55] and Rz is 11.271[10-12.20].

[P = 100%, Q = 25%, C = 3.70%, QTY =1] [T =128.70]

Rule 10: If speed=240 and feed = 0.2 and depth=0.5 Then MRR is 41535.75[22200-85700] and Ra is 3.310[3.05-3.7] and Rz is 13.089 [12.20-14.20].

[P = 100%, Q = 25%, C = 3.70%, QTY =1] [T =128.70]

Rule 11: If speed=240 Then MRR is 13601.40[0-22200] and Ra is 3.310[3.05-3.7] and Rz is 13.089 [12.20-14.20].

[P = 33.33%, Q = 100%, C = 11.11%, QTY =3] [T =144.44]

Rule 12: If speed=160 and feed = 0.1 and depth=1.5 Then MRR is 41535.75[22200-85700] and Ra is 3.310[3.05-3.7] and Rz is 13.089 [12.20-14.20].

[P = 100%, Q = 25.0%, C = 3.70%, QTY =1] [T =128.70]

From the above developed rule for MRR it is shown that rules 18, 19 and 20 contain maximum weightage (T=137.03) among all the rules generated. All the three rules stated that the high MRR is obtained in the range of [85700-130000] when high feed, high cutting speed and high depth is maintained, which is highly recommended as per production point of view. In all the three cases the confidence weightage is around 100% signifies that the input parameters are successfully associated together to generate the rules. From the rules generated for MRR, feed appears to be the most influential parameter followed by speed and depth.

For the rule generation for Ra, rules 15 and 16 have the maximum strength (T=153.97) which states that with high speed and low to moderate feed, high surface roughness Ra is generated in the range of [3.05-3.7] µm. As surface roughness is a non-beneficial property, so low surface roughness is desired. Another important rules, namely 1, 2, 6 and 7, although contain slightly less weight (T=141.11) are very interesting to consider. These rules states that with high feed rate and low to medium speed range and low to medium depth of cut, low surface roughness Ra value is obtained which is desirable. Inspite of the higher weight of the earlier mentioned rule, the later mentioned rule can be considered as the important rule for surface roughness. From the above mentioned rule, feed is most influential criterion for the desired surface roughness of the workpiece followed by cutting speed whereas depth has very low to null influence on the surface roughness as it doesn't appear much while rule formation.

For the rule generation for Rz, similar trend is obtained as for Ra. Rules 15 and 16 appear to be the most weightage rule with total weightage of 153.97 but signifies high surface roughness feature Rz due to low feed and high cutting speed. But rules 1, 2 and 5 appears to be the most important rules because of low surface roughness and slightly low weightage 144.44. The rules states that to generate low surface roughness, high feed with low to medium cutting speed and low depth of cut is essential. Here also feed appears as most beneficial criteria among the three.

When all the three turning responses are taken into consideration while formulating the corresponding decision rules, they become more complicated. Amongst the twelve rules, Rule 6 has the maximum strength of 203.71. It states that when speed is medium and feed is high and depth is high i.e. the operating condition is set at 160 mm/min and 0.4 mm/rev and 1.5 mm respectively, then optimal value of the responses, i.e. high MRR, low Ra and Rz value is obtained. Feed plays the most significant role in controlling all the quality characteristics of the considered turning process, followed by cutting speed and depth of cut. The knowledge extracted for the above algorithm perfectly matches with other papers and clearly validate the algorithm suitable for this type of process.

3.4 Applications of rule based Parametric Analysis on Non-Conventional machining

In order to meet the ever increasing demands for higher production rate and dimensional accuracy, low surface roughness, generation of complex shape geometries in various advanced engineering materials with low machinability etc., the conventional metal removal methods are being continuously substituted by the non-traditional machining (NTM) processes. These processes usually employ different energies, like mechanical, thermal, electrical or chemical energy or combination of them to remove tiny amounts of materials from the workpiece surfaces, even at atomic levels [60]. Due to their enhanced machining capabilities, they have now been extensively deployed to shape ultra-hard alloys in heavy industries and aerospace applications, machine ultra-thin materials in electronic devices as microprocessors, generate complicated shape geometries in turbine blades, and fabricate blind or through holes in jet nozzles. They can even generate micro- and nano-features in diverse hard-to-machine materials with ease [6, 7]. These NTM processes are often characterized by their various controllable (input) parameters and outputs (responses). Their material removal mechanisms are also very complex. Even the most experienced process engineers face the problems to clearly understand the relationships between different NTM process parameters and the corresponding responses. It may lead to variations in dimensional accuracy and surface roughness of the finally machined products/components.

With the increasing automation and rapid development of the computational intelligence, knowledge has received significant attention in manufacturing, specially in the domain of NTM processes, to build competitive advantages. Knowledge induction from data has now become extremely important in NTM processes so as to enhance productivity, understand the process mechanisms and improve the future process performance. It has now become the burden to the computers to quickly and exhaustively establish the relationships between various NTM process parameters and responses through the deployment of different data mining tools and techniques. Data mining is an evolving area of computational intelligence offering new iterative and interactive techniques for processing large volumes of data in order to explore valuable and understandable patterns hidden in the dataset. Availability of huge machining and manufacturing related data in digital form has also accelerated the application of data mining tools to aid the concerned process engineers in identifying the tentative settings of various process parameters to obtain the desired response values. In data mining, development of association rules is one of the important areas of research, requiring more attention to be effectively augmented in the domain of NTM processes for their effective control. Association rules are simple ‘If-Then’ statements to help discover significant relationships between independent and dependent variables. In this context, an attempt is put forward to develop the related association rules for three most widely used NTM processes, i.e. electrochemical machining (ECM), ultrasonic machining (USM) and electrical discharge machining (EDM) to identify their most favorable parametric settings so as to achieve the target response values. These rules would also assist the concerned process engineers in understanding the effects of the considered NTM process parameters on the outputs.

3.4.1 Literature review on the Non-Conventional machining processes

Zdrojewski and Paczkowski [61] presented the control method of the research process for erosion machining and construction of the stand. This stand had modular design with separated electrodes drive and machining area and had a controller which adjusted the machining parameters, like feed rate of the working electrode, electrode oscillation frequency, synchronization of electrodes oscillation, inter electrodes gap thickness, using PC program communicating with PLC I/O modules. This type of stand allowed to verify mathematical models of the process and also allowed to develop an active type of on-line control, connecting the theoretical results with measurement of parameters during machining.

Senthilkumar et al. [62] optimized the electrochemical machining of AL/15% SiC_p composite using non-dominated sorting genetic algorithm NSGA-II. The second order polynomial models developed for MRR and R_a were used for optimization. A multiple regression model was applied to represent relationship between the input and output variables and NSGA-II was used to optimize ECM process and a non-dominated solution set was obtained. This paper proposed that the optimization of the output response, e.g. metal removal rate and surface roughness, was helpful to increase the production rate considerable by reducing machining time.

Prasad and Chakraborty [63] developed a decision guidance framework using 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. This paper used to identify the ideal process parameter combinations for the most suitable NTM process. This paper recommended a fine tuning of the machining parameter settings for the optimized results as per the end product requirement and technical specification of the NTM setup.

Uchiyama and Hasegawa [64] described the optimization of the tool design and machining condition in a small curved hole machining method using electrochemical machining. This paper stated that the proposed method could produce smooth holes without special control. A tool electrode device equipped with ultrasonic vibration function was designed and fabricated, for removal of the sludge from the bending cooling channel during machining. In consideration of an application to metal molds, it was found that electrochemical machining attached ultrasonic vibration could reduce machining time of curved holes.

Jeykrishnan et al. [65] investigated the ECM process parameters, e.g. current, voltage and electrolytic concentration, of SKD-12 tool steel using Taguchi technique and Analysis of variance (ANOVA) to ascertain the important parameters on the response characteristics, especially material removal rate. The proposed method stated that the current was the most important parameter for altering the ECM robustness.

Das et al. [66] investigated the effect of process parameters on material removal rate and surface roughness characteristic and parametric optimization of process parameters in ECM of EN31 tool steel using grey relation analysis. This paper conducted experiment which was based on Taguchi's L_{27} orthogonal array using four process parameters namely electrolytic concentration, voltage, feedrate, and inter electrode gap and analysis of variance was applied to get the contribution of each parameter on the performance characteristics. To perfectly validate the results, surface and contour plots were generated to study the effect of input parameters on MRR and surface roughness and scanning microscopy image were used to observe the surface morphology.

Wang et al [67] conducted both simulations and experiments for studying the influence of tool wear on material removal in this work. Three different tool materials i.e. 304 stainless steel, 1045 carbon steel, and tungsten carbide were used. A numerical simulation model utilizing both Smoothed Particle Hydrodynamics (SPH) mesh-free method and Finite Element Method (FEM) was built first to predict tool deformation and fractures of workpiece and abrasive particles. Experiments were then conducted to verify the simulation results. The relation between the material removal and the tool wear was discussed based on these results.

Feucht et al [68] presented the flexible integration of state of the art ultrasonic systems in machining centers. This paper discussed the latest machining test examples of advances materials using ultrasonic assisted machining are discussed. This paper proposed that the reduce process forces allowed very fine structures and increased process reliability which again reduced the operation cost and time consumption of the parts in small series and also proposed that the increases in feed rate could be utilized to further reduce the tool wear and increase surface quality.

Goswami and Chakraborty [69] applied gravitational search algorithm (GSA) and fireworks algorithm (FWA) for parametric optimization of USM processes. The optimization performance of these two algorithms was then compared with that of other popular population-based algorithms, and the effects of their algorithm parameters on the derived optimal solutions and computational speed were also investigated. It was observed that FWA provided the best optimal results for the considered USM processes.

Baroi et al. [70] studied the parametric optimization of Electric discharge machining of titanium grade 2 alloy. This paper studied the variation in material removal rate, tool wear rate and surface roughness with the variation of process parameters, e.g. current and pulse on time. Experiments had been carried out as per the Taguchi L16 orthogonal array design of experiments. The optimum condition for each response had been evaluated by analyzing the effect of input parameters on the mean of the responses. Analysis of variance (ANOVA) had been performed to study the percentage contribution of each input parameter on the output responses.

Gangil et al. [71] presented a literature review on modelling and optimization of electrical discharge machining process using modern techniques. The review period considered was from the year 2006 to 2015. This review study had been classified according to different process as Die Sinking EDM, WEDM, PMEDM, Micro-Machining, and various hybrids and modified versions. This review work became the ready information at one place and it may be very useful for the subsequent researchers to decide their direction of research.

Choudhary and Singh [72] employed Electrical discharge machining to machine AISI M42 tool steel. This paper investigated the effect of specific machining parameter on MRR during machining. For machining EDM-50 oil was used as di-electric fluid and the study revealed that the maximum MRR was observed at negative tool polarity and current was the second most influential parameter for maximising MRR after the tool polarity.

3.4.2 Applications of rule based Parametric Analysis on ECM process

In ECM process, material is removed from the workpiece by anodic dissolution of electrolyte based on the Faraday's law of electrolysis. It involves two electrodes, connected to high voltage power supply, and a very small gap is maintained between them separated by an electrolyte for efficient exchange of ions, causing material removal. Using a METATECH ECM setup and based on Taguchi's orthogonal array design plan, Rao and Padmanabhan [73] performed 27 experiments on LM6 Al/B_4C composite materials while considering voltage, feed rate, electrolyte concentration and percentage of reinforcement of boron carbide particles in the considered alloy matrix as the input parameters. Each of these parameters was set at three different levels, as shown in Table 3.8. In this process, material removal rate (MRR) (in g/min), surface roughness (SR) (in μm) and radial overcut (ROC) (in mm) were the responses. Among them, MRR is the only 'larger-the-better' (LTB) type of quality characteristic, whereas, SR and ROC are 'smaller-the-better' (STB) type of characteristics. The detailed experimental plan and measured response values are provided in Table 3.9.

Table 3.8 ECM process parameters and their levels [73]

Parameter	Symbol	Unit	Level		
			1	2	3
Voltage	VL	V	12	16	20
Feed rate	FR	mm/min	0.2	0.6	1.0
Electrolyte concentration	EC	g/l	10	20	30
Percentage of reinforcement	POR	Wt%	2.5	5.0	7.5

Table 3.9 Experimental plan and responses for the ECM process [73]

Exp. No.	VL	FR	EC	POR	MRR	SR	ROC
1	1	1	1	1	0.268	4.948	0.96
2	1	1	2	2	0.335	5.002	0.94
3	1	1	3	3	0.227	4.591	0.79
4	1	2	1	1	0.353	4.92	0.75
5	1	2	2	2	0.448	4.498	0.65
6	1	2	3	3	0.42	4.725	0.8
7	1	3	1	1	0.689	4.555	0.67
8	1	3	2	2	0.545	4.356	0.64
9	1	3	3	3	0.703	4.232	0.65
10	2	1	1	2	0.321	4.882	0.91
11	2	1	2	3	0.329	4.823	0.94
12	2	1	3	1	0.488	4.254	1.05
13	2	2	1	2	0.379	4.54	0.76
14	2	2	2	3	0.302	4.431	0.69
15	2	2	3	1	0.583	3.998	0.99
16	2	3	1	2	0.615	4.274	0.75
17	2	3	2	3	0.619	4.346	0.7
18	2	3	3	1	0.812	3.598	0.93
19	3	1	1	3	0.282	5.472	0.91
20	3	1	2	1	0.599	4.797	1.1
21	3	1	3	2	0.603	4.64	1.16
22	3	2	1	3	0.526	5.214	0.85
23	3	2	2	1	0.688	4.897	1.03
24	3	2	3	2	0.732	4.531	1.08
25	3	3	1	3	0.688	5.002	0.64
26	3	3	2	1	0.887	4.389	0.99
27	3	3	3	2	0.944	3.989	1

Before generating the corresponding association rules for studying the performance of the ECM process, it is essential to preprocess the initial experimental dataset with an attempt to eliminate redundant information. In Table 3.10, the dependency indexes are estimated for each pair of the attributes. Lower values of these indexes than the threshold limit of 90% validate entire independency between different attributes. Now, using *k*-means algorithm, the responses in Table 3.9 are grouped into suitable number of clusters to transform their continuous values into separate distinguishable ranges. In Figure 3.3, each of the three ECM responses is grouped into two separate clusters, designated as 'Low' and 'High'. For MRR, 'High' values are always preferred, whereas, 'Low' values are desired for the remaining responses. The details of the cluster analysis results for the ECM process are provided in Table 3.11. The mean and range for each cluster for the three responses are shown in columns 3 and 4 respectively. Column 5 highlights the specific objects (experimental runs) and column 6 shows the total number of objects in each cluster. Now, based on the experimental dataset of Table 3.9, the resultant association rules depicting the relationships between various ECM process parameters and responses are generated using ROSE2 (version 2.2) rough sets data explorer. In the first three sets of rules, one or more ECM process parameters are assigned to a single response, while, in the last set, rules accommodating all the three responses are generated.

Table 3.10 Dependency indexes for different ECM attributes

Attribute	VL	FR	EC	POR	MRR	SR	ROC
VL	-	0	0	0	0	0	0
FR	0	-	0	0	0	0	0
EC	0	0	-	0	0	0	0
POR	0	0	0	-	0	0	0
MRR	0	33.33	0	0	-	0	0
SR	0	0	0	0	0	-	0
ROC	0	0	0	0	0	0	-

For MRR:

Rule 1: If VL = 12 V and FR = 0.2 mm/min Then MRR is 0.346 g/min [0.227-0.490] [P = 100%, Q = 25%, C = 11.11%, QTY = 3] [T = 136.11]

Rule 2: If VL = 16 V and FR = 0.2 mm/min Then MRR is 0.346 g/min [0.227-0.490] [P = 100%, Q = 25%, C = 11.11%, QTY = 3] [T = 136.11]

Rule 3: If VL = 12 V and FR = 0.6 mm/min Then MRR is 0.346 g/min [0.227-0.490] [P = 100%, Q = 25%, C = 11.11%, QTY = 3] [T = 136.11]

Rule 4: If VL = 16 V and FR = 0.6 mm/min and EC = 10 g/l Then MRR is 0.346 g/min [0.227-0.490] [P = 100%, Q = 8.33%, C = 3.70%, QTY = 1] [T = 112.03]

Rule 5: If VL = 16 V and FR = 0.6 mm/min and POR = 7.5 Wt% Then MRR is 0.346 g/min [0.227-0.490] [P = 100%, Q = 8.33%, C = 3.70%, QTY = 1] [T = 112.03]

Rule 6: If FR = 0.2 mm/min and EC = 10 g/l Then MRR is 0.346 g/min [0.227-0.490] [P = 100%, Q = 25%, C = 11.11%, QTY = 3] [T = 136.11]

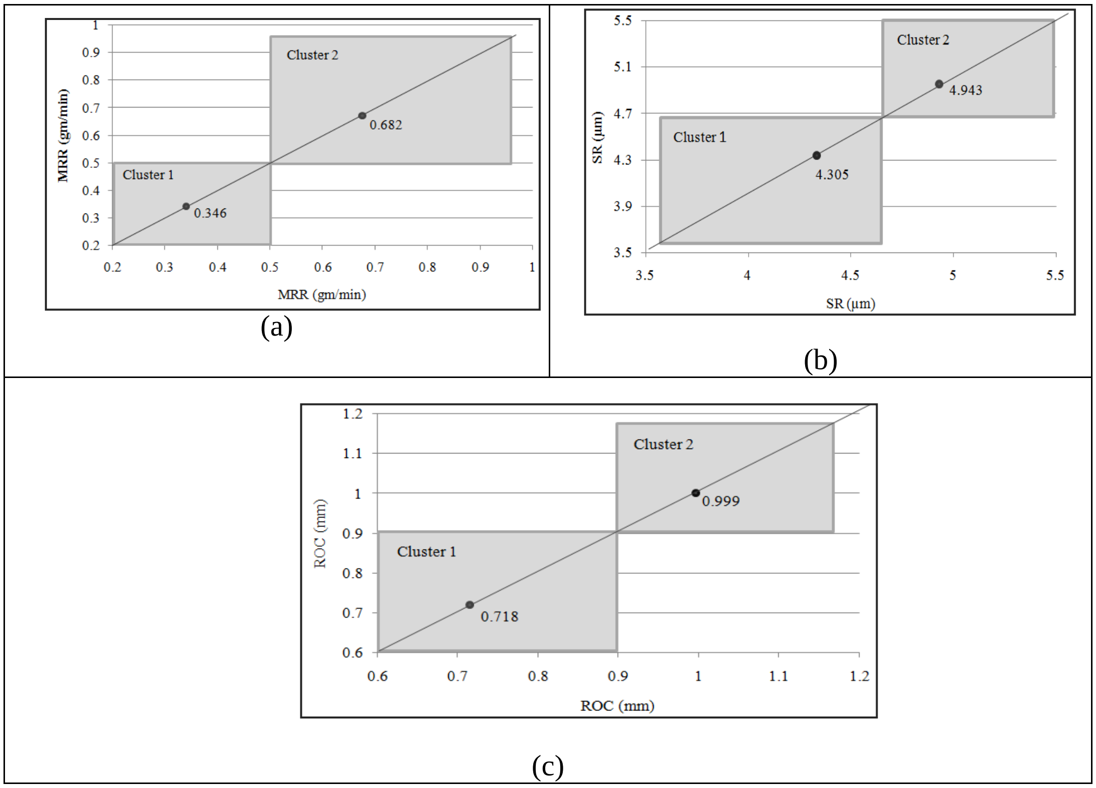

Figure 3.3 Clustering of the ECM responses

Table 3.11 Details of the formed clusters for the ECM process

Response	Cluster number	Mean	Range of each cluster	Objects	Number of objects in each cluster
MRR	Cluster 1	0.346	0.227-0.490	1,2,3,4,5,6,10,11,12,13,14,19	12
	Cluster 2	0.682	0.490-0.944	7,8,9,15,16,17,18,20,21,22,23,24,25,26,27	15
SR	Cluster 1	4.305	3.598-4.600	3,5,7,8,9,12,13,14,15,16,17,18,24,26,27	15
	Cluster 2	4.943	4.600-5.472	1,2,4,6,10,11,19,20,21,22,23,25	12
ROC	Cluster 1	0.718	0.640-0.900	3,4,5,6,7,8,9,13,14,16,17,22,25	13
	Cluster 2	0.999	0.900-1.160	1,2,10,11,12,15,18,19,20,21,23,24,26,27	14

Rule 7: If FR = 1.0 mm/min Then MRR is 0.682 g/min [0.490-0.944] [P = 100%, Q = 60%, C = 33.33%, QTY = 9] [T = 193.33]

Rule 8: If VL = 20 V and FR = 0.6 mm/min Then MRR is 0.682 g/min [0.490-0.944] [P = 100%, Q = 20%, C = 11.11%, QTY = 3] [T = 131.11]

Rule 9: If VL = 20 V and EC = 20 g/l Then MRR is 0.682 g/min [0.490-0.944] [P = 100%, Q = 20%, C = 11.11%, QTY = 3] [T = 131.11]

Rule 10: If VL = 16 V and FR = 0.6 mm/min and EC = 30 g/l Then MRR is 0.682 g/min [0.490-0.944] [P = 100%, Q = 6.67%, C = 3.70%, QTY = 1] [T = 110.37]

Rule 11: If VL = 20 V and EC = 30 g/l Then MRR is 0.682 g/min [0.490-0.944] [P = 100%, Q = 20%, C = 11.11%, QTY = 3] [T = 131.11]

For SR:

Rule 1: If VL = 12 V and FR = 1.0 mm/min Then SR is 4.305 µm [3.598-4.6] [P = 100%, Q = 20%, C = 11.11%, QTY = 3] [T = 131.11]

Rule 2: If VL = 16 V and FR = 0.6 mm/min Then SR is 4.305 µm [3.598-4.6] [P = 100%, Q = 20%, C = 11.11%, QTY = 3] [T = 131.11]

Rule 3: If VL = 16 V and FR = 1.0 mm/min Then SR is 4.305 µm [3.598-4.6] [P = 100%, Q = 20%, C = 11.11%, QTY = 3] [T = 131.11]

Rule 4: If FR = 0.6 mm/min and POR = 5.0 Wt% Then SR is 4.305 µm [3.598-4.6] [P = 100%, Q = 20%, C = 11.11%, QTY = 3] [T = 131.11]

Rule 5: If VL = 12 V and FR = 0.2 mm/min and EC = 30 g/l Then SR is 4.305 µm [3.598-4.6] [P = 100%, Q = 6.67%, C = 3.70%, QTY = 1] [T = 110.37]

Rule 6: If FR = 1.0 mm/min and EC = 30 g/l Then SR is 4.305 µm [3.598-4.6] [P = 100%, Q = 20%, C = 11.11%, QTY=3] [T=131.11]

Rule 7: If VL = 16 V and POR = 2.5 Wt% Then SR is 4.305 µm [3.598-4.6] [P = 100%, Q = 20%, C = 11.11%, QTY = 3] [T = 131.11]

Rule 8: If FR = 1.0 mm/min and EC = 20 g/l Then SR is 4.305 µm [3.598-4.6] [P = 100%, Q = 20%, C = 11.11%, QTY = 3] [T = 131.11]

Rule 9: If VL = 20 V and FR = 0.2 mm/min Then SR is 4.943 µm [4.6-5.472] [P = 100%, Q = 25%, C = 11.11%, QTY = 3] [T = 136.11]

Rule 10: If VL = 12 V and FR = 0.6 mm/min and EC = 10 g/l Then SR is 4.943 µm [4.6-5.472] [P = 100%, Q = 8.33%, C = 3.70%, QTY = 1] [T = 112.03]

Rule 11: If VL = 20 V and POR = 7.5 Wt% Then SR is 4.943 µm [4.6-5.472] [P = 100%, Q = 25%, C = 11.11%, QTY = 3] [T = 136.11]

Rule 12: If FR = 0.2 mm/min and EC = 10 g/l Then SR is 4.943 µm [4.6-5.472] [P = 100%, Q = 25%, C = 11.11%, QTY = 3] [T = 136.11]

Rule 13: If FR = 0.2 mm/min and EC = 20 g/l then SR is 4.943 µm [4.6-5.472] [P = 100%, Q = 25%, C = 11.11%, QTY = 3] [T = 136.11]

Rule 14: If VL = 12 V and FR = 0.6 mm/min and EC = 30 g/l then SR is 4.943 µm [4.6-5.472] [P = 100%, Q = 8.33%, C = 3.70%, QTY = 1] [T = 112.03]

Rule 15: If VL = 20 V and FR = 0.6 mm/min and EC = 20 g/l then SR is 4.943 µm [4.6-5.472] [P = 100%, Q = 8.33%, C = 3.70%, QTY = 1] [T = 112.03]

For ROC:

Rule 1: If VL = 12 V and FR = 0.6 mm/min Then ROC is 0.718 mm [0.64-0.90] [P = 100%, Q = 23.08%, C = 11.11%, QTY = 3][T = 134.19]

Rule 2: If VL = 12 V and FR = 1.0 mm/min Then ROC is 0.718 mm [0.64-0.90] [P = 100%, Q = 23.08%, C = 11.11%, QTY = 3][T = 134.19]

Rule 3: If VL = 16 V and FR = 0.6 mm/min and EC = 20 g/l Then ROC is 0.718 mm [0.64-0.90] [P = 100%, Q = 7.69%, C = 3.70%, QTY = 1] [T = 111.39]

Rule 4: If FR = 0.6 mm/min and EC = 10 g/l Then ROC is 0.718 mm [0.64-0.90] [P = 100%, Q = 23.08%, C = 11.11%, QTY = 3] [T = 134.19]

Rule 5: If FR = 1.0 mm/min and EC = 10 g/l Then ROC is 0.718 mm [0.64-0.90] [P = 100%, Q = 23.08%, C = 11.11%, QTY =3] [T = 134.19]

Rule 6: If VL = 12 V and POR = 7.5 Wt% Then ROC is 0.718 mm [0.64-0.90] [P = 100%, Q = 23.08%, C = 11.11%, QTY = 3] [T = 134.19]

Rule 7: If VL = 16V and FR = 1.0 mm/min and EC = 20 g/l Then ROC is 0.718 mm [0.64-0.90] [P = 100%, Q = 7.69%, C = 3.70%, QTY = 1] [T = 111.39]

Rule 8: If VL = 16 V and POR = 2.5 Wt% Then ROC is 0.999 mm [0.9-1.16] [P = 100%, Q = 21.43%, C = 11.11%, QTY = 3] [T = 132.54]

Rule 9: If VL = 20 V and EC = 20 g/l Then ROC is 0.999 mm [0.9-1.16] [P = 100%, Q = 21.43%, C = 11.11%, QTY = 3] [T = 132.54]

Rule 10: If VL = 20 V and POR = 5.0 Wt% Then ROC is 0.999 mm [0.9-1.16] [P = 100%, Q = 21.43%, C = 11.11%, QTY = 3] [T = 132.54]

Rule 11: If FR = 0.2 mm/min and EC = 10 g/l Then ROC is 0.999 mm [0.9-1.16] [P = 100%, Q = 21.43%, C = 11.11%, QTY = 3] [T = 132.54]

Rule 12: If FR = 0.2 mm/min and EC = 20 g/l Then ROC is 0.999 mm [0.9-1.16] [P = 100%, Q = 21.43%, C = 11.11%, QTY = 3] [T = 132.54]

For all the responses:

Rule 1: If VL = 12 V and FR = 0.2 mm/min and EC = 30 g/l and POR = 7.5 Wt% Then MRR is 0.346 g/min [0.227-0.490] and SR is 4.305 μm [3.598-4.6] and ROC is 0.718 mm [0.64-0.90] [P = 100%, Q = 25%, C = 3.70%, QTY = 1] [T = 128.70]

Rule 2: If FR = 0.6 mm/min Then MRR is 0.346 g/min [0.227-0.490] and SR is 4.305 μm [3.598-4.6] and ROC is 0.718 mm [0.64-0.90] [P = 33.33%, Q = 75%, C = 11.11%, QTY = 3] [T = 119.44]

Rule 3: If VL = 16 V and FR = 0.2 mm/min and EC = 30 g/l and POR = 2.5 Wt% Then MRR is 0.346 g/min [0.227-0.490] and SR is 4.305 µm [3.598-4.6] and ROC is 0.999 mm [0.9-1.16] [P = 100%, Q = 100%, C = 3.70%, QTY = 1] [T = 203.70]

Rule 4: If VL = 12 V and FR = 0.6 mm/min Then MRR is 0.346 g/min [0.227-0.490] and SR is 4.943 µm [4.6-5.472] and ROC is 0.718 mm [0.64-0.90] [P = 66.67%, Q = 100%, C = 7.41%, QTY = 2] [T = 174.08]

Rule 5: If FR = 0.2 mm/min Then MRR is 0.346 g/min [0.227-0.490] and SR is 4.943 µm [4.6-5.472] and ROC is 0.999 mm [0.9-1.16] [P = 55.56%, Q = 100%, C = 18.52%, QTY = 5] [T = 174.08]

Rule 6: If FR = 1.0 mm/min Then MRR is 0.682 g/min [0.490-0.944] and SR is 4.305 µm [3.598-4.6] and ROC is 0.718 mm [0.64-0.90] [P = 55.56%, Q = 100%, C = 18.52%, QTY = 5] [T = 174.08]

Rule 7: If VL = 20V and FR = 1.0 mm/min and EC = 20 g/l and POR = 2.5 Wt% Then MRR is 0.682 g/min [0.490-0.944] and SR is 4.305 µm [3.598-4.6] and ROC is 0.999 mm [0.9-1.16] [P = 100%, Q = 20%, C = 3.70%, QTY = 1] [T = 123.70]

Rule 8: If EC = 30 g/l Then MRR is 0.682 g/min [0.490-0.944] and SR is 4.305 µm [3.598-4.6] and ROC is 0.999 mm [0.9-1.16] [P = 44.44%, Q = 80%, C = 14.81%, QTY = 4] [T = 139.25]

Rule 9: If VL = 20 V and EC = 10 g/l and POR = 7.5 Wt% Then MRR is 0.682 g/min [0.490-0.944] and SR is 4.943 µm [4.6-5.472] and ROC is 0.718 mm [0.64-0.90] [P = 66.67%, Q = 100%, C = 7.41%, QTY = 2][T = 174.08]

Rule 10: If VL = 20 V Then MRR is 0.682 g/min [0.490-0.944] and SR is 4.943 µm [4.6-5.472] and ROC is 0.999 mm [0.9-1.16] [P = 33.33%, Q = 100%, C = 11.11%, QTY = 3] [T = 144.44]

Now, for response MRR, rule 7 has the maximum strength of 193.33 which signifies that higher MRR (between 0.490 and 0.944 g/min) can be achieved when the FR during the ECM operation is set at 1.0 mm/min (level 3). An increment in FR causes MRR to increase. It can also be observed that approximately 33.33% of the experiment trials justify fulfilment of this particular rule. Similarly, for response SR, all the rules 9, 11, 12 and 13 have the same maximum strength of 136.11. Based on these rules, it can be propounded that high VL, low FR, low or moderate EC and high POR would cause higher SR of the machined components. On the contrary, it can be concluded that for lower SR (a STB characteristic), low or moderate VL, moderate or high FR, high EC and low or moderate POR are most desirable. Rules 1, 2, 3, 4, 6, 7 and 8 all have the same strength of 131.11, support the recommended parametric settings. For this response, FR has the maximum impact, followed by VL and EC. For ROC response, rules 1, 2, 4, 5 and 6 appear to be predominant, all having the same maximum strength of 134.19. It can be revealed from these rules that for achieving lower ROC, the process engineer must operate the ECM setup at low or moderate VL, moderate or high FR, low EC and high POR. The input parameter VL has the maximum influence on ROC, followed by FR. But, from a practical point of view, it is almost impossible to operate an ECM setup at different parametric combinations for simultaneously attaining the most desired values of all the responses. Looking at the last set of rules, developed combining three responses together, rule 3 (maximum strength of 203.70) states that an ECM parametric mix as VL = medium, FR = low, EC = high and POR = low tries to achieve the simultaneous fulfilment of all the responses. In this case, lower SR (the most important response from real time machining point of view) is attained, while sacrificing MRR and ROC. But, rule 6 appears to be more interesting to the process engineers as it has the maximum support (C=18.52%), and would achieve the desired response values of higher MRR, lower SR and lower ROC only at high FR.

Based on the same experimental dataset, Rao and Padmanabhan [73] observed that FR was mainly responsible for higher MRR, SR was influenced by EC and VL was accountable for ROC. It was also noticed that for higher MRR, the optimal parametric mix would be VL = High, FR = High, EC = High and POR = Low. On the other hand, for lower SR and ROC values, the corresponding parametric combinations would be VL = Moderate, FR = High, EC = High and POR = Low, and VL = Low, FR = High, EC = Low and POR = High respectively. It can be interestingly observed that the parametric settings of the considered ECM process as derived based on the association rules closely match with those of Rao and Padmanabhan [73].

3.4.3 Applications of rule based Parametric Analysis on USM process

In this process, material is primarily removed from the workpiece with the help of high frequency vibrating tool in the presence of abrasive slurry (mixture of fine abrasives with water). Kumar and Khamba [74] used Sonic-Mill ultrasonic machine (AP-500 model) for making holes in pure titanium (ASTM Grade-I) work material. Type of the tool material, abrasive type, grit size and power rating of the machining setup were considered as the input parameters, while, MRR (in mm^3/min), SR (in μm) and tool wear rate (TWR) (in mm^3/min) were the responses. Abrasive type, grit size and power rating had three different operating levels each, and type of the tool material had five levels, as exhibited in Table 3.12. Based on Taguchi's L_{18} orthogonal array, 18 experiments were conducted and the corresponding response values were measured, as shown in Table 3.13. Among those responses, MRR is of LTB type, and SR and TWR are STB type of quality characteristics.

Table 3.12 USM process parameters and their different levels [74]

Parameter	Symbol	Unit	Level 1				
			1	2	3	4	5
Tool material	TM		HCS	HSS	Titanium	Ti alloy	Cemented carbide
Abrasive type	AT		Alumina	SiC	Boron carbide		
Grit size	GS	Mesh size	220	320	500		
Power rating	PR	W	100	250	400		

Table 3.13 Experimental plan and responses for the USM process [74]

Exp. No.	TM	AT	GS	PR	MRR	TWR	SR
1	1	1	1	1	0.31	0.44	0.92
2	1	2	2	2	0.66	0.65	1.16
3	1	3	3	3	1.1	0.88	0.66
4	2	1	1	2	0.33	0.49	1.03
5	2	2	2	3	0.72	1.02	1.23
6	2	3	3	1	0.17	0.34	0.59
7	3	1	2	1	0.11	0.17	0.63
8	3	2	3	2	0.29	0.33	0.83
9	3	3	1	3	1.22	1.13	2.1
10	4	1	3	3	0.3	0.19	0.66
11	4	2	1	1	0.18	0.15	0.67
12	4	3	2	2	0.46	0.43	0.84
13	5	1	2	3	0.6	0.68	1.04
14	5	2	3	1	0.32	0.57	0.67
15	5	3	1	2	1.27	1.18	1.74
16	1	1	3	2	0.16	0.2	0.75
17	1	2	1	3	1.44	1.57	2.24
18	1	3	2	1	0.37	0.36	0.81

Following the same procedure as adopted in the first example, the corresponding dependency indexes between the considered USM process attributes are estimated and based on these values, it can be observed that all the attributes are entirely independent to each other and there is no scope of any data deduction. Using *k*-means algorithm and based on the experimental data of Table 3.13, all the three responses are grouped into three clusters each, as shown in Figure 3.4. The details of these clusters are provided in Table 3.14. Now, the corresponding association rules are developed using ROSE2 software for individual as well as combined responses.

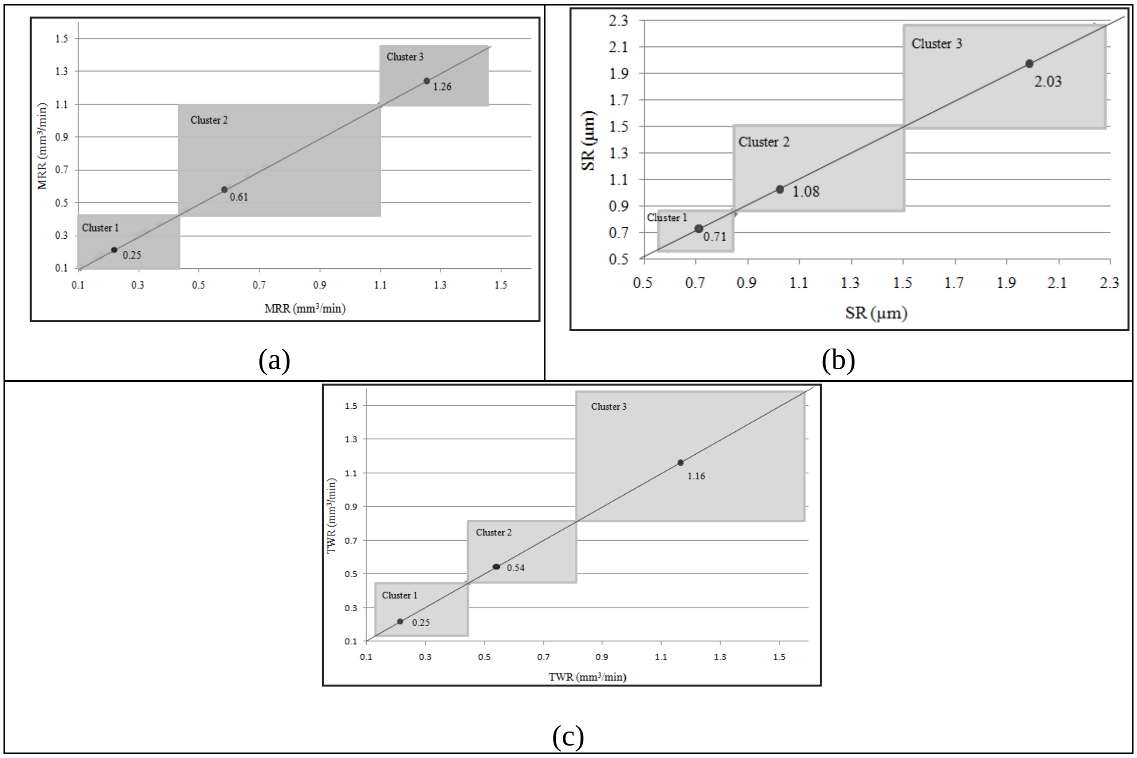

Figure 3.4 Formation of clusters for the USM responses

Table 3.14 Details of the formed clusters for the USM process

Response	Cluster number	Mean	Range of cluster	Objects	Number of objects in each cluster
MRR	Cluster 1	0.25	0.11-0.45	1,4,6,7,8,10,11,14,16,18	10
	Cluster 2	0.61	0.45-1.10	2,5,12,13	4
	Cluster 3	1.26	1.10-1.44	3,9,15,17	4
SR	Cluster 1	0.71	0.59-0.85	3,6,7,8,10,11,12,14,16,18	10
	Cluster 2	1.08	0.85-1.50	1,2,4,5,13	5
	Cluster 3	2.03	1.50-2.24	9,15,17	3
TWR	Cluster 1	0.25	0.17-0.42	6,7,8,10,11,16,18	7
	Cluster 2	0.54	0.42-0.80	1,2,4,12,13,14	6
	Cluster 3	1.16	0.80-1.57	3,5,9,15,17	5

For MRR:

Rule 1: If PR = 100 W Then MRR is 0.25 mm^3/min [0.11-0.45] [P = 100%, Q = 60%, C = 33.33%, QTY = 6] [T = 193.33]

Rule 2: If AT = Alumina and GS = 500 mesh size Then MRR is 0.25 mm^3/min [0.11-0.45] [P = 100%, Q = 20%, C = 11.11%, QTY = 2] [T = 131.11]

Rule 3: If TM = HSS and PR = 250 W Then MRR is 0.25 mm^3/min [0.11-0.45] [P = 100%, Q = 10%, C = 5.56%, QTY = 1] [T = 115.56]

Rule 4: If TM = Titanium and AT = SiC Then MRR is 0.25 mm^3/min [0.11-0.45] [P = 100%, Q = 10%, C = 5.56%, QTY = 1] [T = 115.56]

Rule 5: If AT = SiC and GS = 320 mesh size Then MRR is 0.61 mm^3/min [0.45-1.10] [P = 100%, Q = 50%, C = 11.11%, QTY = 2] [T = 161.11]

Rule 6: If TM = Ti alloy and GS = 320 mesh size Then MRR is 0.61 mm^3/min [0.45-1.10] [P = 100%, Q = 25%, C = 5.56%, QTY = 1] [T = 130.56]

Rule 7: If TM = Cemented carbide and AT = Alumina Then MRR is 0.61 mm^3/min [0.45-1.10] [P = 100%, Q = 25%, C = 5.56%, QTY = 1] [T = 130.56]

Rule 8: If AT = Boron carbide and GS = 220 mesh size Then MRR is 1.26 mm^3/min [1.10-1.44] [P = 100%, Q = 50%, C = 11.11%, QTY = 2] [T = 161.11]

Rule 9: If TM = HCS and PR = 400 W Then MRR is 1.26 mm^3/min [1.10-1.44] [P = 100%, Q = 50%, C = 11.11%, QTY = 2] [T = 161.11]

For SR:

Rule 1: If GS = 500 mesh size Then SR is 0.71 µm [0.59-0.85] [P = 100%, Q = 60%, C = 33.33%, QTY = 6] [T = 193.33]

Rule 2: If AT = Boron carbide and GS = 320 mesh size Then SR is 0.71 µm [0.59-0.85] [P = 100%, Q = 20%, C = 11.11%, QTY = 2] [T = 131.11]

Rule 3: If TM = Titanium and PR = 100 W Then SR is 0.71 µm [0.59-0.85] [P = 100%, Q = 10%, C = 5.56%, QTY = 1] [T = 115.56]

Rule 4: If TM = Ti alloy Then SR is 0.71 µm [0.59-0.85] [P = 100%, Q = 30%, C = 16.66%, QTY = 3] [T = 146.66]

Rule 5: If AT = Alumina and GS = 220 mesh size Then SR is 1.08 µm [0.85-1.50] [P = 100%, Q = 40%, C = 11.11%, QTY = 2] [T = 151.11]

Rule 6: If AT = SiC and GS = 320 mesh size Then SR is 1.08 µm [0.85-1.50] [P = 100%, Q = 40%, C = 11.11%, QTY = 2] [T = 151.11]

Rule 7: If TM = Cemented carbide and AT = Alumina Then SR is 1.08 µm [0.85-1.50] [P = 100%, Q = 20%, C = 5.56%, QTY = 1] [T = 125.56]

Rule 8: If AT = Boron carbide and GS = 220 mesh size Then SR is 2.03 µm [1.50-2.24] [P = 100%, Q = 66.67%, C = 11.11%, QTY = 2] [T = 177.78]

Rule 9: If TM = HCS and AT = SiC and GS = 220 mesh size Then SR is 2.03 µm [1.50-2.24] [P = 100%, Q = 33.33%, C = 5.56%, QTY = 2] [T = 138.89]

For TWR:

Rule 1: If AT = Alumina and GS = 320 mesh size Then TWR is 0.25 mm^3/min [0.17-0.42] [P = 100%, Q = 28.57%, C = 11.11%, QTY = 2] [T = 139.68]

Rule 2: If AT = Boron carbide and PR = 100 W Then TWR is 0.25 mm^3/min [0.17-0.42] [P = 100%, Q = 28.57%, C = 11.11%, QTY = 2] [T = 139.68]

Rule 3: If TM = Titanium and AT = Alumina Then TWR is 0.25 mm^3/min [0.17-0.42] [P = 100%, Q = 14.29%, C = 5.56%, QTY = 1] [T = 119.85]

Rule 4: If TM = Titanium and AT = SiC Then TWR is 0.25 mm^3/min [0.17-0.42] [P = 100%, Q = 14.29%, C = 5.56%, QTY = 1] [T = 119.85]

Rule 5: If TM = Ti alloy and AT = SiC Then TWR is 0.25 mm^3/min [0.17-0.42] [P = 100%, Q = 14.29%, C = 5.56%, QTY = 1] [T = 119.85]

Rule 6: If AT = Alumina and GS = 220 mesh size Then TWR is 0.54 mm^3/min [0.42-0.80] [P = 100%, Q = 33.33%, C = 11.11%, QTY = 2] [T = 144.44]

Rule 7: If GS = 320 mesh size and PR = 250 W Then TWR is 0.54 mm^3/min [0.42-0.80] [P = 100%, Q = 33.33%, C = 11.11%, QTY = 2] [T = 144.44]

Rule 8: If TM = Cemented carbide and AT = Alumina Then TWR is 0.54 mm^3/min [0.42-0.80] [P = 100%, Q = 16.67%, C = 5.56%, QTY = 1] [T = 122.23]

Rule 9: If TM = Cemented carbide and AT = SiC Then TWR is 0.54 mm^3/min [0.42-0.80] [P = 100%, Q = 16.67%, C = 5.56%, QTY = 1] [T = 122.23]

Rule 10: If TM = HCS and PR = 400 W Then TWR is 1.16 mm^3/min [0.80-1.57] [P = 100%, Q = 40%, C = 11.11%, QTY = 2] [T = 151.11]

Rule 11: If AT = Boron carbide and GS = 220 mesh size Then TWR is 1.16 mm^3/min [0.80-1.57] [P = 100%, Q = 40%, C = 11.11%, QTY = 2] [T = 151.11]

Rule 12: If TM = HSS and AT = SiC Then TWR is 1.16 mm^3/min [0.80-1.57] [P = 100%, Q = 20%, C = 5.56%, QTY = 1] [T = 125.56]

For all the responses:

Rule 1: If PR = 100 W Then MRR is 0.25 mm^3/min [0.11-0.45] and SR is 0.71 µm [0.59-0.85] and TWR is 0.25 mm^3/min [0.17-0.42] [P = 66.67%, Q = 57.14%, C = 22.22%, QTY = 4] [T = 146.03]

Rule 2: If GS = 500 mesh size Then MRR is 0.25 mm^3/min [0.11-0.45] and SR is 0.71 µm [0.59-0.85] and TWR is 0.25 mm^3/min [0.17-0.42] [P = 50%, Q = 42.86%, C = 16.67%, QTY = 3] [T = 109.53]

Rule 3: If TM = Cemented carbide and AT = SiC and GS = 500 mesh size and PR = 100 W Then MRR is 0.25 mm^3/min [0.11-0.45] and SR is 0.71 µm [0.59-0.85] and TWR is 0.54 mm^3/min [0.42-0.80] [P = 100%, Q = 100%, C = 5.56%, QTY = 1] [T = 205.56]

Rule 4: If AT = Alumina and GS = 220 mesh size Then MRR is 0.25 mm^3/min [0.11-0.45] and SR is 1.08 μm [0.85-1.50] and TWR is 0.54 mm^3/min [0.42-0.80] [P = 100%, Q = 100%, C = 11.11%, QTY = 2] [T = 211.11]

Rule 5: If GS = 320 mesh size Then MRR is 0.61 mm^3/min [0.45-1.10] and SR is 1.08 μm [0.85-1.50] and TWR is 0.54 mm^3/min [0.42-0.80] [P = 33.33%, Q = 100%, C = 11.11%, QTY = 2] [T = 144.44]

Rule 6: If TM = Ti alloy and AT = Boron carbide and GS = 320 mesh size and PR = 250 W Then MRR is 0.61 mm^3/min [0.45-1.10] and SR is 0.71 μm [0.59-0.85] and TWR is 0.54 mm^3/min [P = 100%, Q = 100%, C = 5.56%, QTY = 1] [T = 205.56]

Rule 7: If TM = HSS and AT = SiC and GS = 320 mesh size and PR = 400 W Then MRR is 0.61 mm^3/min [0.45-1.10] and SR is 1.08 μm [0.85-1.50] and TWR is 1.16 mm^3/min [0.80-1.57] [P = 100%, Q = 100%, C = 5.56%, QTY = 1] [T = 205.56]

Rule 8: If GS = 220 mesh size Then MRR is 1.26 mm^3/min [1.10-1.44] and SR is 2.03 μm [1.50-2.24] and TWR is 1.16 mm^3/min [0.80-1.57] [P = 50%, Q = 100%, C = 16.67%, QTY = 3] [T = 166.67]

Rule 9: If TM = HCS and AT = Boron carbide and GS = 500 mesh size and PR = 400 W Then MRR is 1.26 mm^3/min [1.10-1.44] and SR is 0.71 μm [0.59-0.85] and TWR is 1.16 mm^3/min [0.80-1.57] [P = 100%, Q = 100%, C = 5.56%, QTY = 1] [T = 205.56]

For MRR response, rule 1 with the maximum strength of 193.33 states that for low PR, MRR would also be low, and it mostly influences MRR with a high support (C=33.33%). But, rules 8 and 9 are equally important (strength of 161.11) from real time machining standpoint which signify that when AT is boron carbide, GS is low, TM is HCS and PR is high, the achievable MRR would be high. For SR, it can be revealed that GS has the maximum influence on it and high GS would provide better SR value. Rule 1 for SR justifies this observation with maximum support (C=33.33%) and maximum strength (T = 193.33). Similarly, in case of TWR, rules 10 and 11 with the same maximum strength of 151.11 state that TM as HCS, AT as boron carbide, low GS and high PR are responsible for higher TWR. But as the lower value of TWR is always preferred, rules 1 and 2 with strength 139.68 seem to be useful for the process engineers. According to these rules, AT as alumina or boron carbide, moderate GS and low PR lead to lower TWR. When all the three responses are considered together for the generation of association rules, rule 4 with maximum strength of 211.11 supports that AT as alumina and low GS would achieve lower MRR, moderate SR and moderate TWR. But, another rule, i.e. rule 9 also appears to be significant which states that TM as HCS, AT as boron carbide, high GS and high PR lead to higher MRR, lower SR and higher TWR. Although this rule has less strength (T = 205.56) than rule 4, but it identifies the most desirable parametric settings of the considered USM process with higher MRR and lower SR while satisfying the requirements of the present day manufacturing industries.

Based on the experimental data and employing utility concept, Kumar and Khamba [74] identified the individual optimal parametric combinations for maximum MRR: TM = cemented carbide, AT = boron carbide, GS = 220 mesh size and PR = 400 W; and for minimum SR and TWR: TM = titanium alloy, AT = alumina, GS = 500 mesh size and PR = 100 W. On the other hand, the parametric mix as TM = titanium alloy, AT = boron carbide, GS = 500 mesh size and PR = 400 W would simultaneously provide the optimal values of responses, MRR = 0.70 mm^3/min, SR = 0.77 µm and TWR = 0.50 mm^3/min. The association rule-based parametric setting would produce MRR as 1.26 mm^3/min, SR as 0.71 µm and TWR as 1.16 mm^3/min.

3.4.4 Applications of rule based Parametric Analysis on EDM process

Taking H-11 die steel as the work material, Tripathy and Tripathy [75] conducted 27 Taguchi methodology-based experiments in a powder-mixed EDM setup with concentration of the chromium powder in the dielectric medium (commercial grade EDM oil), peak current, pulse-on time, duty cycle and gap voltage as the controllable process parameters. On the other hand, MRR (in mm^3/min), TWR (in mm^3/min), electrode wear ratio (EWR) (in %) and SR (in µm) were the responses. Each of those EDM process parameters was set at three different levels, as exhibited in Table 3.15. Table 3.16 shows the detailed experimental plan along with the response values. It is worthwhile to mention here that MRR is the only LTB characteristic, and the remaining responses are of STB type.

Table 3.15 EDM process parameters and their different operating levels [75]

Parameter	Symbol	Unit	Level		
			1	2	3
Concentration of chromium powder	CCP	g/l	0	3	6
Peak current	PC	A	3	6	9
Pulse-on time	PT	µs	100	150	200
Duty cycle	DC	%	70	80	90
Gap voltage	GV	V	30	40	50

For this NTM process, the calculated dependency indexes between different attributes ensure that they are totally independent to each other and the original dataset can be adopted for the subsequent association rules generation. Now, the values of all the four responses are categorized into three clusters each, as depicted in Figure 3.5. Table 3.17 provides the details of the generated clusters. Finally, ROSE2 software is adopted for development of the related association rules showing the relationships between the input EDM process parameters and responses. At the initial stage rules for individual response are developed then at the later stage the rule for combined responses are generated to get effective knowledge.

Table 3.16 Experimental plan and response values for the EDM process [75]

Exp. No.	CCP	PC	PT	DC	GV	MRR	TWR	EWR	SR
1	0	3	100	70	30	2.564	0.017	0.671	3.8
2	0	3	100	70	40	2.649	0.019	0.735	4.1
3	0	3	100	70	50	2.735	0.022	0.821	4.5
4	0	6	150	80	30	4.529	0.027	0.611	4.87
5	0	6	150	80	40	5.47	0.03	0.561	5.45
6	0	6	150	80	50	6.666	0.036	0.55	5.86
7	0	9	200	90	30	9.401	0.389	4.143	6.5
8	0	9	200	90	40	10.256	0.486	4.747	7.47
9	0	9	200	90	50	10.94	0.524	4.792	9.2
10	3	3	150	90	30	2.735	0.008	0.3	2.86
11	3	3	150	90	40	3.076	0.009	0.318	3.14
12	3	3	150	90	50	5.475	0.007	0.14	3.54
13	3	6	200	70	30	6.666	0.017	0.257	4.07
14	3	6	200	70	40	7.222	0.01	0.146	4.56
15	3	6	200	70	50	7.435	0.026	0.36	4.91
16	3	9	100	80	30	8.511	0.045	0.529	5.2
17	3	9	100	80	40	11.829	0.057	0.489	5.63
18	3	9	100	80	50	15.947	0.082	0.516	5.97
19	6	3	200	80	30	6.239	0.004	0.076	2.4
20	6	3	200	80	40	7.435	0.003	0.046	2.84
21	6	3	200	80	50	8.376	0.007	0.088	2.98
22	6	6	100	90	30	12.82	0.003	0.026	3.12
23	6	6	100	90	40	13.076	0.007	0.054	3.36
24	6	6	100	90	50	14.017	0.009	0.069	3.68
25	6	9	150	70	30	16.153	0.034	0.214	4.07
26	6	9	150	70	40	16.692	0.042	0.256	4.68
27	6	9	150	70	50	17.0684	0.049	0.289	5.04

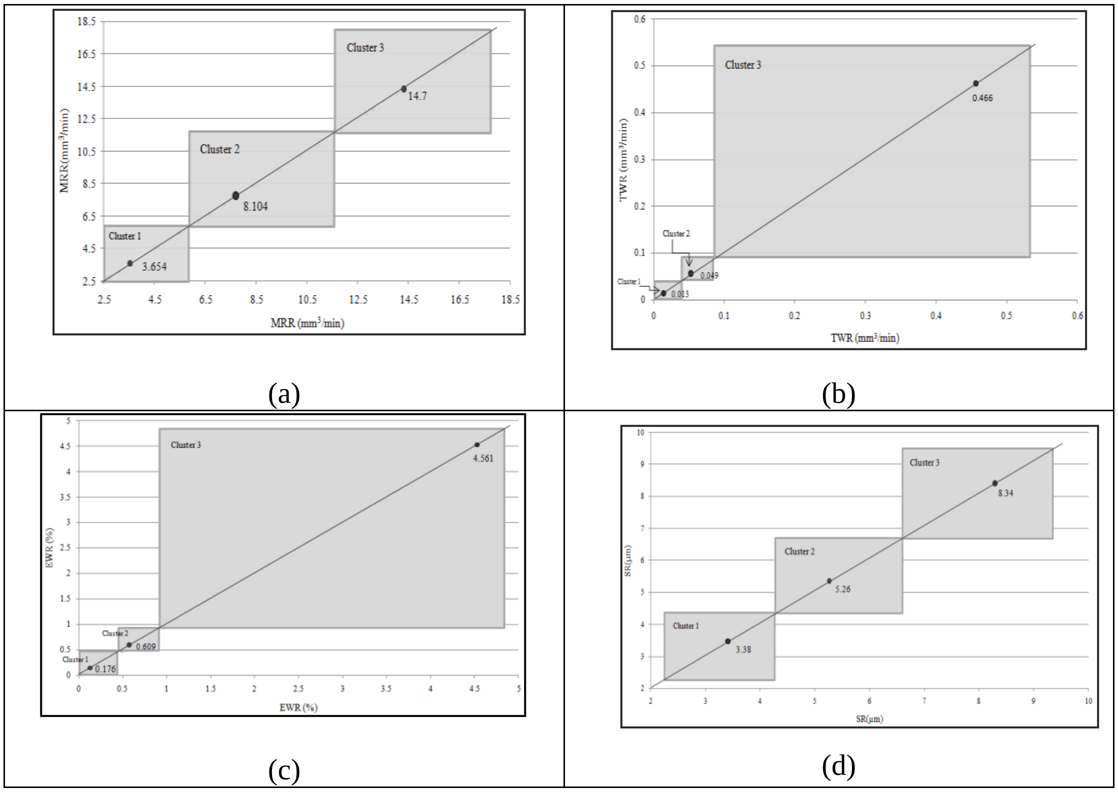

Figure 3.5 Clusters formed for the EDM responses

Table 3.17 Cluster details for the EDM process

Response	Cluster type	Mean	Range of cluster	Object	Number of objects in each cluster
MRR	Cluster 1	3.654	2.564-5.480	1,2,3,4,5,10,11,12	8
	Cluster 2	8.104	5.480-10.96	6,7,8,9,13,14,15,16,19,20,21	11
	Cluster 3	14.7	10.96-17.068	17,18,22,23,24,25,26,27	8
TWR	Cluster 1	0.013	0.003-0.033	1,2,3,4,5,10,11,12,13,14,15,19,20,21,22,23,24	17
	Cluster 2	0.049	0.033-0.086	6,16,17,18,25,26,27	7
	Cluster 3	0.466	0.086-0.524	7,8,9	3
EWR	Cluster 1	0.176	0.026-0.481	10,11,12,13,14,15,19,20,21,22,23,24,25,26,27	15
	Cluster 2	0.609	0.481-0.830	1,2,3,4,5,6,16,17,18	9
	Cluster 3	4.561	0.830-4.792	7,8,9	3
SR	Cluster 1	3.38	2.4-4.2	1,2,10,11,12,13,19,20,21,22,23,24,25	13
	Cluster 2	5.26	4.2-6.7	3,4,5,6,7,14,15,16,17,18,26,27	12
	Cluster 3	8.34	6.7-9.2	8,9	2

For MRR:

Rule 1: If CCP = 0 g/l and PC = 3 A Then MRR is 3.654 m^3/min [2.564-5.480] [P = 100%, Q = 37.50%, C = 11.11%, QTY = 3] [T = 148.61]

Rule 2: If CCP = 3 g/l and PT = 150 µs Then MRR is 3.654 mm^3/min [2.564-5.480] [P = 100%, Q = 37.50%, C = 11.11%, QTY = 3] [T = 148.61]

Rule 3: If PT = 150 µs and DC = 80% and GV = 30 V Then MRR is 3.654 mm^3/min [2.564-5.480] [P = 100%, Q = 12.50%, C = 3.70%, QTY = 1] [T = 116.20]

Rule 4: If PT = 150 µs and DC = 80% and GV = 40 V Then MRR is 3.654 mm^3/min [2.564-5.480] [P = 100%, Q = 12.50%, C = 3.70%, QTY = 1] [T = 116.20]

Rule 5: If PT = 200 µs Then MRR is 8.104 mm^3/min [5.480-10.96] [P = 100%, Q = 81.82%, C = 33.33%, QTY = 9] [T = 215.15]

Rule 6: If PC = 6 A and PT = 150 µs and GV = 50V Then MRR is 8.104 mm^3/min [5.480-10.96] [P = 100%, Q = 9.09%, C = 3.70%, QTY = 1] [T = 112.79]

Rule 7: If PT = 100 µs and DC = 80% and GV = 30 V Then MRR is 8.104 mm^3/min [5.480-10.96] [P = 100%, Q = 9.09%, C = 3.70%, QTY = 1] [T = 112.79]

Rule 8: If CCP = 6 g/l and PC = 9 A Then MRR is 14.7 mm^3/min [10.96-17.068] [P = 100%, Q = 37.50%, C = 11.11%, QTY = 3] [T = 148.61]

Rule 9: If CCP = 6 g/l and PT = 100 µs Then MRR is 14.7 mm^3/min [10.96-17.068] [P = 100%, Q = 37.50%, C = 11.11%, QTY = 3] [T = 148.61]

Rule 10: If PT = 100 µs and DC = 80% and GV = 40 V Then MRR is 14.7 mm^3/min [10.96-17.068] [P = 100%, Q = 12.50%, C = 3.70%, QTY = 1] [T = 116.20]

Rule 11: If PT = 100 µs and DC = 80% and GV = 50 V Then MRR is 14.7 mm^3/min [10.96-17.068] [P = 100%, Q = 12.50%, C = 3.70%, QTY = 1] [T = 116.20]

For TWR:

Rule 1: If PC = 3 A Then TWR is 0.013 mm^3/min [0.003-0.033] [P = 100%, Q = 52.94%, C= 33.33%, QTY = 9] [T = 186.27]

Rule 2: If CCP = 3 g/l and PC = 6 A Then TWR is 0.013 mm^3/min [0.003-0.033] [P = 100%, Q = 17.65%, C = 11.11%, QTY = 3] [T = 128.76]

Rule 3: If CCP = 6 g/l and PC = 6 A Then TWR is 0.013 mm^3/min [0.003-0.033] [P = 100%, Q = 17.65%, C = 11.11%, QTY = 3] [T = 128.76]

Rule 4: If PT = 150 µs and DC = 80% and GV = 30 V Then TWR is 0.013 mm^3/min [0.003-0.033] [P = 100%, Q = 5.88%, C = 3.70%, QTY = 1] [T = 109.58]

Rule 5: If PT = 150 µs and DC = 80% and GV = 40 V Then TWR is 0.013 mm^3/min [0.003-0.033] [P = 100%, Q = 5.88%, C = 3.70%, QTY = 1] [T = 109.58]

Rule 6: If CCP = 3 g/l and PC = 9 A Then TWR is 0.049 mm^3/min [0.033-0.086] [P = 100%, Q = 42.86%, C = 11.11%, QTY = 3] [T = 153.97]

Rule 7: If CCP = 6 g/l and PT = 150 µs Then TWR is 0.049 mm^3/min [0.033-0.086] [P = 100%, Q = 42.86%, C = 11.11%, QTY = 3] [T = 153.97]

Rule 8: If PT = 150 µs and DC = 80% and GV = 50 V Then TWR is 0.049 mm^3/min [0.033-0.086] [P = 100%, Q = 14.29%, C = 3.70%, QTY = 1] [T = 117.99]

Rule 9: If CCP = 0 g/l and PC = 9 A Then TWR is 0.466 mm^3/min [0.086-0.524] [P = 100%, Q = 100%, C = 11.11%, QTY = 3] [T = 211.11]

For EWR:

Rule 1: If CCP = 6 g/l Then EWR is 0.176% [0.026-0.481] [P = 100%, Q = 60%, C = 33.33%, QTY = 9] [T = 193.33]

Rule 2: If CCP = 3 g/l and PC = 3 A Then EWR is 0.176% [0.026-0.481] [P = 100%, Q = 20%, C = 11.11%, QTY = 3] [T = 131.11]

Rule 3: If CCP = 3 g/l and PC = 6 A Then EWR is 0.176% [0.026-0.481] [P = 100%, Q = 20%, C = 11.11%, QTY = 3] [T = 131.11]

Rule 4: If CCP = 0 gm/l and PC = 3 A Then EWR is 0.609% [0.481-0.830] [P = 100%, Q = 33.33%, C = 11.11%, QTY = 3] [T = 144.44]

Rule 5: If CCP = 0 g/l and DC = 80% Then EWR is 0.609% [0.481-0.830] [P = 100%, Q = 33.33%, C = 11.11%, QTY = 3] [T = 144.44]

Rule 6: If CCP = 3 g/l and PC = 9 A Then EWR is 0.609% [0.481-0.830] [P = 100%, Q = 33.33%, C = 11.11%, QTY = 3] [T = 144.44]

Rule 7: If CCP = 0 gm/l and PC = 9 A Then EWR is 4.561% [0.830-4.792] [P = 100%, Q = 33.33%, C = 11.11%, QTY = 3] [T = 144.44]

For SR:

Rule 1: If CCP = 3 g/l and PC = 3 A Then SR is 3.38 µm [2.4-4.2] [P = 100%, Q = 23.08%, C = 11.11%, QTY = 3] [T = 134.19]

Rule 2: If CCP = 6 g/l and PC = 3 A Then SR is 3.38 µm [2.4-4.2] [P = 100%, Q = 23.08%, C = 11.11%, QTY = 3] [T = 134.19]

Rule 3: If CCP = 6 g/l and PT = 100 µs Then SR is 3.38 µm [2.4-4.2] [P = 100%, Q = 23.08%, C = 11.11%, QTY = 3] [T = 134.19]

Rule 4: If DC = 70% and GV = 30 V Then SR is 3.38 µm [2.4-4.2] [P = 100%, Q = 23.08%, C = 11.11%, QTY = 3] [T = 134.19]

Rule 5: If PT = 100 µs and DC = 70% and GV = 40 V Then SR is 3.38 µm [2.4-4.2] [P = 100.00%, Q = 7.69%, C = 3.70%, QTY = 1] [T = 111.39]

Rule 6: If CCP = 3 g/l and PC = 9 A Then SR is 5.26 µm [4.2-6.7] [P = 100%, Q = 25%, C = 11.11%, QTY = 3] [T = 136.11]

Rule 7: If CCP = 0 g/l and PC = 6 A Then SR is 5.26 µm [4.2-6.7] [P = 100%, Q = 25%, C = 11.11%, QTY = 3] [T = 136.11]

Rule 8: If DC = 70% and GV = 50 V Then SR is 5.26 µm [4.2-6.7] [P = 100%, Q = 25%, C = 11.11%, QTY = 3] [T = 136.11]

Rule 9: If PT = 200 µs and DC = 90% and GV = 30 V Then SR is 5.26 µm [4.2-6.7] [P = 100%, Q = 8.33%, C = 3.70%, QTY = 1] [T = 112.03]

Rule 10: If CCP = 3 g/l and DC = 70% and GV = 40V Then SR is 5.26 µm [4.2-6.7] [P = 100%, Q = 8.33%, C = 3.70%, QTY = 1] [T = 112.03]

Rule 11: If PT = 150 µs and DC = 70% and GV = 40V Then SR is 5.26 µm [4.2-6.7] [P = 100%, Q = 8.33%, C = 3.70%, QTY = 1] [T = 112.03]

Rule 12: If PT = 200µs and DC = 90% and GV = 40V Then SR is 8.34 µm [6.7-9.2] [P = 100%, Q = 50.0%, C = 3.70%, QTY = 1] [T = 153.71]

Rule 13: If PT = 200 µs and DC = 90% and GV = 50 V Then SR is 8.34 µm [6.7-9.2] [P = 100%, Q = 50.0%, C = 3.70%, QTY = 1] [T = 153.71]

For all the responses:

Rule 1: If CCP = 0 g/l and PC = 3 A and PT = 100 µs and DC = 70% Then MRR is 3.654 mm^3/min [2.564-5.480] and TWR is 0.013 mm^3/min [0.003-0.033] and EWR is 0.609% [0.481-0.830] and SR is 3.38 µm [2.4-4.2] [P = 66.67%, Q = 100%, C = 7.40%, QTY = 2] [T = 174.07]

Rule 2: If CCP = 0 g/l Then MRR is 3.654 mm^3/min [2.564-5.480] and TWR is 0.013 mm^3/min [0.003-0.033] and EWR is 0.609% [0.481-0.830] and SR is 5.26 µm [4.2-6.7] [P = 33.33%, Q = 100%, C = 11.11%, QTY = 3] [T = 144.44]

Rule 3: If CCP = 3 g/l and PC = 3 A and PT = 150 µs and DC = 90% Then MRR is 3.654 mm^3/min [2.564-5.480] and TWR is 0.013 mm^3/min [0.003-0.033] and EWR is 0.176% [0.026-0.481] and SR is 3.38 µm [2.4-4.2] [P = 100.0%, Q = 100%, C = 11.11%, QTY = 3] [T = 211.11]

Rule 4: If DC = 80% Then MRR is 8.104 mm^3/min [5.480-10.96] and TWR is 0.049 mm^3/min [0.033-0.086] and EWR is 0.609% [0.481-0.830] and SR is 5.26 µm [4.2-6.7] [P = 22.22%, Q = 100%, C = 7.42%, QTY = 2] [T = 129.62]

Rule 5: If CCP = 0 g/l and PC = 9 A and PT = 200 µs and DC = 90% and GV = 30V Then MRR is 8.104 mm^3/min [5.480-10.96] and TWR is 0.466 mm^3/min [0.086-0.524] and EWR is 4.561% [0.830-4.792] and SR is 5.26 µm [4.2-6.7] [P = 100%, Q = 100%, C = 3.70%, QTY = 1] [T = 203.70]

Rule 6: If CCP = 0 g/l and PC = 9 A and PT = 200 μs and DC = 90% Then MRR is 8.104 mm^3/min [5.480-10.96] and TWR is 0.466 mm^3/min [0.086-0.524] and EWR is 4.561% [0.830-4.792] and SR is 8.34 μm [6.7-9.2] [P = 66.67%, Q = 100%, C = 7.40%, QTY = 2] [T = 174.07]

Rule 7: If CCP = 3 g/l and PC = 6 A and PT = 200 μs and DC = 70% and GV = 30 V Then MRR is 8.104 mm^3/min [5.480-10.96] and TWR is 0.013 mm^3/min [0.003-0.033] and EWR is 0.176% [0.026-0.481] and SR is 3.38 μm [2.4-4.2] [P = 100%, Q = 25%, C = 3.70%, QTY = 1] [T = 128.70]

Rule 8: If CCP = 6 g/l and PC = 3 A and PT = 200 μs and DC = 80% Then MRR is 8.104 mm^3/min [5.480-10.96] and TWR is 0.013 mm^3/min [0.003-0.033] and EWR is 0.176% [0.026-0.481] and SR is 3.38 μm [2.4-4.2] [P = 100%, Q = 75%, C = 11.11%, QTY = 3] [T = 186.11]

Rule 9: If CCP = 3 g/l and PC = 6 A and PT = 200 μs and DC = 70% Then MRR is 8.104 mm^3/min [5.480-10.96] and TWR is 0.013 mm^3/min [0.003-0.033] and EWR is 0.176% [0.026-0.481] and SR is 5.26 μm [4.2-6.7] [P = 66.67%, Q = 100%, C = 7.40%, QTY = 2] [T = 174.07]

Rule 10: If CCP = 3 g/l and PC = 9 A and PT = 100 μs and DC = 80% Then MRR is 14.7 mm^3/min [10.96-17.068] and TWR is 0.049 mm^3/min [0.033-0.086] and EWR is 0.609% [0.481-0.830] and SR is 5.26 μm [4.2-6.7] [P = 66.67%, Q = 100%, C = 7.40%, QTY = 2] [T = 174.07]

Rule 11: If CCP = 6 g/l and PC = 6 A and PT = 100 μs and DC = 90% Then MRR is 14.7 mm^3/min [10.96-17.068] and TWR is 0.013 mm^3/min [0.003-0.033] and EWR is 0.176% [0.026-0.481] and SR is 3.38 μm [2.4-4.2] [P = 100%, Q = 100%, C = 11.11%, QTY = 3] [T = 211.11]

Rule 12: If CCP = 6 g/l and PC = 9 A and PT = 150 μs and DC = 70% and GV = 30 V Then MRR is 14.7 mm^3/min [10.96-17.068] and TWR is 0.049 mm^3/min [0.033-0.086] and EWR is 0.176% [0.026-0.481] and SR is 3.38 μm [2.4-4.2] [P = 100%, Q = 100%, C = 3.70%, QTY = 1] [T = 203.70]

Rule 13: If CCP = 6 g/l and PC = 9 A and PT = 150 μs and DC = 70% Then MRR is 14.7 mm^3/min [10.96-17.068] and TWR is 0.049 mm^3/min [0.033-0.086] and EWR is 0.176% [0.026-0.481] and SR is 5.26 μm [4.2-6.7] [P = 66.67%, Q = 100%, C = 7.40%, QTY = 2] [T = 174.07]

Amongst the rules generated for MRR, rule 5 having the maximum strength of 215.15 states that high PT leads to moderate value of MRR. Rules 1, 2, 8 and 9 all have the same second maximum strength of 148.61. But rules 1 and 2 lead to lower MRR, while rules 8 and 9 provide higher MRR (most desirable) values. Based on these two rules, CCP in the dielectric medium emerges out as the most important EDM process parameter, followed by PC and PT for attaining higher values of MRR. High concentration of chromium is responsible for higher MRR. Likewise, high PC and low PT would provide higher MRR. For TWR, rule 9 emerges out as the most important rule with the maximum strength of 211.11 and high support of 11.11. In this rule, high PC and zero CCP are responsible for higher TWR. Practically, as the lower value of TWR is always preferable, rule 1 with a slightly low strength of 186.27 appears to be interesting to the process engineers. It states that low PC is responsible for achieving lower TWR values. For EWR, rule 1 is the most reliable rule with a maximum strength of 193.33. Based on this rule, it can be concluded that for attaining lower EWR, high CCP in the dielectric medium is required. In case of SR response, both the rules 12 and 13 have the maximum strength of 153.71. From these two rules, it can be observed that PT, DC and GV greatly influence SR. High values of PT, DC and GV would cause higher SR which is not at all desired for fulfilling the end requirements. Thus, for lower SR, the values of PT, DC and GV should be kept low. For the rules developed taking into consideration all the four responses, rules 3 and 11 have the maximum strength of 211.11. In order to attain the desired values of the responses, all the EDM process parameters play significant roles. It is always required to have higher value of MRR, and lower values of TWR, EWR and SR. Based on this consideration, rule 11 appears to be the most significant one. It depicts that the parametric combination of CCP = 6 g/l, PC = 6 A, PT = 100 μs and DC = 90% would provide higher MRR (~14.7 mm^3/min), lower TWR (~0.013mm^3/min), lower EWR (~0.176%) and lower SR (~3.38 μm). It is quite interesting to notice that for this powder-mixed EDM process, GV has no significant influence on the responses.

Tripathy and Tripathy [75] employed TOPSIS and grey relational analysis for parametric optimization of the said power-mixed EDM process. For TOPSIS method, a parametric combination of CCP = 6 g/l, PC = 6 A, PT = 100 μs, DC = 90% and GV = 50 V; and for GRA method, a parametric mix of CCP = 6 g/l, PC = 3 A, PT = 150 μs, DC = 70% and GV = 30 V would simultaneously optimize all the four responses. The results derived based on the association rules exactly corroborate with the parametric combination attained using TOPSIS method which strongly justifies the application potentiality and reliability of the adopted data mining technique in parametric analysis of the considered EDM process.

4.0 SUPPORT VECTOR MACHINE BASED PARAMETRIC STUDY OF ELECTROCHEMICAL MACHINING PROCESS

4.1 Need for the application of SVM in data mining

In machining operation, high degree of accuracy and precession are required. In order to achieve it more and more samples are tested to get the optimal settings for the machining process. But it is economically unsuitable for production purpose. So the researchers are seeking for the machine learning tool which can analyses the machining pattern and thus develop a model that can predict the values of various response without performing actual machining operation. Support vector machine (SVM) is a supervised batch learning system which is firmly grounded in the framework of statistical learning theory. Due to its robustness and good generalization performance in the real world applications, it is one of the leading choices of researchers to generate good classifier or to predict the operation by developing a statistical model with a minimal number of training examples. In production, there will be no need for a human operator to train the SVM with hundreds or thousands of training examples to achieve good generalization. The advantage with SVM is that good accuracy can be achieved with only a couple of training examples if the training examples are well designed.

Firstly, the algorithm proposed was evaluated experimentally. The experiments consisted of correct handling of classification performance on training examples. Secondly, the results from the experiments were tested in a simulated environment. By using only a few training examples the SVM reached perfect performance.

4.2 Review of the literature on SVM

Aich and Banerjee [76] modeled Electro discharge machine responses through support vector regression algorithm. In that paper, Gaussian radial basis function and ε-insensitive loss function were incorporated as kernel function and loss function respectively. Here particle swarm optimization was also employed in order to optimize SVM parameter combinations. Distinct model for material removal rate, average surface roughness were established by minimizing the mean absolute percentage error of the training data for each set of SVM parameter combinations. The proposed models were then tested with distinct testing data sets. Finally a new termination criterion (coefficient of variation) of particles' position was suggested in order to ensure global optimization in PSO algorithm.

Yu et al. [77] adopted support vector regression to establish a real-time stage forecasting model. The lags associated with the input variables were determined by applying the hydrological concept of the time of response, and a two-step grid search method was applied to find the optimal parameters. In that paper, two structures of models were used to perform multiple-hour stage forecast and validated the results from the flood evens in Lang-Yang River, Taiwan. The proposed model was efficient to predict the flood stage forecasts one-to-six hour ahead. Finally that paper presented a sensitivity analysis on the lags associated with the input variables. That paper proposed the scope for implementation of different loss function and properties of kernel function into the system in order to forecast more efficient.

Levis and Papageorgiou [78] proposed a systematic optimization-based approached for customer demand forecasting through support vector regression (SVR) analysis. In that paper, the three-step algorithm was proposed to extract information from the training points and determine the regression function while the final step exercised a recursive methodology to present customer demand forecasting. Here the historical customer demand patterns were used as training points attributes for the SVR. This paper illustrated three examples in order to check the effectiveness of the proposed model and found that the proposed methodology processed successfully complex nonlinear customer demand patterns and obtained forecasts with prediction accuracy of more than 93% in all illustrations.

Cherkassky and Ma [79] demonstrated practical selection of hyper-parameters for support vector machine regression with $\boldsymbol{\varepsilon}$-insensitive zone and regularization parameter C. Here analytic parameters were directly selected from the training data and described a new analytical prescription for setting the value of insensitive zone $\boldsymbol{\varepsilon}$ and regularization parameter. The importance of Vapnik's $\boldsymbol{\varepsilon}$-insensitive loss for regression problems with finite samples was pointed out and compared the generalization performance of SVM regression with the regression using 'least modulus' loss ($\boldsymbol{\varepsilon}$=0) and standard squared loss and finally compared superior generalization performance of SVM regression under sparse sample setting for various types of additive noise

Iranmehr et al. [80] designed a constructive procedure to extend SVM's standard loss function to optimize the classifier with respect to class imbalance or class cost. The resulting classifier guarantees Bayes consistency was shown by drawing connections between risk minimization and probability elicitation. The primal and the dual objective functions were analyzed and the objective function was obtained in a regularized risk minimization framework. That paper performed experimental analysis on class imbalance, cost-sensitive learning with given class and showed that the proposed algorithm delivered superior generalization performance as compared with the conventional algorithms.

Aich and Banerjee [81] applied the advance structured minimization based learning system, SVM, to capture the random variation of EDM responses. Here TLBO, a modified teaching learning based optimization procedure, was applied to optimized internal parameter of SVM-C, $\boldsymbol{\varepsilon}$ and σ. The developed SVM model was used to generate the responses at the different points in the experimental space and power law models were fitted to the estimated data. Here Pseudo Pareto front passing through the optimum results and obtained a guideline for selection of optimum achievable value of ASR for a specific demand of MRR. Finally, inverse solution procedure was elaborated to find the near-optimum setting of process parameters in EDM machine to obtain the specific need based MRR-ASR combination.

Aoyagi et al. [82] proposed a simple method to construct a process map for additive manufacturing using a support vector machine. Here the surface of the built parts were observed deeply and classified them into good or bad levels, in order to predict a process condition that is effective at fabricating a parts with low pore density. The proposed technique was validated in a biomedical CoCr alloy system and was useful to reduce the number of experiments necessary to tailor an optimized process condition and thus reduced the time to objects with few defects. The proposed technique was expected to be simple and efficient method to construct a process map of AM technologies.

Çaydaş and Ekici [83] developed three different types of support vector machine tools namely least square SVM, Spider SVM and SVM-KM and an artificial neural network model was developed to estimate the surface roughness values of AISI 304 austenitic stainless steel in CNC turning operation. Here cutting speed, feed rate and depth of cut were selected as the turning input parameters and a predictive model was developed. A three-level full factorial design of experiments method was developed to collect the surface roughness values. Further a feed forward neural network based on back propagation with 15 hidden neurons was placed in between input and output layers. It was proposed that the SVM's results better than ANN's results with high correlations between the predicted and experimentally measured values.

Aich et al. [84] suggested the application of robust unified learning system, multi-objective modeling with SVM in abrasive water jet machining to study the gross erosion behavior of borosilicate glass. Here water pressure, abrasive flow rate, traverse speed and standoff distance were taken as the control parameters and material removal rate and depth of cur were taken as the response parameters. The responses were trained through support vector machine based learning system for regression purpose. By minimizing the training errors with the help of PSO algorithm, an optimal single set of internal parameters of SVM were predicted for both MRR and DOC with the Langrangian multipliers. The scanning electron micrographs were also examined deeply to reveal the possible erosion behavior of borosilicate glass.

Lela et al. [85] examined the influence of input parameter of face milling with the output response like surface roughness. Here the input parameters were cutting speed, feed and depth of cut. In that paper three different modeling methodologies-regression analysis, Bayesian neural network and support vector machine had been studied over to demonstrate the influence of input with the output parameter and the results were well compared. The outcome of the proposed models dictated as BNN was the best prediction model with the relative prediction error of 6.10% followed by SVR with 7.82% and RA with 7.85%. The result also predicted that the feed had the largest affect on the surface roughness while the depth of cut had the least affect.

Ramesh et al. [86] proposed an automated intelligent manufacturing system for the estimation and control of the surface finish using SVM. An intelligent surface finish control support system was built to provide assistance to the operator in *apriori* estimation of surface finish for a given set of input parameters-feed rate, spindle speed and depth of cut. The results were compared with the required surface finish specifications. That paper suggested that the proposed intelligent system was useful as a support alternative to assist the machine operator in selecting optimum operating conditions to ensure the desired surface finish.

Zhang et al. [87] adopted support vector machine to establish a micro-EDM process model to optimize the combination of processing parameters for minimizing processing time and electrode wear. A new multi-objective optimization genetic algorithm (GA) based on the idea of non-dominated sorting was proposed to optimize the processing parameters. The experimental results dictated that the proposed multi-objective GA method was precise and effective in obtaining pareto-optimal solutions of parameter settings. The proposed model highly reduced the processing time while maintaining low electrode wear making it as efficient and stable algorithm.

4.3 Application of SVM based model in Electrochemical Machining process

In this context the SVM based model is applied to a machining process to validate the effectiveness of the model with the real time manufacturing applicability. In order to achieve this, electrochemical process is taken into consideration.

Rao and Padmanabhan [73] optimized the machining parameters in ECM of composite using Taguchi method. Here samples of 25 mm diameter and 20 mm length of LM6 composites were reinforced with boron carbide particles of 30 micron size matrix with 2.5%, 5% and 7.5% by weight. The composites were made to machine using electrochemical machining process, where the input parameters are applied voltage, feed rate, electrolyte concentration and percentage of reinforcement and the responses considered for the selection included material removal rate (MRR), surface roughness (SR) and radial overcut (ROC). MRR is considered as beneficial criteria and SR and ROC are considered as non-beneficial criteria. The factors and their levels for the proposed ECM process is shown in Table 4.1. The data for the proposed ECM process is shown in Table 4.2.

Table 4.1 Factors and their levels [73]

Symbol	Factors	Level 1	Level 2	Level 3
A	Voltage (V)	12	16	20
B	Feed Rate (mm/min)	0.2	0.6	1.0
C	Electrolyte Concentration (g/lit)	10	20	30
D	Percentage of Reinforcement (Wt %)	2.5	5.0	7.5

Table 4.2 Data for ECM process [73]

Experiment number	A	B	C	D	MRR	SR	ROC
1	12	0.2	10	2.5	0.268	4.948	0.96
2	12	0.2	20	5	0.335	5.002	0.94
3	12	0.2	30	7.5	0.227	4.591	0.79
4	12	0.6	10	2.5	0.353	4.92	0.75
5	12	0.6	20	5	0.448	4.498	0.65
6	12	0.6	30	7.5	0.42	4.725	0.8
7	12	1.0	10	2.5	0.689	4.555	0.67
8	12	1.0	20	5	0.545	4.356	0.64
9	12	1.0	30	7.5	0.703	4.232	0.65
10	16	0.2	10	5	0.321	4.882	0.91
11	16	0.2	20	7.5	0.329	4.823	0.94
12	16	0.2	30	2.5	0.488	4.254	1.05
13	16	0.6	10	5	0.379	4.54	0.76
14	16	0.6	20	7.5	0.302	4.431	0.69
15	16	0.6	30	2.5	0.583	3.998	0.99
16	16	1.0	10	5	0.615	4.274	0.75
17	16	1.0	20	7.5	0.619	4.346	0.7
18	16	1.0	30	2.5	0.812	3.598	0.93
19	20	0.2	10	7.5	0.282	5.472	0.91
20	20	0.2	20	2.5	0.599	4.797	1.1
21	20	0.2	30	5	0.603	4.64	1.16
22	20	0.6	10	7.5	0.526	5.214	0.85
23	20	0.6	20	2.5	0.688	4.897	1.03
24	20	0.6	30	5	0.732	4.531	1.08
25	20	1.0	10	7.5	0.688	5.002	0.64
26	20	1.0	20	2.5	0.887	4.389	0.99
27	20	1.0	30	5	0.944	3.989	1

In this paper three models of the machine learning are applied. The detailed descriptions are mentioned below:

4.3.1 Linear regression

After applying the linear regression analysis for all the three responses from the data table, from Table 4.2, the following regression equations obtained through 'Minitab 17' statistical software, after omitting the insignificant factors, are shown in Table 4.3.

Table 4.3 Linear regression equations for ECM process

Response	Equation	R^2 (%)
MRR	$MRR = -0.1705 + 0.02724 \times A + 0.4236 \times B + 0.00773 \times C - 0.02824 \times D$	90.67
SR	$SR = 4.889 + 0.0179 \times A - 0.704 \times B - 0.02297 \times C + 0.0594 \times D$	73.73
ROC	$ROC = 0.6166 + 0.02653 \times A - 2486 \times B + 0.00694 \times C - 0.03333 \times D$	89.09

From these equations, the predicted values for MRR, SR and ROC are obtained. These equations are used to compare this model with the other types of model.

4.3.2 Quadratic regression

Again the quadratic regression is also modeled, through 'Minitab 17' statistical software, in order to compare the effectiveness of the regression model with high DOF with SVM based model. The higher degree polynomial equations obtained are shown in Table 4.4.

Table 4.4 Quadratic regression equations for ECM process

Response	Equation	R^2 (%)
MRR	$MRR = \begin{matrix} 0.766 - 0.0884 \times A - 0.031 \times B + 0.00486 \times C + 0.0056 \times D \\ + 0.00361 \times A^2 + 0.379 \times B^2 + 0.000072 \times C^2 - 0.00339 \times D^2 \end{matrix}$	95.08
SR	$SR = \begin{matrix} 9.98 - 0.642 \times A + 0.159 \times B - 0.0063 \times C - 0.0101 \times D \\ + 0.02068 \times A^2 - 0.668 \times B^2 - 0.00545 \times C^2 + 0.0164 \times D^2 \end{matrix}$	94.22
ROC	$ROC = \begin{matrix} 0.799 + 0.0076 \times A - 0.469 \times B + 0.00050 \times C - 0.0031 \times D + \\ 0.00059 \times A^2 + 0.184 \times B^2 + 0.000161 \times C^2 - 0.00302 \times D^2 \end{matrix}$	90.51

These quadratic regression equations are used to predict the MRR, SR and ROC values. The predicted results are then compared with other types of model to check their effectiveness.

4.3.3 Support vector machine

Here 527 data are selected out of which 500 are selected for training purpose and the remaining are selected for testing purpose for the SVM model. The results are compared well with linear and quadratic regression models. There are several types of SVM based models like nu-regression, epsilon regression, etc. and several types of kernel function models like linear, polynomial, radial biased function (RBF), etc. But as per the previous literature review the best result would be obtained if the SVM parameters are set at epsilon regression model and kernel function is set at RBF model. Henceforth the same SVM parametric setups are chosen. After that, the SVM kernel parameter like epsilon and sigma and the regularization parameter are optimized through 'RStudio version-1.1.463' software. The range for kernel parameter epsilon is set at [0, 1] and the regularization parameter C is set at [1, 1000].

The grid search with 10 k-fold validation with the training data is performed to optimize the best kernel and regularization parameter. The optimal results are best shown in Figure 4.1.

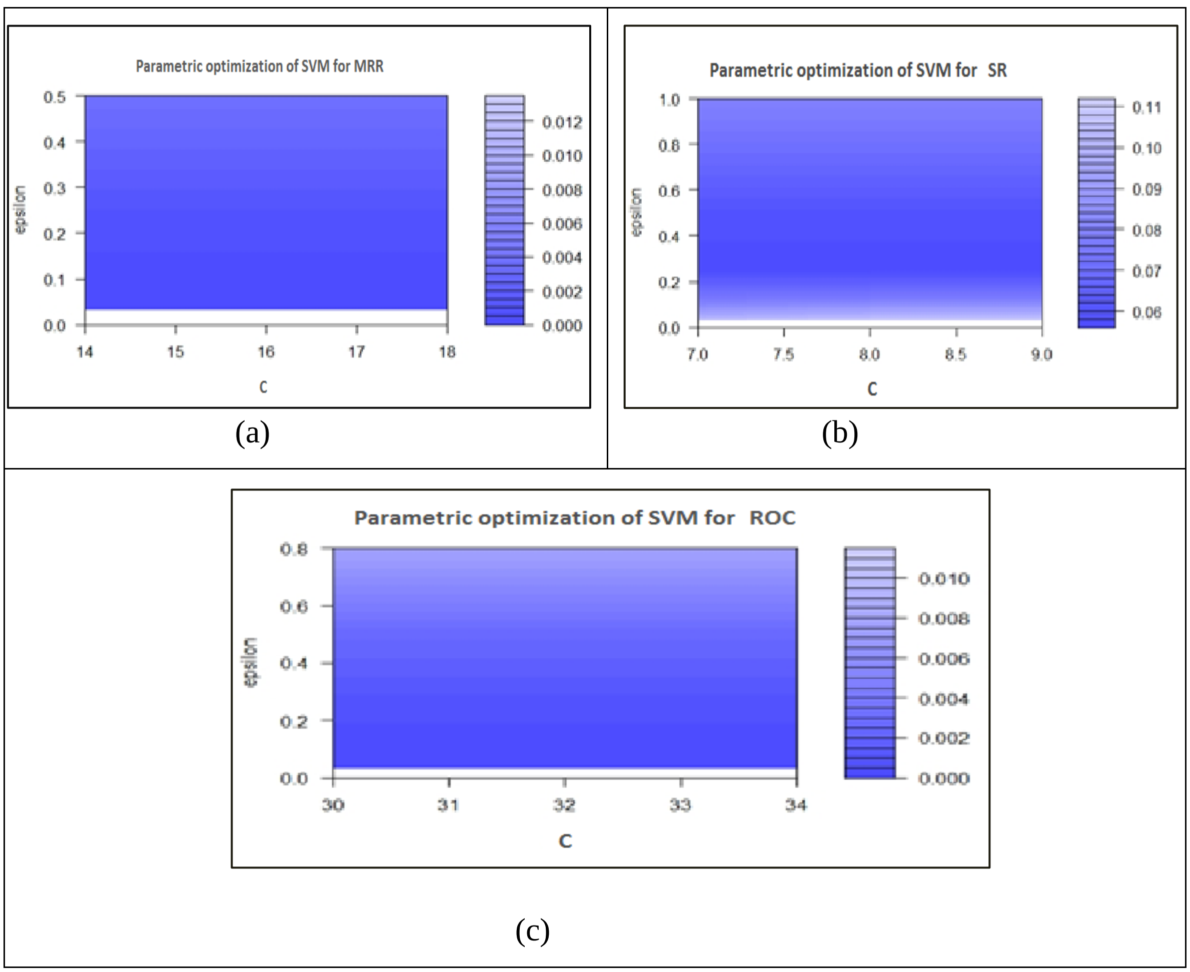

Figure 4.1 Parametric optimization of SVM for the considered responses

From Figure 4.1 (a), the SVM parameters for MRR are found to be epsilon =0.0625, C =16, and sigma =0.14057. From Figure 4.1 (b), the optimal SVM parameters for SR are epsilon =0.25, C =8 and sigma =0.15355 and from Figure 4.1(c), the optimal SVM parameters for ROC are epsilon = 0.125, C=32 and sigma = 0.140572. Now after setting the above parameters into SVM based model, the performance results for the optimized model are shown in Table 4.5.

Table 4.5 Performance results of SVM model for the considered responses

Responses	Number of Support Vectors	Training error	Cross validation error
MRR	281	0.004762	0.000277
SR	20	0.049243	0.0467
ROC	148	0.008615	0.000303

Now, the test data should be validated with the obtained models. The calculated results of different responses for different algorithms are shown in Table 4.6, 4.7 and 4.8 for MRR, SR and ROC respectively. Figure 4.2 defines the scatter plot of actual values and the predicted values for considered responses. In this figure it is seen that there are very low deviation in the values derived from SVM with the best fit line, while is linear and quadratic regression is densely deviated throughout.

Table 4.6 The calculated values for MRR using regression analysis and SVM based model

Experiment number	A	B	C	D	Experimental	Linear regression	Quadratic regression	SVM based model
1	12	0.2	10	2.5	0.268	0.3108	0.282613	0.280279
2	12	0.2	20	5	0.335	0.3175	0.30325	0.363658
3	12	0.2	30	7.5	0.227	0.3242	0.295913	0.251172
4	12	0.6	10	2.5	0.353	0.48024	0.391493	0.374552
5	12	0.6	20	5	0.448	0.48694	0.41213	0.460211
6	12	0.6	30	7.5	0.42	0.49364	0.404793	0.432215
7	12	1.0	10	2.5	0.689	0.64968	0.621653	0.70131
8	12	1.0	20	5	0.545	0.65638	0.64229	0.57836
9	12	1.0	30	7.5	0.703	0.66308	0.634953	0.71528
10	16	0.2	10	5	0.321	0.34916	0.28377	0.33101
11	16	0.2	20	7.5	0.329	0.35586	0.262033	0.3343
12	16	0.2	30	2.5	0.488	0.57436	0.488133	0.50029
13	16	0.6	10	5	0.379	0.5186	0.39265	0.39122
14	16	0.6	20	7.5	0.302	0.5253	0.370913	0.33068
15	16	0.6	30	2.5	0.583	0.7438	0.597013	0.59523
16	16	1.0	10	5	0.615	0.68804	0.62281	0.62724
17	16	1.0	20	7.5	0.619	0.69474	0.601073	0.63084
18	16	1.0	30	2.5	0.812	0.91324	0.827173	0.81132
19	20	0.2	10	7.5	0.282	0.38752	0.358073	0.29436

Table 4.6 (contd.) The calculated values for MRR using regression analysis and SVM based model

20	20	0.2	20	2.5	0.599	0.60602	0.569773	0.60929
21	20	0.2	30	5	0.603	0.61272	0.60481	0.6093
22	20	0.6	10	7.5	0.526	0.55696	0.466953	0.5257
23	20	0.6	20	2.5	0.688	0.77546	0.678653	0.70024
24	20	0.6	30	5	0.732	0.78216	0.71369	0.74428
25	20	1.0	10	7.5	0.688	0.7264	0.697113	0.70024
26	20	1.0	20	2.5	0.887	0.9449	0.908813	0.89273
27	20	1.0	30	5	0.944	0.9516	0.94385	0.95622

Table 4.7 The calculated values for SR using regression analysis and SVM based model

Experiment number	A	B	C	D	Experimental	Linear regression	Quadratic regression	SVM based model
1	12	0.2	10	2.5	4.948	4.8818	5.21875	5.025122
2	12	0.2	20	5	5.002	4.8006	5.2745	4.900699
3	12	0.2	30	7.5	4.591	4.7194	5.42625	4.692491
4	12	0.6	10	2.5	4.92	4.6002	5.06859	4.818579
5	12	0.6	20	5	4.498	4.519	5.12434	4.599409
6	12	0.6	30	7.5	4.725	4.4378	5.27609	4.623488
7	12	1.0	10	2.5	4.555	4.3186	4.70467	4.568086
8	12	1.0	20	5	4.356	4.2374	4.76042	4.254431
9	12	1.0	30	7.5	4.232	4.1562	4.91217	4.333455
10	16	0.2	10	5	4.882	5.1019	5.24916	4.9349
11	16	0.2	20	7.5	4.823	5.0207	5.50991	4.800759
12	16	0.2	30	2.5	4.254	4.494	4.40491	4.355366
13	16	0.6	10	5	4.54	4.8203	5.099	4.641145
14	16	0.6	20	7.5	4.431	4.7391	5.35975	4.532416
15	16	0.6	30	2.5	3.998	4.2124	4.25475	4.008566
16	16	1.0	10	5	4.274	4.5387	4.73508	4.375348
17	16	1.0	20	7.5	4.346	4.4575	4.99583	4.244467
18	16	1.0	30	2.5	3.598	3.9308	3.89083	3.699541
19	20	0.2	10	7.5	5.472	5.322	6.14633	5.370803
20	20	0.2	20	2.5	4.797	4.7953	5.15033	4.898431
21	20	0.2	30	5	4.64	4.7141	5.09708	4.695756
22	20	0.6	10	7.5	5.214	5.0404	5.99617	5.198132
23	20	0.6	20	2.5	4.897	4.5137	5.00017	4.795556
24	20	0.6	30	5	4.531	4.4325	4.94692	4.429595
25	20	1.0	10	7.5	5.002	4.7588	5.63225	4.900715
26	20	1.0	20	2.5	4.389	4.2321	4.63625	4.490256
27	20	1.0	30	5	3.989	4.1509	4.583	4.09052

Table 4.8 The calculated values for ROC using regression analysis and SVM based model

Experiment number	A	B	C	D	Experimental	Linear regression	Quadratic regression	SVM based model
1	12	0.2	10	2.5	0.96	0.732515	0.883195	0.9779591
2	12	0.2	20	5	0.94	0.57979	0.87212	0.9597756
3	12	0.2	30	7.5	0.79	0.427065	0.855495	0.8097946
4	12	0.6	10	2.5	0.75	0.633075	0.754475	0.7455534
5	12	0.6	20	5	0.65	0.48035	0.7434	0.6697914
6	12	0.6	30	7.5	0.8	0.327625	0.726775	0.8131503
7	12	1.0	10	2.5	0.67	0.533635	0.684635	0.6897996
8	12	1.0	20	5	0.64	0.38091	0.67356	0.6597868
9	12	1.0	30	7.5	0.65	0.228185	0.656935	0.6697983
10	16	0.2	10	5	0.91	0.75531	0.9153	0.9289596
11	16	0.2	20	7.5	0.94	0.602585	0.866475	0.9490444
12	16	0.2	30	2.5	1.05	0.699835	1.118475	1.0698451
13	16	0.6	10	5	0.76	0.65587	0.78658	0.7660861
14	16	0.6	20	7.5	0.69	0.503145	0.737755	0.7098141
15	16	0.6	30	2.5	0.99	0.600395	0.989755	1.0098487
16	16	1.0	10	5	0.75	0.55643	0.71674	0.7564918
17	16	1.0	20	7.5	0.7	0.403705	0.667915	0.707678
18	16	1.0	30	2.5	0.93	0.500955	0.919915	0.9498055
19	20	0.2	10	7.5	0.91	0.778105	0.928535	0.9265004
20	20	0.2	20	2.5	1.1	0.875355	1.148335	1.1082601
21	20	0.2	30	5	1.16	0.72263	1.16946	1.1567052
22	20	0.6	10	7.5	0.85	0.678665	0.799815	0.8343884
23	20	0.6	20	2.5	1.03	0.775915	1.019615	1.0498376
24	20	0.6	30	5	1.08	0.62319	1.04074	1.0998425
25	20	1.0	10	7.5	0.64	0.579225	0.729975	0.6532017
26	20	1.0	20	2.5	0.99	0.676475	0.949775	1.0097725
27	20	1.0	30	5	1	0.52375	0.9709	1.0189854

Table 4.9 shows the comparison of various algorithms with respect to the correlation coefficient (R^2) and root mean square error (RMSE). From the comparison table, it is clearly demonstrated that the SVM based model gives the more efficient model among the three. The predicted values of responses with the minimum correlation of 97.69% with the original values and with a maximum error of 0.09 (RMSE) are obtained through SVM based tool which is very valuable for production point of view.

Table 4.9 The comparison table of different algorithm for corresponding responses

Response	Pair type	R	R^2	RMSE
MRR	Actual vs. SVM	0.9993	0.9986	0.015
	Actual vs. Linear regression	0.9522	0.9067	0.087
	Actual vs. Quadratic regression	0.9751	0.9508	0.043
SR	Actual vs. SVM	0.9769	0.9543	0.09
	Actual vs. Linear regression	0.8479	0.7189	0.2112
	Actual vs. Quadratic regression	0.8846	0.7825	0.5163
ROC	Actual vs. SVM	0.9983	0.9966	0.0165
	Actual vs. Linear regression	0.6674	0.4454	0.3043
	Actual vs. Quadratic regression	0.9514	0.9052	0.4836

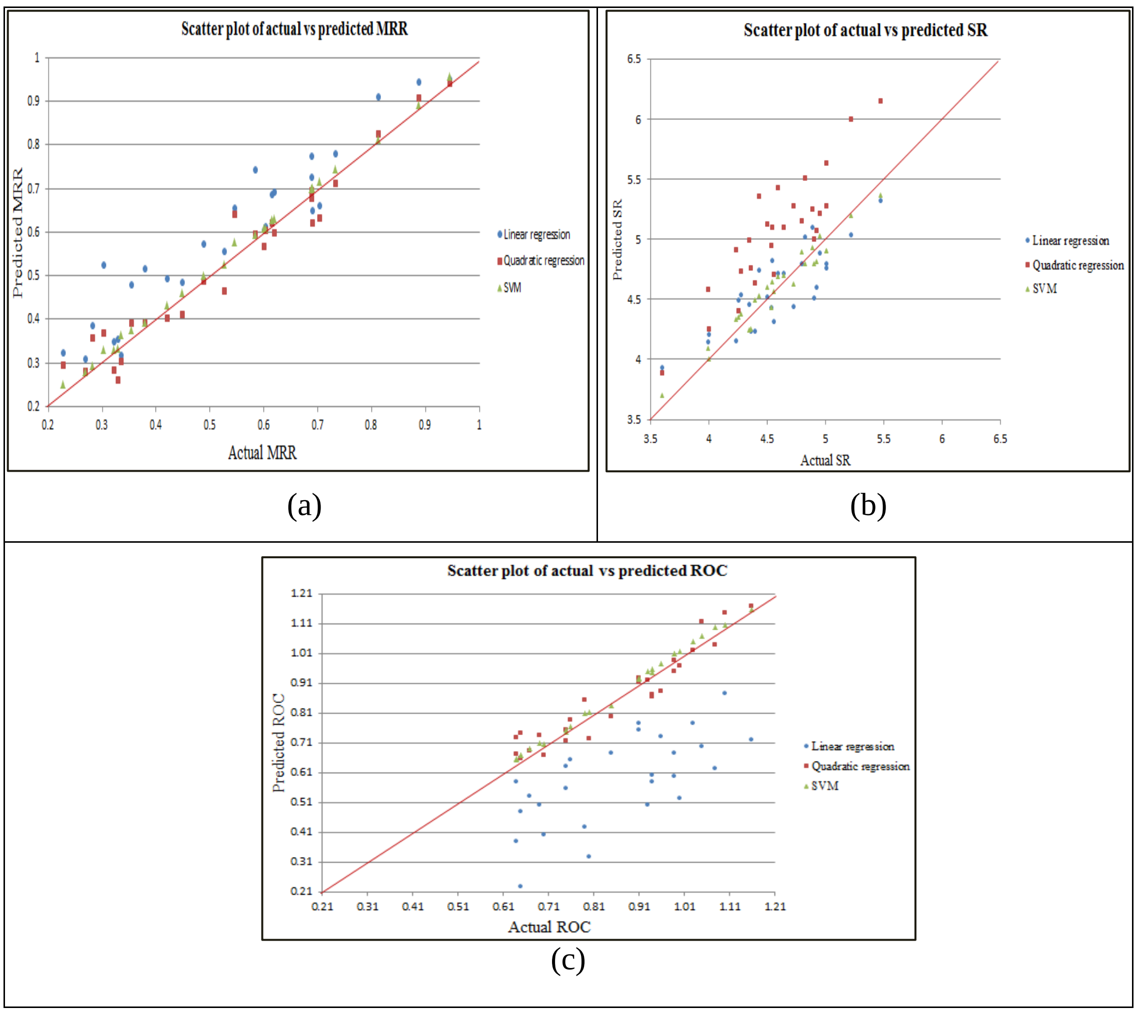

Figure 4.2 Scatter plots of actual and predicted values for corresponding responses

Figure 4.3 shows the comparison of different algorithms for MRR, SR and ROC. Figure 4.3(a) and 4.3(c) shows that the SVM based model best correlate with the experimental data whereas the linear regression model predicts the worst and the quadratic regression lies in between. Whereas Figure 4.3(b) defines that the SVM based model is the best among three whereas the quadratic regression model defines the worst and the linear regression model lies in between. In all the three response cases, SVM based model emerges as the best model for prediction purpose.

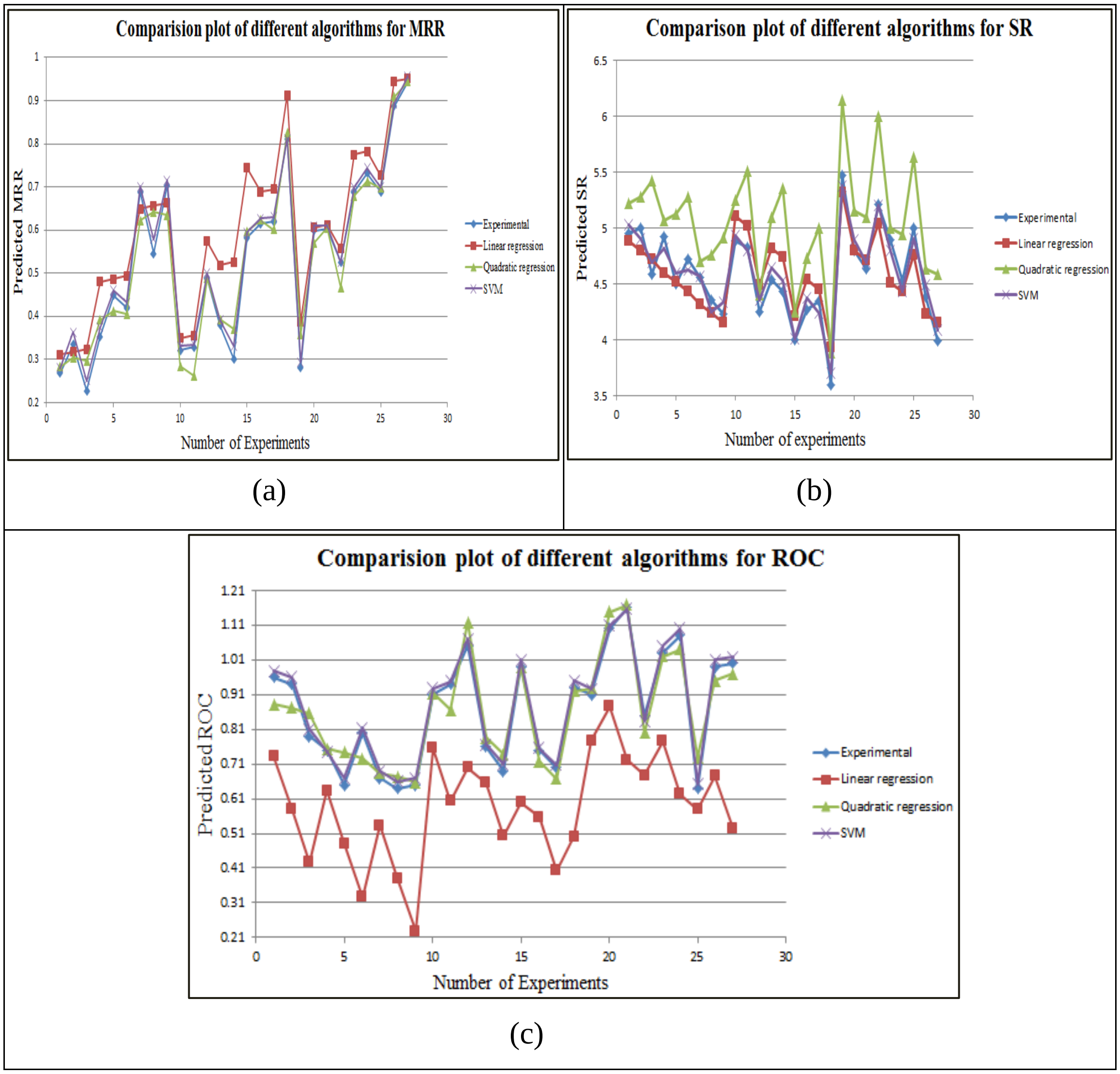

Figure 4.3 Comparison plots of different algorithm for corresponding responses

5.0 GENERAL CONCLUSIONS AND FUTURE SCOPE

Based on the set objectives and the result obtained while using the association rule development and SVM model development, the following general conclusions can be drawn:

a) For the grinding process, low spindle speed leads to better surface roughness whereas higher spindle speed leads to higher grinding efficiency but higher amplitude of vibration.
b) For the turning process, when the operating condition is set at medium value of speed, high feed and high depth of cut then the optimized value of MRR, surface roughness can be achieved.
c) For the ECM process, only by setting the feed rate at its high level, higher value of MRR, and lower values SR and ROC can be simultaneously achieved.
d) For the USM process, tool material as HCS, abrasive type as boron carbide, high grit size and high power rating would help to attain satisfactory values for MRR, SR and TWR.
e) A high concentration of chromium powder in the dielectric medium, moderate peak current, low pulse-on time and high duty cycle would simultaneously optimize MRR, TWR, EWR and SR in the considered EDM process.
f) For classifier and prediction purpose, SVM comes out to be the best model among other models with very high correlation with the experimental results and very less margin of error.

The future scope of this research work includes the following:

a) to develop a multi-response rules making software to ease the rules generation for multiple responses at a time.
b) to apply the proposed SVM methodology in other domains of manufacturing.
c) to incorporate the effect of non-linear SVM parametric function, e.g. gamma, into the proposed SVM model.
d) to apply other data mining tools like decision tree and ANN into the manufacturing domain.

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