EXPERIMENTAL INVESTIGATION AND OPTIMISATION IN EDM PROCESS OF AISI P20 TOOL STEEL

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Ritanjali Sethy

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Certificate

This is to certify that thesis entitled, **"Experimental Investigation and Optimisation in EDM Process of AISI P20 Tool Steel"** submitted by Miss. Ritanjali Sethy bearing Roll No. 611ME302 in partial fulfilment of the requirements for the award of the degree of Master of Technology by research in the Department of Mechanical Engineering with Production Engineering Specialization. It is a bonafide record of the work carried out by her under our supervision and guidance. It is further certified that no part of this thesis is submitted for the award of any degree.

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ABSTRACT

Electro Discharge Machining (EDM) is an extremely prominent machining process among newly developed non -traditional machining techniques for "difficult to machine" conducting materials such as heat treated tool steels, composites, super alloys, ceramics, hastelloys, nitralloy, nemonic alloys, carbides, heat resistant steels etc. In EDM, the material removal of the electrode is achieved through high frequency sparks between the tool and the work-piece immersed into the dielectric. The Material Removal Rate (MRR), Tool Wear Rate (TWR) and surface integrity are some of the important performance attributes of EDM process. The objective of EDM is to get high MRR along with achieving reasonably good surface quality of machined component. The machining parameters that achieve the highest MRR strongly depend on the size of the machining surface i.e. the engaged electrode and work-piece surface. With upcoming worldwide applications of AISI P20 machining has become an important issue which needs to be investigated in detail. The AISI P20 steel is applied by the tooling industry as material for injection molding tools. These steel are categorized as "difficult to machine" materials, since they posses greater strength and toughness. Therefore, AISI P20 steel is usually known to create major challenges during conventional and non- conventional machining.

Keeping this in view, an experimental investigation to explore the productivity, quality, surface integrity, and accuracy on the EDM surface. The work has been carried out by conducting a set of experiments using AISI P20 tool steel work-piece with copper electrode. Important machining parameters like Discharge current (Ip), Pulse on Time (T_{on}), Pulse off Time (T_{off}), Lift Time (T_{up}) and Work Time (T_w) are considered for investigation. The effect of the machining parameters on the responses such as MRR, TWR, Surface Roughness (SR), and Micro hardness were investigated. Now-a-days optimization and modeling of EDM process is a highly demanding re-

search area. Single objective optimization method creates problem, when more than one response variables need to be optimized simultaneously. So, many attempts have been made to model performance parameters of EDM process by using multi-objective optimization approach like Principal Component Analysis (PCA) based approaches and Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method. In this thesis, both single and multi-objective optimisation methods have been reported to study some aspects of machining of AISI P20 tool steel.

A well-designed experimental were conducted with L_{18} Orthogonal Array (OA) based on the Taguchi method with input factors Discharge current, Pulse on Time, Lift Time and Flushing pressure. The Signal-to-Noise (S/N) ratios associated with the observed values were plotted and the factor effecting the micro-hardness of the work-piece has been obtained. It is inferred that micro- hardness value increases with increase in Ip and decreases with increase in T_{on}. The optimal condition for minimum hardness was found to be $Fp1$, $Ip1$, $T_{on}3$, $T_{up}3$.

Fuzzy TOPSIS method have been implemented and the result obtained has been illustrated in detail. Important machining parameters like Discharge current, Pulse on Time, Lift Time, Inter Electrode gap and Work Time were considered for the study. The experiments were conducted to study the effect of the machining parameters on the responses such as MRR, TWR and SR. It was observed that the optimal process condition for higher MRR and lower TWR and SR is Ip= 8A, Ton= 500μs, Tup= 0s, Tw= 1s and IEG = 90μm. A sensitivity analysis was carried out to determine the influence of criteria weights on the decision making process. The optimal parameter values were having 55.56 % votes. It was observed that 97.22% optimal Ip, 88.88 % optimal Ton, 100% optimal Tup, 66.67% optimal Tw, 100% optimal IEG were robust against the variation of Decision Maker (DM)s preferences.

Taguchi design has been implemented to investigate the effect of Discharge current, Pulse on Time, Lift Time and Flushing pressure on the responses MRR and TWR and SR. Three different PCA based approaches (Grey Relational Analysis (GRA),Weighted Principal Component (WPC) and Proportion of Quality Loss Reduction (PQLR)) were used to get a single output for optimisation of the above three responses. A study was performed if the reduction of principal components effect optimality and it was concluded that it doesn't effect. It was observed that the optimal process condition for Overall Quality Performance Index (OQPI) and Multi-response Performance Index (MPI) is $Ip1$, $Ton3$, $Tup3$ and $Fp1$. The optimal process condition for Weighted Score (WS) is $Ip1$, $Ton2$, $Tup1$ and $Fp2$. PCA-based PQLR method yields better optimisation and can be an effective approach for optimisation of multiple correlated responses.

Keywords: Electric Discharge Machining (EDM), AISI P20 tool steel, Taguchi method, Micro Hardness, Principal Component Analysis, Fuzzy TOPSIS, Material Removal Rate, Tool Wear Rate, Surface Roughness.

List of Acronyms

ANOVA Analysis of Variance

CCD Central Composite Design

DOE Design of Experiments

EDM Electro Discharge Machining

PMEDM Powder Mixed Electro Discharge Machining

WEDM Wire Electro Discharge Machining

MEDM Micro Electro Discharge Machining

GRA Grey Relational Analysis

GRC Grey Relational Coefficient

GRG Grey Relational Grade

HAZ Heat Affective Zone

MRR Material Removal Rate

OA Orthogonal Array

OC Radial Over cut

RSM Response Surface Methodology

SCD Surface Crack Density

SEM Scanning Electron Microscopy

SR Surface Roughness

TWR Tool Wear Rate

TOPSIS Technique for Order of Preference by Similarity to Ideal Solution

WLT White Layer Thickness

FEM Finite Element Method

ANN Artificial Neural Network

SEM Scanning Electron Microscope

S/N Signal-to-Noise

MPCI Multi Performance Criteria Index

PCA Principal Component Analysis

WPC Weighted Principal Component

PQLR Proportion of Quality Loss Reduction

MPI Multi-response Performance Index

OQPI Overall Quality Performance Index

WS Weighted Score

HTB Higher-The-Better

LTB Lower-The-Better

NTB Nominal-The-Better

ANN Artificial Neural Network

GA Genetic Algorithm

UT Utility Theory

PCS Principal Component Scores

DM Decision Maker

PM Powder Mettalurgy

FPIS Fuzzy Positive Ideal Solution

FNIS Fuzzy Negative Ideal Solution

CCI Closeness Coefficient Index

MOO Multi Objective Optimization

SOO Single Objective Optimization

MMC Metal Matrix Composite

PPI Process Performance Index

ANFIS Adaptive Neuro-Fuzzy Inference System

NOMENCLATURE

T_{up}	Lift Time
T_w	Work Time
γ	Grey relation coefficient
ρ_t	Density of tool
τ	Duty Cycle
ζ	Distinguishing coefficient
Fp	Flushing pressure
Ip	Discharge current
p	Machining Polarity
T_a	Weight of tool after machining
T_b	Weight of tool before machining
T_{off}	Pulse off Time
T_{on}	Pulse on Time
V	Voltage
W_a	Weight of work-piece after machining
W_b	Weight of work-piece before machining
ρ_w	Density of work-piece
n	Number of repeated experiments

R^2 Coefficient of determination

R^2_{adj} Adjusted coefficient of determination

y_{ijk} the experimental value of j^{th} response in i^{th} trial at k^{th} replication

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Chapter I

Introduction

1. INTRODUCTION

1.1 Introduction on EDM

1.1.1 Overview on EDM

In this technological era, manufacturing industries are facing challenges from such advanced difficult- to- machine materials, viz. super alloys, ceramics and composites and stringent design requirements (high surface quality, high precision, high strength, complex shapes, high bending stiffness, good damping capacity, low thermal expansion and better fatigue characteristics) and machining costs. There is a growing trend to use light weight and compact mechanical component in the recent years; therefore there has been an increased interest in the advance materials in modern day industries. The new concept of manufacturing uses non-conventional energy sources like sound, light, mechanical, chemical, electrical, electrons and ions. The machining processes are non-conventional in the sense that they do not employ traditional tools for metal removal and instead they directly use other forms of energy. For the last few years, EDM has been used to machine advanced materials with desired shape, size and required accuracy. EDM is a non- conventional machining process, where electrically conductive materials is machined by using precisely controlled sparks that occur between an electrode and a work-piece in the presence of a dielectric fluid. It uses thermoelectric energy sources for machining extremely low machinability materials; complicated intrinsic- extrinsic shaped jobs regardless of hardness have been its distinguishing characteristics. Machining of any electrically conductive material irrespective of its hardness, by the application of thermal energy is one of the prime advantages of EDM process. As EDM does not make direct contact (an inter electrode gap is maintained throughout the process) between the electrode and the work-piece, its eradicate mechanical stresses, chatter and vibration problems during machining. Various types of EDM process are available, but here the concern is about die- Sinking (also known as ram) type EDM machines and there are many input machining parameter which can be wide- ranging in the EDM process that have different effects on the EDM performances characteristics. EDM has been replacing traditional machining operations and is now a well-established machining option in many manufacturing industries throughout the world. Modern EDM developed in late 1940s, has been accepted worldwide as a standard process in manufacturing. The history of EDM techniques was discovered by Sir Joseph Priestley an English Scientist. It took more than a century to make use of some practical use. The popularity of this machining was grown by leaps and bounds in last sixty years.

1.1.2 Types of EDM

Basically, there are three different types of EDM

1. Die Sinking EDM
2. Micro Electro Discharge Machining (MEDM)
3. Wire Electro Discharge Machining (WEDM)

1. Die Sinking EDM: It is the most basic one EDM, which is a non-contact machining process in which metal is removed by a series of periodically electrical discharges between a tool work-piece submerged in an insulating liquid are connected to a suitable power supply. A schematic diagram of such a machine is shown in Fig. 1.1. It uses thermoelectric energy sources for machining low machinability materials; complicated intrinsic- extrinsic shaped jobs regardless of hardness have been its distinguishing characteristics. According to Droza (1998), any electrically conductive material can be used as work-piece and tool electrode. EDM founds its wide applicability in manufacturing of plastic moulds, forging dies, press tools, die castings, automotive, surgical components, tool, die, and mould making industries and aerospace (Ho and Newman, 2003).

1.1.3 Equipments of EDM

(a) Dielectric system: The dielectric system consists of dielectric fluid, delivery device, pumps, and filters. In EDM, material removal mainly occurs due to thermal

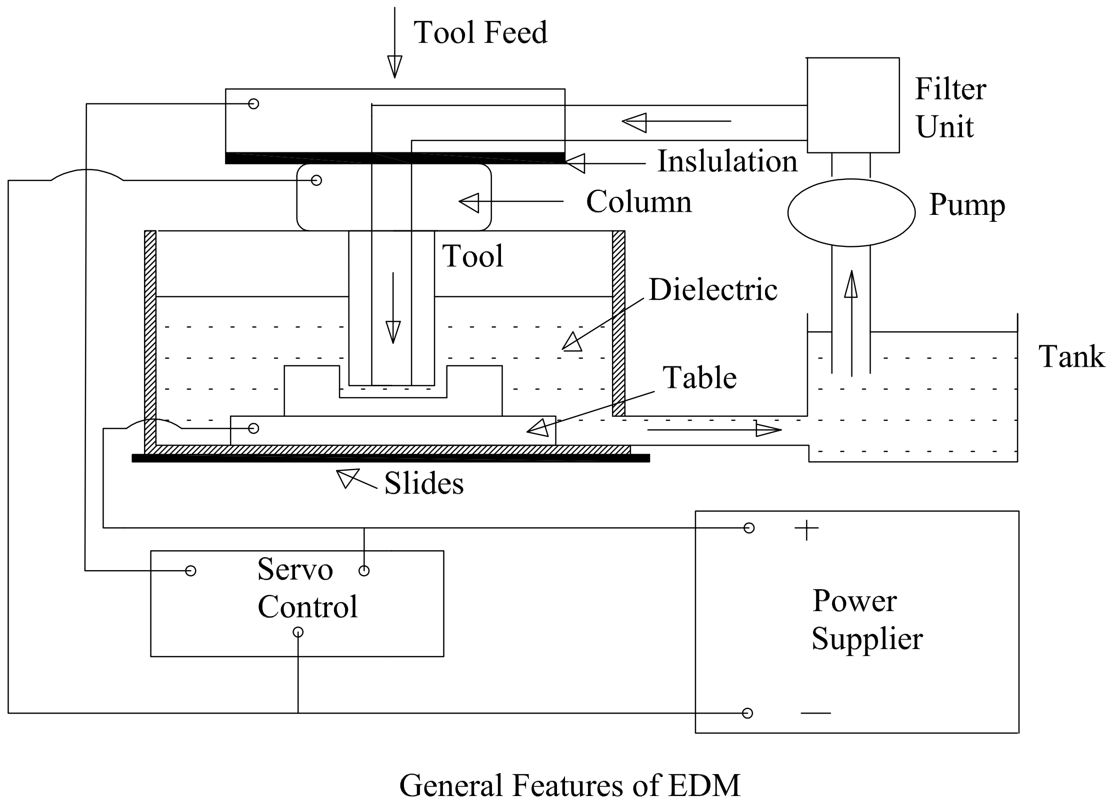

Fig. 1.1: Schematic of an electric discharge machining machine

evaporation and melting which is required to be carried out in absence of oxygen so that the process can be controlled and oxidation avoided. Hence, dielectric system should provide an oxygen free machining environment.

(b) Electrode: It is the tool determining shape of the cavity generated. It depends upon material and design. Requirements for selection: should be readily available, easily machinable, exhibit low wear, electrically conductive and provide good surface finish. The different electrode materials which are used commonly in the industry are:

- Graphite
- Electrolytic oxygen free copper
- Tellurium copper 99% Cu + 0.5% tellurium
- Brass

(c) Servo System: It is commanded from signals of gap voltage sensor system in power supply and controls the in-feed of electrode or work-piece to match material removal.

(b) Power Supply: It transforms the alternating current from the main utility electrical supply to pulse DC required to produce spark discharges at the machining gap.

1.1.4 Working principle of EDM

In EDM process, the principle is the conversion of electrical energy into thermal energy through a series of discrete sparks occurring between the tool electrode and a conductive work-piece immersed in a dielectric medium and separated by a small gap. Short duration discharges are generated in a liquid dielectric gap, which separates tool and work-piece. In this process electrical energy is used to generate the electrical spark and thermal energy is used for material removal. The electrode is moved towards the work-piece until the gap is small enough to ionize the dielectric. The dielectric flush eroded particles from the gap and it is really important to maintain this flushing continuously. As the work-piece remain fixed by the fixture arrangement, tool helps in focusing the discharge or intensity of generated heat at the place of shape disclose. Application of heat raises the temperature of work-piece in the region of tool position, which subsequently melts and evaporates the metal. In this way the machining process removes small volumes of work-piece material by the mechanism of melting and vaporization during a discharge.

The erosion process due to a single electric spark in EDM generally passes through the following phases which shown in Fig. 1.2 and also described below.

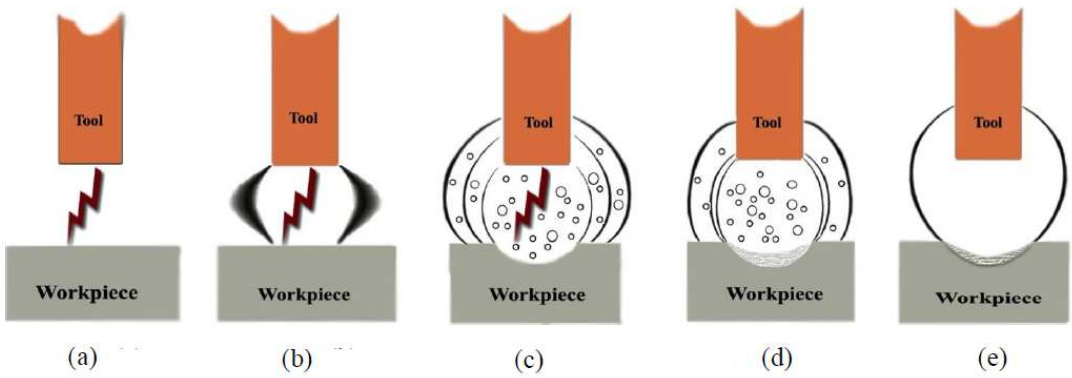

Fig. 1.2: (a) Pre-breakdown phase (b) Breakdown phase (c) Discharge phase (d) End of the discharge and (e) Post-discharge phase

(a) Pre-breakdown: In this phase, the electrodes are held at a small distance where the electrode moves close to the work-piece and a high potential difference is applied between the electrodes.

(b) Breakdown: When the applied voltage crosses the boundary limit of strength of used dielectric fluid, the breakdown of the dielectric is originated. The spot of breakdown is normally between the closest points of the electrode and the work-piece, but it is also depend on conductive particles or debris present in the gap. When the breakdown occurs the voltage falls and a current rises quickly. In this phase the dielectric gets ionized and a plasma channel is created between the electrodes.

(c) Discharge: In this phase the flow of discharge current is maintained at constant level for a continuous attack of ions and electrons on the electrodes leads to cause strong heating of the work-piece material, leading to temperature rise between 8,000 ◦C and 12,000 ◦C. This results rapidly creating a small molten metal pool at the electrodes surface. Also a small amount of metal are directly vaporized due to the tremendous amount of heat. In this phase, the plasma channel expands; therefore the radius of the molten metal pool also increases with time. The Inter Electrode Gap is an important parameter throughout the discharge phase.

(d) End of the discharge: In this phase, current and voltage supply are cut off and therefore, plasma collapses under the pressure enforced by the surrounding dielectric.

(e) Post-discharge: In this phase, there will be no plasma. Here a small portion of metal will be machined and a small thin layer (white layer) will be deposited because of plasma is collapsing and cooling. Accordingly, the molten metal pool is strongly sucked up into the dielectric, producing a tiny crater on the work-piece surface.

Finally, the machining process removes small volumes of work-piece material, molten or vaporized during a discharge and is carried away from the inter-electrode gap by the dielectric flow in the form of debris. The gap increases after material removal at the point of spark, and the position of the next spark shifts to a different place, where gap is smallest on the work-piece surface. In this manner thousands of sparks occur at different locality over the whole surface of the work-piece corresponding to the inter electrode gap. As a consequence, a replica of the tool surface shape is produced in the work-piece.

1.1.5 EDM process parameters

Different EDM machines have different set of parameters due to their designs. To perform an efficient machining one should have to identify important process parameters which influence the responses which are described below. The complete set of parameters is machine dependent. The machining parameter can be categorized into;

Input /process parameters: The parameters are voltage (V), discharge current (Ip), pulse- on time (T_{on}), pulse-off time (T_{off}), duty factor (τ), flushing pressure (Fp), work-piece material, tool material, inter-electrode gap (IEG), Lift Time (T_{up}), Work Time (T_w) and polarity (p) which affects the performance of machining process.

(a) Voltage: Open-circuit voltage specifies the voltage of applied pulses that influences the spark energy. This de-ionizes the dielectric medium, which depends upon the electrode gap and the strength of the dielectric, prior to the flow of current.

(b) Pulse-on time: It is the time during which actual machining takes place or it is the duration of time for which the current is allowed to flow per cycle. The longer the pulse duration higher will be the spark energy that creates wider and deeper crated. it is because the material removal is directly proportional to the amount of energy applied during this on-time. During pulse duration, the lengths of ignition delay and discharge duration depend on the gap state. Together with discharge current, pulse duration sets the amount of energy generated during a single electrical discharge.

(c) Discharge current: The current increases until it reaches a preset level which is expressed as discharge current. The setting of discharge current on static pulse generators generally determines the number of power units connected parallel to the gap. The larger discharge current means the higher power intensity during electrical discharge. It is the most important machining parameter in EDM because it relates to power consumption of power while machining.

(d) Duty cycle: It is the percentage of on-time relative to the total pulse period. At higher duty cycle, the spark energy is supplied for longer duration of the pulse period which gives higher machining efficiency.

(e) Pulse-off time: It is the duration of time between the sparks during which the supply voltage is cut off as a consequence the discharge current becomes to zero. This time allows the molten material to solidify and to be wash out of the arc gap. This parameter affects the speed and the stability of the cut. Thus, if the off-time is too short, it will cause unstable sparks.

(f) Polarity: It specifies to the potential of the work-piece with respect to tool, depending on the application, the polarity can be either way. Carbide, Titanium and copper are generally cut with negative polarity.

(g) Inter Electrode Gap: It is the distance between the electrode and the part during the process of EDM. It is also called spark gap. It is the most important requirements for spark stability and proper flushing. Gap width is not measurable directly, but can be inferred from the average gap voltage. The tool servo mechanism is responsible for maintaining working gap at a set value.

(h) Dielectric fluid: The dielectric fluid is act as an electrical insulator carry out for most important purposes in the EDM. Most commonly used dielectric fluids are paraffin, deionized water, light transformer oil and kerosene. It cools down the electrodes, also provides a high plasma pressure and therefore a high removing force on the molten metal, and it also helps in flushing away these eroded particles.

(i) Flushing pressure: Flushing is an important factor in EDM of supplying clean filtered dielectric fluid into the machining zone. Flushing is difficult if the cavity is deeper, inefficient flushing may initiate arcing and may create unwanted cavities which can destroys the work-piece. There are several methods generally used to flush the gap: injection flushing, suction flushing, side-flushing, motion flushing and impulse flushing. The usual range of pressure used is between 0.1 to 0.4 kgf/cm^2.

(j) Lift time: It is the time in which tool lifts up and flushing takes place in the Inter Electrode Gap.

Response /performance measures: The parameters are MRR, TWR, SR and Surface integrity, used to evaluate the machining process in both qualitative and quantitative terms.

(a) MRR: The material MRR is expressed as the ratio of the difference of weight of the workpiece before and after machining to the machining time and density of the material. Material removal determines both machining rate and tool electrode wear rate. The anode has larger material removal with shorter pulse duration while the cathode has larger material removal with longer pulse duration. The higher the material removal rate in the EDM process, the better is the machining performance. Hence, the MRR is the higher-the-better performance characteristic.

(b) TWR: It defined as the volumetric ratio of material removal on tool electrode. The smaller the TWR in the EDM process, the better is the machining performance. Therefore, TWR is the lower-the-better performance characteristics.

(c) SR: A profilemeter (Talysurf) was used to measure the machined surface roughness. The average surface roughness Ra that is the most widely used surface roughness parameter in industry was selected in this study. The smaller SR in the EDM process, the better is the machining performance. So, SR are the lower-the-better performance characteristics.

(d) Surface Integrity: The electrode machined surface is made up of three distinctive layers consisting of White Layer Thickness (WLT), Heat Affective Zone (HAZ) and unaffected parent metal can be characterized by geometrical shape of the surface, metallurgical and chemical characteristics, and mechanical properties. SR is increases with discharge energy. The sparks produce a surface layer that consists of resolidified layer on the top of heat- affected-zone and the white layer is the topmost layer exposed to the environment. Due to the presence of powders in the dielectric fluid increases the micro- hardness and reduces the micro-cracks on the EDMed surface due to a reduction of losing alloying elements residing onto the work-piece.

2. WEDM: It uses a thin single-strand metal wire (diameter 0.1 mm, generally in steel, brass or copper), which cuts the work-piece during the process. Deionized water is used as dielectric which directly injected around the wire and controlling its resistivity and other electrical properties with filters and de-ionizer units. Therefore, WEDM is commonly used when low residual stresses are desired. The wire in WEDM applications acts almost like an electrical saw and it is capable of achieving very small cutting angles. The quality of the machining, i.e. precision and surface rugosity, is directly related to the discharge parameters (current, voltage, discharge duration, polarity), and also on the dielectric cleanliness. Sparks with low current will produce small craters: the surface rugosity is low but the removal rate is also low. WEDM is typically used to cut plates as thick as $300mm$ and to make punches, tools, and dies from hard metals.

3. MEDM: It a powerful bulk micro-machining processes, generates highly complex 3-D features with high-precision positioning stages. It is applicable to all kinds of metals and alloys, any type of electrical conductor. The unique features and the extensive material base available to MEDM have led to the process being leveraged for industrial applications, such as micro-mechanical tooling, ink-jet nozzle fabrication, and micro-machining of magnetic heads for digital VCRs. In the beginning, MEDM was applied mostly for fabricating small holes in metal foils but currently it is used in a lot of applications.

1.2 Characteristics of EDM

1.2.1 Benefits of EDM

1. It is a non-traditional process that generates no cutting forces, produces burr-free edges, permitting the production of small, fragile pieces.

2. EDM machines allows the production of intricate parts and superior finishes with minimum operator intervention.

3. Since material removing by melting and evaporation in EDM, so there is no limitation of machining hard materials eliminating the deformation caused by heat treatment.

4. Machining of complex shapes, three dimensional micro work pieces.

5. Material that is electrically conductive can be cut and very accurate structures can be machined using the EDM process.

1.2.2 Limitations of EDM

a) Low material removal rates.
b) Lead time is needed to produce specific, consumable electrode shapes.
c) The work-piece has to be electrically conductive.
d) High specific energy consumption.
e) Thermal stresses are induced in the work-piece surface due to thermal shocks.

1.2.3 Applications of EDM

1. It is the most widely used in machining of very hard metals and alloys and to meet increasing demands for smaller components usually highly complicated, multi- functional parts used in the field of micro-electronics.

2. It is used for drilling of curved holes and used for forging, extrusion, wire drawing, thread cutting.

3. It is used for internal thread cutting and helical gear cutting and machining sharp edges and corners.

4. Higher Tolerance limits can be obtained in EDM machining.

Chapter II

Literature Survey

2. LITERATURE SURVEY

Literature provides a strong impression in relation to the scope as well as interest in the field of Electro Discharge Machining (EDM) and it reveals that traditional methods are very straightforward (consisting of a number of assumptions) and not free from limitations. Various aspects on EDM were addressed by pioneer researchers throughout the World. The earlier work related to the present research area by other researchers have been explored and the progressive account of the work has been enumerated in this chapter. According to Taguchi quality concept, the objective of response optimisation can be defined as to determine the parametric settings that can minimise the overall quality loss.

Here in the primary phase (1st phase), literature review has been done on Single Objective Optimization (SOO) modelling in EDM process, to find out shortcomings if any and for investigating in the direction of improvising the efficiency in modelling of the EDM process. In the 2nd phase of literature review, an investigation has been made on the Multi Objective Optimization (MOO) in EDM process.

2.1 Single objective optimisation on EDM

2.1.1 Taguchi method

Chen et al. (2013) had utilized the Taguchi design methodology to optimize the EDM processing parameters for the machining of A6061-T6 aluminium alloy. They have taken four EDM parameters, namely; the pulse current (Ip), the pulse-on duration (T_{on}), the duty cycle (τ), and the machining duration to observed the Surface Roughness (SR). The optimal machining parameters and the relative influence of each parameter on the SR are determined by analysing the experimental data using the analysis of means (ANOM) and Analysis of Variance (ANOVA) techniques. The results shows that the magnitude of the SR is determined primarily by the Ip and τ

parameters. A $CuZn_40$ brass alloy specimen is machined using the optimal processing parameters and is found to have a lower mean SR than the A6061-T6 work-piece.

Guleryuz et al. (2013) had investigated the effect of EDM parameters on the SR for machining of Al/SiCp metal matrix composites produced with the Powder Mettalurgy (PM). Ip, electrode type, T_{on}, particle reinforcement weight ratio and V were used as the process parameters. An experimental plan L_{18} was constituted by using the Taguchi orthogonal design. Results showed that T_{on} (34%) and Ip (31.26%) is the most influencing parameters. Besides this, the percentage contribution of particle reinforcement on the SR is 6.71%.

Das et al. (2012) presented an investigation on the effect and optimization of machining parameters namely, T_{on}, T_{off}, Ip and V on Material Removal Rate (MRR) in EDM of EN31 tool steel. The settings of machining parameters are determined by using Taguchi's L_{27} Orthogonal Array (OA). The level of importance of the machining parameters on MRR was determined by ANOVA and the optimum machining parameter combination is obtained by the analysis Signal-to-Noise (S/N) ratio. The analysis shows that Ip has the most significant effect on MRR followed by T_{off} and V. It has been seen that with an increase in Ip and T_{off}, MRR also increases.

Manikandan and Venkatesan (2012) have shown an investigation the feasibility of micron size hole manufacturing using Micro Electro Discharge Machining (MEDM). This study investigates the effect of machining parameters such as Ip, T_{on}, T_{off} on the optimization of machining characteristics namely, Radial Over cut (OC), MRR, Tool Wear Rate (TWR) for machining in MEDM. The cutting of the Inconel 718 using MEDM with a brass electrode by using Taguchi methodology has been reported. Geometry of the machined micro-holes and resolified material around the hole entrance are observed. Several descriptive pictures, obtained by Scanning Electron Microscope (SEM) are included to understand this work.

Chen and Lee (2010) have shown an investigation and to optimize the EDM parameters for machining ZrO2 ceramic. During the EDM process, the surface of the electrically non-conductive ceramic was covered with adhesive conductive copper and aluminium foils to attain the threshold of electrical conductivity for the EDM process. The machining characteristics, such as MRR, TWR, and SR were explored through the experimental study according to an L_{27} OA based on the Taguchi experimental design method. The results shows that Ip and pulse duration significantly affected MRR and SR, and the adhesive conductive material was the significant parameter correlated with TWR. A convenient process for shaping electrically non-conductive ceramics was developed with the features of high efficiency, high precision, and excellent surface integrity.

Huertas Talon et al. (2010) proposed a method of manufacturing a spur tooth gear made up of in Ti-6Al-4V alloy using a Wire Electro Discharge Machining (WEDM) and implemented using the program MATLAB to obtain the interpolation points. This program simplifies the task of solving the equations originated by the mathematical model which allows the wire path to be calculated. The electro-erosion parameters namely; power, pause, V, amperage tested for this alloy were applied to an ONA PRIMA S-250. The Taguchi OA method was chosen to obtain the optimum values for cutting Ti alloy. The WEDM method used here is a commendable alternative for machining electrically conductible materials which are difficult to work with using conventional machine tools (milling, turning or boring). Furthermore, the WEDM process reduces or even eliminates the need for subsequent polishing processes due to the high-quality finish achieved.

Marafona and Araujo (2009) developed a model using Taguchi methodology with the influence of the hardness of the alloy steel on the MRR and SR. The results shows that MRR and SR are directly dependent on the work-piece hardness and the result for SR was a strong confirmation and for MRR was poor confirmation due to an Interaction of parameters. Hence for SR, this type of outcome allows the use of the additive model to predict with an average error of 0.4 % and for MRR, this type of outcome does not allow the additive model to predict with accuracy. Therefore, a linear regression model was developed for MRR using work-piece hardness and its interactions, among other variables. This model predicts the MRR with an average error of 1.06%. It demonstrates that EDM process is not only influenced by the thermal properties of the work- piece but also by its hardness.

Lajis et al. (2009) discussed the feasibility of machining Tungsten Carbide ceramics by EDM with a graphite electrode by using Taguchi methodology. Taguchi method was used to formulate the experimental layout, to analyse the effect of each parameters such as Ip, V, pulse duration and interval time on the machining characteristics namely, MRR, TWR and SR and to predict the optimal choice. It is found that these parameters have a significant influence on machining characteristic. The analysis of the Taguchi method reveals that, in general the Ip significantly affects the TWR and SR, while, the pulse duration mainly affects the MRR.

Lin et al. (2008) examined the effects of attached magnetic force on EDM machining characteristics such as MRR, TWR, SR using Electrolytic Copper as Tool and work-piece is SKD61 steel. Taguchi's L_{18} OA was adopted to design the parameters namely p, Ip, pulse duration, high-voltage auxiliary Current (IH), no-load voltage and servo reference voltage (Sv). The benefits of using the magnetic force assisted EDM from the analysis of discharge waveforms and from the micrograph observation of surface integrity would be proven to attain a high efficiency, better machining stability and high quality of surface integrity to meet the demand of modern industrial applications. The results shows that the magnetic force assisted EDM have a higher MRR almost three times as large as the value of standard EDM, a lower relative electrode wear ratio (REWR), and a smaller SR as compared with standard EDM.

Kansal et al. (2007) had analysed the effect of silicon powder mixing into the kerosene as dielectric fluid of EDM on machining characteristics of AISI D2 die steel. Six process parameters, namely Ip, T_{on} and T_{off}, concentration of powder, gain, and nozzle flushing have been considered. The process performance is measured in terms of machining rate (MR). This study indicated that all the selected parameters except nozzle flushing have a significant effect on the mean and variation in MR. Optimization to maximize MR has also been undertaken using the Taguchi method. The ANOVA indicates that the percentage contribution of Ip and powder concentration toward MR is maximum among all the parameters.

Lin et al. (2006) had investigated the effects of the machining parameters in EDM on the machining characteristics i.e. MRR, TWR and SR, in the machining of SKH57 high- speed steel. The experiments were conducted with the L_{18} OA based on the Taguchi method. The significant parameters i.e. p, Ip, auxiliary current with high voltage (IH), pulse duration, no load voltage and Servo reference voltage that critically influenced by the machining characteristics. MRR and SR increased with the Ip. As the pulse duration extended, the MRR and also SR initially increased and then fell. The TWR declined as the pulse duration increased at a particular peak current.

Simao et al. (2003) presented a research work on the deliberate surface alloying of various work-piece materials using EDM. Operations involving PM tool electrodes and the use of powders suspended in the dielectric fluid, typically aluminium, nickel, titanium, etc. experiments conducted on the surface alloying of AISI H13 hot work tool steel during a die sink operation using partially sintered WC/ Co electrodes operating in a hydrocarbon oil dielectric. A L_8 fractional factorial Taguchi experiment was used to identify the effect of key operating factors on output measures (TWR, SR,etc.). With respect to micro-hardness, the percentage contribution ratios (PCR) for Ip, p and T_{on} were 24, 20 and 19%, respectively.

Nikalje et al. (2013) used Taguchi method to determine the influence of process parameters and optimization of MDN 300 steel in EDM. Important performance measures such as, MRR, TWR, SR and relative wear ratio (RWR). The experiment were conducted under taking the machining variables namely, Ip, T_{on} and T_{off}. Results showed that that the optimal level of the factors for TWR and SR were same but differed from the optimum levels of the factors for MRR and RWR. Analysis of structural features of machined surface was done by using SEM to understand the influence of parameters.

2.1.2 Full factorial design

Kodlinge and Khire (2013) had presented detailed investigation on MRR of Tungsten carbide for EDM operation using Kerosene as dielectric medium. The parameters considered were Ip, electrode diameter and T_{on} designed according to 2^3 factorial design. ANOVA indicates that among the three factors investigated Ip has a strongest effect on MRR.

Atefi and Amini (2012) has been investigated the influence of different EDM parameters named as Ip, V, T_{on} and T_{off} on the TWR as a result of application copper electrode to hot work steel DIN1.2344. Design of Experiments (DOE) was chosen as full factorial. Artificial Neural Network (ANN) has been used to choose proper machining parameters and to reach certain TWR. Finally a hybrid model has been designed to reduce the ANN errors. The results indicated a good performance of proposed method in optimization of such a complex and non-linear problems.

Pradhan and Jayswal (2011) presented a detailed experimental investigation according to 2^3 full factorial design to consider the machining characteristics in EDM process of EN-8 alloy steel with copper and aluminium as tool electrode. The hardened work material was machined with the two electrodes at different values of Ip, T_{on} and duty factor. It has been found that copper showed better results than aluminium in term of surface finish (μm) in same dielectric media. Therefore, copper was recommended as a good electrode material.

Amini et al. (2010) evaluated the influence of different EDM parameters Ip, V, T_{on} and T_{off} in finishing stage on the SR as a result of application copper electrode to hot work steel DIN 1.2344. DOE was chosen full factorial. Statistical analysis has been done and ANN has been used to choose proper machining parameters and to reach certain SR. Finally a hybrid model has been designed to reduce the ANNerrors. The results indicated a good performance of proposed method in optimization of such a complex and nonlinear problems.

Ali and Mohammad (2008) had analysed the optimization of the process parameters of conventional WEDM of a copper substrate for micro-fabrication. Statistical models were established to predict the SR and peak-to-valley height (Rt) in terms of Ip, T_{on} and gap voltage. The SR increased with higher Ip and gap voltage and decreased with increase of T_{on}. Using the optimized parameters, miniaturized spur gears, and plate-shaped hot embossing micro tools were fabricated where an average surface roughness of about 1μm and dimensional accuracy of 12% were achieved.

Dhar et al. (2007) presented a work aimed on evaluates the effect of Ip, T_{on} and air gap voltage on MRR, TWR, ROC of EDM with Al4Cu6Si alloy10 wt. % SiCP composites. The PS LEADER ZNC EDM machine and a cylindrical brass electrode of 30 mm diameter and three factors, three levels full factorial design was using to analysing the results. A second order, non-linear mathematical model has been developed for establishing the relationship among machining parameters. The significant of the models were checked using technique ANOVA and finding the MRR, TWR and ROC increase significant in a non-linear fashion with increase in current. The MRR and radial ROC increases with increase in pulse duration.

Lee and Tai (2003) presented a study of the relationship between EDM parameters and surface cracks by using a full factorial design, based upon Ip and T_{on} parameters on D2 and H13 tool steels as materials. The formation of surface cracks is explored by considering SR, White Layer Thickness (WLT), and the stress induced by the EDM process. Increased T_{on} will increase both the average WLT and the induced stress. When the Ip is increased, the increase in MRR causes a high deviation of thickness of the white layer. Compared to a thin white layer, a thick white layer has a tendency to crack more readily. Its use will provide a valuable aid in improving the quality of the EDM process.

2.1.3 RSM method

Gopalakannan et al. (2012) had conducted experiment on the newly engineered Metal Matrix Composite (MMC) of aluminium 7075 reinforced with 10 wt% of Al2O3 particles were prepared by stir casting method. EDM was employed to machine MMC with copper electrode. A mathematical model has been formulated by applying Response Surface Methodology (RSM) in order to estimate the machining characteristics such as MRR, TWR and SR. ANOVA was applied to investigate the influence of process parameters and their interactions viz., Ip, T_{on}, V and T_{off} on MRR, TWR and SR. The objective was to identify the significant process parameters that affect the output characteristics.

Rahman et al. (2010) has been reported on modelling, optimization and to develop of mathematical model of MRR for Ti-5Al-2.5Sn using RSM. The EDM was carried out on this material employing positive polarity of copper electrode. Ip, T_{on}, V and T_{off} was considered as input parameter to correlate with MRR. The validity test of the fit and adequacy of the proposed models has been carried out through ANOVA. It was observed that the developed model was within the limits of the agreeable error and Ip effectively influences the performance measures.

Habib (2009) proposed a comprehensive mathematical model for MRR, TWR, Gap Size and SR in EDM for correlating the interactive and higher order influences of various EDM parameters(Ip, T_{on}, SiC percentage and gap voltage) through RSM. The analysis showed the MRR increases with an increase of Ip, T_{on}, relatively with gap voltage and decreases with increase of SiC percentage. TWR increases with an increase of both Ip, T_{on}, and decreases with increase of both of SiC percentage and gap voltage. The gap size decreases with the increase of SiC percentage and increases with the increase of Ip, T_{on}, and gap voltage. Finally, the SR increases with the increase of Ip, T_{on}, SiC percentage, and gap voltage.

Soveja et al. (2008) reported the experimental study of the operating factors on the surface laser texturing of TA6V alloy using two experimental approaches: Taguchi methodology and RSM. They had determined a correlation between process operating factors and performance indicators, such as SR and MRR. Results analysis showed that the laser pulse energy and frequency are the most important operating factors. MRR is directly proportional to linear effects of the pulse energy and frequency, while the SR is inversely proportional to them. Here, the optimal set of influencing factors, which enable the maximisation of MRR, while preserving a small SR (Sao5 mm), are a 12.5 kHz pulse frequency and a 5 mJ pulse energy.

Kung and Chiang (2008) proposed a mathematical models of the MRR and SR to correlate the dominant machining parameters, including the Ip, T_{on}, duty factor, and wire speed, in the WEDM process of aluminium oxide based ceramic material (Al2O3 + TiC). An face centred Central Composite Design (CCD)-based on the RSM has been employed to carry out the experimental study on the performance characteristics of MRR and SR. It has been concluded that the proposed mathematical models in this study would fit and predict values of the performance characteristics, which would be close to the readings recorded in experiment with a 95 % confidence level.The significant parameters that critically affect the performance characteristics are examined.

2.1.4 ANN method

Prajapati et al. (2013) studied the effect of WEDM process parameters named as; T_{on}, T_{off}, V, Wire Feed and Wire Tension on MRR, SR, Kerf and Gap current by conducting an experiment. ANN was used for Predict of output parameters of

WEDM of AISI A2 giving very accurate result. The training, testing and validation data set are collected by conducting experiment on work-piece material AISI A2. From Comparison of Experimental result and ANN Predicted result was found that error is very less and the maximum error is 0.14. T_{on} has more importance on output parameter.

Ndaliman et al. (2012) reported that this study involves the use of ANN technique with 16 experimental runs to develop behavioural models for predicting the values of electrical conductivity, thermal conductivity and density for Cu-TaC compacted electrodes produced by PM method for use in EDM. Twenty hidden layer used with feed forward back-propagation hierarchical neural networks were designed with MATLAB 2009b Neural Network Toolbox. Here, Cu-TaC electrode compacts were produced at two levels each of the composition and the compacting pressures from copper and tantalum carbide powders for use in EDM. Results showed that the sintered electrodes are not suitable for EDM because they lost their electrical conductivity. The pre sintered electrodes (green compacts) were however found to suitable for EDM. They found that ANN models were capable of predicting the electrode properties with high degree of prediction accuracy compared to the experimental results.

Jia et al. (2011) presented a new progressive mapping method and modes for accomplishment of three mappings namely fuzzy identification mode, learning vector quantification (LVQ) neural network classification mode, and a judging mode. Fuzzy rules were used to combine the complementary signals with V, Ip and then a scalar in a range representing a state of the sampled point through the first mapping is deduced. A LVQ ANN was adopted to convert this scalar to the corresponding state vector. The ratios in the vector clarify the discharging pulses through the third mapping, judging mode. Results were presented to verify the effectiveness of this discharging pulses discriminator for MEDM and showed that this discriminator can quickly and accurately classify the discharging pulses for MEDM.

Thillaivanan et al. (2010) proposed a method of optimizing cutting parameters for EDM under the minimum total machining time based on Taguchi method and ANN. Here a feed forward- backpropagation neural network was developed for getting the parameters i.e. Ip and feed for a required total machining time, oversize and taper of a hole to be machined by EDM, It has been found that Ip has a significant influence on the total machining time. This methodology could be applied to different machining conditions such as different work material, electrode etc. so as to build a CAPP expert system of EDM with the goal of automation.

Joshi and Pande (2009) developed a two-dimensional axisymmetric thermal Finite Element Method (FEM) model of single-spark EDM process based on assumptions such as Gaussian distribution of heat flux, time and energy dependent spark radius, etc. to predict the shape of crater cavity, MRR, TWR using FEM and ANN. ANN based process model was proposed to establish relation between input process conditions (discharge power, spark on time, and duty factor) and the process responses (crater geometry, MRR and TWR) for various work materials. The ANN model was trained, tested, and tuned using the data generated from the numerical (FEM) simulations. The ANN model was found to accurately predict EDM process responses for chosen process conditions.

Esme et al. (2009) used two techniques, namely factorial design and neural network (NN) for modelling and predicting the SR considering pulse duration, open voltage, wire speed and dielectric flushing pressure as input parameters of AISI 4340 steel. Relationships between SR and WEDM cutting parameters have been investigated by using regression analysis method. The level of importance of the WEDM cutting parameters on the SR was determined by using the ANOVA. Results shows that, NN is a good alternative to empirical modeling based on full factorial design.

Gao et al. (2008) applied ANN in EDM to how improve generalization performance. Here, machining process models have been established based on different training algorithms of ANN, namely Levenberg-Marquardt algorithm (LM), Resilient algorithm (RP), Scaled Conjugate Gradient algorithm (SCG) and Quasi-Newton algorithm (BFGS). All models have been trained by same experimental data, checked by another group data, their generalization performance are compared.

Krishna Mohana Rao and Hanumantha Rao (2010) developed multi-perceptron neural network models using Neuro solutions package to optimizing the hardness of surface produced in EDM. Hardness were measured on Ti6Al4V, HE15, 15CDV6 and M-250 by considering the simultaneous affect of various input variables such as, Ip,

V. It was found that the developed model was within the limits of the agreeable error when experimental and network model results were compared. Sensitivity analysis was also done to find the relative influence of factors on the performance measures.

2.1.5 Nero-fuzzy modelling

Suganthi et al. (2013) developed the Adaptive Neuro-Fuzzy Inference System (ANFIS) and back propagation - based on ANN model in MEDM process for prediction of multiple quality responses such as MRR, TWR and SR. The Feed rate, capacitance, gap voltage, and threshold values were selected as a input parameter. It was observed that the proposed ANFIS-based model out performs the ANN model in terms of modelling and prediction accuracy.

Caydas et al. (2009)developed ANFIS model for prediction of responses namely, SRand WLT in WEDM. The pulse on time, open circuit voltage, dielectric flushing pressure and wire feed rate are consider as a control parameter. The model combined modelling function of fuzzy inference with the learning ability of ANN. The experimental results were compared with models predictions for verifying the approach.

Gostimirovic et al. (2012) used ANFIS to estimate MRR in EDM. The selected control parameters are discharge Ip and T_{on}. Research showed that ANFIS model gives accurate prediction on MRR. Here, Ip affecting the MRR first and then T_{on}.

Tsai and Wang (2001) had analysed the comparison of modelling the MRR for various materials considering the change of polarity by taking six different neural networks with a neuro-fuzzy network. The six neuro networks are such as, Logistic sigmoid multi-layered perception (LOGMLP), hyperbolic tangent sigmoid multi-layered perception (TANMLP), fast error back- propagation hyperbolic tangent multi-layered perception (error TANMLP), redial basis function network (RBFNs), adaptive sigmoid multi layered perception and the adaptive basis function network and the ANFIS have been trained and compared by using DOE. It wa concluded that the best is the ANFIS with Bell - shape membership function.

2.2 Multi Objective Optimisation on EDM

When more than one response is to be optimized simultaneously, some procedures have been developed for optimizing multi response problems in recent years. Many researchers have attempted several approaches for establishing an objective method for determining the optimal parametric settings that can optimise multiple performance measures to a single quality parameter of EDM process, which can be optimised easily (Aslan, 2008; Gaitonde et al., 2006). Relationship between process parameters and response parameters in EDM process are very much stochastic, random and non-linear in nature. Multi -attribute optimisation is a highly demanded research area of recent trend in EDM process.

Grey-fuzzy logic :

Prabhu and Vinayagam (2013) have made an attempt to study the optimisation of multiple quality characteristics such as, SR and MRR of EDM of carbon nano tube (CNT) mixed dielectric fluid in EDM process. They have used Grey Relational Analysis (GRA) integrated with fuzzy logic system to conduct experiments for examine precision and accuracy of EDM process parameter, and comparing each parameter influencing the machining for with and without using CNT mixed dielectric fluid. Atomic force microscope (AFM) was used to analysis the surface characteristics such as surface roughness, micro cracks and topography of CNT-based machining surface.

Lin and Lin (2005) have presented multiple process responses namely, MRR, TWR and SR optimisation on EDMapplying the grey-fuzzy logics method based on OA.The selected machining parameter are pulse on time, duty factor and discharge current with the SKD11 alloy steel as a work-piece material. Grey Relational Coefficient (GRC), Grey Relational Grade (GRG) and ANOVA are applied to study the performance characteristics.

Grey relation analysis :

Murugesan and Balamurugan (2012) described the optimisation of EDM process with multiple quality characteristics under which a blind hole can be drilled using a multi hole electrode. The GRA was used to determine the relationships among the characteristics based on Taguchi's OA. Machining parameter were selected as; p, Ip,

T_{on}, T_{off} and dielectric pressure to optimizing the multiple responses like machining time, TWR and SR. The Ip was found to be most significant factor.

Pradhan (2012) developed a model which combination of RSM, GRA and Principal Component Analysis (PCA) on AISI D2 tool steel in EDM. The experiments are designed using GRA, and the weights of the responses are evaluated by PCA. These method were used for the determination of the optimum process parameters that maximises MRR without compromising the surface quality considering control parameters such as; Ip, T_{on}, τ and V. Using the RSM the interactive effects of the machining parameters on the responses were evaluated and found that the GRG was dominantly influenced by Ip and their interactions with the other parameters.

Dhanabalan et al. (2012) described the optimisation of multiple optimisation process based on the OA with the GRA in EDM process They carried out the MRR, TWR and SR with two different Titanium grades using brass electrodes.

Natarajan and Arunachalam (2011) used GRA and Taguchi method to optimise multi- performance characteristics of MEDM. The input process parameters namely, Ip, T_{on} and gap voltage were used to optimize responses like higher MRR, lower TWR and lower OC and verified through a confirmatory experiment. It was concluded that an improvement of MRR , TWR and OC is 12.88, 14.57 and 6.1% respectively.

Beri et al. (2011a) have been made an attempt to correlate the multi-response over the process parameters of PM electrodes in EDM using GRA based on Taguchi's L_{18} OA. In this experiment using AISI D2 tool steel as a work-piece material with copper CuW (25% Cu and 75% W) electrode in kerosene. The control parameter were selected as, electrode material, duty cycle, flushing pressure and discharge current on the response of MRR, SR and surface hardness. It was found that copper tungsten PM electrode gives better multi-objective performance than conventional copper electrode.

Beri et al. (2011b) had described that the multi response parametric optimisation of EDM process by Taguchi's L_{36} OA integrated with GRA performed on Inconel 718 with three different electrodes. Process parameters were taken as, (p, Ip, T_{on}, electrode type, duty cycle, gap voltage, retract distance and flushing pressure) on the responses of MRR, TWR and SR. It has been found that the optimal machining parameter combination gives significant improvement of theGRGby 8.72%.

Jung and Kwon (2010) analysed the optimality under which the micro-hole can be formed to a minimum diameter and a maximum aspect ratio by using GRA with Taguchi method to optimising the multiple characteristics. It was found that the electrode wear and the entrance and exit clearances have a significant effect on the diameter of the micro-hole when the diameter of the electrode is identical. The input voltage and the capacitance were found to be the most significant factors.

Panda (2010) investigated the characterize spark-eroded craters formed on both anode and cathode surfaces based on L_9 OA. Here dielectric and thermo-physical properties of electrode material act as associated parameters. GRA has been implemented to significance of the process parameters. Finally, confirmatory experiments have been done to recognize the nature of the relative erosion of anode and cathode with respect to EDM process parameters.

Singh et al. (2004) had optimised multi responses such as, MRR, TWR, taper, OC, and SR using OA with GRA for EDM process on EDM of $Al - 10\% SiC_P$ as cast metal matrix composites using OA. The application of this technique converts the multi response variable to a single response GRG and, therefore, simplifies the optimization procedure.

Lin and Lin (2002) used OA with GRA to optimize the EDM process with multiple performance characteristics namely, MRR, TWR and SR. By taking the input parameters, namely p, Ip, T_{on}, τ, open discharge voltage and dielectric fluid, a GRG obtained from the GRA was used to find the best setting for the EDM process. It concluded that the performance characteristics of the EDM process are improved together by using the method proposed.

Fuzzy logic :

Zhang et al. (2012) introduced type-2 fuzzy logic theory to solve uncertainties caused by features of high frequency, serious signal distortion, and high noise in MEDM process. Based on interval type-2 fuzzy logic, a two-stage fuzzy controller was proposed. The first stage was used to detect the discharge state and the second stage was used to detect the servo feed speed. They proved, the proposed interval type-2 fuzzy logic based two-stage servo feed controller is an effective way to enhance the efficiency and stability MEDM.

Reddy et al. (2010) had proposed the modelling and analysis of the responses such as, cutting velocity and SR in WEDM using Taguchi's DOE. The experimental results of WEDM process is modelled using fuzzy logic and showed that the discharge current is the most significant parameter influencing the SR and cutting velocity.

Tzeng and Chen (2007)described the optimisation of multiple responses like machining precision and accuracy using fuzzy logic techniques integrated with Taguchi method in high speed EDM. From the ANOVA it was identified that, Ip, T_{on} and τ as the most significant parameters. Optimisation of Multi Performance Criteria Index (MPCI)s in the process has been achieved through the proper system model simulation.

Puri and Deshpande (2004) used Taguchi method couple with fuzzy logics system for the optimisation of multi responses such as, SR and MRR in WEDM process on the High-Chromium-High- Carbon die steel as work-piece material. From the result it was concluded that this approach is simple, effective and efficient and both the responses can be improved through this approach.

Lin et al. (2000) had presented the optimisation of multiple responses for MRR and TWR using Taguchi method integrated with fuzzy logic on EDM and predict the best optimum conditions with a confirmatory test. The selected control parameters such as p, Ip, T_{on}, τ, V, dielectric fluid on the SKD11 as work-piece material. In this experiment his proved MRR and TWR are greatly improved through this study. Experiment was conducted for this approach and showed that the optimization methodology useful in improving multiple performance characteristics and effective.

Fuzzy TOPSIS :

Sivapirakasam et al. (2011) proposed a model of combination of Taguchi's L_9 OA and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to solve the multi objective parameter optimization problem in green EDM. Experiment was carried out to analyse the sensitivity of attributes to the variations in process parameters such as, peak current, pulse duration, dielectric level and flushing pressure. An analytical structure was developed to perform multi-criteria decision making. Triangular fuzzy numbers were used to assign preference values to the output responses and the optimum factor level combinations were identified based on the Closeness Coefficient Index (CCI) values. From CCI values, it was concluded that the peak current was the most effective parameter.

Utility theory :

Chakravorty et al. (2013) applied two sets of past experimental data on EDM processes and analysed using four different methods and then compared. The results showed that weighted signal-to- noise ratio (WSN) and Utility Theory (UT) give better optimisation performance than GRA-based and other approaches.

Chakravorty et al. (2012a) made an attempt to describe the PCA-based UT approach on EDM processes. They analysed two sets of past experimental data and the results shows that the modified PCA- based UT gives better optimisation performance. It proved that this method is very useful technique for optimising the EDM processes.

Desirability function :

Assarzadeh and Ghoreishi (2013) has proposed a model to optimize the multi responses such as, MRR and TWR in Powder Mixed Electro Discharge Machining (PMEDM). In this experiment using aluminium oxide (Al_2O_3) fine abrasive powders with particle concentration and size of 2.5-2.8 g/L and 4550 μm. The CK45 heat-treated die steel selected as a work-piece and copper was used as tool electrode. Experiments were analysed using RSM employing a face-CCD design considering the input parameters named as, Ip, T_{on} and V, and they were optimized based on the use of desirability functions with the machining regime of finishing, semi finishing and roughing. Result showed that the error between experimental and anticipated values at the optimal combination settings of input parameter are all less than 11 %, checking the feasibility and effectiveness of the adopted approach.

Gopalakannan and Senthilvelan (2013) reported that this study involves aluminium based metal matrix nano-composites reinforced with nano-sized SiC particles were successfully fabricated in ultrasonic cavitation method. The experiment was carried out using face CCD design of RSM by conducting 30 experiments for four factors at three levels and investigate the influence of process parameters by using ANOVA. It was found that pulse current to be the most important factor affecting all the output parameters such as MRR, TWR and SR.

Sivasankar et al. (2012) investigated the maintainability of ZrB2 using EDM with different tool materials such as graphite, aluminium, tantalum, niobium, copper, brass, silver, tungsten and titanium. The output responses for this process were Roundness, geometry of hole, and diameter of the hole at different diametric planes,SR, MRR and TWR measured. Desirability function analysis was employed to rate the performances of tools. They developed a new theory which relates recast layer thickness with melting point and thermal conductivity of the tool materials and found that graphite is the best tool.

El-Taweel (2008) had presented the MRR and TWR in EDM process of CK45 steel using AlCuSiTiC PM electrode were modelled and analysed through RSM. In this experiment, titanium carbide percent (TiC%), peak current, dielectric flushing pressure, and pulse on- time are taken as input process parameters and the results were experimentally verified. ANOVA had also been carried out to check the adequacy of the models. AlCuSiTiC PM electrodes are found to be more sensitive to peak current and pulse on time.

Loss function :

Dave et al. (2012) had proposed the multi response optimisation using Taguchi's loss function for EDM process. In this research using Inconel 718 as work-piece under orbital tool actuation and orbital tool radius and orbital speed along with considering input parameters were Ip, T_{on} and V and duty factor. Taguchi's L_{25} OA was conducted to measure MRR, TWR and SR and to identify the significant level of the input parameters by using ANOVA.

Principal component analysis :

Pradhan (2013) presented the effect of process parameters on MRR, TWR and OC of EDM with AISI D2 tool steel. The control parameter were selected as Ip, T_{on}, V and τ. Thirty experiments were conducted based on a face centred-CCD design. The experimental results obtained were used in GRA, and the weights of the responses were determined by the PCA and further evaluated using RSM. The results indicate that the GRG was significantly affected by the machining parameters considered and some of their interactions.

Gauri and Chakraborty (2009) had described some modifications in the PCA-based approach and two sets of experimental data published by the past researchers are analysed using modified procedure. It was observed that the PCA-based optimisation can give better results than the constrained optimisation and Multi Response S/N ratio based methods, which can be attributed to the fact that the possible correlation among the multiple responses was taken care in the PCA- based approach.

Chakravorty et al. (2012b) had presented four PCA-based optimization methods to simplify multi response problems and using L_{18} orthogonal array and two sets of past experimental data on EDM processes, found that among the four PCA- based approaches, PCA- based Proportion of Quality Loss Reduction (PQLR) method results in the best optimization performance on on machining characteristics, MRR, TWR and SR.

Su and Tong (1997) proposed an effective procedure on the basis of PCA to optimize the multi-response problems in the Taguchi method. With the PCA, a set of original responses can be transformed into a set of uncorrelated components. Two case studies were evaluated, indicating that the proposed procedure yields a satisfactory result.

Genetic algorithm :

Non-sorted Genetic Algorithm (GA) has been implemented to optimise the responses of EDM technology using a powder-mixed dielectric by (Padhee et al., 2012). They used mathematical models for prediction of MRR and SR through the knowledge of four process variables such as discharge current, concentration of powder (silicon) in the dielectric fluid, pulse on time and duty cycle with EN-31 tool steel as a work-piece material. RSM was adopted to study the effect of control variable on responses and develop predictive models.

Experiential models developed for concerning the SR and MRR with machining parameters like Ip, T_{on} and T_{off} by Baraskar et al. (2013). They used multi optimisation method for non-dominating sorting GA-II, and to obtain the Pareto-optimal set of solutions. With the RSM has been applied for evolving the models using the technique of DOE and multi linear regression analysis.

Golshan et al. (2012) examined the effect of EDM on SR and MRR in metal matrix composite Al/SiC. They studied the correlation between four input variable such as Ip, T_{on}, average gap voltage and percent volume fraction of SiC and process outputs. From this study they found optimal conditions for outputs extracted from non-dominated sorting GA-II.

Kuruvila and Ravindra (2011) had investigated the multi objective optimization using single GA in which the objective function is define as composite function of the responses OC, SR and MRR defined as objective = OC+SR-MRR. The objective function was minimized by executing the GA. They used L_{16} OA based on Taguchi method with the control parameters are Ip, T_{on} and T_{off}, Bed-speed and Flushing rate.

Somashekhar et al. (2009) described the optimisation of multi response optimisation of WEDM using GA. They defined the effect of responses such as SR and OC in the control input variables for gap voltage, capacitance and feed rate. ANOVA was performed to find out the implication of each factor. Regression models were established for the experimental results of SR and OC of the micro slots produced on aluminium.

Su et al. (2004) had proposed an ANN integrated with GA-based for multi- objective namely, SR, TWR and MRR optimization in EDM process. A neural network model with back- propagation learning algorithm was developed to establish a relation between the 8 process parameters such as; T_{on} and T_{off}, T_w, high- voltage discharge current, low- voltage discharge current, gap size, servo-feed, jumping time. From all the optimised results indicate that the developed neural network with the aid of a GA has sufficient prediction and reasoning capability to generate optimal process parameters from rough cutting stage to finish cutting stage.

Wang et al. (2003) discussed the development and application of a hybrid ANNand GA methodology to modelling and optimisation of EDM. This research aimed to find some solution for modelling and optimisation of manufacturing processes. The developed methodology with the model is highly beneficial to manufacturing industries, such as aerospace, automobile and tool making industries. Further work to be carried out include testing the model with more data, verification of the results and optimising the model with respect to the structure of the neural network.

Other Research Papers

Ekmekci et al. (2005) presented an experimental work to measure residual stresses and hardness depth in EDMed surfaces of plastic mold steel with de-ionized water as dielectric fluid. Layer removal method is used to express the residual stress profile. The residual stress pattern does not change with respect to the machining parameters. This pattern can be related to the thermal properties of the work piece material and the dielectric liquid. Corresponding deformations due to stress relaxation are recorded for each removal to determine the stress profile from elasticity theory. These stresses increases rapidly with respect to depth, attaining to its maximum value, around the the ultimate tensile strength of the material.

Guu and Hou (2007) had applied Atomic Force Microscopy (AFM) technique on Fe-Mn-Al alloy to analyse the surface characteristics in EDM and to obtain a three-dimensional image with a nanometer scale based on the experimental data. Experimental results indicate that the EDM process causes a ridged surface and induces machining damage in the surface layer, and increases the surface roughness. The chemical compositions of the machined surface differed from the initial materials due to the diffusion of the electrode material. The effect of the magnitude of the pulse-on duration was more dominant than the pulsed current. There was no significant difference between the hardness of the EDM surface and the hardness of the non-EDM work-piece.

Krishna Mohana Rao et al. (2008) had conducted 27 experiments considering the input parameters such as Ip, T_{on} and duty factor to characterizing the EDM on Maraging steels. The performance characteristics like MRR, SR and micro-hardness were measured. It was found that MRR, SR increases with increase in Ip, duty factor. But, in case of T_{on} increases MRR, SR decreases. micro-hardness value increases as the Ip, increases and then decreases. The same effect is observed as in case of duty factor and pulse on-time. Average crack length and recast layer thickness increases with increase in Ip and duty factor but, decreasing in case of pulse-on-time.

Table 2.1: EDM literature review on AISI P20 tool steel

Author with Year	Machining variables ranges						Response variable	Remark
	Ip (A)	$T_{on}(\mu s)$	$T_{off}(\mu s)$	Tau (%)	V	Other variable		
Joshi and Pande (2011)	5-40	200-700		50 -80	30-50		Crater Size, MRR and TWR	Integrated FEMANNGA for multi optimisation of MRR,TWR and crater size.
Reza et al. (2010)	0.8-1.8	2-56	1-55		60-100	Polarity	MRR, TWR and SR	The +ve polarity was found optimum MRR, TWR and SR.
Joshi and Pande (2010)	5-40	25-700		50-80	30-50		MRR, crater cavity	Developed the thermo-physical model of EDM process using the FEM in shape of crater cavity and the MRR.
Kiyak and Cakir (2007)	6-24	2-100	2 and 3				SR	Low current and pulse time with high pulse off time produces better SR. SR increases as tool wears out.

Continued on next page

Table 2.1: *EDM literature review on AISI P20 tool steel*

Author with Year	Machining variables ranges						Response variable	Remark
	Ip (A)	$T_{on}(\mu s)$	$T_{off}(\mu s)$	Tau (%)	V	Other variable		
Amorima and Weingaertner (2007)	3-8	6.4 -100			160	Polarity	MRR, TWR, SR	Comparative experimental study of Graphite and copper as tool material with +ve and -ve polarity. Higher MRR were obtained with -ve graphite electrodes. Graphite and copper tools yielded similar MRR for +ve polarity. For graphite and copper tools the lowest TWR with +ve polarity. The best SR was obtained for copper electrodes under -ve polarity.

Continued on next page

Table 2.1: *EDM literature review on AISI P20 tool steel*

Author with Year	Machining variables ranges						Response variable	Remark
	Ip (A)	$T_{on}(\mu s)$	$T_{off}(\mu s)$	Tau (%)	V	Other variable		
Curodeau et al. (2005)	5-10	50-100			100-150		MRR, TWR and SR	Hybrid EDM process with a polymer-carbon electrode in deionised water. A better surface finish achieved for smaller Ton and Ip. Minimise TWR with low V, +ve impulse polarity and low flushing pressure.
Amorima and Weingaertner (2005)	3-8	6.4-200			160-200	Polarity	MRR, TWR, SR	Experimental were performed the MRR, TWR and SR of AISI P20 material of both positive and negative polarity.
Curodeau et al. (2004)	1-1.5	60-90	120-180		150		SR	Described thermoplastic composite electrode and air as dielectric in EDM for used automated polishing of tool steel cavity.

The following are the critical conclusions of the literature survey:

1. Optimization aspects of EDM have been highlighted in literature, but to a limited extent. In most of the cases optimization has been performed on a single objective function. But in practice, it has been found that optimizing one response may not be favourable for other responses on that particular optimal parameter setting. This invites complexity to the multi-objective optimization problem towards optimizing multiple objective functions (may be contradicting in nature) simultaneously. The introduction of multi objective optimization technique provides optimal solution among the confiscatory parameters.

2. The goal is not simply to optimize an arbitrary objective function, but rather to reduce the sensitivity of engineering designs to uncontrollable factors or noise. In order to overcome this, Effort has been made to study the influence of process parameters on performance of various aspects of machining like; MRR, TWR, SR. Mathematical models have also been developed to understand the functional relationship among process parameters with aforesaid process responses.

3. Various research works carried out with work-piece materials like tool steels, composites and alloys but with very limited work on machining parameters optimization for AISI P20. Therefore, the present research has aimed to highlight multi-objective extended optimization methodologies to be applied in machining of AISI P20 with different machining environments for continuous quality improvement and off-line quality control.

2.3 Problem definition

The outcome of the present literature survey stimulate the following problems:

1. Taguchi methodology used to study single objective (micro-hardness) on AISI P20 steel to obtain optimised value considering the various input parameters.

2. Fuzzy TOPSIS combined with Taguchi method are used in to convert optimize multiple response parameters to single quality parameter of EDMprocess.

3. To optimise the multi responses simultaneously using the machining parameters like Ip, T_{on}, T_{up} and Fp by PCA based techniques.

2.4 Organisation of Thesis

The present work is an effort to propose an integrated methodology to state the machining characteristics in order that it may be competitive as regards of productivity, quality and accuracy and to develop various prediction models from the experiment trials. Productivity relates to maximise MRR and accuracy related to minimise TWR and SR. Owing to this issue, in the present reporting two integrated multi-response optimization and one single response optimization philosophies viz. (i) Taguchi analysis has been adopted for assessing favourable (optimal) machining condition during the machining (ii) Fuzzy TOPSIS method combined with Taguchi framework and (i) PCA based approaches .

The entire thesis has been divided in six chapters.

Chapter 1 presents the background of research related to EDM.

Chapter 2 covers an extensive literature survey also depicts the necessity of developing an efficient integrated optimization methodology applicable in product/ process optimization in manufacturing production context.

Chapter 3: In this chapter, Taguchi analysis used to study micro-hardness on AISI P20 steel to obtain single objective optimisation considering the input parameters like Ip, T_{on}, T_{up} and Fp.

Chapter 4: TOPSIS can be efficiently used to identify the best alternative solution from a finite set of points. In this chapter, Fuzzy TOPSIS method are used in combination with Taguchi method to convert optimize multiple response parameters to single quality parameter of EDM. The proposed methodology and the result obtained thereof has been illustrated in detail.

Chapter 5: In this chapter, PCA based approaches are described, and the influences of the process parameters are studied. Important machining parameters like Ip, T_{on}, T_{up} and Fp are considered for investigation. Optimal parameter setting was obtained and compared using the prediction errors.

Overall conclusion and scope for future work have been highlighted in Chapter 6.

Chapter III

Micro-Hardness study on AISI P20 steel using Taguchi Method

3. MICRO-HARDNESS STUDY ON AISI P20 STEEL USING TAGUCHI METHOD

3.1 Introduction

The present work aimed at optimizing the hardness of surface produced in this process. The micro- hardness of a substance is an important parameter to define the strength of its material. This property is basically related to the crystal structure of the material. A typical hardness profile for a steel part produced by Electro Discharge Machining (EDM), is characterized by a zone of very high hardness expanding across the recast layer and the martensitic Heat Affective Zone (HAZ). This hard zone can be followed by a tempered zone (in case of pre- hardened steel), that finally evolves towards the hardness of the base material. The main reason for the high hardness is an increased amount of dendritic cementite that results from absorption of carbon originating from pyrolysis of the oil dielectric (Bleys et al., 2006).

Over the years, several industries have employed the Taguchi method to improve the performance of products and processes. The method is robust for the design or production stage, so that manufacturers can produce higher-quality products in less time and at a lower cost. According to Tong et al. (2007), Taguchi method is an implemented experimental technique, which uses an orthogonal array to perform experiments and employes the Signal-to-Noise (S/N) ratio as the quality measurement index, to optimize only a single response, *i.e.*, the parametric settings can be optimised with respect to only one performance characteristic at a time. It is a best combination/set of factor levels of quality improvement that seeks to obtain the lowest-cost solution to the product design specification based on the requirements of the customer.

The experiments were carried out on AISI P20 by considering the simultaneous effect of various input parameters and the corresponding values of hardness were measured. It is observed that type of material effectively influences the performance measures. This paper proposes Taguchi analysis approach to determine parameter design on EDM for single quality characteristics *i.e.* micro-hardness.

3.2 Experimental equipment and design

The experiment was conducted on Electronica Electraplus PS 50ZNC die-sinking EDM machine with 12 mm diameter of cylindrical copper tool electrode and EDM oil (specific gravity =0.763, flash point= 94°C) as dielectric. The experimental setup is shown in Appendix A (Fig. A.1). The work-piece material was AISI P20 tool steel which is a semicircular shaped work-piece material (100 mm diameter and 10 mm thickness), "the composition and properties for AISI P20 work-piece material are shown in (Table A.2) and (Table A.3) of Appendix A respectively".

The effect of four process parameters, namely, current (Ip), pulse-on-time (T_{on}), lift time (T_{up}), flushing pressure (Fp) was studied on micro-hardness of the EDM process as shown in Table 3.1 along with the fixed parameters like duty cycle (τ), voltage (V) , and polarity (p).

Table 3.1: Control parameter and their levels

Control Parameter				
Parameter	Level			Unit
	1	2	3	
Discharge current (Ip)	2	5	8	A
Pulse on Time (T_{on})	100	300	500	μs
Lift Time (T_{up})	0	0.7	1.4	s
Flushing Pressure (Fp)	0.2	0.4		kgf/cm^2
Fixed Parameter				
Duty Cycle (τ)		90		%
voltage (V)		45		V
polarity (p)		+ve		

It uses a special design of Orthogonal Array (OA) to study the entire parameter space with only a small number of experiments. Usually, there are three categories of performance characteristics in the analysis of the S/N ratios: Lower-The-Better (LTB), Higher-The-Better (HTB) and Nominal-The-Better (NTB).

For LTB response variable,

$$\eta_{ij} = -10 \times \log_{10}(\frac{1}{n}\sum_{k=1}^{n} y_{ijk}^2) \tag{3.1}$$

For HTB response variable,

$$\eta_{ij} = -10 \times \log_{10}(\frac{1}{n}\sum_{k=1}^{n} \frac{1}{y_{ijk}^2}) \tag{3.2}$$

For NTB response variable,

$$\eta_{ij} = 10 \times \log_{10}(\frac{\bar{y}_{ij}^2}{s_{ij}^2}) \tag{3.3}$$

Where, n represents the number of repeated experiments, y_{ijk} is the experimental value of j^{th} response variable in i^{th} trial at k^{th} replication. The number of experimental run $= m$ and p is the number of responses.

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In this study, the modelling was done with the help of software (Minitab16, 2011) using Taguchi L_{18} OA to study the effects of various machining parameters on micro-hardness of the surface produced in EDM process. Micro-hardness was determined with a micro-hardness tester (Vickers hardness machine), which is shown in Appendix A (Fig. A.4). Basically, micro-hardness is considered to be LTB response. So, the S/N ratio (η_{ij}) for j^{th} response variable corresponding to i^{th} trial ($i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, p$) can be computed using Equation 3.1.

The influence of different input parameters on micro-hardness was evaluated with various experimental conditions and the experimental layout is given in Table 3.2. Micro-hardness depth profile measurements were made on hardness tester with a Vickers indenter. The principle is based on pressing a diamond indenter (square based pyramid with an angle of 136 $\circ$ into the work-piece under test with 200g and loading time was 15s. Consequently, the linear value (d) of the diagonal of the impression shown in Fig. 3.1 was measured. Lengths of the indentation diagonals were precisely measured at 400X magnification an a optical microscope. The hardness number (HV) is defined as the ratio of applied load to contact area between the indenter and sample by using Equation 3.4.

$$HV = (\frac{P}{A}) \tag{3.4}$$

3.3 Results and discussions

Three sample readings were taken on each work-piece and it is tabulated in Table 3.2. The images of the indentations for different experiments runs (with one representative image coresponding to each work-piece) are presented in Fig. 3.2, Fig. 3.3, Fig. 3.4.

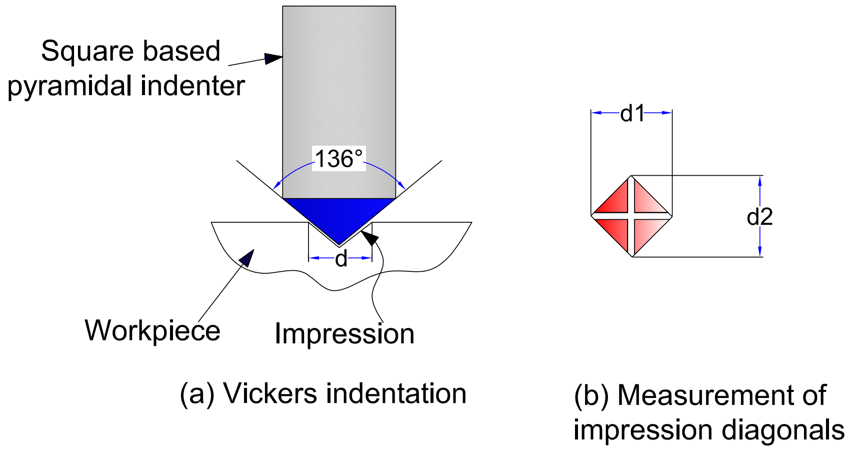
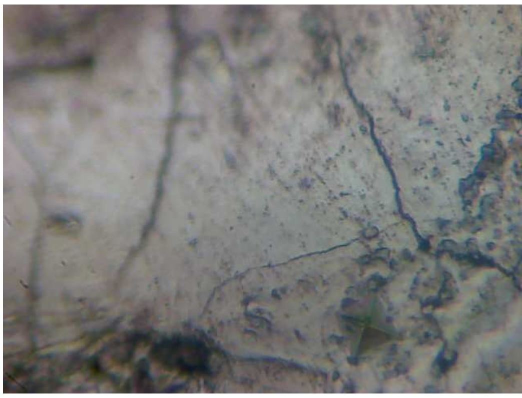


Fig. 3.1: Vickers test scheme

It can be concluded from the main effect plot shown in Fig. 3.5, that Vickers hardness value increases with increase in Ip. When Ip was increased, more number of carbon particles were deposited on machined surface and hence, due to higher heat generation and rapid chilling of the re- solidified layer the hardness of the machined surface was increased (Krishna Mohana Rao et al., 2008). Whereas, the hardness value decreased with increase in T_{on}, because with longer pulse on-time and high current cause more frequent cracking of the dielectric fluid, as there was more frequent melt expulsion leading to the formation of deeper and larger craters on the surface of the work-piece. It gave rougher surface characteristics with more craters, globules

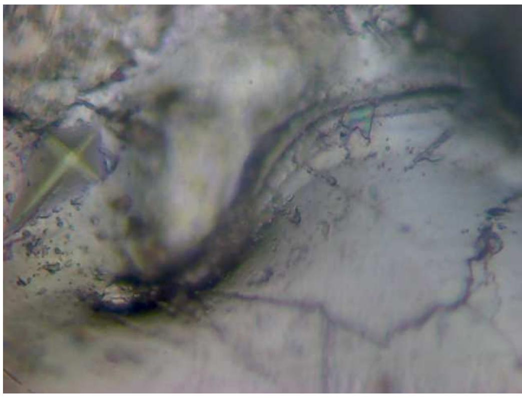
(a) Run no.1

(b) Run no.2



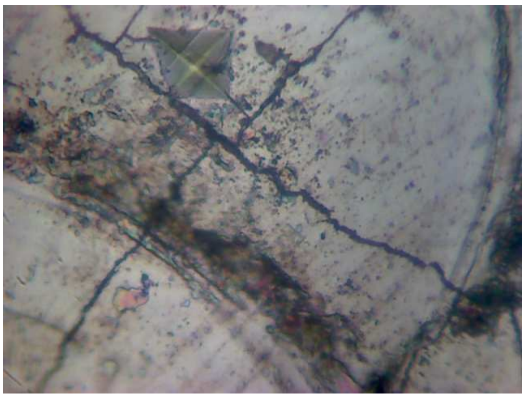
(c) Run no.3

(d) Run no.4



(e) Run no.5

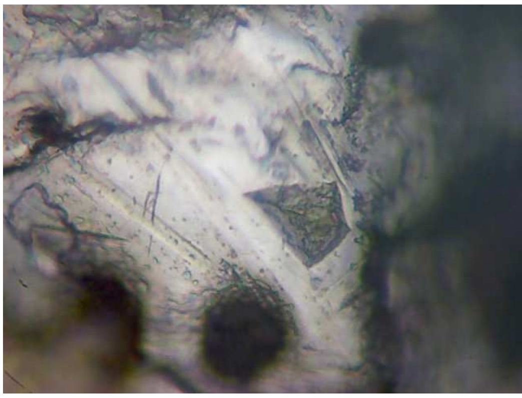
(f) Run no.6



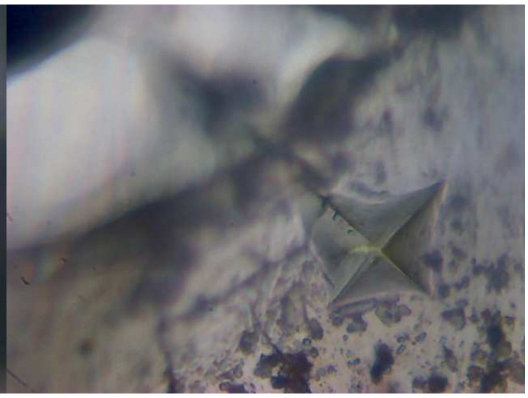
(g) Run no.7

(h) Run no.8

Fig. 3.2: Indentations on work-piece after Vickers hardness test.

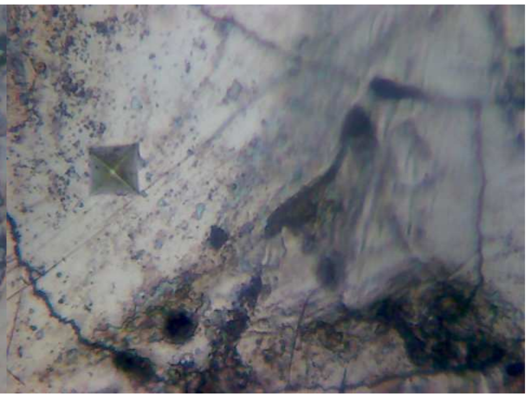


(a) Run no.9

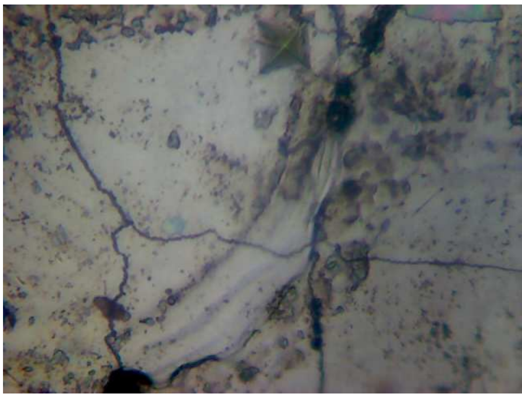


(b) Run no.10

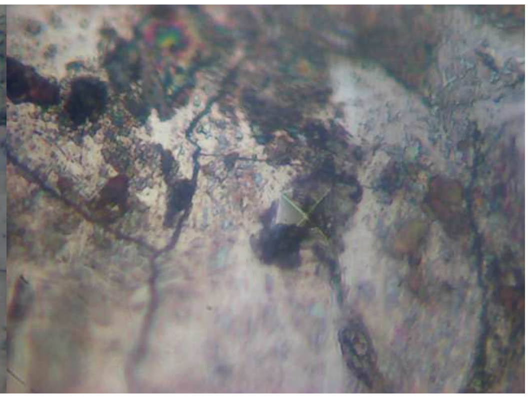
(c) Run no.11



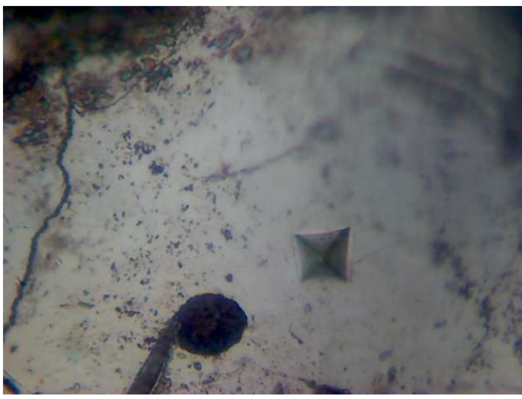
(d) Run no.12



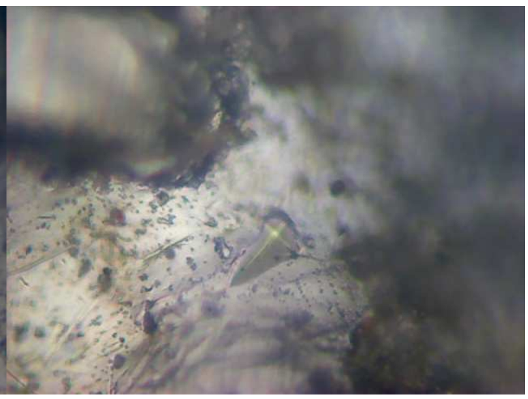
(e) Run no.13



(f) Run no.14

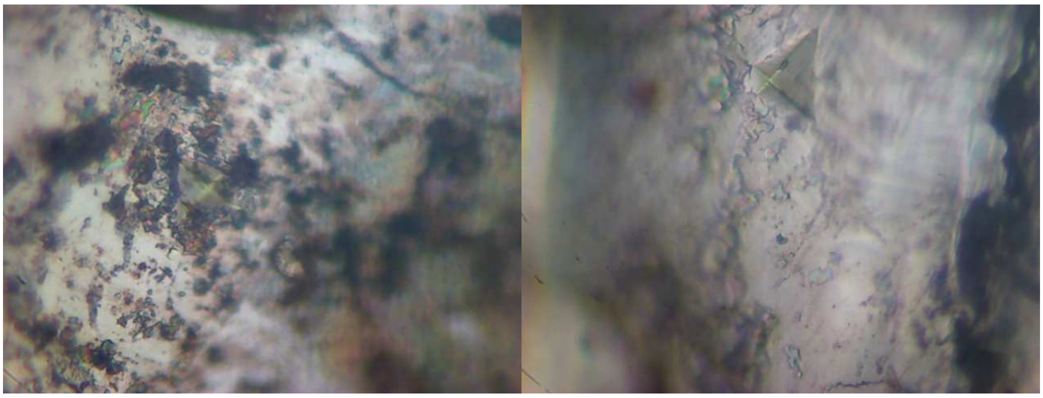


(g) Run no.15



(h) Run no.16

Fig. 3.3: Indentations on work-piece after Vickers hardness test.



(a) Run no.17 *(b)* Run no.18

Fig. 3.4: Indentations on work-piece after Vickers hardness test.

Table 3.2: Experimental layout

Run	*Fp*	*Ip*	*Ton*	*Tup*	Micro hardness(HV)			Avg. (HV)
					1st	2nd	3rd	
1	0.2	2	100	0.0	215	221	212	216
2	0.2	2	300	0.7	221	213	199	211
3	0.2	2	500	1.4	173	160	165	166
4	0.2	5	100	0.0	232	218	228	226
5	0.2	5	300	0.7	216	236	229	227
6	0.2	5	500	1.4	177	186	198	187
7	0.2	8	100	0.7	232	242	252	242
8	0.2	8	300	1.4	240	231	246	239
9	0.2	8	500	0.0	219	232	227	226
10	0.4	2	100	1.4	209	221	227	219
11	0.4	2	300	0.0	196	207	212	205
12	0.4	2	500	0.7	168	175	185	176
13	0.4	5	100	0.7	229	242	234	235
14	0.4	5	300	1.4	227	219	238	228
15	0.4	5	500	0.0	181	207	197	195
16	0.4	8	100	1.4	254	243	262	253
17	0.4	8	300	0.0	232	242	255	243
18	0.4	8	500	0.7	229	218	210	219

of debris, micro-cracks and arcing phenomena increased that led to drop in micro-hardness. The hardness was not significantly affected by T_{up} and Fp. Since, micro-hardness is considered LTB factor optimality, so from the Fig. 3.5, the optimal input factor combination is $Fp1$, $Ip1$, $T_{on}3$, $T_{up}3$.

The Analysis of Variance (ANOVA) table (Table 3.3) shows that Ip and T_{on} are most significant parameters at 95% confidence level for micro- hardness among all variables. In this model only interaction between Ip and T_{on} was possible which was not significant in the range of the experiment conducted.

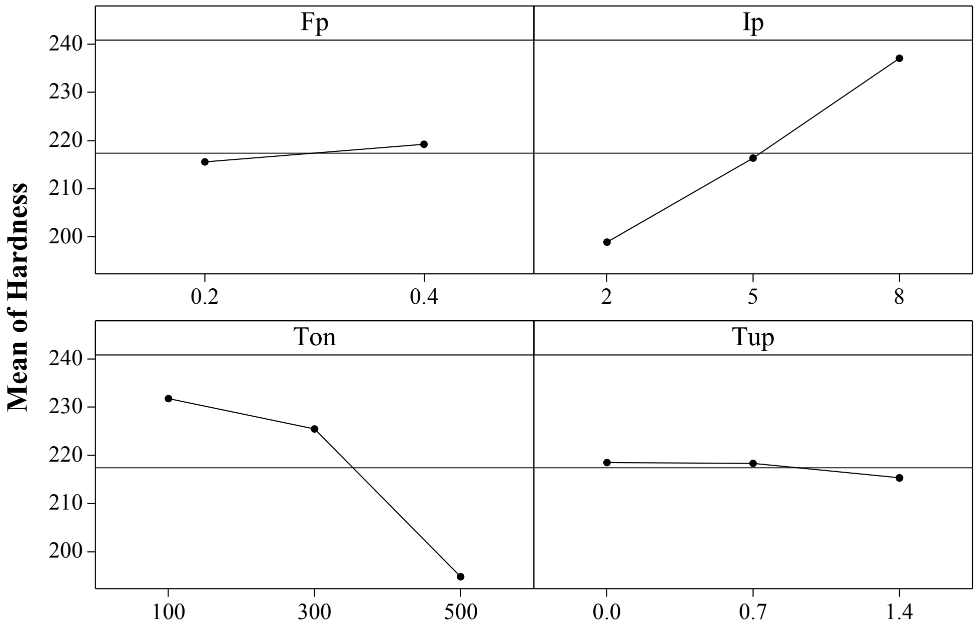


Fig. 3.5: Main effect plot of Micro Hardness

Residual plots are an important accompaniment to the model calculations. The residual plots of micro-hardness are shown in below. The standardised residuals are plotted on a normal probability plot to check the departure of the data from normality (Fig. 3.6). It can be seen that the residuals are almost falling with in the confidence interval, which indicates that the residues are almost normally distributed. The histogram plot of standardised residue for all the observations shows the symmetry of the residues (Fig. 3.7). It is in the form of Gaussian distribution (bell shape). The

Table 3.3: ANOVA for micro hardness

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Fp	1	60.50	60.50	60.50	2.10	0.198*
Ip	2	4380.11	4380.11	2190.06	75.86	0.000
Ton	2	4699.11	4699.11	2349.56	81.38	0.000
Tup	2	38.11	4.78	2.39	0.08	0.922*
Ip×Ton	4	289.22	289.22	72.31	2.50	0.151*
Residual Error	6	173.22	173.22	28.87		
Total	17	9640.28				

* = insignificant at 95%

plot of the residues versus run order illustrates that there is no unusual structure present in the data (Fig. 3.8). The fitted values to offer a visual check on the model assumptions which indicate the variance is constant and a nonlinear relationship exists as well as no outliers exist in the data (Fig. 3.9).

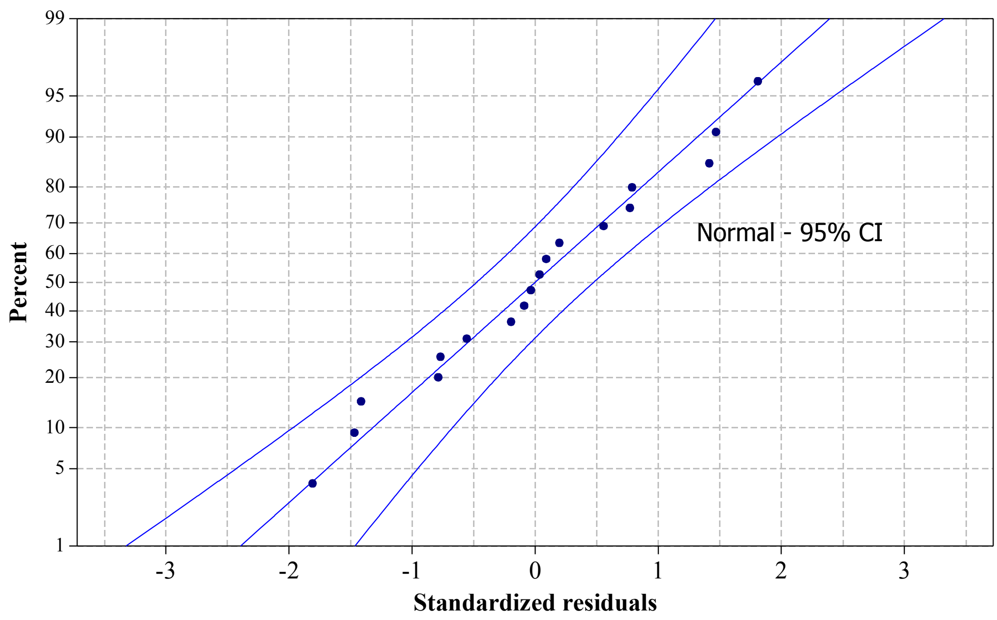


Fig. 3.6: Normal probability plot

The coefficients of model for mean of micro-hardness are shown in Table 3.4. The parameter R^2 describes the amount of variation observed in micro-hardness is explained by the input factors. $R^2 = 98.2$ % indicate that the model is able to predict the response with high accuracy. The standard deviation of errors in the modelling, S= 5.373. Comparing the p-value with a commonly used confidence level = 0.05, it is

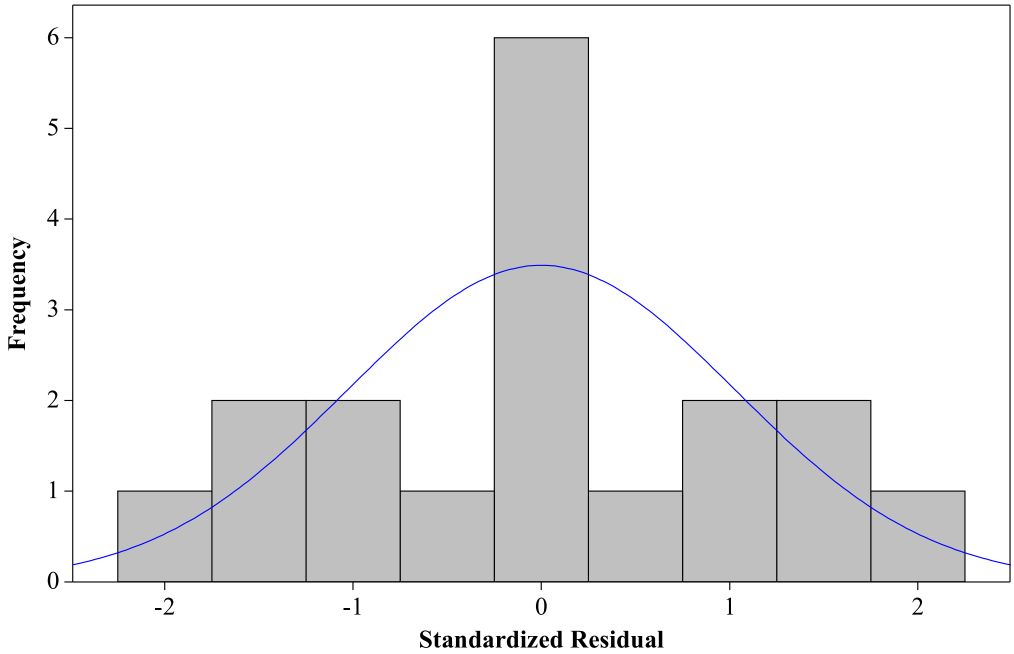


Fig. 3.7: Histogram plot

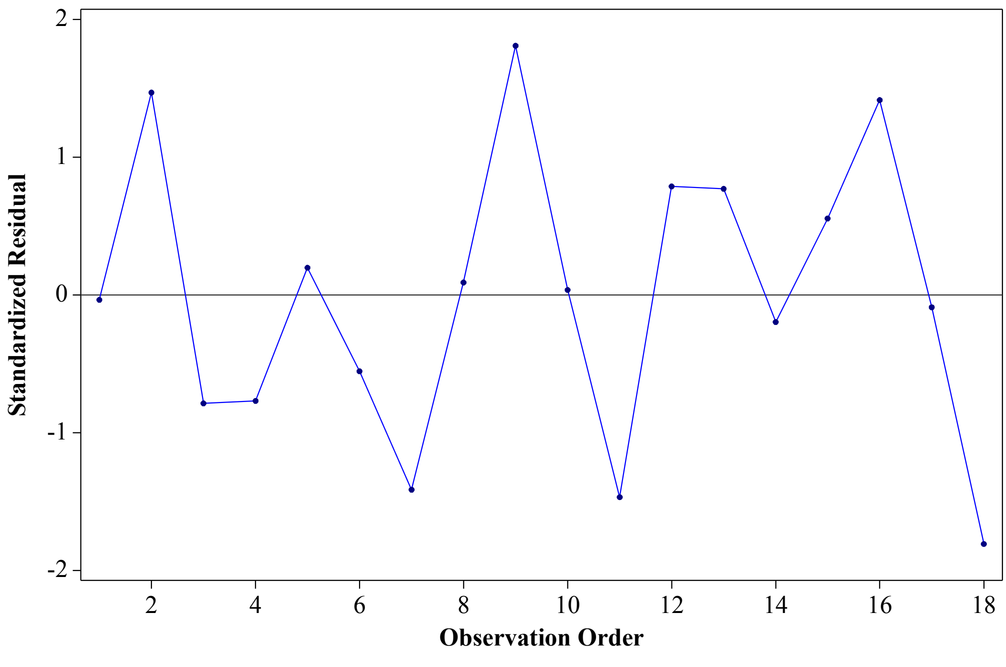


Fig. 3.8: Run order plot

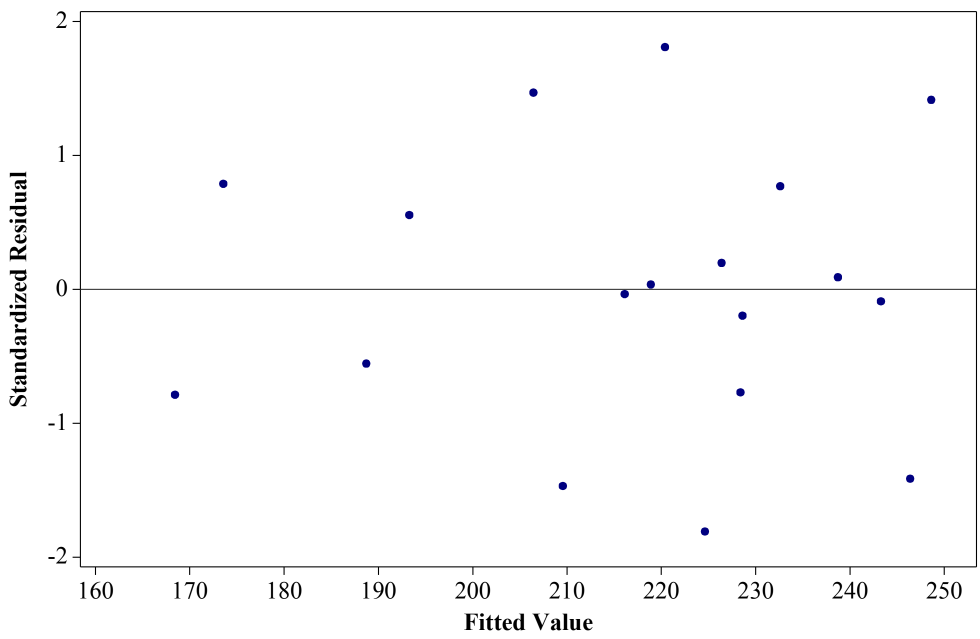


Fig. 3.9: Fit value plot

found that if the p-value is less than or equal to confidence level, it can be concluded that the effect is significant (shown in bold), otherwise it is not significant.

3.4 Conclusions

Following conclusions are drawn on the effect of EDM parameters on hardness of the machined surface.

1. Experimental results indicate that in AISI P20 steel in EDM process causes a ridged surface and induces machining damage in the surface layer, and increases the micro-hardness.

2. When Ip was increased the Vickers micro-hardness value also increased.

3. Micro-hardness decreased with increase in T_{on}.

4. Hardness was unaffected by the input factors Fp and T_{up}.

5. The optimal condition was found to be $Fp1$, $Ip1$, $T_{on}3$, $T_{up}3$.

Table 3.4: Estimated model for MH

Term	Coef	SE Coef	T	P
Constant	217.389	1.266	171.651	**0.000**
Fp 0.2	-1.833	1.266	-1.448	0.198
Ip 2	-18.556	1.791	-10.36	**0.000**
Ip 5	-1.056	1.791	-0.589	0.577
Ton 100	14.444	1.791	8.065	**0.000**
Ton 300	8.111	1.791	4.529	**0.004**
Tup 0.0	0.111	2.068	0.054	0.959
Tup 0.7	0.667	2.068	0.322	0.758
Ip*Ton 2 100	4.556	2.736	1.665	0.147
Ip*Ton 2 300	0.667	2.736	0.244	0.816
Ip*Ton 5 100	-0.667	2.736	-0.244	0.816
Ip*Ton 5 300	3.111	2.736	1.137	0.299
S = 5.373 R-Sq = 98.2% R-Sq(adj) = 94.9%				

Chapter IV

Optimization of Multiple Quality Characteristics based on Fuzzy TOPSIS

4. OPTIMIZATION OF MULTIPLE QUALITY CHARACTERISTICS BASED ON FUZZY TOPSIS

4.1 Introduction

Currently trends in globalization and technological advancement at a very high rate have made today's market extremely competitive. Quality as well as productivity are the two major parameters of concern for every manufacturing or production unit in order to achieve high quality product towards fulfillment of the need and satisfaction of the customers in an economic way. Single objective optimization method often creates conflict, when more than one response need to be optimized simultaneously. Literature survey described in Chapter 2 reveals that traditional methods are very straightforward (consisting of a number of assumptions) and not free from limitations. In order to minimize cost and to maximize production rate simultaneously; multi-objective optimization approach should be explored.

This research adopts the fuzzy-TOPSIS as a fuzzy multi-criteria decision making technique to determine the weights of each criterion and the importance of alternatives w.r.t to criteria. In Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach, an alternative that is nearest to the Fuzzy Positive Ideal Solution (FPIS) and farthest from the Fuzzy Negative Ideal Solution (FNIS) is chosen as optimal. This technique is criticised due to neglect uncertainity. On the other hand, fuzzy logic is able to model the uncertainity. It uses linguistic variable instead of traditional quantitative expression, which is very helpful concept for dealing with situations which are too complex or not well- defined enough.

Application of Fuzzy Set Theory was first formalised by Professor Lofti Zadeh at the University of California in 1965. The fuzzy set theory appears as an important tool to provide a multi -criteria decision framework that incorporates the vagueness and imprecision inherent in the justification and selection of advanced manufacturing systems. An effective way to express factors including flexibility, quality of the products, enhanced response to market demand, and reduction in inventory, which can neither be assessed by crisp values nor random processes, is using linguistic variables or fuzzy numbers. To express an imprecise value, the fuzzy number is used associated with a membership function. Fuzzy-TOPSIS is one of the most classical method that can help in objective and systematic evaluation of responses on multiple criteria. TOPSIS approach, which assigns the best alternatives among a pool of feasible alternatives by calculating the distances from the FPIS and FNIS. FPIS is composed of the best performance values for each alternative *i.e.*, the solution that maximizes the benefit criteria and minimizes the cost criteria whereas the FNIS consists of the worst performance values i.e. the solution that maximizes the cost criteria and minimizes the benefits criteria.

A number of Fuzzy-TOPSIS based methods and applications have been developed in recent years. The review of the literature indicates that the fuzzy TOPSIS method has received much less attention in Electro Discharge Machining (EDM). Hence, the objective of this chapter is to establish mathematical model of Material Removal Rate (MRR), Tool Wear Rate (TWR) and Surface Roughness (SR) of EDM process using the fuzzy-based Taguchi method and to optimize these multi response process performance characteristics simultaneously.

4.2 Equipment and Experimental Design

The experiment was conducted on die-sinking EDM machine with a cylindrical copper tool electrode having 12 mm diameter and EDM oil (specific gravity =0.763, freezing point= 94($\circ$C) as dielectric. The work material chosen was AISI P 20 tool steel which was semicircular shaped (100 mm diameter and 10 mm thickness). Machining was carried out for 60 min for each experimental run. In this study, the effect of five process parameters, namely, current (Ip) , pulse-on-time (T_{on}), lift time (T_{up}), work time (T_w), inter electrode gap (IEG) was studied on three performance characteristics (responses) *i.e.*, MRR, TWR, SR of the EDM process that are shown in Table 4.1. The other fixed parameters include duty cycle (τ), voltage (V), flushing pressure (F_p) and polarity (p).

Table 4.1: Control parameter and their levels with unit

Control Parameter				
Parameter	Level			Unit
	1	2	3	
Discharge current (Ip)	2	5	8	A
Pulse on Time (T_{on})	100	300	500	μs
Lift Time (T_{up})	0	0.7	1.4	s
Work time (T_w)	0.2	0.6	1	s
Inter Electrode gap (IEG)	90	70	250	μm
Fixed Parameter				
Duty Cycle (τ)		90		%
voltage (V)		45		V
Flushing Pressure (Fp)		0.3		kgf/cm^2

Experimental data on MRR and TWR were collected from Dewangan and Biswas (2013), where they performed simultaneous optimisation of those two responses by using Grey Relational Analysis (GRA) method. Their experimental data on MRR and TWR were analysed in the current work for multi objective optimisation along with SR as the third response. The MRR and the TWR were calculated by taking the weights of the work-piece and tool, before and after the experiment, using Equation 5.1 and Equation 5.2 (Chapter 5). Precision balance was used to measure the weigh of the work-piece and tool is shown in Appendix A (Fig. A.2).

The SR was measured with Talysurf. The modelling was done with the help of MINITAB16 software using Taguchi L_{27} Orthogonal Array (OA). Taguchi Method is an optimization methodology used to formulate the experimental layout and it uses a special design of orthogonal array to study the entire parameter space with only a small number of experiments. Then the proposed method was applied based on concepts of positive ideal and negative ideal points for solving decision making problems with multi- judges and multi-criteria in a fuzzy environment. In this method, the performance rating values of each alternative under the selected criteria as well as the weights of criteria are linguistic variables expressed as triangular fuzzy numbers. The current research uses triangular fuzzy number for fuzzy TOPSIS because of ease using a triangular fuzzy number for the decision-makers to calculate. Then a new collective index is introduced to discriminate among alternatives in the evaluation process by constructing ideal separation and anti-ideal separation matrices simultaneously. To avoid complicated aggregation of irregular fuzzy numbers, these weighted ratings are de-fuzzified into crisp values by the ranking method and then, Closeness Coefficient Index (CCI) is defined to determine the ranking order of alternatives by calculating the distances of alternatives to both the ideal and negative- ideal solutions.

4.3 Proposed Optimization Procedure

The preceding study highlights on procedural steps for the multi-response optimization based on Fuzzy-TOPSIS. Optimal factorial combination (parameter setting) has been evaluated finally by optimizing CCI using Taguchi method. The linguistic variables were described using triangular fuzzy numbers known as Membership function of Responses which is shown in Fig. 4.1. These linguistic values are denoted by fuzzy numbers that are shown in Table 4.2. The four decision makers give their decisions of responses for each attribute weight in linguistic term and aggregated fuzzy weight of each output parameters are that are shown in Table 4.3.

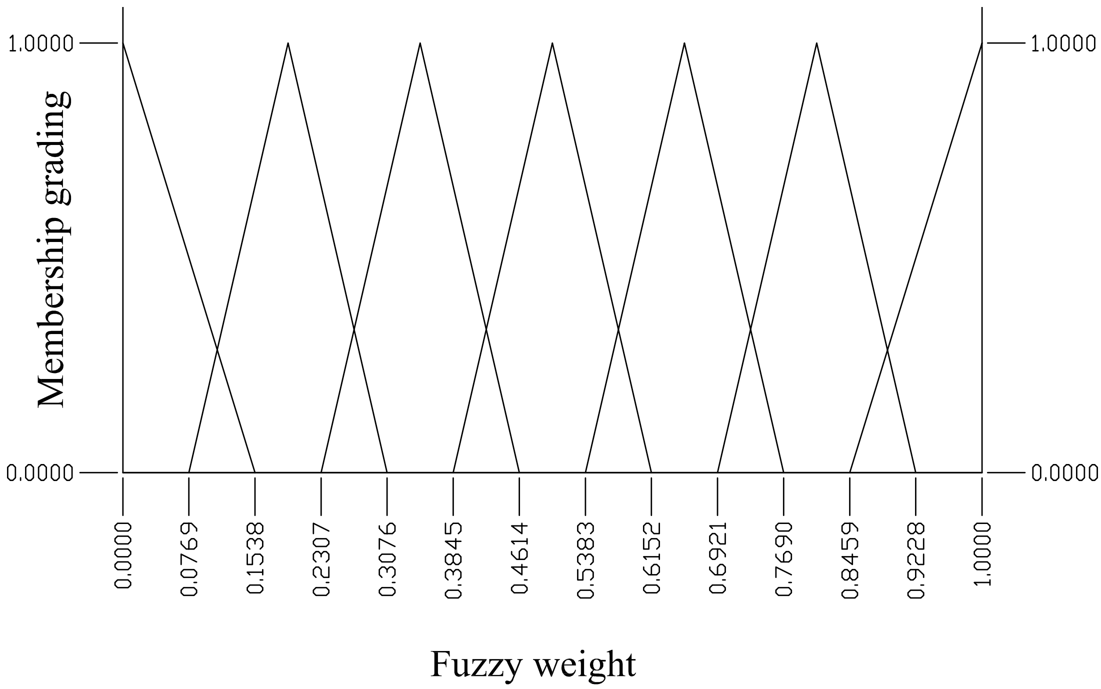


Fig. 4.1: Membership Function of Response

The optimisation procedure includes the following steps:

Table 4.2: Linguistic variables

Fuzzy subset	Fuzzy weight
Very small(VS)	(0.0769, 0.1538, 0.3076)
Small(S)	(0.2307, 0.3076, 0.4614)
Medium(M)	(0.3845, 0.4614, 0.6152)
High(H)	(0.5383, 0.6152, 0.7690)
Very High(VH)	(0.6921, 0.7690, 0.9228)
Extremely High(EH)	(0.8459, 1.000, 1.000)

Table 4.3: Decision maker and aggregated fuzzy weight

Responses	Decision maker				Fuzzy weight($\tilde{w_j}$)
	DM1	DM2	DM3	DM4	
MRR	H	H	M	VH	(0.5383, 0.6152, 0.7690)
TWR	VS	S	ES	M	(0.1730, 0.2307, 0.3845)
SR	S	M	VS	M	(0.2690, 0.3460, 0.4990)

Step 1: Construct the fuzzy decision matrix.

$$\mathbf{D}_{27\times 3} = [x_{ij}] \tag{4.1}$$

where, x_{ij} represents the actual value of j^{th} attribute of i^{th} experimental run.

Step 2: Normalising the fuzzy decision matrix using the following equation.

$$r_{ij} = (\frac{x_{ij}}{\sqrt{\sum_{i=1}^{27} x_{ij}^2}}) \tag{4.2}$$

where, r_{ij} represents the corresponding normalised value. The above normalisation method preserves the property that the ranges of normalised responses belong to 0 and 1.

The experimental design matrix with normalised response r_{ij}'s are presented in Table 4.4.

Step 3: Compute the weighted normalised matrix.

The weighted normalised decision matrix $\widetilde{\mathbf{V}}$ can be computed by multiplying the importance weights ($\tilde{w_j}$) of evaluated criteria with the values of normalised fuzzy decision matrix r_{ij} which are shown in Table 4.5.

$$\widetilde{\mathbf{V}}_{27\times3} = [\widetilde{v}_{ij}] \tag{4.3}$$

where, $\widetilde{v}_{ij} = r_{ij} \times \tilde{w}_j$

Step 4: Determine the FPIS and FNIS.

Since, the positive triangular fuzzy numbers are included in the interval [0,1], FPIS denoted by A^+ and FNIS denoted by A^- are computed as:

$$A^+ = \left(\widetilde{v}_1^+, \widetilde{v}_2^+, \widetilde{v}_3^+\right) \tag{4.4}$$

where, $\widetilde{v}_j^+ = \max_i \{v_{ij}\}$

i= 1, 2, . . . , 27 ; j= 1, 2, 3

$$A^- = \left(\widetilde{v}_1^-, \widetilde{v}_2^-, \widetilde{v}_3^-\right) \tag{4.5}$$

where, $\widetilde{v}_j^- = \min_i \{v_{ij}\}$

i= 1, 2, . . . , 27 ; j= 1, 2, 3

These values are given in Table 4.6.

Step 5: Compute the distance of each alternative from FPIS and FNIS.

The distances (d_i^+, d_i^-) of each experimental result from positive and negative ideal solutions can be obtained using the following expression:

$$d_i^+ = \sum_{j=1}^{3} d\left\{\widetilde{v}_{ij}, \widetilde{v}_j^+\right\} \tag{4.6}$$

i= 1, 2, . . . , 27

$$d_i^- = \sum_{j=1}^{3} d\left\{\widetilde{v}_{ij}, \widetilde{v}_j^-\right\} \tag{4.7}$$

i= 1, 2, . . . , 27

where, d(x, y) is the distance measurement between two triangular fuzzy numbers and it can be calculated using the following equation.

$$d(x,y) = \left(\tfrac{1}{3}[(x_1-y_1)^2+(x_2-y_2)^2 + (x_3-y_3)^2]\right)^{\frac{1}{2}} \tag{4.8}$$

These values are given in Table 4.7.

Step 6: Compute the CCI of each alternative and the values are given Table 4.4

$$CCI_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{4.9}$$

i= 1, 2, . . . , 27

Step 7: Rank the alternatives

The different alternatives are ranked according to the CCI. The alternative with highest closeness coefficient represents the best alternative and is closest to the FPIS and farthest from the FNIS.

4.4 Results and Discussions

The machining run with the greatest CCI value will indicate the optimal combination of parameters. The main effect plot for CCI is shown in Fig. 4.2. The mean values of CCI at various levels of input parameters are tabulated in Table 4.8 It is clearly observed that the optimal machining parameters for the EDM are Ip= 8A (level 3), T_{on}= 500μs (level 3), T_{up}= 0s (level 1), T_w= 1s (level 3) and IEG= 90μm

Table 4.4: Experimental result with final output

Run	*Ip*	*Ton*	*Tup*	*Tw*	IEG	r_{ij}			CCI
	A	μs	s	s	μm	MRR	TWR	SR	
1	1	1	1	1	1	0.084	0.075	0.137	0.347
2	1	1	1	1	2	0.087	0.131	0.133	0.329
3	1	1	1	1	3	0.083	0.142	0.127	0.323
4	1	2	2	2	1	0.027	0.056	0.096	0.324
5	1	2	2	2	2	0.029	0.093	0.085	0.317
6	1	2	2	2	3	0.028	0.131	0.081	0.304
7	1	3	3	3	1	0.014	0.112	0.060	0.314
8	1	3	3	3	2	0.013	0.020	0.067	0.340
9	1	3	3	3	3	0.015	0.112	0.063	0.313
10	2	1	2	3	1	0.058	0.142	0.165	0.279
11	2	1	2	3	2	0.071	0.206	0.189	0.250
12	2	1	2	3	3	0.067	0.261	0.181	0.224
13	2	2	3	1	1	0.021	0.093	0.168	0.274
14	2	2	3	1	2	0.023	0.085	0.172	0.279
15	2	2	3	1	3	0.019	0.120	0.207	0.245
16	2	3	1	2	1	0.131	0.070	0.075	0.429
17	2	3	1	2	2	0.139	0.122	0.088	0.419
18	2	3	1	2	3	0.115	0.031	0.098	0.413
19	3	1	3	2	1	0.179	0.316	0.253	0.359
20	3	1	3	2	2	0.164	0.393	0.249	0.315
21	3	1	3	2	3	0.167	0.419	0.271	0.310
22	3	2	1	3	1	0.432	0.318	0.306	0.686
23	3	2	1	3	2	0.425	0.261	0.290	0.709
24	3	2	1	3	3	0.442	0.291	0.278	0.714
25	3	3	2	1	1	0.301	0.159	0.268	0.612
26	3	3	2	1	2	0.283	0.056	0.282	0.601
27	3	3	2	1	3	0.302	0.093	0.296	0.616

Table 4.5: weighted normalised matrix

Run	$\widetilde{v}_{ij}$								
	MRR			TWR			SR		
1	0.0451	0.0515	0.0644	0.0129	0.0173	0.0288	0.0368	0.0474	0.0683
2	0.0468	0.0535	0.0669	0.0227	0.0303	0.0504	0.0359	0.0461	0.0665
3	0.0449	0.0513	0.0641	0.0245	0.0327	0.0545	0.0343	0.0441	0.0635
4	0.0143	0.0163	0.0204	0.0097	0.0130	0.0217	0.0259	0.0333	0.0480
5	0.0158	0.0181	0.0226	0.0161	0.0215	0.0359	0.0229	0.0295	0.0425
6	0.0153	0.0175	0.0218	0.0227	0.0303	0.0504	0.0217	0.0279	0.0402
7	0.0077	0.0088	0.0110	0.0193	0.0258	0.0430	0.0162	0.0208	0.0300
8	0.0068	0.0078	0.0097	0.0035	0.0047	0.0078	0.0181	0.0233	0.0335
9	0.0080	0.0091	0.0114	0.0193	0.0258	0.0430	0.0168	0.0217	0.0312
10	0.0310	0.0354	0.0443	0.0245	0.0327	0.0545	0.0444	0.0572	0.0824
11	0.0384	0.0439	0.0549	0.0356	0.0475	0.0792	0.0509	0.0655	0.0944
12	0.0362	0.0414	0.0517	0.0452	0.0603	0.1005	0.0486	0.0625	0.0902
13	0.0110	0.0126	0.0158	0.0161	0.0215	0.0359	0.0453	0.0583	0.0840
14	0.0126	0.0143	0.0179	0.0146	0.0195	0.0325	0.0462	0.0595	0.0858
15	0.0100	0.0114	0.0143	0.0207	0.0276	0.0460	0.0556	0.0715	0.1031
16	0.0703	0.0803	0.1004	0.0122	0.0162	0.0271	0.0202	0.0259	0.0374
17	0.0750	0.0857	0.1072	0.0212	0.0282	0.0471	0.0238	0.0306	0.0441
18	0.0620	0.0708	0.0885	0.0054	0.0071	0.0119	0.0265	0.0340	0.0491
19	0.0965	0.1103	0.1379	0.0547	0.0729	0.1215	0.0680	0.0875	0.1262
20	0.0885	0.1012	0.1265	0.0679	0.0906	0.1510	0.0670	0.0862	0.1243
21	0.0898	0.1026	0.1283	0.0725	0.0967	0.1611	0.0729	0.0937	0.1352
22	0.2328	0.2660	0.3325	0.0550	0.0733	0.1222	0.0822	0.1057	0.1525
23	0.2290	0.2617	0.3272	0.0452	0.0603	0.1005	0.0780	0.1004	0.1447
24	0.2377	0.2717	0.3396	0.0503	0.0670	0.1117	0.0747	0.0961	0.1386
25	0.1620	0.1852	0.2315	0.0276	0.0368	0.0613	0.0721	0.0928	0.1338
26	0.1522	0.1739	0.2174	0.0097	0.0130	0.0217	0.0758	0.0975	0.1407
27	0.1623	0.1855	0.2319	0.0161	0.0215	0.0359	0.0795	0.1023	0.1476

Table 4.6: Positive Ideal and negative ideal solutions for each criterion

A^+	A^-
0.2377	0.0068
0.2717	0.0078
0.3396	0.0097
0.0035	0.0725
0.0047	0.0967
0.0078	0.1611
0.0162	0.0822
0.0208	0.1057
0.0300	0.1525

Table 4.7: Calculated distance measures

Run	d_i^+	d_i^+
1	0.2341	0.1242
2	0.2334	0.1142
3	0.2358	0.1126
4	0.2694	0.1290
5	0.2679	0.1241
6	0.2695	0.1179
7	0.2779	0.1269
8	0.2779	0.1435
9	0.2776	0.1262
10	0.2542	0.0983
11	0.2502	0.0832
12	0.2557	0.0738
13	0.2766	0.1046
14	0.2749	0.1062
15	0.2811	0.0914
16	0.2020	0.1516
17	0.1981	0.1429
18	0.2120	0.1493
19	0.2026	0.1135
20	0.2194	0.1009
21	0.2246	0.1007
22	0.1253	0.2733
23	0.1111	0.2710
24	0.1121	0.2803
25	0.1270	0.2007
26	0.1338	0.2020
27	0.1296	0.2078

(level 1), which is the best multi-performance characteristics among the twenty seven experiments shown in bold. From Analysis of Variance (ANOVA) of CCI (Table 4.9), Ip, T_{on}, T_{up} and T_w were the significant machining parameters affecting the multiple performance characteristics. Only IEG has been found to be insignificant among five machining parameters.

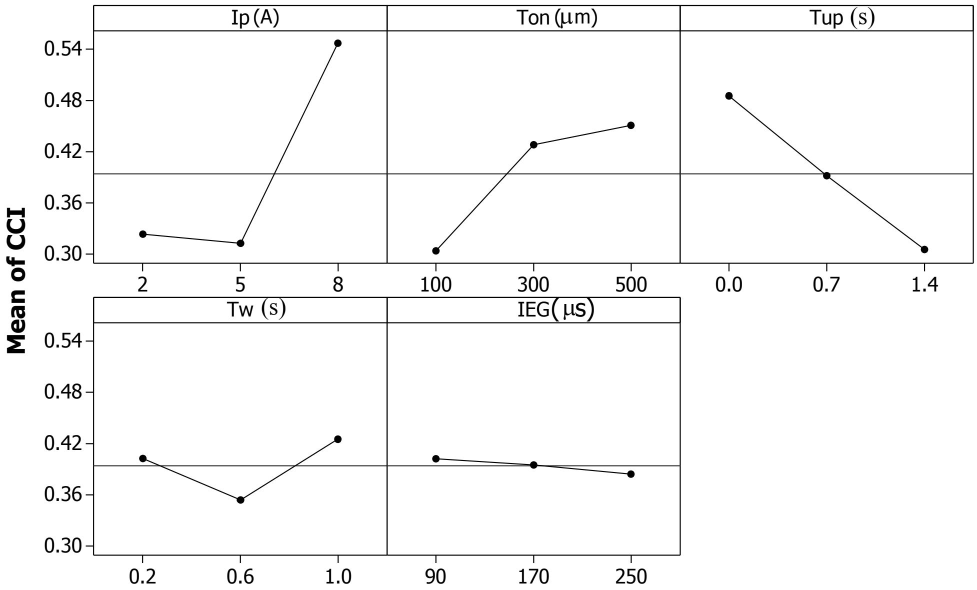


Fig. 4.2: Main effect plot for CCI

Table 4.8: Response Table for mean of CCI (optimal values in bold)

Level	Ip	Ton	Tup	Tw	IEG
1	0.3233	0.3038	**0.4854**	0.4030	**0.4026**
2	0.3124	0.4281	0.3919	0.3544	0.3954
3	**0.5470**	**0.4508**	0.3054	**0.4254**	0.3847

4.4.1 Sensitivity Analysis

Sensitivity analysis is a useful tool applied to determine the effect of criteria weights on decision making because of inherent instability and graphically exposes the importance of criteria weights in selecting the optimal alternative among the feasible alternatives. The main goal of the present study is to understand which criteria is most significant in influencing the decision making process and how sensitive the

Table 4.9: Analysis of Variance for CCI

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Ip	2	0.315466	0.315466	0.157733	650.70	0.000
Ton	2	0.112714	0.112714	0.056357	232.49	0.000
Tup	2	0.145836	0.145836	0.072918	300.81	0.000
Tw	2	0.023663	0.023663	0.011831	48.81	0.000
IEG	2	0.001449	0.001449	0.000725	2.99	0.079*
Residual Error	16	0.003878	0.003878	0.000242		
Total	26	0.603007				

* = insignificant at 95%

alternatives change with the importance of the criteria. This technique generates different scenarios that may change the priority of alternatives and is needed to reach a final solution. If the ranking order be changed by increasing or decreasing the importance of the criteria, the results are expressed to be sensitive otherwise it is robust. Sensitivity analysis technique is becoming increasingly demanding in many fields.

It is assumed that a committee of four Decision Maker (DM)s (DM1, DM2, DM3 and DM4) is formed to act as DMs and every one is preferring the same weight of each of these three responses from among the linguistic terms shown in Table 4.3. Thus, thirty six experiments were conducted by a full factorial design to investigate the sensitivity to the variation of each weight. The Fuzzy-TOPSIS technique is applied on these 36 combinations of DMs preferences, namely DMs preferences on MRR known as Pref-MRR, similarly, Pref-TWR, Pref-SR. According the optimal levels of Ip (Opt Ip), T_{on} (Opt T_{on}), T_{up} (Opt T_{up}) and T_w(Opt T_w) are obtained, which are shown in Table 4.10. The individual plot for the Opt Ip versus DMs preferences is plotted in Fig. 4.3a. It can be concluded that Opt Ip is level 3 for all the DMs judgements except for one DM judgement combination. Whereas, the Opt Ton varies between level 2 and level 3 for any DM preferences as shown in Fig. 4.3b. Fig. 4.4a shows that whatever the decision makers prefer, the optimal T_{up} is level 1. But, Opt T_w widely varies from level 1 to level 3 with the DMs judgements shown in Fig. 4.4b.

The Opt Ip is found to be 97.22% robust against the variation of DMs preferences, whereas the same for T_{on}, T_{up}, T_w and IEG are 88.88%, 100%, 66.67% and 100%, respectively. The overall matching of the optimal parameter values is 55.56% with the results given in Table 4.8.

Table 4.10: Sensitivity Analysis Result

Run no.	Decision makers preferences			optimal level				
	Pref-MRR	Pref-TWR	Pref-SR	Opt-Ip	Opt-Ton	Opt-Tup	Opt-Tw	Opt-IEG
1	VH	VS	VS	3	2	1	3	1
2	VH	S	VS	3	3	1	3	1
3	H	ES	VS	3	3	1	3	1
4	M	VS	M	3	3	1	3	1
5	H	ES	M	3	3	1	3	1
6	M	S	VS	3	3	1	1	1
7	H	VS	VS	3	3	1	3	1
8	H	M	VS	3	3	1	1	1
9	H	ES	S	3	3	1	3	1
10	H	VS	S	3	3	1	3	1
11	VH	ES	S	3	3	1	3	1
12	M	M	VS	3	3	1	1	1
13	M	ES	VS	3	3	1	3	1
14	VH	ES	M	3	3	1	3	1
15	H	M	M	3	3	1	1	1
16	M	S	M	3	3	1	1	1
17	VH	VS	M	3	3	1	3	1
18	M	M	S	3	3	1	1	1
19	M	ES	S	3	3	1	3	1
20	H	S	VS	3	3	1	3	1
21	VH	M	M	3	3	1	1	1
22	VH	S	M	3	3	1	3	1
23	VH	S	S	3	3	1	3	1
24	H	S	S	3	3	1	3	1
25	M	M	M	1	3	1	1	1
26	VH	M	VS	3	3	1	1	1
27	H	VS	M	3	3	1	3	1
28	H	VS	VS	3	3	1	3	1
29	H	ES	VS	3	2	1	3	1
30	H	VS	S	3	2	1	3	1

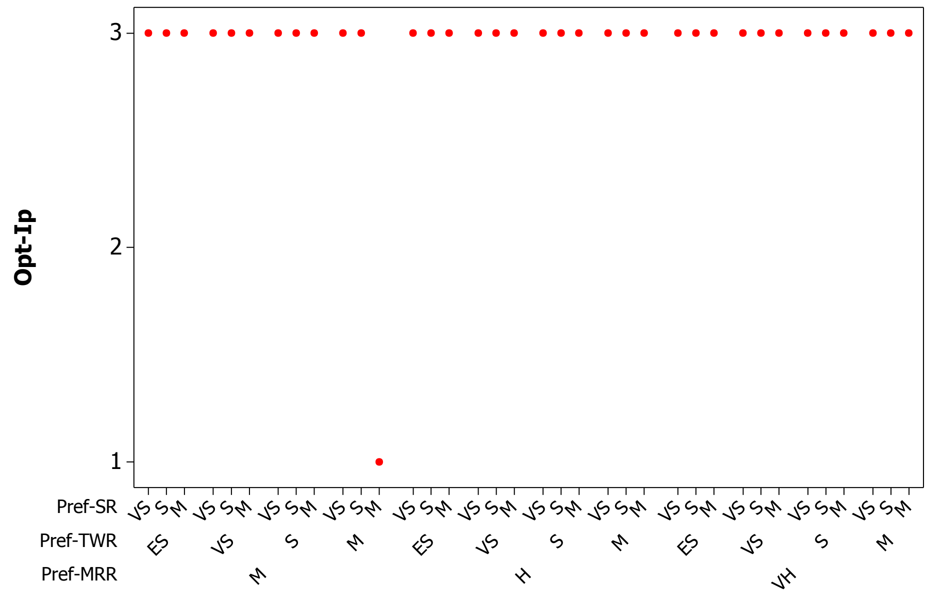
4.5 Conclusions

1. The present study aimed as converting the multiple responses in to a single optimum setting of process parameters which is known as CCI, estimate the factor effects on the CCI and determine the optimal factor-level combination.

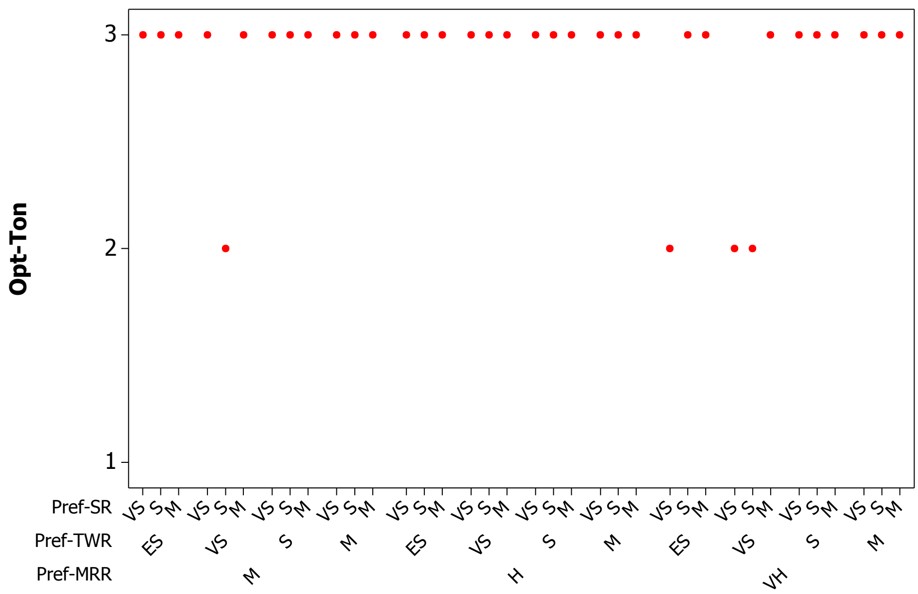
2. It was observed that the optimal process condition for higher MRR and lower TWR and SR is Ip= 8A, T_{on}= 500μs, T_{up}= 0s, T_w= 1s and IEG= 90μm.

3. A sensitivity analysis was carried out to determine the influence of criteria weights on the decision making process. The optimal parameter values had 55.56% votes.

4. It was observed that 97.22% Opt Ip, 88.88% T_{on}, 100% T_{up}, 66.67% T_w, 100% IEG robust against the variation of DMs preferences respectively.

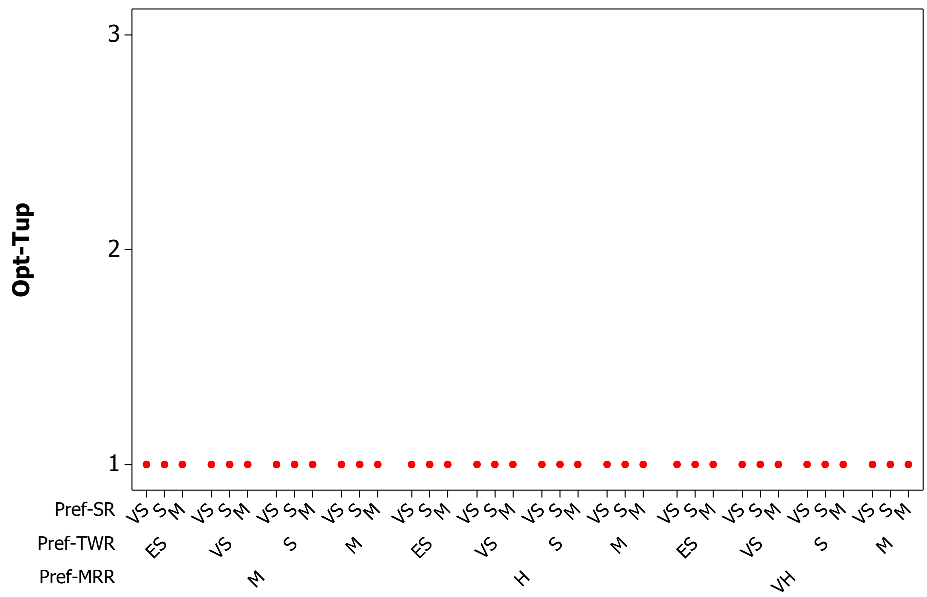


(a) Opt-Ip

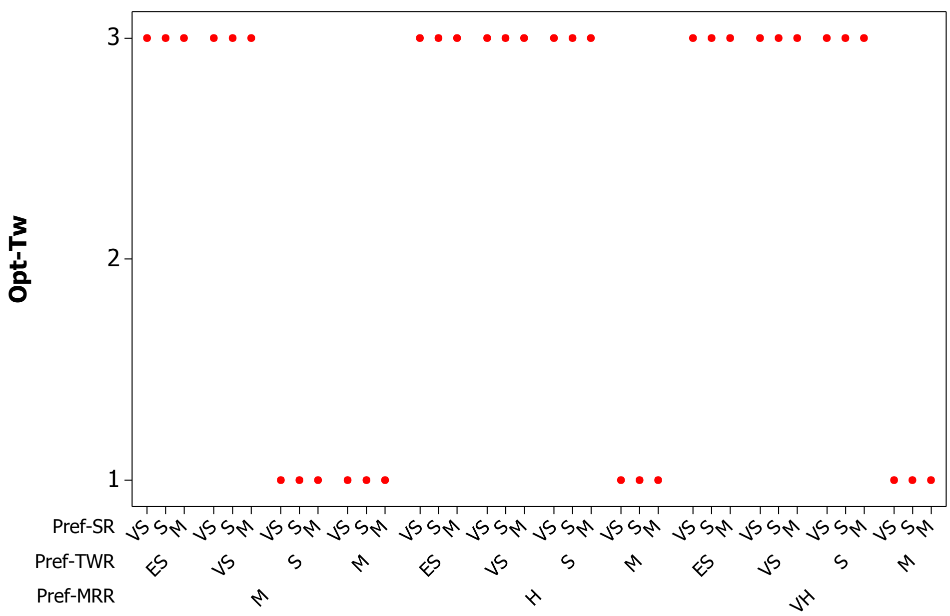


(b) Opt-Ton

Fig. 4.3: Individual plot of (a) Opt-Ip (b) Opt-Ton



(a) Opt-Tup



(b) Opt-Tw

Fig. 4.4: Individual plot of (a) Opt-Tup (b) Opt-Tw

Chapter V

PCA Based Multi objective optimization

5. PCA BASED MULTI OBJECTIVE OPTIMIZATION

5.1 Introduction

In modern-day engineering, high demands are being placed on components in relation to their dimensional precision. Industries are now concerned on focusing towards refined product quality and increased productivity. So the main goal is to find the optimum solution to satisfy customers multiple needs of the product performance in an economic cost. With the development of work-piece material of better hardness, strength and higher temperature resistance, it has become difficult to process them by conventional machining methods. Extensive research and development in the field has finally shown the way to a number of modern machining methods to machine such difficult to machine materials.

Many attempts have been made to model performance parameters of Electro Discharge Machining (EDM) process using Principal Component Analysis (PCA) method. PCA is considered as an effective means of determining a small number of uncorrelated linear combinations which account for most of the variance in the original number of responses. All principal components are uncorrelated with each other. The sum of variances of the principal components or eigenvalues is equal to the sum of variances of the original responses. The main advantage of PCA is that once the patterns in data have been identified, the data can be compressed, *i.e.*, by reducing the number of dimensions, without much loss of information. Therefore, the conflict for determining the optimal settings of the design parameters for the multi- response problems can be reduced. Generally, it is desired that a manufactured product satisfies multiple quality characteristics of interest and many of them may be correlated. PCA is an effective means of determining a small number of constructs which account for the main sources of variation in a set of correlated quality characteristics. It is, therefore, thought that the PCA approach can be an efficient method for optimisation of process parameters in EDM process. The PCA-based procedure for optimisation of multi-response processes was originally proposed by Su and Tong Su and Tong (1997).

In this chapter, PCA technique has been integrated with Taguchis philosophy towards solving multi- objective optimization problem in machining of material on EDM. It would optimise the process parameters for Higher-The-Better (HTB) Material Removal Rate (MRR) and Lower-The-Better (LTB) Tool Wear Rate (TWR), Surface Roughness (SR). Optimal cutting condition has been aimed to be evaluated to satisfy contradicting multi-requirements of product quality as well as productivity.The following paragraph describes some of the important investigations carried out by pioneers towards successful implementation of PCA based methods.

5.2 *Experimental equipment and design*

The experiment was conducted on a die-sinking EDM machine with a cylindrical copper tool electrode on AISI P20 tool steel. The copper tool and machined workpiece are shown in Fig. 5.1. The details of the experiment is described in Chapter 3 Section 3.2.

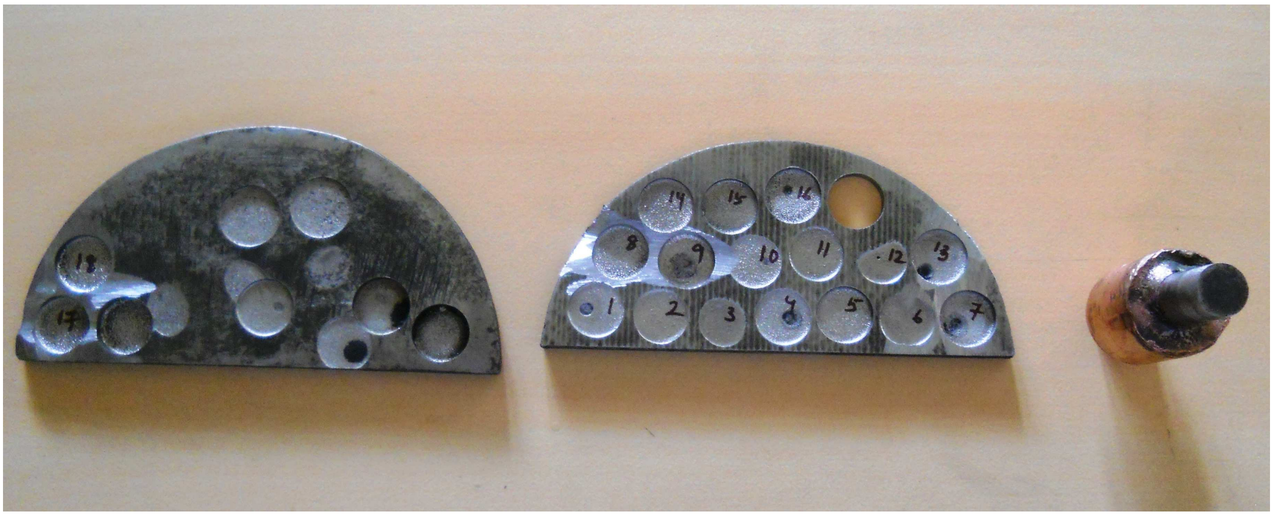


Fig. 5.1: Copper electrode and AISI P20 work-piece

Machining was carried out for 60 min for each experimental run. MRR and TWR were calculated by weight loss method using following Equation 5.1 and 5.2 and

Precision balance was used to measure the weigh of the work-piece and tool is shown in Appendix A (Fig. A.2).

$$\mathrm{M}RR = (\frac{W_b - W_a}{t \times \rho_w}) \tag{5.1}$$

$$\mathrm{TW}R = (\frac{T_b - T_a}{t \times \rho_t}) \tag{5.2}$$

where, W_b and W_a are the weights of work-piece, before and after machining and t_m is the machining time and ρ_w is the density of work-piece (7.85 g/cm^3). T_b and T_a are the weights of tool, before and after machining and t_m is the machining time and ρ_t is the density of tool (8.92 g/cm^3). The SR was measured with Talysurf (Model: Taylor Hobson, Surtronic 3+) which shown in Appendix A (Fig. A.3) with parameters, sample length, L_n= 4 mm, cut-off length, L_c=0.8 mm and filter=2CR ISO. The effect of four process parameters, namely, current (Ip), pulse on- time (T_{on}), lift time (T_{up}), flushing Pressure (Fp) was studied on three performance characteristics (responses) *i.e.*, MRR, TWR, SR.

In this study, L_{18} Orthogonal Array (OA) based on Taguchi design is used for multi- response optimisation of EDM process. The experimental layout and Signal-to-Noise (S/N) ratios for the three response variables; MRR, TWR and SR are given in Table 5.1. Basically here only two types S/N ratios are used *i.e.*, LTB for TWR and SR and HTB for MRR. The S/N ratio (η_{ij}) for j^{th} response variable corresponding to i^{th} trial ($i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, p$) can be computed using Equation 3.1 and Equation 3.2. The modeling is done by Minitab16 (2011) software with PCA technique or method.

5.3 Multi objective optimization methods

The process modelling is performed using three types of PCA based methods namely, PCA-based Grey Relational Analysis (GRA), PCA-based Proportion of Quality Loss Reduction (PQLR) and Weighted Principal Component (WPC) methods. The three

Table 5.1: Experimental layout and computed S/N ratios

Run	*Ip* (A)	*Ton* (μs)	*Tup* (s)	*Fp* (kgf/cm^2)	S/N MRR	S/N TWR	S/N SR
1	0.2	2	100	0.0	0.7580	0.0149	2.9
2	0.2	2	300	0.7	0.5032	0.0075	3.8
3	0.2	2	500	1.4	0.1507	0.0168	3.8
4	0.2	5	100	0.0	0.8365	0.0112	6.7
5	0.2	5	300	0.7	2.8705	0.0131	8.5
6	0.2	5	500	1.4	0.7665	0.0131	7.1
7	0.2	8	100	0.7	5.8004	0.0934	7.7
8	0.2	8	300	1.4	7.2930	0.0355	10
9	0.2	8	500	0.0	7.5499	0.0411	8.5
10	0.4	2	100	1.4	0.5223	0.0262	3.1
11	0.4	2	300	0.0	0.7919	0.0131	3.6
12	0.4	2	500	0.7	0.1890	0.0112	4.5
13	0.4	5	100	0.7	3.1762	0.0542	4.5
14	0.4	5	300	1.4	1.8110	0.0112	6.7
15	0.4	5	500	0.0	2.1996	0.0168	8.0
16	0.4	8	100	1.4	5.8726	0.0981	7.1
17	0.4	8	300	0.0	9.8599	0.0842	7.4
18	0.4	8	500	0.7	7.2442	0.0562	8.2

PCA-based methods assuming possible correlation between the responses and the multiple responses are converted into a single response known as Process Performance Index (PPI). The basic approach of estimating the factor effects on the PPI and determine the optimal factor-level combination that can optimize the PPI value are discussed. The detailed procedures for computing the PPI values and the optimal factor level in these three methods are described in Appendix.

5.3.1 PCA-Based GRA Method:

GRA is a method in grey system theory that can provide a solution of a system in which the model is unsure or the information is incomplete. Besides, it provides an efficient solution to the uncertainty, multi -input and discrete data problem. The relation between machining parameters and performance can be found out with GRA. Also, the Grey Relational Grade (GRG) will utilize the discrete measurement method to measure the distance.

The computed PPI in the PCA-based GRA method is known as Overall Quality Performance Index (OQPI) which are calculated by the steps described in Appendix B. The eigenvalues and the corresponding eigenvectors obtained from the S/N ratios are given in Table 5.2 for PCA based GRA method. These values are used to calculate the Principal Component Scores (PCS)s using Equation B.1 which is shown in Table 5.3. These PCSs values are normalised using Equation B.2 and are given in Table 5.4. With these normalised values, the Grey Relational Coefficient (GRC) are calculated using Equation B.3 which are shown in Table 5.5. By using these values, output (OQPI) is evaluated from Equation B.4, shown in Table 5.16. There are three different OQPI values for the i^{th} trial that are calculated from the principal components and are given below:

1. $OQPI3_i$ = OQPI value considering all the three principal components.
2. $OQPI2_i$ = OQPI value considering first two principal components.
3. $OQPI1_i$ = OQPI value considering first principal component only.

The optimality of the process can be checked by HTB category. These three OQPI value are used to obtain the optimal setting which are described in Section 5.4.

Table 5.2: Eigen analysis for PCA based GRA

PC	Eigen value	Proportion of variation explained	Eigen vector
PC1	2.2653	0.755	[-0.640, 0.546, 0.542]
PC2	0.6106	0.204	[0.007,-0.700, 0.714]
PC3	0.1242	0.041	[-0.769,-0.461,-0.444]

5.3.2 PCA-Based WPC Method

WPC method can defeat many defects of multi-response optimization problems as responses become uncorrelated and weights are easily estimated by percentage of variation explained by each component. It uses the explained variation as the weight to combine all principal components in order to form a Multi-response Performance Index (MPI).

The computed PPI in the WPC method is called MPI, which are calculated by the steps described in Appendix C. The experimental findings in Table 5.1 are used to

Table 5.3: Calculated Principal Component Scores(PCSs)

Run no.	PCS1	PCS2	PCS3
1	-1.3140	0.7343	-2.6741
2	-1.3480	1.4546	-3.8102
3	-0.8060	2.1686	-4.2542
4	-2.1200	2.9029	-6.9283
5	-2.7300	3.6295	-8.7565
6	-1.2920	4.3337	-8.1239
7	-1.1340	5.0519	-9.0293
8	-2.0640	5.7820	-11.2420
9	-0.5620	6.4855	-10.5325
10	3.4360	7.1617	-6.8239
11	3.6580	7.8792	-7.6524
12	3.6240	8.5995	-8.7885
13	4.1660	9.3135	-9.2325
14	3.3000	10.0429	-11.3683
15	3.0100	10.7660	-12.8120
16	4.1280	11.4737	-12.5639
17	4.4780	12.1898	-13.2386
18	4.5080	12.9094	-14.2978

Table 5.4: Normalized individual principal components

Run no.	nor pcs1	nor pcs2	nor pcs3
1	0.7899	0.5519	0.3678
2	0.9161	0.1107	0.4193
3	1.0000	0.4730	1.0000
4	0.6980	0.0346	0.4407
5	0.4421	0.0000	0.0963
6	0.6828	0.0773	0.5139
7	0.0666	0.9405	0.2398
8	0.1280	0.3819	0.0139
9	0.1244	0.5237	0.0000
10	0.7635	0.7731	0.6240
11	0.7714	0.3915	0.3681
12	0.9962	0.2119	0.8725
13	0.3154	0.9392	0.2280
14	0.5717	0.0381	0.1755
15	0.4589	0.1408	0.2274
16	0.0691	1.0000	0.2295
17	0.0000	0.9139	0.0284
18	0.0924	0.6823	0.0716

Table 5.5: GRC values

Run no.	gr1	gr2	gr3
1	0.7041	0.5274	0.4416
2	0.8563	0.3599	0.4627
3	1.0000	0.4868	1.0000
4	0.6234	0.3412	0.4720
5	0.4726	0.3333	0.3562
6	0.6118	0.3514	0.5070
7	0.3488	0.8936	0.3968
8	0.3644	0.4472	0.3364
9	0.3634	0.5121	0.3333
10	0.6789	0.6879	0.5707
11	0.6862	0.4511	0.4417
12	0.9925	0.3882	0.7968
13	0.4220	0.8915	0.3931
14	0.5386	0.3420	0.3775
15	0.4802	0.3679	0.3929
16	0.3494	1.0000	0.3935
17	0.3333	0.8531	0.3397
18	0.3552	0.6114	0.3500

calculate the normalized MRR, TWR, SR, which are presented in Table 5.6. On the normalized S/N ratios, PCSs named (Z_{il}) are obtained using Equation C.2 in PCA, which are shown in Table 5.7. The eigenvalues and the corresponding eigenvectors obtained from the above method are given in Table 5.8. By using these values, the output MPIs are evaluated from Equation C.3 as shown in Table 5.16. For the i^{th} trial, the three different MPI values are calculated from the principal components, that are

1. $MPI3_i$ = MPI value considering all the three principal components.

2. $MPI2_i$ = MPI value considering first two principal components.

3. $MPI1_i$ = MPI value considering first principal component only.

Three MPI values are used to find optimality of the process with HTB category.

5.3.3 PCA-Based PQLR Method

The S/N ratios can be transformed into PQLR that represents the average proportion of quality loss reduction from an initial or any arbitrary process setting to a new

Table 5.6: Normalised S/N ratios

Run no.	nor SN MRR	nor SN TWR	nor SN SR
1	0.3863	0.7307	1.0000
2	0.2883	1.0000	0.7817
3	0.0000	0.6850	0.7817
4	0.4099	0.8425	0.3235
5	0.7048	0.7826	0.1313
6	0.3890	0.7826	0.2767
7	0.8731	0.0188	0.2111
8	0.9279	0.3947	0.0000
9	0.9361	0.3377	0.1313
10	0.2972	0.5133	0.9461
11	0.3968	0.7826	0.8253
12	0.0540	0.8425	0.6451
13	0.7290	0.2304	0.6451
14	0.5947	0.8425	0.3235
15	0.6412	0.6850	0.1803
16	0.8761	0.0000	0.2767
17	1.0000	0.0594	0.2432
18	0.9263	0.2160	0.1603

Table 5.7: Calculated PCs

Run no.	PC1	PC2	PC3
1	0.6937	0.2052	-1.0779
2	0.7851	-0.1399	-1.0298
3	0.7976	0.0786	-0.6628
4	0.3730	-0.3559	-0.8472
5	0.0474	-0.4491	-0.9611
6	0.3283	-0.3476	-0.7828
7	-0.4341	0.1437	-0.7738
8	-0.3783	-0.2698	-0.8955
9	-0.3436	-0.1361	-0.9339
10	0.6028	0.3183	-0.8853
11	0.6207	0.0442	-1.0324
12	0.7750	-0.1288	-0.7164
13	0.0088	0.3044	-0.9533
14	0.2548	-0.3546	-0.9893
15	0.0614	-0.3463	-0.8889
16	-0.4107	0.2037	-0.7965
17	-0.4757	0.1391	-0.9044
18	-0.3880	-0.0302	-0.8830

Table 5.8: Eigen analysis for PCA based WPC

PC	Eigen value	Proportion of variation explained	Eigen vector
PC1	2.2653	0.755	[-0.640, 0.546, 0.542]
PC2	0.6106	0.204	[0.007,-0.700, 0.714]
PC3	0.1242	0.041	[-0.769,-0.461,-0.444]

setting. The computed PPI in this method is known as Weighted Score (WS) which is calculated by the steps described in Appendix D.

In this method, S/N ratios are transformed into PQLR using Equation D.1 and the values are shown in Table 5.9. These values are normalized by using Equation D.2 as shown in Table 5.10. On the normalized PQLR values, conduct PCA to get PCSs named (Z_{il}) using Equation D.3, which are shown in Table 5.12. The eigenvalues and the corresponding eigenvectors obtained from the PCA are given in Table 5.11. By using these eigenvalues, output WSs are shown in Table 5.16, which are evaluated from Equation D.4.

The optimality of WS setting is LTB type and the three different WS values for the i^{th} trial, that are calculated from the principal components, are

1. $WS3_i$ = WS value considering all the three principal components.
2. $WS2_i$ = WS value considering first two principal components.
3. $WS1_i$ = WS value considering first principal component only.

The multi-response optimisation has been performed and discussed in Section 5.4.4.

5.4 Results and discussions

5.4.1 Influence on MRR

During the process of EDM, the effects of various machining parameters like Ip, T_{on}, T_{up}, Fp on MRR are shown in Fig. 5.2. This figure indicates that Ip is significant to MRR because an increase in pulse current produces stronger spark, which in turn produces the higher temperature, causing more material to melt and erode from the work-piece. MRR initially increased with increase in T_{on} from 100 to 300 μs. Further

Table 5.9: PQLR values

Run no.	PQLR MRR	PQLR TWR	PQLR SR
1	169.2183	4.0000	1.0000
2	383.9610	1.0000	1.7170
3	4278.2594	5.0625	1.7170
4	138.9285	2.2500	5.3378
5	11.7986	3.0625	8.5911
6	165.4891	3.0625	5.9941
7	2.8895	156.2492	7.0500
8	1.8278	22.5624	11.8908
9	1.7055	30.2498	8.5911
10	356.3802	12.2499	1.1427
11	155.0123	3.0625	1.5410
12	2722.7251	2.2500	2.4079
13	9.6365	52.5622	2.4079
14	29.6405	2.2500	5.3378
15	20.0939	5.0625	7.6101
16	2.8189	172.1335	5.9941
17	1.0000	126.8005	6.5114
18	1.8525	56.6283	7.9954

Table 5.10: Normalised PQLR values

Run no.	nor pqlr MRR	nor pqlr TWR	nor pqlr SR
1	0.0393	0.0175	0.0000
2	0.0895	0.0000	0.0658
3	1.0000	0.0237	0.0658
4	0.0322	0.0073	0.3983
5	0.0025	0.0121	0.6970
6	0.0385	0.0121	0.4586
7	0.0004	0.9072	0.5555
8	0.0002	0.1260	1.0000
9	0.0002	0.1709	0.6970
10	0.0831	0.0657	0.0131
11	0.0360	0.0121	0.0497
12	0.6363	0.0073	0.1293
13	0.0020	0.3013	0.1293
14	0.0067	0.0073	0.3983
15	0.0045	0.0237	0.6069
16	0.0004	1.0000	0.4586
17	0.0000	0.7351	0.5061
18	0.0002	0.3251	0.6423

Table 5.11: Eigen analysis for PCA based PQLR

PC	Eigen value	Proportion of variation explained	Eigen vector
PC1	1.6279	0.543	[-0.619, 0.501, 0.615]
PC2	0.7894	0.263	[-0.379,-0.865,0.330]
PC3	0.5827	0.194	[0.697,-0.032, 0.716]

Table 5.12: PCs values

Run no.	z1	z2	z3
1	-0.0152	-0.0301	0.0269
2	-0.0140	-0.0122	0.1095
3	-0.5566	-0.3778	0.7434
4	0.2290	0.1129	0.3074
5	0.4332	0.2186	0.5004
6	0.2646	0.1263	0.3548
7	0.7959	-0.6016	0.3690
8	0.6780	0.2209	0.7121
9	0.5142	0.0821	0.4937
10	-0.0096	-0.0840	0.0652
11	0.0147	-0.0077	0.0603
12	-0.3044	-0.2048	0.5358
13	0.2292	-0.2187	0.0843
14	0.2445	0.1226	0.2896
15	0.3824	0.1781	0.4369
16	0.7828	-0.7138	0.2966
17	0.6795	-0.4689	0.3388
18	0.5578	-0.0693	0.4496

increase in T_{on} resulted in decrease in MRR. It can be said that with increasing spark energy (higher Ip and T_{on}), increases material removal rate. As the T_{on} increases, the total energy supply to the work-piece is more, so more material is eroded from work-piece. MRR usually decreases with T_{up} because, with increase in T_{up}, the tool temperature decreases considerably. MRR increased with increase in Fp due to the fact that flushing of the spark gap keeps the gap clean and removes spark eroded particles from the gap. Table 5.13 clearly indicates that Ip is the only significant factors at 95% confidence level for MRR where as T_{on}, T_{up}, Fp are not significant in influencing MRR.

Residual plots are important accompaniment to the model calculations. The residual plots of MRR are shown in below. This is useful to determine whether the model meets the assumptions of the analysis. The normal probability plot is a graphical technique for evaluating whether a data set is approximately normally distributed. The standardised residuals are plotted on a normal probability plot to check the departure of the data from normality (Fig. 5.3). It can be seen that the residuals are almost falling with in the confidence interval, which indicates that the residues are normally distributed. The histogram plot of standardised residue for all the observations shows the symmetry of the residues (Fig. 5.4). It is in the form of Gaussian distribution (bell shape), and the residues are distributed with mean zero but here it is approximately in bell shape. In addition, the plot of the residues versus run order illustrates that there is no noticeable pattern or unusual structure present in the data (Fig. 5.5). The residues which lie in the range of -2 to 2 are scattered randomly about zero. The fitted values to offer a visual check on the model assumptions which indicate the variance is constant and a nonlinear relationship exists as well as no outliers exist in the data (Fig. 5.6).

5.4.2 Influence on TWR

Influence of EDM process variables on TWR is shown in Fig. 5.7 which indicates that Ip is directly proportional to TWR. At higher T_{on}, more energy is released between IEG resulting in dissociation of dielectric fluid, thus carbon particles are released. These particles get deposited on the copper tool surface forming a protective layer,

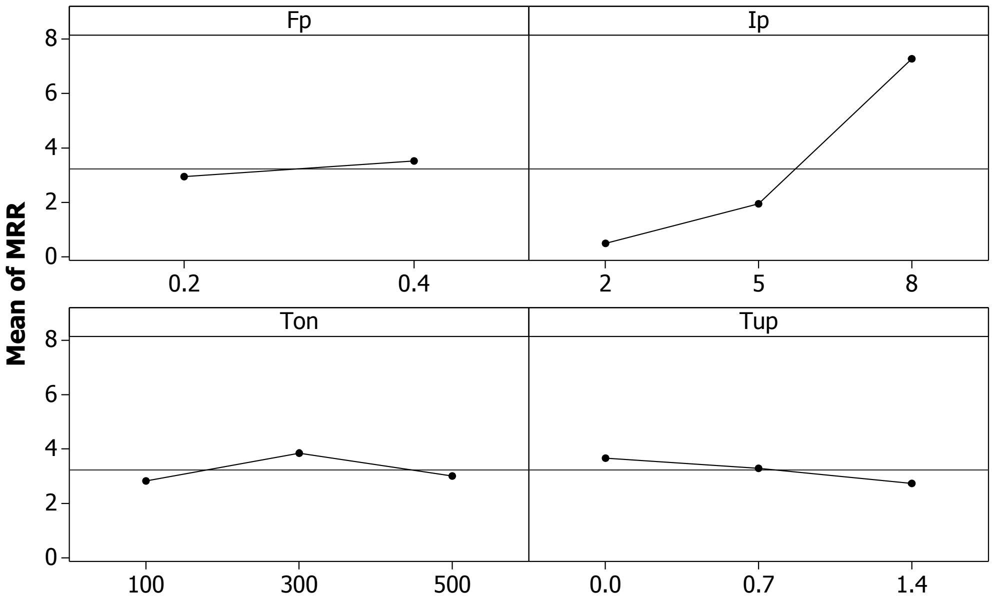


Fig. 5.2: Main effect plot for MRR

Table 5.13: ANOVA for MRR

Source	DF	Seq SS	Adj MS	F	P
Fp	1	1.467	1.4666	1.69	0.222*
Ip	2	153.044	76.5218	88.40	0.000
Ton	2	3.587	1.7937	2.07	0.177*
Tup	2	2.631	1.3157	1.52	0.265*
Residual Error	10	8.657	0.8657		
Total	17	169.386			

* = insignificant at 95%

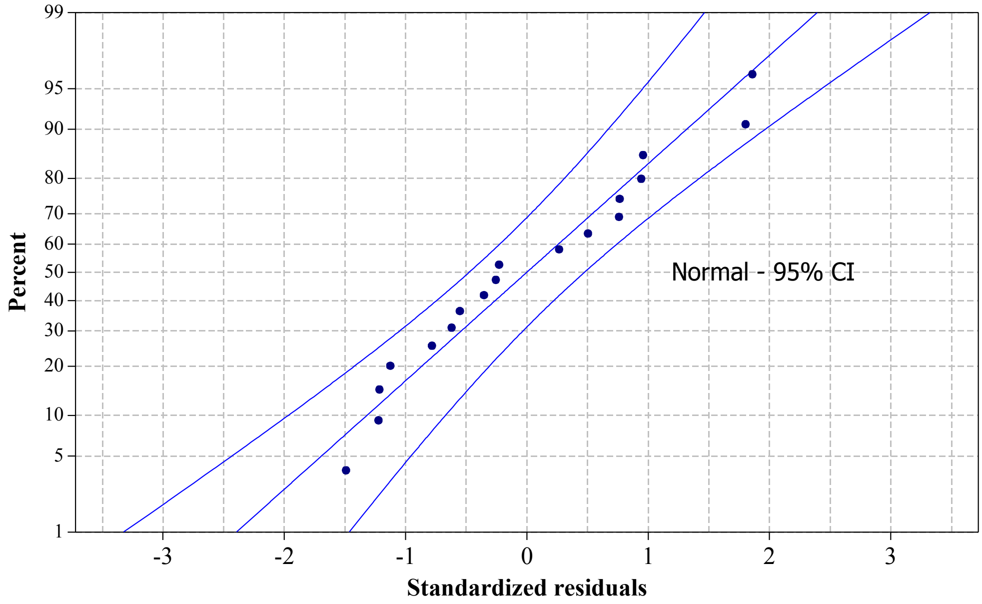


Fig. 5.3: Normal probability plot

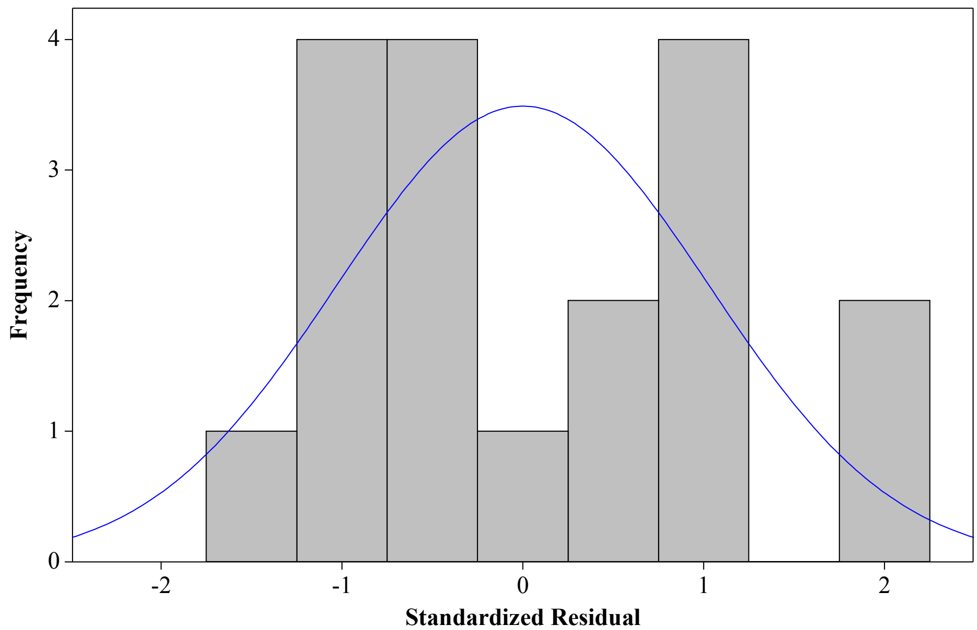


Fig. 5.4: Histogram plot

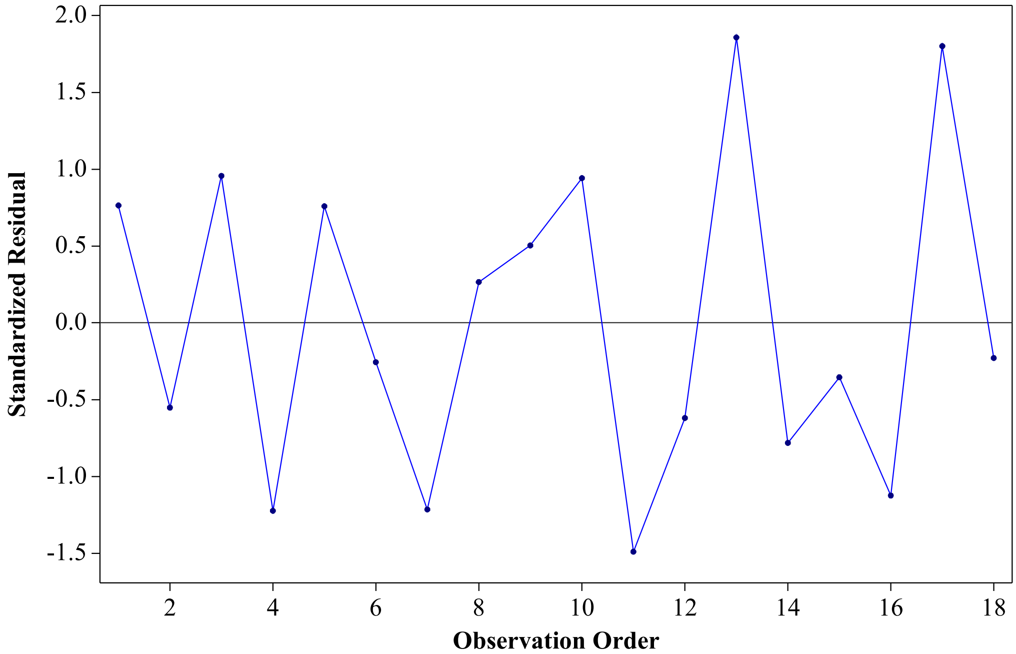


Fig. 5.5: Run order plot

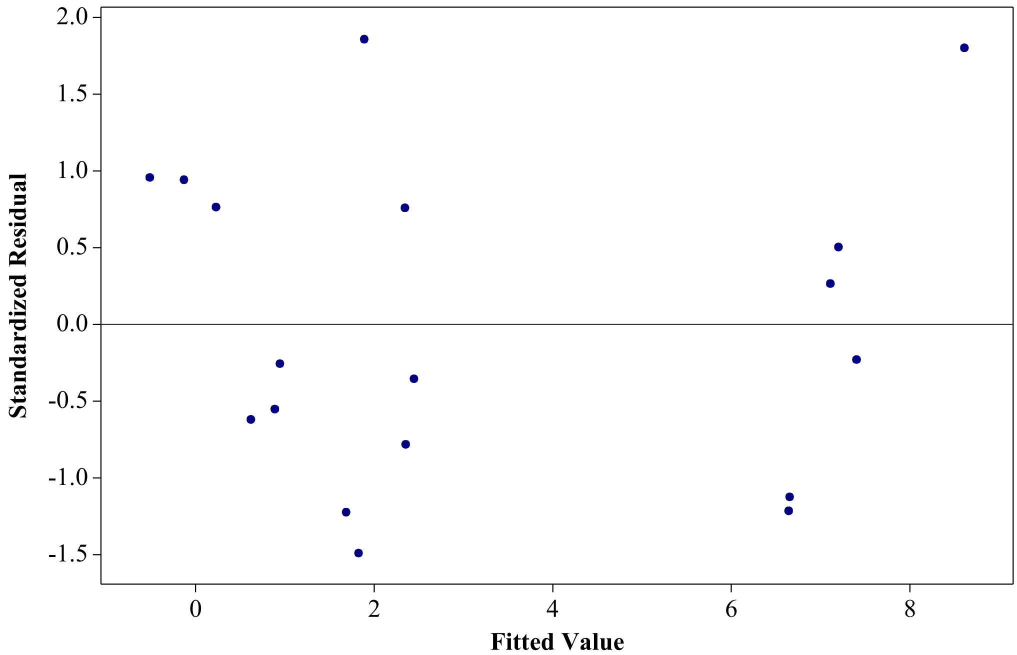


Fig. 5.6: Fit value plot

which is basically a thick carbon layer that reduces TWR. TWR increases with T_{up} from 0.0s to 0.7s and then decreased. In addition, TWR increased with increase in Fp because increased flushing of the debris of the work-piece reduced the possibility of carbon formation on tool affecting the TWR. From Table 5.14, it is observed that Ip and T_{on} are the significant factors at 95% confidence level for TWR, where as T_{up} and Fp are not important in influencing TWR.

The residual plot of TWR in the graph and the interpretation of each residual plot shows that; Normal probability plot indicate outliers dont exist in the data, because standardized residues are between -2 and 2 (Fig. 5.8). Histogram shows the data are not skewed and not outline exist (Fig. 5.9). Residual versus order of the data indicate that systematic effects in the data due to time of data collection order (Fig. 5.10). Residuals versus fitted values indicate the variation is constant (Fig. 5.11).

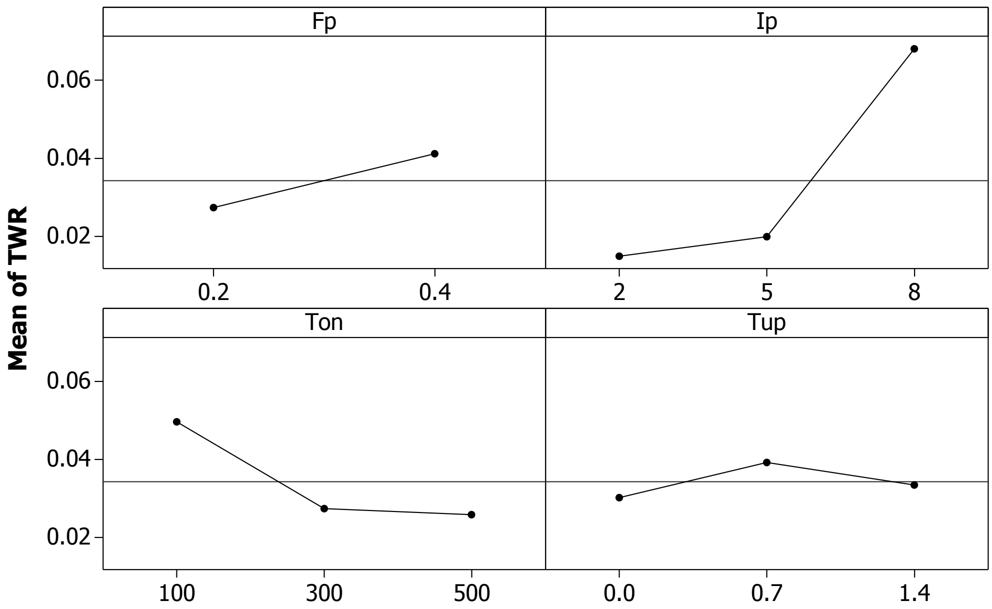


Fig. 5.7: Main effect plot for TWR

5.4.3 Influence on SR

Influence of EDM process variables on SR is shown in Fig. 5.12, SR increased with increases the Ip because of generation of more heat energy in the work-piece tool interface that led to increased melting and evaporation of the electrode. SR also increased with increases the T_{on} and it decreases, it almost remains constant. Since

Table 5.14: ANOVA for TWR

Source	DF	Seq SS	Adj MS	F	P
Fp	1	0.000861	0.000861	4.06	0.072*
Ip	2	0.010333	0.005167	24.36	0.000
Ton	2	0.002126	0.001063	5.01	0.031
Tup	2	0.000252	0.000126	0.59	0.570*
Residual Error	10	0.002121	0.000212		
Total	17	0.015693			

* = insignificant at 95%

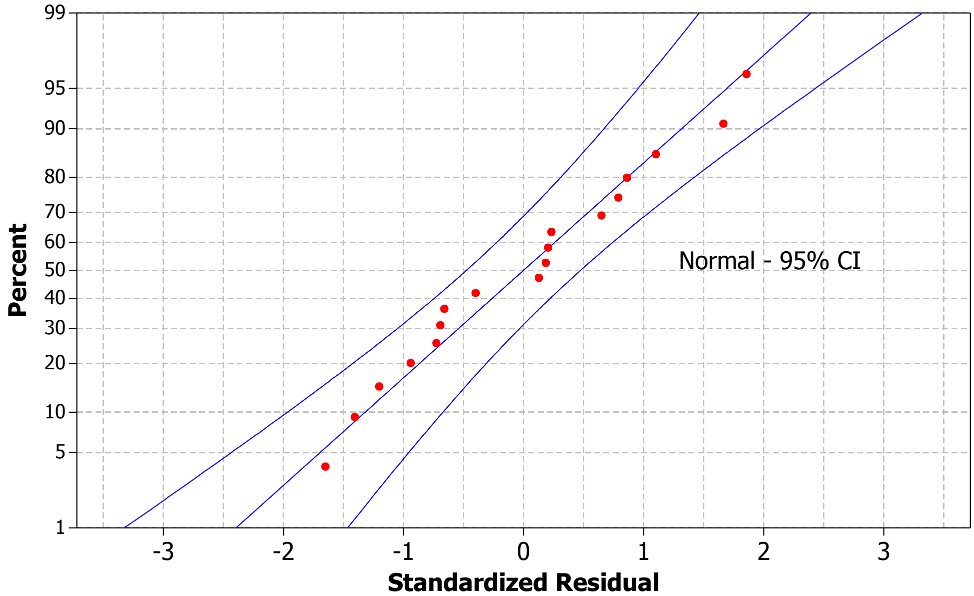


Fig. 5.8: Normal probability plot

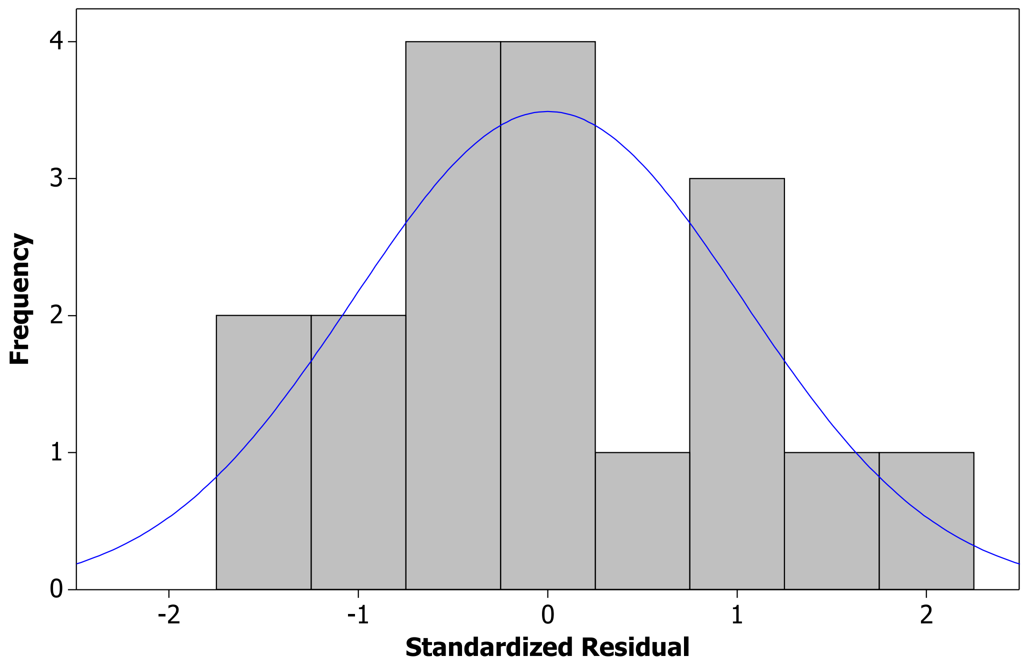


Fig. 5.9: Histogram plot

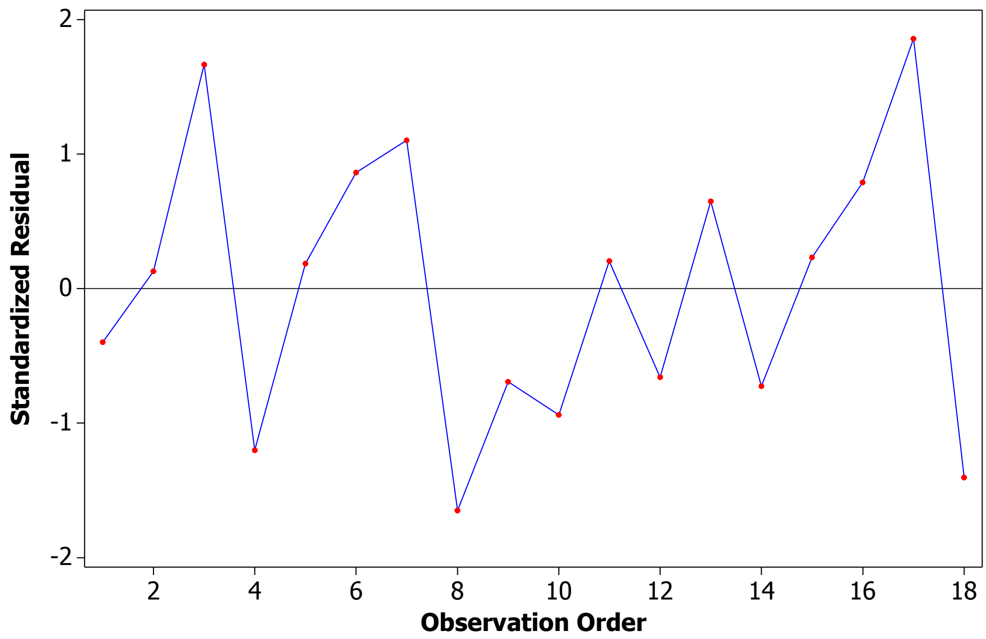


Fig. 5.10: Run order plot

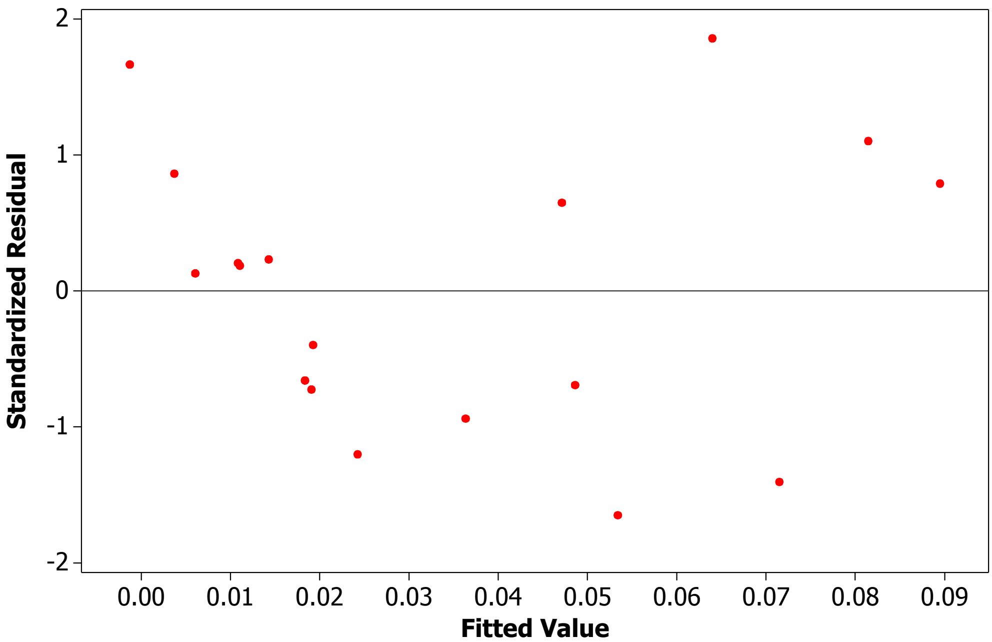


Fig. 5.11: Fit value plot

SR having LTB characteristics, affecting lower Ip and T_{on} values would lead to better surface finish. SR increases with T_{up}. From Table 5.15, it is observed that Ip and T_{on} are the most significant factors at 95% confidence level for SR followed by T_{up}, Fp which are not significant in influencing SR.

The residual plot for SR in the graph for normal probability plot indicates that, the data are normally distributed and variables are influencing the response (Fig. 5.13). Histogram proved the data are neither skewed and nor outline (Fig. 5.14). Residual versus order of the data indicates that there are systematic effects in the data due to time or data collection order (Fig. 5.15). Residuals versus fitted value indicate the variation is constant (Fig. 5.16).

5.4.4 Influence on PPI

The computed PPI values corresponding to various trials for the PCA-based GRA method, known as OQPI, are given in Table 5.16. From this table, the main effect plots for $OQPI3$, $OQPI2$ and $OQPI1$ are drawn and are shown in Fig. 5.17. Larger values of OQPI's signify better quality and the optimal levels (bold faced) of the control factors of the three OQPI's are tabulated in Table 5.17. It is evident that the

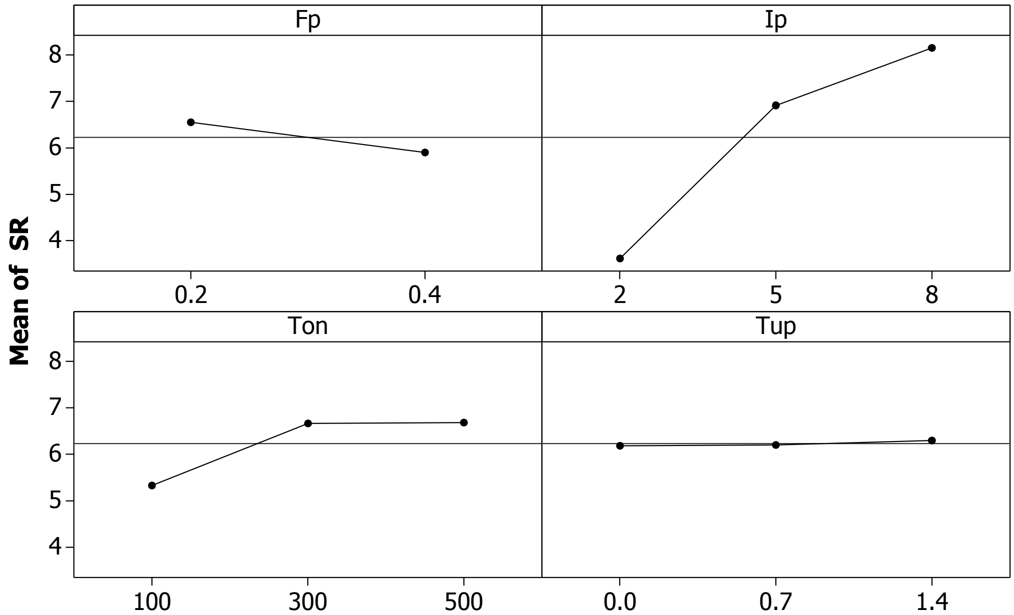


Fig. 5.12: Main effect plot for SR

Table 5.15: ANOVA for SR

Source	DF	Seq SS	Adj MS	F	P
Fp	1	1.9339	1.9339	2.58	0.140*
Ip	2	65.9244	32.9622	43.90	0.000
Ton	2	7.2011	3.6006	4.80	0.035
Tup	2	0.0478	0.0239	0.03	0.969*
Residual Error	10	7.5089	0.7509		
Total	17	82.6161			

* = insignificant at 95%

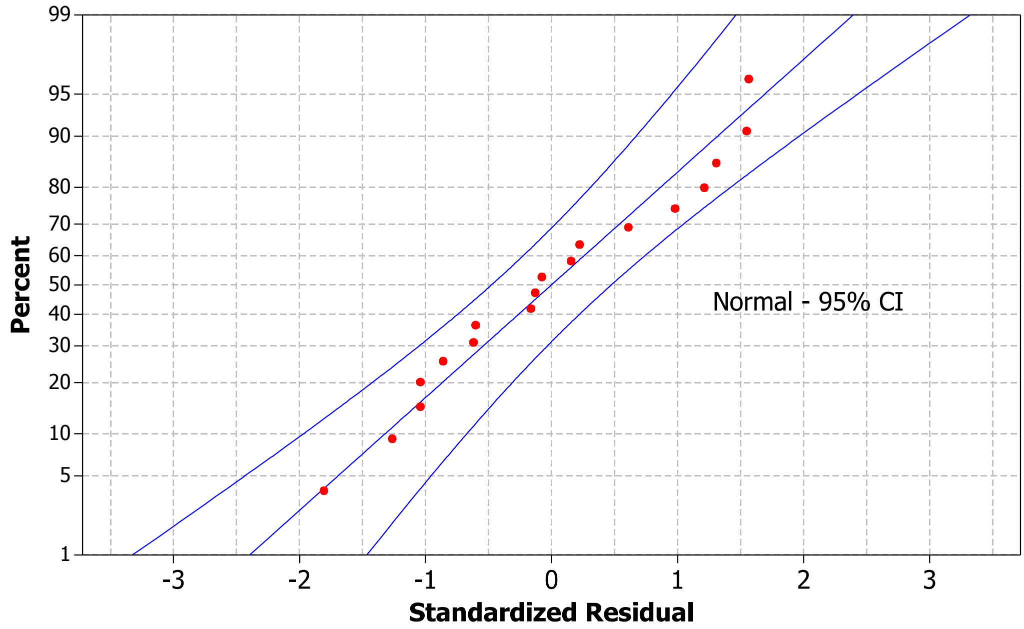


Fig. 5.13: Normal probability plot

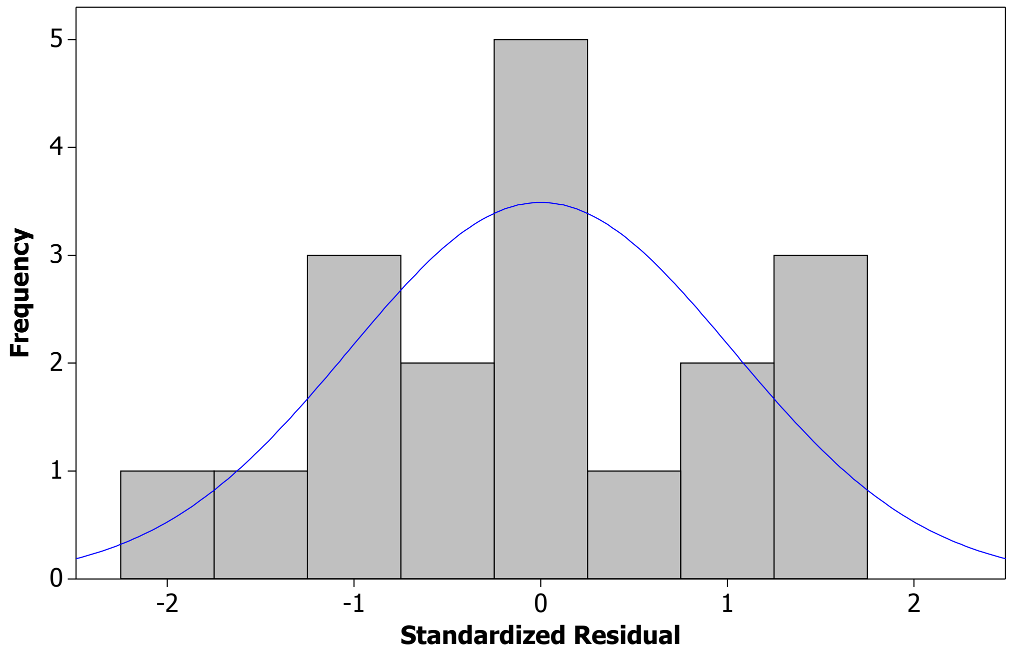


Fig. 5.14: Histogram plot

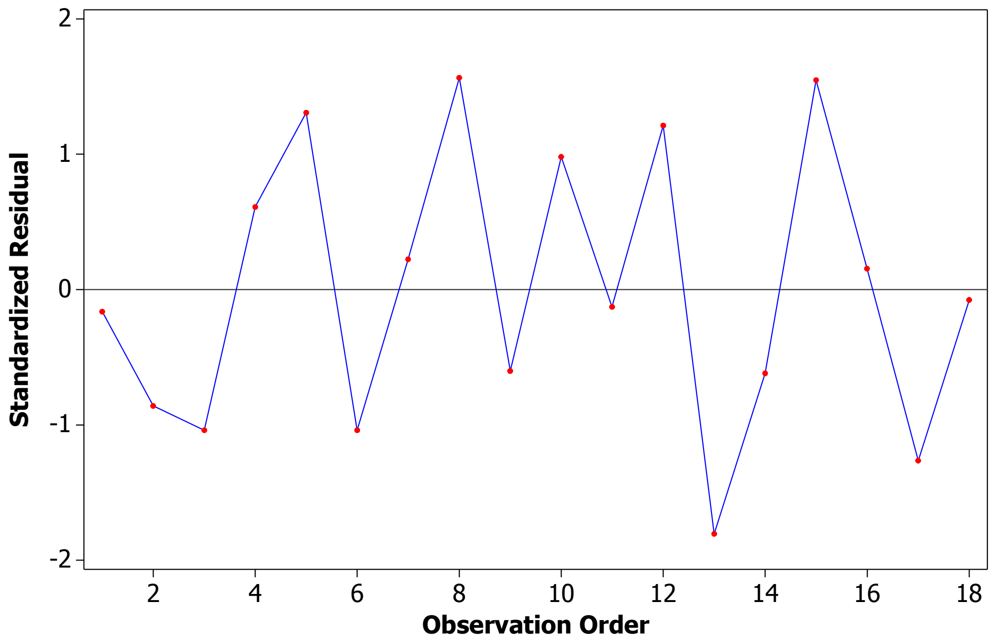


Fig. 5.15: Run order plot

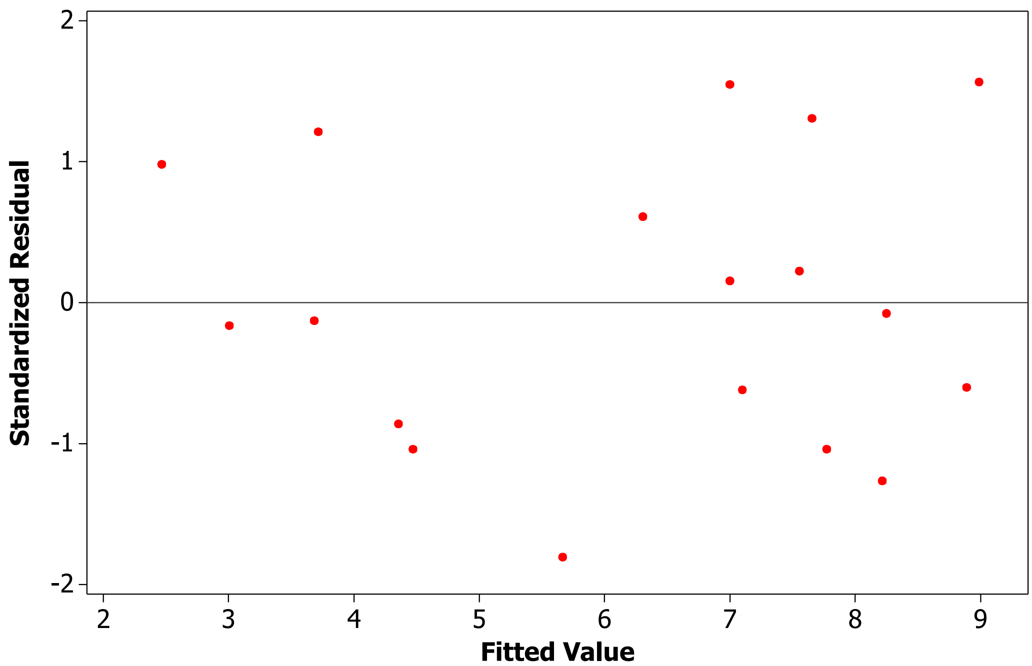


Fig. 5.16: Fit value plot

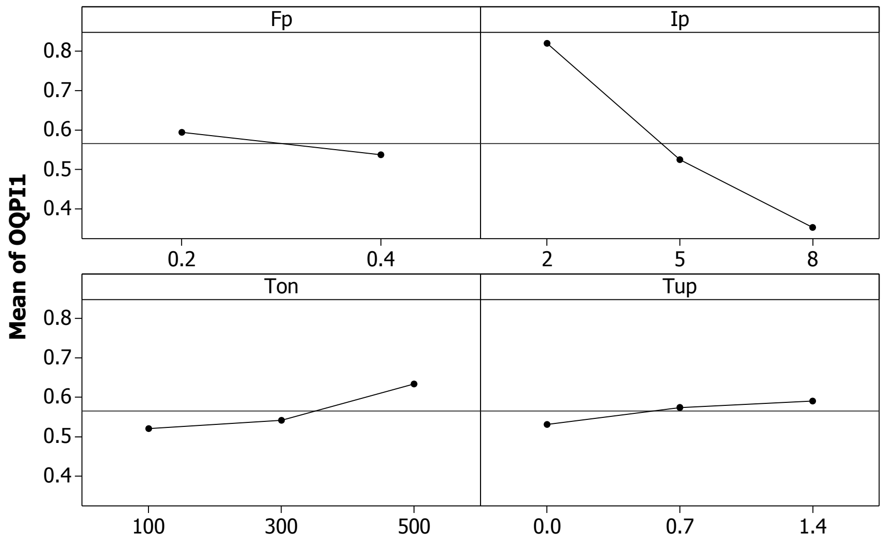
optimal parameter settings for all the three OQPI's are found to be $Ip1$, $Ton3$, $Tup3$ and $Fp1$. So, it can be concluded that reduction of principal components doesnt affect optimality.

Table 5.16: PPI values

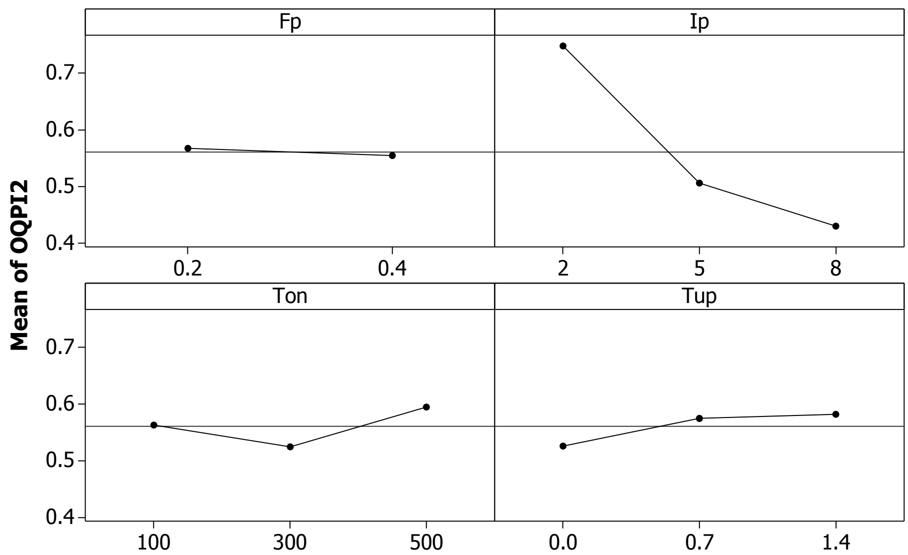
Run	OQPI			MPI			WS		
	OQPI3	OQPI2	OQPI1	MPI3	MPI2	MPI1	WS3	WS2	WS1
1	0.6573	0.6659	0.7041	0.5214	0.5895	0.6937	0.0214	0.0200	0.0152
2	0.7389	0.7502	0.8563	0.5220	0.5882	0.7851	0.0321	0.0134	0.0140
3	0.8953	0.8902	1.0000	0.5911	0.6444	0.7976	0.5458	0.4978	0.5566
4	0.5596	0.5630	0.6234	0.1743	0.2181	0.3730	0.2137	0.1909	0.2290
5	0.4394	0.4426	0.4726	-0.0953	-0.0579	0.0474	0.3898	0.3628	0.4332
6	0.5544	0.5560	0.6118	0.1449	0.1847	0.3283	0.2457	0.2193	0.2646
7	0.4619	0.4640	0.3488	-0.3301	-0.3112	-0.4341	0.6620	0.7317	0.7959
8	0.3801	0.3816	0.3644	-0.3774	-0.3549	-0.3783	0.5644	0.5283	0.6780
9	0.3925	0.3946	0.3634	-0.3255	-0.2992	-0.3436	0.3966	0.3728	0.5142
10	0.6763	0.6801	0.6789	0.4838	0.5419	0.6028	0.0400	0.0339	0.0096
11	0.6282	0.6357	0.6862	0.4353	0.4979	0.6207	0.0217	0.0124	0.0147
12	0.8612	0.8634	0.9925	0.5295	0.5826	0.7750	0.3231	0.2716	0.3044
13	0.5166	0.5212	0.4220	0.0297	0.0715	0.0088	0.1984	0.2256	0.2292
14	0.4919	0.4964	0.5386	0.0794	0.1253	0.2548	0.2212	0.2045	0.2445
15	0.4537	0.4559	0.4802	-0.0608	-0.0251	0.0614	0.3393	0.3154	0.3824
16	0.4839	0.4870	0.3494	-0.3012	-0.2801	-0.4107	0.6703	0.7595	0.7828
17	0.4396	0.4432	0.3333	-0.3679	-0.3449	-0.4757	0.5580	0.6102	0.6795
18	0.4072	0.4092	0.3552	-0.3353	-0.3118	-0.3880	0.4083	0.3980	0.5578

Similarly, for MPI's and WS's values are also shown in Table 5.16. The main effects for MPI's and WS's are drawn and the desired optimal levels (bold faced) of the control factors are shown in Table 5.17. Larger values of MPI's signify better quality, whereas it is smaller the better for WS's. All the three graphs for MPI's and WS's are having similar nature and the optimal settings are the same as are shown in Fig. 5.18 and Fig. 5.19. Consequently, the optimal conditions with respect to $MPI3$, $MPI2$, and $MPI1$ values are found to be $Ip1$, $Ton3$, $Tup3$ and $Fp1$. And, the optimal conditions are $Ip1$, $Ton2$, $Tup1$ and $Fp2$ for all the three WS's. So, similar conclusions can be drawn that reduction of principal components doesnt effect optimality.

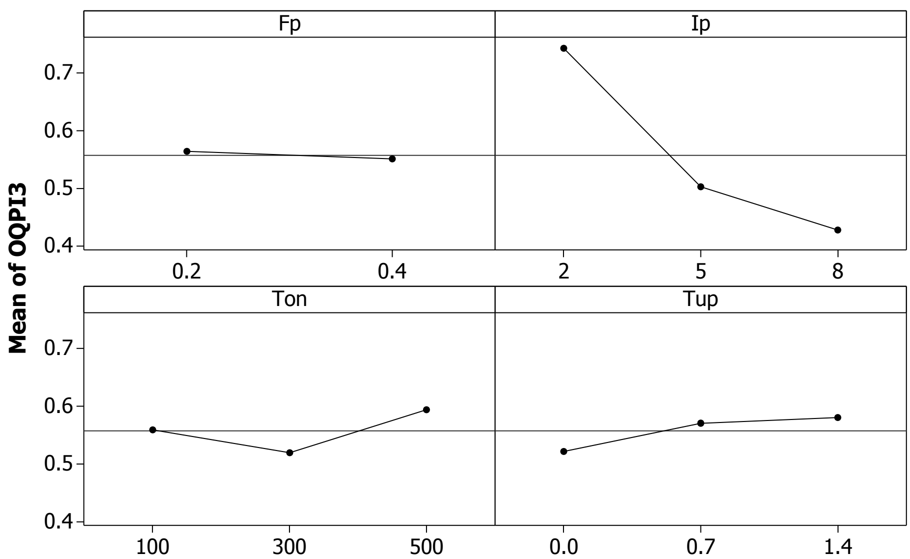
One natural interest is to determine how well the performances of the optimal solutions are with respect to the expected total S/N ratio values. The S/N ratios



(a) OQPI1

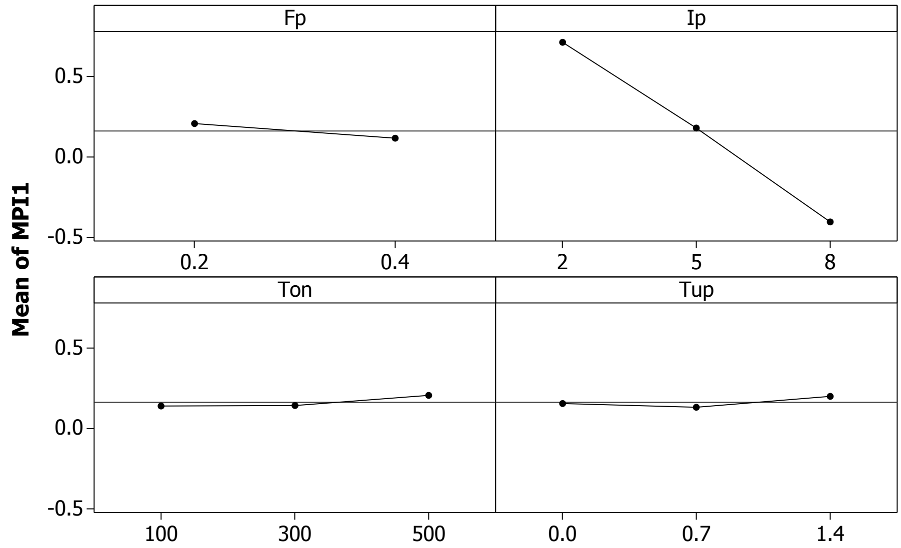


(b) OQPI2

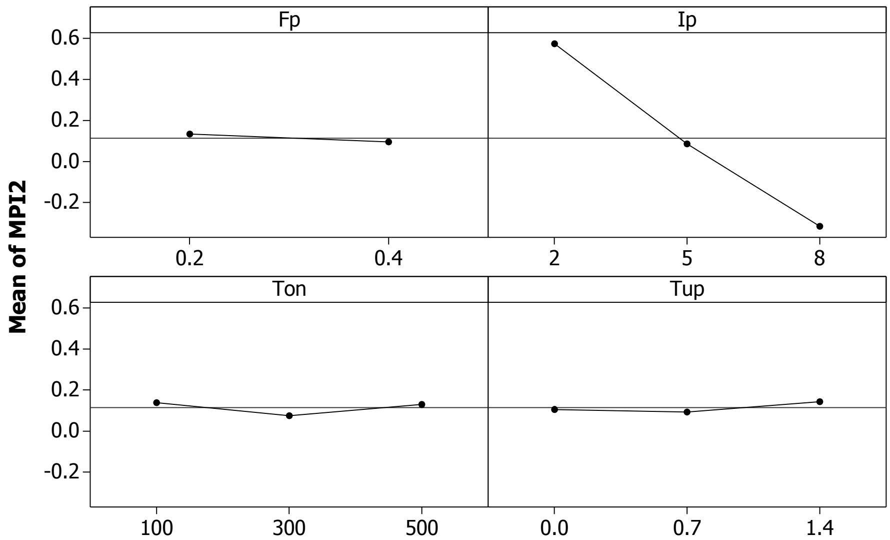


(c) OQPI3

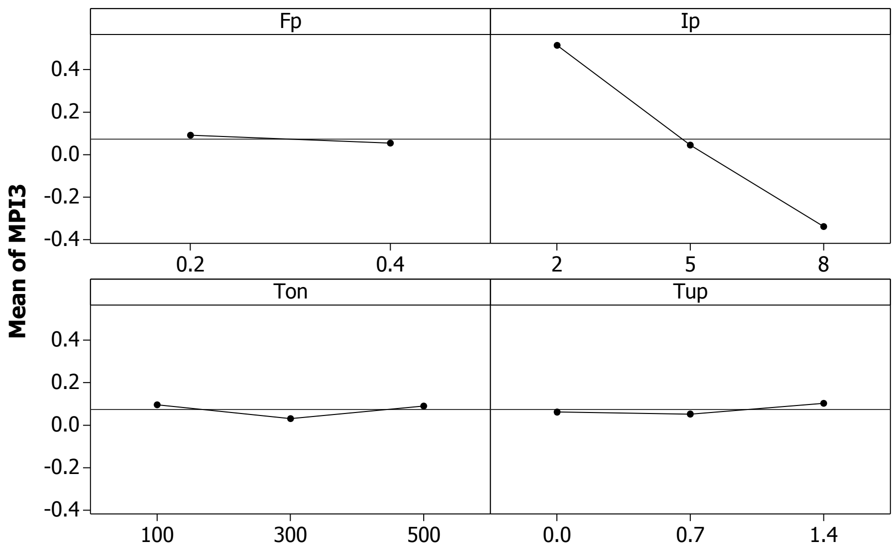
Fig. 5.17: Main effect plots for OQPI's



(a) MPI1

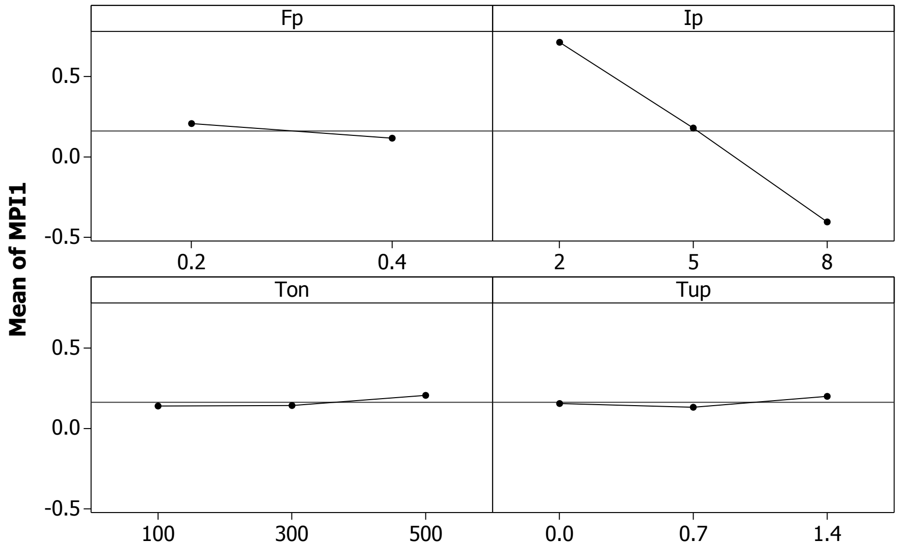


(b) MPI2

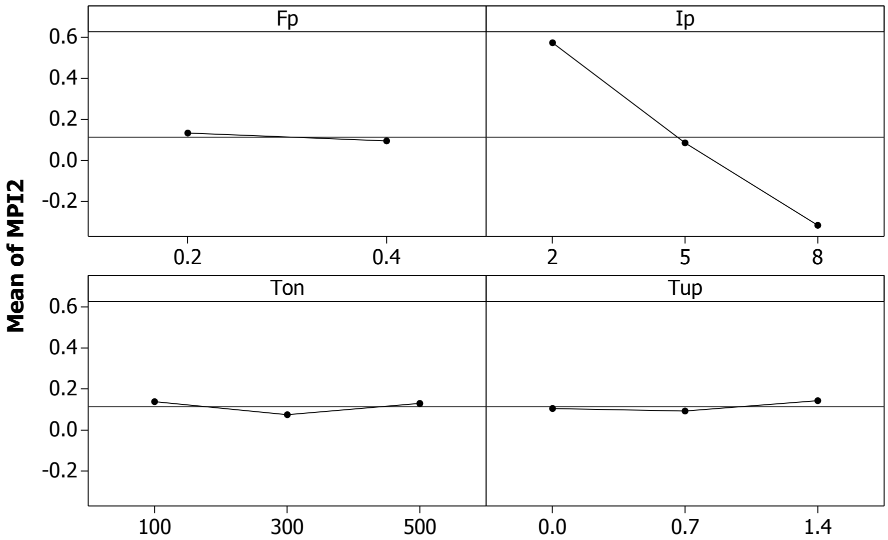


(c) MPI3

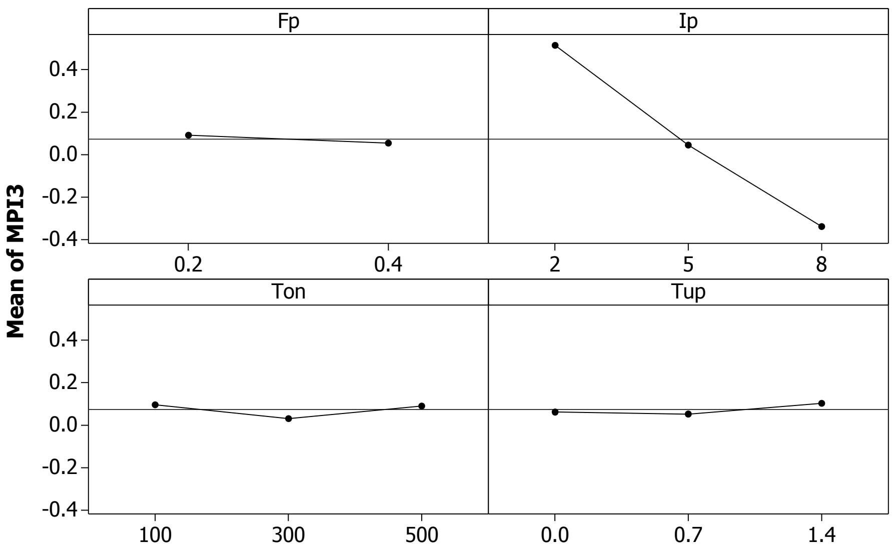
Fig. 5.18: Main effect plots for MPI's



(a) WS1



(b) WS2



(c) WS3

Fig. 5.19: Main effect plots for WS's

Table 5.17: Mean values of PPI

Factors	Levels	OQPI3	OQPI2	OQPI1	MPI3	MPI2	MPI1	WS3	WS2	WS1
	1	**0.743**	**0.748**	**0.820**	**0.514**	**0.574**	**0.713**	**0.164**	**0.142**	**0.152**
Ip	2	0.503	0.506	0.525	0.045	0.086	0.179	0.268	0.253	0.297
	3	0.428	0.430	0.352	-0.340	-0.317	-0.405	0.543	0.567	0.668
	1	0.559	0.564	0.521	0.096	0.138	0.139	0.301	0.327	0.344
T_{on}	2	0.520	0.525	0.542	0.033	0.076	0.142	**0.298**	**0.289**	**0.343**
	3	**0.594**	**0.595**	**0.634**	**0.091**	**0.129**	**0.205**	0.377	0.346	0.430
	1	0.522	0.526	0.532	0.063	0.106	0.155	**0.258**	**0.254**	**0.306**
T_{up}	2	0.571	0.575	0.575	0.053	0.094	0.132	0.336	0.334	0.389
	3	**0.580**	**0.582**	**0.591**	**0.103**	**0.144**	**0.199**	0.381	0.374	0.423
	1	**0.564**	**0.568**	**0.594**	**0.092**	**0.134**	**0.208**	0.341	0.326	0.389
Fp	2	0.551	0.555	0.537	0.055	0.095	0.117	**0.309**	**0.315**	**0.356**

of the individual responses under each optimal condition are displayed in Table 5.18 while applying different PCA-based approaches. From this table, it was concluded that PCA-based PQLR method has the highest value of total S/N ratio comparing with another two methods. So, results show that the optimal condition obtained using the PCA-based PQLR method leads to the best optimality.

Table 5.18: Optimal parameter setting

Optimization Method (PCA based)	Optimal condition	Predicted S/N ratio			Total S/N ratio
		MRR	TWR	SR	
GRA method	*Ip1 Ton3 Tup3 Fp1*	-16.43	35.48	-11.59	7.45
WPC method	*Ip1 Ton3 Tup3 Fp1*	-16.43	35.48	-11.59	7.45
PQLR method	*Ip1 Ton2 Tup1 Fp2*	-2.03	37.67	-11.13	**24.52**

5.5 Conclusions

Following conclusions are drawn from the PCA-based multi-objective optimisation of EDM performance measures.

1. The reduction of principal components doesn't affect the optimality.

2. It is observed that the optimal process condition for OQPI and MPI is $Ip1$, $Ton3$, $Tup3$ and $Fp1$.

3. The optimal process condition for WS has been found to be $Ip1$, $Ton2$, $Tup1$ and $Fp2$.

4. PCA-based PQLR method yield better optimisation and can be an effective approach for optimisation of multiple correlated responses.

Chapter VI

Conclusion

6. CONCLUSION

This research work was focused on assessing the Electro Discharge Machining (EDM) behaviour of AISI P20 tool steel as work-piece and copper as electrodes. The experiments were analysed against the variation of some of the most important EDM parameters namely, current (Ip), pulse on-time (T_{on}), lift time (T_{up}), flushing pressure (Fp), work time (T_w), Inter Electrode Gap (IEG) that influence the process performance. The measured technological outputs were Material Removal Rate (MRR), Tool Wear Rate (TWR), Surface Roughness (SR), micro-hardness. The most important conclusions of the work are summarised below:

6.1 Most important conclusions

6.1.1 Taguchi analysis for Micro hardness

- Micro-hardness value increased with increase in Ip and decreased with increase in T_{on}.
- The optimal condition was found to be $Fp1$, $Ip1$, $T_{on}3$, $T_{up}3$.

6.1.2 Fuzzy TOPSIS modelling for MRR, TWR and SR

- It was observed that the optimal process condition for higher MRR and lower TWR and SR is Ip= 8A, Ton= 500μs, Tup= 0s, Tw= 1s and IEG= 90μm.
- A sensitivity analysis was carried out to determine the influence of criteria weights on the decision making process. The optimal parameter values were having 55.56 % votes.
- It was observed that 97.22% optimal Ip, 88.88% optimal Ton, 100% optimal Tup, 66.67% optimal Tw, 100% optimal IEG were robust against the variation of Decision Maker (DM)s preferences.

6.1.3 PCA-based modelling for MRR, TWR and SR

- The reduction of principal components doesn't affect the optimality.

- It was observed that the optimal process condition for Overall Quality Performance Index (OQPI) and Multi-response Performance Index (MPI) was $Ip1$, $Ton3$, $Tup3$ and $Fp1$.

- The optimal process condition for Weighted Score (WS) is $Ip1$, $Ton2$, $Tup1$ and $Fp2$.

- Principal Component Analysis (PCA)-based Proportion of Quality Loss Reduction (PQLR) method yielded better optimisation and can be an effective approach for optimisation of multiple correlated responses.

6.2 Scope for future work

- The influence of type of steel (hardenable steels and non-hardenable steels) on EDM surface integrity (roughness, micro-hardness, residual stress distribution, White Layer Thickness (WLT) and Surface Crack Density (SCD)) can be studied.

- Finite element method (FEM) model can be attempted for WLT, SCD, MRR and TWR.

- Using different type of electrode materials, the multi objective optimisation can be performed of all these responses.

APPENDIX

A. EQUIPMENTS USED

Table A.1: Technical Specifications of electro discharge machine

Machine Tool	PS50 ZNC
Work tank internal dimensions (W x D x H)	800 x500 x 350 mm
Work table dimensions	550 x 350 mm
Transverse(X,Y,Z)	300, 200, 250 mm
Maximum job weight	300 kg
Maximum electrode weight	100 kg
Maximum job height above the table	250 mm
Feed motor / servo system for Z axis	DC Servo
Position measuring system (X, Y, Z)	Incremental linear scale
Dielectric system	Integral with the machine tool
Dielectric capacity	400 Litres
Filter element	10 μ paper cartridge 2 nos.
Pulse Generator	S 50 ZNC
Pulse generator type	MOSFET
Current range, Ip	0-50 A
Pulse on time range Ton	0.5-4000 μs
Duty factor range, Tau	50-93%
open circuit voltage, V	40-60 v
Power supply	3 phase, AC 415 V*, 50 Hz
Connected load	6KVA includes PF unit

Table A.2: Chemical composition of AISI P20 (wt %)

C	Mn	Si	Cr	Mo	Cu	P	S
0.28-0.40	0.60-1.00	0.20-0.80	1.40-2.00	0.30-0.55	0.25	0.03	0.03

Machine and Equipment

This machine was used to machine on the AISI P20 tool steel for conducting the experiments

Fig. A.1: Die Sinker EDM, Brand : Electronica Elektra Plus; Model : PS 50ZNC

Table A.3: Mechanical properties of workpiece material

Temperature T(°C)	Density (kg/m^3)	Poison's ratio ν	modulus of elasticity E (GPA)
25	7.85	0.27-0.30	190-210

Weighing machine

Precision balance was used to measure the weigh of the workpiece and tool.

Fig. A.2: Electronic Balance
Brand:SHINKO DENSHI Co. LTD, JAPAN, Model: DJ 300S
Capacity: 300 gram
Accuracy: 0.001 gram

Surface Roughness Analyser

Surface roughness of the EDMed component was measured using this machine.

Fig. A.3: Talysurf Surface Roughness Analyser
Brand : Taylor Hobson, Model : Surtronic 3^+

Micro Hardness Tester

Fig. A.4: Vickers microhardness tester
Range: 20 Vickers to 1500 Vickers, Total Magnification: 400x, Indenter: diamond pyramid with an angle of 136 (°C)

B. PCA BASED GRA

Step 1: Calculate the Signal-to-Noise (S/N) ratio (η_{ij}) for the j^{th} response variable and i^{th} trial, where ($i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, p$).

Step 2: To obtain uncorrelated Principal Component Scores (PCS)s, conduct PCA on the S/N ratios, by subjecting η_{ij} to PCA. The PCS value of l^{th} component ($l = 1, 2, \ldots, p$) corresponding to i^{th} trial, PCS_{il} can be obtained as follows:

$$PCS_{il} = a_{l1}\eta_{i1} + a_{l2}\eta_{i2} + \ldots + a_{lp}\eta_{ip} \tag{B.1}$$

where $a_{l1}^2 + a_{l2}^2 + \ldots + a_{lp}^2 = 1$. The coefficients of the l^{th} component, i.e., $a_{l1}, a_{l2}, \ldots a_{lp}$ are the elements of the eigenvector corresponding to the l^{th} eigenvalue of the correlation matrix of the response variables. The performing PCA is available in statistical software MINITAB.

Step 3: Since a larger PCS is always desired, normalized the PCS for l^{th} principal component in i^{th} trial (X_{il}) can be obtained as follows:

$$X_{il} = \frac{PCS_{il} - PCS_l^{min}}{PCS_l^{max} - PCS_l^{min}} \tag{B.2}$$

where, PCS_l^{min}
$= min(PCS_{1l}, PCS_{2l}, \ldots PCS_{ml})$
and PCS_l^{max}
$= max(PCS_{1l}, PCS_{2l}, \ldots PCS_{ml})$.

Step 4: Based on normalised PCS, calculate the Grey Relational Coefficient (GRC) of l^{th} component. Normalized PCS in i^{th} trial γ_{il} is computed as follows:

$$\gamma_{il} = \frac{\Delta_l^{min} + \zeta\Delta_l^{max}}{\Delta_{il} + \zeta\Delta_l^{max}} \tag{B.3}$$

where, $\Delta_{il} = \mid 1 - X_{il} \mid$,

$\Delta_l^{min} = min(\Delta_{1l}, \Delta_{2l}, \ldots \Delta_{ml})$,

$\Delta_l^{max} = max(\Delta_{1l}, \Delta_{2l}, \ldots \Delta_{ml})$,

ζ is the distinguishing coefficient, which has been set to 0.5.

Step 5: Calculate the OQPI's values for i^{th} trial can be obtained using the following expression:

$$OQPI3_i = 0.755\gamma_{i1} + 0.204\gamma_{i2} + 0.041\gamma_{i3} \tag{B.4}$$

$$OQPI2_i = [0.755\gamma_{i1} + 0.204\gamma_{i2}]\frac{1}{0.755+0.204} \tag{B.5}$$

$$OQPI1_i = \gamma_{i1} \tag{B.6}$$

The weights for each γ_{il} are the proportion of variance explained by l^{th} principal component, which are given in Table 5.8.

C. PCA BASED WPC

Step 1: Calculate the S/N ratio, η_{ij} for the j^{th} response variable in the i^{th} trial.

Step 2: Calculate the normalized S/N ratio value for the j^{th} response variable in the i^{th} trial (Y_{ij}) can be obtained by Equation C.1.

$$Y_{ij} = \frac{\eta_{ij} - \eta_j^{min}}{\eta_j^{max} - \eta_j^{min}} \tag{C.1}$$

where, $\eta_j^{min} = min(\eta_{1j}, \eta_{2j}, \ldots \eta_{mj})$,
$\eta_j^{max} = max(\eta_{1j}, \eta_{2j}, \ldots \eta_{mj})$.

Step 3: To obtain uncorrelated principal components perform PCA on the normalized S/N ratios of the response variables. The value of l^{th} principal component corresponding to the i^{th} trial (Z_{il}) can be obtained by using Equation C.2.

$$Z_{il} = a_{l1}Y_{i1} + a_{l2}Y_{i2} + \ldots + a_{lp}Y_{ip} \tag{C.2}$$

Step 4: Calculate the MPI for each trial. The MPI for the i^{th} trial MPI_i is computed as follows:

$$MPI3_i = \quad 0.755Z_{i1} + 0.204Z_{i2} + 0.041Z_{i3} \tag{C.3}$$

$$MPI2_i = \quad [0.755Z_{i1} + 0.204Z_{i2}]\frac{1}{0.755+0.204} \tag{C.4}$$

$$MPI1_i = \quad Z_{i1} \tag{C.5}$$

The weights for each Z_{il} are the proportion of variance explained by l^{th} principal component, which are given in Table 5.8.

D. PCA BASED PQLR

Step 1: Corresponding to each trial, calculate the S/N ratio of each response variable

Step 2: For each response variable, calculate the main effect (in terms of S/N ratio) of each control factor.

Step 3: For each response variable, estimate the expected S/N ratio at the starting condition (or any arbitrary condition).

Step 4: Corresponding to each trial using Equation D.1, transform the computed S/N ratio of each response variable into PQLR value.

$$PQLR = \frac{L^{'}}{L} = 10^{-(\eta^{'} - \eta_0)}/10 \tag{D.1}$$

Where, η_0 represents the S/N ratio of the response for the stating condition and their quality loss is L. $\eta^{'}$ is S/N ratio for an existing a new process condition and their quality loss $L^{'}$.

Step 5: Normalize the PQLR value for the j^{th} response variable in the i^{th} trial (Y_{ij}) can be obtained by using Equation D.2.

$$Y_{ij} = \frac{PQLR_{ij} - PQLR_j^{min}}{PQLR_j^{max} - PQLR_j^{min}} \tag{D.2}$$

where,

$PQLR_j^{min} = min(PQLR_{1j}, PQLR_{2j}, \ldots PQLR_{mj})$,

$PQLR_j^{max} = max(PQLR_{1j}, PQLR_{2j}, \ldots PQLR_{mj})$.

Step 6: Perform PCA on the normalized PQLR values and obtain the values of the principal components (Z_{il}) by using Equation D.3.

$$Z_{il} = a_{l1}Y_{i1} + a_{l2}Y_{i2} + \ldots + a_{lp}Y_{ip} \tag{D.3}$$

Step 7: Take the absolute value of Z_{il} and then compute the WS for each trial as follows:

$$\begin{aligned} WS3_i = \quad & 0.543 \mid Z_{i1} \mid +0.263 \mid Z_{i2} \mid \\ & +0.194 \mid Z_{i3} \mid \end{aligned} \tag{D.4}$$

$$\begin{aligned} WS2_i = \quad & [0.543 \mid Z_{i1} \mid +0.263 \mid Z_{i2} \mid] \\ & \tfrac{1}{0.543+0.263} \end{aligned} \tag{D.5}$$

$$WS1_i = \quad \mid Z_{i1} \mid \tag{D.6}$$

The weights for each $\mid Z_{il} \mid$ are the proportion of variance explained by l^{th} principal component, which are given in Table 5.11.

E. DESIGN OF EXPERIMENTS

Much of our knowledge about products and processes in the engineering and scientific disciplines is derived from experimentation. An experiment is a series of tests conducted in a systematic manner to increase the understanding of an existing process or to explore a new product or process. Design of Experiments (DOE), is a tool to develop an experimentation strategy that maximizes learning using a minimum of resources. DOE is extensively used by engineers and scientists concerned in the improvement of manufacturing processes to maximize yield and reduce unpredictability. Quite often engineers works on products or processes where no scientific theory or principles are directly applicable. In such circumstances, to develop new products and processes in a cost-effective and confident manner experimental design techniques become extremely important to explain the statistical significance of an effect that a particular factor exerts on the dependent variable of interest. However, in case of industrial goal, it is usually to extract the maximum amount of unbiased information about the factors which affecting a production process from as few observations as possible. In general, experiments are extensively used to study the performance of processes and systems.

DOE helps in:

- Identifying relationships between cause and effect.
- Providing an understanding of interactions among causative factors.
- Determining the levels at which to set the controllable factors (product dimension, alternative material, alternative designs, etc.) in order to optimize reliability.
- Minimizing experimental error (noise).

- Improving the robustness of the design or process to variation.

Typical application of DOE

Experimental design is a critically important tool in the engineering tool in the engineering world for improving the performance of a manufacturing process. It also has extensive application in the development of new processes.

The application of experimental design techniques early in the process development can be result in

- Improve process yield
- Reduced variability and closer conformance to nominal or target requirement
- Reduced development time
- Reduced overall costs

Experimental design methods also play a major role in engineering design activities, where new products are developed and existing ones improved. Some applications of experimental design in engineering design include:

- Evaluation and comparison of basic design configurations
- Evaluation of material alternatives
- Selection of design parameters so that the product will work well under a wide variety of field condition, that is robust
- Determination of key product design parameters that can impact product performance

Why DOE?

With the advance of modern technology, products and processes are becoming extremely complicated. Since the expense of experimentation climbing quickly, it is becoming difficult for the analyst, who is already constrained by resources and time, to investigate the various factors that are affecting these complex processes by trial and error methods. Thus analyst will be interested for a technique which will identify "vital few" factors in most efficient manner then directs the process to its best setting to meet the growing demand for enhanced quality and better productivity. To achieve these objectives, DOE technique provides a powerful and efficient method. Designed experiments are much more efficient than that of one-factor-at-a-time experiments, which involve changing a single factor at a time to study the effect of the factor on the response. When the effect that a factor has on the response is changed due to the presence of one or more other factors, that relationship is called an 'interaction'. Sometimes the interaction effects are more significant than the individual factor effect. This is due to the fact that the application environment of the response comprises the presence of many of the factors together instead of isolated occurrences of single factors at different times.

Procedures of Experimental Design

The outline of procedures to use statistical methods in designing and analysing an experiment, as given below

- Problem Statement or Definition.
- Selection of Response Variable.
- Choice of Factors, Levels, and Ranges.
- Selection of Experimental Design.
- Conduction of the Experiment.
- Analysis and Interpretation of the Data.

  Statistical methods are involved in data analysis and interpretation to obtain objective conclusions from the experiment. There are many software packages designed to assist in data analysis, such as STATISTICA, MINITAB, DESIGN EXPERT, etc.

Conclusions and Recommendations.

After data analysis, the experimenter usually conducts a confirmation experiment to verify the reproducibility of the optimum recommendation. If the result is not established or is unsatisfactory, additional experimentation may be requisite. Based on the results of the confirmation experiment and the previous analysis, the experimenter can develop sound conclusions and recommendations. The entire process is actually a learning process, where hypotheses about a problem are tentatively formulated, experiments are conducted to investigate these hypotheses, and new hypotheses are then formulated based on the experimental results. By continuous improvement, this iterative process moves us closer to the "truth" as we learn more about the system at each stage.

Types of DOE techniques

The most prevalent experimental approaches are Factorial design, Taguchi's design, and Response Surface Methodology (RSM). The first Design of Experiments (DOE) technique are used 'Factorial' or 'Classical DOE', which allows to differentiate which factors are most significant and helps in identifying important interactions among the factors. The main objective of Taguchi's design is to find a 'robust' response that is insensitive to factor variations and noise. RSM consists of an experimental approach for exploring the settings of input parameter and to develop a quadratic model suitably approximating relationship between the response and the input parameters. Subsequently, optimising the levels or values of the input variables that produce desirable response value.

E.1 Taguchi method

Dr. Genichi Taguchi, a Japanese management consultant developed an efficient methodology to optimize only a single performance characteristic and is widely being applied now-a-days for continuous improvement. It produced better quality products at a low cost (Ross, 1988). In this method is the "robust" parameter design, the main aim is to find factor settings that minimize response deviation, while adjusting (or keeping) the process on target. After you determine which factors affect deviation, that are find to settings for controllable factors that will either reduce the deviation, make the product insensitive to changes in (noise) factors, or both (Minitab16, 2011).

Taguchis concepts are as follows: 1. Quality should be designed into the product and not inspected into it. 2. Quality is best achieved by minimizing the deviation from the target. It is immune to uncontrollable environmental factors. 3. The cost of quality should be measured as a function of deviation from the standard and the losses should be measured system-wide.

According to Taguchi, Quality characteristics are of three types as shown below.

1. Nominal-is-the-Best (NTB) or Target-the-Best (TTB) 2. Lower-the-Better (LTB) 3. Higher-the-Better (HTB)

E.2 Response Surface Methodology (RSM)

RSM is a collection of mathematical and statistical techniques that are useful for modelling and analysis of problems in which output or response is influenced by several variables and the goal is to find the correlation between the response and the variables (Montgomery, 2001).

E.2.1 Procedure of RSM

RSM is sequential in nature and at the outset, screening experiments are conducted to reduce the list of contestant variables to a comparatively few. The techniques for the analysis of the second-order model are presented by Myers and Montgomery (1995). The steps shown below are typical of a response surface experiment. Depending on the experiment, one may carry out some of the steps in a different order, perform a given step more than once, or eliminate a step.

- Choose the response for an experimental investigation. Determine what the influencing factors are, that is, what the process conditions are those influence the values of the response variable.

- Create the response surface experiment design according to a central composite design.

- Set the factor levels and replicate the design.
- Randomize the design to change the order of the runs.
- Perform the experiment and collect the response data.
- Analyse the response surface design to fit a model to the experimental data.
- Optimize the response to obtain a numerical and graphical analysis.

Analysis of Variance (ANOVA)

Experimental factors will influence the response and so will be due to unknown causes or measurement errors in experiments, there exists some variability. Every experimental data set is most likely to shown certain variability, but wheather such change is due to inputs factors or dur to random factors is to be answered by ANOVA. The method tries to carry out the following.

- Decomposes the deviation of the experimental data in relation to possible sources; the source may be from the main effect, from the interaction, or may be from experimental error.
- Measures the magnitude of variation due to all sources.
- Recognize the main and interactions effects which have significant effects on variation of data.

Sum of Squares (SS)

The distance between any point in a set of data and the mean of the data is the deviation. Sum of Squares is the sum of all such squared deviations. SS_{Total} is the total variation in the data. $SS_{Regression}$ is the portion of the variation explained by the model, while SS_{Error} is the portion not explained by the model and is attributed to error. The calculations are:

$$SS_{Total} = \sum_{i}^{n}\sum_{j}^{r}(y_{ij} - \bar{y}_{..})^2 \tag{E.1}$$

$$SS_{Error} = \sum_{i}^{n}\sum_{j}^{r}(y_{ij} - \hat{y}_i)^2 \tag{E.2}$$

$$SS_{Regression} = SS_{Total} - SS_{Error} \tag{E.3}$$

where $y_{ij} = i^{th}$ observed response of j^{th} replicate, $\hat{y}_i = i^{th}$ fitted response, and $\bar{y}_{..} =$ mean of all $(n \times r)$ obeservations.

The sum of squares for r set of replicates are calculated and added together to create the pure error sum of squares (SS_{PE}). Sum of square error SS_{Error} is the sum of pure error sum of squares SS_{PE} and sum of squares lack of fit SS_{LOF}.

$$SS_{PE} = \sum_{i}^{n}[\sum_{j}^{r}(y_{ij} - \bar{y}_{i.})^2] \tag{E.4}$$

$$SS_{LOF} = SS_E - SS_{PE} \tag{E.5}$$

where $\bar{y}_{i.} =$ mean of r replicates of i^{th} observed response.

Degree of Freedom

It depicts the number of independent variables needed to calculate the sum of squares the response data. The degrees of freedom for each component of the model are:

$$\begin{aligned} DF_{Regression} &= t - 1 \\ DF_{Error} &= n - t \\ DF_{Total} &= n - 1 \\ DF_A &= a - 1 \\ DF_B &= b - 1 \\ DF_{AB} &= (a-1)(b-1) \\ DF_{PE} &= n - m \end{aligned} \tag{E.6}$$

where n = number of observations, t = number of terms in the model, a, b = number of levels of factors A and B, respectively. DOF of pure error DF_{PE} is n - m, where n = number of observations and m = the number of distinct x-values.

Mean Square

In an ANOVA, the term Mean Square refers to an estimate of the population variance based on the variability among a given set of measures. The calculation for the mean square for the model terms is:

$$MS_{Term} = \frac{AdjSS_{Term}}{DF_{Term}} \tag{E.7}$$

F-value: F-value is the measurement of distance between individual distributions. More the F-value, less is the P-value. F is a test to determine whether the interaction and main effects are significant. The formula for the model terms is:

$$F = \frac{MS_{Term}}{MS_{Error}} \tag{E.8}$$

Larger values of F support rejecting the null hypothesis that there is not a significant effect

P-value: P-value is used in hypothesis tests helps to decide whether to reject or fail to reject a null hypothesis. The p-value is the probability of obtaining a test statistic that is at least as extreme as the actual calculated value, if the null hypothesis is true. A commonly used cut-off value for the p-value is 0.10.

Model Adequacy Check

The adequacy of the underlying model can be checked from ANOVA as follows: It is always necessary to examine the fitted model to ensure that it provides an adequate approximation to the true system.

R^2 (R-sq): Coefficient of determination; indicates how much variation in the response is explained by the model. The higher the R^2, the better the model fits your data. The formula is:

$$R^2 = 1 - \frac{SS_{Error}}{SS_{Total}} \tag{E.9}$$

Another presentation of the formula is:

$$R^2 = \frac{SS_{Regression}}{SS_{total}} \tag{E.10}$$

Adjusted R^2 (R-sq adj): Adjusted R^2 accounts for the number of factors in your model. The formula is:

$$R^2 = 1 - \frac{MS_{(Error)}}{SS_{Total}/DF_{Total}} \tag{E.11}$$

Lack-of-fit test: This test checks the straight line fit of the model. To calculate the pure error lack-of-fit test:

1. Calculate the pure error mean square:

$$MS_{PE} = \frac{SS_{PE}}{DF_{PE}}$$

2. Calculate the lack-of-fit mean square:

$$MS_{LOF} = \frac{SS_{LOF}}{DF_{SSE} - DF_{PE}}$$

3. Calculate the F-statistic = MS_{LOF}/MS_{PE} and corresponding p-value.

   Large F-values and small p-values suggest that the model is inadequate.

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