Non-conventional Machining of Metal Matrix Composites: Parametric Appraisal and Multi-Objective Optimization

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By

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Certificate of Approval

This is to certify that the thesis entitled **NON-CONVENTIONAL MACHINING OF METAL MATRIX COMPOSITES: PARAMETRIC APPRAISAL AND MULTI-OBJECTIVE OPTIMIZATION** submitted by ***Ms. Amruta Rout*** has been carried out under my supervision in partial fulfillment of the requirements for the Degree of ***Master of Technology*** in ***Production Engineering*** at **National Institute of Technology**, **NIT Rourkela**, and this work has not been submitted elsewhere before for any other academic degree/diploma.

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Abstract

Al, SiCp MMCs have wide range of applications in aerospace, automotive and electronics engineering due to its excellent properties compared to other conventional materials. Conventional machining process shows difficulties in machining of these advanced materials due to several reasons like high tool wear, poor surface roughness, high machining cost etc. Therefore, different researchers have utilized several advanced machining methods like electro discharge machining, electrochemical machining, ultrasonic machining etc. for effective machining of these composites. In this present work, ECM and EDM have been selected for machining of MMCs towards obtaining high product quality and satisfactory process performance yield. It is utmost important that several process parameters of ECM and EDM need to be precisely controlled as well as optimized. Taguchi method is generally used only for optimizing single response. As these processes are involved with multiple response characteristics; exploration of an appropriate multi-objective optimization technique is indeed essential. Therefore, this thesis work represents case study on selection of optimal machining parameters in ECM of Al/15%SiC composites using Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) integrated with Taguchi method and further utilizing another hybrid method Grey-Fuzzy Logic coupled with Taguchi's optimization philosophy. The performance characteristics: Material Removal Rate (MRR) and surface roughness have been considered for optimizing the machining parameters (feed rate, voltage and electrolytic concentration). Experimental results have been validated to illustrate the effectiveness of this approach. Similarly, for obtaining the optimal parameter setting of EDM of Al/10%SiC composites, another hybrid optimization technique utilizing Principal Component Analysis (PCA) and TOPSIS combined with Taguchi method has been proposed to take care of correlation between various response features (performance parameters) of EDM. Further another advanced optimization technique Multi-objective Optimization by Ratio Analysis (MOORA) with Taguchi method has been employed for evaluating the optimal setting of process parameters of EDM. The response characteristics: Material Removal Rate (MRR), tool wear rate, surface roughness and overcut has been considered for optimizing process parameters: voltage, pulse on current, pulse on time and duty cycle.

Key words: *metal matrix composites, electro discharge machining, electrochemical machining, Taguchi method, Grey-Fuzzy approach, PCA, TOPSIS method, MOORA.*

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B Chapter 1: Introduction

A composite material comprises of two or more chemically and/or physically apparent phases. Composite materials, also termed as composition materials or known as composites, are naturally or engineered appearing materials produced from two or more composing materials with considerably different chemical or physical properties which persist distinct and separate within the finished structure. The constituent elements, mainly comprises of a reinforcing elements, fillers, and a composite matrix binder which differ in composition or form on a macro-scale. The constituent elements preserve their own characters means they do not merge or dissolve completely into one another although they act in concert. Normally, the constituents exhibit an interface between one another and can be physically identified [1-2].

Composites which are of heterogeneous structures accommodate the necessities of specific function and design, infused with ambitious properties which limit the scope for classification. However, this blunder is made up for, by the reality new varieties of composites are being invented, each with their own specific characteristics and purpose like the particulate, flake, laminar and filled composites. Particles or fibers entrenched in matrix of another material are the most suitable example of modern-day composite materials, which are mostly structural.

The present study deals with machining and machinability aspects of Metal Matrix Composites (MMCs) (Hybrid Composites) emphasizing parametric appraisal and multi-objective optimization in relation to machining performance features. The following sections accumulate basic knowledge on MMCs.

1. METAL MATRIX COMPOSITES

A **metal matrix composite** (**MMC**) is composite material with at least two constituent parts, one being a metal. The other material may be a different metal or another material, such as a ceramic or organic compound. When at least three materials are present, it is called a **hybrid composite**. An MMC is complementary to a cermet.

1.1 Composition

MMCs are made by dispersing a reinforcing material into a metal matrix. The reinforcement surface can be coated to prevent a chemical reaction with the matrix. For example, carbon fibers are commonly used in aluminum matrix to synthesize composites showing low density and high strength. However, carbon reacts with aluminum to generate a brittle and water-soluble compound Al_4C_3 on the surface of the fiber. To prevent this reaction, the carbon fibers are coated with nickel or titanium boride.

1.2 Matrix

The matrix is the monolithic material into which the reinforcement is embedded, and is completely continuous. This means that there is a path through the matrix to any point in the material, unlike two materials sandwiched together. In structural applications, the matrix is usually a lighter metal such as aluminum, magnesium, or titanium, and provides a compliant support for the reinforcement. In high temperature applications, cobalt and cobalt-nickel alloy matrices are common.

1.3 Reinforcement

The reinforcement material is embedded into the matrix. The reinforcement does not always serve a purely structural task (reinforcing the compound), but is also used to change physical properties such as wear resistance, friction coefficient, or thermal conductivity. The reinforcement can be either continuous, or discontinuous. Discontinuous MMCs can be isotropic, and can be worked with standard metalworking techniques, such as extrusion, forging or rolling. In addition, they may be machined using conventional techniques, but commonly would need the use of polycrystalline diamond tooling (PCD).

Continuous reinforcement uses monofilament wires or fibers such as carbon fiber or silicon carbide. Because the fibers are embedded into the matrix in a certain direction, the result is an anisotropic structure in which the alignment of the material affects its strength. One of the first MMCs used boron filament as reinforcement. Discontinuous reinforcement uses "whiskers", short fibers, or particles. The most common reinforcing materials in this category are alumina and silicon carbide.

2. Applications of Metal Matrix Composites

- Carbide drills are often made from a tough cobalt matrix with hard tungsten carbide particles inside.
- Some tank armors may be made from metal matrix composites, probably steel reinforced with boron nitride. Boron nitride is a good reinforcement for steel because it is very stiff and it does not dissolve in molten steel.
- Some automotive disc brakes use MMCs. Early Lotus Elise models used aluminum MMC rotors, but they have less than optimal heat properties and Lotus has since switched back to cast-iron. Modern high-performance sport cars, such as those built by Porsche, use rotors made of carbon fiber within a silicon carbide matrix because of its high specific heat and thermal conductivity. 3M sells a preformed aluminum matrix insert for strengthening cast aluminum disc brake calipers, allowing them to weigh as much as 50% less while increasing stiffness. 3M has also used alumina preforms for AMC pushrods.

- Ford offers a Metal Matrix Composite (MMC) driveshaft upgrade. The MMC driveshaft is made of an aluminum matrix reinforced with boron carbide, allowing the critical speed of the driveshaft to be raised by reducing inertia. The MMC driveshaft has become a common modification for racers, allowing the top speed to be increased far beyond the safe operating speeds of a standard aluminum driveshaft.
- Honda has used aluminum metal matrix composite cylinder liners in some of their engines, including the B21A1, H22A and H23A, F20C and F22C, and the C32B used in the NSX.
- Toyota has since used metal matrix composites in the Yamaha-designed 2ZZ-GE engine which is used in the later Lotus Elise S2 versions as well as Toyota car models, including the eponymous Toyota Matrix. Porsche also uses MMCs to reinforce the engine's cylinder sleeves in the Boxster and 911.
- The F-16 Fighting Falcon uses monofilament silicon carbide fibers in a titanium matrix for a structural component of the jet's landing gear.
- Specialized Bicycles has used aluminum MMC compounds for its top of the range bicycle frames for several years. Griffen Bicycles also makes boron carbide-aluminum MMC bike frames, and Univega briefly did so as well.
- Some equipment in particle accelerators such as Radio Frequency Quadrupoles (RFQs) or electron targets use copper MMC compounds such as Glidcop to retain the material properties of copper at high temperatures and radiation levels.
- Copper-silver alloy matrix containing 55 vol. % diamond particles, known as Dym alloy, is used as a substrate for high-power and high density multi-chip modules in electronics for its very high thermal conductivity.

MMCs are nearly always more expensive than the more conventional materials they are replacing. As a result, they are found where improved properties and performance can justify the added cost. Today these applications are found most often in aircraft components, space systems and high-end or "boutique" sports equipment. The scope of applications will certainly increase as manufacturing costs are reduced.

In comparison with conventional polymer matrix composites, MMCs are resistant to fire, can operate in wider range of temperatures, do not absorb moisture, have better electrical and thermal conductivity, are resistant to radiation damage, and do not display out-gassing. On the other hand, MMCs tend to be more expensive, the fiber-reinforced materials may be difficult to fabricate, and the available experience in use is limited.

3. Al,SiC$_p$ COMPOSITES

While a variety of matrix materials has been used for making MMCs, the major emphasis has been on the development of lighter MMCs using aluminum and titanium alloys, due to the significant potential of improvement in the thrust to-weight ratio for the aerospace, space and automotive engines.

Aluminium alloy matrix composites are suited to applications below the temperatures of 400°C (750°F). Aluminium and its alloys have attracted the most attention as matrix material in metal matrix composites. Commercially, pure aluminium has been used for its good corrosion resistance. Aluminium alloys, such as 201, 6061, and 1100, have been used for their higher tensile strength to weight ratios. Amore common reinforcement for aluminium alloys is Silicon Carbide (SiC).

Continuous silicon carbide fibre reinforced metals have been successfully applied on aerospace development programs fulfilling primary design objective of high specific strength over conventional monolithic materials. The high specific strength of silicon carbide metal matrix composites has generated significant interest for the' aircraft industry. The principal areas of interest are for high performance structures such as aircraft, missiles and engines.

4. PROCESSING OF METAL MATRIX COMPOSITES

Metal-matrix composites can be processed by several techniques. Some of these important techniques are described below.

4.1. Liquid-State Processes

- **Casting or liquid infiltration** involves infiltration of a fibrous or particulate reinforcement preform by a liquid metal.
- ***Squeeze casting or pressure infiltration*** involves forcing a liquid metal into a fibrous or particulate preform .Pressure is applied until solidification is complete.

4.2. Solid-State Processes

- ***Diffusion bonding*** is a common solid-state processing technique for joining similar or dissimilar metals. Inter-diffusion of atoms between clean metallic surfaces, in contact at an elevated temperature, leads to bonding.
- ***Deformation processing*** can also be used to deform and/or densify the composite material.
- ***Powder processing*** methods in conjunction with deformation processing are used to fabricate particulate or short fiber reinforced composites. This typically involves cold pressing and sintering, or hot pressing to fabricate primarily particle- or whisker-reinforced MMCs

- ***Sinter-forging*** is a novel and low cost deformation processing technique (12). In sinter-forging a powder mixture of reinforcement and matrix is cold compacted, sintered, and forged to nearly full density.
- ***Deposition techniques*** for metal-matrix composite fabrication involve coating individual fibers in a tow with the matrix material needed to form the composite followed by diffusion bonding to form a consolidated composite plate or structural shape.

4.3. *In Situ* Processes

In these techniques, the reinforcement phase is formed *in situ*. The composite material is produced in one step from an appropriate starting alloy, thus avoiding the difficulties inherent in combining the separate components as done in a typical composite processing. Controlled unidirectional solidification of a eutectic alloy is a classic example of *in situ* processing,

5. ADVANTAGES OF NONCONVENTIONAL MACHINING OVER CONVENTIONAL MACHINING FOR MMCs

Metal matrix composites (MMC) possess higher stiffness and specific strength than that of conventional structural materials that are used in aerospace and automotive industries. MMCs generally consist of light weight metal as matrix element, and the fibers, whiskers or particles as the reinforcing elements. In MMC reinforcement helps in improving the material properties which otherwise the metal does not have. Metal Matrix Composites show considerable improvement in stiffness, elastic limit, tensile strength and fatigue strength when compared to matrix material, Apart from this they also possess high creep strength even at elevated temperature and adequate thermal fatigue resistance. Conventional machining such as turning, milling, drilling etc. shows ineffectiveness in advanced materials, since it results in a poor material removal rate, excessive tool wear and increased surface roughness. Traditional machining causes serious tool wear due to abrasive nature of reinforcing SiC particles, thereby shortening the life of the tool. In the view of high tool wear and high tool costs of tooling that are experienced with conventional machining, Due to matrix-fiber two phase structure, many difficulties are encountered in machining of composites e.g. delamination and fiber splitting. Delamination is defined as "*the separation of the layers of material in a laminate*." Delamination can occur at any time in the life of a laminate for various reasons and has various effects. It can affect the tensile strength performance depending on the region of delamination. Among the various defects that are caused by drilling, delamination is recognized as the most critical. Many researchers over the past years have tried to study the machinability of composites using traditional machining methods and reported considerable improvement in dimensional and performance characteristics like surface roughness, hole quality and tolerance. However, due to advancements in product designs and advent of new high cost materials, rigorous surface finish and tolerance requirements pose a challenge in machining of composites. Therefore, to meet these challenges various researchers have utilized advance machining methods like electric discharge machining, ultrasonic machining and electro chemical machining etc. to successfully machine composite materials, fulfilling stringent dimensional and performance constraints So non-contact material removal process offer an attractive alternative. This will also minimize dust and noise problem. In addition, extensive plastic deformation and consequent heat generation associated with conventional machining of composites can be minimized. Nonconventional machining appears to be promising technique, since in many areas of applications, it offers special advantages including higher machining rate, better precision and control and wide range of material that can be machined.

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Chapter 2: State of Art and Problem Statement

2.1Introduction

The main aim of this chapter is to provide the background information about the proposed study from an extensive literature survey. From this literature review a planning and understanding of present work has been achieved. Selection of material, their modern day's applications, brief information about the processes involved in fabrication of metal matrix composites, recent advancements in processing and machining, evolution and efficient employment of different optimization technique have been surveyed through this chapter.A lot of researches and investigations have been carried out to analyze the efficient way for fabrication and efficient machining of Al, SiCp reinforced composite.

2.2 Al,SiCp Metal Matrix Composite

Composite material consists of two or more materials (the matrix binder and the reinforcement or filler elements), altering in composition or form on a macro-scale. For metal matrix composite the matrix material is a metal. Rosso [3] discussed that metal matrix composites have a number of advantageous properties as compared to monolithic metals including higher specific strength, higher specific modulus, and resistance to elevated temperatures, better wear resistance and lower coefficients of thermal expansion. Also MMCs have several superior mechanical properties over polymer matrix composites which include greater transverse stiffness and strength, better temperature capabilities, greater compressive and shear strengths. There also many beneficiary physical properties of MMCs like resistance to most radiations, non-inflammability, no significant moisture absorption properties and high thermal and electrical conductivities. Lindroos and Talvitie [4] showed that in past two decades, metal matrix composites have been generating broad range of research fraternity in material science. Major of the applications and works have been demanding aluminium and other light matrices for purposes desiring high strength and stiffness along with light weight. Therefore, the major prominence has been on the development of lighter MMCs using aluminum and other light alloys. Aluminium alloy-based metal matrix composites (AMMCs) have been now proved themselves as a most acceptable wearresistant material especially for sliding wear applications [6].As these MMCs have significant potential of improvement in the thrust to-weight ratio, corrosion, ductility properties for applications like aerospace, sports, leisure and automotive engines. Also other potential applications of these advanced MMCs include joints and attachment fittings for truss structures, electronic packages, longerons, mechanism housings, thermal planes and bushings [8,9]. It is indeedessential to find most effective method for processing and machining of this advanced composite material.

2.3. Powder Metallurgy Route

For processing of MMCs different types of methodologies like liquid state processing,solid state processing and *in situ* processing etc. have been utilized. All the processing technologies have their own benefits and disadvantage. But commercial industries and producers have targeted particulate reinforced composite because of cost issues of fabrication techniques. These include powder metallurgy, casting, and thixoforming and spray deposition [10-14]. Thixoforming and conventional casting methods include technical problems likehigh localized residual porosity reinforcement segregation and clustering,interfacial chemical reaction, and poor interfacial bonding which confine the utility of these processing routes. The composite material fabricated by Spray deposition process involves difficulties in obtaining repeatability of reinforcement quantities, over-spray management, and the costly atmospheric conditions and also the problems associated in the production of netshape or near net shape composites have limited theuse of this useful method. The powder metallurgy technique has been persistently producing enhanced property composites.It is advantageous and beneficiary to process Al, SiCp MMCs utilizing powder metallurgy (PM) route because the produced composites exhibits a higher dislocation density, limited segregation of particles and small sub-grain size resulting in superior mechanical properties [15,16].It has been observed that with variation in percentage of SiC reinforcement it influences different properties of MMC. It is evident from different investigations that with increase in volume fraction of SiC reinforcement from 5%, mechanical properties like wear resistance, flexural strength, tensile strength, density, machinability etc. increases. But after 25% the enhancement in these properties decreases also the value of Youngs' Modulus reduces which degrade the plasticity of composites. So, for commercial applications like automobile, air craft, space industries usually composites with 10-15% volume fraction of SiC reinforcement is utilized for fabrication of MMCs [17-21].The conventional powder metallurgy route for fabrication of involves proper blending or mixing of appropriate weight percentage of powders to obtain a homogenous mixture, cold uniaxial compaction for obtaining green sample, sintering at appropriate sintering temperature and finally heat treatment like ice quenching and ageing for enhancing various mechanical properties [21-25].

2.4 Non-Conventional Machining

While machining of Al,SiCp MMCs by conventional machining like turning, milling, drilling etc. high rate of tool wear has been achieved due to abrasive nature of SiC reinforcement. Also other difficulties like poor surface roughness, difficulties in achieving dimension constraint and complex shapes, increased machining cost have been observed which restrict the utilization of this conventional machining method[26,27]. So, different researchers have been utilizing different nonconventional machining methods like electro discharge machining, electro chemical machining, laser machining, abrasive water jet machining etc. for effective machining of these composites. Though for rough cutting operation laser machining shows effective productivity, but there are limitations like striation patterns on the cut surface, burrs at the exit of the laser and poor surface quality. Similarly abrasive water jet machining is very acceptable for rough cutting operations but it also has some disadvantages likeslotted-edge damage on the top of the cut surface, relatively rough surface. Also these methods are used for only linear cutting operations [28,29]. In comparison to these in EDM, ECM better surface quality, machining of complex shape and structure, high precision and dimensional constraints for finishing operation can be achieved very efficiently. There is neither subsurface damage nor tool wear while machining under correct conditions [30-32].

2.5Electro Discharge Machining (EDM)

One of themost exclusively utilized advanced material removal processes is Electro discharge machining (EDM). English physicist *Joseph Priestley* in 1970 first accomplished the erosive effect of electrical discharges.EDM is especially used for machining of hardmetals and advanced materials or those that would be very difficult to machine with conventional machining methods.EDM, generally also termed as spark eroding, spark machining, die sinking or wire erosion.Its exclusive aspect of utilizing thermal energy to machine electrically conductive parts disregarding the hardness has been its unique advantage in the manufacture of die, mould, aerospace, automotive and surgical components. In addition to these, in EDM there is no direct contact between the electrode and the work piece removing the mechanical stresses, vibration and chatter problems during machining [33-34].

2.5.1Stateof Art on Electro Discharge Machining

During EDM, material is removed from the work piece by a series of rapidly recurring spark discharges between two electrodes (tool electrode as cathode and work piece as anode), separated by a dielectric fluid and subjected to an electric voltage.When a suitable voltage in range of is applied, the dielectric breaks down and electrons are emitted from the cathode and the gap gets ionized when a suitable voltage and inter electrode gap is applied. In fact, a small ionized fluid column is created leading advancing an avalanche of electrons in the spark gap. When fluxes of electrons are collected in the gap it results in resistance drop causing electric spark to jump from tool to work piece surface. The generation of compression shock waves due to spark develops a local rise in temperature which is sufficient to melt a part of metals. The tensile force produced by electric and magnetic fields caused by the spark tear off particles of molten and soften metal from work piece. Once the current flow stops, new dielectric fluid is usually flushed into the inter-electrode volume enabling the debris to be carried away and the insulating properties of the dielectric to be restored commonly known as flushing [34-35].

Chen and Mahdivian [36] showed that sparks are generated by electrical circuits of several types and of different wave form of current and voltage of its own and the material removal is a function of discharge energy. Yadav et al.[37] illustrated that the high temperature gradient generated at the inter electrode gap results in large localized stress which lead to removal of material. Lawers et al.[38] identified that there is three types of material removal mechanism i.e. melting or evaporation, spalling and oxidation or decomposition. Singh and Ghosh [39] argued that the stress distribution and electrostatic forces acting on the cathodeelectrode are main reasons of metal removal for short pulses. Hocheng et al. [27] analyzed the material removal of Al,SiC MMC by a single spark and investigated heat conduction model of finite step heat source that well explains the material removal in crater formation by single discharge and also recommended large current and short on time for effective machining of Al,SiC MMC.

Singh et al.[40]reported that copper electrodes offer comparatively low electrode wear for the aluminium work piece and also copper is comparatively a better electrode material compared to other tool electrode material as it gives better surface finish, high MRR, low diametric overcut and less electrode wear. Kumar et al. [41] emphasized on the potential of EDM process for surface modification.

Material removal rate, tool wear, surface roughness, circularity, overcut etc. are most important response parameters of Die sink EDM.Several researchers carried out various investigations for improving the process performance. Proper selection of machining parameters for achieving the best process performance is still a challenging job. To solve this type of multi-optimization problemLin et al. [42] utilized grey relation analysis based on an orthogonal array and fuzzy based Taguchi method and used grey-fuzzy logic for the optimization of EDM process, as the performance parameters are fuzzy in nature, such as Lower-is-Better (LB) (tool wear and surface roughness), and Higher-is-Better (HB) (example MRR) contain certain degree of uncertainty. Grey relational coefficient analyzes the relational degree of the multiple responses (electrode wear ratio, material removal rate and surface roughness). Fuzzy logic is used to perform a fuzzy reasoning of the multiple performance characteristics. Zhang et al. [43] proposed an empirical model, built on both peak current and pulse duration, for the machining of ceramics. It was realized that the discharge current has a greater effect on the MRR; while the pulse-on time has more influence on the SR and white layer.Wang et al. [44] used Genetic Algorithm (GA) with Artificial Neural Network (ANN) in order to find out optimal process parameters for optimal yield of performances. ANN is used to model the process, where weights are updated by GA. In the optimization phase Gen-Hunter Software is used to solve multi-objective optimization problem. Two output parameters, MRR and surface roughness considered here to be optimized as a process performance. Optimization of the EDM parameters, from the rough cutting to the finish cutting stage, has been done by Su et al. [45].Marafona and Wykes [46] used the Taguchi method to improve the TWR by introducing high carbon content to the electrode prior to the normal sparking process. Kiyak and Akır [47] observed that surface roughness of work piece and electrode were influenced by pulsed current and pulse time, higher values of these parameters increased surface roughness and lower current, lower pulse time and relatively higher pulse pause time produced a better surface finish.

2.6Electrochemical Machining (ECM)

Gussef in 1929 first patentedthe process resembling ECM. Significant advances during the 1950sand 1960s emerged ECM as an efficient technology in the aerospace and aircraft industries.Electrochemical machining is also another advanced machining technology which offers a betteralternative or sometimes the only alternative in achieving precise 3-D complex shaped features and components of difficult to machine materials. The advantages of ECM over other traditional machining processes include its applicability disregarding the material hardness, comparable high material removal rate, no tool wear, and achievement of fine surface features and the production of components of complex geometry with crack-free and stress-free surfaces. Therefore, ECM has been utilized in many industrial applications including engine casings, turbine blades, gears, bearing cages, molds and dies and surgical implants [48-49].

2.6.1State of Art onElectrochemical Machining

ECM is often termed as 'reverse electroplating', in which it removes material in place of adding it. This is totally based on Faradays law of electrolysis. Rajukar et al.[48] explained that a D.C. voltage(generally about 10to 25 volts) is applied across theinterelectrode gap between an anode work piece and pre-shaped cathode tool. The electrolyte (e.g. NaCl, $NaNO_3$aqueous solution etc.) flows at a high speed through the inter electrode gap (about 0.1to 0.6 mm). According to Faraday's law, the anode work piece isdissolved with currentdensity of 20 to 200 A/cm^2.The electrolyte flow takes away the dissolvedmaterial (generally metal hydroxide) and other by-productsgenerated in the process such as cathodic gas from the gap. The finalshape of the work piece is nearly negative mirror image of the tool electrode.

Hocheng et al. [50] proposed a computational model to predict the erosion profile in the use of a simple flat end electrode during ECM process and also discussed that the material removal increases with increasing electric voltage, molar concentration of electrolyte, machining time and reduced initial gap. Bhattacharyya et al. [51] presented a computer simulation of cut and try procedure for designing tool shape in the ECM of prescribed work geometry and showed that an optimum valueof the feed-back factor for iterative modification of the tool shape exists. Neto et al.[52] studied on the intervening variables in electrochemical machining of SAE-XEV-F valve steel and concluded that irregular removal of material is more likely to occur at low feed rates whereas surface roughness decreases with feed rate.

Asokan et al. [53] utilized grey relational analysis combined with ANN and multiple regression model for multi-objective optimization of MRR and surface roughness as objectives and current, voltage, flow rate and gap rate as machining parameter in ECM of hardened steel and finally used ANOVA to identify the significance of the proposed model. Tang and Yang [54] used orthogonal array experiment and grey relational analysis method to find the optimal setting of process parameters electrolyte concentration, electrolyte pressure and the feed speed for material removal rate, side gap and surface roughness in ECM of a special stainless steel. Jain and Jain [55] described optimization of three most important ECM control parameters namely tool feed rate, applied voltage and electrolyte flow velocity with an objective tominimize geometrical inaccuracy subjected to temperature, passivity and choking constraints using real-coded genetic algorithms. Rao and Padmanabhan [56] modeled electrochemical machining of Al-B_4C MMC withthe help of non-linear regression model taking the MRR as response andmachining parameters, namely voltage, feed rate, electrolyte concentration and percentage of reinforcementas inputs of the model and developed a mathematical model using response surfacemethodology which was analyzed using ANOVA.From this it has been found that MRR and increases with increase in feed rate, voltage and electrolyteconcentration and decreases with theincrease in percentage of reinforcement.

2.7. Multi-Objective Optimization

As ECM is a very complex process a most effective multi-objective optimization technique is required for achieving the most efficient optimal setting. Different researchers have been utilized different techniques for optimization of performance characteristics of ECM of Al,SiCp MMCs.

Senthilkumar et al. [57] developed a mathematical model by using RSM for revealing optimal machining environment during electrochemical machining of LM25 Al/10%SiC composites produced through stir casting. The research focused on the effects of electrochemical process parameters such as applied voltage, electrolyte concentration, electrolyte flow rate and tool feed rate on the metal removal rate (MRR), and surface roughness (R_a). Senthilkumar et al. [58]

proposed a regression model based on non-dominated sorting genetic algorithm-II (NSGA-II) for improving the cutting performance of electrochemical machining of Al/15% SiC composites. Kumar and Sivasubramanian [59] established a mathematical model by using artificial neural network with back propagation for modeling the experimental data of material removal rate in ECM of Al,SiCp MMCs. A comparison made between predicted values and experimental values revealed a close matching with an average prediction error of 6.48%. Kumar et al.[30] used Taguchi's L_{27} orthogonal array and conducted experiments to study the effect ofvarious parameters like applied voltage, electrolyte concentration, feed rate andpercentage reinforcement on maximizing the material removal rate and developed a mathematical model using the regression method. Goswami [60] studied the effect of electrolyte concentration, supply voltage, depth of cut, and electrolyteflow rate on the evaluation ofmaterial removal rate (MRR), surface finish, and cuttingforces during electrochemical grinding of Al_2O_3/Al interpenetratingphase composite using Taguchi based design. Rao and Padmanabhan [61] employed Taguchi Methods, the Analysis of Variance (ANOVA), and regression analyses to find the optimal process parameter levels and to analyze the effect of these parameters on metal removal rate values in electrochemical machining of LM6 Al/5%SiC composites.

Literature highlights that immense effort attempted by pioneer researchers to optimize various process parameters during machining operation of MMC composites.Motivated by this, present work aims to add value to the previous research and proposes application of TOPSIS integrated with Taguchi philosophy and grey embedded fuzzy approach coupled with Taguchi's philosophy for simultaneous optimization of quality and productivity in machining of MMCs.

TOPSIS method has been utilized by different pioneer researchers for various sectors of quality improvement programme. Opricovic and Tzeng [62] showed a comparative analysis of VIKOR and TOPSIS which are based on an aggregating function representing closeness to the ideal, which originated in the compromise programming method. It has been observed that TOPSIS has advantages of consideration of relative importance of distances from the ideal solutions and utilization vector normalization. Athawale and Chakraborty [63] presented a logical procedure to evaluate the CNC machines in terms of system specification and cost by using TOPSIS method. It has been observed that the use of TOPSIS method is quite capable and computationally easy to select and evaluate proper machine tool from a given set of alternatives. Lan [64] showed the multi objective optimization of responses surface roughness, tool wear and material removal rate in CNC machining industry using TOPSIS integrated with Taguchi philosophy. It has been found that TOPSIS method is a novel parametric optimization technique as it contributed satisfactory solution for multiple CNC turning objectives with profound incentives. Chakladar and Chakraborty [65] proposed TOPSIS-AHP combined method to select the most appropriate non-traditional manufacturing machining processfor a specific work material and shape feature combination, while taking in account different attributes affecting the machining process selection decision.

Grey-Fuzzy is another efficient technique to convert the multi-objectives into single objective widely applied in industrial applications. Grey relational analysis uses the quantitative analysis to describe the degree of relationship between an objective sequence (a collection of measurements or experimental results) and a reference sequence (target value) in the grey system. Further, the experimental data are also constrained to impreciseness and uncertainty. Hence, fuzzy inference system is employed to modify multiple responses into a single objective termed as multi-performance characteristic index (MPCI) considering the uncertainty and impreciseness. Horng and Chiang[66] developed a fast and effective algorithm to determine the optimum manufacturing conditions for tuning Hadfield steel with Al_2O_3/TiC mixed ceramic tool by integrating grey relational analysis with fuzzy logic.It has been shown that the required performance characteristics viz.,flank wear and surface roughness have great improvement through this proposed algorithm. Chiang and Chang [67] illustrated an effective approach for the optimization of machining parameters to an injection-molded part with a thin shell feature (example of cell phone shell consist of PC/ABS material) based on the orthogonal array with the grey relationalanalysis and fuzzy logic analysis. It has been observed that through the grey-fuzzy logic analysis, the optimization of complicated multiple performancecharacteristics can be effectively converted into the optimization of a single grey-fuzzy reasoning grade.

Selection of appropriate machining parameters for any particular material in EDM is very difficult. Many researchers have been adopted different multi-objective techniques for machining of Al, SiCp MMCs in EDM. Singh et al. [68] proposed multi-response optimization of the process parameters viz., metal removal rate (MRR), tool wear rate (TWR), taper (T), radial overcut (ROC), and surface roughness (SR) on electric discharge machining (EDM) of Al–10%SiCp as cast metal matrix composites using orthogonal array (OA) with grey relational analysis. Karthikeyan et al.[69] used nonlinear goal programming to optimize EDM characteristics such as material removal rate, tool wear rate and surface roughness in terms of the process parameters such as volume fraction of SiC, current and pulse time while machining of SiCp/LM25 Al composites. Velmurgan et al. [70] investigated the effect of parameters like Current(I), Pulse on time(T), Voltage(V) and Flushing pressure(P) on metalremoval rate (MRR),tool wear rate(TWR) as well as surface roughness(SR) in the electro discharge machining of hybrid Al6061 metal matrix composites reinforced with 10% SiC and 4%graphite particles.The method of least squares technique was used to calculate the regression coefficients and Analysis of Variance (ANOVA) technique was used to check the significance of the models developed. Purohit and Sahu [71] reported the effect of pulse-on time (Ton), pulse current (Ip), and gap voltage (Vg) on metal removalrate (MRR), tool wear rate (TWR) and radial over cut (ROC) during ECM of Al-alloy- 20 wt. % SiCp composites utilizing a three-level-3 factor full factorial design of experiment.

The EDM process parameters are found to be correlated conflicting in nature. A hybrid optimization technique PCA has been applied to convert the correlated responses into fewnumbers of uncorrelated and independent principal components and further TOSIS method has been utilized to convert the multi-objective problem into a single equivalent objective. Different researchers have been exploited these techniques for solving different decision making problems in industrial applications. Tong et al. [72] proposed PCA combined with TOPSIS for solving various multi-response problems. It has been found that PCA is used to simplify multi-response problems and determine the optimization direction by using a variation mode chart and the optimal factor/level combination is also determined based on the overall performance index for multiple responses obtained from TOPSIS. Chakravorty et al.[73] proposed PCA based proportion of quality loss reduction method for adequate optimization of correlated EDM performance characteristics MRR and TWR.

Another robust optimization technique *Multi-Objective Optimization by Ratio Analysis* (MOORA) with Taguchi philosophy has been utilized for optimization of EDM characteristics while machining of Al,15% SiCp MMC. Brauers and Zavadskaset [74] represented the robustness of MOORA method over other multi-objective optimization techniques. It has been found that in terms of robustness MOORA is the most acceptable technique because of its simplicity, very less computational time, mathematical calculation and very good stability compared to other MODMs. Chakraborty [75] discussed the application of MOORA method to solve different decision-making problems as frequently encountered in the real-timemanufacturing environment.

2.8 PROBLEM STATEMENT

Metal cutting is one of the most widelyandimportant utilized manufacturing processes in engineering industries. The study of metal cutting focuses mainly on the input work materials, properties and features of tools, and machine parameter settings affecting output quality characteristics and process efficiency. A great improvement in process efficiency can be achieved by process parameter optimization that determines and identifies the regions of critical process control factors leading to responses or desired quality characteristics with acceptable variations promising a lower cost ofmanufacturing. The technology of metal cutting has advanced substantially over time with a common goal of achieving higher machining process efficiency. Selection of optimal machining condition(s) is the essential factor in achieving this goal. In any advanced metal cutting operation, the manufacturer wants to set the process-related controllable variable(s) at their optimal operatingconditions with minimum variability in the output(s) and effect of uncontrollable variables on the levels. Todesign and implement an effective process control for metal cutting operation by parameter optimization, amanufacturer seeks to balance between cost and quality at each stage of operation. The Taguchi method is a systematic methodology of design and analysis of experiments for the intention of designing and improving product quality. The Taguchi method has been become a powerful tool for improving productivity during research so that high quality products can be manufactured quickly and at low cost.However, the original Taguchi method is designed and utilized to optimize a single quality characteristic or response. Furthermore, optimization of multiple objectives or responses is much more difficult than optimization of a single objective.Improving one particular quality characteristic would likely cause deliberate degradation of the other critical quality characteristics. It leads to increment of uncertainty at the time of decision-making process. Therefore, in this research various multi-objective techniques have been used with Taguchi method to optimize the processing parameters of various nonconventional machining methods used for machining of Al,SiC_p metal matrix composites.

2.9 Closure

The investigations of different pioneer researchers have been reviewed exhaustively and theirabsolute recommendations have been extracted concerning the fabrication and efficient machining of composites. Powder metallurgy route is considered for adequate fabrication of the composites. Electrochemical machining and Electro discharge machining have been chosen for precise machining of the composites. Machining parameters affecting quality and productivity characteristics in themachining process are studied in details. For achieving optimization of all the machining performance characteristics; different multi-objective techniques have been discussed.TOPSIS with Taguchi philosophy and again grey-fuzzy embedded with Taguchi philosophy have been adopted for predicting the optimal setting of process parameters while ECM of Al,15%SiCp MMCs. Another two multi-objective techniques viz. PCA-TOPSIS combined with Taguchi philosophy and MOORA with Taguchi method have been utilized to predict the optimal parameter setting for EDM of Al,10%SiCp MMCs.

Chapter 3: Experimentation

3.1 Introduction

This chapter contains the details of experimental work done for present project work. The characteristics, composition of the raw materials required for manufacturing of MMC work specimen is provided. The details of each step for fabrication of Al, SiCp MMC with specific composition is described with. The images of each process involved in fabrication method are provided for detail study. Then different non-conventional machining operations are carried out on the fabricated MMC samples for further experimentation and analysis. The details of nonconventional machining methods and their performance characteristics are explained herewith.

3.2. Raw Materials

Al alloy powders (A2265), SiC powder were purchased from RFCL Limited, New Delhi, India. The composition and specification are described below:

3.2.1 Al Powder

The Al alloy powder contains 99.7% Al, 0.1% Cu, 0.17% Fe, and 0.03% Zn. The atomic weight of Al powder is 26.88 and particle size is 110 meshes.

3.2.2 SiC Powder

Fine powder of SiC is purchased from open market with 99% metal. The particle size is of 325 meshes.

3.3 Work piece Fabrication

The fabrication technique for composites is an important consideration. By the processing technique, the essential link between required properties and cost estimation is estimated for a given set of elements. In general, fabrication is concerned with the prelude of reinforcement into the matrix metal with a uniform distribution.

The main aim is to achieve proper bonding between the matrix and the reinforcement with enhanced mechanical and physical properties.

Now a days, the primary industrial processing routes available for the fabrication of Al based metal matrix composites comprises of thixoforming, spray deposition, casting and powder metallurgy techniques. Spray deposition processes such as the codeposition methods have been found to fabricate particle reinforced Al based metal matrix composites with good material and low segregation properties. But this method has limitations like the costly atmospheric conditions, difficulties involved in production of net shape and in achieving repeatability for reinforcement quantities, which restricts the use of this upcoming technique.

The technical difficulties like poor interfacial bonding, high localised residual porosity reinforcement clustering and segregation are more often seen in conventional casting methods and thixoforming which restrict the usefulness of these fabrication methods. The powder metallurgy processing technique is finding attraction due to several reasons. A very wide range of MMCs may be fabricated using powder metallurgy techniques; including wide range of variations in volume fraction of reinforcement in particulate, short fibre and long fibre form. Mechanical alloying of powders of Al, SiC results in great enhancement in hardness, indirect strength and compressive strength of composites. This is a lower temperature processing technique and so, theoretically proposes better control of interface kinetics. This process employs micro-structural control of the phases which is not present in the liquid phase route. The powder metallurgy processing route also offers matrix alloy compositions and micro-structural refinements that are only accessible through the application of rapidly solidified powders. The fabrication of SiC particulate reinforced aluminium matrix composites in the form of net shape components can be obtained successfully by the use of conventional powder metallurgy.

From literature survey it has been found that % weight of SiC affects the properties of composite in different ways. When the (%) weight of SiC increases from 5%; the properties like indirect tensile strength, hardness, compressive strength, abrasive wear increase. But, when it reaches 20%, it has been found that the indirect tensile strength, machinability show their maximum value after that gradually decrease. Also the porosity increases with increase in weight % of SiC reinforcement. So from papers it has been that for automobile and aerospace applications generally 10-15% weight of SiC reinforcement is employed to get the best properties.

3.4 Powder Metallurgy Route

The Al, SiCp MMCs are fabricated using powder metallurgical cold uniaxial pressing and sintering technology. The steps used to fabricate the net shaped MMCs are described below.

3.4.1 Ball Mill Mixing of Powders

Aluminium alloy (A2265) powders of average size 20μm were blended with abrasive grade SiC particles of average size 37μm to form a mechanical mixture of Al, SiC powder 90% and 85% of Al powder and 10% and 15% of SiC powder by weight are mixed to form a composite of 10 gram each. Blending of powders are carried out in ball planetary mill (Model-PULVERISETTE-5, Make-FRITSCH, Germany) shown in Fig. 3.1. It comprises of three cylindrical containers of chrome steel within which 10 balls made up of chrome steel of sizes 10 mm. To achieve a homogenous distribution of the reinforcement in the mixture the blending machine continues rotations for 3 Lakh revolutions.

Fig 3.1: Ball Planetary Mill

3.4.2 Compaction of Powder Mix

Following the blending operation, the mixture is then pressed at room temperature in a die punch arrangement made up of stainless steel at pressures which make the powders adhere to each other. This process is called cold compaction. The blended powders must be compacted into a 'green compact form', with appropriate density typically by cold isostatic pressing. About 10 gm of the powder mixture was taken adopting a method of coning and quartering for compaction.

3.4.2.1 Cold Uniaxial Press

For each component, approximately 10 gm of powder was measured out and poured into the die cavity. The equipment used for this machine is cold uniaxial pressing machine (Make-SOILLAB, Type-Hydraulic) as shown in Fig. 3.2. To fabricate the green circular test samples of 25 mm outer diameter a load of 18 ton was applied, which accounted 3600 bar pressure. For this purpose, a stainless steel die of 25 mm internal diameter was used. To prevent the specimen from sticking on to the walls and to allow the powder to flow freely, stearic acid was applied to the walls of the die and punch as lubricant. The die body was split, with slight pressure applied to the green component and both sides of the die were pulled from the component. The pressure on the component was then released completely, the top punch was removed and the component was ejected by downward movement of the floating die body.

Fig. 3.2: Cold Uniaxial Pressing Machine

3.4.3 Sintering of Green Compact Samples

Sintering was also carried out within a sealed unit, in an atmosphere of argon at pressure of 1 bar. The process is carried out in horizontal tubular furnace (Make-Naskar and Co., Type-Vacuum and Control Atmosphere) as shown in Fig. 3.3.

The green samples are sintered at an elevated temperature but just below the melting point of main component for an ample of time. A batch of nine green samples from each of powder mixture containing 10% and 15% SiC were baked at two different temperatures $600^{o}C$ and $650^{0}C$ respectively for a holding time of one hour. The aluminium particle is always surrounded by an oxide layer. The high temperature sintering process causes this aluminium surrounded oxide layer in the particle melt and expand in volume to rupture due to high sintering temperature. Then the aluminium melt from one particle come in contact with melted aluminum escaping from neighborhood particles and welding takes place in between them. The presence of silicon carbide particles obstructs the aluminum melt from one particle to weld melt from another. So, increasing silicon carbide content increases the sintering temperature needed to achieve high strength composite. Also, the oxide layer fragmented into small shell pieces disrupted in the aluminum matrix restraining the increment in strength and the movement of dislocation. Then furnace is left to cool to room temperature for a time span of 24 hours. Then, the pallets are taken from the furnace and kept in desiccators which contain concentrated H2SO4. The average thickness and diameter of pallets are 9 mm and 22 mm respectively.

Fig. 3.3: Horizontal Tubular Furnace

3.4.4 Heat Treatment

Refinement of the grain structures occurs inside a material part, by the process of heat treatment, thus it improves its different mechanical properties.

3.4.4.1 Quenching

After sintering the samples were then solution heat treated in a heat treatment furnace (local made) as shown in Fig. 3.4. Quenching was carried out at a temperature of 500 ^{0}C for a span of one hour and then quenched in iced water.

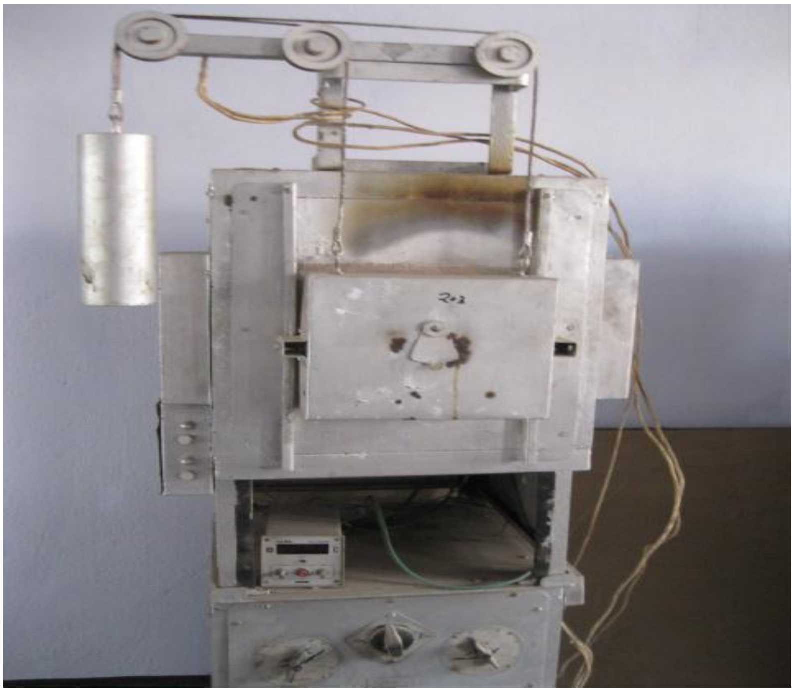


Fig. 3.4: Heat Treatment Furnace

3.4.4.2 Ageing

After quenching operation, there is initiation of natural ageing in the composites. In order to prevent it, all the quenched samples were artificially aged immediately after solution heat treatment. The ageing operation was carried out in a closed muffle furnace as shown in Fig. 3.5.

All samples were aged at temperature of 200^0C for span of eight hour and allowed to cool in it to room temperature.

Fig. 3.5: Closed Muffle Furnace

The metal matrix composite samples fabricated by the above discussed powder metallurgy route are shown in Fig. 3.6. These sintered samples are ready for further machining processes.

Fig.3.6: Fabricated Al, SiCp MMCs

3.5. Density Calculation of Composites

The actual densities of the samples are obtained through water immersion method and the average actual density was found to be 0.00238 g/mm^3. Theoretically, the densities of the composites are measured using the following equation.

$$\rho_C = \frac{1}{\left(\left(\frac{W_{Al}}{\rho_{Al}}\right) + \left(\frac{W_{SiC}}{\rho_{SiC}}\right)\right)} \tag{3.1}$$

Here,

ρ_C = Composite density, g/mm3

W_{Al} = Weight fraction of aluminium

ρ_{Al} = Density of aluminium

W_{SiC} = Weight fraction of silicon carbide

ρ_{SiC} = Density of silicon carbide

Using above relation, the theoretical density of the MMC is found to be 0.00268 g/mm^3.The difference in density is assumed due to presence of voids in the samples.

As discussed before conventional machining such as turning, milling, drilling etc. shows ineffectiveness in advanced materials like MMCs, since it results in a poor material removal rate, excessive tool wear and increased surface roughness and so increase production cost. So, pioneer researchers have utilized different nonconventional machining methods like EDM, ECM etc. to efficiently machine advanced composites like Al,SiCp MMCs and to fulfill rigorous dimensional and performance restriction.

3.6 Electro Chemical Machining Process (ECM)

The preceding study aims at investigating the influence of different process parameters of ECM on the performance parameters like Material Removal Rate (MRR), surface roughness (R_a). The experimental set up used for the experimentation is a model of MCMAC (Make: METATECH INDUSTRIES, INDIA) ECM set up as shown in Fig.3.7.

Fig. 3.7: Electrochemical Machining Setup

NaCl solution is used as electrolyte. A center flushing system is employed for effective flushing of electrolyte in between tool and work piece. Each run of experiment was conducted for 10 minutes to get more accurate result. The work piece material used is Al, 15%SiCp metal matrix composite. For tool electrode a cylindrical copper tool is utilized. The density of copper tool taken is 0.00896 kg/m^3. The tool is used as cathode (positive polarity) and work piece as anode (negative polarity). The images of the Al, SiCp MMCs after machining are shown in Fig. 3.8.

Fig. 3.8: MMCs after Electrochemical Machining

3.6.1 Process Parameters

3.6.1.1 Feed Rate:

Increase in tool feed rate results in an increase of the material removal rate It results in decreasing the equilibrium inter electrode machining gap and improves the surface finish.

3.6.1.2 Electrolyte Type:

Generally two types of electrolytes have been utilized classified i.e. passivity electrolyte containing oxidizing anions and non-passivity electrolyte containing relatively dexterous anion such as sodium chloride. In many of the investigations researchers have suggested NaCl, $NaNO_3$ and $NaClO_3$ solution with variation in concentration for electrochemical machining (ECM).

3.6.1.2 Electrolyte Concentration:

In industrial practice optimum concentration is found by trial and error to give the desired specification. Furthermore, the lower concentrations generate comparatively less sludge by not only giving lower amounts of precipitates but also by minimizing the machining allowance. One disadvantage however is that low conductivity increases the heat generated in the gap.

3.6.1.3 Electrolyte Flow Rate:

Electrolyte flow rate is another important process parameter which influences different performance characteristics in different ways. Generally MRR increases with increase in electrolyte flow rate. This is due to increase in electrolyte flow rate flushes the reaction products from the machining zone and also fresh electrolyte directed into IEG which enhances the conductivity of the electrolyte. Also surface roughness decreases with increase in electrolyte flow rate surface. Because the more the flow rate is, the more rapidly the heat and electrolytic debris can be removed away from the inter electrode gap and fresh electrolyte can be entered successively into the machining gap.

3.6.1.4 Nature of Machining Pulse and Power Supply:

The nature of applied power supply is of two types, such as pulse DC and full wave rectified DC. Continuous voltage is supplied by a full wave rectified DC where the current efficiency is greatly dependent on the current density. The accuracy of the form of the work piece enhances, with reducing the current density.

3.6.1.5 Voltage:

The equilibrium-machining gap decreases with lowering of voltage and results in achievement of better tolerance control and surface characteristics.

3.6.1.6 Shape, Size and Material of the Tool:

The tool shape must be equivalent to the desired dimension of the profile to be machined. It also depends on the material of work piece. The material used for manufacturing of tools in ECM must have good corrosion resistance, electrical and thermal conductivity; should be stiff enough to tolerate the electrolytic pressure without vibrating and highly machinable.

3.6.2. Performance Parameters:

Material Removal Rate (MRR) and surface roughness have been used for assessing machining performance extent.

3.6.2.1 Material Removal Rate (MRR):

MRR is calculated using the volume loss from the work piece material as cubic millimeter per minute (mm^3/min). The weight loss i.e. difference between the weight of work piece before machining and the weight of the work piece after machining is measured by an electronic balance weight measuring machine (Sansui (Vibra), Shinko Denshi Co. Ltd. Made in Japan) with a least count of 0.001 gm and shown in Fig. 3.9.

Fig. 3.9: Weight Measuring Machine

MRR is expressed as,

$$MRR = \frac{W_i - W_f}{\rho_w t} \qquad (3.2)$$

Here,

W_i = Initial weight of work piece

W_f = Final weight of work piece

ρ_w = Density of work piece

t = Machining time

3.6.2.2 Surface Roughness (R_a)

The surface profiles of the ECM specimens are measured by utilizing a portable stylus type profilometre like Talysurf (Taylor Hobson). It is based on carrier modulating principle has stylus which skids over the surface to measure the roughness and shown in Fig. 3.10.

Fig. 3.10: Portable Stylus Type Profilometre like Talysurf

Surface roughness can be expressed as,

$$R_a = \frac{1}{L}\int \left| y(x) \right| dx \tag{3.3}$$

Here,

L = The sampling length (0.8 mm),

y = The profile curve and

x = The profile direction

3.7 Electro Discharge Machining (EDM)

This work aims to investigate the influence of major process parameters of EDM on different performance parameters of electro discharge machining process. Experiments are carried out in an Electronica Electraplus PS 50ZNC Die Sinking Fuzzy Logic based Electrical Discharge Machine shown in Fig. 3.11. A lateral flushing system is utilized for efficient cooling purpose and flushing of machining debris from the inter electrode gap region. Commercial grade EDM oil (specific gravity = 0.763, freezing point= 94°C) is employed as dielectric fluid. The work piece material used is Al, 10%SiCp metal matrix composite. A cylindrical copper tool with a diameter of 10 mm is used as a tool electrode for machining. Density of copper tool taken is 0.00896 kg/m^3 shown in Fig. 3.12. Each run of experiment is carried out for thirty minutes, to get more accurate results. The tool is employed as anode (negative polarity) and work piece as cathode (positive polarity). The images of the Al, 10%SiCp MMCs after machining are shown in Fig. 3.13.

3.7.1 Process Parameters

Various process parameters associated with electro discharge machining are of prime importance to researchers as these effects the performance measures of EDM process in several ways, both predictable and unpredictable fashion. The important process parameters involved with EDM operation are discussed as follows:

Fig. 3.11: Electro Discharge Machining Setup

Fig. 3.12: Copper Tool

Fig. 3.13: Work Piece after Machining

3.7.1.1 On time (T_{on})

All the work is done during on time. The spark gap is bridged, current is generated and the work is accomplished. The longer the spark is sustained more is the material removal. Consequently the resulting craters will be broader and deeper; therefore the surface finish will be rougher. Obviously with shorter duration of sparks the surface finish will be better. Except during roughing; all the sparks that leave the tool result in a microscopic removal of particles of the surface. More sparks produce much more wear; hence this process behaves quite opposite to normal processes in which the tool wears more during finishing than roughing.

3.7.1.2 Off time (T_{off})

While most of the machining takes place during on time of the pulse, the off time during which the pulse rests and the deionization of the die-electric takes place. During the off time the debris are removed from the machining zone and speed up the operation in a large way. The Off time also governs the stability of the process. An insufficient off time can lead to erratic cycling and retraction of the advancing servo, slowing down the operation cycle.

3.7.1.3 Peak Current (I_p)

The average current is the average of the amperage in the spark gap measured over a complete cycle. This is read on the ammeter during the process. The theoretical average current can be measured by multiplying the duty cycle and the peak current (max. current available for each pulse from the power supply /generator). Avg. current is an indication of the machining operation efficiency with respect to MRR. The concept of maximum peak amperage that can be applied to the electrode is an important factor. Actually very high currents are not used as they often lead to heat damage of the work surface, the depth of the recast layer might not entirely clean up, the intense heat generated can sink deeply into the surrounding areas of the work piece which might undergo an uncontrolled heat treating or annealing process.

3.7.1.4 Voltage (V)

The voltage used is usually a DC power source of 40 to 400 Volts. An AC power source can also be used but it is usually coupled with a DC rectifier. The preset voltage determines the width of the spark gap between the leading edge of the electrode and the work piece. High voltage settings increase the gap and hence the flushing and machining.

3.7.1.5 Duty factor (τ)

This is an important parameter in the EDM process. This is given by the ratio of the on time to the total time, as follows:

$$\tau = \frac{T_{on}}{T_{on} + T_{off}} \qquad (3.4)$$

τ = Duty factor

T_{on} = Pulse on time

T_{off} = Pulse off time

If we have a high duty factor, the flushing time is very less and this might lead to the short circuit condition. A small duty factor indicates a high off time and low machining rate. Therefore, there has to be a compromise between the two depending on the tool used and the work piece and the conditions prevailing.

3.7.1.6 Polarity

Polarity refers to the electrical conditions determining the direction of the current flow relative to the electrode. The polarity of the electrode can be either positive or negative. Depending on the application, some electrode/work metal combination gives better results when the polarity is changed.

3.7.1.7 Gap Size

This is one of the most crucial parts of the EDM system. The size of the gap is governed by the servo control system whose motion is controlled by gap width sensors. They control the motion of the ram head or the quill which in turn governs the gap size. Typical values of the gap size are between 0.010 to 0.050 mm, although gap sizes as small as of several hundred to several thousands of micrometers can be found depending on the application, current, voltage, and the die-electric media. To maintain a constant gap size the feed rate should be equal to the MRR. The gap size governs the possibility of sparking and arcing.

3.7.1.8 Frequency

This is a measure of the number of time the current is turned on and off. During roughing the on time is increased significantly for high removal rates and there are fewer cycles per second, hence a lower frequency setting. Finish cycles will have many cycles per second hence a larger frequency setting. Frequency should not be confused with the duty cycle, as this is a measure of efficiency.

3.7.2 Performance Parameters

Material removal rate, Tool wear rate, surface roughness and overcut have been used for assessing machining performance extent.

3.7.2.1 Material Removal Rate (MRR)

MRR is expressed as the volumetric loss from the work piece material as cubic millimeter per minute (mm^3/min) as described in **Section 3.6.2.1**.

3.7.2.2 Tool Wear Rate (TWR)

TWR is calculated using volume loss from the tool electrode material per unit time. The weight loss is measured by the same electronic balance weight measuring machine (Sansui (Vibra), Shinko Denshi Co. Ltd. Made in Japan) as shown in Fig. 3.11.

TWR is expressed as,

$$TWR = \frac{T_i - T_f}{\rho_t t} \tag{3.5}$$

Here,

T_i = Initial weight of tool

T_f = Final weight of tool

ρ_t = Density of tool

t = Machining time

3.7.2.3 Surface Roughness (R_a)

The surface roughness of the electro discharge machined specimens is measured by utilizing a portable stylus type profilometre like Talysurf (Taylor Hobson) as described in **Section 3.6.2.2**.

3.7.2.4 Overcut (Z)

Overcut is calculated by measuring diameter of machined area of workpiece and diameter of tool using optical microscope (RADIAL INSTRUMENT with Samsung camera setup, 45-X magnification) shown in Fig. 3.14.

Fig. 3.14: Optical Microscope

Overcut is measure by,

$$z = \frac{d_m - d_t}{2} \qquad (3.6)$$

Here,

d_m = Diameter of machined area of workpiece

d_t = Diameter of tool

3.8 Design of Experiment

Design Of Experiments (DOE) is a powerful statistical tool to study the effect of multiple variables simultaneously introduced by *R.A. Fisher* in England in the 1920's. DOE can be effectively utilized to optimize product and process designs, study the effects of multiple factors (i.e. parameters, variables, constituent etc.) on the performance, and solve production problems by considerately laying out the investigative experiments. DOE has advantages of less number of experiments required for preciseness in effect estimation, improvement quality of a product or process, consistency of performance [76]. In ECM and EDM it is difficult to find a single optimal combination of process parameters for multiple performance characteristics since process parameters influence them differently. For the present investigation, Taguchi's Orthogonal Array has been utilized for design of experiment for continuous improvement of quality and productivity.

3.8.1 Taguchi's Orthogonal Array (OA)

The Taguchi method was developed by *Dr. Genichi Taguchi* of Japan which involves reducing the variation around the target in a process through robust design of experiments. Taguchi developed Orthogonal Array (OA) for designing experiments to examine how different control parameters influence the mean and variance of a performance characteristic that defines how well the process is running. Orthogonal arrays involves to organize the process parameters factors most affect product quality with a minimum amount of experimentation and the levels at which they should be varies, thus saving time and resources [77]. The levels of performance parameters are decided depending up on ranges of values the factors can assume within practical limits.

ECM has a number of process parameters which influence the machining characteristics which have been mentioned in **Section 3.6.1**. Based on literature survey [53-61] and initial trial three machining parameters feed, voltage, electrolyte concentration are selected as control parameters as these has been found most significant parameters in literature review. In the present investigation, all the process parameters have been varied into four different levels. It is represented in Table 3.1.

Table 3.1: Domain of experiment

Factors	Notation	Unit	Level 1	Level 2	Level 3	Level 4
Feed rate	F	mm/min	0.1	0.2	0.3	0.4
Voltage	V	volt	8	10	12	14
Electrolytic concentration	C	gm/lit.	10	15	20	25

For this L_{16} orthogonal array has been chosen appropriate for further experimentation as shown in Table 3.2.

Table 3.2: Taguchi's L_{16} orthogonal array

Run No.	F	V	C
1	1	1	1
2	1	2	2
3	1	3	3
4	1	4	4
5	2	1	2
6	2	2	1
7	2	3	4
8	2	4	3
9	3	1	3
10	3	2	4
11	3	3	1
12	3	4	2
13	4	1	4
14	4	2	3
15	4	3	2
16	4	4	1

Similarly EDM has various process parameters which influence the performance characteristics in different ways which have been described in **Section 3.6.1**. Based on initial trial and literature survey [42-46; 68-71] four machining parameter voltage, pulse on current, pulse on time, duty cycle are selected as control parameters as these have been found most significant parameters in literature review. In this present investigation, all the control parameters all have been varied into four different levels. It is represented in Table 3.3.

Table 3.3: Domain of experiment

Factors	Notation	Unit	Level 1	Level 2	Level 3	Level 4
Voltage	V	Volt	42	44	46	48
Pulse on current	Ip	Ampere	3	4	5	6
Pulse on time	Ton	sec	40	70	100	130
Duty cycle	τ		70	75	80	85

For this L_{16} orthogonal array has been selected for further experimentation and analysis as shown in Table 3.4.

Table 3.4: L_{16} Orthogonal Array

Run No.	V	Ip	Ton	τ
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	1	4	4	4
5	2	1	2	3
6	2	2	1	4
7	2	3	4	1
8	2	4	3	2
9	3	1	3	4
10	3	2	4	3
11	3	3	1	2
12	3	4	2	1
13	4	1	4	2
14	4	2	3	1
15	4	3	2	4
16	4	4	1	3

Chapter 4: Methodologies for Data Analysis

4.1 Introduction

The term optimization is procured from Latin word “optime”, which means the best. Optimization is the achievement of the best result subjected to given situations/ constraints. Depending on the circumstances, the word ‘optimum’ may be taken as ‘minimum’ or ‘maximum’. In production, design, planning, construction, and maintenance of any manufacturing or engineering system, engineers or researchers have to draw many managerial and technological decisions at different phases. All such decisions primarily aim either or to maximize the desired benefit or to minimize the effort required. As the benefit required or effort desired in any practical circumstance can be articulated as a function of many decision variables. Optimization can be defined as maximizing or minimizing an objective functions by consistently selecting input values under given constraints. While designing products and systems needs a profound interpretation of effects that accomplish desirable performance, the requirement for a systematic and efficient decision-making approach initiates the essence for optimization strategies. The need of objective functions to contribute a scalar quantitative performance measure which requires be maximizing or minimizing. The objective function can be the system’s profit, production cost yield etc. For illustration of behavior of the system a predictive model is needed. This modulates into a number of equations and inequalities that is known constraints in optimization problem. In the predictive model the variables must be accorded to satisfy the constraints. This can mostly be achieved with different situation of variable values, persuading to a feasible region which is obtained by a subspace of these variables [78-79].

The process of optimizing simultaneously and systematically set of objective functions are termed as multi-objective Optimization (MOO) or vector optimization. Since the late 1940s, an ample of effort has been done into generating algorithms for interpretation of different types of optimization problems and implementation of good software executions [80-81]. In case of advanced machining methods like ECM and EDM is difficult to find a single optimal combination of process parameters for multiple response characteristics since process parameters influence them differently/ indirectly. In order to obtain the best productivity and quality characteristics; the control parameters affecting the machining process require to be optimized. So, there is an essence for a multiple objective optimization method to obtain the solutions to this problem. In this discussion, the challenge is to procure a model, from a group of promising models, which perfectly suits the experimental data. The parameters of machining are considered as variables and the performance parameters are considered as objective functions which need to be optimized. For ECM a most popular multi-objective optimization technique, *Technique for Order Preference by Similarity to Ideal Solution* (TOPSIS) combined with Taguchi is employed for getting the optimal setting of the process parameters. Then another hybrid optimization technique: grey-fuzzy combined with Taguchi method is employed for further analysis and comparison. In EDM the parameters are found to be correlated. Therefore, a hybrid optimization technique combined Principal Component Analysis (PCA)-TOPSIS with Taguchi method is utilized for getting the optimal solution. Then again another efficient multi-objective optimization technique MOORA combined with Taguchi method is employed for further analysis.

4.2 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

Hwang and Yoon in 1981 firstly came up with this advanced and efficient multi response optimization technique. This method is based on the concept that the selected alternative should have the shortest distance from the positive ideal solution and the farthest distance from negative ideal solution. The solution that maximizes the benefit criteria and minimizes adverse criteria is known as positive ideal solution; whereas, the solution that maximizes the adverse criteria and minimizes the benefit criteria is known as negative ideal solution [62-65; 82]. The steps involved for calculating the TOPSIS values are as follows:

Step 1: The matrix format is developed in this step. The alternatives are represented by row of this matrix and attributes are allocated to each column of the matrix. The decision making matrix can be expressed as:

$$D = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{ij} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \tag{4.1}$$

Here $A_i (i = 1,2.....m)$ represents the possible alternatives $X_j (j = 1,2.......n)$ represents the attributes relating to alternative performance, $j = 1,2,.....n$ and x_{ij} is the performance of A_i with respect to attribute X_j.

Step 2: Normalization of decision matrix is performed in this step. This can be obtained by formula as follows:

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

Here, r_{ij} represents the normalized performance of A_i with respect to attribute X_j.

Step 3: Development of weighted normalized decision matrix,

$$V = [v_{ij}] \tag{4.3}$$

can be found as,

$$V = w_j r_{ij} \tag{4.4}$$

$$\sum w_j = 1 \tag{4.5}$$

Step 4: The positive ideal (best) and negative ideal (worst) solutions are found in this step. The ideal and negative ideal solution can be represented as:

a) The positive ideal solution:

$$A^{+} = \left\{\left(\max v_{ij}, j \in J\right), \left(\min v_{ij}, j \in J^{'}\right)\right\} \tag{4.6}$$

$$= \left\{v_1^{+}, v_2^{+}, \ldots\ldots\ldots v_j^{+}, \ldots\ldots\ v_n^{+}\right\}$$

b) The negative ideal solution:

$$A^{-} = \left\{(\min v_{ij}, j \in J), (\max v_{ij}, j \in J^{'}\right\} \tag{4.7}$$

$$= \left\{v_1^{-}, v_2^{-}, \ldots\ldots v_j^{-}, \ldots\ldots\ldots\ v_n^{-}\right\}$$

Here,

$$J = \{j = 1,2 \ldots\ldots\ldots\ n\}$$

[Associated with the beneficial attributes]

$$J^{'} = \{j = 1,2 \ldots\ldots\ n\}$$

[Associated with the non-beneficial attributes]

Step 5: Determination the distance measures. The separation of each alternative from the ideal solution is obtained by n- dimensional Euclidean distance from the following equations:

$$S_i^{+} = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^{+}\right)^2}, i = 1,2, \ldots\ldots\ m \tag{4.8}$$

$$S_i^- = \sqrt{\sum \left(v_{ij} - v_j^-\right)^2}, i = 1,2,\dots\dots\dots \; \dots m \tag{4.9}$$

Step 6: Calculation the relative closeness to the ideal solution and is represented as:

$$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-} \tag{4.10}$$

Step 7: Ranking of the preference order. The best choice can be obtained by alternative with largest relative coefficient

In this study C_i^+ for each run has been termed as Multi-Performance Characteristic Index (MPCI) which has been optimized by Taguchi method.

4.3 Grey Relational Analysis (GRA)

The grey system theory was initiated by *Deng*in 1982. This method has been convinced as an advantageous methodology for approaching with incomplete, poor and uncertain information. To resolve the complex interrelationships among the multiple performance characteristics efficiently, the grey relational analysis can be implemented which is based on grey system theory. It also gives an effective solution to the discrete data problem. With the employment of grey relational analysis, the relation between machining parameters and performance can be procured [83, 84].

The principal steps of GRA are firstly the performances of all alternatives are converted into a comparability sequence. This step is known as grey relational generation. A reference sequence (ideal target sequence) is developed according to these sequences. Then, calculation of the grey relational coefficient between the reference sequence and all the comparability sequence is done. Finally, the calculation of grey relational grade between every comparability sequences and the reference sequence is performed based on these grey relational coefficients. The alternative will be chosen as best choice, if the comparability sequence derived from that alternative has the highest grey relational grade between itself and the reference sequence [66-67; 83-84].

4.3.1 Grey Relational Generation

The effect of some attributes may be over sighted, when the units or dimensions in which performance is measured are different for different attributes. This may also occur that some performance attributes have a very large range. In addition, if the directions and goals of these attributes are different, it will develop unreliable outcomes in the analysis. Therefore, it is essential for translation of all performance values for every alternative into a comparability sequence, in a method equivalent to normalization. This processing is termed as grey relational generating in GRA.

For a multi-attribute decision making problem, if there are m alternatives and n attributes, the ith alternative can be expressed as $Y_i = (y_{i1}, y_{i2}, \ldots\ldots\ldots y_{ij}, \ldots\ldots, y_{in})$ where y_{ij} is the performance value of attribute j of alternative i. The term Y_i can be translated into the comparability sequence $X_{ij} = (x_{i1}, x_{i2}, \ldots\ldots, x_{ij}, \ldots\ldots\ldots, x_{in})$ by the use of one of Equations.

$$x_{ij} = \frac{y_j - Min\{y_{ij}, i = 1,2,\ldots\ldots m\}}{Max\{y_{ij}, i = 1,2,\ldots\ldots, m\} - Min\{y_{ij}, i = 1,2\ldots\ldots m\}} \tag{4.11}$$

for $i = 1,2,\ldots.m$, $j = 1,2\ldots..n$

$$x_{ij} = \frac{Max\{y_{ij}, i = 1,2\ldots\ldots. m\} - y_{ij}}{Max\{y_{ij}, i = 1,2\ldots. m\} - Min\{y_{ij}, i = 1,2,\ldots\ldots m\}} \tag{4.12}$$

for $i = 1,2,\ldots\ldots. m$ $j = 1,2,\ldots\ldots. n$

$$x_{ij} = 1 - \frac{\left| y_{ij} - y_{ij}^{*} \right|}{Max \left\{ Max \left\{ y_{ij}, i = 1,2,\ldots\ldots m \right\} - y_{ij}^{*}, y_{ij}^{*} - Min \left\{ y_{ij}, i = 1,2,\ldots\ldots m \right\} \right\}} \quad (4.13)$$

For $i = 1,2,\ldots\ldots\ m \quad j = 1,2,\ldots\ldots\ n$

Eq. (4.11) is utilized for the larger-the-better attributes, Eq. (4.12) is for the smaller-the-better attributes and Eq. (4.13) is utilized for the closer-to-the-desired value-y_j -the-better.

4.3.2 Reference Sequence Definition

All performance values will be scaled into [0, 1] after the grey relational generating procedure. For an attribute j of alternative i, if the value x_{ij} which has been obtained by grey relational generating process, is equal to 1, or nearer to 1 than the value for any other alternative, then it concludes that the performance of alternative i is the best one for the attribute j. Hence, if all of the performance values of an alternative are closest to or equal to 1 then that alternative will be the best choice. However, this type of alternative generally does not exist. The reference sequence can be represented as $X_0(x_{01}, x_{02}, \ldots\ldots x_{0j}, \ldots\ldots\ldots, x_{0n}) = (1,1\ldots\ldots\ 1, \ldots.\ 1)$ and then targets to obtain the alternative whose comparability sequence is the nearest to the reference sequence.

4.3.3 Grey Relational Coefficient Calculation

For dictating how close x_{ij} is to x_{0j}, the grey relational coefficient has been utilized. The larger the value of grey relational coefficient, the closer x_{ij} is to x_{0j} be. The calculation of grey relational coefficient can be obtained by Eq. (4.14).

$$\gamma_{ij} = \frac{\Delta_{min} + \zeta \Delta_{max}}{\Delta_{ij} + \zeta \Delta_{max}} \quad (4.14)$$

for $i = 1,2,\ldots\ldots m \quad j = 1,2,\ldots\ldots n$

Here, $\gamma(x_{0j}, x_{ij})$ is the grey relational coefficient between x_{ij} and x_{0j} and

$$\Delta_{ij} = \left| x_{0j} - x_{ij} \right|, \tag{4.15}$$

$$\Delta_{\min} = Min \left\{ \Delta_{ij}, i = 1,2,\ldots\ldots m;\ j = 1,2\ldots\ldots,\ n \right\} \tag{4.16}$$

$$\Delta_{\max} = Max \{ \Delta_{ij}, i = 1,2\ldots\ldots m;\ j = 1,2\ldots\ldots n \} \tag{4.17}$$

ζ is the distinguishing coefficient, $\xi \in [0,1]$.

Compression or expansion of the range of the grey relational coefficient is the aim of the distinguishing coefficient. Based on the decision maker exercising apprehension, the distinguishing coefficient can be adjusted. Also different results of GRA are obtained by different distinguishing coefficients. In this work, the distinguishing coefficient was set as 0.5.

4.3.4 Grey Relational Grade Calculation

The grey relational grade can be then calculated after calculating the entire grey relational coefficient, $\gamma\left(x_{0j}, x_{ij}\right)$ using Eq. (5).

$$\Gamma\left(X_0, X_i\right) = \sum_{j=1}^{n} w_j \gamma\left(x_{0j}, x_{ij}\right) \text{ for } i = 1,2\ldots\ldots,\ m \tag{4.18}$$

Here, $\Gamma\left(X_0, X_i\right)$ is the grey relational grade between X_i and X_0. The level of correlation between the comparability sequence and the reference sequence is represented by this.

w_j is the weight of attribute j and generally depends on the structure of the proposed problem or decision-makers' judgment. Also, $\sum_{j=1}^{n} w_j = 1$.

The degree of similarity between the reference sequence and the comparability sequence is determined by the grey relational grade. As mentioned before, on each attribute, the best performance that could be achieved by any among the comparability sequences is represented by the reference sequence. Therefore, the comparability sequence for an alternative having highest grey relational grade with the reference sequence, is most similar to the reference sequence, and that alternative would be the best choice.

4.4 Fuzzy Logic

Fuzzy inference is the method in which the mapping from a given input to an output is formulated utilizing fuzzy logic. Then decisions can be drawn, or patterns discerned on the basis of mapping. Fuzzy logic can potentially acquire human decision making, commonsense reasoning, and other perspectives of human apprehension. The fuzzy-rule based methodology is a core reasoning process where experts' experience and subject knowledge can possibly be implemented and translated into the machine language. The following elements involve the process of fuzzy inference: Membership Functions, If-THEN Rules and Logical Operations [66-67]. Generally two kinds of fuzzy inference systems can be utilized: *Mamdani* type and *Sugeno* type. Depending on the way in which outputs are determined, these two types of inference systems are varied. The most commonly utilized fuzzy methodology is *Mamdani's* fuzzy inference method. This was developed by *Ebrahim Mamdani* in 1975 as an effort to control a boiler and stem engine combination by incorporating a set of linguistic control rules accessed from human operators' experiences [85-86]. *Mamdani* fuzzy model is developed on the basis of the combinations of IF-THEN rules taking account both consequent predicts and fuzzy antecedent. In this model, the rule base is usually developed by an expert and therefore, it is diaphanous to study and understand is the advantage of this model. Because of its ease implementation, for sorting out a numerous real world problems, Mamdani model is still most primarily utilized.

A fuzzy system generally consists of four components i.e. fuzzifier, an inference engine, a knowledge base and a defuzzifier. The membership functions are first utilized by fuzzifier to convert the crisp inputs into fuzzy sets. Then the fuzzy values are generated by the action of inference engine on fuzzy rules performing fuzzy reasoning. After that the defuzzifier defuzzifies these fuzzy values into crisp outputs [42; 87-88].

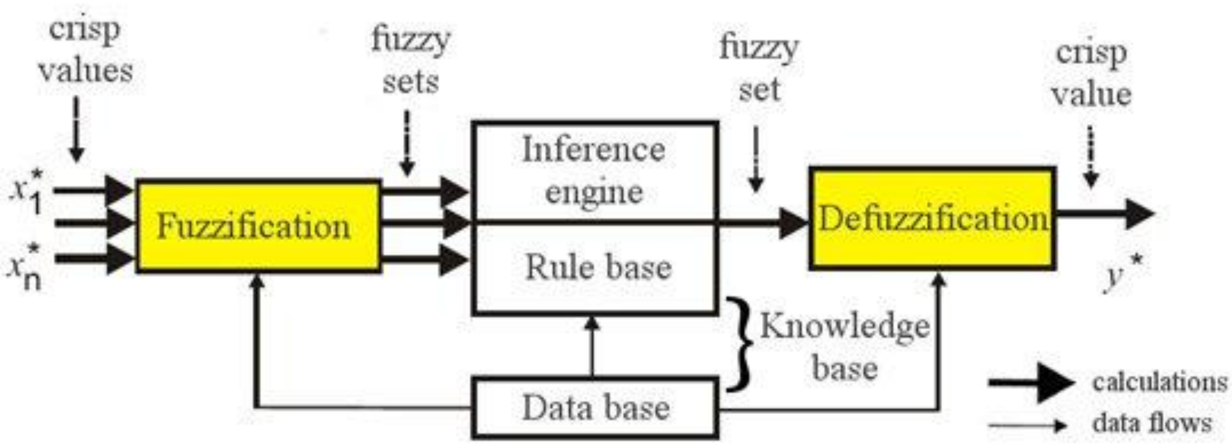


Fig.4.1: Basic Structure of FIS

[Image credit: www.cvis.cz]

These four components are explained below:

- *Fuzzifier*: The real input (response values) in the form of crisp value which encloses absolute information about the definite attribute is assigned to the fuzzifier. This absolute quantity is converted to the form of imprecise quantity like 'Large', 'Medium', 'High' etc. by the fuzzifier which has a degree of appurtenances with it. Typically, the value falls within the range 0 to 1.

- *Knowledge base*: The important component of the fuzzy system is the knowledge base. In this both database and rule base are combinely assigned. The rule base consists of a set of fuzzy IF-THEN rules and the database describes the membership function utilized in fuzzy set theory.
- *Inference engine*: The inference system is also known as the decision-making unit. The inference operations on the rules are performed by this. The ways in which the rules are combined are manipulated by this.
- *Defuzzifier*: An absolute world structure will invariably need the output of the fuzzy system to the form of real output or crisp value. But fuzzy natured output is always achieved by the inference engine. The defuzzifier aims at receiving the fuzzy input and converting it into real world output. It acts adverse to the input block in action.

The membership functions, which characterize the degree of participation of an object in a fuzzy set, evaluate the fuzzy values. For selecting the appropriate structure of the membership functions for the fuzzy set of process variables still there no standard method. Generally, trial and error methods are implemented for this. The *Mamdani* inference method based on fuzzy rules is utilized in this present study for fuzzy inference reasoning.

To develop a rule,

R_i : If x_1 is A_{i1}, x_2 is A_{i2} and x_s is A_{im}

Then y_i is C_i

Here, $X_j\ (j = 1,2\ldots\ldots, s)$ are the input variables, y_i are the output variables and A_{ij} and C_i are fuzzy sets designed by the membership functions $\mu_{Aij}(x_j)$ and $\mu_{Ci}(y_i)$ respectively. M is the total number of fuzzy rules. The aggregated output for the M rules based on the Mamdani implication method is as follows:

$$\mu_{Ci}(y_i) = \max\{\min[\mu_{Ai1}(x_1), \mu_{Ai2}(x_2), \ldots\ldots\ldots \ldots, \mu_{Ais}(x_s)]\},$$

$$i = 1,2,\ldots\ldots\ldots .M \quad (4.19)$$

Then fuzzy set for each output variable requires defuzzification, after the aggregation process. Fuzzy values can be converted into one single crisp output value utilizing the defuzzification method. One of the well-known techniques *the centre of gravity method* is utilized for defuzzifying fuzzy output functions is used in this study. The formula to calculate the centroid of the combined output $\hat{y}_i$ is given by:

$$\hat{y}_i = \frac{\int y_i \mu_{Ci}(y_i) dy}{\int \mu_{Ci}(y_i) dy} \quad (4.20)$$

4.5 Principal Component Analysis (PCA)

Different researchers and engineers have pioneered different multi-response optimization techniques but because of anonymous correlations between the multi performance characteristics (MPCs) many of the recommended methods enhances uncertainties. PCA is a commendable statistical methodology to resolve the correlation problem amongst the responses. Because of its many beneficial attributes like it is simple to implement and also a non-parametric method for deriving appropriate information from ambiguous data sets, Principal Component Analysis (PCA) is a most popular conventional technology in modern data resolution in various sectors from computer graphics to neuroscience. *Pearson in 1901* first came up with this methodology, and developed as a statistical tool by *Hotelling* in 1993 [72-73].

It is most appropriate to implement PCA when there are acquired measures on a number of observed variables and aspire to achieve a fewer number of counterfeit variables known as principal components which will consider for most of the variance in the observed variables. In succeeding studies the principal components may then be utilized as criterion or predictor variables. So, PCA is a most useful methodology with benefits of simplifying a number of correlated variables into equal to less number of independent and uncorrelated principal components conserving considerable original information by utilizing linear combination and considerably easing stowing. By anticipating the eigenvectors of the covariance matrix of the original inputs, the principal components are evaluated. The evaluated variables are ordered in accordance with their variance indicating an abbreviating importance in consideration of acquiring the complete information element of the original data set. The Principal Components, can be utilized for the adequate illustration of the system under investigation as represented as linear combinations of the original variables and are orthogonal to each other. The data are normalized before evaluating the principal components, to maintain some variables or observations from extricating the calculations. Avoidance and elimination of the effects of the units and the relative spread of the data used for evaluating the multiple performance characteristics and effects of units can be achieved by such data preprocessing. An adequate of information for deciding the optimal levels of control parameters is accommodated by the normalization of data. The original data are translated values ranging from values 0 to 1 with 1 considering as the best performance and 0 as the worst [72, 89]. The formula for normalization of Higher-is-Better (HB) characteristic is as follows:

$$x_i^*(j) = \frac{x_i - [\min (x_i(j))]}{[\max (x_i(j))] - [\min (x_i(j))]} \tag{4.21}$$

The normalization formula for lower the better criteria are:

$$x_i^*(j) = \frac{[\max(x_i(j))] - x_i(j)}{[\max(x_i(j))] - [\min(x_i(j))]} \quad (4.22)$$

The steps of PCA are described as follows:

i. Inspecting for correlation among each pair of quality characteristics:

Let $Q_i = \{X_0^*(i), X_1^*(i), \ldots\ldots, X_m^*(i)\}$, where $i = 1,2,3\ldots\ldots n$ (4.23)

It is the normalized series of the *ith* quality characteristic. The correlation coefficient among two quality characteristics is evaluated by the following equation:

$$\rho_{jk} = \frac{Cov(Q_j, Q_k)}{\sigma_{Qj} * \sigma_{Qk}} \quad (4.24)$$

here,

$j = 1,2\ldots\ldots\ldots\ \ldots n$

$k = 1,2\ldots\ldots\ldots\ .n$

$j \neq k$

here, ρ_{jk} is correlation coefficient, σ_{Qj}, σ_{Qk} denotes standard deviation of the quality characteristics j and quality characteristics of k respectively.

ii .Computation of the principal component score:

a. Calculate the Eigen value λ_k and the corresponding Eigen vector β_{kj}, $k = (1,2,3\ldots\ldots\ldots\ n)$ from the correlation matrix developed by all the quality characteristics.

b. Calculate the principal component scores of the comparative sequence and normalized reference sequence utilizing the equation shown below:

$$Y_i(K) = \sum_{j=1}^{n} x_i^*(j)\beta_{kj}, \; i = 0,1,2,3........m, \; k = 1,2,3.........n \tag{4.25}$$

Here, $Y_i(k)$ is the principal component score of the *kth* element in the *ith* series. $X_i^*(j)$ is the normalized value of the *jth* element in the *ith* sequence, and β_{kj} is the *jth* element of the Eigen vector β_k .

iii. Estimation of quality loss $\Delta_{0,i}(k)$***:***

Loss estimate $\Delta_{0,i}(k)$ is defined as the absolute value of the difference between *ith* experimental value for *kth* response and the desired (ideal) value. If responses are correlated then on the contrary of using $[X_0(k)X_i(k)]$; $[Y_0(k)Y_i(k)]$ should be utilized for calculation of $\Delta_{0,i}(k)$.

4.6 Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA)

MOORA method was first proposed by *Brauers* to elucidate different types of complicated decision making problems associated with manufacturing environment, this multi-objective optimization technique can be successfully implemented. The objectives (responses) must be computable and their output values should be measured for every individual alternative, in a decision making problem. Among the contradictory responses or attributes, some are non-beneficial (where minimum criteria values are always desired) and some are beneficial (where maximum values are required); this method takes in to account both beneficial and non-beneficial attributes for choosing or ranking one or more alternatives from a convenient series of available alternatives. This method has broad range of utilizations to obtain decisions in complex and conflicting area of product and process design, supplier selection, supply chain environment, Warehouse location selection etc. [74-75]. The steps of MOORA method are described as follows:

Step 1: The first step in this method is to select the objective and to recognize the relevant evaluation attributes.

Step 2: Then represent all the experimental values for the attributes in the form of a decision matrix.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \tag{4.26}$$

Here,

x_{mj} = The performance measure of *ith* alternative on *jth* attributes

m = The number of alternatives,

n = The number of attributes

Then a ratio system is evaluated in which each performance of an alternative on an attribute is compared to a denominator which is a representative for all the alternatives concerning that attribute.

Step 3: Brauers and Zavadskas [90] concluded that for this denominator, the best choice is the square root of the sum of squares of each alternative per attribute. This ratio can be expressed as below:

$$x_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \quad (i = 1,2,3 .... \ n) \tag{4.27}$$

Here x_{ij}^{*} is a dimensionless number which belongs to the interval $[0,1]$ representing the normalized performance of *ith* alternative on *jth* attribute.

Step 4: For multi-objective optimization, these normalized performances are added in case of maximization (for beneficial attributes) and subtracted in case of minimization (for no beneficial attributes). Then the optimization problem becomes:

$$y_i = \sum_{j=1}^{g} x_{ij}^{*} - \sum_{j=g+1}^{n} x_{ij}^{*} \tag{4.28}$$

Here, g is the number of attributes to be maximized, $(n-g)$ is the number of attributes to be minimized, and y_i is the normalized assessment value of *ith* alternative with respect to all the attributes.

In many cases, it is often found that some attributes have more importance than the others. An attribute could be multiplied with its corresponding weight in order to contribute more importance to that attribute. When these attribute weights are utilized for analysis then, Eq. 4.28 becomes as follows:

$$y_i = \sum_{j=1}^{g} w_j x_{ij}^{*} - \sum_{j=g+1}^{n} w_j x_{ij}^{*} \tag{4.29}$$

Here w_j is the weight of *jth* attribute, which can be determined using Analytic Hierarchy Process (AHP) (or entropy method).

Step 5: Depending of the totals of its maxima (beneficial attributes) and minima (non-beneficial attributes) in the decision matrix, the y_i value may be positive or negative. The final preference is obtained by an ordinal ranking of y_i. Thus, the best alternative has the highest y_i value, while the worst alternative has the lowest y_i value.

Modified equation for maximizing the benefit criteria is given as:

$$y_i = \sum_{j=1}^{g} x_{ij} \Big/ \sum_{j=g+1}^{n} x_{ij} \qquad (4.30)$$

Then the modified values can be further analyzed by employing Taguchi method employed for getting the optimal setting.

4.7 Taguchi Method

In the late 1940's *Dr. Genichi Taguchi* accomplished many convincing research with optimization techniques as a researcher in *Electronic Control Laboratory in Japan*. Taguchi method, which is also popular as the Robust Design eminently, enhances engineering productivity. The Robust Design method assists assure customer satisfaction, by premeditative taking in to account the noise factors (manufacturing variation, environmental variation during product's usage and component deterioration) and the cost of failure in the field. Robust Design aims at enhancing the basic action of the product or process, thus expediting flexible design and concurrent engineering. Undoubtedly, it is the most dynamic methodology usable enhanced quality and to lower product cost, simultaneously also diminish development interval [76-77].

Highlights of Taguchi Philosophy:

A. Robust Design – a systematic, analytic and efficient process.

B. Quantify design reliability in dramatically less time and resources

C. Develop superior products at significantly lower cost in reduced time

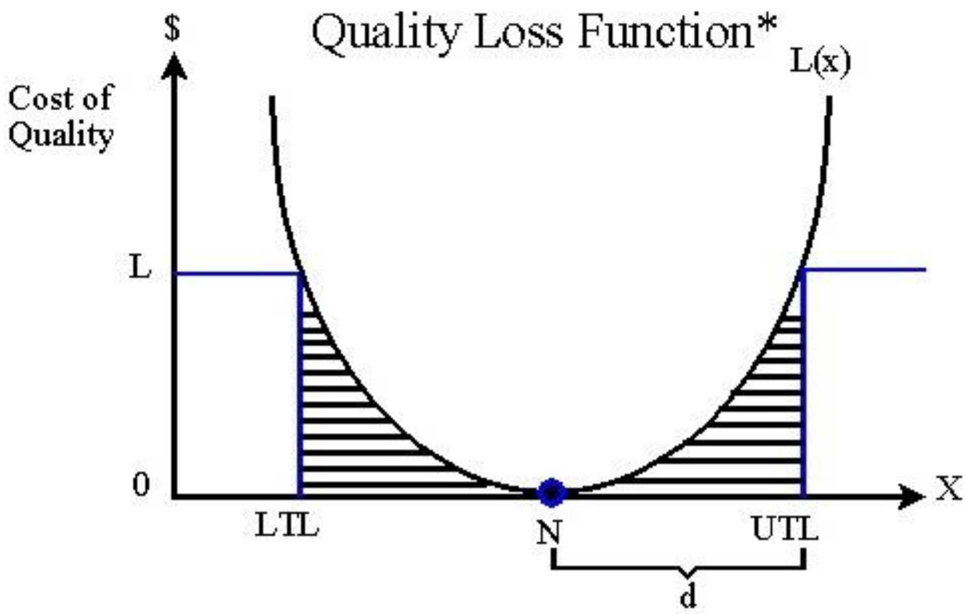


Fig. 4.2: Taguchi's Quality Loss Function

[Image credit: Anderson & Sedatole's Fig. 2, page-218]

L = Loss associated with producing outside of tolerance limits in the traditional quality loss function

$L(x)$ = Loss associated with producing anything other than the nominal specification in the Taguchi Loss Function

LTL = Lower tolerance limit

UTL = Upper tolerance limit

N = Nominal specification

d = Difference between nominal specification and tolerance limit

4.7.1 Taguchi's Rule of Manufacturing

Taguchi apprehended that the best chance to remove variation is at the time of design of a product and its manufacturing process. Hence, he developed a strategy for quality engineering that can be utilized in both circumstances. The process has three stages:

1. System design

2. Parameter design

3. Tolerance design

For this present work parameter design is utilized.

4.7.2 Taguchi's Approach to Parameter Design

Designers can utilize standard and systematic approach for executing experimentation to obtain optimum settings of design parameters for quality and cost very efficiently. The method gives priority to move quality back to the design stage, pursuing to design a/process or product. Orthogonal arrays are utilized in course of Taguchi method, to analyze a large number of variables with a fewer number of experiments. The conclusions made from small-scale experiments are genuine over the complete experimental domain consists of the control factors and their corresponding level settings. This method can decrease the cost of advancement and research by investigating an enormous number of parameters simultaneously. The Taguchi method utilizes a statistical measure of performance called Signal-to-Noise (S/N) ratio, in order to examine the results. The S/N ratio takes into account both the mean and the variability of the response data. After performing the statistical analysis of S/N ratio, an Analysis of Variance (ANOVA) requires to be applied for estimating the relative importance of various factors and for computing error variance. The predicted optimum setting need not correspond to one of the rows of the matrix experiment in Taguchi method for parameter design. Therefore, an experimental confirmation is run utilizing the predicted optimum levels for the process parameters being investigated. The intention is to confirm that the optimum conditions suggested by the matrix experiments do indeed contribute the projected improvement. If the projected improvements and observed match, the suggested optimum conditions will be adopted [77, 91].

4.7.3 Taguchi's S/N ratio for Performance Evaluation

There is a loss function which describes the deviation from the target and further transformed into S/N ratio. The transformed S/N ratio is also defined as quality evaluation index. The least variation and the optimal design are obtained by analyzing S/N ratio. The higher the S/N ratio, the more stable the achievable quality. It also reduces the sensitivity of the system performance to source of variation [91-92].

There are three Signal-to-Noise ratios of common interest for optimization of Static Problems;

(i) Nominal-the-Best (NB): In this approach, the closer to the target value, the better and the deviation is quadratic. The formula for these characteristics is:

$$S/N\ Ratio = -10 \log \frac{y}{S_y^2} \tag{4.31}$$

(ii) Lower-is-Better (LB): The Lower-is-Better approach held when a company desires smaller values. The formula for these characteristics is:

$$S/N\ ratio = -10 \log \frac{1}{n} \sum y^2 \tag{4.32}$$

(iii) Higher-is-Better (HB): Higher-is-Better (HB) is required when a manufacturer desires higher values of a characteristic. The formula for these characteristics is:

$$S/N\ Ratio = -10 \log \frac{1}{n} \sum \frac{1}{y^2} \tag{4.33}$$

Here,

y = Average of observed values;

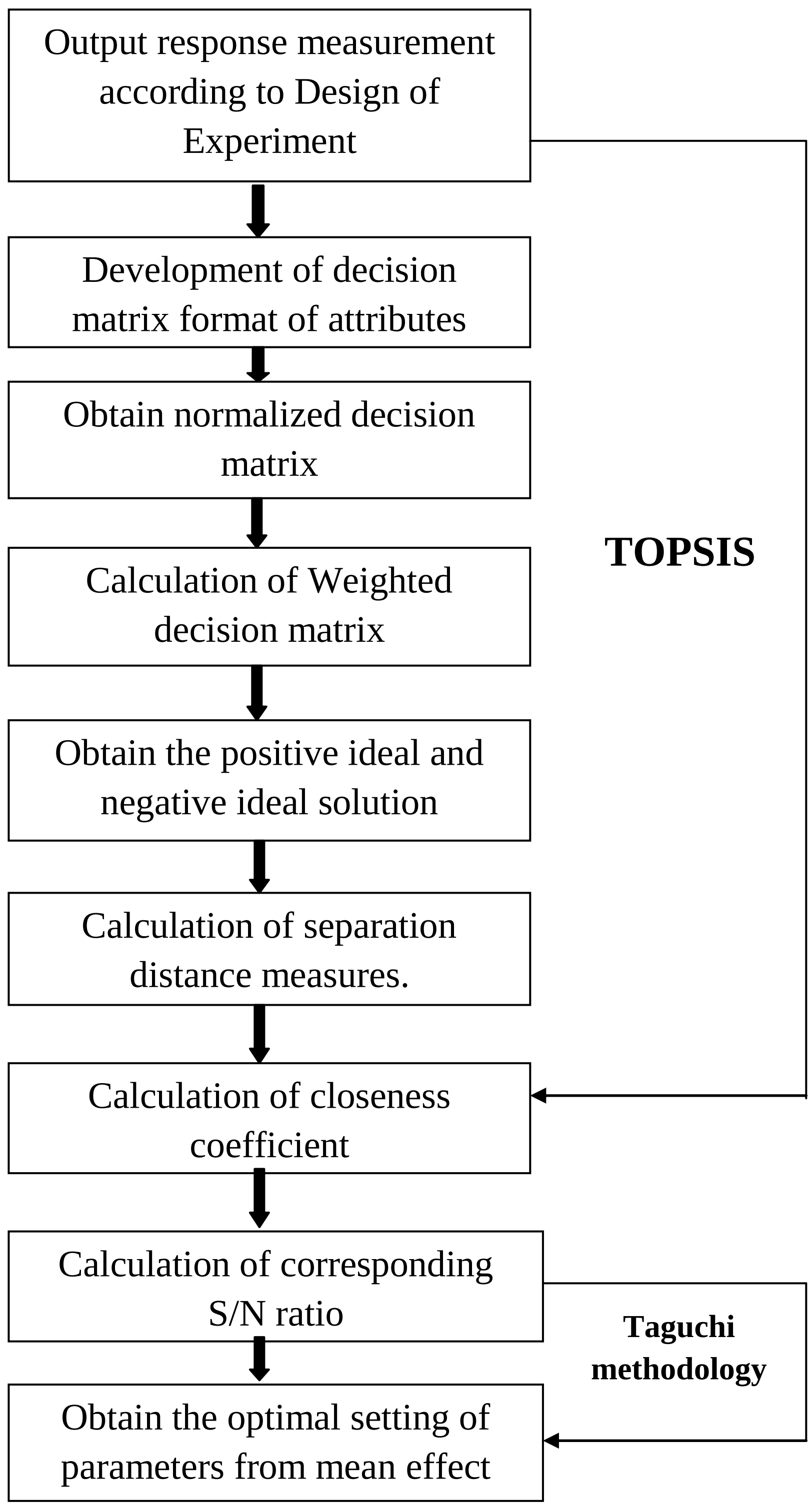
S_y^2 = Variance of y;

N = Number of observations

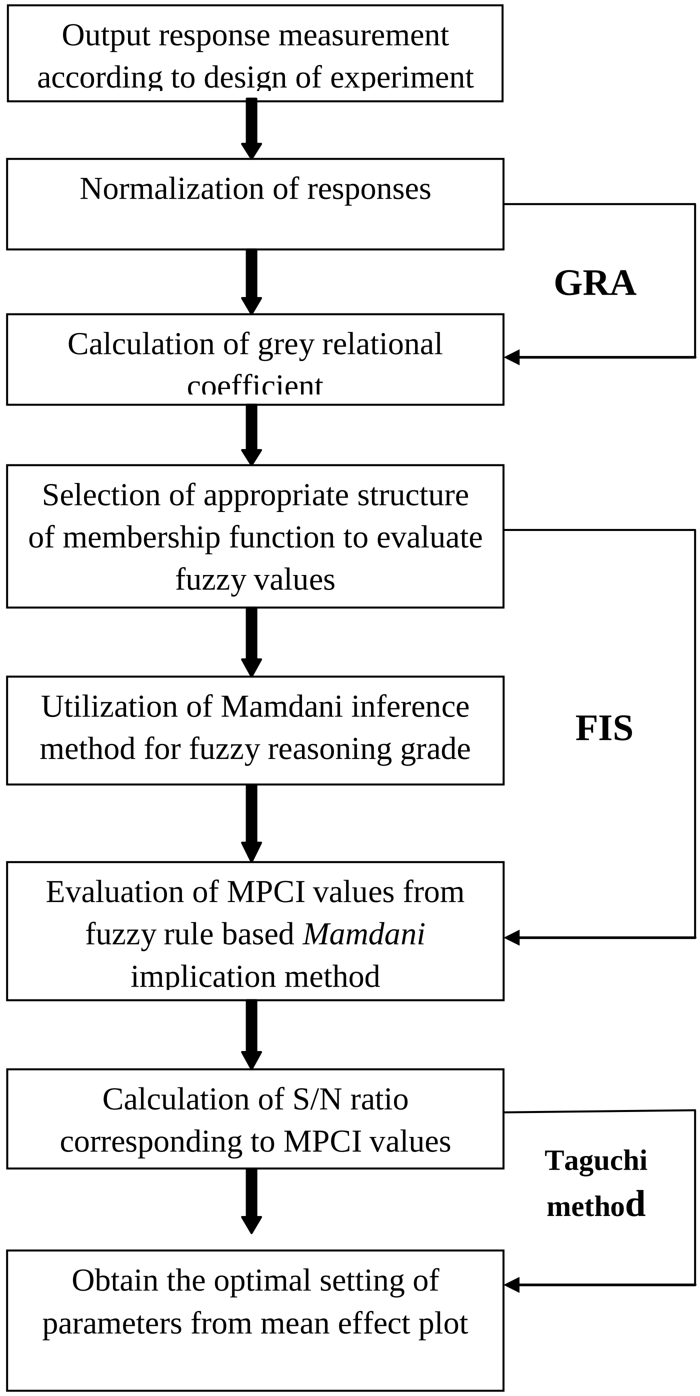
However, Taguchi method is considered only for single objective optimization problems. It cannot be utilized for getting the single optimal setting of process parameters considering more than one performance parameter.

4.8 Proposed Methodology for Analysis of ECM Data

4.8.1 TOPSIS Combined with Taguchi Methodology

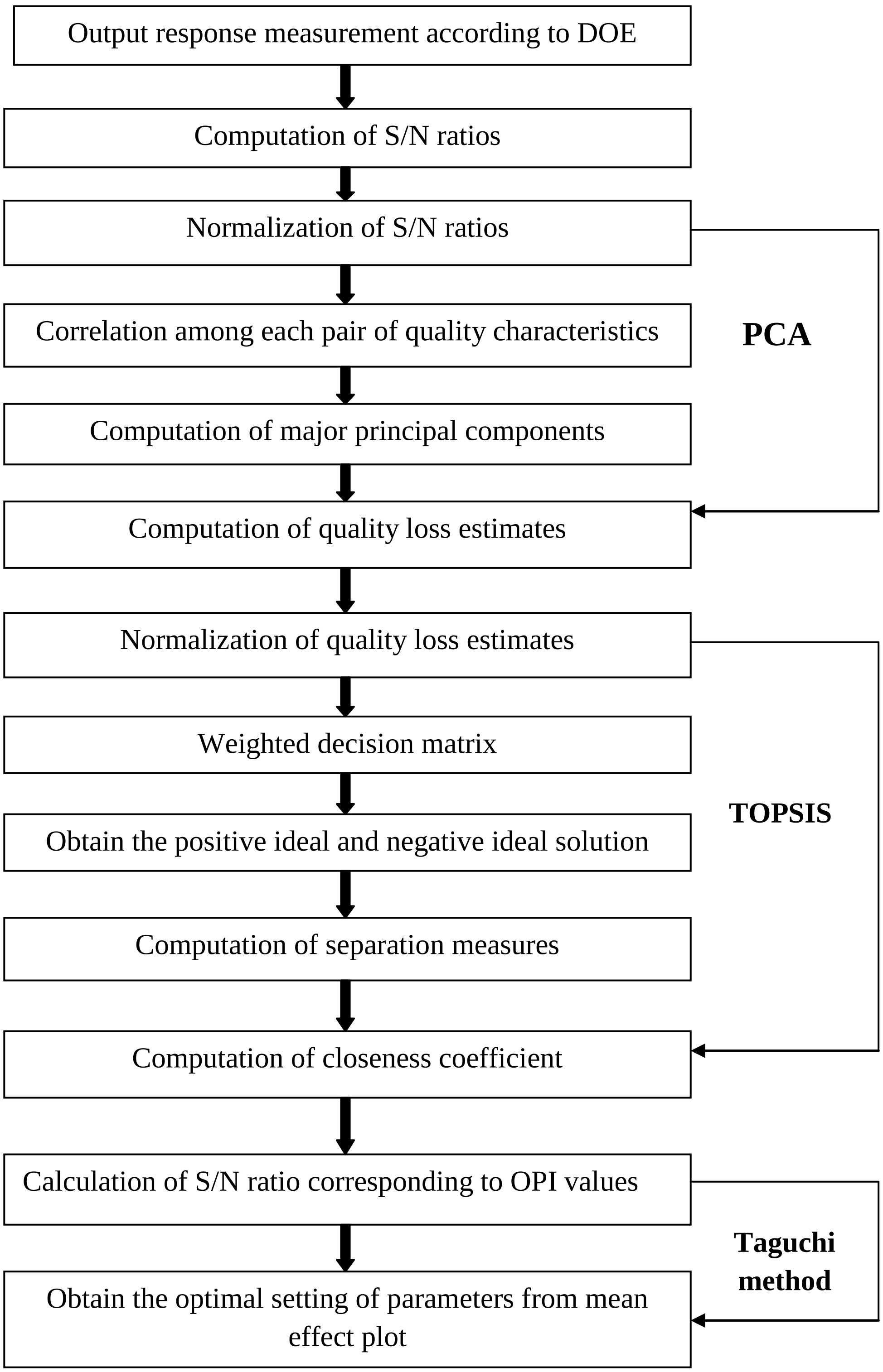


4.8.2 Grey-Fuzzy Combined with Taguchi Methodology

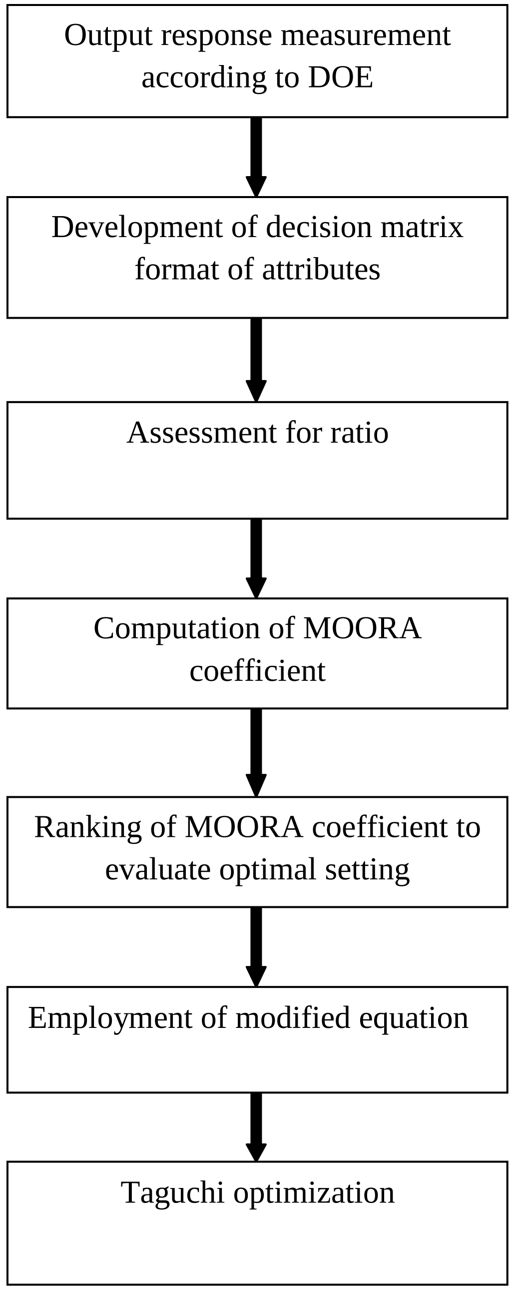


4.9 Proposed Methodology for Analysis of EDM Data

4.9.1 PCA-TOPSIS Combined with Taguchi Philosophy



4.9.2 MOORA Combined with Taguchi Philosophy



Chapter 5: Data Analysis

5.1 Introduction

This chapter contains the analysis of experimental data by different optimization techniques discussed in **Chapter4**. Optimal parameter settings are calculated by different hybrid and multi-objectiveoptimization approaches.

5.2 Electrochemical Machining Data Analysis

The three machining parameters feed (F), voltage (V), electrolyte concentration (C) are varied at four different levels.For getting the optimal parameter setting for electro chemical machining TOPSIS integrated Taguchi method has been utilized. Further grey-fuzzy approach has also been employed. The level values of each process parameter corresponding to L_{16} orthogonal array are shown in Table 5.1.

Table5.1:Taguchi L_{16} OA for ECM process parameters

Run No.	F	V	C	F(mm/min)	V(volt)	C(%)
1	1	1	1	0.1	8	10
2	1	2	2	0.1	10	15
3	1	3	3	0.1	12	20
4	1	4	4	0.1	14	25
5	2	1	2	0.2	8	15
6	2	2	1	0.2	10	10
7	2	3	4	0.2	12	25
8	2	4	3	0.2	14	20
9	3	1	3	0.3	8	20
10	3	2	4	0.3	10	25
11	3	3	1	0.3	12	10
12	3	4	2	0.3	14	15
13	4	1	4	0.4	8	25
14	4	2	3	0.4	10	20
15	4	3	2	0.4	12	15
16	4	4	2	0.4	14	15

The observed values of performance parameters according to setting of parameters of each run is measured and shown in Table5.2.

Table5.2:Experimental data

Run Number	F(mm/min)	V(volt)	C(%)	MRR (mm^3/min)	R_a (μm)
1	0.1	8	10	11.46154	15.06667
2	0.1	10	15	2.538462	10.13333
3	0.1	12	20	10.53846	9.066667
4	0.1	14	25	14.69231	5
5	0.2	8	15	13.38462	9.2
6	0.2	10	10	21.7693	8.2
7	0.2	12	25	18.07692	9.933333
8	0.2	14	20	9.538462	11.8
9	0.3	8	20	15.07692	10
10	0.3	10	25	17.46154	15.8
11	0.3	12	10	18.92308	8.666667
12	0.3	14	15	16.76923	5.4
13	0.4	8	25	30.38462	22.6
14	0.4	10	20	9.384615	10.8
15	0.4	12	15	3.076923	8.933333
16	0.4	14	15	20.15385	7.6

5.2.1 Application of TOPSIS Integrated with Taguchi Method

Step1: The matrix of attributes has been obtained by taking each attribute as one column as described in Eq. 4.1.

Step2:A normalized value of each alternative has been calculated according to (Eq.4.2) and shown in Table 5.3.

Table5.3:Normalized values of corresponding alternatives

Run Number	MRR	Ra	Norm(MRR)	Norm(R_a)
1	11.46154	15.06667	0.178262	0.33312

2	2.538462	10.13333	0.039481	0.224045
3	10.53846	9.066667	0.163905	0.200461
4	14.69231	5	0.22851	0.110549
5	13.38462	9.2	0.208171	0.203409
6	21.7693	8.2	0.338579	0.1813
7	18.07692	9.933333	0.281151	0.219623
8	9.538462	11.8	0.148352	0.260895
9	15.07692	10	0.234492	0.221097
10	17.46154	15.8	0.27158	0.349333
11	18.92308	8.666667	0.294311	0.191617
12	16.76923	5.4	0.260812	0.119392
13	30.38462	22.6	0.472573	0.499679
14	9.384615	10.8	0.145959	0.238785
15	3.076923	8.933333	0.047855	0.197513
16	20.15385	7.6	0.313454	0.168034

Step3: Weighted normalized matrix has been developed utilizing (Eqs. 4.3-4.5).For this present work, both the parameters are given equal weighs. As there are two performance parameters, so weighs given to each parameter is equal to 0.5.Table 5.4 represents the values of weighted normalized matrix.

Table5.4: Weighted normalized value of performance parameters

Run Number	V(MRR)	V(R_a)
1	0.089131	0.16656
2	0.01974	0.112022
3	0.081953	0.100231
4	0.114255	0.055274
5	0.104086	0.101705
6	0.169289	0.09065
6	0.140575	0.109812
7	0.074176	0.130447
8	0.117246	0.110549
9	0.13579	0.174667
10	0.147156	0.095809
11	0.130406	0.059696
12	0.236287	0.24984
13	0.07298	0.119392

14	0.023928	0.098757
15	0.156727	0.084017
16	0.089131	0.16656

Step4: Ideal positive and ideal negative solution of each attribute are computed by utilizing the (Eqs. 4.6-4.7)and shown in Table 5.5.

Table5.5:Positive-ideal and negative-ideal solutions

Sl.No.	Ideal positive	Ideal negative
1	0.236287	0.01974
2	0.055274	0.24984

Step5: The separation of each alternative from ideal solution is calculated using (Eqs. 4.8-4.9)and presented in Table 5.6.

Table5.6:Separation measures of attributes from ideal solution

Run Number	S+	S-
1	0.034039	0.011751
2	0.050113	0.018994
3	0.02584	0.026253
4	0.014892	0.046789
5	0.019633	0.029058
6	0.00574	0.047707
7	0.012135	0.034209
8	0.031931	0.017218
9	0.017226	0.02891
10	0.024354	0.019119
11	0.009587	0.03996
12	0.013166	0.048402
13	0.037856	0.046892
14	0.03078	0.019851
15	0.046987	0.022844
16	0.007156	0.457956

Step6: Finally the closeness coefficient is calculated using Eq. 4.10. Finally Taguchi method is employed for obtaining the final optimal setting.The closeness coefficient is treated as overall performance index(OPI) for further optimization.Higher-is-Better (HB)criteria have been utilized for calculating the S/N ratio of OPI. As larger the value of closeness coefficient betters the proximity to ideal solution. The values of closeness coefficient and corresponding S/N ratio are shown in Table 5.7.

Table5.7: Closeness coefficient and corresponding coefficient ratio

Run Number	C_i^+	S/N ratio	Predicted S/N ratio
1	0.25662	-11.8142	-1.79961
2	0.274846	-11.2182	
3	0.503965	-5.95199	
4	0.758566	-2.40013	
5	0.596786	-4.48362	
6	0.892601	-1.98686	
7	0.738154	-2.63706	
8	0.350321	-9.11067	
9	0.626621	-4.0599	
10	0.439783	-7.13524	
11	0.806501	-1.8679	
12	0.786152	-2.08987	
13	0.553314	-5.14056	
14	0.607931	-4.32291	
15	0.327129	-9.70562	
16	0.550271	-5.18847	

The optimal setting of parameters is obtained from mean effect plot of S/N ratio using MINITAB-16 software and shown in Fig.5.1.

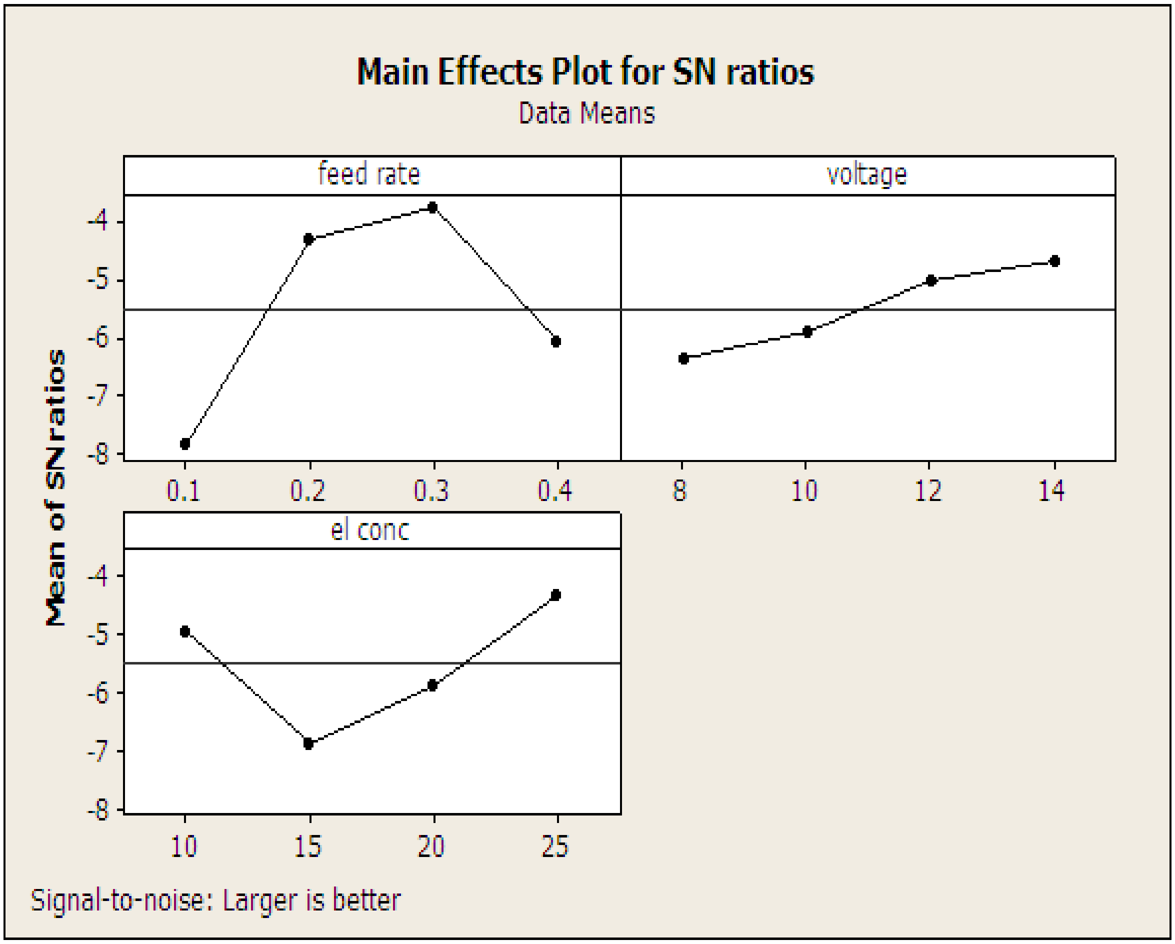


Fig.5.1:S/N ratio plot of OPI

The optimal setting of process parameters obtained from S/N ratio plot is presented in Table 5.8.

Table5.8:Optimal combination factors

Factor	Feed rate	voltage	El. concentration
level	0.3mm/min	14 V	25%

5.2.2 Combined Grey-Fuzzy and Taguchi Approach

Step1: The normalized values of each response have been calculated using Eq. 4.11.Higher-is-Better (HB)criterion has been used for MRR and Lower-is-Better (LB)criterion has been used for R_a so that all the attributes of equivalent dimension. The calculated values of normalized responses are shown in Table 5.9.

Table5.9: Normalized MRR and R_a values

Run Number	MRR	Ra	Norm(MRR)	Norm(R_a)
1	11.46154	15.06667	0.320442	0.42803
2	2.538462	10.13333	0.0000	0.708333
3	10.53846	9.066667	0.287293	0.768939
4	14.69231	5	0.436464	1.000000
5	13.38462	9.2	0.389503	0.761364
6	21.7693	8.2	0.69061	0.818182
7	18.07692	9.933333	0.558011	0.719697
8	9.538462	11.8	0.251381	0.613636
9	15.07692	10	0.450276	0.715909
10	17.46154	15.8	0.535912	0.386364
11	18.92308	8.666667	0.588398	0.791667
12	16.76923	5.4	0.51105	0.977273
13	30.38462	22.6	1	0.0000
14	9.384615	10.8	0.245856	0.670455
15	3.076923	8.933333	0.019337	0.776515
16	20.15385	7.6	0.632597	0.852273

Step2: Grey relational theory has been implemented to convert the normalized values of each response into corresponding grey relational coefficient using Eq. 4.14 and shown in Table 5.10.

Table5.10: Grey relational coefficient $[\gamma_i(k)]$

Run Number	$[\gamma_i(k)]$ of MRR	$[\gamma_i(k)]$ of R_a
1	0.423887565	0.466431095
2	0.33333333	0.631578947

3	0.412300663	0.683937824
4	0.470129834	1
5	0.450248726	0.676923077
6	0.617749247	0.733333333
7	0.530791733	0.640776699
8	0.400442461	0.564102564
9	0.476315751	0.637681159
10	0.51862459	0.448979592
11	0.548484786	0.705882353
12	0.505586545	0.956521739
13	0.999999669	0.333333333
14	0.398678397	0.602739726
15	0.337686563	0.691099476
16	0.576433047	0.771929825

Step 3: Fuzzy logic has been implemented for accessing the values of Multi Performance Characteristic index(MPCI*).* *Mamdani* type fuzzy inference methodology has been implemented for this present work. Individual grey relation coefficients (for MRR and roughness)have been fed as inputs to the proposed Fuzzy Inference System(FIS) as shown in Fig. 5.2.

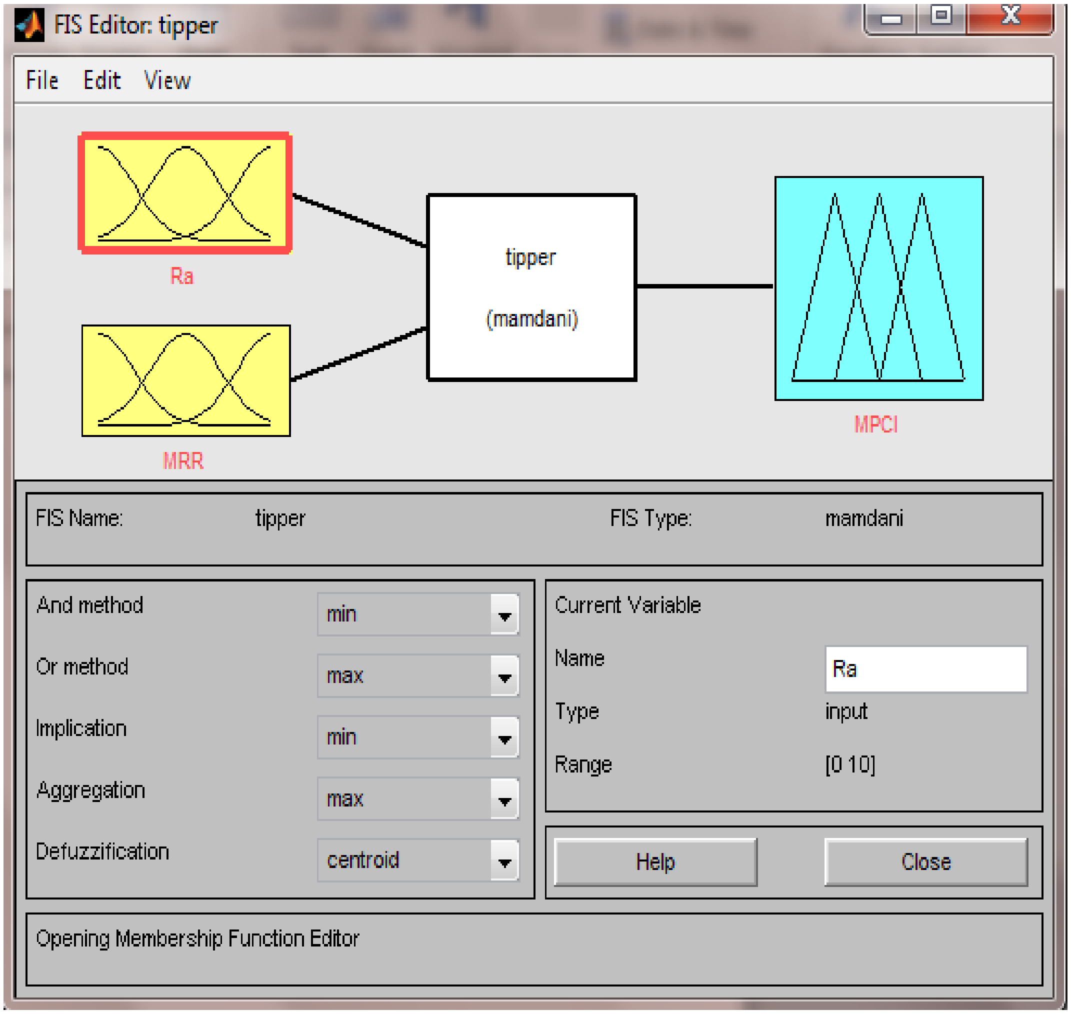
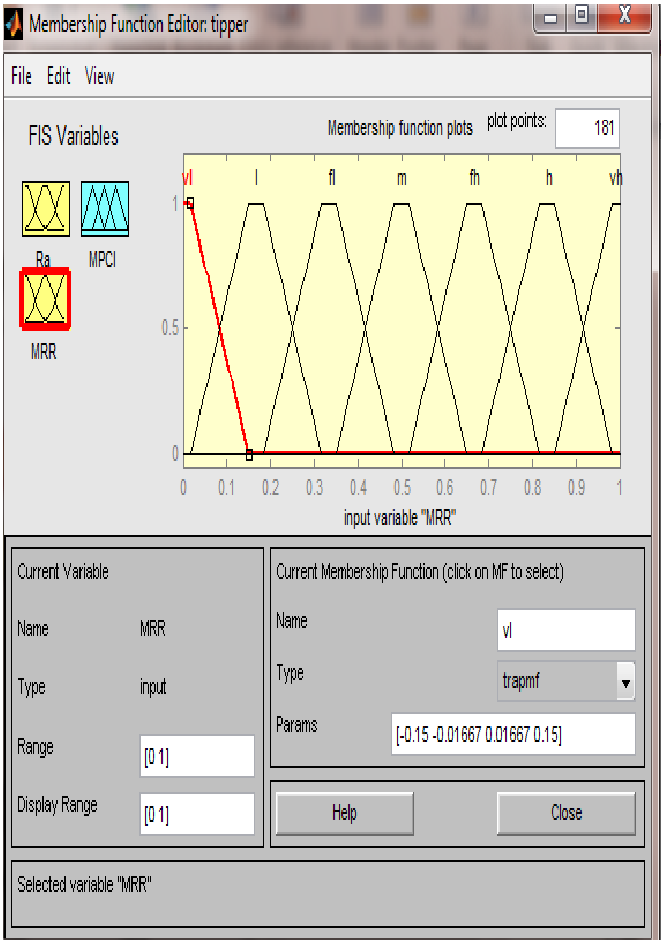


Fig.5.2:Proposed Fuzzy Inference System

Each input factor has been expressed using seven linguistic variables viz. “Very Low (VL)”, “Low(L)”, “Fairly Low (FL)”, “Medium (M)”, “Fairly High (FH)”, “High (H)”, “Very High (VH)” as shown as shown in Fig.5.3 and Fig. 5.4.

In present analysis, the trapezoidal membership function has been used to convert crisp inputs into fuzzy values.Membership function for MPCI is shown in Fig. 5.5.



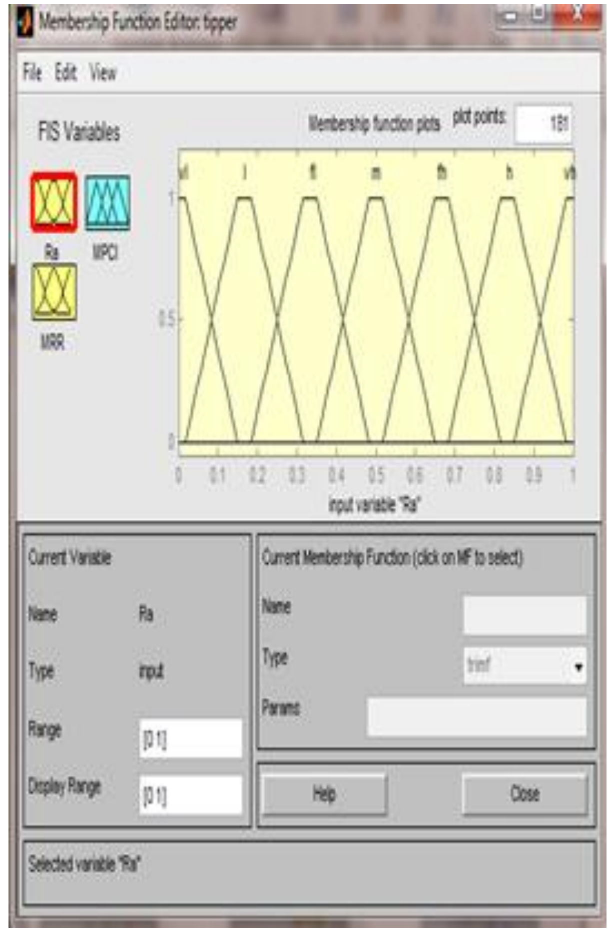


Fig.5.3: Membership Function of MRRFig.5.4: Membership Function for R_a

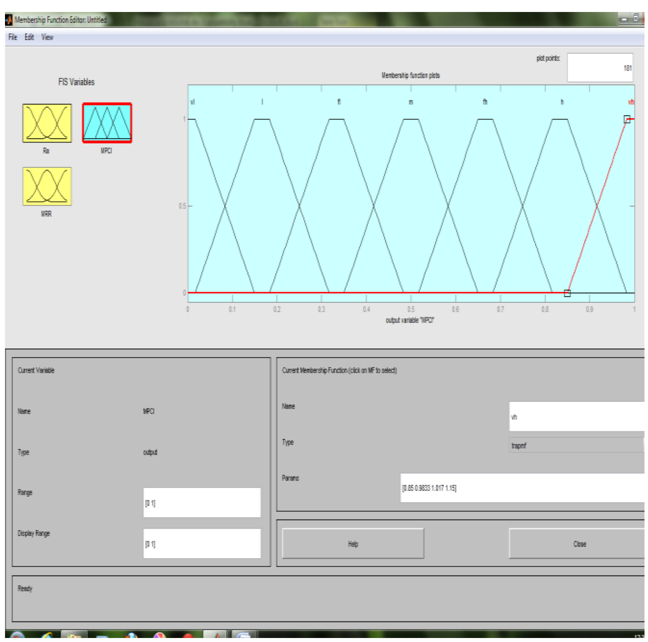


Fig.5.5: Membership Function of MPCI

Step4: The fuzzy rule matrix has been developed using the seven different linguistic variables for each response and shown in Table 5.11.

Table 5.11:Fuzzy rule matrix

MPCI		MRR						
		VL	***L***	***FL***	***M***	***FH***	***H***	***VH***
Ra	***VL***	***VL***	***VL***	***L***	***L***	***FL***	***FL***	***M***
	L	***VL***	***VL***	***L***	***FL***	***FL***	***M***	***M***
	FL	***L***	***L***	***FL***	***FL***	***M***	***M***	***FH***
	M	***L***	***L***	***FL***	***M***	***M***	***FH***	***H***
	FH	***L***	***FL***	***FL***	***M***	***FH***	***H***	***H***
	H	***L***	***FL***	***M***	***FH***	***FH***	***H***	***VH***
	VH	***FL***	***FL***	***M***	***FH***	***H***	***H***	***VH***

On the basis of fuzzy rules The *Mamdani* implication method has been employed for fuzzy inference reasoning on the basis of fuzzy rules as shown in Fig.5.6.

Step 5: The MPCI value for each alternative has been evaluated from FIS output. Then Taguchi method is employed for determining the optimal machining condition by using S/N ratio plot of MPCI as shown in Fig. 5.7. For computing the S/N ratio, Higher-is-Better (HB) criterion has been adopted. The values of individual MPCI values and corresponding S/N ratio are shown in Table 5.9. The predicated S/N ratio of MPCI (-2.83586) has been evaluated which has been seemed highest among all calculated S/N ratio values of MPCIs entered in Table 5.12.

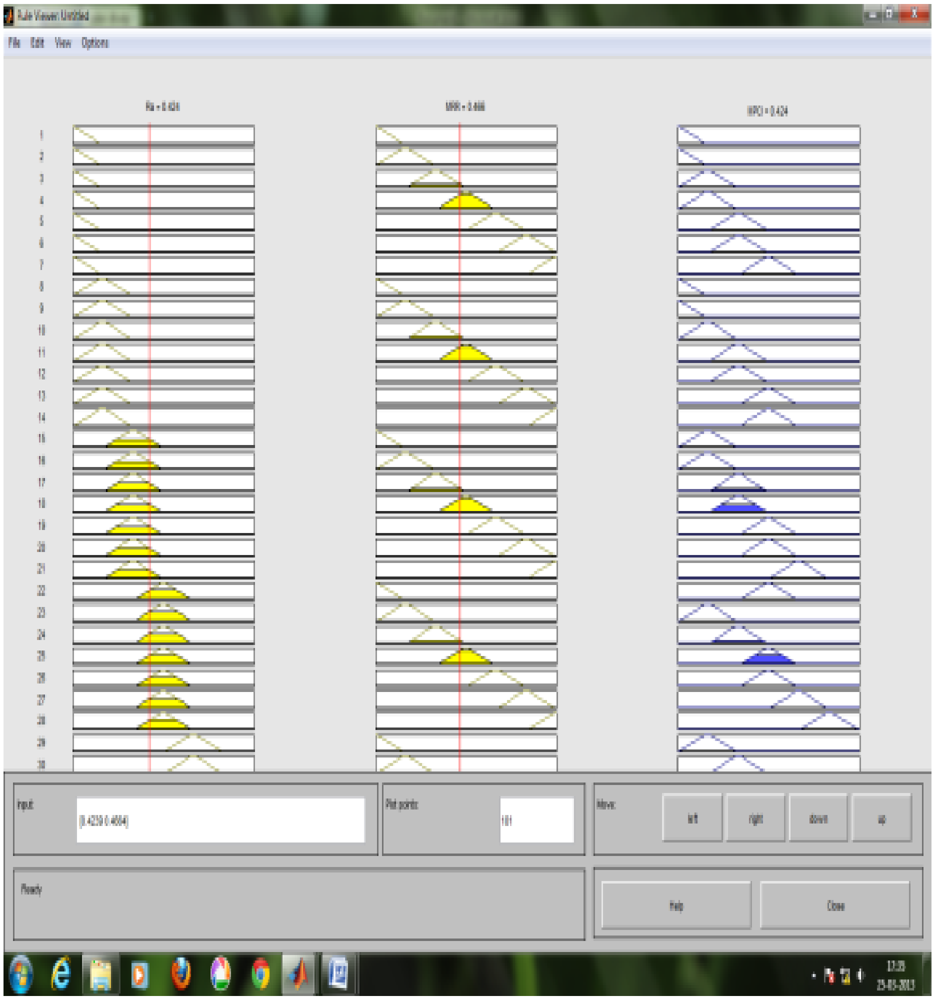


Fig.5.6:Fuzzy rule base

Table5.12:Values of MPCI and corresponding S/Nratio

Run Number	MPCI	S/N ratio	Predicted S/N ratio
1	0.424	-7.45268	-2.83586
2	0.333	-9.55112	
3	0.413	-7.68100	
4	0.646	-3.79535	
5	0.453	-6.87804	
6	0.617	-4.19430	
7	0.522	-5.64659	
8	0.400	-7.95880	
9	0.488	-6.23160	

10	0.452	-6.89723	
11	0.545	-5.27207	
12	0.667	-3.51748	
13	0.667	-3.51748	
14	0.398	-8.00234	
15	0.346	-9.21848	
16	0.602	-4.40807	

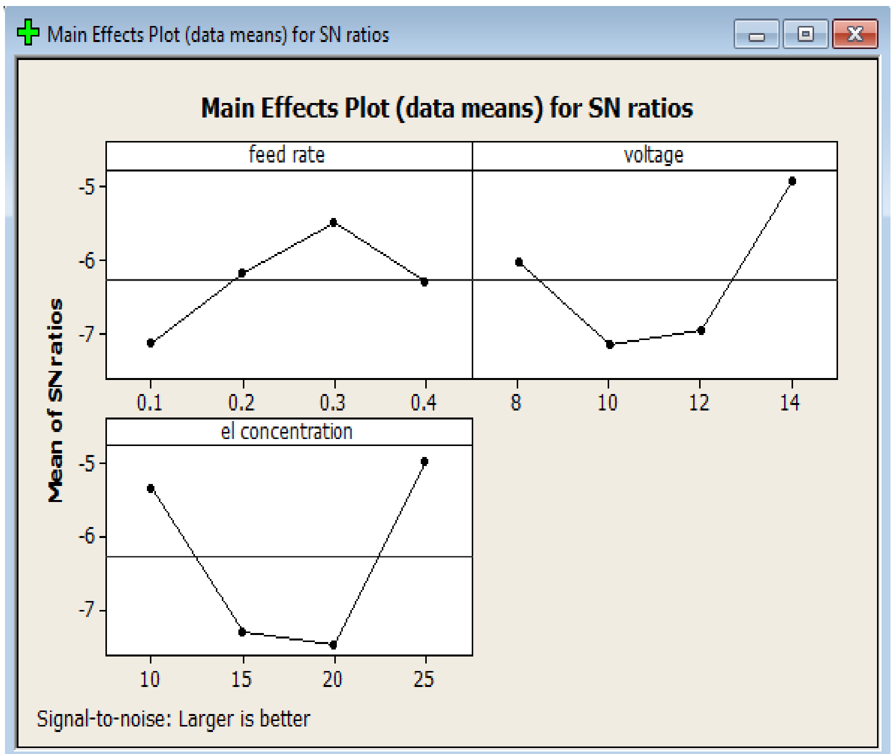


Fig.5.8:S/N ratio plot of MPCI

The optimal setting of process parameters with highest S/N ratio is obtained from S/N ratio plot as shown in Table 5.13.

Table 5.13:Optimal parameter setting

Factors	Feed rate	voltage	El. concentration
level	0.3mm/min	14 V	25%

5.3 Electro Discharge Machining Data Analysis

The four machining parameters voltage(V),pulse on current(Ip),pulse on time (Ton),duty cycle(τ) are varied at four different levels. For getting the optimal parameter setting for electro discharge machining a hybrid optimization technique combined PCA-TOPSIS integrated Taguchi method has been utilized. Then further MOORA method has also been employed for further optimization analysis and comparison. The values of each alternative corresponding to each level values in L_{16} orthogonal array (OA) as shown in Table5.14.

Table5.14:L_{16} Orthogonal Array

Run Number	V	Ip	Ton	τ	V	Ip	Ton	τ
1	1	1	1	1	42	3	40	70
2	1	2	2	2	42	4	70	75
3	1	3	3	3	42	5	100	80
4	1	4	4	4	42	6	130	85
5	2	1	2	3	44	3	70	80
6	2	2	1	4	44	4	40	85
7	2	3	4	1	44	5	130	70
8	2	4	3	2	44	6	100	75
9	3	1	3	4	46	3	100	85
10	3	2	4	3	46	4	130	80
11	3	3	1	2	46	5	40	75
12	3	4	2	1	46	6	70	70
13	4	1	4	2	48	3	130	75
14	4	2	3	1	48	4	100	70
15	4	3	2	4	48	5	70	85
16	4	4	1	3	48	6	40	80

The observed values of performance parameters viz.Material Removal Rate (MRR),Surface roughness(R_a), Tool wear rate(TWR), overcut(Z) according to setting of parameters for each run are measured and shown in Table5.15.

Table5.15: Experimental data

Run Number	V (V)	Ip (Amp)	T_{on} (Sec)	τ	MRR (mm^3/min)	TWR (mm^3/min)	R_a (µm)	Z (mm)
1	42	3	40	70	1.344538	0.04857997	5.8	0.0945
2	42	4	70	75	0.483193	0.028026906	7.333333	0.1495
3	42	5	100	80	0.168067	0.016816143	6.8	0.0955
4	42	6	130	85	1.848739	0.028026906	7.933333	0.2095
5	44	3	70	80	1.533613	0.039237668	7.133333	0.1725
6	44	4	40	85	1.764706	0.033632287	9.2	0.018
7	44	5	130	70	8.865546	0.022421525	8.6	0.167
8	44	6	100	75	4.222689	0.044843049	8.133333	0.1965
9	46	3	100	85	0.882353	0.05044843	7.6	0.102
10	46	4	130	80	1.97479	0.022421525	8.866667	0.0745
11	46	5	40	75	1.44958	0.011210762	6.933333	0.0055
12	46	6	70	70	10.13025	0.056053812	5.466667	0.2895
13	48	3	130	75	6.953782	0.033632287	8.466667	0.136
14	48	4	100	70	0.798319	0.016816143	8.4	0.032
15	48	5	70	85	2.184874	0.061659193	9.8	0.1295
16	48	6	40	80	12.4916	0.151345291	6.466667	0.245

5.3.1 Combined PCA-TOPSIS Integrated with Taguchi Approach

Step1: S/N ratio for each alternative has been calculated using Higher-is-Better (HB) criteria for MRRusing Eq. 4.33;Lower-is-Better criteria (LB) for TWR, R_a and Z using Eq. 4.32 and shown in Table 5.16.

Table5.16: S/N ratio values of each performance parameters

Run Number	MRR	TWR	Ra	Z
1	2.57146	26.27086	-15.2686	20.49136
2	-6.31758	31.0485	-17.306	16.50718
3	-15.4903	35.48547	-16.6502	20.39993
4	5.337514	31.0485	-17.9891	13.57632
5	3.714318	28.12594	-17.0659	15.26422
6	4.933447	29.46487	-19.2758	34.89455
7	18.95411	32.9867	-18.69	15.54567
8	12.51178	26.9661	-18.2054	14.13275
9	-1.08715	25.94305	-17.6163	19.828
10	5.910418	32.9867	-18.9552	22.55687
11	3.224843	39.0073	-16.8188	45.19275
12	20.1124	25.0279	-14.7545	10.76703
13	16.84442	29.46487	-18.5542	17.32922
14	-1.95647	35.48547	-18.4856	29.897
15	6.788528	24.20004	-19.8245	17.7546
16	21.93236	16.40062	-16.2136	12.21668

Step2: Normalized values corresponding to each S/N values has been obtained using Eq. 4.21.Higher-is-Better (HB) criteria for normalization has been utilized and furnished in Table 5.17.

Table5.17: Normalized values corresponding to S/N ratio values

Run Number	MRR	TWR	R_a	Z
Ideal solution	1	1	1	1
1	0.48264	0.436607	0.89860752	0.282473
2	0.24511	0.647945	0.49673994	0.1667401
3	0	0.844213	0.62609896	0.2798171
4	0.55656	0.647945	0.36200906	0.0816044
5	0.51318	0.518666	0.54411235	0.1306346
6	0.54576	0.577893	0.10823342	0.7008574
7	0.92042	0.73368	0.22377337	0.1388102
8	0.74827	0.467361	0.31935475	0.0977676
9	0.38488	0.422107	0.43554796	0.2632034
10	0.57187	0.73368	0.17145806	0.342472
11	0.5001	1	0.59283203	0.9999999

12	0.95137	0.381625	1.00000949	0
13	0.86404	0.577893	0.25054256	0.1906189
14	0.36165	0.844213	0.26408566	0.5556883
15	0.59533	0.345005	0	0.2029754
16	1	0	0.7122072	0.0421095

Step3: Using PCA on normalized S/N ratios for the responses, the Eigen values, eigenvectors, accountability proportion (AP) and cumulative accountability proportion (CAP) has been obtained by Principal Component Analysis and shown in Table5.18.

Table5.18: PCA Results: Eigen values, eigen vectors,AP,CAP

	PC1	PC2	PC3	PC4
Eigen value	2.0733	0.9799	0.6053	0.3416
Eigen vector	$\begin{vmatrix} 0.415 \\ 0.695 \\ -0.247 \\ 0.562 \end{vmatrix}$	$\begin{vmatrix} -0.418 \\ -0.045 \\ -0.907 \\ 0.019 \end{vmatrix}$	$\begin{vmatrix} -0.683 \\ 0.087 \\ 0.324 \\ 0.649 \end{vmatrix}$	$\begin{vmatrix} -0.337 \\ 0.782 \\ 0.106 \\ -0.513 \end{vmatrix}$
AP	0.518	0.245	0.151	0.085
CAP	0.518	0.763	0.915	1.000

Step4: The major principal component scores of the normalized series have been computed using Eq. 4.24 and shown in Table 5.19.

Step 5: Quality loss estimates of the major principal component scores have been computed as the absolute value of difference between the ideal (desired) value and the values of individual major principal component score and shown in Table 5.20.

Table5.19: Major principal component scores

RunNo.	PC1	PC2	PC3
Ideal solution	0.435	0.515	1.743
1	-0.0336009	0.627573	0.842103

2	0.248169	0.374076	0.49294
3	0.5218017	0.600545	0.457904
4	0.07943606	0.123309	0.606751
5	0.00397561	0.299858	0.656701
6	0.45240205	-0.11727	0.912954
7	0.01834689	-0.15139	0.855065
8	-0.10689968	-0.00395	0.718648
9	0.10942103	0.248157	0.611531
10	0.31825926	-0.05702	0.732231
11	0.78301991	0.354656	1.269647
12	-0.48322982	0.52651	1.006988
13	-0.02705213	-0.11154	0.845304
14	0.58724285	0.115788	0.766658
15	0.03156214	-0.23718	0.568357
16	-0.64724966	0.227172	0.941084

Table5.20: Computed quality loss estimates PC1 to PC3

RunNo.	PC1	PC2	PC3
1	0.468601	0.11257	1.855573
2	0.186831	0.140924	1.602076
3	0.0868	0.08554	1.828545
4	0.355564	0.391691	1.351309
5	0.431024	0.215142	1.527858
6	0.0174	0.632271	1.110729
7	0.416653	0.666393	1.076607
8	0.5419	0.518947	1.224053
9	0.325579	0.266843	1.476157
10	0.116741	0.572019	1.170981
11	0.34802	0.160344	1.582656
12	0.91823	0.01151	1.75451
13	0.462052	0.626544	1.116456
14	0.15224	0.399212	1.343788
15	0.403438	0.752179	0.990821
16	1.08225	0.287828	1.455172

Step6: TOPSIS method has been employed from this step for converting the multiple objective functions into single objective function. Normalized values of quality loss estimates have been computed using Eq. 4.2 and shown in Table5.21.

Table5.21: Normalized values of quality loss estimates for major PCs

RunNo.	PC1	PC2	PC3
1	0.243733	0.065237	0.324543
2	0.097176	0.081669	0.280206
3	0.045147	0.049573	0.319816
4	0.184939	0.226996	0.236346
5	0.224189	0.124681	0.267225
6	0.00905	0.366418	0.194269
7	0.216714	0.386193	0.188301
8	0.281858	0.300744	0.214089
9	0.169343	0.154643	0.258183
10	0.06072	0.3315	0.204807
11	0.181015	0.092924	0.27681
12	0.477598	0.00667	0.306867
13	0.240327	0.363099	0.19527
14	0.079185	0.231354	0.235031
15	0.20984	0.435908	0.173296
16	0.56291	0.166804	0.254512

Step7: Weighted normalized matrix has been developed utilizing (Eqs.4.3-4.5).For this present work all the factors are given equal weightage, so weightage given to each parameter is equal to 0.3333.Table 5.22 represents the values of weighted normalized matrix.

Table5.22: Weighted normalized values of quality loss estimates

RunNo.	PC1	PC2	PC3
1	0.081244	0.021746	0.108181
2	0.032392	0.027223	0.093402
3	0.015049	0.016524	0.106605
4	0.061646	0.075665	0.078782

5	0.074729	0.04156	0.089075
6	0.003017	0.122139	0.064756
7	0.072238	0.128731	0.062767
8	0.093953	0.100248	0.071363
9	0.056448	0.051548	0.086061
10	0.02024	0.1105	0.068269
11	0.060338	0.030975	0.09227
12	0.159199	0.002223	0.102289
13	0.080109	0.121033	0.06509
14	0.026395	0.077118	0.078344
15	0.069947	0.145303	0.057765
16	0.187636	0.055601	0.084837

Step8: Positive ideal and negative ideal solution for each attribute have been developed utilizing (Eq. 4.6-4.7) and is shown in Table5.23.

Table5.23: Positive ideal and negative ideal solution

Sl. No.	Ideal positive	Ideal negative
1	0.003017	0.187636
2	0.002223	0.145303
3	0.057765	0.108181

Step9: The separation measures of each alternative from the ideal solutions have been computed using (Eqs. 4.8-4.9) and furnished in Table 5.24.

Table5.24: Computed values of separation measures

Run No.	S^-	S^+
1	0.163051	0.095092
2	0.195607	0.052516
3	0.215343	0.052294
4	0.146926	0.096296
5	0.154517	0.087581

6	0.191067	0.12012
7	0.125115	0.144294
8	0.110282	0.134399
9	0.162757	0.078028
10	0.175572	0.11014
11	0.17184	0.072822
12	0.145997	0.162405
13	0.118355	0.141819
14	0.17759	0.081113
15	0.128033	0.15796
16	0.092689	0.194079

Step10: The closeness coefficients have been computed utilizing Eq. 4.10 and further it has been treated as Overall Performance Index(OPI) for employment of Taguchi method. S/N ratio values corresponding to each OPI values have been computed considering Higher-is-Better (HB) criteria and furnished in Table5.25.

Table5.25: Closeness coefficient and corresponding S/N ratio values

Run No.	C_i^+	S/N ratio	Predicted S/N ratio
1	0.631631	-3.99073	-0.473864
2	0.788348	-2.06564	
3	0.804609	-1.88831	
4	0.604082	-4.37809	
5	0.638242	-3.90029	
6	0.613994	-4.23671	
7	0.464406	-6.66204	
8	0.450718	-6.9219	
9	0.675942	-3.40181	
10	0.614507	-4.22947	
11	0.702358	-3.06883	
12	0.473399	-6.49546	
13	0.454908	-6.84154	
14	0.686464	-3.26765	
15	0.44768	-6.98066	
16	0.323221	-9.81002	

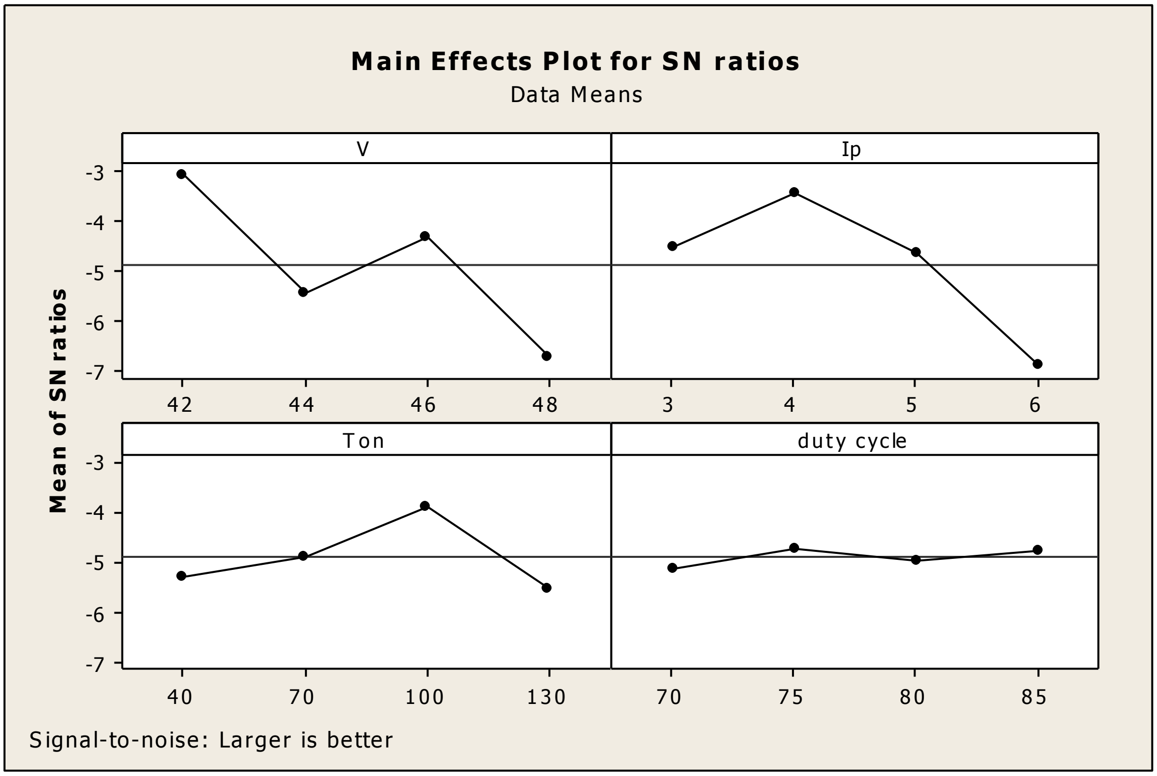


Fig.5.9: S/N ratio plot for optimal setting of process parameters

Table5.26:Optimal process parameter setting

Factors	Voltage	Pulse on current	Pulse on time	Duty cycle
Levels	42V	4A	100sec	75

The optimal setting process parameters with highest S/N ratio is obtained and furnished in Table 5.26.

The optimal setting of parameters is obtained from mean effect plot of S/N ratio using MINITAB-16 software and shown in Fig. 5.9.

5.3.2 Application of MOORA Combined with Taguchi Method

Step1: The decision matrix is formulated by allocating the row of this matrix to one alternative and each column to one attribute and furnished in Table5.27.

Table5.27: Decision matrix of attributes

Run No.	MRR (mm^3/min)	TWR (mm^3/min)	R_a (µm)	Z (mm)
1	1.344538	0.04857997	5.8	0.0945
2	0.483193	0.028026906	7.333333	0.1495
3	0.168067	0.016816143	6.8	0.0955
4	1.848739	0.028026906	7.933333	0.2095
5	1.533613	0.039237668	7.133333	0.1725
6	1.764706	0.033632287	9.2	0.018
7	8.865546	0.022421525	8.6	0.167
8	4.222689	0.044843049	8.133333	0.1965
9	0.882353	0.05044843	7.6	0.102
10	1.97479	0.022421525	8.866667	0.0745
11	1.44958	0.011210762	6.933333	0.0055
12	10.13025	0.056053812	5.466667	0.2895
13	6.953782	0.033632287	8.466667	0.136
14	0.798319	0.016816143	8.4	0.032
15	2.184874	0.061659193	9.8	0.1295
16	12.4916	0.151345291	6.466667	0.245

Step2: The values of normalized ratios for each alternative has been accessed using Eq. 4.27 and presented in Table 5.28.

Table5.28: Computed normalized ratios

Run No.	Norm(MRR)	Norm(TWR)	Norm(R_a)	Norm(Z)
1	0.065097991	0.2320315	0.186548	0.153912
2	0.023394591	0.13386432	0.235865	0.24349
3	0.008137249	0.08031859	0.218711	0.15554
4	0.089509738	0.13386432	0.255163	0.341211
5	0.074252396	0.18741005	0.229432	0.28095
6	0.085441113	0.16063719	0.295903	0.029316
7	0.429239879	0.10709146	0.276605	0.271992
8	0.204448378	0.21418292	0.261595	0.320038
9	0.042720557	0.24095578	0.244442	0.166127
10	0.095612675	0.10709146	0.285182	0.121338
11	0.070183772	0.05354573	0.222999	0.008958
12	0.490472575	0.26772865	0.175826	0.471507
13	0.336678673	0.16063719	0.272317	0.221502
14	0.038651932	0.08031859	0.270172	0.052118
15	0.105784236	0.29450151	0.315201	0.210916
16	0.604801187	0.72286735	0.20799	0.39903

Step3: The MOORA coefficient has been computed utilizing the Eq. 4.28 and accordingly ranking is done with maximum value of coefficient. As illustrated in Table 5.29.The process parameter setting corresponding to highest value of MOORA coefficient represents the optimal setting of control parameter for this present study.

Table5.29: MOORA coefficient and corresponding ranking

Run No.	MOORA coefficient	Ranking
1	-0.50769	9
2	-0.5903	10
3	-0.44673	8
4	-0.64119	14

5	-0.62409	13
6	-0.40047	5
7	-0.22698	1
8	-0.59199	11
9	-0.60913	12
10	-0.41813	6
11	-0.23534	2
12	-0.42551	7
13	-0.31821	3
14	-0.36406	4
15	-0.71524	15
16	-0.72097	16

The optimal setting of process parameters according to the MOORA coefficient ranking is furnished in Table5.30.

Table5.30: Optimal parameter setting

Factors	Voltage	Pulse on current	Pulse on time	Duty cycle
level	44 V	5A	130sec	70

Step4: Modified coefficient ratio has been computed utilizing Eq. 4.29 and corresponding S/N ratio has been obtained utilizing Higher-is-Better (HB) criteria (Table5.30).Further optimal setting of parameters has been concluded from mean effect plot of S/N ratio shown in Fig.5.10.

Table5.31:Modified coefficient ratio and corresponding S/N ratio

RunNo.	Ratio	S/N ratio	Predicted S/N ratio
1	0.113651	-18.8886	2.46049
2	0.038121	-28.3767	
3	0.017889	-34.9482	
4	0.122465	-18.2398	
5	0.106327	-19.4671	
6	0.175836	-15.0978	
7	0.654113	-3.6869	
8	0.256703	-11.8114	
9	0.065538	-23.6702	

10	0.186072	-14.6064	
11	0.24581	-12.188	
12	0.535463	-5.4254	
13	0.514102	-5.779	
14	0.095979	-20.3564	
15	0.128844	-17.7987	
16	0.45619	-6.8171	

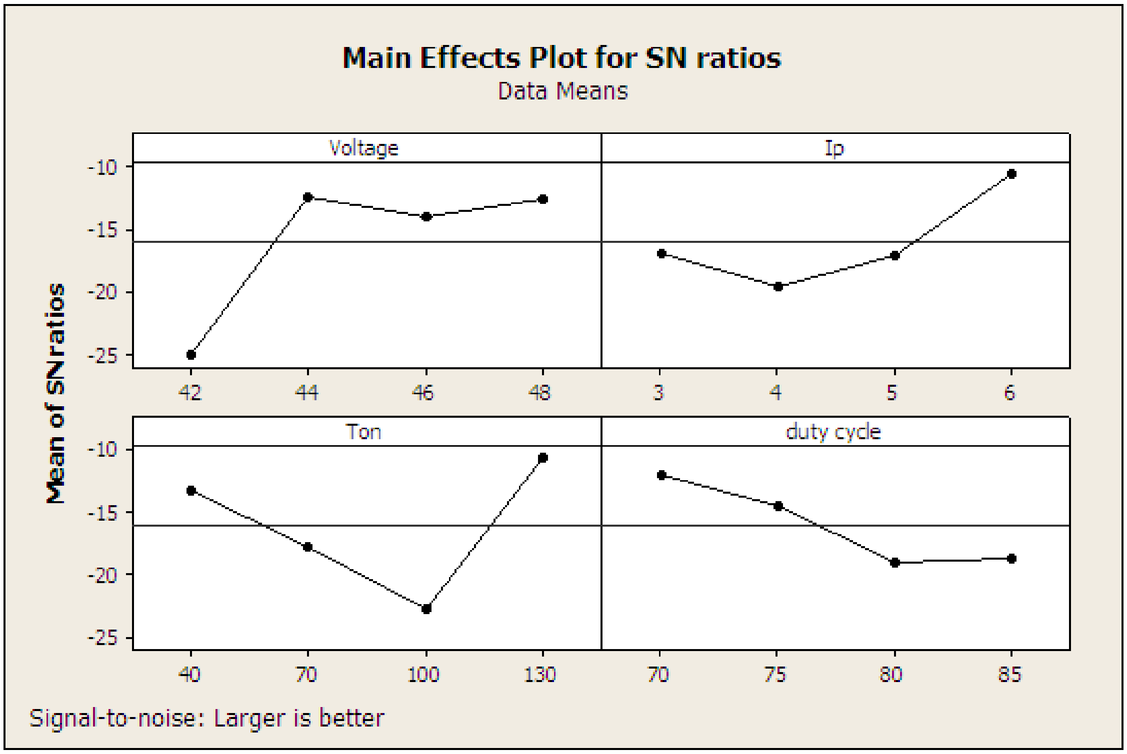


Fig.5.10: Main effect plot of S/N ratio

The optimal setting obtained from Main effect plot corresponding to the highest value of S/N ratio is illustrated in Table5.32.

Table5.32:Optimal setting of process parameters

Factor	voltage	Pulse on current	Pulse on time	Duty cycle
Level	44 V	6A	130sec	70

Chapter 6: Conclusions and Future Scope

In this study, TOPSIS combined with Taguchi philosophy and grey theory combined with fuzzy rule based model have been developed towards optimizing roughness average and MRR in machining Al, 15%SiC composites. It has been found that both the methods concluded with same result. So the optimal setting for ECM is found to be most beneficent. The proposed procedures are simple, effective in developing a robust, versatile and flexible mass production process. In the context of grey-fuzzy based Taguchi method there is no need for checking the correlation among responses as no individual weight has been assigned to responses. FIS can efficiently take care of these aspects into its internal hierarchy thereby overcoming various limitations of existing optimization approaches. This approach can be recommended for continuous quality improvement and off-line quality control of a process of manufacturing industry.

In order to achieve best quality characteristics and satisfactory process performance yield; the machining parameters in EDM of workpiece material Al, 10%SiCp MMCs need to be optimized. Taguchi's philosophy is primarily concerned with the optimization of single response only. Therefore, in this study a multi-objective hybrid optimization technique combining PCA, TOPSIS integrated with Taguchi method; and another efficient technique MOORA combined with Taguchi method have been employed successfully for optimizing performance parameters of EDM reaching to an optimal parameter setting for machining of advanced materials like Al,SiCp MMCs. These integrated approaches can be applied for product quality and process performance improvement in any production processes which involve multiple response features and can be considered as an efficient tool for continuous process improvement and off-line quality control.

Aforesaid work can be extended in the following directions:

Different material parameters like % of SiC, temperature of sintering, mesh size of powders can also be considered for experimental analysis and further quality improvement. Other machining parameters of ECM like flow rate, different electrolytes etc. can be taken into account for analysis. Similarly other machining parameters like pulse on energy, flushing pressure of dielectric fluid etc. can also be taken into account. Machine tool vibration, cryogenic effect on tools etc. can be adopted for analysis. Different mathematical models can be developed for productivity and quality improvement program as well as for optimization of process parameters of EDM,ECM on MMCs.

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List of Publications

1. Kumar Abhishek, **Amruta Rout**, Saurav Datta, Siba Sankar Mahapatra, 'Parametric optimization in ECM of Al/15% SiC MMC using Grey-Fuzzy Approach', **3rd International Conference on Production and Industrial Engineering**, **CPIE 2013**, held during 29-31 March 2013, organized by the Department of Industrial and Production Engineering, National Institute of Technology Jalandhar, Punjab.

2. Kumar Abhishek, **Amruta Rout**, Saurav Datta, Siba Sankar Mahapatra, "Multi-objective optimization in EDM of Al-10%SiCp MMCS using combined PCA-TOPSIS and Taguchi approach', **3rd International Conference on Production and Industrial Engineering**, **CPIE 2013**, held during 29-31 March 2013, organized by the Department of Industrial and Production Engineering, National Institute of Technology Jalandhar, Punjab.

3. Kumar Abhishek[1], **Amruta Rout[1]**, Dr. Saurav Datta[2], Prof. Siba Sankar Mahapatra[3] , 'Optimization in Electric Discharge Machining of Al/10% SiC composites using MOORA method'. ***International Journal of Mechanical Engineering and Research***, ISSN: 2249-0019, Volume 3, Number 1(2013), pp.58-62.