Thesis on

Application of fuzzy logic technique for the modeling of performance characteristics of composites in conventional USM Process

Submitted in partial fulfillment of the requirement for the award of the degree of

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IN

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Submitted By

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CERTIFICATE

This is to certify that the thesis entitled **"Application of fuzzy logic technique for the modeling of performance characteristics of composites in conventional USM Process"** is an authentic record of my study carried out as requirement for the award of the degree of the **Master of engineering in Mechanical(Production and industrial) engineering** to **Thapar University, Patiala,** under the guidance of **Dr. Vinod Kumar Singla** (Associate Professor), Department of Mechanical Engineering, Thapar University, Patiala. This matter embodied in this thesis has not been submitted in part or full to any other University or Institute for the award of any degree.

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This is to certify that the above declaration made by the student concerned is correct to the best of my knowledge and belief.

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ABSTRACT

Ultra sonic machining (USM) is one of the earliest non-traditional machining processes and now a days we know that product and process technology is a very advance, many types of new materials are being developed which have very high strength, high thermal and electrical conductivity which are very difficult to machine by traditional machining methods so non conventional machining methods are used to machine such type of materials, USM is also one of the non conventional machining method which is used to machine such advance hard and brittle materials to satisfy the present day product needs like aerospace, mould, dies and other applications.USM has recently employed to alter the properties or raw materials by using appropriate tool and various types of powders and abrasives in the effects of various input parameters.

In the present study a comparison has been made between the experimental study and the software study comparing the data for the variation of material removal rate, tool wear rate, surface roughness and hardness using MATLAB software. The objective of present study is to build a fuzzy model of different input and output parameters of ultrasonic machining process.

A number of factors and their different levels are selected. Based on factors and their levels number of experiments are selected using orthogonal array. ANOVA used to find the percentage contribution of the factors. The MINITAB 14 software is used to do this work.

ABBREVIATIONS

ANOVA	Analysis of Variance
DOF	Degree of Freedom
D2	High-Carbon High-Chromium steel
MRR	Material Removal Rate
TWR	Tool wear rate
SR	Surface Roughness
S/N	Signal to Noise Ratio

NOTATIONS

OA	Orthogonal array
A	Power (%)
B	Abrasive slurry
C	Slurry concentration
D	Grit size
SS	Sum of squares
SS’	Pure sum of square

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CHAPTER 1

INTRODUCTION

1.1 ULTRASONIC MACHINING

Ultrasonic machining is a ‘non-traditional’ machining technique and is a part of a family of relatively modern material finishing and shaping processes described as ‘chip less machining’. These processes don’t use cutting tools and do not create residual stresses in the work piece. Ultrasonic machining is often used in the combination with other chip less machining techniques, such as electro discharge machining, in the manufacturing of precision components.

In contrast, ultrasonic machining (UM or USM) is a non-thermal, non-chemical and non-electrical machining process that leaves the chemical composition, material microstructure and physical properties of the workpiece unchanged. Sometimes referred to as ultrasonic impact grinding (UIG) or vibration cutting, the UM process can be used to generate a wide range of intricate features in advanced materials.

Ultrasonic machining (USM) is a mechanical material removal process used to erode holes and cavities in hard or brittle work pieces by using shaped tools, high frequency mechanical motion, and an abrasive slurry. . A relatively soft tool is shaped as desired and vibrated against the work piece while a mixture of fine abrasive and water flows between them. The friction of the abrasive particles gradually cuts the work piece.

Materials such as hardened steel, carbides, rubies, quartz, diamonds, and glass can easily be machined by USM. Ultrasonic machining is able to effectively machine all materials harder than HRC 40, whether or not the material is an electrical conductor or an insulator.

UM is a mechanical material removal process that can be used for machining both conductive and non-metallic materials with hardness of greater than 40 HRC (Rockwell Hardness measured in the C scale). The UM process can be used to machine precision micro-features, round and odd-shaped holes, blind cavities, and OD/ID features.

Figure 1.1 Ultrasonic machine [N.T.M Lab, T.U, Patiala]

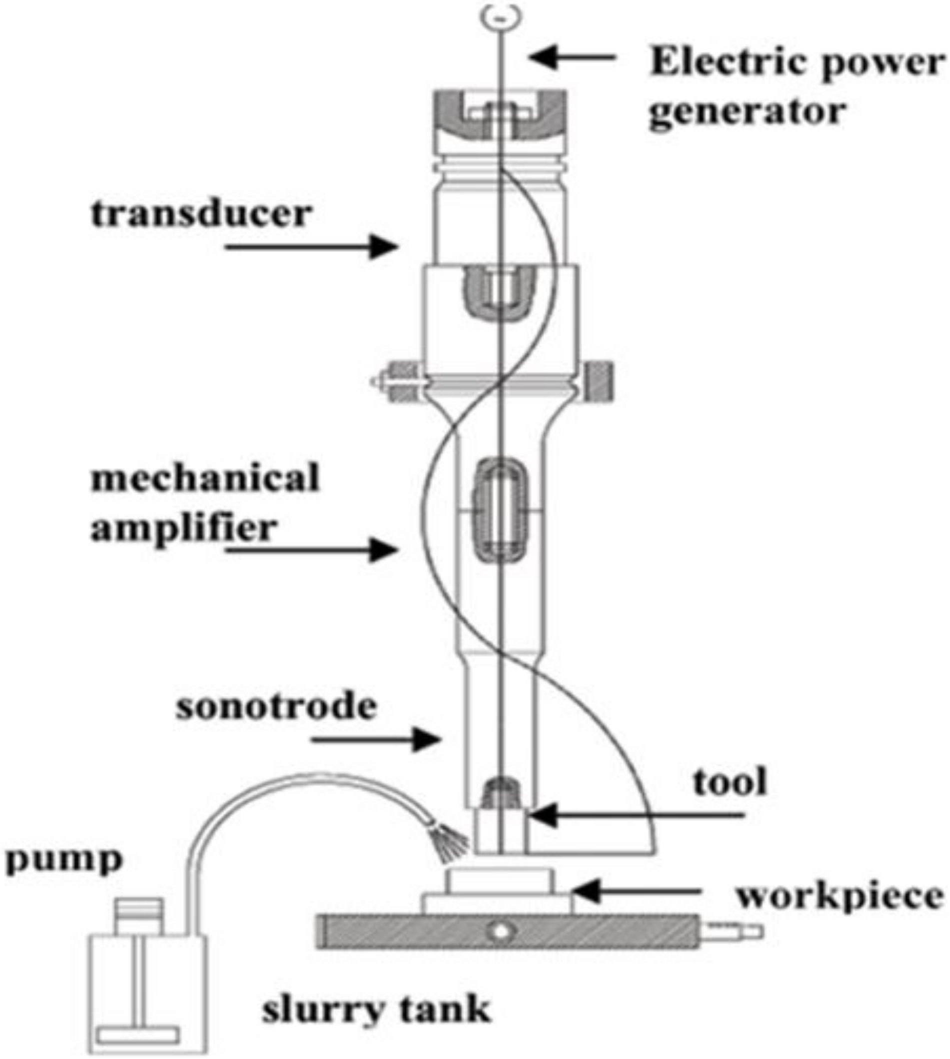


Figure 1.2 Shows the schematic diagram of USM apparatus [28]

A constant stream of abrasive slurry passes between the tool and the work piece. Commonly used abrasives include diamond, boron carbide, silicon carbide and alumina, and the abrasive grains are suspended in water or a suitable chemical solution. In addition to providing abrasive grain to the cutting zone, the slurry is used to flush away debris. The vibrating tool, combined with the abrasive slurry, abrades the material uniformly, leaving a precise reverse image of the tool shape.

Ultrasonic machining is a loose abrasive machining process that requires a very low force applied to the abrasive grain, which leads to reduced material requirements and minimal to no damage to the surface. Material removal during the UM process can be classified into three mechanisms: mechanical abrasion by the direct hammering of the abrasive particles into the work piece (major), micro-chipping through the impact of the free-moving abrasives (minor). Material removal rates and the surface roughness generated on the machined surface depend on the material properties and process parameters, including the type and size of abrasive grain employed and the amplitude of vibration, as well as material porosity, hardness and toughness.

Ultrasonic machines have several specific features:

1. An acoustic head
2. Feed mechanism
3. Abrasive feed system (including pump, pipes, and jet)
4. Electric power generator
5. Table
6. Position Indicator

The acoustic head as shown in Fig. (1.2) contain the electro mechanical converter which drives the tool via a special holder (wave guide). The feed mechanism applies the necessary force (5 8kgs) between tool and work piece. The abrasive feed system continuously brings in fresh abrasive to the cutting area, removes products and cools the components.

The power supplies the ultrasonic current to the acoustic head, various vacuum tube system are in common use and some high power magnetostriction heads have recently been used with high frequency alternators, which appear very promising.

Ultrasonic cutting is a technique as yet they are not very reliable and are costly, and are of very low efficiency. Ultrasonic cutting techniques are only beginning to be exploited. No really reliable methods are available for calculating the dimensions of component, especially cutting tools.

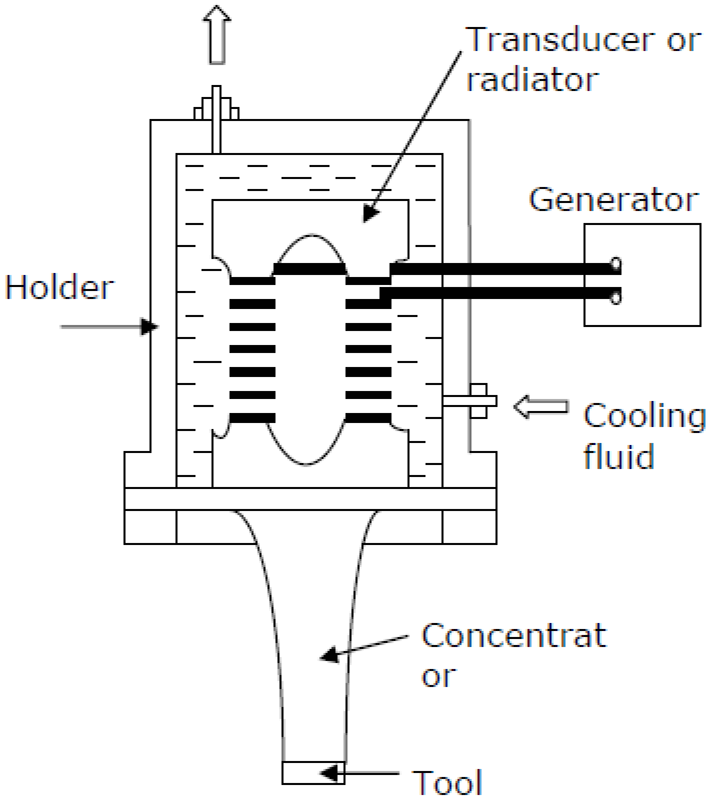


Figure1.3 Schematic diagram of acoustic head [29]

1.2 NEED FOR ULTRASONIC MACHINING

The process is regarded as competitive only when an operation cannot be practically and economically performed on conventional machining equipment. The ultimate value of USM lies in the ability to do work that cannot be practically accomplished in any other way because USM is non-chemical and non-thermal.

Materials are not altered either chemically or metallurgically during ultrasonic machining. USM is used to machine very hard and difficult to machine by conventional methods. Glass is a material difficult to machine by any means but good result have been obtained as a result of ultrasonic machining.

1.3 HISTORICAL BACKGROUND OF ULTRASONIC MACHINING (USM)

The history of ultrasonic machining (USM) began with a paper by R.W. Wood and A.L Loomis in 1927 and the first patent was granted to L. Balamuth in 1945. The use of ultrasonic in machining was first proposed by J.O. Farrer in 1945. Farrer was the patent agent on the first issued patent, British patent no.602801 (1945), issued to an American engineer, L. Balamuth, who discovered ultrasonic machining accidentally in 1942, while he was investigating the dispersion of solid in liquid by means of a magnetostrictively vibrating nickel tube. The United States patent, for the process, no.2580716 was issued in 1962.In 1960's Rozenberg's crediting to Farrer is an exquisite example of the unfortunate high frequency of "noise" when scientific information crosses language barriers.

The first report on the equipment and technology appeared during 1951-52 by 1954, the machine tools, using the ultrasonic principle, had been designed and constructed. Originally USM used to be a finishing operation for the component

processed by the electro spark machines. However, this use becomes less important because of the development in electric discharge machining. But then with the boom in solid state electronics, the machining of electrically non conducting, semi conductive, and brittle material become more and more important and, for this reason, ultrasonic machining again gained importance and prominence. In recent years, various types of ultrasonic machine tool have been developed. The USM technique is still far from perfect.

1.4 PRINCIPLE OF ULTRASONIC MACHINING

In the USM process, a low-frequency electrical signal is applied to a transducer, which converts the electrical energy into high-frequency (~20 KHz) mechanical vibration (see Figure 1.4). This mechanical energy is transmitted to a horn and tool assembly and results in a unidirectional vibration of the tool at the ultrasonic frequency with a known amplitude. The standard amplitude of vibration is typically less than 0.002 in. The power level for this process is in the range of 50 to 3000 watts. Pressure is applied to the tool in the form of static load.

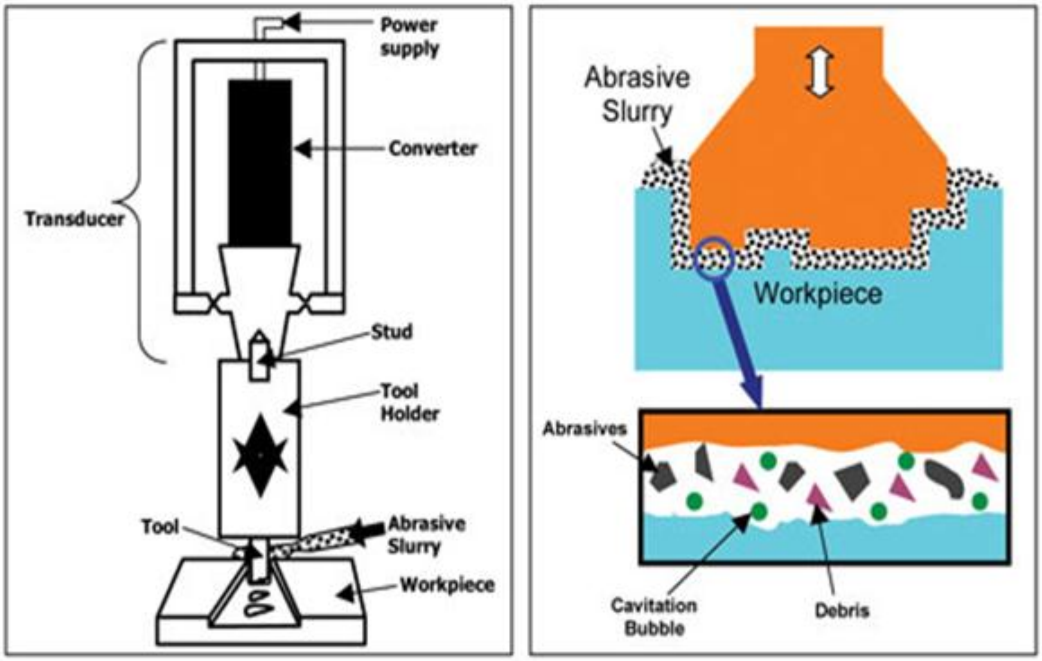


Figure 1.4 Shows the working Principle of USM [30]

High-frequency, low-amplitude energy is transmitted to the tool assembly. A constant stream of abrasive slurry passes between the tool and work piece. The vibrating tool, combined with the abrasive slurry, uniformly abrades the material, leaving a precise reverse image of the tool shape. The tool does not come in contact with the material; only the abrasive grains contact the work piece.

1.5 ELEMENTS OF ULTRASONIC MACHINING PROCESS

The machine for USM ranges from small, table top sized units to large- capacity machine tools. In addition to part size capacity of a USM machine, suitability for a particular application is also determined by the power rating. The power of USM machine is rated in watts and can range from 40 W to 2400W. The material removal rate is directly related to the power capability of the USM machine. The entire USM machine share common subsystem regardless of the physical size or power. The ultrasonic machining process consists of the following basic element

- The high frequency oscillating current generator or oscillator.
- The transducer
- The velocity transformer
- The tool holder

- The tool
- The abrasive slurry
- The work-piece

1.5.1 THE HIGH FREQUENCY OSCILLATING CURRENT GENERATOR OR OSCILLATOR

The power supply for USM is more accurately characterized as a high power sinewave generator that offers the user control over both the frequency and power of the generated signal. It converts low frequency 60 Hz electrical power to high frequency approx. 20 KHz electrical power. This electrical signal is then supplied to the transducer for conversion into mechanical motion.

The main requirements of a generator are:-

(a) Reliability and durability

(b) Efficiency

(c) Simplicity in design and low cost

(d) Compactness and easy to operate

(e) Stable frequency with possibility of being regulated over a specified range.

(f) Controlled power output over a wide range

1.5.2 THE TRANSDUCER

The transducer is a device that converts energy from one form to another. In the case of transducer for USM, electrical energy is converted to mechanical motion. The two types of transducers used for ultrasonic machining are based on two different principles of operations:

1. Piezoelectric Transducer
2. Magnetostrictive Transducer

These are used for USM to generate mechanical motion through the piezoelectric effect by which certain materials, such as quartz or lead Zirconate titanate will generate a small electric current when compressed. Conversely, when an electric current is applied to one of these material, the material increases minutely in size. When the current is removed, the material intently returns to its original shape. Piezoelectric transducer, by nature, exhibit an extremely high electro-mechanical conversion efficiency (up to 96%), which eliminates the need for water cooling of transducer. These transducers are available with power capabilities upto 900W.

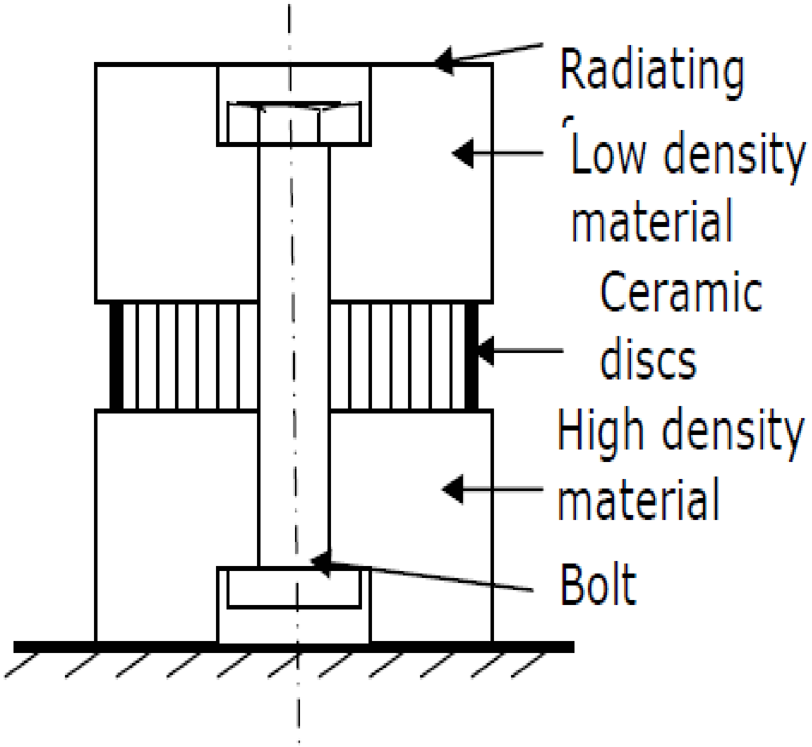


Figure1.5 Piezoelectric ultrasonic transducer [31]

2 MAGNETOSTRICTIVE TRANSDUCER

These are usually constructed from a laminated stock of nickel or nickel alloy sheets which, when influenced by a strong magnetic field, will change length. Magnetostrictive transducers are rugged but have electro-mechanical conversion efficiencies ranging from 20 to 30%. The lower efficiency results in the need to water cool magnetostrictive devices to remove the waste heat. Magnetostrictive transducers are available with power capabilities up to 2400W. The magnitude of the length change that can be achieved by both piezoelectric and magnetostrictive transducer is limited by the strength of transducer material. In both types of transducer the limit is approximately 0.025mm (0.01 in).

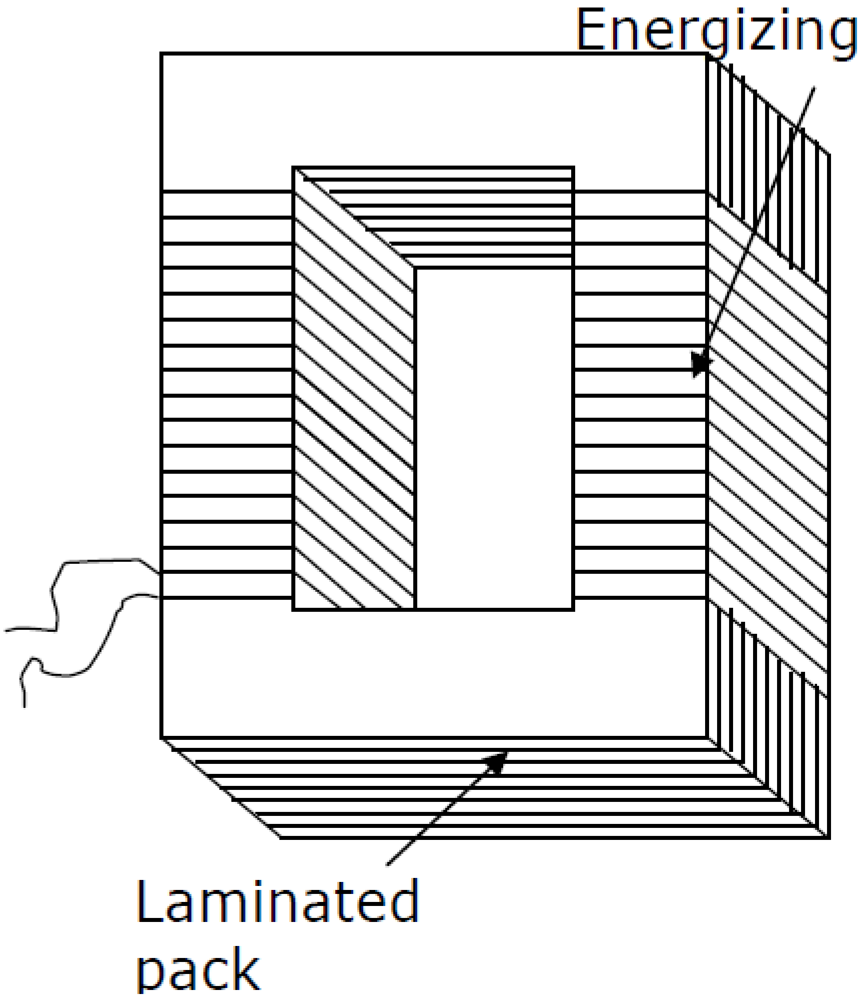


Figure1.6 Magnetostrictive ultrasonic transducer [32]

1.5.3 THE VELOCITY TRANSFORMER (CONCENTRATOR OR HORN)

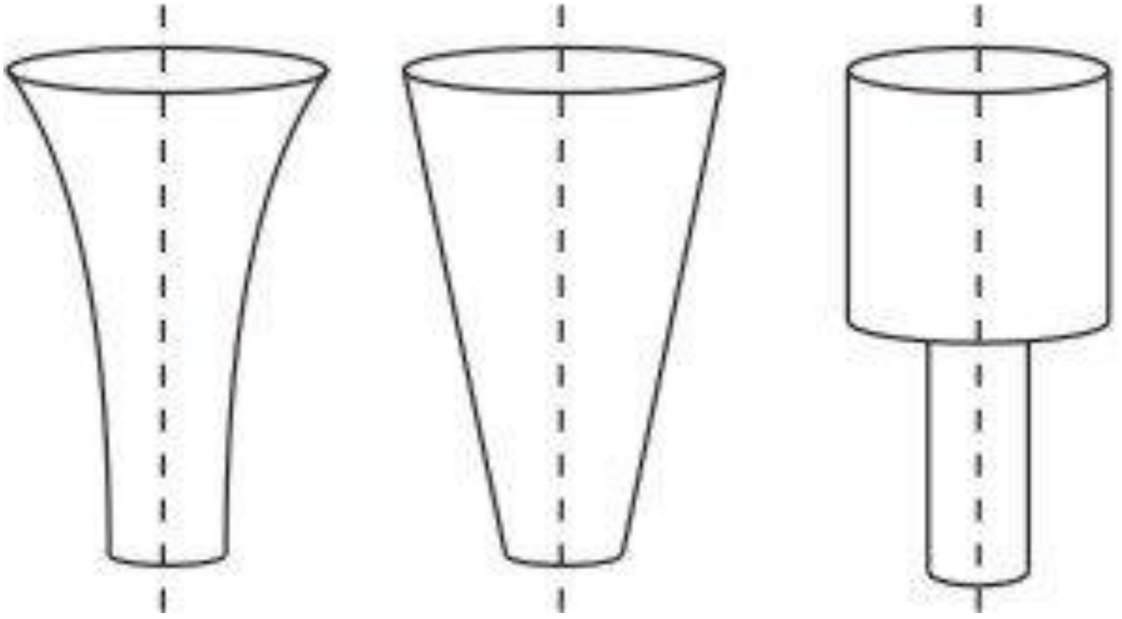
The velocity transformer has got several names like concentrator, trunks. Mechanical focusing device, shank, horn, amplifier, tool cone, transformer stub or convergent wave-guide, etc. it amplifies and focuses the mechanical energy produced by the transducer and imparts this to work-piece in such away that energy utilization is optimum. It is simply a velocity transformer with the exception that it is made slightly shorter than the half wavelength. The amplitude of the vibratory motion of the transducer is small and is usually inadequate for material removal purpose, and hence the tool is connected to the transducer by means of a concentrator which is simply a convergent waveguide to produce the desired amplitude at the tool end. Thus the trunk amplifies and focuses the vibrations of the transducer to intensity necessary to drive the tool to do its work. The increase in amplitude of the vibrations at the tool end is obtained by reducing the cross-section of the trunk at the tool end. The trunks are specially shaped to provide a reduction in cross-section at the tool end because the trunk should be of such sizes and shape that it is mechanically resonant or tuned to the frequency of the transducer vibrations and under working conditions giving maximum amplitude at the tool end with minimum energy losses. The trunk provides increased amplitude in the order of 30 to 120 microns at the tool face.

The horn or concentrator may be of different shapes or configurations. Some typical shapes are as follows

1 Exponential

2 Tapered or conical

3 Stepped



Exponential **Tapered** **Stepped**

Figure1.7 Different types of trunk [33]

1.5.4 THE TOOL HOLDER

The tool holder transfers the vibrations to the tool end and therefore, it must have adequate fatigue strength. Tool holder is removable part which is fastened to the concentrator and is made of monel metal or stainless steel. Generally, the shape of the tool holder is cylindrical or conical or a modified cone with the centre of mass of the tool on the centre line of the tool holder. It should be free from nicks, scratches and tool marks to reduce fatigue failures caused by the repeated reversal of stresses. In some ultrasonic machines, the trunk (horn) acts itself as a concentrator as well as the tool holder.

1.5.5 THE TOOL

For minimum tool wear, tools should be constructed from relatively ductile materials such as stainless steel, brass and mild steel. The harder the tool material the faster its wear rate will be. Depending on the abrasive used, workpiece / tool wear ratios can range from 1:1 to 100:1.

Whenever possible, USM tools to be used for hole drilling are constructed from easily obtained materials such as music wire, stainless steel tubing or hypodermic needles. Solid tools used to produce cavities can be fabricated by machining, casting or coining; however finishing or polishing operations are sometimes necessary because the tool holders should be free from scratches, nicks and heavy machining marks, because these produce risers and lead to early fatigue failure. Because of the overcut that occurs with this process, allowances must be made to use tool are slightly smaller than the desired hole or cavity e.g. to allow for the diameter of tubing to drill holes should be equal to the desired hole diameter minus twice the abrasive particle size. The most desirable method of attaching the tool to the holder is silver brazing. This eliminates the fatigue problems associated with mechanical screw attachment method.

1.5.6 THE ABRASIVE SLURRY

Several abrasives are available in various sizes for ultrasonic machining (grit). The criteria for selection of an abrasive for a particular application include hardness, usable life, cost and particle size. In order of hardness, boron carbide, silicon carbide and aluminium oxide are the most commonly used abrasives. The abrasive used for an application should be harder than the material being machined; otherwise the usable life time of the abrasive will be substantially shortened. Boron carbide is selected when machining the hardest work piece materials or when the highest material removal rates are desired. Although the cost is five to ten times greater than the next hardest abrasive, silicon carbide, the usable life of boron carbide is 200 machine operating hours before cutting effectiveness is lost and disposal is necessary. This compares with a usable life time of approximately 60 hours for silicon carbide. The combination of high removal rates and extended life time justify the higher cost of boron carbide. The size of abrasive particles influences the removal rate and surface finish obtained. Abrasive for USM are generally available in grit sizes ranging from 240 to 800 while the coarser grit exhibit the highest removal rates, they also result in the roughest surface finish and are therefore, used only for roughing operation, conversely, 800 grit abrasives will result in fine surface finishes but at a drastic reduction in metal removal rate. The most popular general purpose abrasive used, based on the above considerations, is 320 grit boron carbide. The abrasive material is mixed with water to from the slurry. The abrasive material is mixed with water to form the slurry. The most common abrasive concentration is 50% by weight; however, this can vary from 30 to 60 percent. The thinner mixtures are used to promote efficient flow when drilling deep holes or when forming complex cavities. Once the abrasive has been selected and mixed with water, it is stored in a reservoir at the USM machine and pumped to the tool work piece interface by recirculating pumps at rates up to 26.5 lit/min. higher power ultrasonic machine require the addition of a light-duty cooling system to remove waste heat from the abrasive slurry.

1.5.7 THE WORK-PIECE

There is no limitation to the range of material that can be machined by USM process, expect that they should not dissolve in the slurry media or react with it. While USM can be applied to ductile materials such as soft steel, copper, and brass but it is best suited to machining operation on hard, brittle materials that are not practical to process by other method. In general, USM is not recommended on the work materials which are softer than Rockwell Hardness Number HRC 45. Ultrasonic machining can be used for metals and non-metals, electrical conductors or nonconductor. The ultrasonic drilling technique is especially suited for hard materials like tungsten carbide, titanium carbide, ceramic and diamond. Materials which exhibit high hardness and which have impact brittleness can be successfully machined by this technique. Such materials are germanium, ferrites, glass and quartz. These materials often cannot withstand the forces needed for ordinary mechanical working. Materials that can be machined by ultrasonic drilling efficiently are shown the table (3.1).

Table (1.1) Material that can be machined by USM process

Agate	Alabaster	Barium carbide (sintered)
Ceramics	Corundum	Diamond
Earthenware	Felspar	Ferrites
Fluorites	Germanium	Glass
Glass-Micanite	Granite	Graphite
Gypsum	Hard alloy (tungsten and titanium carbide)	Marble
Jadeite	Jasper	Mother-of-pearl
Nephrite	Onyx	Porcelain
Quartz (crystalline and fused)	Rock crystal	Ruby
Sapphire	Silicon	Stealite
Thermo corundum	Tourmaline	Zirconium boride

1.6 APPLICATIONS

UM effectively machines precise features in hard, brittle materials such as

- glass
- engineered ceramics
- CVD SiC- Chemical Vapor Deposition Silicon Carbide
- quartz
- single crystal materials
- PCD - Polycrystalline diamond
- ferrite
- graphite
- glassy carbon
- composites
- piezoceramics

Ultrasonic machining is ideal for certain kinds of materials and applications. Brittle materials, particularly ceramics and glass, are typical candidates for ultrasonic machining. Ultrasonic machining is capable of machining complex, highly detailed shapes and can be machined to very close tolerances (±0.01 mm routinely) with properly designed machines and generators. Complex geometric shapes and 3-D contours can be machined with relative ease in brittle materials. Multiple holes, sometimes hundreds, can be drilled simultaneously into very hard materials with great accuracy.

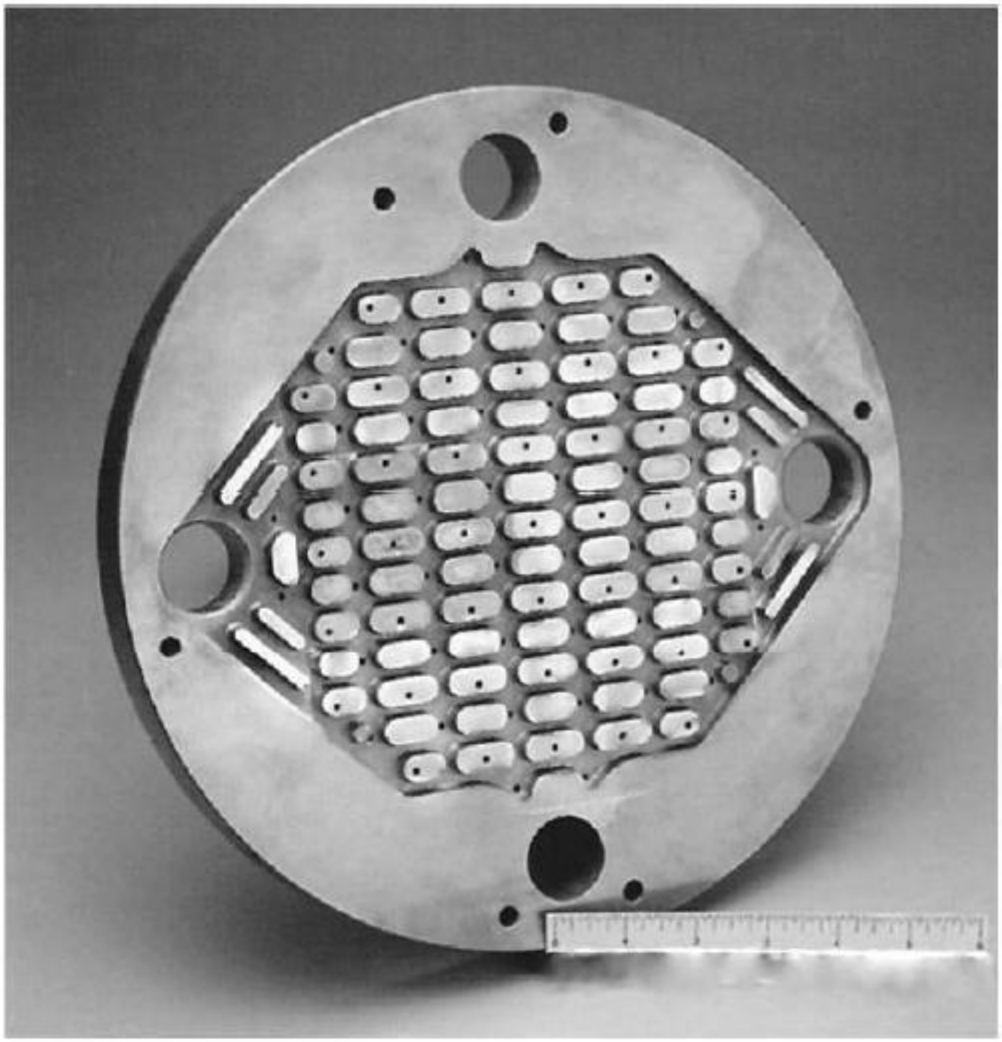


Figure1.8 Shows application of USM [34]

CHAPTER 2

LITREATURE REVIEW

Fuzzy Logic, FL, derived from fuzzy set theory, is a methodology that simulates thinking by incorporating the imprecision inherent in all physical systems. During the past several years, FL and its application to control problems has emerged as one of the most prosperous areas for research in the application of fuzzy set theory. Fuzzy Logic Controllers (FLC) are already a promising alternative approach for controlling processes, especially those that are too complex for analysis by conventional techniques (Gupta and Tsukamoto 1980, Gottwald and Pedrycz 1985, Lee 1990). The rational behind FLCs is that an "expert" human operator can control a process without understanding the details of its underlying dynamics. The effective and real control strategies that the expert learns through experience can often be expressed as a set of condition-action, IF-THEN rules, that describe the process state and recommend actions using linguistic, fuzzy terms instead of classical, crisp, 011 rules.

According to many researchers (Lee 1990, Chen et al. 1992, Daugherity et al. 1992, Sugeno and Yasukawa 1993), FLCs offer three important benefits. First, developing a FLC can be more cost-effective than developing a model-based or other controller with the equivalent performance. Second, FLCs can cover a much wider range of operating conditions than traditional control (PID control, for example),. Third, FLCs are customizable, since it is easier to understand and modify their rules, which not only mimic human operator strategies, but also are expressed in linguistic terms used in natural language.

Based on this current literature, most publications fail to present a "user friendly" explanation for the process of developing a fuzzy controller. In general, the fuzzy machine is configured by a crisp-to-fuzzy transform/fuzzifier, the fuzzy inference, and the fuzzy-to-crisp transform/defuzzifier. In this general scheme, the major drawback of FL is the lack of theoretical justifications for the experimental observations. At present there is no systematic procedure for the design of a FLC. This has partly been due to the novelty of the fuzzy mathematics involved and to the operations required to produce a single valued deterministic control element from the linguistic rules (describing the input-output map of the controller) and the fuzzy language (defining the meaning of the fuzzy sets) (McNeil and Freiberger 1992.) It is important to point out that this characteristic alone could be part of the reason why fuzzy logic has not been promoted much faster. The publications are too cryptic and the ideas presented are too "fuzzy" for the "fuzzy" novice.

2.1 STUDY OF DIFFERENT PARAMETERS OF ULTRASONIC MACHINING

Jainxin et al., (2002) investigate that in ultrasonic machining (USM), the material is removed primarily by repeated impact of the abrasive particles, and the material removal rate (MRR) and surface integrity are influenced by various factors including the material parameters of the work piece materials. In this study, effect of the properties and microstructure of the work piece materials on the MRR in ultrasonic machining of alumina-based ceramic composites was investigated. The distributions of strength of the ultrasonic machined specimens were used to evaluate the surface integrity. Results showed that fracture toughness of the ceramic composite played an important role with respect to MRR. In USM of whisker-reinforced alumina composites, the MRR depended on the whisker orientation. Studies of strength distributions of alumina-based ceramic composites machined by USM demonstrated that the flexural strength varied narrowly from the mean value, and the composites with high fracture toughness showed higher Weibull modulus.

Komaraiah et al., (1988) studied that Experiments were conducted on the ultrasonic machining of different work piece materials—glass, porcelain, ferrite and alumina—using various tool materials. The effects of mechanical properties of the work piece and tool materials on surface roughness and accuracy were analysed. The influences of the type and size of the abrasive grains used and the amplitude of ultrasonic oscillations were studied. An attempt was made to study the influence of the rotation of the work piece, in addition to an ultrasonically oscillated tool, on the material removal rate and surface roughness of the work pieces produced. The rotary mode of ultrasonic machining was found to be superior to conventional ultrasonic machining.

Kainth et al., (1979) investigate that material removal in ultrasonic machining considering direct impact of abrasive grains on the work piece is presented. Non-uniformity of abrasive grains is considered by using a probability distribution for the diameter of the abrasive particles as suggested by Rozenberg. The analysis is applied to calculate material removal rate for the case of glass using 400 mesh Norbide abrasive and mild steel tool for various values of static force and amplitude of tool oscillation.

Rajurkar et al., (1999) investigate that Ultrasonic machining process is an efficient and economical means of precision machining of ceramic materials. However, the mechanics of the process with respect to crack initiation and propagation, and stress development in the ceramic work piece subsurface are still not well understood. This article presents experimental simulation of the process mechanics in an attempt to analyze the material removal mechanism in machining of ceramic (Al_2O_3). It is found that low-impact force causes only structural disintegration and particle dislocation. The high-impact force contributes to cone cracks and subsequent crater damage.

Ichida et al., (2005) investigate that a new non-contact ultrasonic abrasive machining (NUAM) method that is performed using loose abrasives excited by ultrasonic energy in a liquid, and discuss its suitability for application to ultra-precision machining. A horn attached to the ultrasonic generator, having a resonance frequency of 28 kHz and an amplitude of 20 μm, has been used as a processing tool. Machining experiments on aluminum alloy (JIS-2014), using machining fluids mixed with Al_2O_3 abrasive grains with a mean diameter of 1 μm, have been conducted to investigate the fundamental mechanisms of NUAM. In NUAM, the following three kinds of processing modes occur: (a) material removal based on the erosion due to liquid cavitation collapse pressure (impact force), namely, cavitation erosion (Mode-A); (b) removal based on colliding or sliding of the abrasive grains accelerated by the impact force due to cavitation collapse on the work piece surface (Mode-B); and (c) small-scale material removal arising from the abrasive grains excited by ultrasonic energy (Mode-C). The scale of the material removal decreases in order of Modes-A–C. In fact, in Mode-C nanoscale processing marks with a width of just 40–60 nm and a depth of 3–6 nm are generated. By using the NUAM method in Mode-C, a finished surface having a nanoscale roughness can be created.

Singh et al., (2008) investigate that machining of titanium and its alloys with three different slurries (namely silicon carbide, boron carbide and alumina) and details background work on machinability of the same in ultrasonic drilling. Experimental research has been subsequently presented on the production of 5mm diameter holes in pure titanium (TITAN15) and titanium alloy (TITAN3) using ultrasonic drilling. This entailed the use of a 20 kHz piezoelectric transducer with three solid tools of stainless steel, titanium and high-speed steel, operating in silicon carbide, boron carbide and alumina slurry. The data presented includes main effect plots for material removal rate and tool wear rate. The results suggested that boron carbide slurry and stainless steel tool was giving best material removal rate. Also relative hardness of tool–work piece affects the material removal rate in ultrasonic machining.

2.2 APPLICATION OF FUZZY LOGIC APPROACH IN EDM OPERATION

Lin et al., (2005) investigate the use of the grey-fuzzy logic based on orthogonal array for optimizing the electrical discharge machining process with multi-response has been reported. An orthogonal array, grey relational generating, grey relational coefficient, grey-fuzzy reasoning grade and analysis of variance are applied to study the performance characteristics of the machining process. The machining parameters (pulse on time, duty factor and discharge current) with considerations of multiple responses (electrode wear ratio, material removal rate and surface roughness) are effective. The grey-fuzzy logic approach can help to optimize the electrical discharge machining process with multiple process responses.

Yilmaz et al., (2006) studied that a user-friendly intelligent system for the selection of electro discharge machining (EDM) parameters. In this system, a compact selection method based on expert rules, which were obtained from experimental results and extracted from the knowledge of skilled operators, is presented. Expert rules are evaluated by the fuzzy set theory. The developed fuzzy model uses fuzzy-expert rules, triangular membership functions for fuzzification and centroid area method for defuzzification processes. The system was developed on a PC using MATLAB Fuzzy Logic Toolbox. Inevitably, there are many machining parameters (discharge current, pulse duration, pulse interval, gap control, flushing rate, etc.) that should be considered in EDM processes. Selection of these parameters is still an ill-defined problem and generally relies on heuristics, which are not easy to model, and based on the experiences of specialists. In this system, discharge current, pulse duration and pulse interval are the inputs while the outputs are electrode wear, surface roughness and erosion rate. The remaining parameters are considered at constant rate during machining. The system is a compact and homemade tool that can be easily used by an average operator and provides the EDM parameters which lead to less electrode wear, better surface quality and more erosion rate according to the selected operation (finishing, roughing, etc.).

Lin et al., (2001) studied that Wire electrical discharge machining (wire-EDM) has always occupied an important position in some production fields, due to its capability of machining hard materials and intricate shapes. However, the machining accuracy, especially at corner parts, may be destroyed because of some phenomena such as wire de5ection and vibration, etc. The purpose of this paper is to develop a control strategy based on fuzzy logic so that the machining accuracy at corner parts for wire-EDM can be improved. The fuzzy rules based on the wire-EDM's physical characteristics, experimental data, and operator's experience are constructed, so that the reduced percentage of sparking force can be determined by a multi-variables fuzzy logic controller. The objective of the total control is to improve the machining accuracy at corner parts, but still keep the cutting federate at fair values. As a result of experiments, machining errors of corner parts, especially in rough-cutting, can be reduced to less than 50% of those in normal machining, while the machining process time increases not more than 10% of the normal value.

2.3 APPLICATION OF FUZZY LOGIC APPROACH IN DRILLING OPERATION

Krishnamoorthy et al.,(2012) studied that Carbon Fibre Reinforced Plastic (CFRP) composite materials have potential applications in various domains. In machining, drilling is essentially required to join different structures. But CFRP drilling poses many problems that decrease the quality of holes. In this paper, Taguchi's L_{27} orthogonal array is used to perform drilling of CFRP composite plates. To improve the quality of the holes drilled, the optimal combination of drilling parameters is chosen using grey relational analysis. Grey fuzzy optimization of drilling parameters is based on five different output performance characteristics, namely, thrust force, torque, entry delamination, exit delamination and eccentricity of the holes. Analysis of variance (ANOVA) is used to find the percentage contribution of the drilling parameters and found that feed rate is the most influential factor in drilling of CFRP composites.

Nandi et al., (2009) studied that Nowadays the increasing interest to perform machining operations is in dry/near-dry environments. The reason includes health and safety of operator, cost, ease of chip recyclability, etc. However one important process, which is difficult to perform in dry, is drilling. Without coolant, drilling leads to excessive thermal distortion and poor tool life. In order to tackle these conflicting requirements, the essentiality of study on machining performances with minimum quantity lubricant (MQL) becomes important.

Fuzzy logic rules, which are derived based on fuzzy set theory, are used to develop fuzzy rule based model (FRBM). The performance of FRBM depends on two different aspects: structures of fuzzy rules and the associated fuzzy sets (membership function distributions, MFDs). The aim of this study is to investigate the performances of FRBMs based on Mamdani and TSK-types of fuzzy logic rules with different shapes of MFDs for prediction and performance analysis of machining with MQL in drilling of aluminum alloy. A comparison of the model predictions with experimental results and those published in the literature shows that FRBM with TSK-type fuzzy rules describes excellent trade-off with experimental measurements.

Garrouch et al., (2001) investigate that the development of an expert system for screening wells that could be drilled underbalanced, and for aiding in the preliminary selection of appropriate underbalanced drilling fluids for a given range of wellbore and reservoir conditions. This approach combines a qualitative rule-based analysis for assessing formation damage and lost circulation potentials with quantitative analysis for assessing wellbore stability using geomechanical and petrophysical data. To make the analysis complete, a variety of other factors such as pipe sticking potential, wellbore geometry, type of fluid influx anticipated, pore pressure value, and cost benefit are also included in the expert-system decision trees. The main advantage of the expert system, developed in this study, is the use of fuzzy logic for handling cases that lend themselves to partial truth. This feature makes the system a powerful tool for analyzing ambiguous drilling scenarios.

Results of compared field cases are encouraging and conformal to field practices. Allowing for human input, when essential data are lacking, makes the system a useful tool that can help less experienced individuals function near the level of proficient drilling engineers.

2.4 APPLICATION OF FUZZY LOGIC APPROACH IN MILLING OPERATION

Iqbal et al., (2007) investigate that expert system technology in order to use the experimental data for optimization of milling parameters so as to achieve targets of enhancing tool life and improving work piece surface finish. Hard-milling experiments were conducted to study the effects of work piece material hardness, cutter’s helix angle, milling orientation and coolant upon tool life, work piece surface roughness, and cutting forces. The experimental data were converted to useful information using ANOVA and numeric optimization, and this information was used to develop the knowledge-base in form of IF–THEN rules. Expert system utilized fuzzy logic for its reasoning mechanism, while, fuzzy data sets and crisp sets were freely mixed in antecedents and consequents of the rules. Effectiveness of the expert system was based upon two modules, namely optimization module and prediction module, with each of them operating upon different set of rules. Optimization module provides the optimal selection and combination of aforementioned milling parameters according to the desired objective, while the prediction module provides the prediction of performance measures for the combination of parameters finalized by the optimization module.

Liang et al., (2002) investigate that a fuzzy control system for power regulation in end milling processes. This control system is capable of adjusting both feed rate and spindle speed simultaneously. Experiments have been carried out using both steel and aluminum work pieces of various cutting geometries. Different tools (HSS and carbide tools of different diameters and different number of teeth) have been used for aluminum work pieces. Both full immersion slotting and partial immersion cutting were tested. Our test results show that the system was in sensitive to work piece and tool changes and cutting power was well regulated around the target levels for various types of variations in depth of cut. Our test results also show that as compared to single parameter (feed rate) adjustment, further savings in machining time can be achieved by adjusting both feed rate and spindle speed.

CHAPTER 3

FUZZY LOGIC

3.1 THE ROLE OF FUZZY LOGIC IN ARTIFICIAL INTELLIGENCE

Fuzzy logic is perhaps the most promising advancement to come along in the Artificial Intelligence community in recent history. What exactly lies behind the term "fuzzy", what can fuzziness bring to the advancement of AI and what would fuzzy AI mean for the future.

Fuzzy logic in its simplest terms expands the dichotomy of true or not true to include a range of answers in between. The usual example is say instead of being black or white, fuzziness allows for shades of gray. Since fuzzy logic allows this extra bandwidth in fuzzy answers, fuzzy rules used in programming can cover a much broader area. A fuzzy rule such as "When it rains, you get wet" can cover a lot of ground. It would be able to several instantions of itself such as "when it rains a lot, you get wet a lot" or "when it rains a little, you get wet a little".

Rules like this are beautiful because they are human rules. They are a much better model of how we think. It is not often that questions that arise in life have bivalent answers. There are a few that do such as "Are you married?". Other questions such as "Do you like your job?" would tend to elicit a range of a response falling somewhere between yes and no.

How exactly is a fuzzy rule able to cover so much ground? By the use of a patches. A fuzzy rule will define a fuzzy patch. Say for example that you would like to use fuzzy logic to control an air conditioner (Kosco's example). You could define a fuzzy set for the temperature range as COLD, COOL, JUST RIGHT, WARM and HOT. A system could be composed of a few sloppy rules with wide patches, or many precise rules with narrow patches. Perhaps the air conditioner system is representative of other real systems. That is, an optimal solution involves some wide sloppy rules, and some precise ones.

The fuzzy rules that would go with the air conditioner system would be:

Rule 1: If the temperature is cold, the motor speed stops.

Rule 2: If the temperature is cool, the motor speed slows.

Rule 3: If the temperature is just right, the motor speed is medium.

Rule 4: If the temperature is warm, the motor speed is fast.

Rule 5: If the temperature is hot, the motor speed blasts.

Another wonderful aspect of fuzziness is that it does not disclude the old bivalent system of logic. The fuzzy spectrum of greys, completely true and completely false simply fit in as black and white. That the old system fits into the new fuzzy system gives me the feeling the old way was on the right track, and fuzzy logic has added a robustness and ingenious efficiency on top of the old system. Also it allows to move forward slowly from the old system rather than taking a radical step away from it.

If fuzziness is so wonderful, what can it really contribute to the development of AI? Let's first look at some things that have already been developed with fuzzy logic. First of all, there are the microwaves in the dorms here that can cook perfect popcorn. There are air conditions with similar rules sets as described above. This system prevents overshoot-undershoot temperature oscillation and consumes less power. There is an auto transmission that uses fuzzy logic to select gear ratio based on engine load, driving style, and road conditions. There is fuzzy factory control software that schedules takes and assembly line strategies. There is even a fuzzy golf diagnotic system that selects golf clubs based on golfer's physique and swing. The list is lengthy and amazing. From toasters to train systems, fuzzy logic is making machines "smarter".

To make apparent the contribution that fuzzy logic can make to AI (here I am thinking of human AI), let's look at some of the products that display intelligence in more humanlike tasks. Sony has developed a fuzzy based palm top computer that can recognize handwritten Kanji characters. Epson has made a translator that recognizes and translates words in a pencil sized unit. Most interesting was a washing machine that adjusts its washing strategy based on sensed dirt level, fabric type, load size and water level and used a neural network to tune the rules to a user's tastes.

This kind of system is an example of adaptive fuzzy logic. With the help of a neural net, it can learn from the data it has collected and adjust its rules. This kind of set up has tremendous possibilities.

3.2 WHAT IS FUZZY LOGIC

Fuzzy logic is a form of many-valued logic; it deals with reasoning that is approximate rather than fixed and exact. In contrast with traditional logic theory, where binary sets have two-valued logic: true or false, fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. Fuzzy logic has been extended to handle the concept of partial truth, where the truth value may range between completely true and completely false. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions.

Fuzzy logic began with the 1965 proposal of fuzzy set theory by Lotfi Zadeh. Fuzzy logic has been applied to many fields, from control theory to artificial intelligence.

3.3 HISTORY OF FUZZY LOGIC

When we look at the history of Fuzzy Logic, we find that the first important person for its development was Buddha. He lived in India about 500 BC and founded a religion called Buddhism. His philosophy was based on the thought that the world is filled with contradictions, that almost everything contains some of its opposite, or in other words, that things can be A and not-A at the same time. Here we can see a clear connection between Buddha's philosophy and modern fuzzy logic.

About 200 years later, the Greek scholar Aristotle developed binary logic. In contrary to Buddha, Aristotle thought that the world was made up of opposites, for example male versus female, hot versus cold, dry versus wet, active versus passive. Everything has to be A or not-A, it can't be both.

Over the centuries, these two philosophies developed and spread independently. Buddhism expanded as the religion of India and surrounding states. Aristotle's logic, however, was accepted by the Greek scholars and later got spread all over Europe; first by the Romans and then through Christianity. The Christian church created a devil to opposite God, talked about heaven and hell, and put a holly Maria against a sinful Eve.

Aristotle's binary logic became the base of science; if something got proven with logic, it was and still is accepted as scientifically correct. Like many others, Russell tried to reduce math to logic. When he discovered his paradox while working, he got scared himself. It did, however, give him the honor of being one of the fathers of fuzzy logic.

In 1964, professor Zadeh started wondering, if there wasn't a better logic to use in machinery. He had the idea that if you could tell an air-conditioner to work a little faster when it gets hotter, or similar problems, it would be much more efficient than having to give a rule for each temperature.

Anyway, that was the day fuzzy logic the way we know it today was born; with fuzzy logic you can tell an air-conditioner to slow down as soon as it gets chilly.

It took a long time until fuzzy logic got accepted even though it fascinated some people right from the beginning. Besides engineers, philosophers, psychologists, and sociologists soon became interested in applying fuzzy logic into their sciences.

In the year 1987, the first subway system was built which worked with a fuzzy logic-based automatic train operation control system in Japan. It was a big success and resulted in a fuzzy boom. Universities as well as industries got interested in developing the new ideas. First, this was mainly the case in Japan. Since the relegions in Japan accepted that things can contain parts of their opposites, it wasn't such a frightening idea as in most other parts of the world. And fuzzy logic promised lots of money to the industries, which was of course welcome too. Today, almost every intelligent machine has fuzzy logic technology inside it.

3.4 BASIC CONCEPTS

The notion central to fuzzy systems is that truth values(in fuzzy logic) or membership values(in fuzzy sets) are indicated by a value on the range[0.0-1.0], with 0.0 representing absolute falseness and 1.0 representing absolute truth.

Ex. “Jane is old.”

If Jane’s age was 75, we might assign the statement the truth value of 0.80.

The statement could be translated into set terminology as follows:

“Jane is a member of the set of Old people.”

The statement would be rendered symbolically with fuzzy sets as:

mOLD(Jane) =0.80

where m is the membership function, operating in this case on the fuzzy sets of old people, which returns a value between 0.0 and 1.0.

At this juncture it is important to point out the distinction fuzzy system and probability. Both operate over the same numeric range and at first glance both have similar values: 0.0 representing false(or non membership) and 1.0 representing true(or membership). However there is a distinction to be made between the statements: The probabilistic approach yields the natural language statements.”There is an 80% chance that Jane is old,” while the fuzzy terminology corresponds to “Jan’s degree of membership with in the set of old people is 0.80.” The semantic difference is significant: The first view suppose that Jane is or is not old(still catch in the law of the excluded middle): It is just that we only have an 80% chance of knowing which set she is in.

By contrast, fuzzy terminology suppose that Jane is ”more or less” old, or some other term corresponding to the value of 0.80.

3.5 DEGREES OF TRUTH

Fuzzy logic and probabilistic logic are mathematically similar – both have truth values ranging between 0 and 1 – but conceptually distinct, due to different interpretations—see interpretations of probability theory. Fuzzy logic corresponds to "degrees of truth", while probabilistic logic corresponds to "probability, likelihood"; as these differ, fuzzy logic and probabilistic logic yield different models of the same real-world situations.

Both degrees of truth and probabilities range between 0 and 1 and hence may seem similar at first. For example, let a 100 ml glass contain 30 ml of water. Then we may consider two concepts: Empty and Full. The meaning of each of them can be represented by a certain fuzzy set. Then one might define the glass as being 0.7 empty and 0.3 full. Note that the concept of emptiness would be subjective and thus would depend on the observer or designer. Another designer might equally well design a set membership function where the glass would be considered full for all values down to 50 ml. It is essential to realize that fuzzy logic uses truth degrees as a mathematical model of the vagueness phenomenon while probability is a mathematical model of ignorance.

3.6 APPLYING TRUTH VALUES

A basic application might characterize sub ranges of a continuous variable. For instance, a temperature measurement for anti-lock brakes might have several separate membership functions defining particular temperature ranges needed to control the brakes properly. Each function maps the same temperature value to a truth value in the 0 to 1 range. These truth values can then be used to determine how the brakes should be controlled.

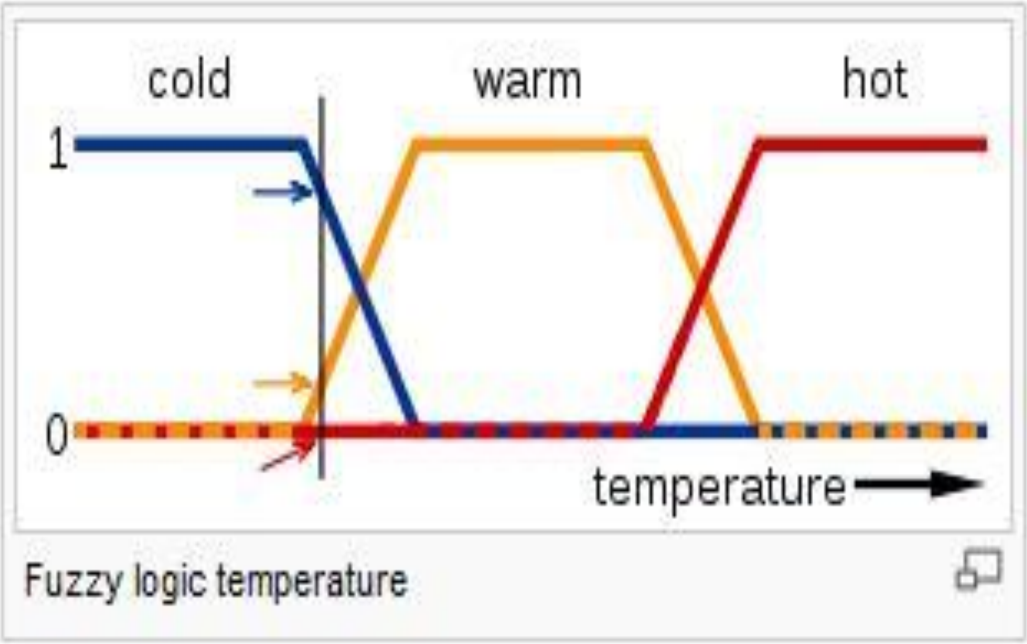


Figure 3.1 fuzzy logic temperature [35]

In this image, the meaning of the expressions cold, warm, and hot is represented by functions mapping a temperature scale. A point on that scale has three "truth values"—one for each of the three functions. The vertical line in the image represents a particular temperature that the three arrows (truth values) gauge. Since the red arrow points to zero, this temperature may be interpreted as "not hot". The orange arrow (pointing at 0.2) may describe it as "slightly warm" and the blue arrow (pointing at 0.8) "fairly cold".

3.7 LINGUISTIC VARIABLES

While variables in mathematics usually take numerical values, in fuzzy logic applications, the non-numeric linguistic variables are often used to facilitate the expression of rules and facts.

A linguistic variable such as age may have a value such as young or its antonym old. However, the great utility of linguistic variables is that they can be modified via linguistic hedges applied to primary terms. The linguistic hedges can be associated with certain functions.

3.8 COMPARISON TO PROBABILITY

Fuzzy logic and probability are different ways of expressing uncertainty. While both fuzzy logic and probability theory can be used to represent subjective belief, fuzzy set theory uses the concept of fuzzy set membership (i.e., how much a variable is in a set), and probability theory uses the concept of subjective probability (i.e., how probable do I think that a variable is in a set).

While this distinction is mostly philosophical, the fuzzy-logic-derived possibility measure is inherently different from the probability measure, hence they are not directly equivalent. However, many statisticians are persuaded by the work of Bruno de Finette that only one kind of mathematical uncertainty is needed and thus fuzzy logic is unnecessary. On the other hand, Bart Kosko argues that probability is a sub theory of fuzzy logic, as probability only handles one kind of uncertainty. He also claims to have proven a derivation of Bayes' theorem from the concept of fuzzy subset hood. Lotfi Zadeh argues that fuzzy logic is different in character from probability, and is not a replacement for it. He fuzzified probability to fuzzy probability and also generalized it to what is called possibility theory.

CHAPTER 4

PROBLEM FORMULATION

4.1 INTRODUCTION

The objective of present work is to study the application of fuzzy logic technique for the modeling of performance characteristics of composites in conventional USM Process.

The different input parameters has been taken for performing the experimentation work

1. Power rating of the machine
2. Type of abrasive slurry
3. Concentration of abrasive slurry
4. Abrasive grit size

The output parameters are:

1. Material removal rate
2. Tool wear rate
3. Surface roughness
4. Rockwell Hardness

4.2INPUT PARAMETERS :-

4.2.1 Power rating of the machine (%)

- 20
- 60

4.2.2 Type of abrasive slurry

- Aluminum oxide
- Silicon carbide
- 50%Al_2O_3+50%Sic

4.2.3 Concentration of abrasive slurry

- 20%
- 25%
- 30%

4.2.4 Abrasive grit size

- 280
- 400

- 600

4.3 OUTPUT PARAMETERS TAKEN:-

4.3.1 Material removal rate

It is expressed as penetration rate in mm/min for a given cross-section of the tool, or expressed as volume material removal rate in mm^3/min.

4.3.2 Tool wear rate

Gradual erosion of the tool material takes place. The tool wears as a result of contact with the abrasive, which tend to erode the tool, cavitations and other such effect also affect the tool. Most of wear occur at the end and the wear sides is about ten times less. It is expressed as volume material removal rate in mm^3/min.

4.3.3 Surface roughness

Surface roughness of the machined surface of work piece is expressed in microns. The characteristics of the layer of the work material just below the machined surface can also be evaluated.

4.3.4 Rockwell Hardness

The Rockwell scale is a hardness scale based on the indentation hardness of a material. The Rockwell test determines the hardness by measuring the depth of penetration of an indenter under a large load compared to the penetration made by a preload. There are different scales, denoted by a single letter, that use different loads or indenters. The result is a dimensionless number noted as HRB, where B is the scale letter.

Figure 4.1 Rockwell hardness tester [S.O.M Lab, T.U, Patiala]

4.4 TOOL USED:- HIGH CARBON HIGH CHROMIUM STEEL

For minimum tool wear, tools should be constructed from relatively ductile materials such as stainless steel, brass and mild steel. The harder the tool material the faster its wear rate will be. Depending on the abrasive used, work piece / tool wear ratios can range from 1:1 to 100:1.The cutting tool have been used in this experiment is made of High Carbon high chromium Steel (D2).

Typical Composition of cutting tool material

C	Mn	Si	Cr	Mo	V
2.0	0.30	0.30	12.00	0.75	0.90

D2 tool steel(DENSITY-7.8gm/cc) is a versatile high-carbon, high-chromium, air-hardening tool steel that is characterized by a relatively high attainable hardness and numerous, large, chromium- rich alloy carbides in the microstructure. These carbides provide good resistance to wear from sliding contact with other metals and abrasive materials. Although other steels with improved toughness or improved wear resistance are available. Tool steel (D2) provides an effective combination of wear resistance and toughness, tool performance, price, and a wide variety of product forms.

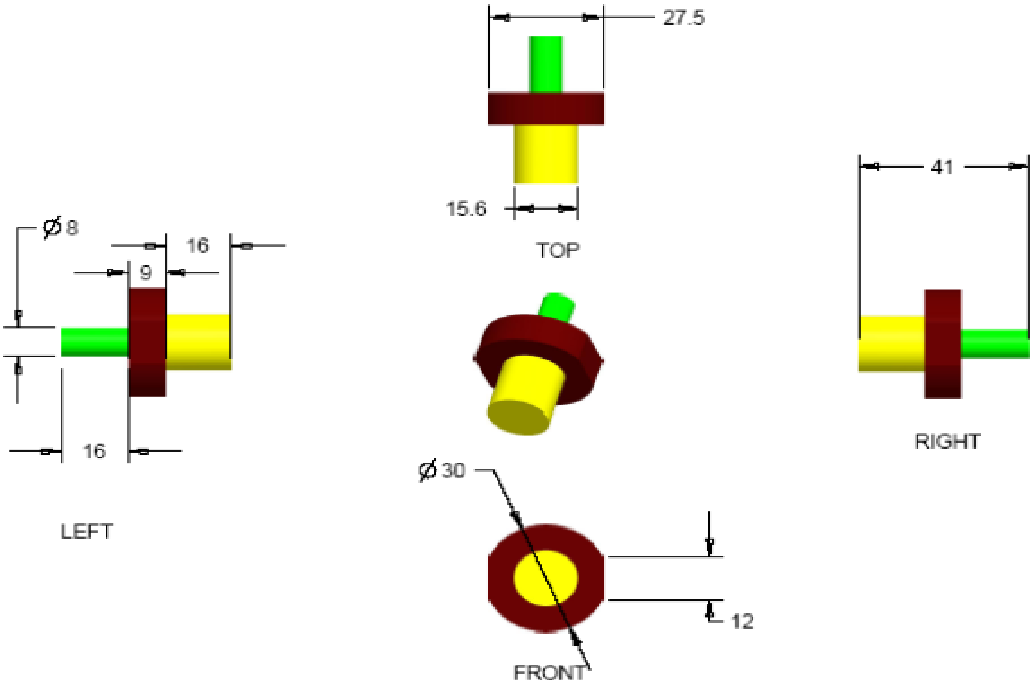


Figure 4.2 Detail Drawing of the tool

Figure 4.3 High Carbon High Chromium Steel Tool

4.5 WORK MATERIAL:-

Glass fibre reinforced polymer (GFRP)

4.2.5 Properties of GFRP:-

- GFRP has low density and high strength
- High strength to weight ratio
- High stiffness

Density of GFRP= 1.8 gm/cc

Figure 4.4 Glass fibre reinforced polymer (GFRP)

CHAPTER 5

EXPERIMENTAL SETUP, DESIGN AND ANALYSIS OF DATA

An experimental study was conducted to investigate the effect of different process parameters on material removal rate, tool wear rate, surface roughness and hardness.

5.1 OUTLINE OF THE THESIS WORK

The recent study consists of experimentations, analysis using MINITAB 14 software and finally theoretical modeling using MATLAB 7.0 software. The experiment has been conducted by working on glass fibre reinforced polymer (GFRP) using a high carbon high chromium steel tool on ultrasonic machine. The different combinations of input parameters are used for conducting the experiments. The output value for surface roughness is taken by a surface roughness tester machine (MODEL- SJ400). The output value for hardness is calculated on Rockwell hardness tester. Here we use a number of factors and their different levels are selected. Based on factors and their levels number of experiments are selected using orthogonal array. ANOVA used to find the percentage contribution of the factors. The MINITAB 14 software is used to do this work. a comparison has been made between the experimental study and the software study comparing the data for the variation of material removal rate, tool wear rate, surface roughness and hardness using MATLAB software. The objective of present study is to build a fuzzy model of different input and output parameters of ultrasonic machining process.

5.2 SELECTION OF FACTOR LEVEL

As the objective of study aimed to carry out result on ultrasonic machining of GFRP (as work material) using high carbon high chromium steel tool to know their impact on material removal rate (MRR), tool wear rate (TWR), surface roughness, hardness by the use of different input parameters. In light of above objective, the factor levels have been decided depending upon commercial availability, experimental constraints and machine tool capacity. Table 5.1 shows different control variables and their levels.

Table 5.2.1 Control variables and their levels

S. NO	Factors	Levels	Level1	Level2	Level3
A	Power rating (%)	2	20	60	
B	Abrasive slurry	3	Al_2O_3	SiC	50% Al_2O_3+50%SiC
C	Slurry concentration (%)	3	20	25	30
D	Grit size	3	280	400	600

For the selection of a particular orthogonal array, the numbers of parameters, the numbers of levels, and their possible interactions must be taken into consideration. The case under study involves four parameters, one of two levels and three of three levels. Now as per requirements of the study L18 orthogonal array comes out as one of the solution. The L18 orthogonal array is shown in table 5.2.2.

Table 5.2.2 L18 Orthogonal array

Experiment Number	Columns			
	A	B	C	D
1	1	1	1	1
2	1	1	2	2
3	1	1	3	3
4	1	2	1	1
5	1	2	2	2
6	1	2	3	3
7	1	3	1	2
8	1	3	2	3
9	1	3	3	1
10	2	1	1	3
11	2	1	2	1
12	2	1	3	2
13	2	2	1	2
14	2	2	2	3
15	2	2	3	1
16	2	3	1	3
17	2	3	2	1
18	2	3	3	2

Table 5.2.3 Response variables

Response number	Response 1	Response2	Response 3	Response 4
Response name	MRR	TWR	SR	Hardness
Response units	mm^3/min	mm^3/min	Microns	HRB
Response type	Higher the better	Lower the better	Lower the better	Higher the better

Table 5.2.4 Representation of factor level

Factor level	Level 1	Level 2	Level 3
Power rating (%)	A1	A2	
Ab. Slurry	B1	B2	B3
Slurry conc.	C1	C2	C3
Grit size	D1	D2	D3

A- POWER RATING (%)

A1- 20

A2-60

B- Ab. Slurry

B1- Al_2O_3

B2- SiC

B3-50% Al_2O_3+50%SiC

C- Slurry concentration

C1- 20%

C2- 25%

C3- 30%

D- Grit size

D1- 280

D2- 400

D3- 600

CHAPTER 6

RESULTS AND ANALYSIS OF MRR

6.1 INTRODUCTION

The effects of parameters i.e Type of abrasive slurry, Concentration of abrasive slurry, Power rating of the machine, Abrasive grit size and interaction between Power rating of the machine in percentage of max. (500 watts) and abrasive slurry were evaluated using ANOVA and factorial design analysis. A confidence interval of 95% has been used for the analysis. One repetition for each of 18 trails was completed to measure the Signal to Noise ratio(S/N Ratio).

6.2 RESULTS FOR MRR

The results for MRR for each of the 18 treatment conditions with repetition are given in Table 6.1. MRR of each sample is calculated from weight difference of work piece before and after the performance trial, which is given by:

$$\mathrm{MRR} = \frac{(\mathrm{Wi}-\mathrm{Wf})}{\rho \times \mathrm{t}} \times 1000\ \mathrm{mm}^3/\mathrm{min} \qquad \text{(Equation-6.1)}$$

Where W_i = Initial weight of workpiece material (gms)

Wf = Final weight of workpiece material (gms)

t = Time period of trails in minutes

ρ = Density of workpiece in gms/cc

Table 6.1: Results for MRR

Trail No:	Power (%)	Ab. Slurry	Slurry Concentration	Grit Size	MRR mm^3/min	S/N Ratio	Mean
1	20	Aluminium Oxide	20	280	1.734	4.7810	1.734
2	20	Aluminium Oxide	25	400	2.545	8.1138	2.545
3	20	Aluminium Oxide	30	600	4.034	12.1147	4.034
4	20	Silicon Carbide	20	280	5.060	14.0830	5.060

Trail No:	Power (%)	Ab. Slurry	Slurry Concentration	Grit Size	MRR mm^3/min	S/N Ratio	Mean
5	20	Silicon Carbide	25	400	6.990	16.8895	6.990
6	20	Silicon Carbide	30	600	8.332	18.4150	8.332
7	20	Mixture	20	400	6.090	15.6923	6.090
8	20	Mixture	25	600	6.852	16.7163	6.852
9	20	Mixture	30	280	7.932	17.9877	7.932
10	60	Aluminium Oxide	20	600	4.050	12.1491	4.050
11	60	Aluminium Oxide	25	280	7.980	18.0401	7.980
12	60	Aluminium Oxide	30	400	8.770	18.8600	8.770
13	60	Silicon Carbide	20	400	7.440	17.4315	7.440
14	60	Silicon Carbide	25	600	9.900	19.9127	9.900
15	60	Silicon Carbide	30	280	11.390	21.1305	11.390
16	60	Mixture	20	600	8.750	18.8402	8.750
17	60	Mixture	25	280	9.270	19.3416	9.270
18	60	Mixture	30	400	9.440	19.4994	9.440

6.3 ANALYSIS OF VARIANCE - MRR

The results for MRR were analyzed using ANOVA for identifying the significant factors affecting the performance measures. The Analysis of Variance (ANOVA) for the mean MRR at

95% confidence interval is given in Table 6.2. The variance data for each factor and their interactions were P value to find significance of each. From Table 6.2 Power rating (%), Ab. Slurry, slurry Conc. have the P value less the 0.05 that means these factor are significant. Interaction between Ab. Slurry and power (%) has the P value less the 0.05 that means this factor is significant. Grit size has value more then 0.05 that means it is insignificant. Table 5.3.3 shows ranks to various input parameters in terms their relative significance

Table6.2: Analysis of Variance for Means

Source	Seq SS	DF	Adj MS	F	P	SS'	% contribution	Status
Power (%)	41.773	1	41.7728	50.95	0.001	40.940	34.56	Significant
Ab. Slurry	42.778	2	21.3892	26.09	0.000	41.112	34.71	significant
Slurry conc.	23.903	2	11.9517	14.58	0.002	22.237	18.77	significant
Grit size	0.382	2	0.1912	0.23	0.797			Insignificant
power(%)*Ab. Slurry	3.059	2	1.5294	1.87	0.216			Insignificant
Residual error	6.559	8	0.8199					
Total	118.455	17						
e-pooled	10	12	0.833				11.96	

Table6.3: Response Table for Means of MRR

Level	Power	Ab. Slurry	Slurry Conc.	Grit size
1	5.508	4.852	5.521	7.228
2	8.554	8.185	7.256	6.879
3		8.056	8.316	6.986
Delta	3.047	3.333	2.796	0.349
Rank	2	1	3	4

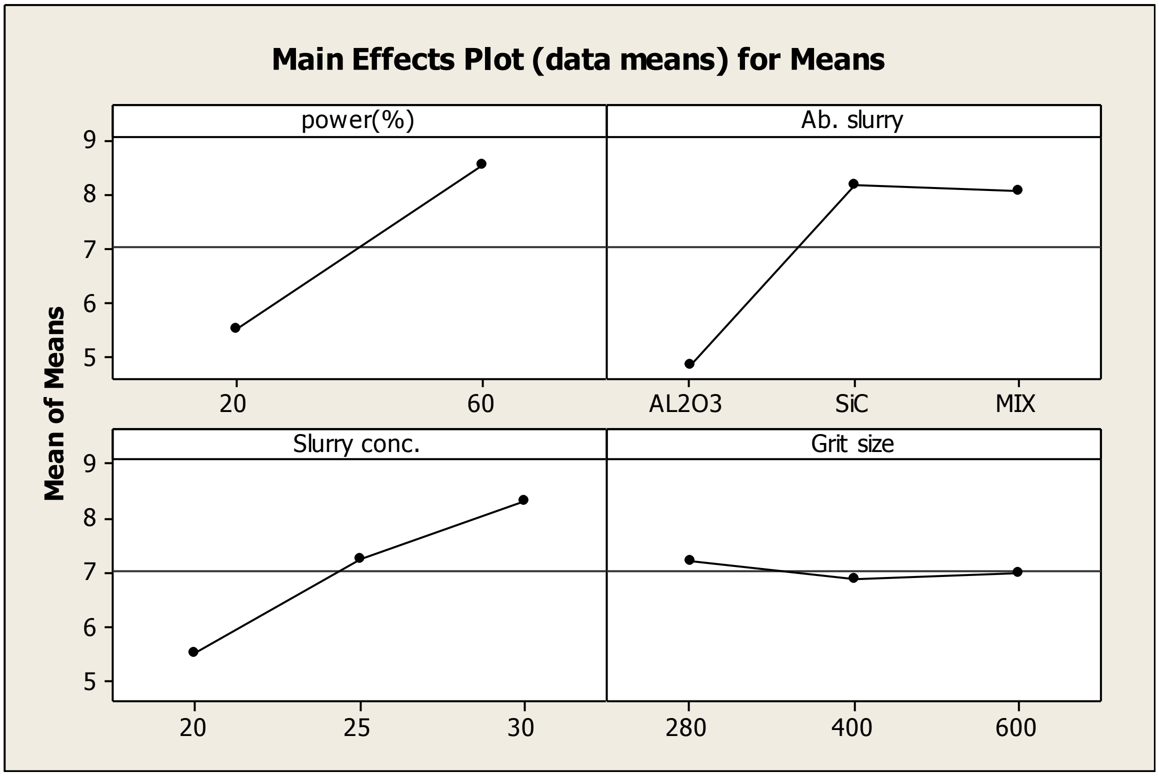


Figure 6.1: Main effect plot of MRR for Means

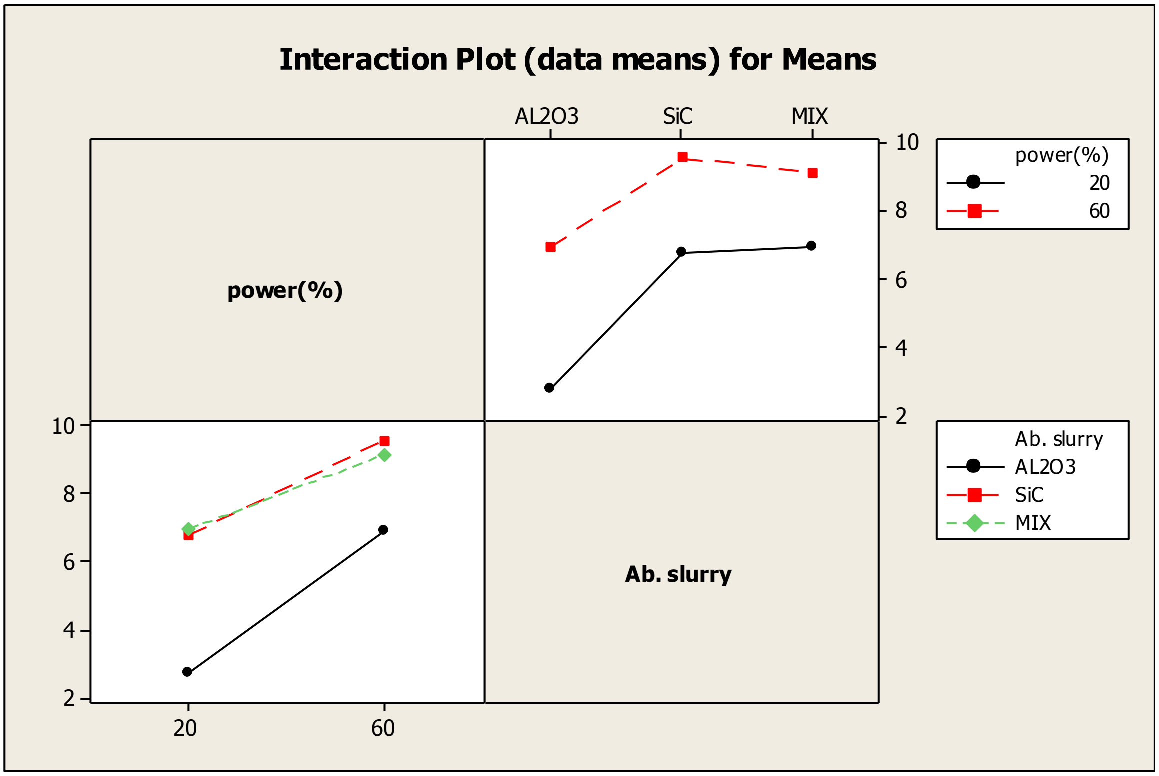


Figure 6.2: Interaction plot for MRR

6.4: RESULTS FOR S/N RATIO OF MRR

The S/N ratio consolidates several repetitions into one value and is an indication of the amount of variation present. The S/N ratios have been calculated to identify the major contributing factors and interactions that cause variation in the MRR. MRR is “Higher is better” type response which is given by:

$$(S/N)_{HB} = -10 \log (MSD_{HB}) \quad \text{(Equation-6.2)}$$

$$\text{Where } MSD_{HB} = \frac{1}{r}\sum_{j=1}^{r}\left(\frac{1}{{y_j}^2}\right) \quad \text{(Equation-6.3)}$$

$MSD_{HB=}$ Mean square deviation for higher-the-better response

Table 6.4 shows the ANOVA results for S/N ratio of MRR at 95% confidence interval. Ab. Slurry was observed to be the most significant factor affecting the MRR, followed by power(%) and Slurry conc. are significant according to p value. the interactions between power(%) and Ab. Slurry is significant. Main effects plot and interaction plot of S/N ratio for MRR are shown in the figure 6.3and 6.4 respectively.

Table 6.4: Analysis of Variance for SN ratio of MRR

Source	Seq. SS	DF	Adj. MS	F	P	SS’	% contribution	Status
Power (%)	90.728	1	90.7278	37.85	0.001	86.726	27.09	Significant
Ab. Slurry	127.779	2	63.8893	26.66	0.000	119.775	37.42	Significant
Slurry conc.	53.587	2	26.7937	11.18	0.005	45.58	14.24	Significant
Grit size	0.654	2	0.3270	0.14	0.874			Insignificant
power(%)*Ab. Slurry	28.197	2	14.0987	5.88	0.027	20.193	6.31	Significant
Residual error	19.174	8	2.3968					
Total	320.119	17						
e-pooled	48.025	12	4.002				14.94	

Table 6.5: Response Table for S/N ratio of MRR

Level	Power (%)	Ab. Slurry	Slurry Conc.	Grit size
1	13.87	12.34	13.83	15.89
2	18.36	17.98	16.50	16.08
3		18.01	18.00	16.36
Delta	4.49	5.67	4.17	0.46
Rank	2	1	3	4

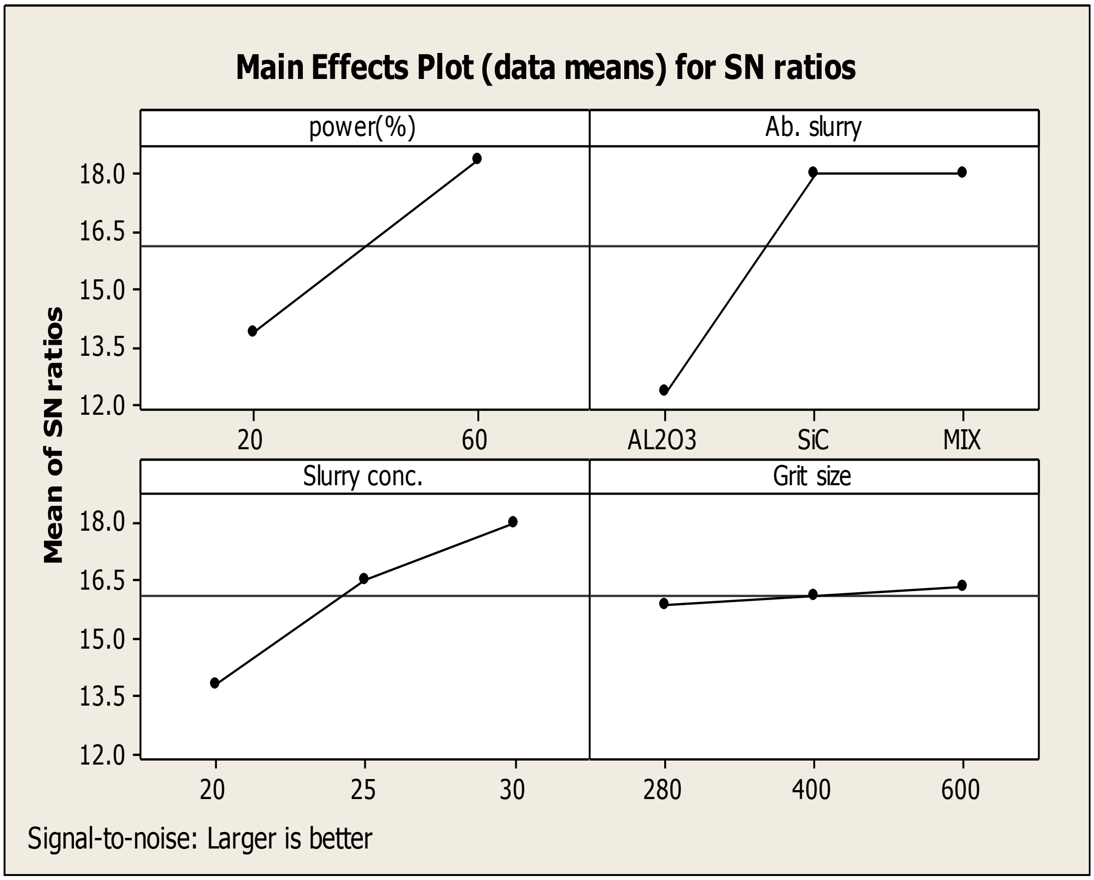


Figure 6.3: Main effect plot for MRR of S/N ratio

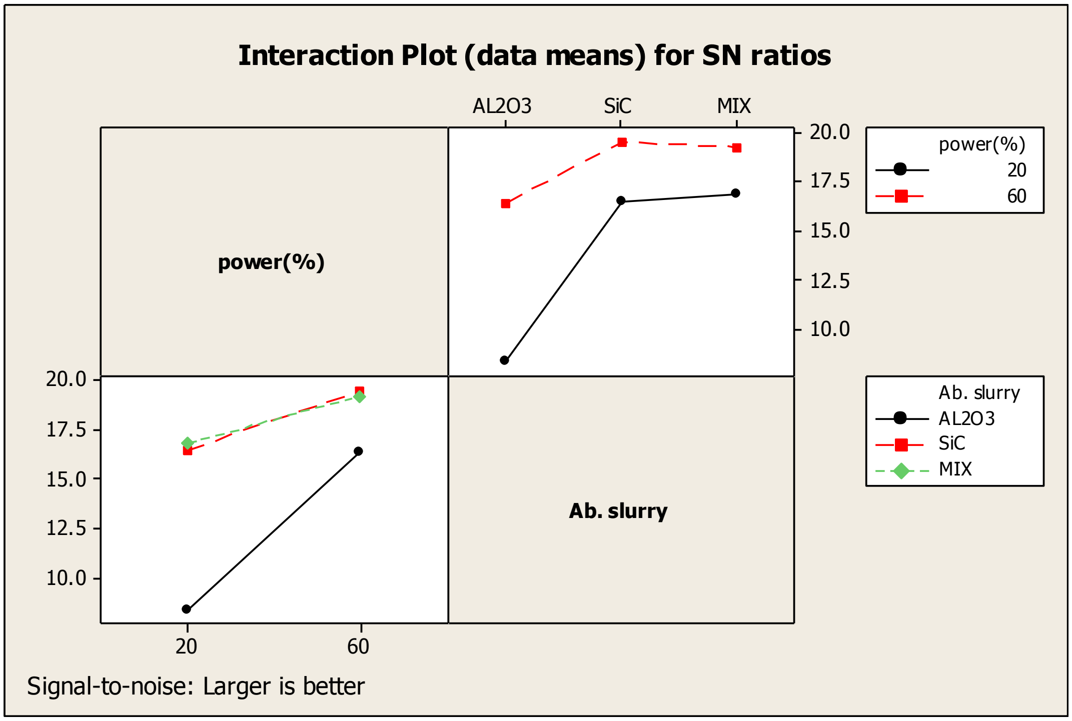


Figure 6.4: Interaction plot for MRR of S/N ratio

6.5: OPTIMAL DESIGN FOR MRR

In this experimental analysis, the main effect plot and interaction plot in Figure 6.1 and Figure 6.2 used to estimate the mean MRR. From the, Table 6.6 it is concluded that highest MRR was observed when Work-piece is machined on Power Rate 60%, abrasive slurry Silicon Carbide and slurry concentration 30%. It also observes that Grit size and the interaction AxB is not any effect on the MRR. The best MRR value was compromised to get best results. MRR Assumed to be achieved best result if GFRP work piece is machined at Power Rate 60%, abrasive slurry Silicon Carbide and slurry concentration 30%.

Table 6.6 Significant factor and interaction

Factor	Affecting mean		Affecting variation	
	Contribution	Best level	Contribution	Best level
Power (%)	Significant	Level-2(60)	Significant	Level-2(60)
Ab. Slurry	Significant	Level-2(Sic)	Significant	Level-3(Sic)
Slurry conc.	Significant	Level-3(30)	Significant	Level-3(30)
Grit size	Insignificant		Insignificant	
Power(%)*Ab. Slurry	Insignificant		Significant	

Estimating the mean

In experimental analysis, the MRR is a higher average response is better (HB) characteristic. Depending on the characteristic, different treatment combinations has chosen to obtain satisfactory results. After conducting the experiments the optimum treatment condition within the experiments determined on the basis of prescribed combination of factor levels is determined to one of those in the experiment.

Mean Value for MRR

$\mu A_2B_2C_3 = A_2 + B_2 + C_3 - 2T$(Mean of all experiments) (Equation-6.4)

= 8.554+8.056+8.316-2x7.03= 10.866 mm^3/min

Confidence interval around the estimated mean

The confidence interval is a maximum and minimum value between which the true average should fall at some stated percentage of confidence. The estimate of the mean μ is only a point estimate based on the averages of results obtained from the experiment. Statistically this provides a 50% chance of the true averages being greater than μ and a 50% chance of the true average being less than μ .

$$CI_1 = \sqrt{\frac{F_{\alpha, v_1, v_2} V_e}{n_{eff}}}$$

Where $F\alpha v_1 v_2$= F ratio

α = risk (0.05) confidence= 1-α

v_1 = D.O.F for mean which is always=1

v_2 = D.O.F for error =v_e

v_e = Variance of e-pooled

η_{eff} = number of test under that condition using the participating factors

η_{eff}= N/ (1+$dof_{A,B,C}$) = 18/(1+1+2+2) = 3.0

$$CI_1 = \sqrt{\frac{F_{\alpha, v_1, v_2} V_e}{n_{eff}}}$$

$CI_1 = \sqrt{(4.75X0.833)}/3$ = 1.15 mm^3/min

So the confidence interval around the MRR is given by 10.87±1.15 mm^3/min.

CHAPTER 7

RESULTS AND ANALYSIS OF TWR

7.1 INTRODUCTION

The effects of parameters i.e Type of abrasive slurry, Concentration of abrasive slurry, Power (%) of the machine, Abrasive grit size and some of their interactions were evaluated using ANOVA and factorial design analysis. A confidence interval of 95% has been used for the analysis. One repetition for each of 18 trails was completed to measure the Signal to Noise ratio(S/N Ratio).

7.2 RESULTS FOR TWR

The results for TWR for each of the 18 treatment conditions with repetition are given in Table 7.1. The TWR is calculated from the loss in length in electrode during performance trial:

$$\mathrm{TWR} = \frac{A \times L}{t} \ \ \mathrm{mm}^3/\mathrm{min}$$

(Equation-7.1)

Where A = front area of electrode (mm2)

L = Loss in length of electrode (mm)

t = time period of trial (minutes)

Table 7.1: Results for TWR

Trail No:	Power (%)	Ab. Slurry	Slurry Concentration	Grit Size	TWR mm^3/min	S/N Ratio	Mean
1	20	Aluminium Oxide	20	280	0.2429	12.2914	0.2429
2	20	Aluminium Oxide	25	400	0.2485	12.0935	0.2485
3	20	Aluminium Oxide	30	600	0.2046	13.7819	0.2046
4	20	Silicon Carbide	20	280	0.2498	12.0482	0.2498
5	20	Silicon Carbide	25	400	0.2597	11.7106	0.2597

Trail No:	Power (%)	Ab. Slurry	Slurry Concentration	Grit Size	TWR mm^3/min	S/N Ratio	Mean
6	20	Silicon Carbide	30	600	0.2196	13.1674	0.2196
7	20	Mixture	20	400	0.2408	12.3669	0.2408
8	20	Mixture	25	600	0.2126	13.4487	0.2126
9	20	Mixture	30	280	0.2308	12.7353	0.2308
10	60	Aluminium Oxide	20	600	0.2738	11.2513	0.2738
11	60	Aluminium Oxide	25	280	0.3089	10.2036	0.3089
12	60	Aluminium Oxide	30	400	0.2959	10.5771	0.2959
13	60	Silicon Carbide	20	400	0.3048	10.3197	0.3048
14	60	Silicon Carbide	25	600	0.3105	10.1588	0.3105
15	60	Silicon Carbide	30	280	0.3189	9.9269	0.3189
16	60	Mixture	20	600	0.2952	10.5977	0.2952
17	60	Mixture	25	280	0.2979	10.5186	0.2979
18	60	Mixture	30	400	0.2893	10.7730	0.2893

7.3: ANALYSIS OF VARIANCE - TWR

The results for TWR were analyzed using ANOVA for identifying the significant factors affecting the performance measures. The Analysis of Variance (ANOVA) for the mean TWR at 95% confidence interval is given in Table 7.2. The variance data for each factor and their interactions were P value to find significance of each. From Table 7.2 Power rating (%), Ab. Slurry, Grit size have the P value less the 0.05 that means these factor are significant. Slurry Conc. and interaction between Ab. slurry and grit size have value more then 0.05 that means it is insignificant. Table 7.3 shows ranks to various input parameters in terms their relative significance

Table 7.2: Analysis of Variance for TWR OF Means

Source	Seq. SS	DF	Adj. MS	F	P	SS'	% contribution	Status
Power (%)	0.019071	1	0.019071	181.52	0.000	0.018953	81.455	Significant
Ab. Slurry	0.000960	2	0.000480	4.57	0.047	0.000724	3.11	significant
Slurry conc.	0.000528	2	0.000264	2.52	0.142			Insignificant
Grit size	0.001823	2	0.000912	8.68	0.010	0.001587	6.82	significant
power(%)*Grit size	0.000044	2	0.000022	0.21	0.814			Insignificant
Residual error	0.000841	8	0.000105					
Total	0.023268	17						
e-pooled	0.001413	12	0.000118				8.615	

Table 7.3: Response Table for TWR of Means

Level	Power (%)	Ab. Slurry	Slurry Conc.	Grit size
1	0.2344	0.2624	0.2679	0.2749
2	0.2995	0.2772	0.2730	0.2732
3		0.2611	0.2599	0.2527
Delta	0.0651	0.0161	0.0132	0.0221
Rank	1	3	4	2

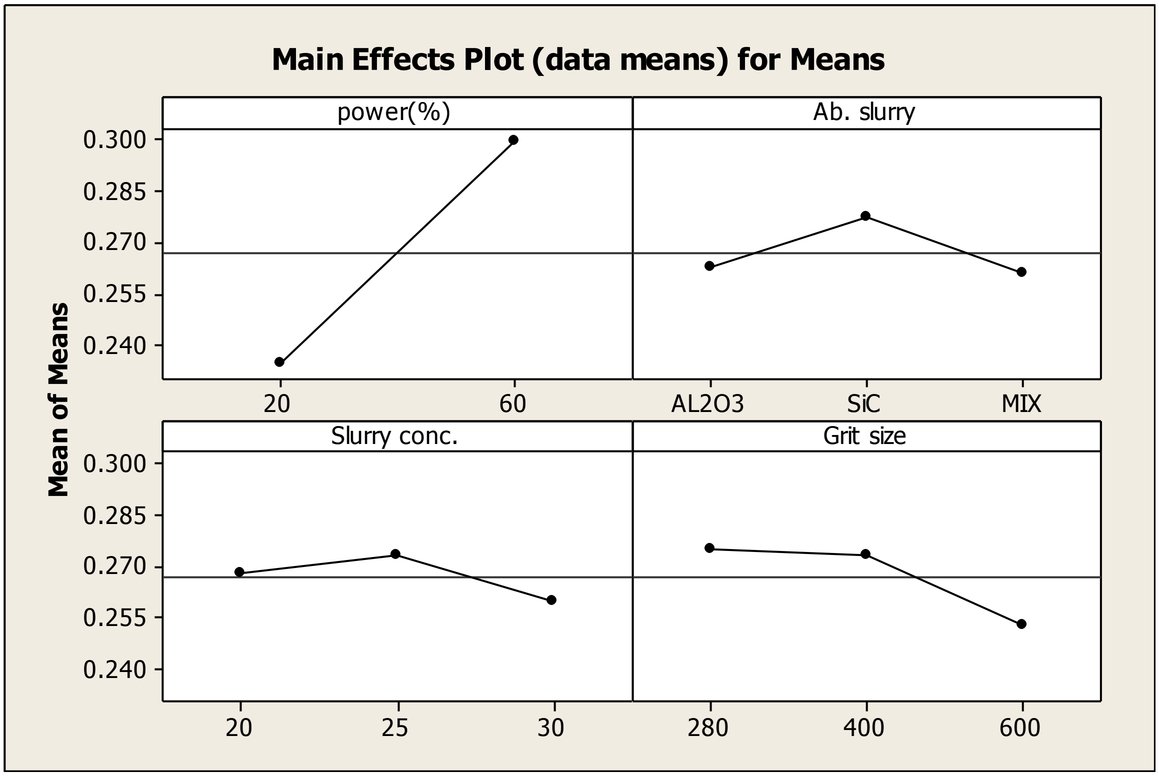


Figure 7.1: Main effects plot for TWR of means

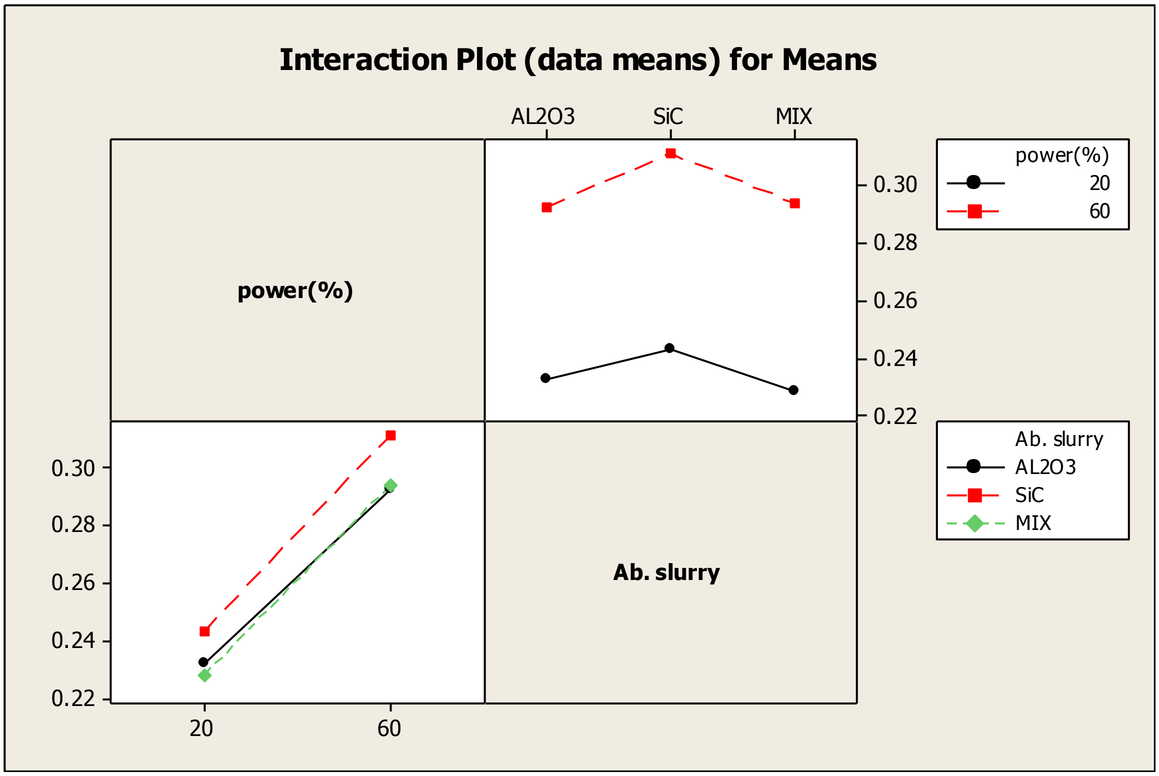


Figure 7.2: Interaction plot for TWR

7.4: ANOVA FOR S/N RATIO FOR TWR

The S/N ratio consolidates several repetitions into one value and is an indication of the amount of variation present. The S/N ratios have been calculated to identify the major contributing factors and interactions that cause variation in the TWR. TWR is ‘Lower is better’ type response which is given by:

$$S/N_{LB} = -10\log(MSD) = -10\log[(\frac{1}{r}\sum_{i=1}^{r} y^{2}{}_{i})$$

$$\text{Where } MSD_{LB} = \frac{1}{r}\sum_{j=1}^{r}(y_{j}^{2})$$

(Equation-7.2)

Table 7.4 shows the ANOVA results for S/N ratio of TWR at 95% confidence interval. power(%) was observed to be the most significant factor affecting the TWR, followed by Grit size and Ab. Slurry are significant according to p value. The interactions between power(%) and Grit size is also significant. Main effects plot and interaction plot of S/N ratio for TWR are shown in the figure 7.3and 7.4 respectively.

Table 7.4: Analysis of Variance for S/N ratio of TWR

Source	Seq. SS	DF	Adj. MS	F	P	SS’	% contribution	Status
Power (%)	20.7304	1	20.7304	157.23	0.000	20.58072	79.40	Significant
Ab. Slurry	0.9969	2	0.4985	3.78	0.050	.69754	2.70	significant
Slurry conc.	0.7166	2	0.3583	2.72	0.126			Insignificant
Grit size	2.3762	2	1.1881	9.01	0.009	2.22652	8.60	significant
power(%)*Ab. slurry	0.0248	2	0.0124	0.09	0.911			Insignificant
Residual error	1.0548	8	0.1318					
Total	25.8997	17						
e-pooled	1.7962	12	0.14968				9.30	

Table 7.5: Response Table for S/N ratio of TWR

Level	Power (%)	Ab. Slurry	Slurry Conc.	Grit size
1	12.63	11.70	11.48	11.29
2	10.48	11.22	11.36	11.31
3		11.74	11.83	12.07
Delta	2.15	0.52	0.47	0.78
Rank	1	3	4	2

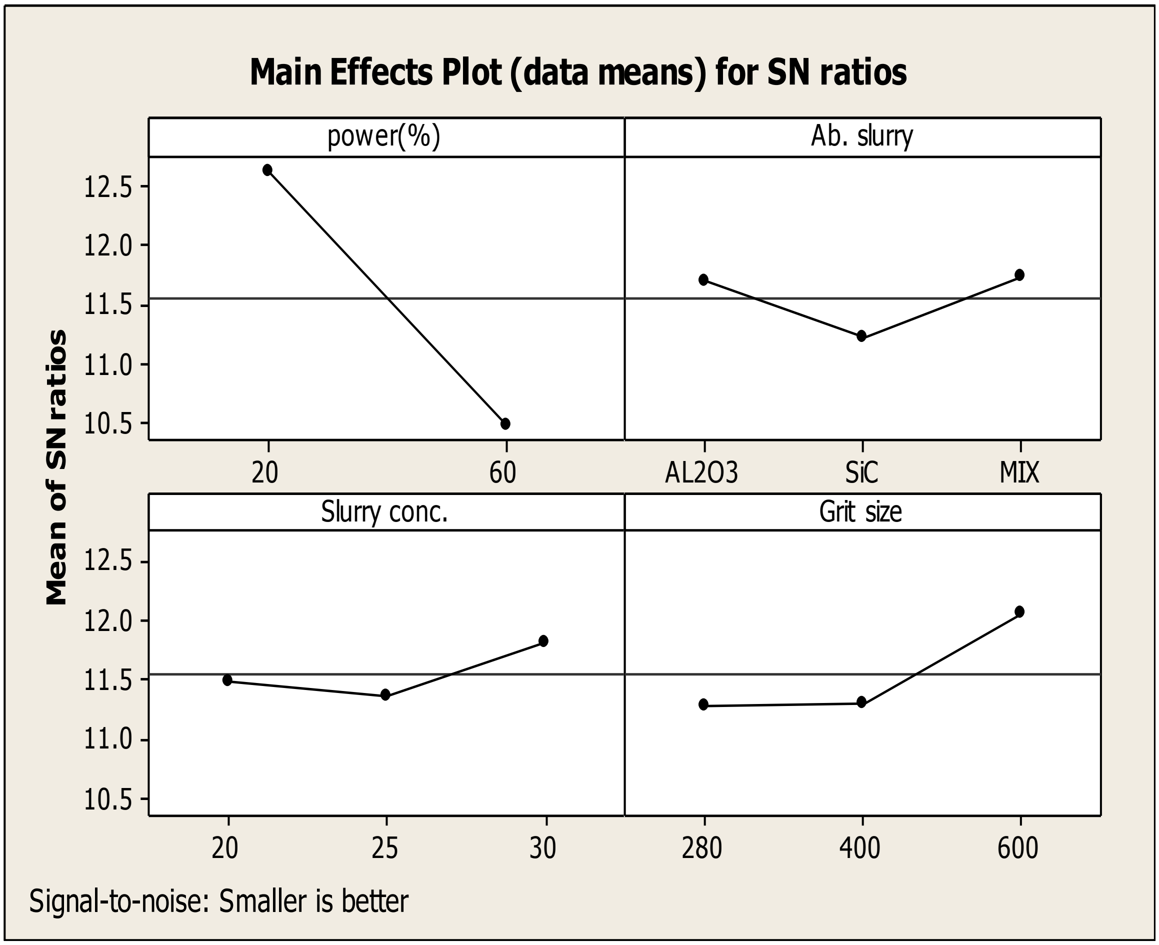


Figure 7.3: Main effect plot for TWR of S/N ratio

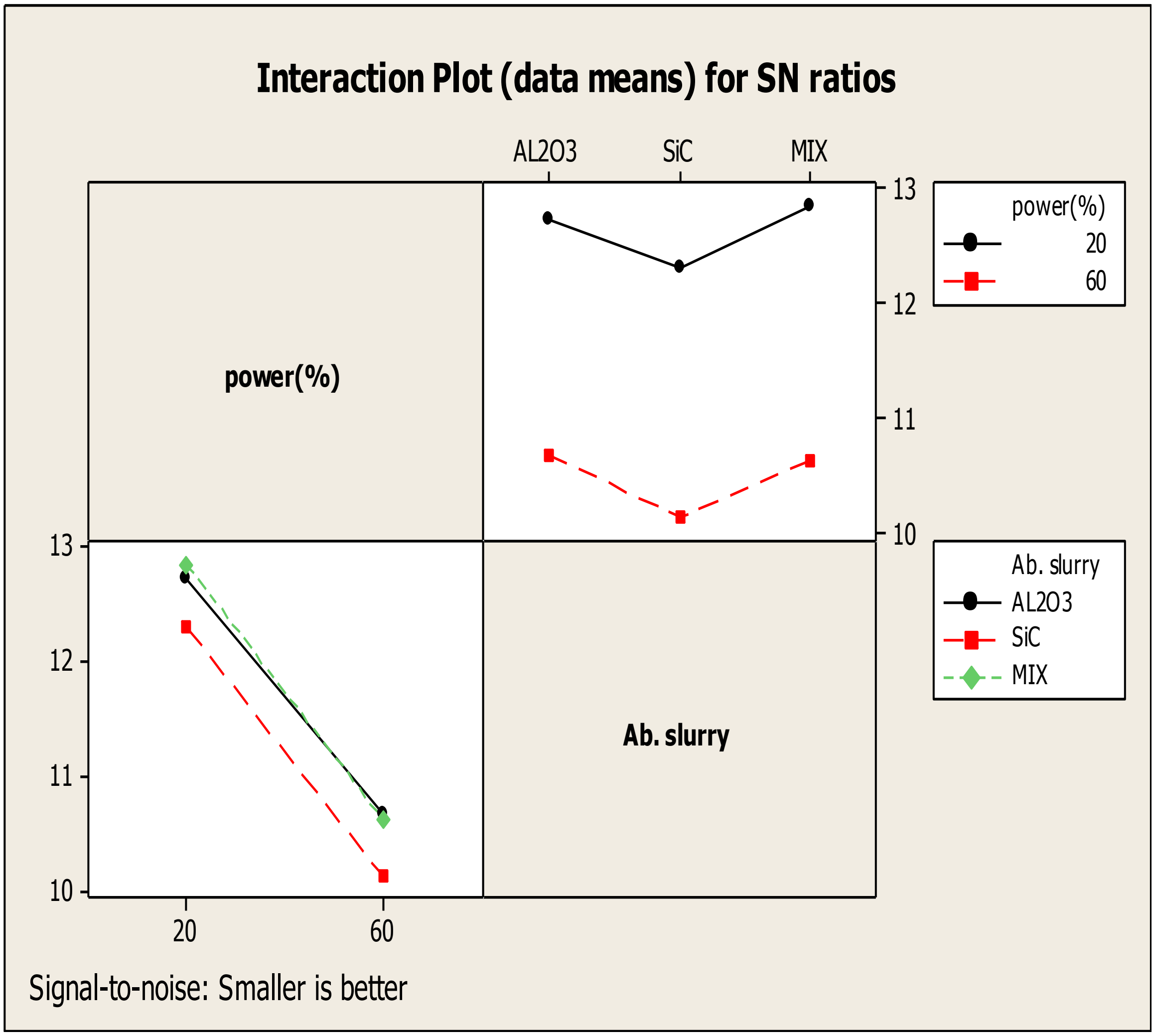


Figure 7.4: Interaction plot for TWR of S/N ratio

7.5 OPTIMAL DESIGN FOR TWR

In this experimental analysis, the main effect plot and interaction plot in Figure 7.1 and Figure 7.2 used to estimate the mean MRR. From the, Table 7.6 it is concluded that highest TWR was observed when Work-piece is machined on Power Rate 20%, abrasive slurry Silicon Carbide+Aluminum oxide and Grit size 600. It also observes that slurry concentration and the interaction AxB is not any effect on the TWR. The best TWR value was compromised to get best results. TWR Assumed to be achieved best result if GFRP work piece is machined at Power Rate 20%, abrasive slurry Silicon Carbide+Aluminum oxide and Grit size 600.

Table 7.6: Significant factors and interactions

Factor	Affecting mean		Affecting variation	
	Contribution	Best level	Contribution	Best level
Power (%)	Significant	Level-1(20)	Significant	level 2(60)
Ab. Slurry	Significant	Level-3(MIX)	Significant	Level 2(Sic)
Slurry conc.	Insignificant		Insignificant	
Grit size	Significant	Level-3(600)	Significant	Level-1(280)
Power(%)*Ab. Slurry	Insignificant		Insignificant	

Estimating the mean

In experimental analysis, the TWR is a Smaller average response is better (SB) characteristic. Depending on the characteristic, different treatment combinations has chosen to obtain satisfactory results. After conducting the experiments the optimum treatment condition within the experiments determined on the basis of prescribed combination of factor levels is determined to one of those in the experiment.

Mean Value for TWR

$\mu A_1B_3D_3 = A_2 + B_2 + D_3 - 2T$(Mean of all experiments) (Equation-7.3)

$= 0.2344+0.2611+0.2527-2\text{x}0.2669= 0.2144\ \text{mm}^3/\text{min}$

Confidence interval around the estimated mean

The confidence interval is a maximum and minimum value between which the true average should fall at some stated percentage of confidence. The estimate of the mean μ is only a point estimate based on the averages of results obtained from the experiment. Statistically this provides a 50% chance of the true averages being greater than μ and a 50% chance of the true average being less than μ .

$$CI_1 = \sqrt{\frac{F_{\alpha, v_1, v_2} V_e}{n_{eff}}}$$

Where $F\alpha v_1 v_2$= F ratio

α = risk (0.05) confidence= 1-α

v_1 = D.O.F for mean which is always=1

v_2 = D.O.F for error =v_e

v_e = Variance at e-pooled

η_{eff} =number of test under that condition using the participating factors

η_{eff}= N/ (1+$dof_{A,B,D}$) = 18/(1+1+2+2) = 3.0

$$CI_1 = \sqrt{\frac{F_{\alpha, v_1, v_2} V_e}{n_{eff}}}$$

CI $_1$ = $\sqrt{(4.75X0.000118)/3}$ = 0.0137 mm^3/min

So the confidence interval around the TWR is given by 0.2144±0.0137 mm^3/min.

CHAPTER 8

RESULTS AND ANALYSIS OF SR

8.1: INTRODUCTION

Surface roughness of the machined surface of work piece is expressed in microns. The characteristics of the layer of the work material just below the machined surface can also be evaluated.

8.2: RESULTS FOR SURFACE ROUGHNESS

The results for surface roughness are shown in table 8.1.

Table 8.1: Results for Surface Roughness (Ra)

Trail No:	Power (%)	Ab. Slurry	Slurry Concentration	Grit Size	SR (μm)	S/N Ratio	Mean
1	20	Aluminium Oxide	20	280	0.89	1.01220	0.89
2	20	Aluminium Oxide	25	400	0.81	1.83030	0.81
3	20	Aluminium Oxide	30	600	0.75	2.49877	0.75
4	20	Silicon Carbide	20	280	0.68	3.34982	0.68
5	20	Silicon Carbide	25	400	0.56	5.03624	0.56
6	20	Silicon Carbide	30	600	0.52	5.67993	0.52
7	20	Mixture	20	400	0.75	2.49877	0.75
8	20	Mixture	25	600	0.86	1.31003	0.86
9	20	Mixture	30	280	0.71	2.97483	0.71

Trail No:	Power (%)	Ab. Slurry	Slurry Concentration	Grit Size	SR (µm)	S/N Ratio	Mean
10	60	Aluminium Oxide	20	600	1.49	-3.46373	1.49
11	60	Aluminium Oxide	25	280	1.23	-1.79810	1.23
12	60	Aluminium Oxide	30	400	0.96	0.35458	0.96
13	60	Silicon Carbide	20	400	1.06	-0.50612	1.06
14	60	Silicon Carbide	25	600	0.91	0.81917	0.91
15	60	Silicon Carbide	30	280	0.88	1.11035	0.88
16	60	Mixture	20	600	1.35	-2.60668	1.35
17	60	Mixture	25	280	1.44	-3.16725	1.44
18	60	Mixture	30	400	1.29	-2.21179	1.29

8.3: ANALYSIS OF VARIANCE - SURFACE ROUGHNESS (Ra)

The results for SR were analyzed using ANOVA for identifying the significant factors affecting the performance measures. The Analysis of Variance (ANOVA) for the mean SR at 95% confidence interval is given in Table 8.2. The variance data for each factor and their interactions were P value to find significance of each. From Table 8.2 Power rating (%), Ab. Slurry, slurry Conc. have the P value less the 0.05 that means these factor are significant. Grit size and interaction between Power(%) and Ab. slurry have value more then 0.05 that means it is insignificant. Table 8.3 shows ranks to various input parameters in terms their relative significance.

8.2: Analysis of Variance for Roughness of Means

Source	Seq. SS	DF	Adj. MS	F	P	SS’	% contribution	Status
Power (%)	0.92480	1	0.92480	91.36	0.000	0.9129	61.55	Significant
Ab. Slurry	0.31041	2	0.15521	15.33	0.002	0.28661	19.32	significant
Slurry conc.	0.10501	2	0.05251	5.19	0.036	0.08121	0.05	significant
Grit size	0.02028	2	0.01014	1.00	0.409			Insignificant
power(%)*Ab. slurry	0.04163	2	0.02082	2.06	0.190			Insignificant
Residual error	0.08098	8	0.01012					
Total	1.48311	17						
e-pooled	0.14289	12	0.01190				18.63	

Table 8.2: Response Table for Roughness of Means

Level	Power (%)	Ab. Slurry	Slurry Conc.	Grit size
1	0.7256	1.0217	1.0367	0.9717
2	1.1789	0.7683	0.9683	0.9050
3		1.0667	0.8517	0.9800
Delta	0.4533	0.2983	0.1850	0.0750
Rank	1	2	3	4

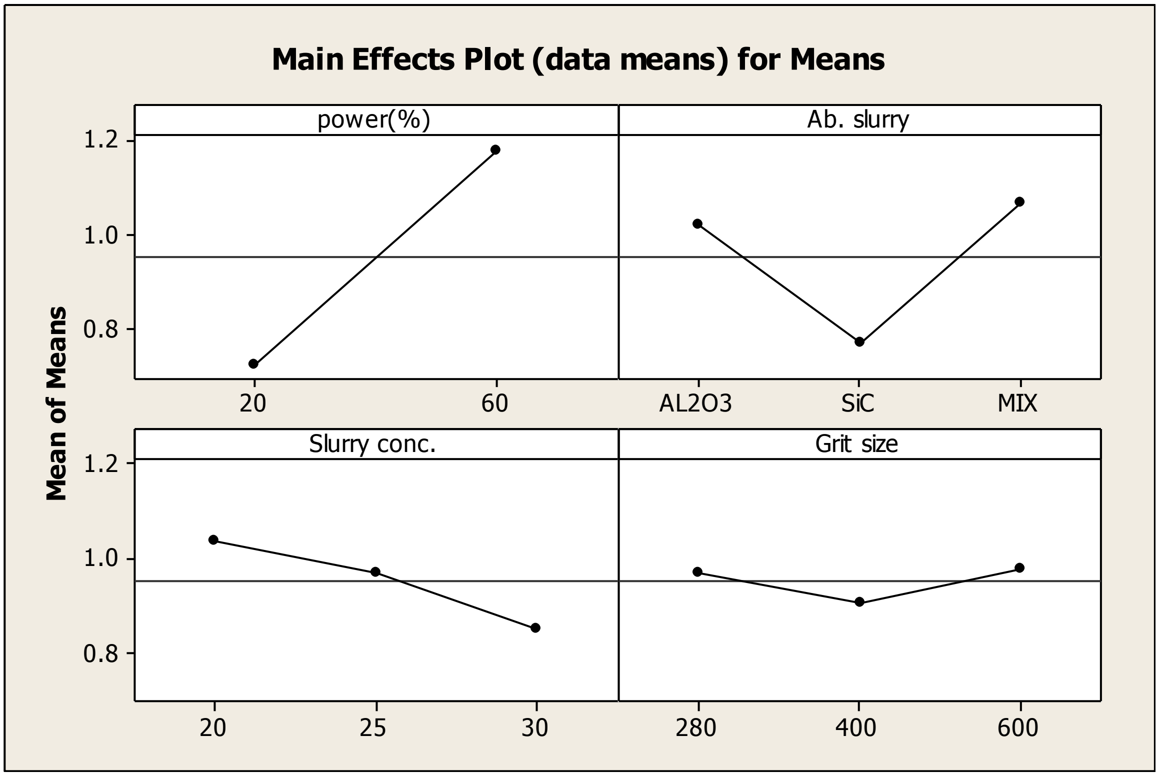


Figure 8.1: Main effects plot for surface roughness of Means

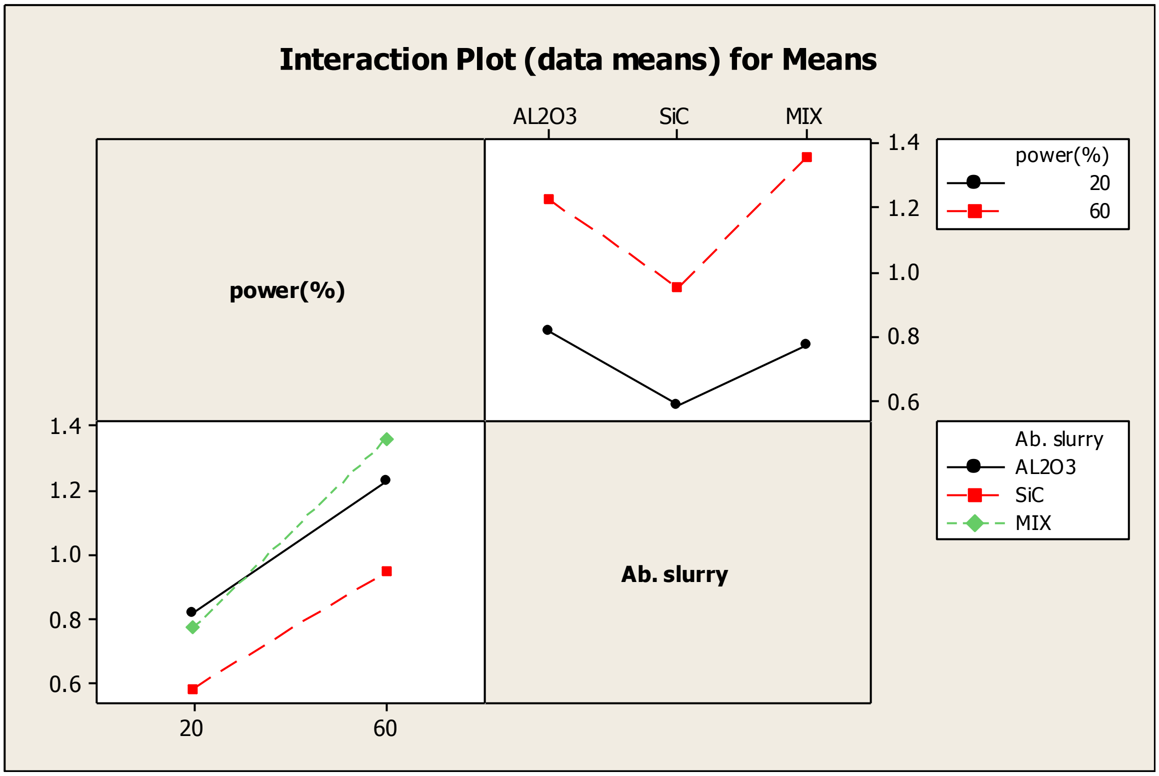


Figure 8.2: Interaction plot surface roughness of Means

8.4: ANALYSIS OF VARIANCE FOR S/N RATIO FOR SURFACE ROUGHNESS (RA)

The S/N ratio consolidates several repetitions into one value and is an indication of the amount of variation present. The S/N ratios have been calculated to identify the major contributing factors and interactions that cause variation in the SR. SR is ‘Lower is better’ type response which is given by:

$$S / N_{LB} = -10 \log(MSD) = -10 \log[(\frac{1}{r} \sum_{i=1}^{r} y^2{}_i)$$

$$\text{Where } MSD_{LB} = \frac{1}{r} \sum_{j=1}^{r} \left(y_j{}^2 \right)$$

(Equation-8.1)

Table 8.4 shows the ANOVA results for S/N ratio of MRR at 95% confidence interval. power(%) was observed to be the most significant factor affecting the SR, followed by Ab. Slurry and slurry conc. are significant according to p value. The grit size and interactions between power(%) and Ab. slurry is insignificant. Main effects plot and interaction plot of S/N ratio for SR are shown in the figure 5.5.3and 5.5.4 respectively.

Table 8.4: Analysis of Variance FOR S/N ratio for roughness (ra)

Source	Seq. SS	DF	Adj. MS	F	P	SS’	% contribution	Status
Power(%)	78.795	1	78.7951	129.32	0.000	78.1513	63.30	Significant
Ab. Slurry	28.219	2	14.1096	23.16	0.000	26.9315	21.81	Significant
Slurry conc.	8.731	2	4.3654	7.16	0.016	7.4435	6.03	Significant
Grit size	1.145	2	0.5724	0.94	0.430			Insignificant
power(%)*Ab. slurry	1.705	2	0.8526	1.40	0.301			Insignificant
Residual error	4.875	8	0.6093					
Total	123.470	17						
e-pooled	7.725	12	0.64375				8.86	

Table 8.5: Response Table for S/N Ratios for roughness (ra)

Level	Power (%)	Ab. Slurry	Slurry Conc.	Grit size
1	2.91010	0.07234	0.04738	0.58031
2	-1.27440	2.58157	0.67173	1.16700
3		-0.20035	1.73444	0.70625
Delta	4.18450	2.78191	1.68707	0.58669
Rank	1	2	3	4

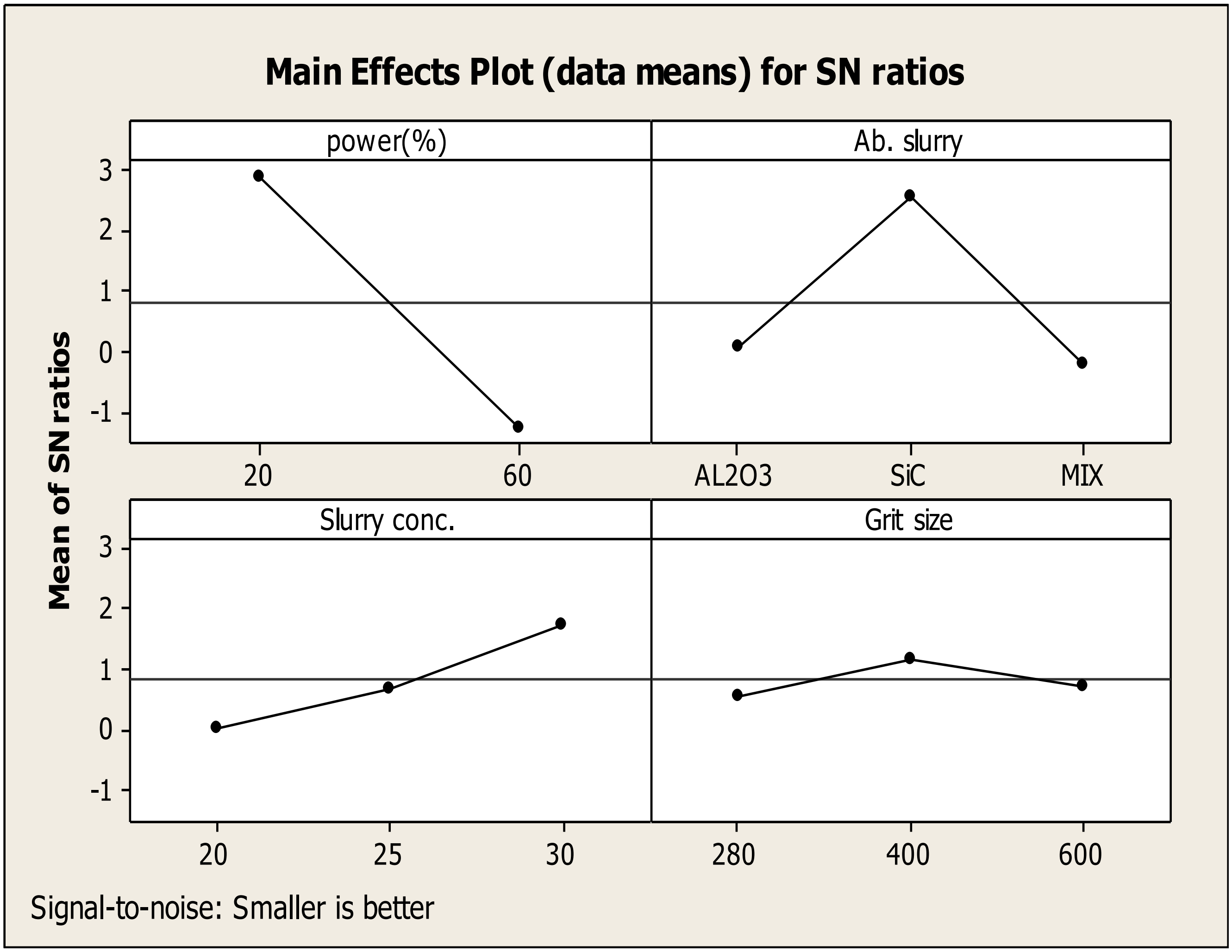


Figure 8.3: Main effects plot for S/N ratio for surface roughness

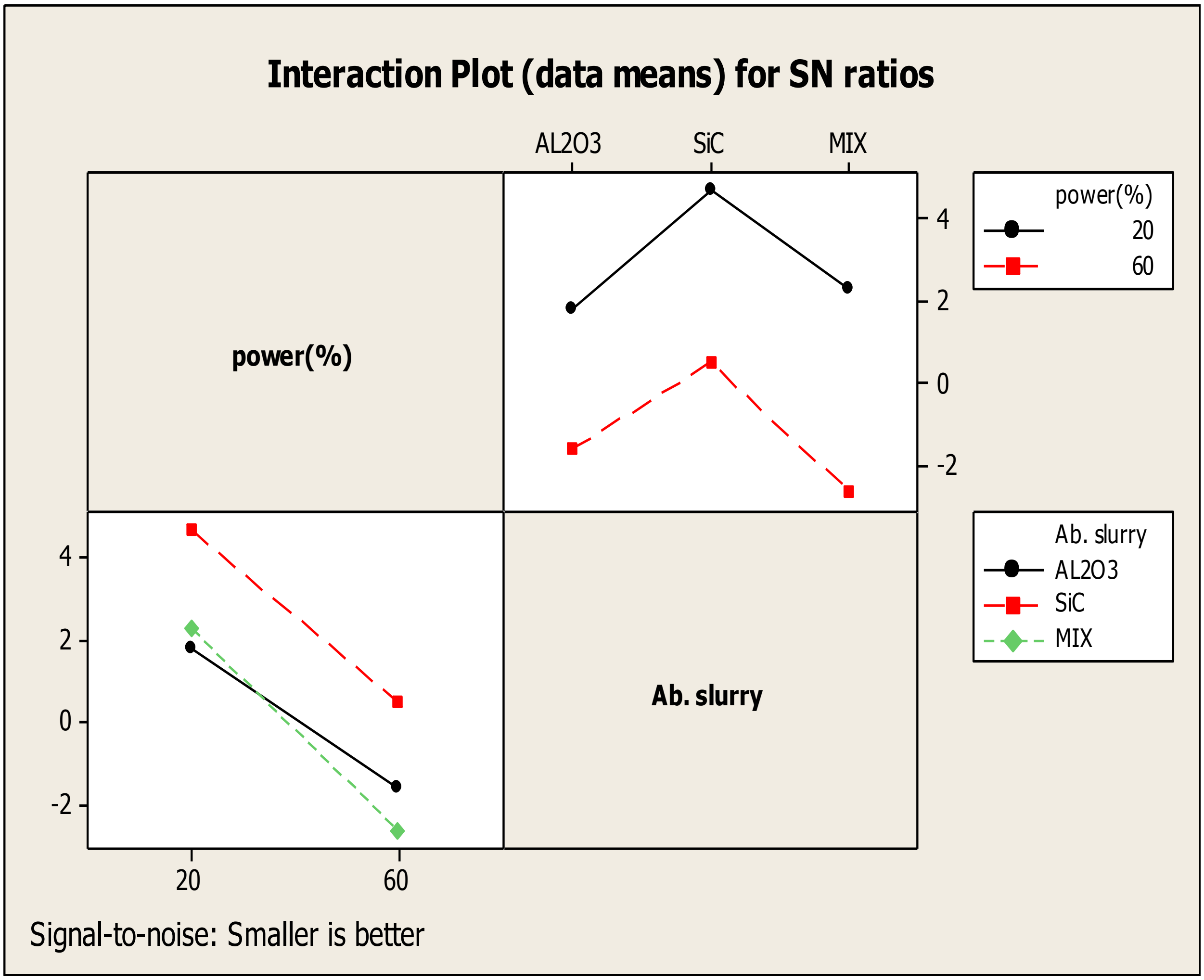


Figure 8.4: Interaction plot for of S/N ratio for roughness

8.5: OPTIMAL DESIGN FOR SR

In this experimental analysis, the main effect plot and interaction plot in Figure 8.1 and Figure 8.2 used to estimate the mean MRR. From the, Table 8.6 it is concluded that highest SR was observed when Work-piece is machined on Power Rate 20%, abrasive slurry Silicon Carbide and slurry concentration 30%. It also observes that Grit size and the interaction AxB is not any effect on the SR. The best SR value was compromised to get best results. SR Assumed to be achieved best result if GFRP work piece is machined at Power Rate 20%, abrasive slurry Silicon Carbide and slurry concentration 30%.

Table 8.6 Significant factor and interaction

Factor	Affecting mean		Affecting variation	
	Contribution	Best level	contribution	Best level
Power (%)	Significant	Level-1(20)	Significant	Level-2(60)
Ab. Slurry	Significant	Level-2(SiC)	Significant	Level-3(mix)
Slurry conc.	Significant	Level-3(30)	Significant	Level-1(20)
Grit size	Insignificant		insignificant	
Power(%)*Ab. Slurry	Insignificant		insignificant	

Estimating the mean

In experimental analysis, the SR is a Smaller average response is better (SB) characteristic. Depending on the characteristic, different treatment combinations has chosen to obtain satisfactory results. After conducting the experiments the optimum treatment condition within the experiments determined on the basis of prescribed combination of factor levels is determined to one of those in the experiment.

Mean Value for SR

$\mu A_1B_2C_3 = A_1 + B_2 + C_3 - 2T$(Mean of all experiments) (Equation-8.2)

$= 0.7256+0.7683+0.857-2\text{x}0.9522= 0.4479\ \mu\text{m}$

Confidence interval around the estimated mean

The confidence interval is a maximum and minimum value between which the true average should fall at some stated percentage of confidence. The estimate of the mean μ is only a point estimate based on the averages of results obtained from the experiment. Statistically this provides a 50% chance of the true averages being greater than μ and a 50% chance of the true average being less than μ .

$$CI_1 = \sqrt{\frac{F_{\alpha, v_1, v_2} V_e}{n_{eff}}}$$

Where $F\alpha v_1 v_2$= F ratio

α = risk (0.05) confidence= 1-α

v_1 = D.O.F for mean which is always=1

v_2 = D.O.F for error =v_e

v_e = Variance at e-pooled

$\eta_{eff\,=}$number of test under that condition using the participating factors

η_{eff}= N/ (1+$dof_{A,B,C}$) = 18/(1+1+2+2) = 3.0

$$CI_1 = \sqrt{\frac{F_{\alpha, v_1, v_2} V_e}{n_{eff}}}$$

CI $_1$ = $\sqrt{(4.75X0.01190)/3}$ = 0.137µm

So the confidence interval around the SR is given by 0.4479±0.137 µm.

CHAPTER 9

RESULTS AND ANALYSIS OF ROCKWELL HARDNESS

9.1: INTRODUCTION

The Rockwell scale is a hardness scale based on the indentation hardness of a material. The Rockwell test determines the hardness by measuring the depth of penetration of an indenter under a large load compared to the penetration made by a preload.

9.2: Results for hardness

The results for Hardness for each of the 18 treatment conditions with repetition are given in Table 9.1.

Table 9.1: Results for Hardness

Trail No:	Power (%)	Ab. Slurry	Slurry Concentration	Grit Size	Hardness (HRB)	S/N Ratio	Mean
1	20	Aluminium Oxide	20	280	73.0	37.2665	73.0
2	20	Aluminium Oxide	25	400	73.5	37.3257	73.5
3	20	Aluminium Oxide	30	600	74.0	37.3846	74.0
4	20	Silicon Carbide	20	280	73.5	37.3257	73.5
5	20	Silicon Carbide	25	400	74.0	37.3846	74.0
6	20	Silicon Carbide	30	600	74.5	37.4431	74.5
7	20	Mixture	20	400	75.0	37.5012	75.0
8	20	Mixture	25	600	75.5	37.5589	75.5
9	20	Mixture	30	280	74.5	37.4431	74.5
10	60	Al_2O_3	20	600	75.5	37.5589	75.5

Trail No:	Power (%)	Ab. Slurry	Slurry Concentration	Grit Size	Hardness (HRB)	S/N Ratio	Mean
11	60	Aluminium Oxide	25	280	73.0	37.2665	73.0
12	60	Aluminium Oxide	30	400	74.5	37.4431	74.5
13	60	Silicon Carbide	20	400	75.5	37.5589	75.5
14	60	Silicon Carbide	25	600	76.5	37.6732	76.5
15	60	Silicon Carbide	30	280	76.0	37.6163	76.0
16	60	Mixture	20	600	76.5	37.6732	76.5
17	60	Mixture	25	280	75.5	37.5589	75.5
18	60	Mixture	30	400	76.0	37.6163	76.0

9.3: ANALYSIS OF VARIANCE - HARDNESS

The results for Hardness were analyzed using ANOVA for identifying the significant factors affecting the performance measures. The Analysis of Variance (ANOVA) for the mean Hardness at 95% confidence interval is given in Table 9.2. The variance data for each factor and their interactions were P value to find significance of each. From Table 9.2 Ab. Slurry, Power (%), Grit size have the P value less the 0.05 that means these factor are significant. Slurry conc. and interaction between Power(%) and Ab. slurry have value more then 0.05 that means it is insignificant. Table 9.3 shows ranks to various input parameters in terms their relative significance.

Table 9.2: Analysis of Variance for Hardness of Means

Source	Seq. SS	DF	Adj. MS	F	P	SS’	% contribution	Status
Power (%)	7.3472	1	7.34722	43.18	0.000	7.1180	32.25	Significant
Ab. Slurry	7.8611	2	3.93056	23.10	0.000	7.4027	33.54	significant
Slurry conc.	0.1944	2	0.09722	0.57	0.586			Insignificant
Grit size	4.1111	2	2.05556	12.08	0.004	3.6527	16.55	significant
power(%)*Ab. slurry	1.1944	2	0.59722	3.51	0.080			Insignificant
Residual error	1.3611	8	0.17014					
Total	22.0694	17						
e-pooled	2.7499	12	0.2292				17.66	

Table 9.3: Response Table for Hardness of Means

Level	Power (%)	Ab. Slurry	Slurry Conc.	Grit size
1	74.17	73.92	74.83	74.25
2	75.44	75.00	74.67	74.75
3		75.50	74.92	75.42
Delta	1.28	1.58	0.25	1.17
Rank	2	1	4	3

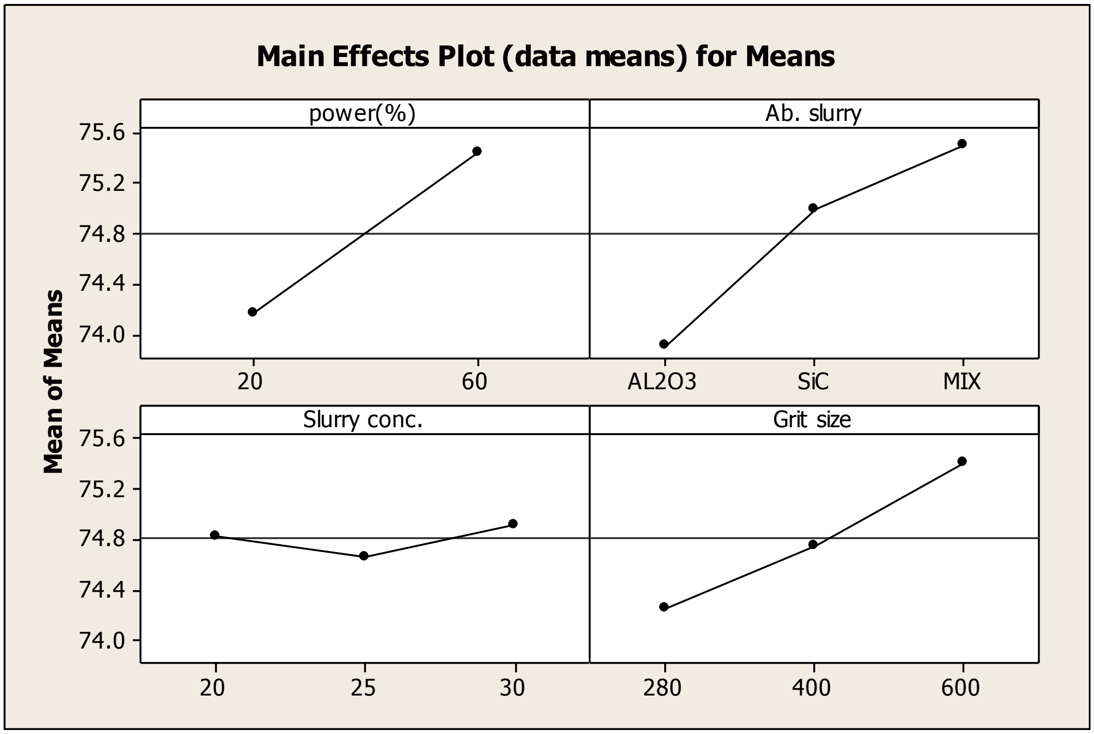


Figure 9.1: Main effects plot for Hardness of Means

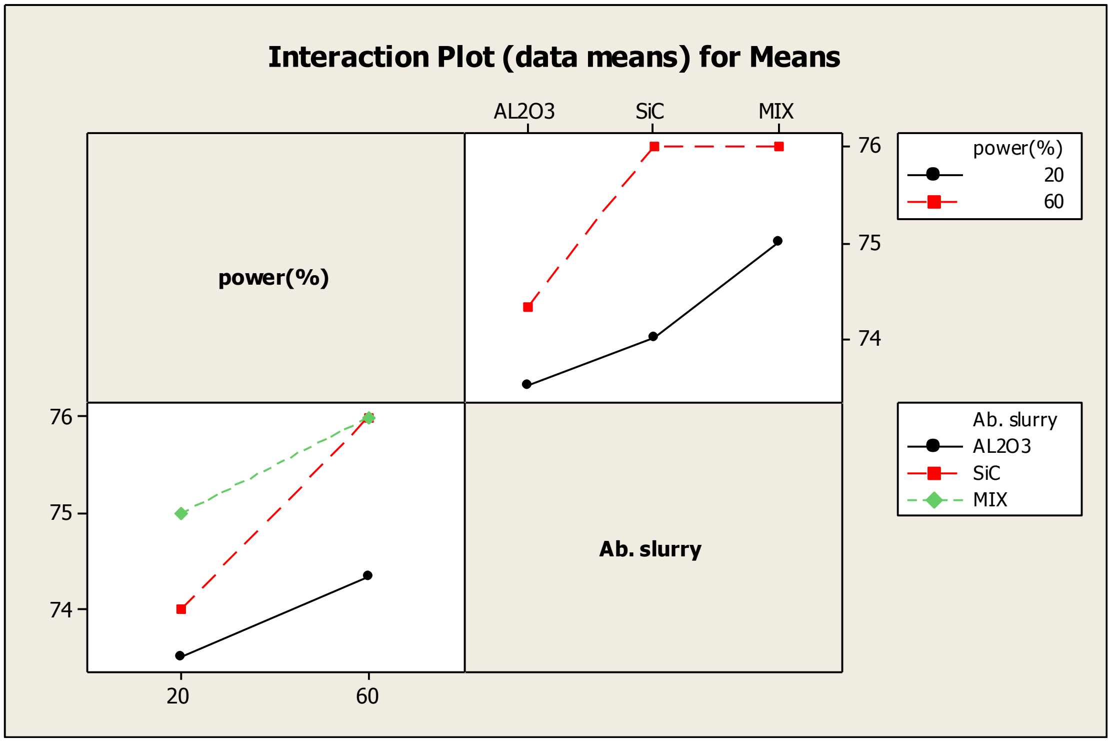


Figure 9.2: Interaction plot Hardness of Means

9.4: ANALYSIS OF VARIANCE OF S/N RATIO FOR HARDNESS

The S/N ratio consolidates several repetitions into one value and is an indication of the amount of variation present. The S/N ratios have been calculated to identify the major contributing factors and interactions that cause variation in the SR. SR is ‘Higher is better’ type response which is given by:

$$S / N_{LB} = -10 \log(MSD) = -10 \log[(\frac{1}{r}\sum_{i=1}^{r} y^2{}_i)$$

$$\text{Where } MSD_{LB} = \frac{1}{r}\sum_{j=1}^{r}\left(y_j{}^2\right)$$

(Equation-9.1)

Table 9.4 shows the ANOVA results for S/N ratio of MRR at 95% confidence interval. Ab. Slurry power(%) was observed to be the most significant factor affecting the Hardness, followed by power(%) and grit size slurry conc. are significant according to p value. The slurry conc. and interactions between power (%) and Ab. slurry is insignificant. Main effects plot and interaction plot of S/N ratio for hardness are shown in the figure 9.3and 9.4 respectively.

Table 9.4: Analysis of Variance of S/N ratio for Hardness

Source	Seq. SS	DF	Adj. MS	F	P	SS’	% contribution	Status
Power(%)	0.098533	1	0.098533	42.40	0.000	0.095423	32.00	Significant
Ab. Slurry	0.106601	2	0.053301	22.93	0.000	0.100381	33.66	Significant
Slurry conc.	0.002741	2	0.001371	0.59	0.577			Insignificant
Grit size	0.055697	2	0.027848	11.98	0.004	0.052587	17.64	Significant
power(%)*Ab. slurry	0.015990	2	0.007995	3.44	0.084			Insignificant
Residual error	0.018593	8	0.002324					
Total	0.298155	17						
e-pooled	0.037324	12	0.00311				16.7	

Table 9.5: Response Table for S/N Ratios for Hardness

Level	Power (%)	Ab. Slurry	Slurry Conc.	Grit size
1	37.40	37.37	37.48	37.41
2	37.55	37.50	37.46	37.47
3		37.56	37.49	37.55
Delta	0.15	0.18	0.03	0.14
Rank	2	1	4	3

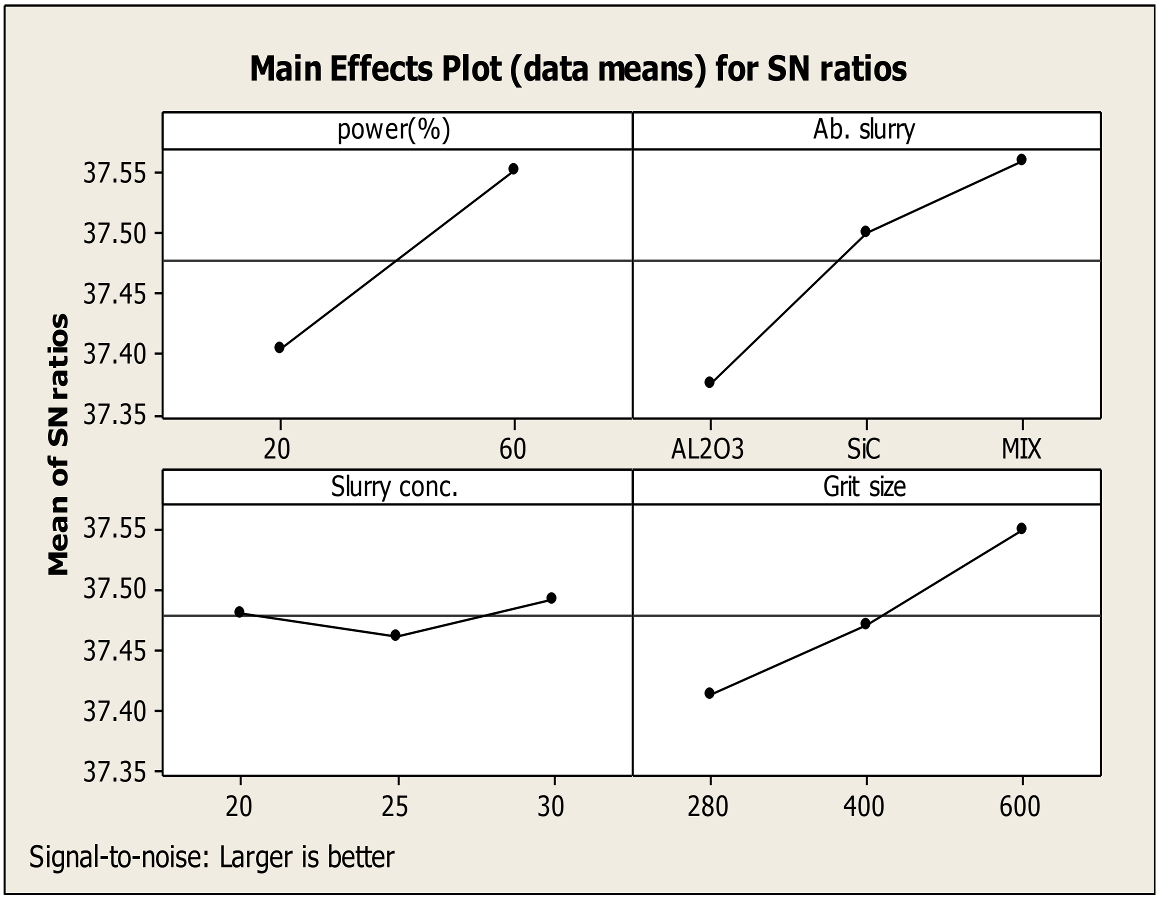


Figure 9.3: Main effects plot for S/N ratio of Hardness

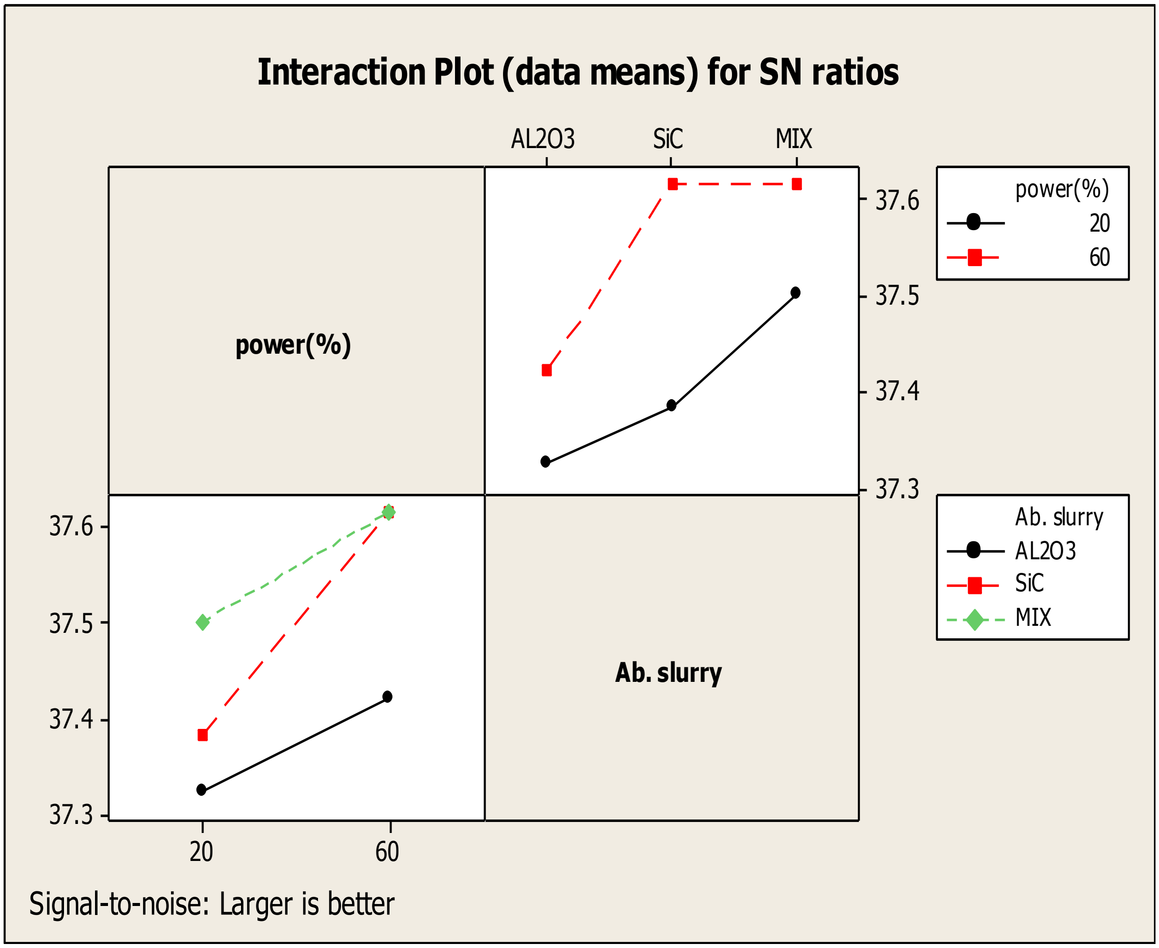


Figure 9.4: Interaction plot for of S/N ratio for Hardness

9.5: OPTIMAL DESIGN FOR HARDNESS

In this experimental analysis, the main effect plot and interaction plot in Figure 9.1 and Figure 9.2 used to estimate the mean MRR. From the, Table 9.6 it is concluded that highest Hardness was observed when Work-piece is machined on Power Rate 60%, abrasive slurry Silicon Carbide+Aluminum oxide and Grit size 600. It also observes that slurry concentration and the interaction AxB is not any effect on the Hardness. The best Hardness value was compromised to get best results. Hardness Assumed to be achieved best result if GFRP work piece is machined at Power Rate 60%, abrasive slurry Silicon Carbide+Aluminum oxide and Grit size 600.

Table 9.6 Significant factor and interaction

Factor	Affecting mean		Affecting variation	
	Contribution	Best level	Contribution	Best level
Power (%)	significant	Level-2(60)	Significant	Level-2(60)
Ab. Slurry	significant	Level-3(mix)	Significant	Level-3(mix)
Slurry conc.	insignificant		insignificant	
Grit size	Significant	Level-3(600)	Significant	Level-3(600)
Power(%)*Ab. Slurry	insignificant		Significant	

Estimating the mean

In experimental analysis, the Hardness is a higher average response is better (HB) characteristic. Depending on the characteristic, different treatment combinations has chosen to obtain satisfactory results. After conducting the experiments the optimum treatment condition within the experiments determined on the basis of prescribed combination of factor levels is determined to one of those in the experiment.

Mean Value for Hardness

$\mu A_1B_3D_3 = A_{2} + B_{3} + D_{3}$ -2T(Mean of all experiments) (Equation-9.2)

= 75.44+75.50+75.42-2x74.80= 76.76 HRB

Confidence interval around the estimated mean

The confidence interval is a maximum and minimum value between which the true average should fall at some stated percentage of confidence. The estimate of the mean μ is only a point estimate based on the averages of results obtained from the experiment. Statistically this provides a 50% chance of the true averages being greater than μ and a 50% chance of the true average being less than μ .

$$CI_1 = \sqrt{\frac{F_{\alpha,v_1,v_2} V_e}{n_{eff}}}$$

Where $F\alpha v_1 v_2$= F ratio

α = risk (0.05) confidence= 1-α

v_1 = dof for mean which is always=1

v_2 = dof for error =v_e

v_e = Variance at e-pooled

η_{eff} =number of test under that condition using the participating factors

η_{eff}= N/ (1+dof$_{A,B,D}$) = 18/(1+1+2+2) = 3.0

$$CI_1 = \sqrt{\frac{F_{\alpha,v_1,v_2} V_e}{n_{eff}}}$$

CI $_1$ = $\sqrt{(4.75X0.2292)/3}$ = 0.60 HRB

So the confidence interval around the Hardness is given by 76.76±0.60 HRB.

CHAPTER 10

FUZZY MODELING

Fuzzy logic is a form of multi-valued logic derived from fuzzy set theory to deal with reasoning that is approximate rather than accurate. Fuzzy logic variables may have a truth value that ranges between 0 and 1. It may be convenient to restrict the possible truth values to a discrete domain, say {0, 0.5, 1} for false, may be true and true. Fuzzy logic and probability are different are different ways of expressing uncertainity. While both fuzzy logic and probability theory can be used to represent subjective belief, fuzzy set theory uses the concept of fuzzy set membership (i.e., how much a variable is in a set), probability theory uses the concept of subjective probability (i.e., how probable do I think that a variable is in a set).

10.1 FUZZY SYSTEM

Note that in this fuzzy system there are 4 inputs, 4 outputs and 18 rules are used. The inputs used are:-

1. Power
2. Ab. Slurry
3. Slurry concentration
4. Grit size

The outputs used are:-

1. MRR
2. TWR
3. Surface roughness (SR)
4. Hardness

Representation of fuzzy inference system is shown in Figure 10.1

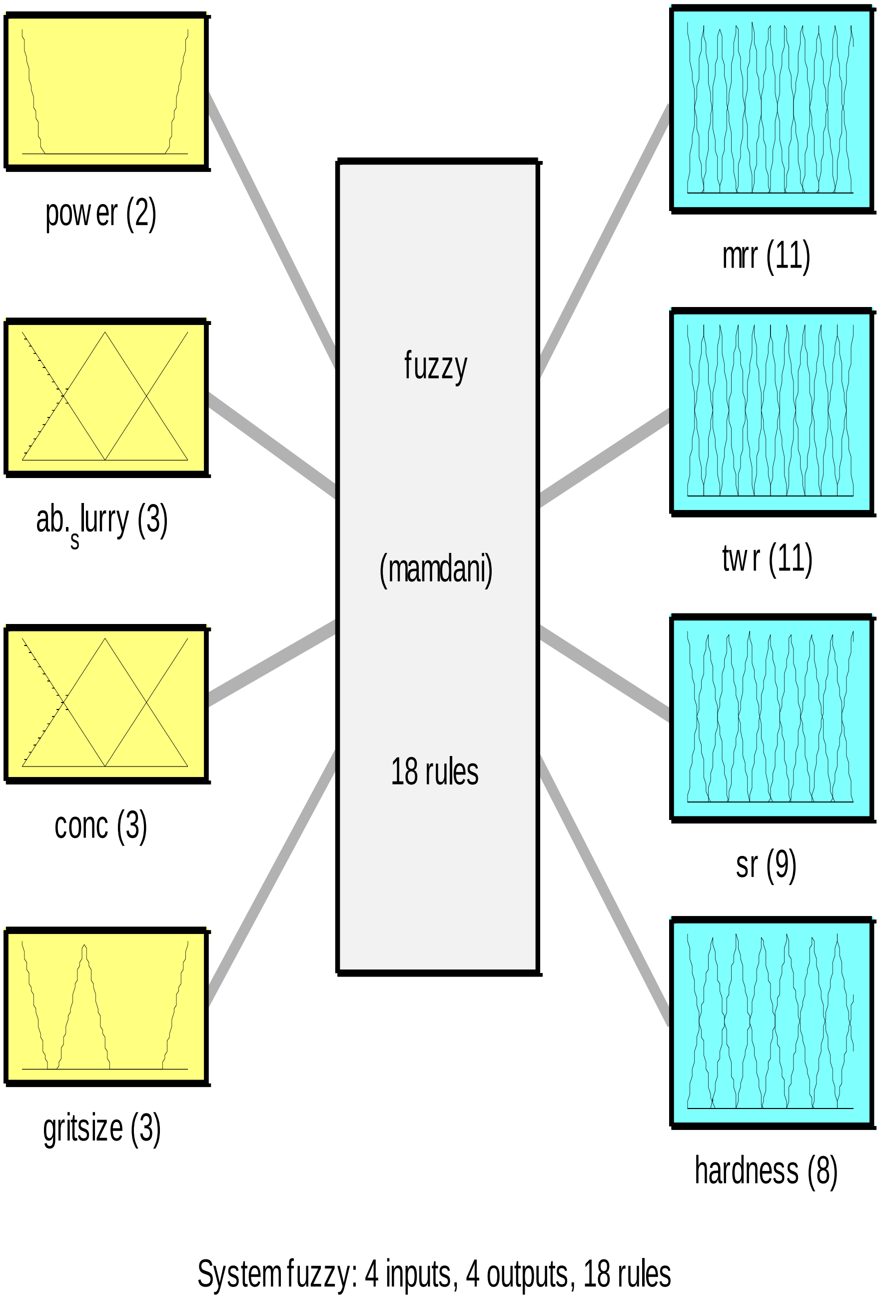


Figure 10.1: Representation of fuzzy inference system

10.2 POWER MEMBERSHIP FUNCTION

Power membership function is input-1 and shown in figure 10.2.

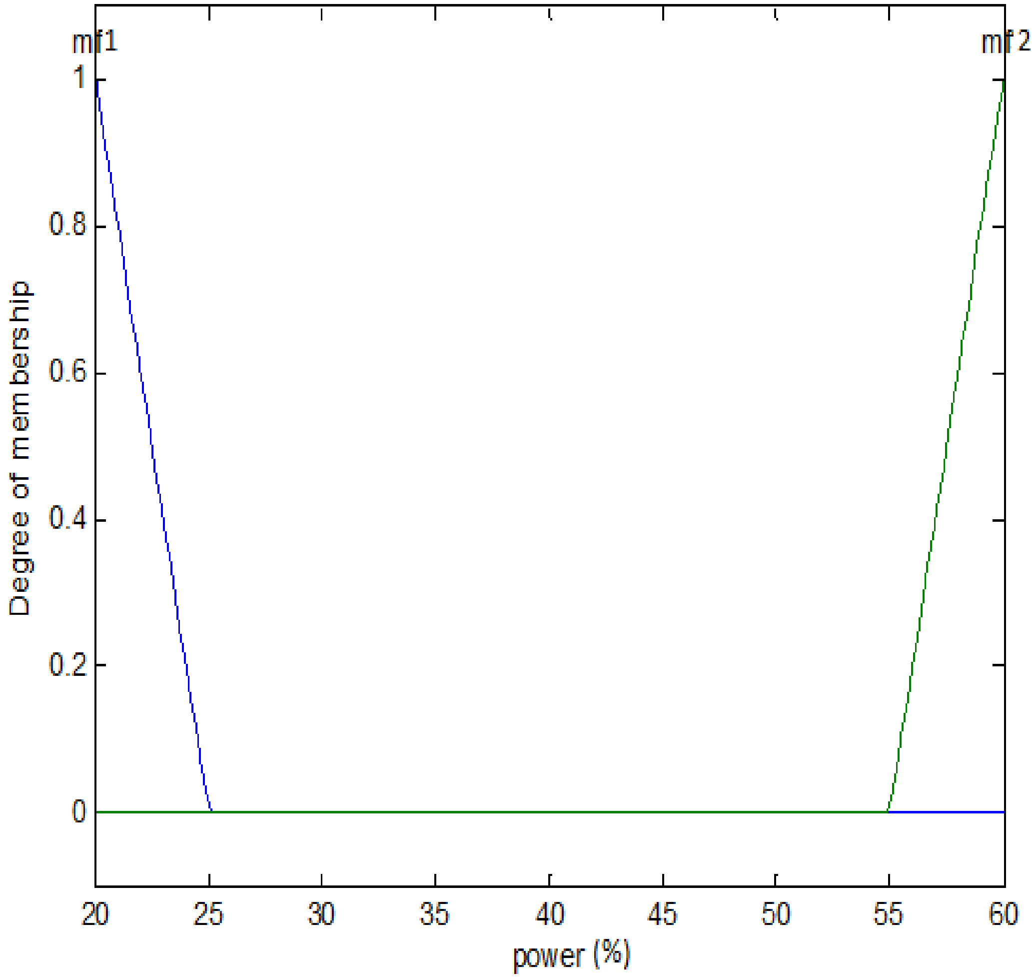


Figure 10.2: Power membership function (input-1)

There are many membership functions based on their input and output transition behavior. In this paper, we used triangular model for input and output. The minimum value of power (%) is shown by mf1 with parameters [15 20 25] and the maximum value of power (%) is shown by mf2 with parameters [55 60 65]. The range of Power membership function is [20 60].

10.3 ABRASIVE SLURRY MEMBERSHIP FUNCTION

Ab. slurry membership function is input-2 and shown in figure 10.3.

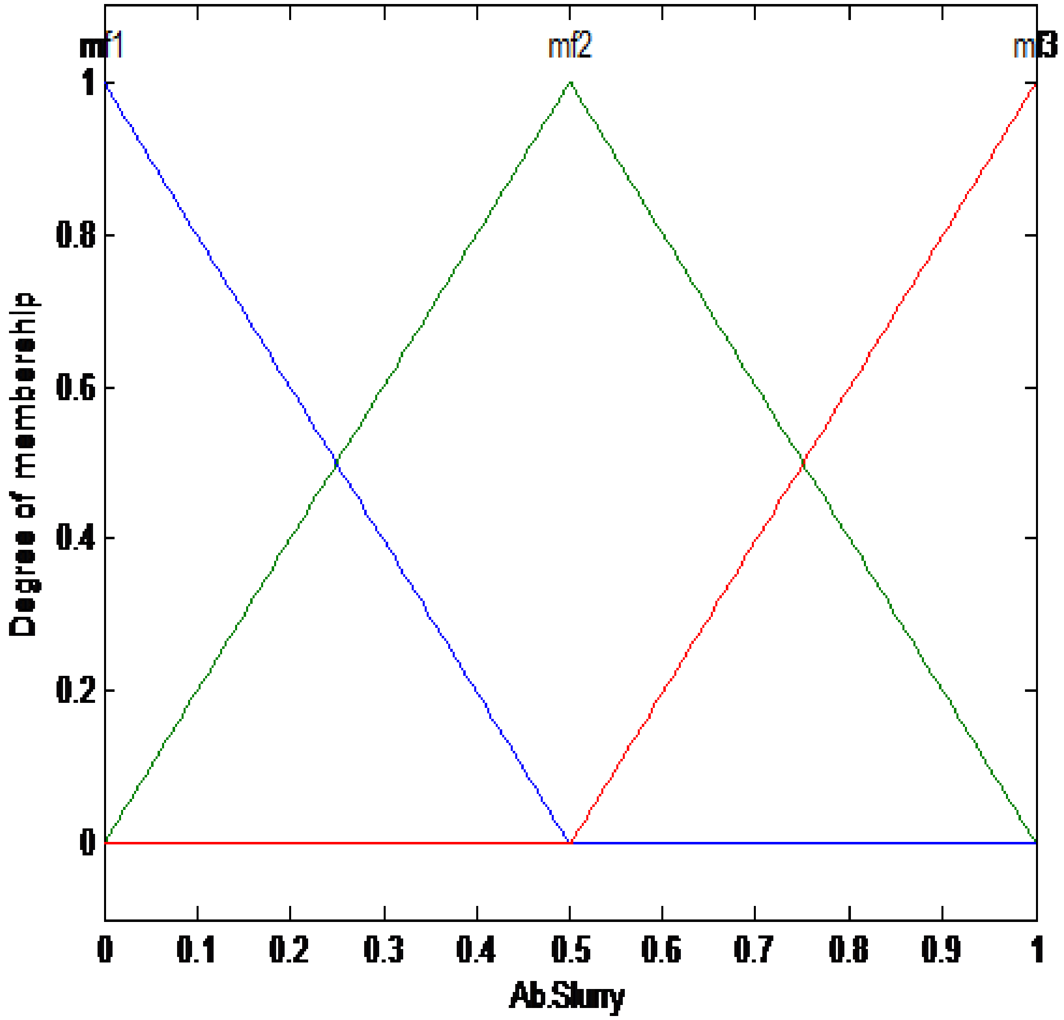


Figure 10.3: Ab. Slurry membership function (input-2)

Let for figure 10.3, we suppose that for Abrasive slurry

- 0 stands for Al_20_3
- 0.5 stands for 50% Al_20_3 + 50%SiC (MIX)
- 1 stands for SiC

10.4 SLURRY CONCENTRATION MEMBERSHIP FUNCTION

Slurry conc. membership function is input-3 and shown in figure 10.4.

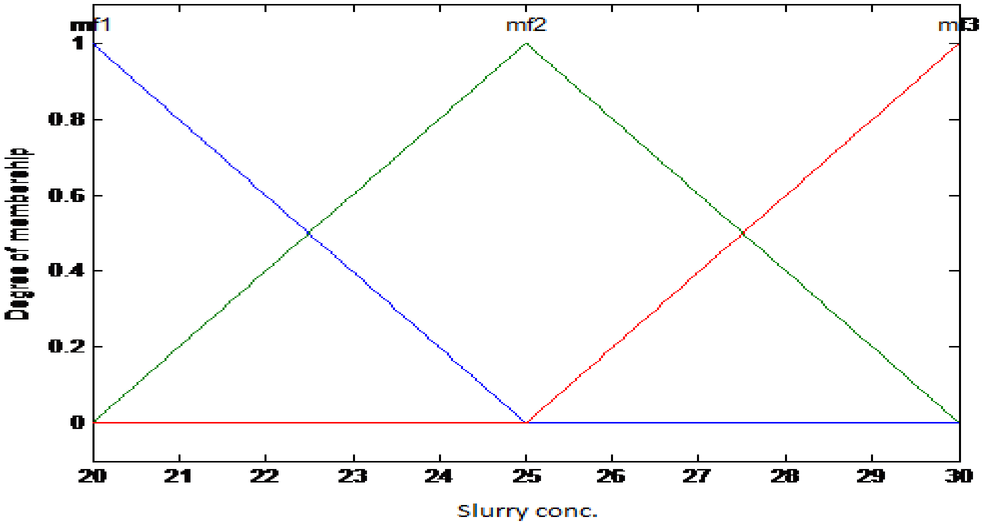


Figure 10.4: Slurry concentration membership function (input-3)

10.5 GRIT SIZE MEMBERSHIP FUNCTION

Grit size membership function is input-4 and shown in figure 10.5.

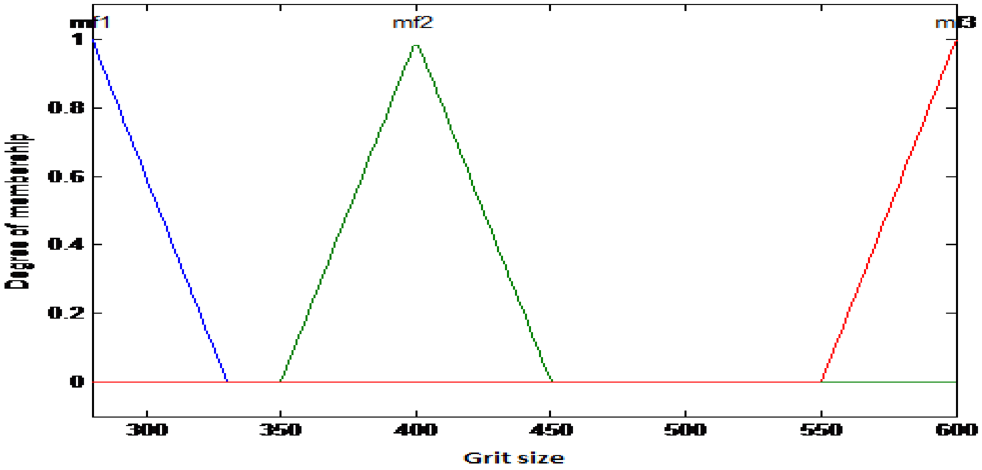


Figure 10.5: Grit size membership function (input-4)

The minimum value of Grit size is shown by mf1 with parameters [230 280 330] and the maximum value of Slurry concentration is shown by mf3 with parameters [550 600 650]. The range of Grit size membership function is [280 600].

10.6 MRR MEMBERSHIP FUNCTION

MRR membership function is output-1 and shown in figure 10.6.

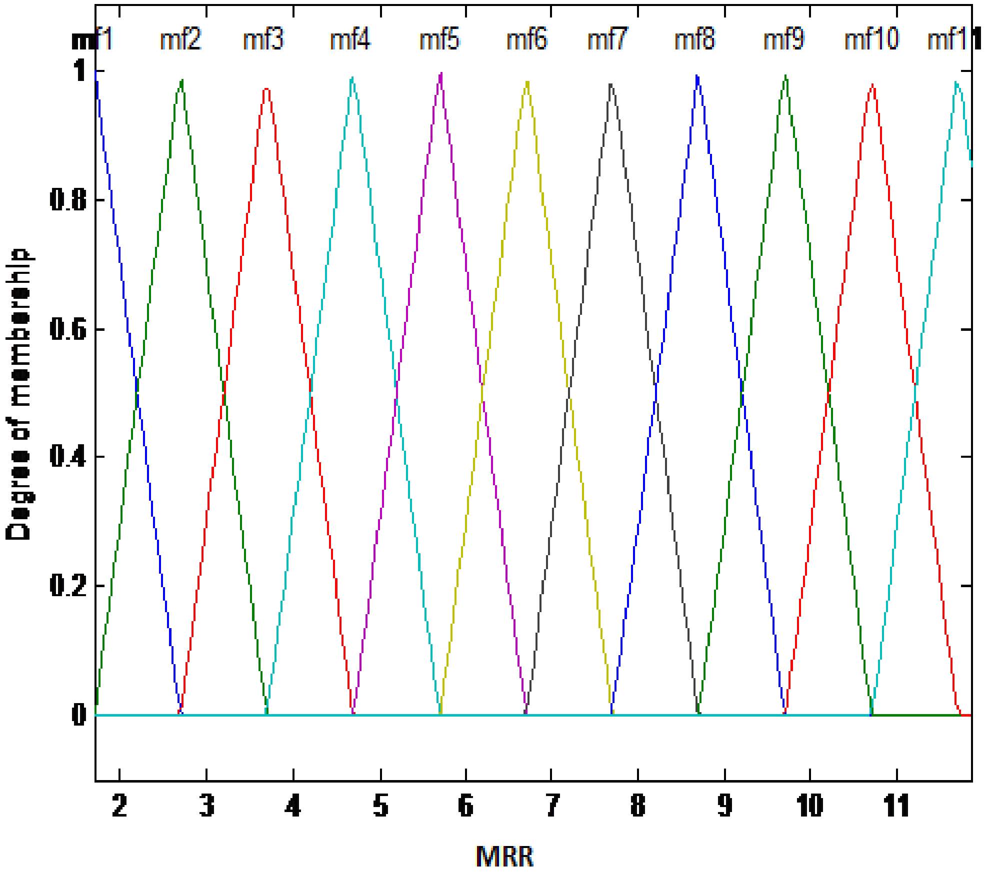


Figure 10.6: Material removal rate (MRR) membership function (output-1)

The minimum value of MRR is 1.7 mm³/min and shown by mf1 with parameters [0.7 1.7 2.7]. The maximum value of MRR is 11.7 mm³/min and shown by mf11 with parameters [10.7 11.7 12.7]. The range of MRR membership function is [1.7 11.7].

10.7 TOOL WEAR RATE (TWR) MEMBERSHIP FUNCTION

TWR membership function is output-2 and shown in figure 10.7.

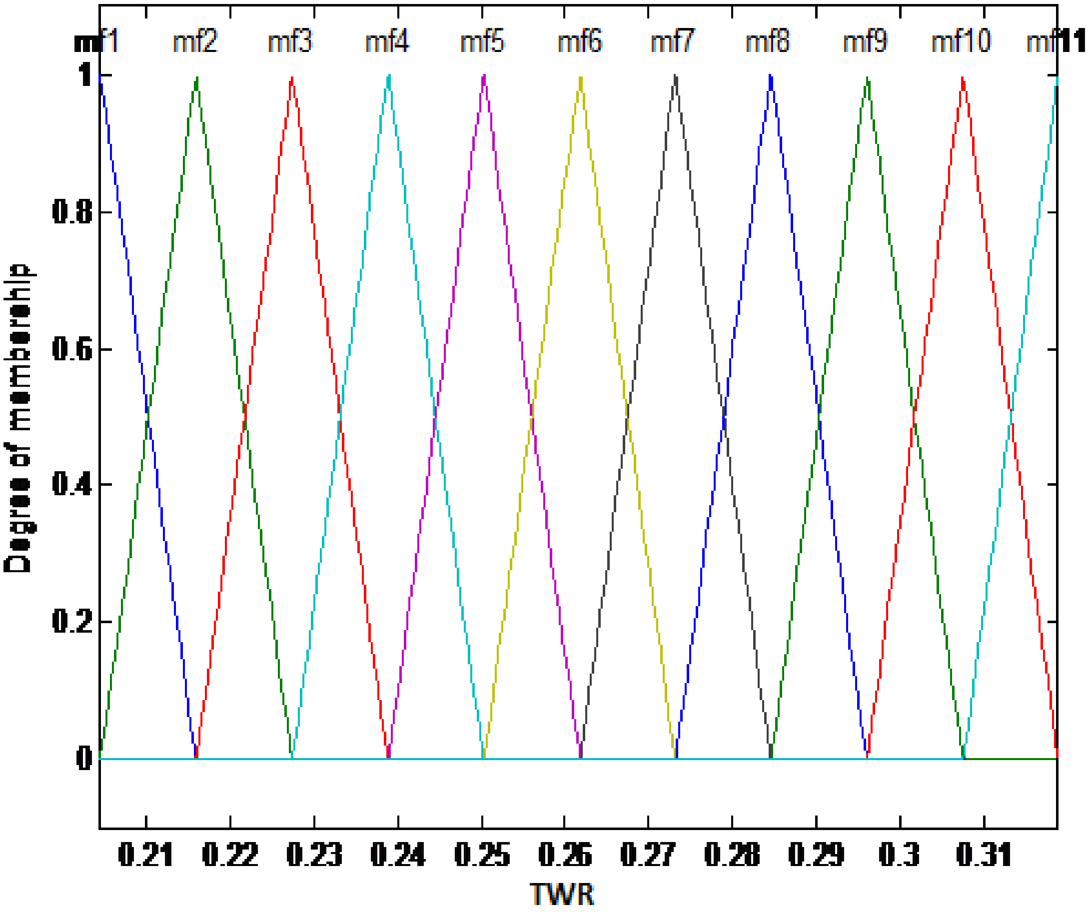


Figure 10.7: Tool wear rate (TWR) membership function (output-2)

The minimum value of TWR is 0.2046 mm³/min and shown by mf1 with parameters [0.1932 0.2046 0.2160]. The maximum value of TWR is 0.3189 mm³/min and shown by mf11 with parameters [0.3075 0.3189 0.3303]. The range of TWR membership function is [0.2046 0.3189].

10.8 SURFACE ROUGHNESS (SR) MEMBERSHIP FUNCTION

SR membership function is output-3 and shown in figure 10.8.

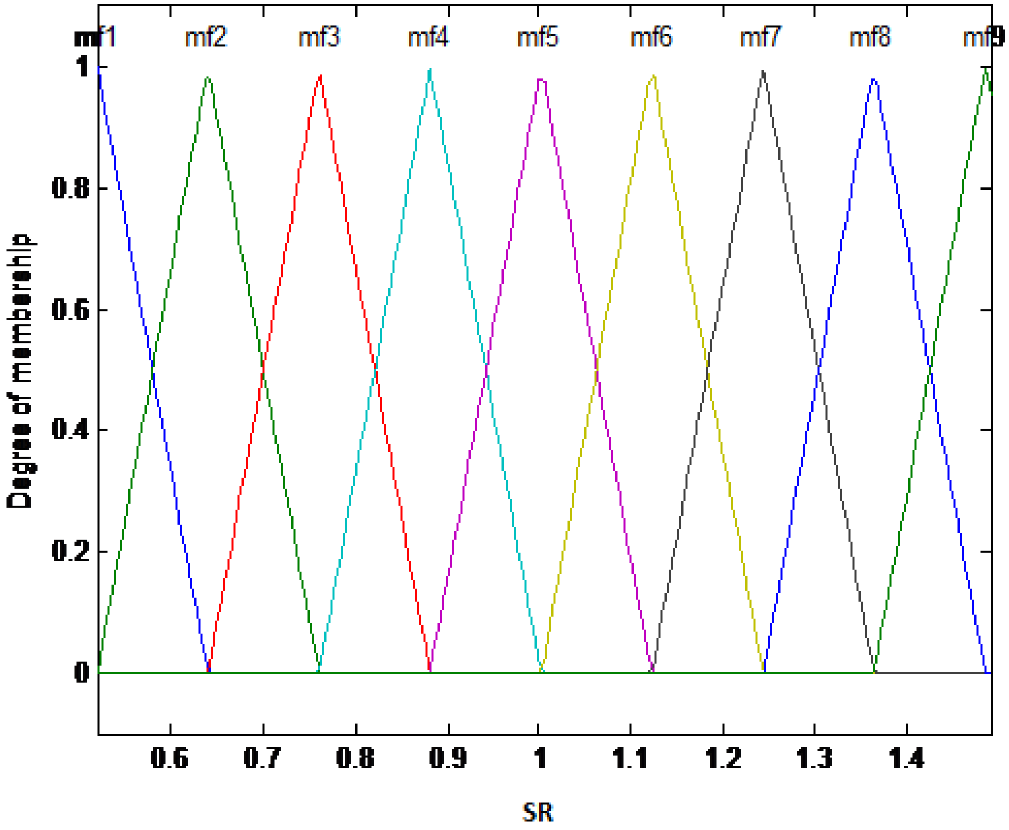


Figure 10.8: Surface roughness (SR) membership function (output-3)

The minimum value of SR is 0.52 µm and shown by mf1 with parameters [0.3995 0.52 0.6405]. The maximum value of SR is 1.49 µm and shown by mf9 with parameters [1.363 1.490 1.604]. The range of SR membership function is [0.52 1.49].

10.9 HARDNESS MEMBERSHIP FUNCTION

Hardness membership function is output-4 and shown in figure 10.9.

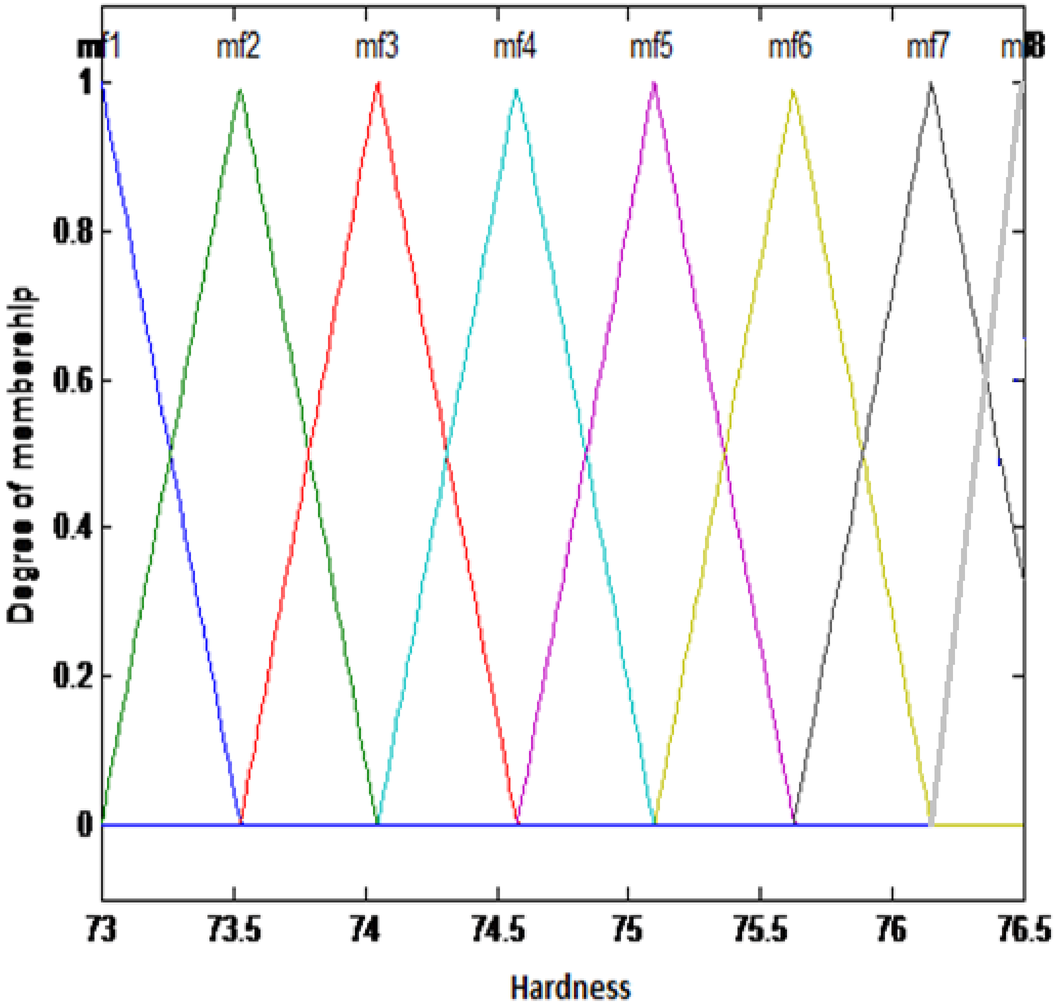
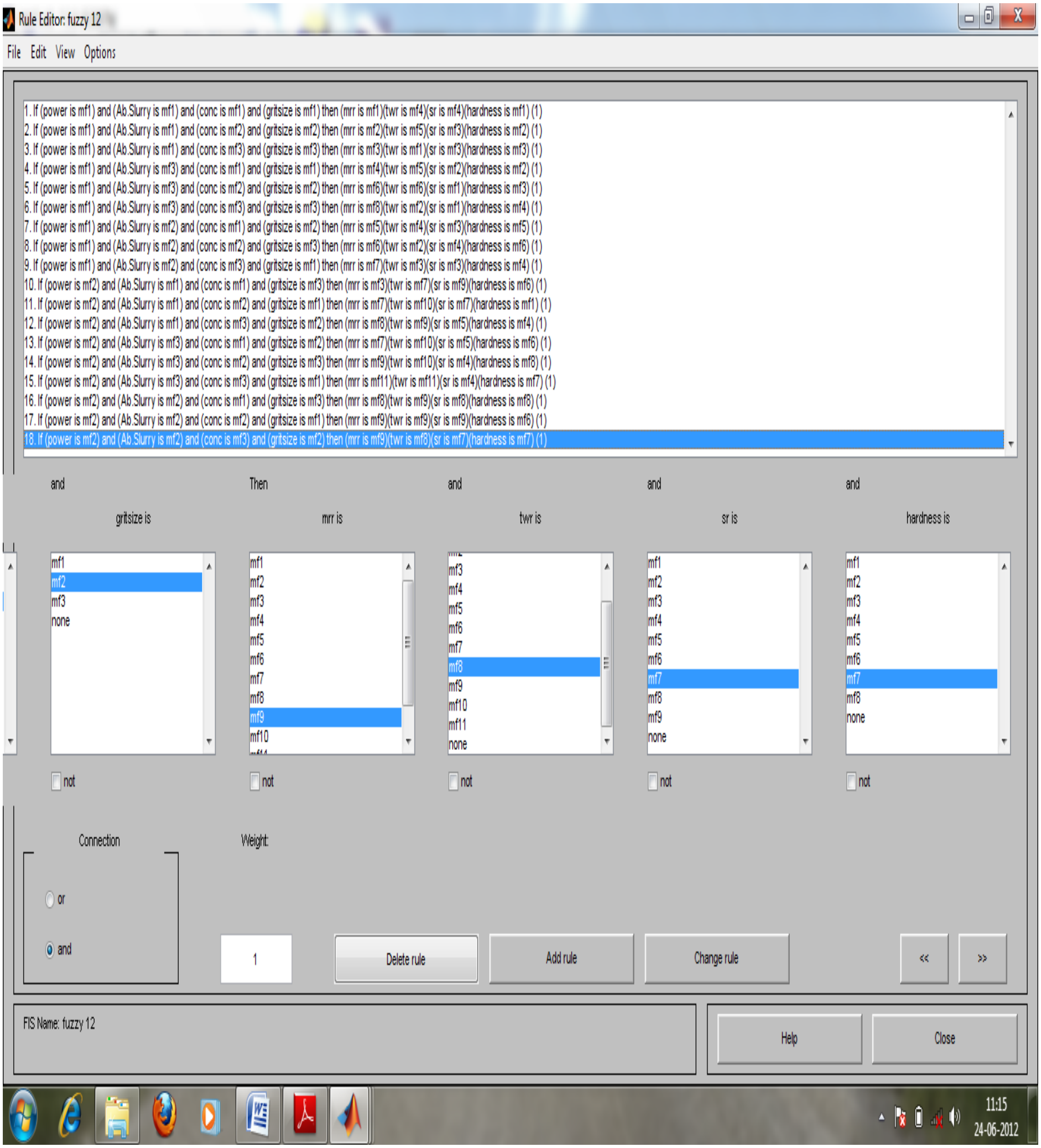


Figure 10.9: Hardness membership function (output-4)

The minimum value of Hardness is 73 HRB and shown by mf1 with parameters [72.47 73 73.53]. The maximum value of Hardness is and shown by mf8 with parameters [76.15 76.5 77.03]. The range of hardness membership function is [73 76.5].

10.10 RULE OF FUZZY SYSTEM

Number of rules applied for this system is 18. The rules used in this system have been shown in figure 10.10.

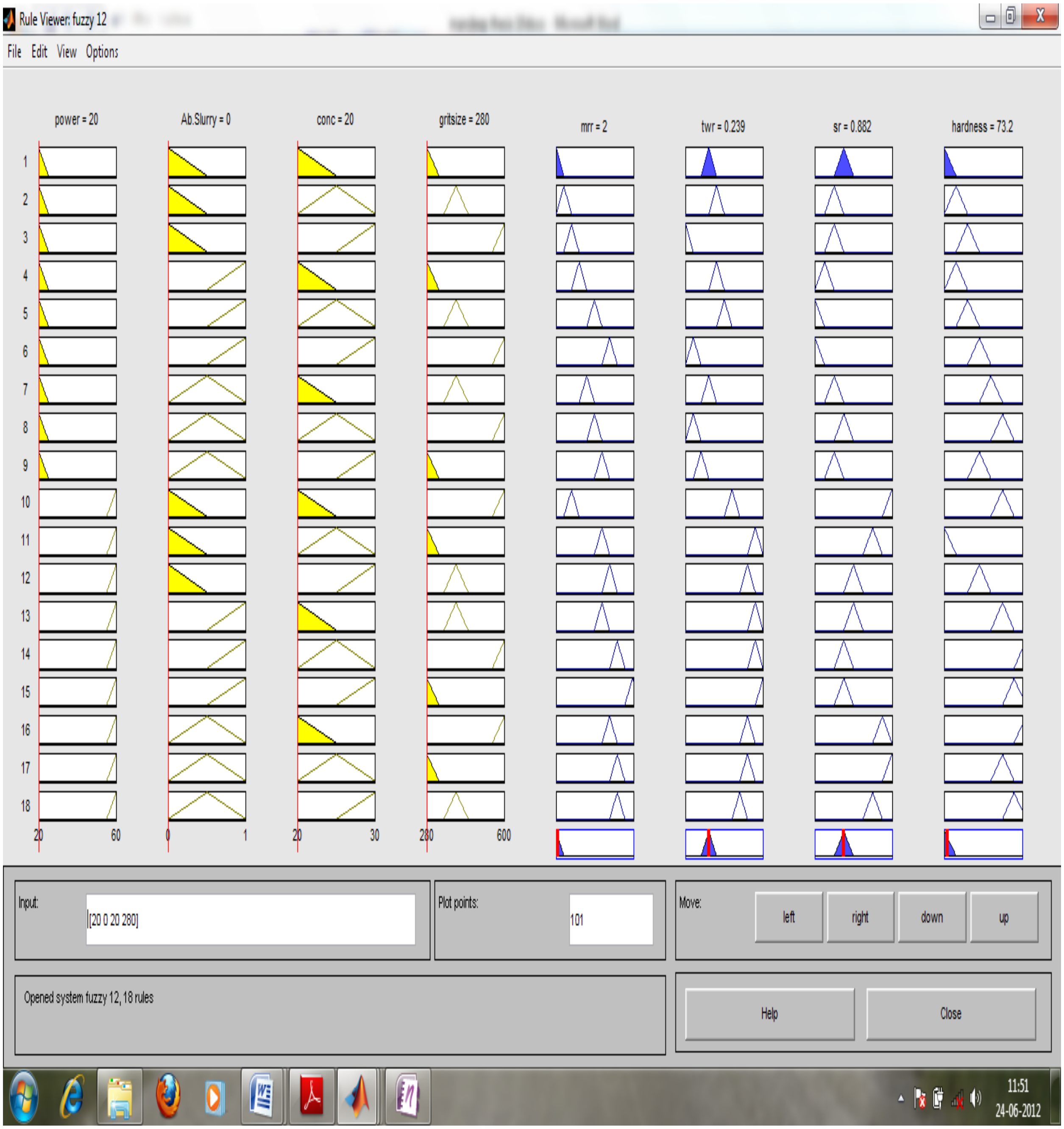


1. If (power is mf1) and (Ab.Slurry is mf1) and (conc is mf1) and (gritsize is mf1) then (mrr is mf1)(twr is mf4)(sr is mf4)(hardness is mf1) (1)
2. If (power is mf1) and (Ab.Slurry is mf1) and (conc is mf2) and (gritsize is mf2) then (mrr is mf2)(twr is mf5)(sr is mf3)(hardness is mf2) (1)
3. If (power is mf1) and (Ab.Slurry is mf1) and (conc is mf3) and (gritsize is mf3) then (mrr is mf3)(twr is mf1)(sr is mf3)(hardness is mf3) (1)
4. If (power is mf1) and (Ab.Slurry is mf3) and (conc is mf1) and (gritsize is mf1) then (mrr is mf4)(twr is mf5)(sr is mf2)(hardness is mf2) (1)
5. If (power is mf1) and (Ab.Slurry is mf3) and (conc is mf2) and (gritsize is mf2) then (mrr is mf6)(twr is mf6)(sr is mf1)(hardness is mf3) (1)
6. If (power is mf1) and (Ab.Slurry is mf3) and (conc is mf3) and (gritsize is mf3) then (mrr is mf8)(twr is mf2)(sr is mf1)(hardness is mf4) (1)
7. If (power is mf1) and (Ab.Slurry is mf2) and (conc is mf1) and (gritsize is mf2) then (mrr is mf5)(twr is mf4)(sr is mf3)(hardness is mf5) (1)
8. If (power is mf1) and (Ab.Slurry is mf2) and (conc is mf2) and (gritsize is mf3) then (mrr is mf6)(twr is mf2)(sr is mf4)(hardness is mf6) (1)
9. If (power is mf1) and (Ab.Slurry is mf2) and (conc is mf3) and (gritsize is mf1) then (mrr is mf7)(twr is mf3)(sr is mf3)(hardness is mf4) (1)
10. If (power is mf2) and (Ab.Slurry is mf1) and (conc is mf1) and (gritsize is mf3) then (mrr is mf3)(twr is mf7)(sr is mf9)(hardness is mf6) (1)
11. If (power is mf2) and (Ab.Slurry is mf1) and (conc is mf2) and (gritsize is mf1) then (mrr is mf7)(twr is mf10)(sr is mf7)(hardness is mf1) (1)
12. If (power is mf2) and (Ab.Slurry is mf1) and (conc is mf3) and (gritsize is mf2) then (mrr is mf8)(twr is mf9)(sr is mf5)(hardness is mf4) (1)
13. If (power is mf2) and (Ab.Slurry is mf3) and (conc is mf1) and (gritsize is mf2) then (mrr is mf7)(twr is mf10)(sr is mf5)(hardness is mf6) (1)
14. If (power is mf2) and (Ab.Slurry is mf3) and (conc is mf2) and (gritsize is mf3) then (mrr is mf9)(twr is mf10)(sr is mf4)(hardness is mf8) (1)
15. If (power is mf2) and (Ab.Slurry is mf3) and (conc is mf3) and (gritsize is mf1) then (mrr is mf11)(twr is mf11)(sr is mf4)(hardness is mf7) (1)
16. If (power is mf2) and (Ab.Slurry is mf2) and (conc is mf1) and (gritsize is mf3) then (mrr is mf8)(twr is mf9)(sr is mf8)(hardness is mf8) (1)
17. If (power is mf2) and (Ab.Slurry is mf2) and (conc is mf2) and (gritsize is mf1) then (mrr is mf9)(twr is mf9)(sr is mf9)(hardness is mf6) (1)
18. If (power is mf2) and (Ab.Slurry is mf2) and (conc is mf3) and (gritsize is mf2) then (mrr is mf9)(twr is mf8)(sr is mf7)(hardness is mf7) (1)

gritsize is: mf2
mrr is: mf9
twr is: mf8
sr is: mf7
hardness is: mf7
Weight: 1
FIS Name: fuzzy 12

Figure 10.10: Rules of fuzzy system

figure 10.11 Pictorial presentation of fuzzy rules

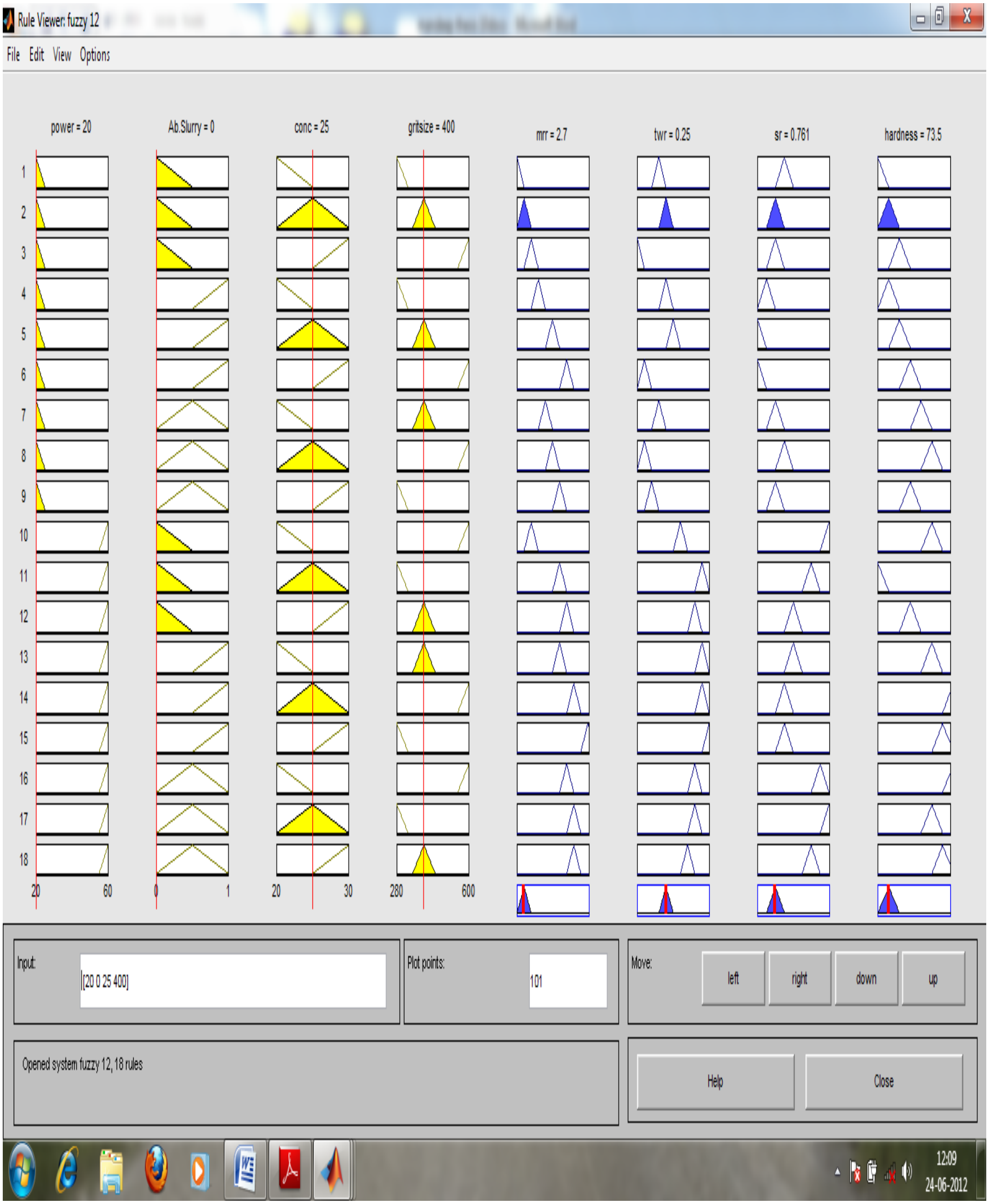


Input: [20 0 20 280]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 1: Pictorial presentation of fuzzy rule base system for power(%)= 20, Ab. Slurry= aluminum oxide, Slurry concentration= 20%, Grit size= 280

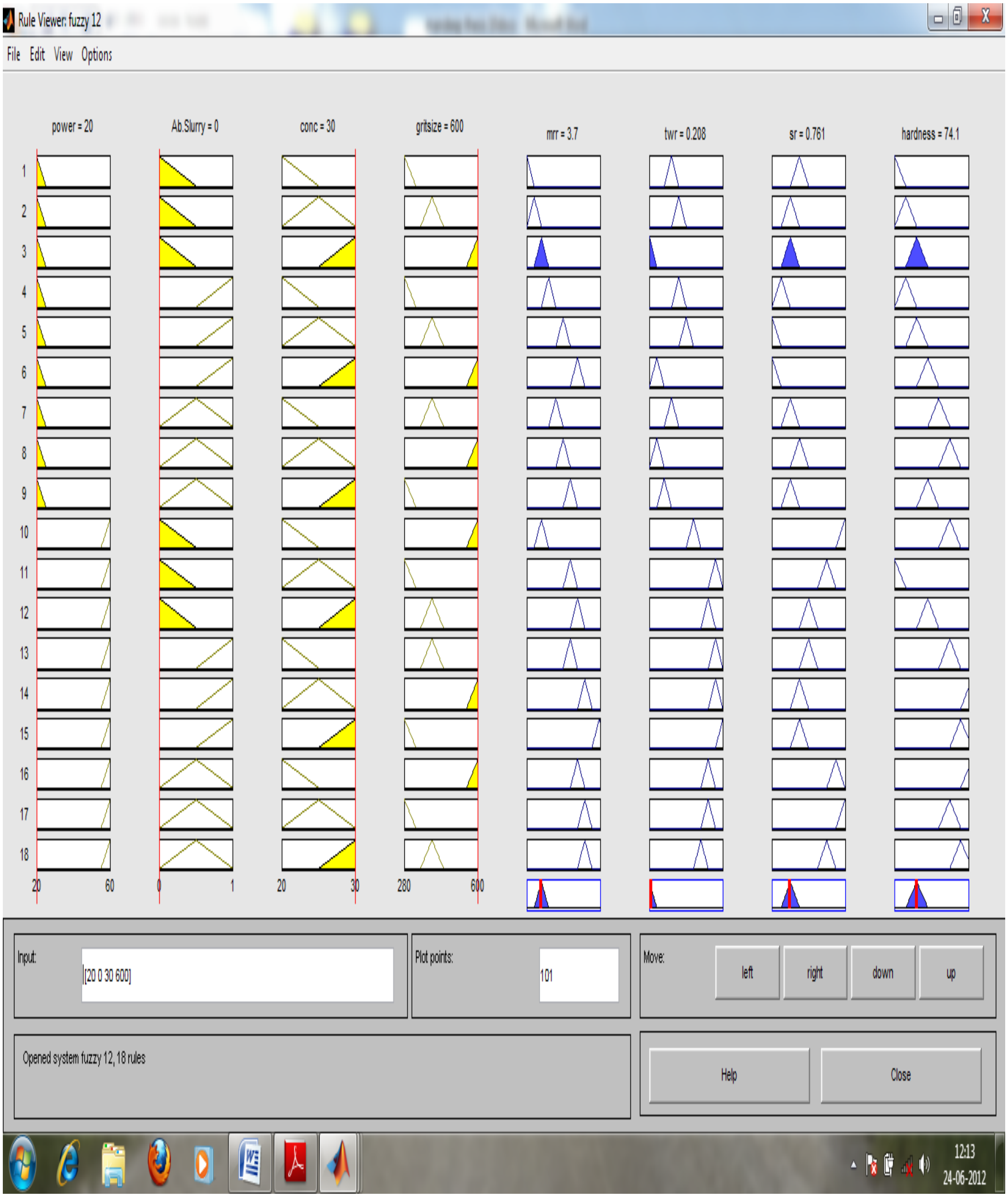


Input: [20 0 25 400]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 2: Pictorial presentation of fuzzy rule base system for power(%)= 20, Ab. Slurry= aluminum oxide, Slurry concentration= 25%, Grit size= 400

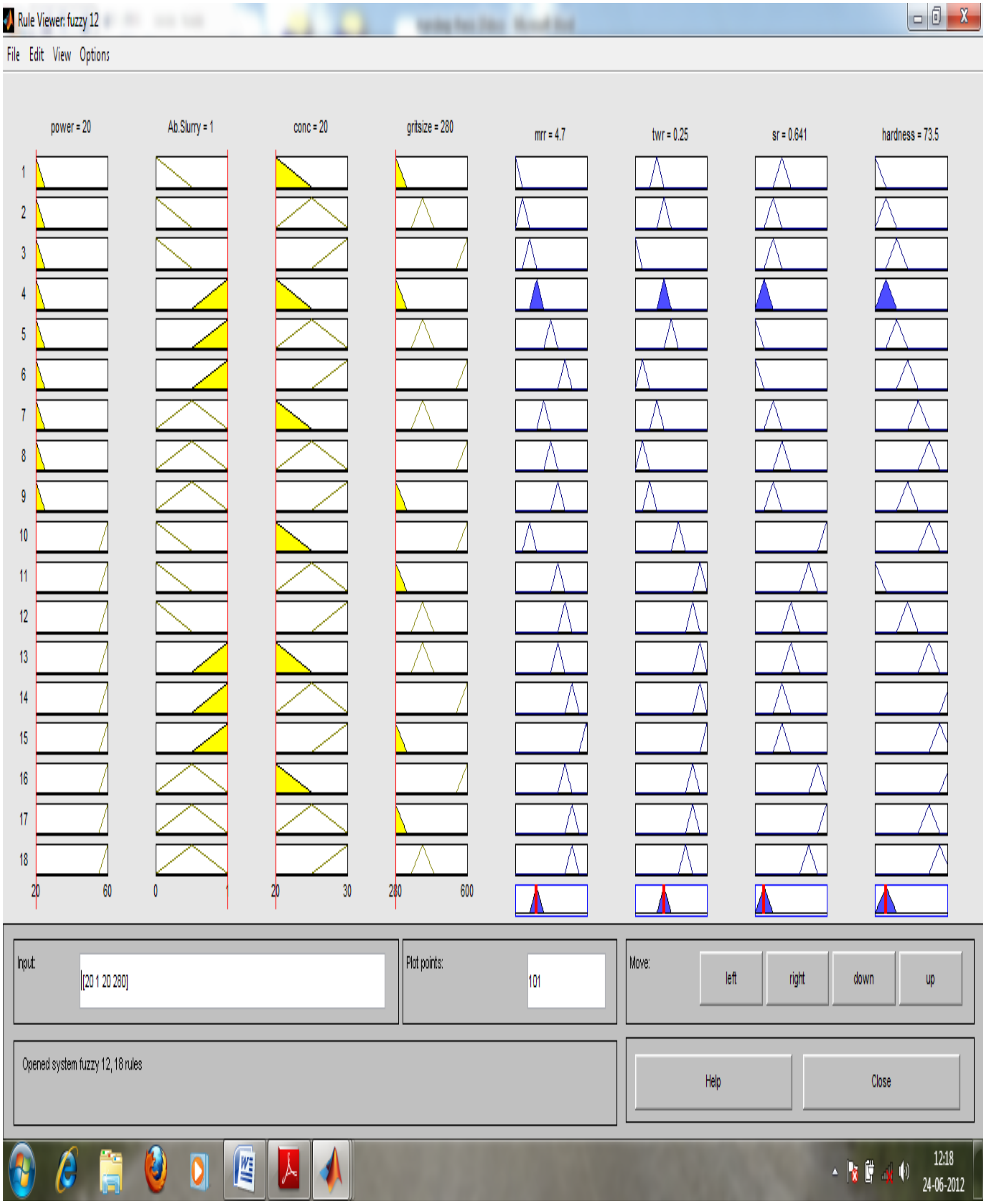


Input: [20 0 30 600]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 3: Pictorial presentation of fuzzy rule base system for power(%)= 20, Ab. Slurry= aluminum oxide, Slurry concentration= 30%, Grit size= 600

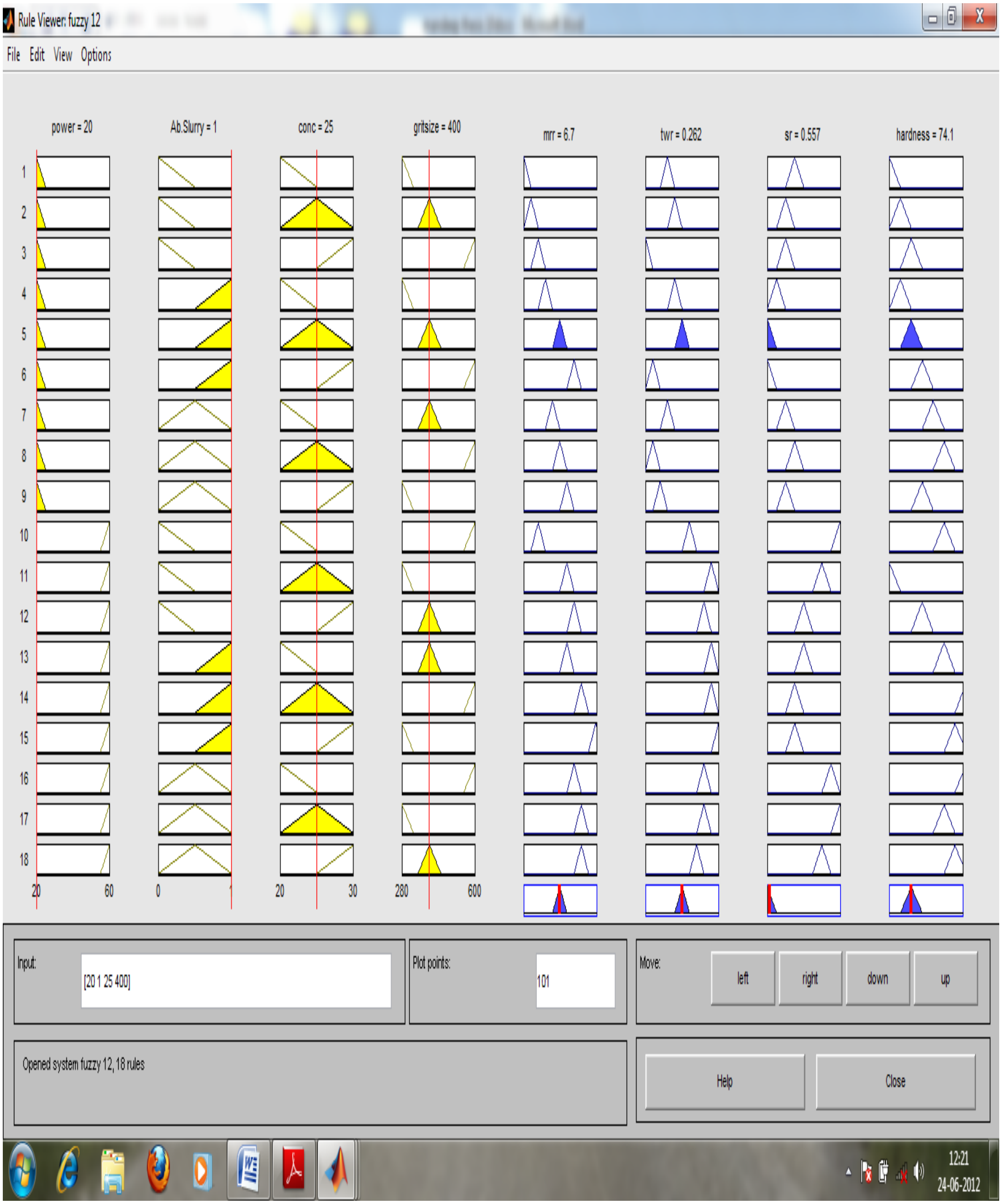


Input: [20 1 20 280]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 4: Pictorial presentation of fuzzy rule base system for power(%)= 20, Ab. Slurry= Silicon carbide, Slurry concentration= 20%, Grit size= 280

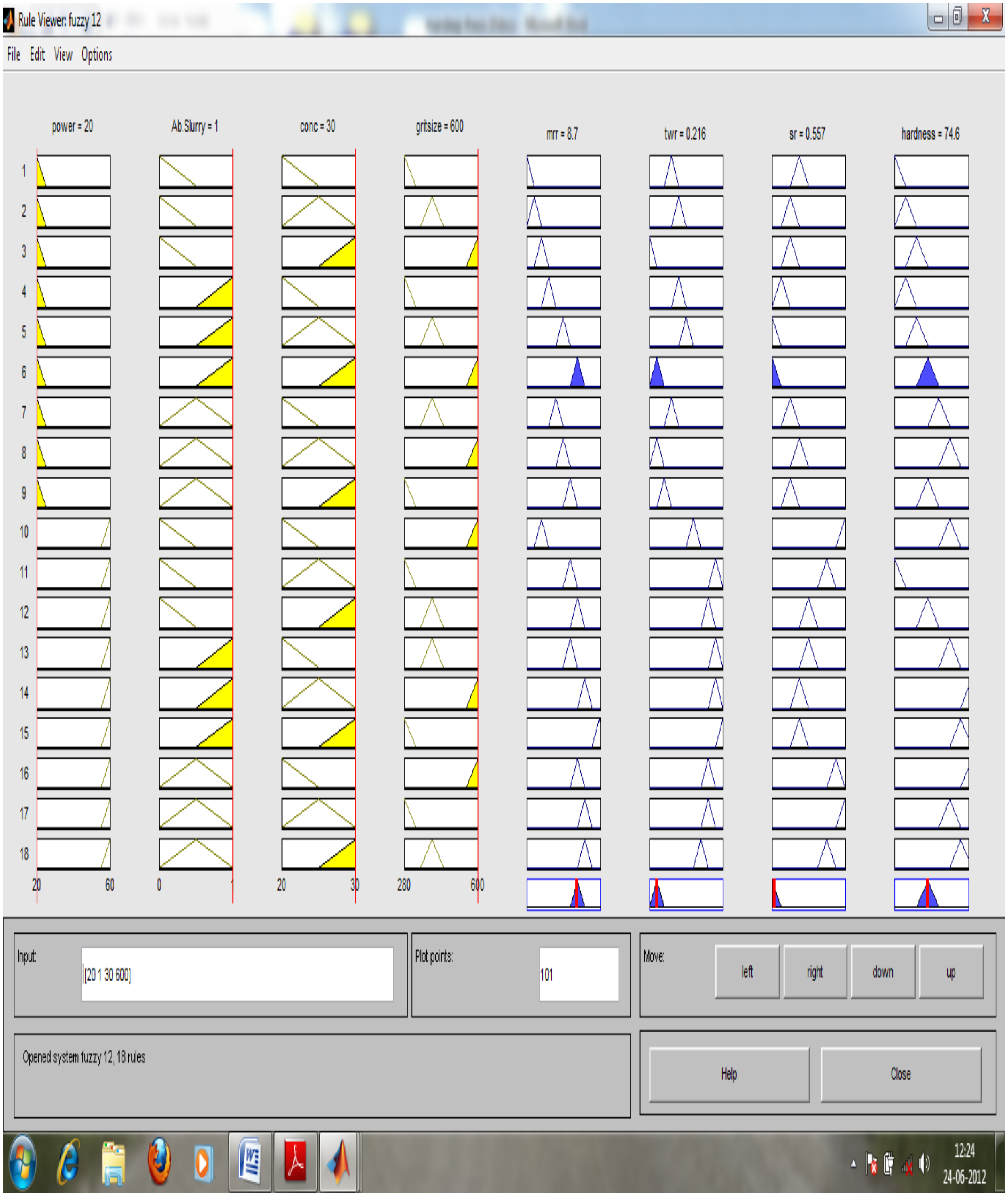


Input: [20 1 25 400]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 5: Pictorial presentation of fuzzy rule base system for power(%)= 20, Ab. Slurry= Silicon carbide, Slurry concentration= 25%, Grit size= 400

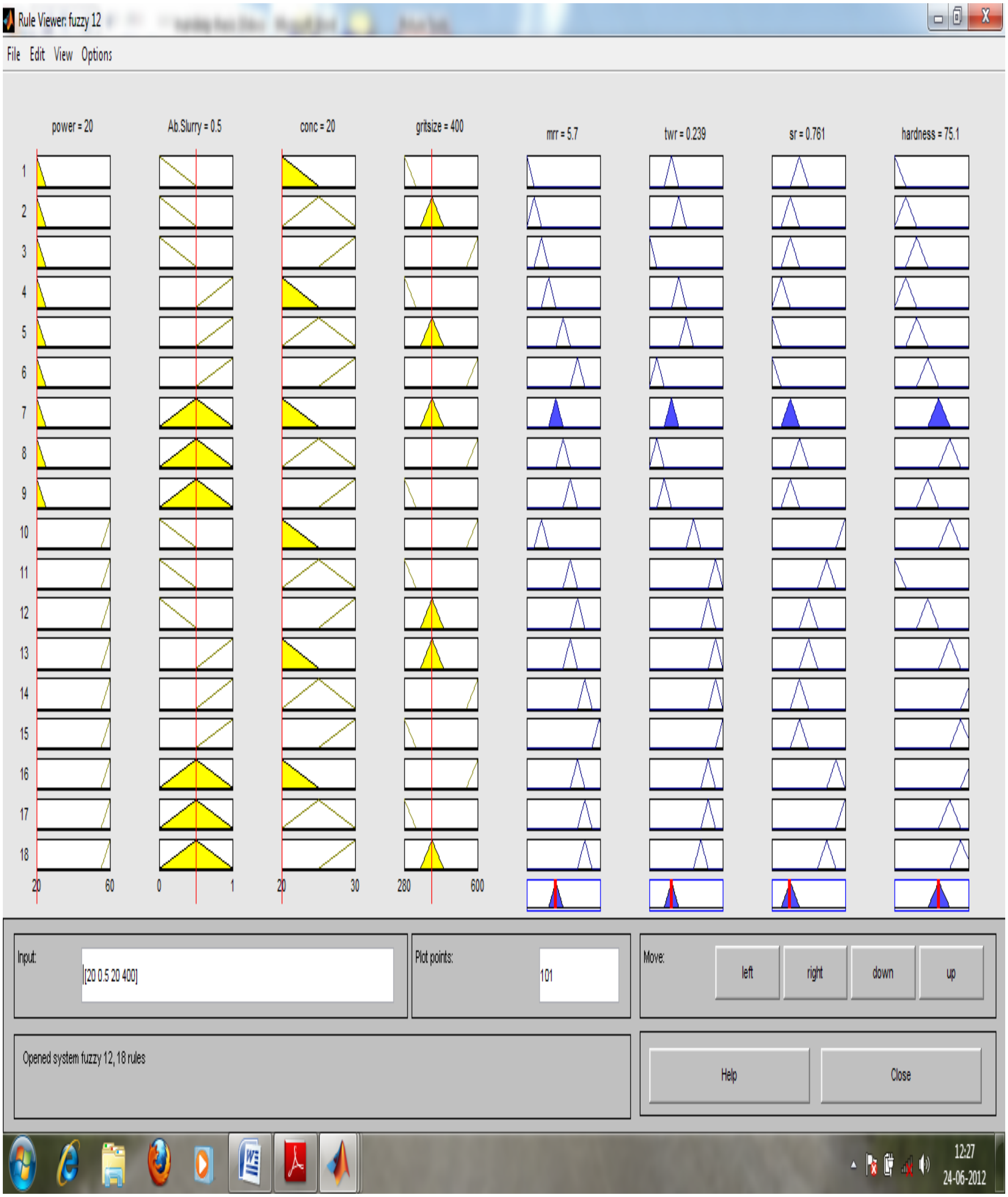


Input: [20 1 30 600]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 6: Pictorial presentation of fuzzy rule base system for power(%)= 20, Ab. Slurry= Silicon carbide, Slurry concentration= 30%, Grit size= 600

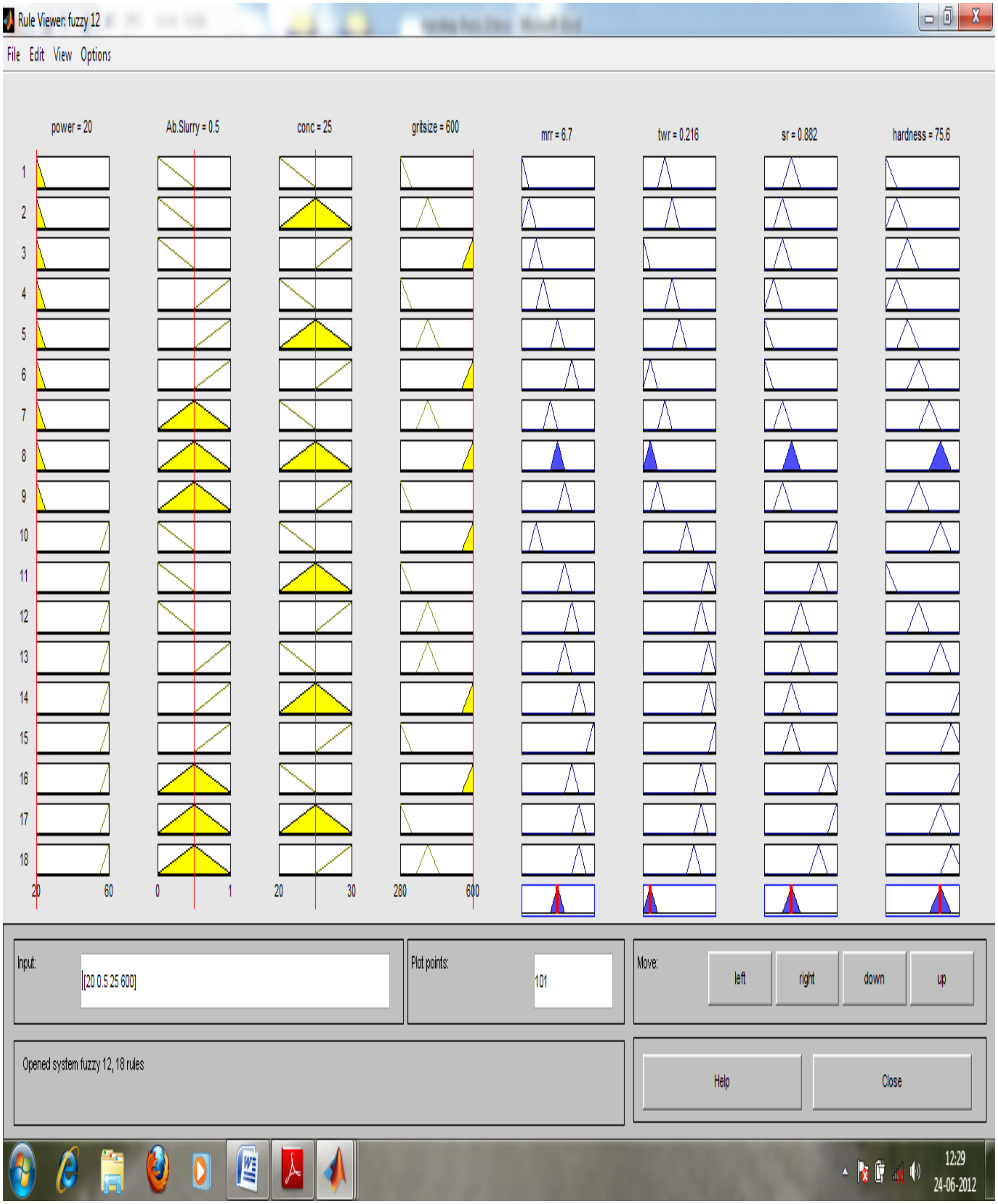


Input: [20 0.5 20 400]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 7: Pictorial presentation of fuzzy rule base system for power(%)= 20, Ab. Slurry= Mix, Slurry concentration= 20%, Grit size= 400



Input: [20 0.5 25 600]

Plot points: 101

Opened system fuzzy 12, 18 rules

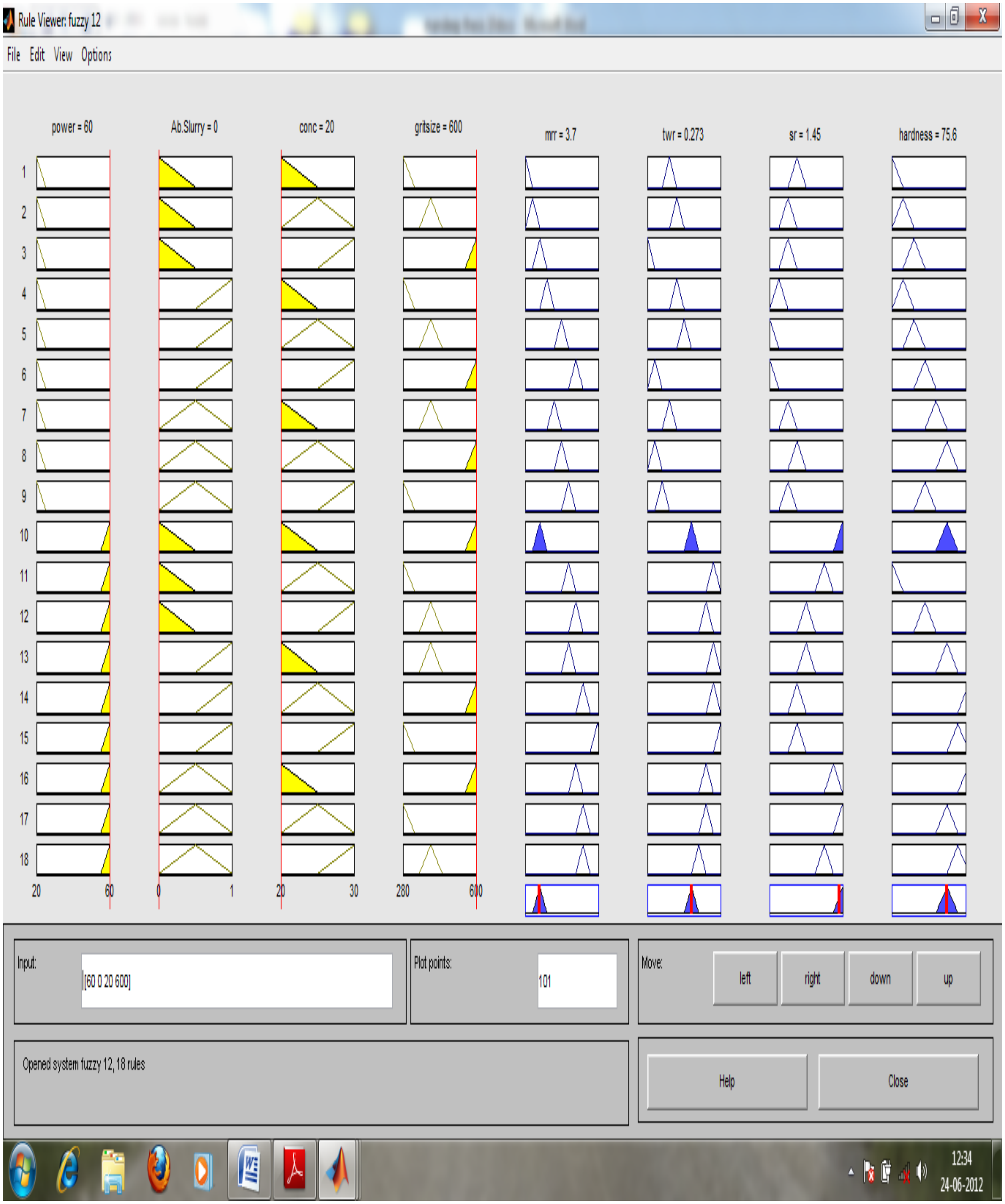
Rule 8: Pictorial presentation of fuzzy rule base system for power(%)= 20, Ab. Slurry= Mix, Slurry concentration= 25%, Grit size= 600

Input: [20 0.5 30 280]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 9: Pictorial presentation of fuzzy rule base system for power(%)= 20, Ab. Slurry= Mix, Slurry concentration= 30%, Grit size= 280



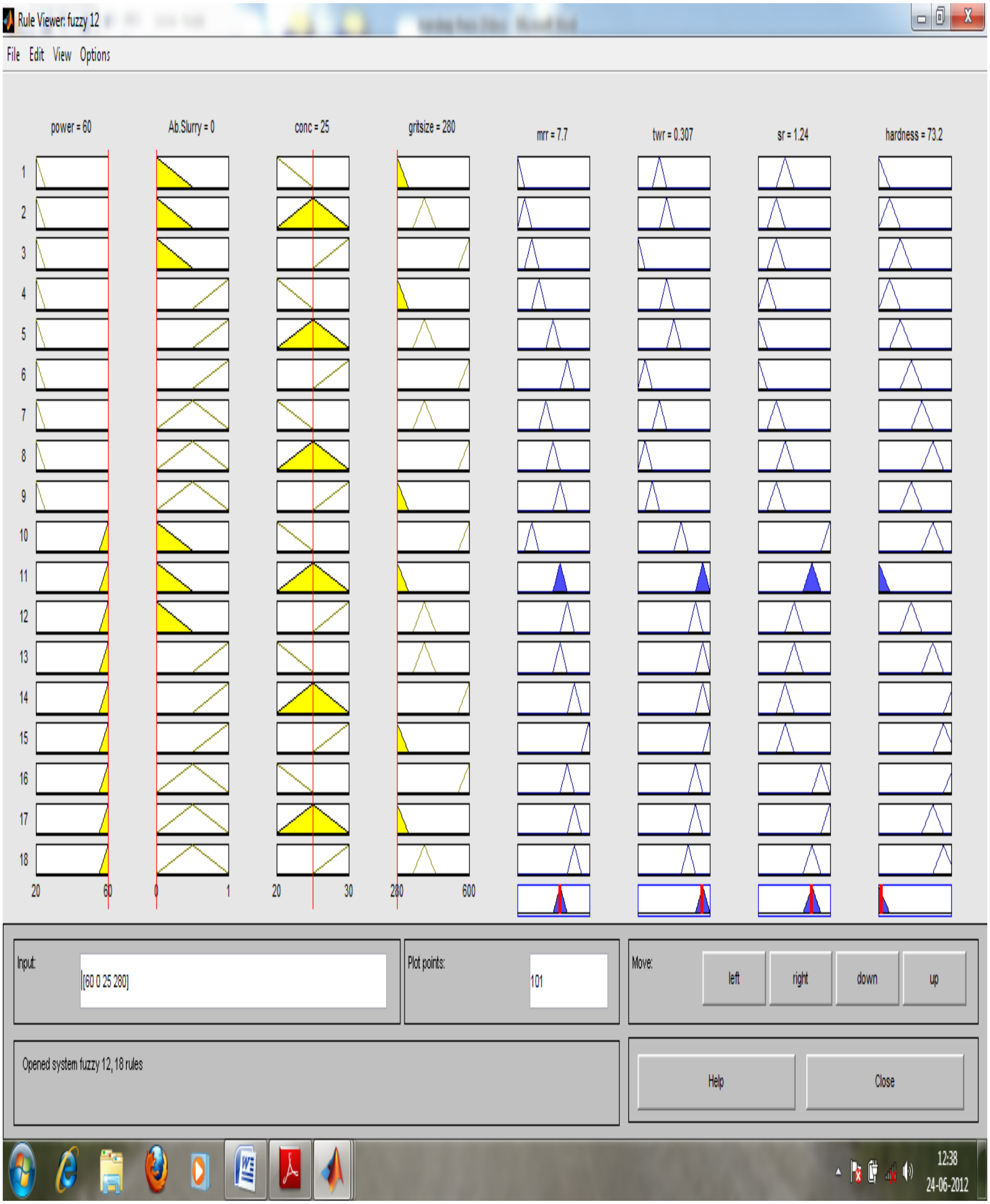
power = 60
Ab.Slurry = 0
conc = 20
gritsize = 600
mrr = 3.7
twr = 0.273
sr = 1.45
hardness = 75.6

Input: [60 0 20 600]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 10: Pictorial presentation of fuzzy rule base system for power(%)= 60, Ab. Slurry= Aluminum oxide, Slurry concentration= 20%, Grit size= 600

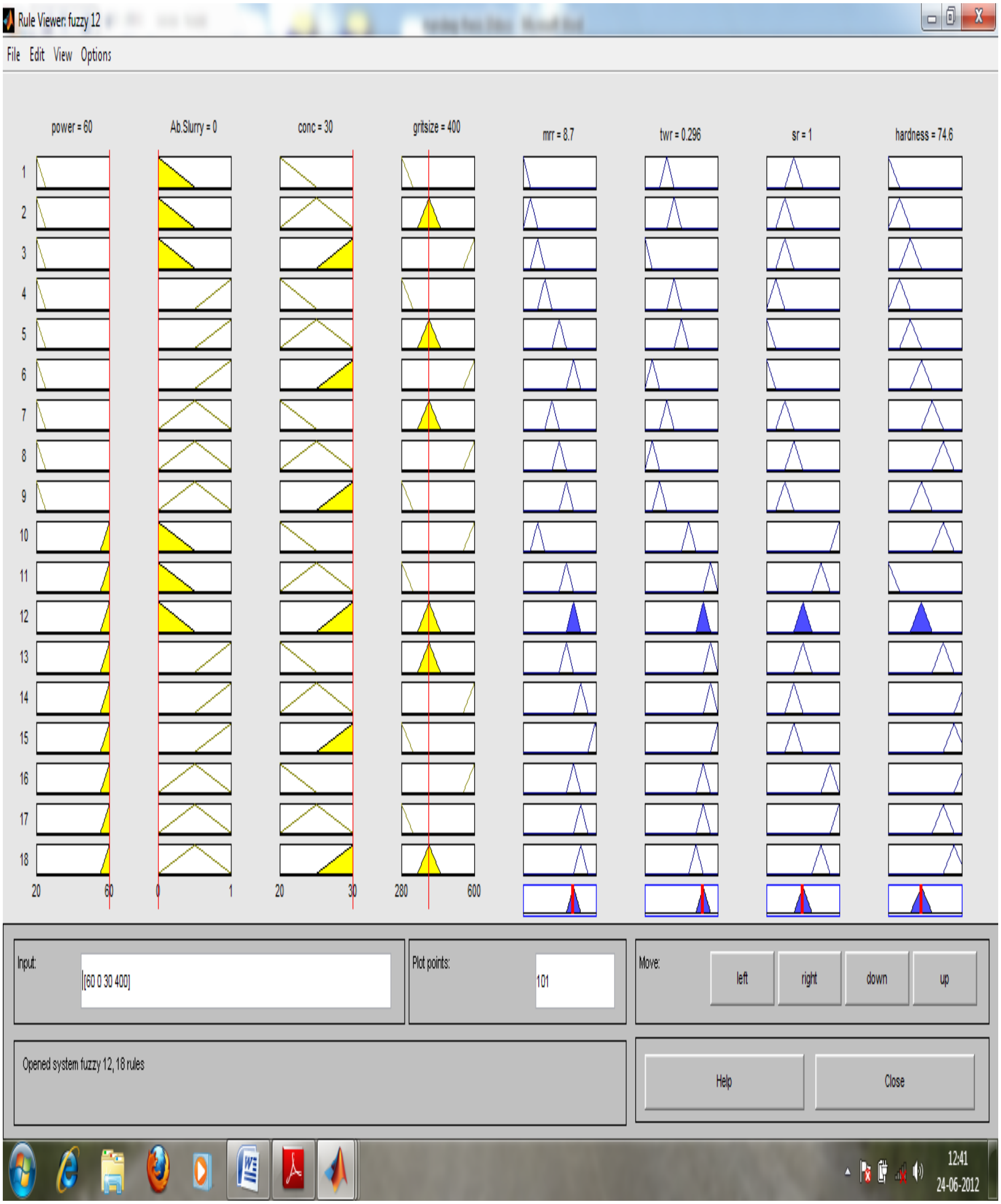


Input: [60 0 25 280]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 11: Pictorial presentation of fuzzy rule base system for power(%)= 60, Ab. Slurry= Aluminum oxide, Slurry concentration= 25%, Grit size= 280



power = 60

Ab.Slurry = 0

conc = 30

gritsize = 400

mrr = 8.7

twr = 0.296

sr = 1

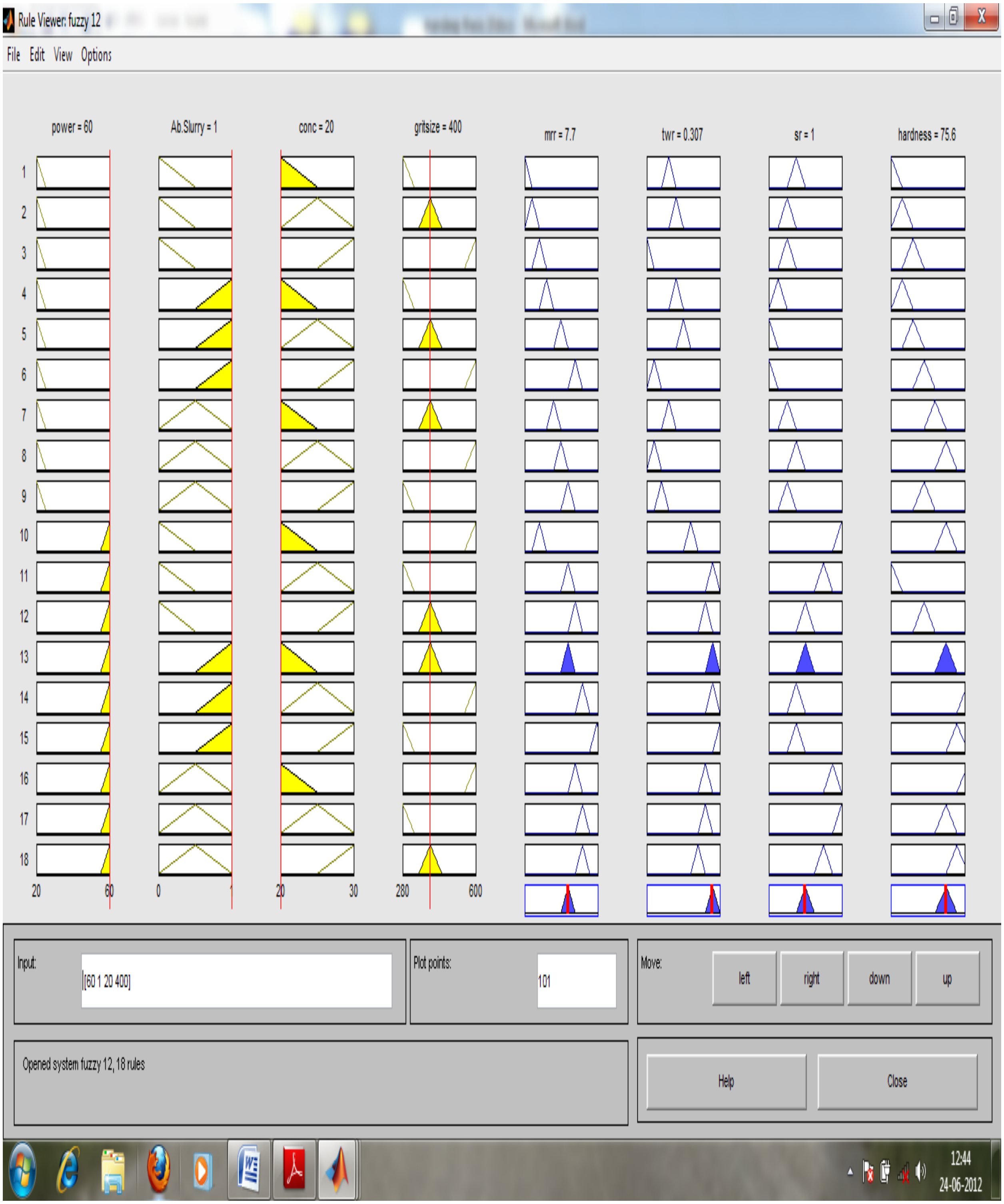
hardness = 74.6

Input: [60 0 30 400]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 12: Pictorial presentation of fuzzy rule base system for power(%)= 60, Ab. Slurry= Aluminum oxide, Slurry concentration= 30%, Grit size= 400

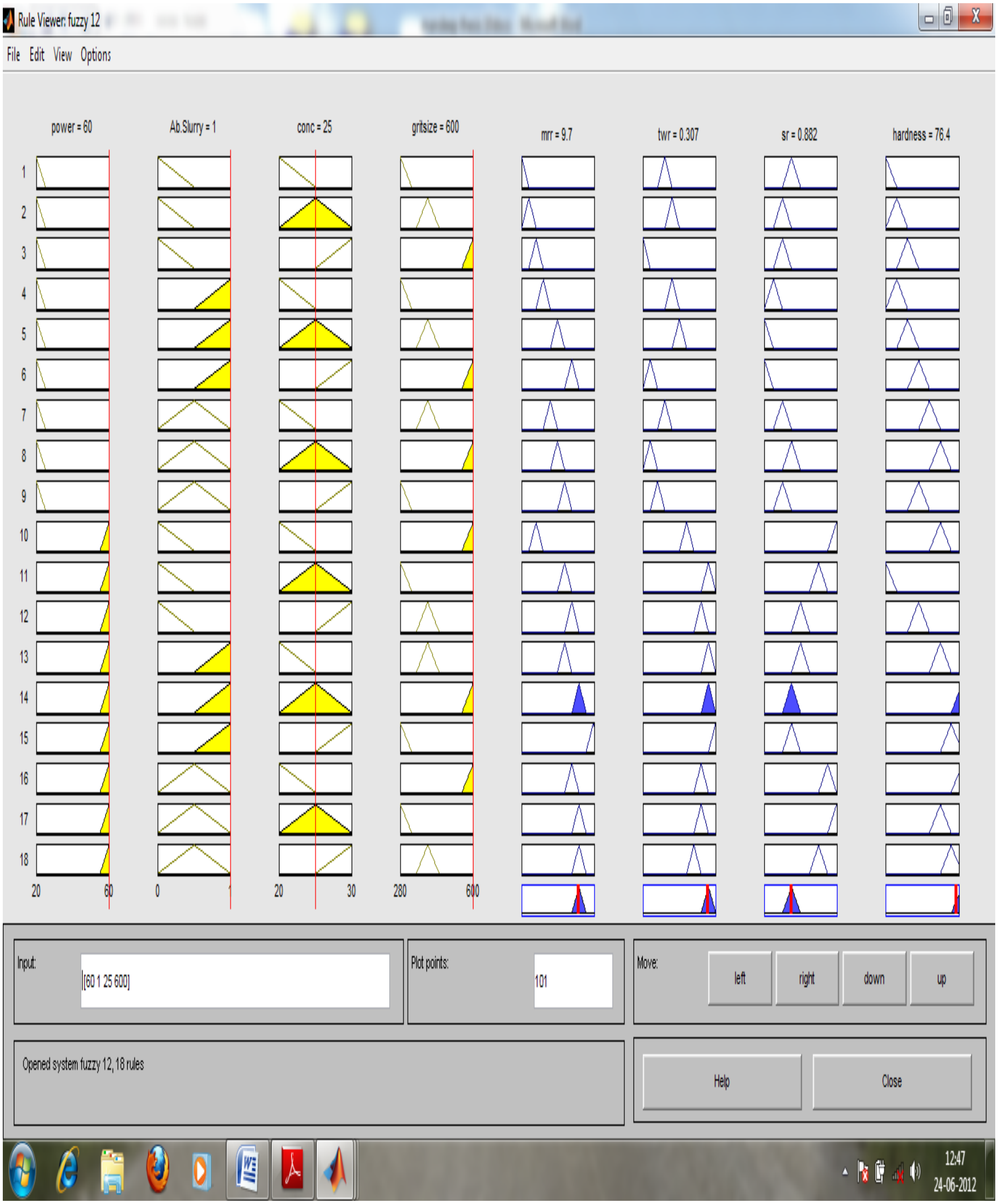


Input: [60 1 20 400]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 13: Pictorial presentation of fuzzy rule base system for power(%)= 60, Ab. Slurry= Silicon carbide, Slurry concentration= 20%, Grit size= 400

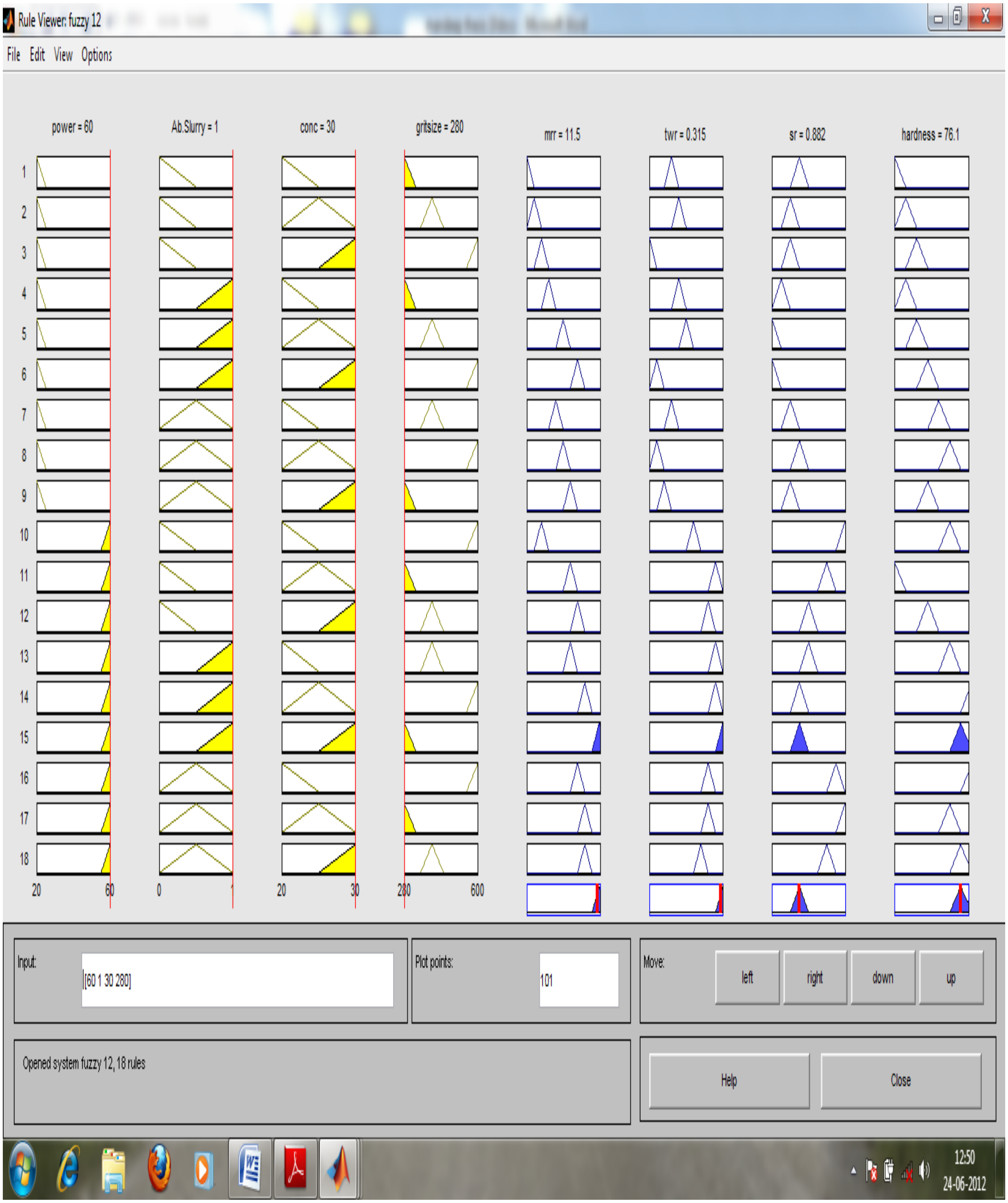


power = 60
Ab.Slurry = 1
conc = 25
gritsize = 600
mrr = 9.7
twr = 0.307
sr = 0.882
hardness = 76.4

Input: [60 1 25 600]
Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 14: Pictorial presentation of fuzzy rule base system for power(%)= 60, Ab. Slurry= Silicon carbide, Slurry concentration= 25%, Grit size= 600



Input: [60 1 30 280]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 15: Pictorial presentation of fuzzy rule base system for power(%)= 60, Ab. Slurry= Silicon carbide, Slurry concentration= 30%, Grit size= 280

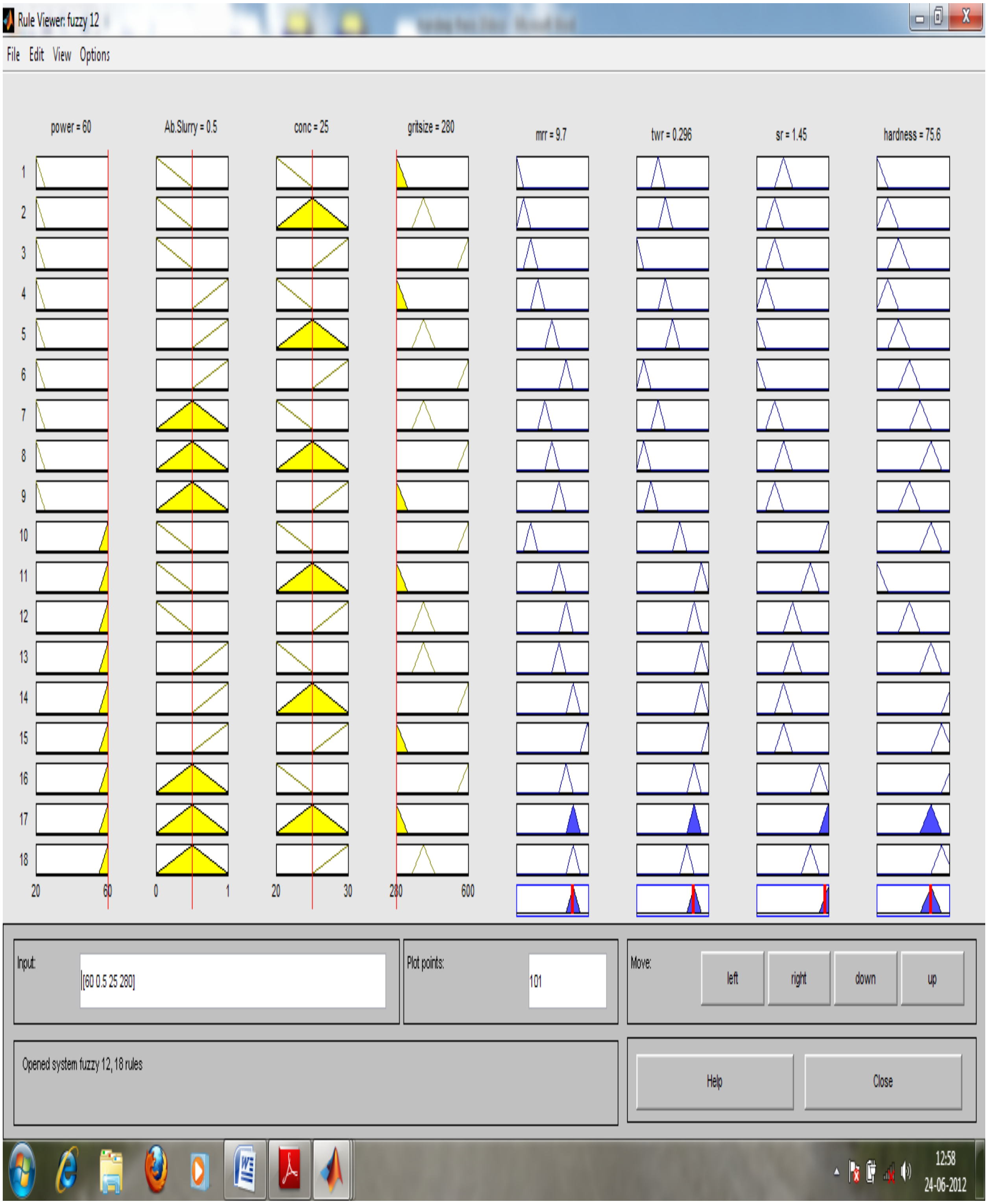
power = 60
Ab.Slurry = 0.5
conc = 20
gritsize = 600
mrr = 8.7
twr = 0.296
sr = 1.36
hardness = 76.4

Input: [60 0.5 20 600]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 16: Pictorial presentation of fuzzy rule base system for power(%)= 60, Ab. Slurry= Mix, Slurry concentration= 20%, Grit size= 600

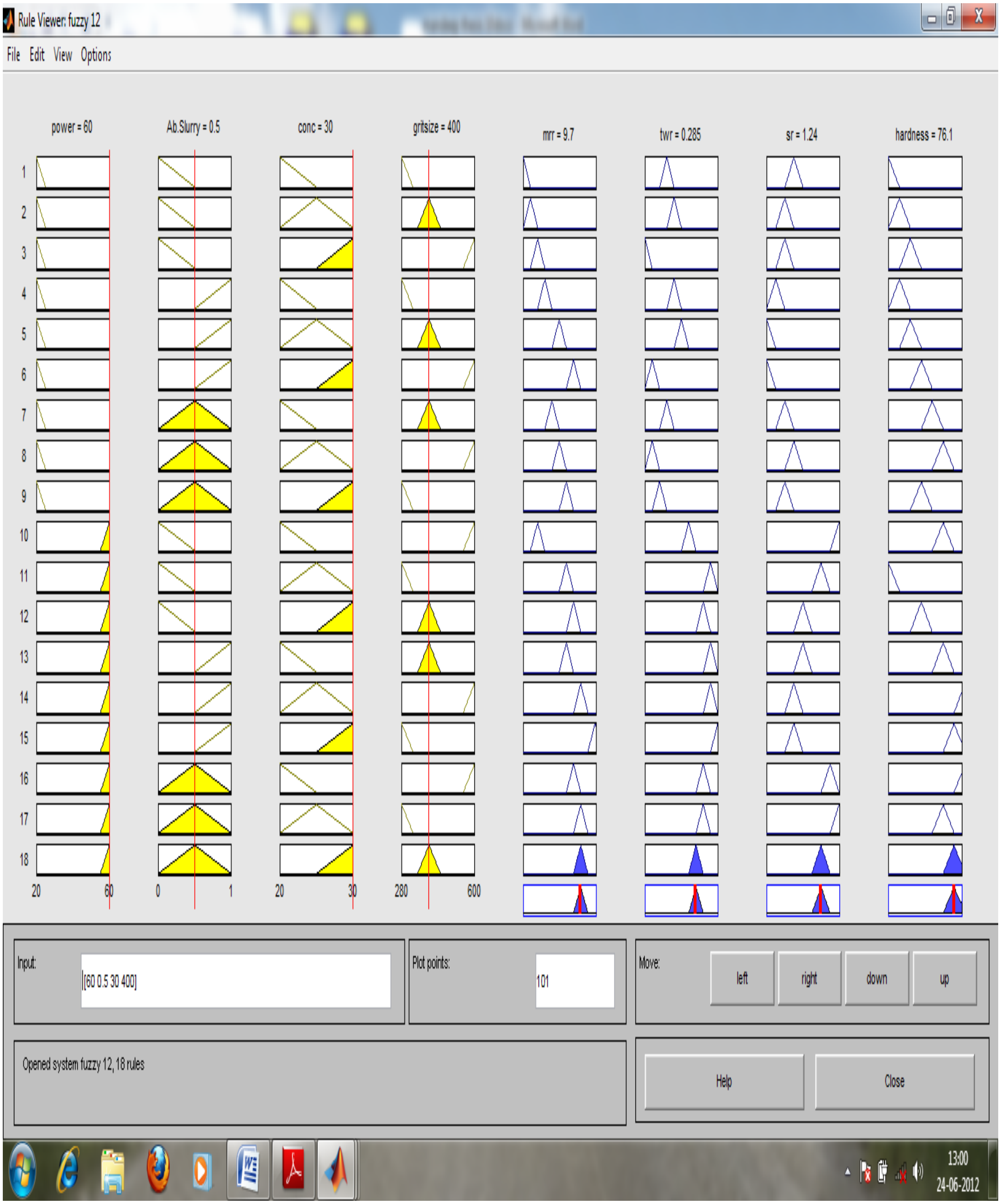


Input: [60 0.5 25 280]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 17: Pictorial presentation of fuzzy rule base system for power(%)= 60, Ab. Slurry= Mix, Slurry concentration= 25%, Grit size= 280



Input: [60 0.5 30 400]

Plot points: 101

Opened system fuzzy 12, 18 rules

Rule 18: Pictorial presentation of fuzzy rule base system for power(%)= 60, Ab. Slurry= Mix, Slurry concentration= 30%, Grit size= 400

From the above pictorial representation of the rules, we can see the different co-relation in the value of the input parameters (power (%), Abrasive Slurry, Slurry concentration, Grit size) and the output parameters (material removal rate, tool wear rate, surface roughness, hardness). We can make the different combination of the input parameters value and get the value for output parameters. If we change any input parameters value then the output parameters value automatically adjust in this fuzzy model. The deviation between experimental value and fuzzy model value is very minimal. The graphs on the left correspond to the input membership functions; the red line indicates the power input value. It can be moved to simulate different input values. The graphs on the right are the output membership functions. The bottom right output function represents the output of the FIS.

CHAPTER 11

RESULTS AND CONCLUSIONS

11.1 RESULTS

The effect of parameters i.e. Power Rate Concentration, Type of Abrasive slurry, Slurry concentration and Grit Size and interactions between power rate and abrasive slurry evaluated using ANOVA design analysis and fuzzy logic technique. The purpose of the ANOVA was to identify the important parameters in prediction of MRR, TWR, Surface Roughness and Rockwell Hardness. Some results consolidated from ANOVA and plots are given below:

11.1.1 MATERIAL REMOVAL RATE

The effect of parameters i.e, power rate, abrasive slurry, slurry concentration and grit size and some other interaction were evaluated using ANOVA and factorial design analysis. A confidence interval of 95.0% has been used for the analysis. One repetition for each 18 trails was completed to measure the Signal to Noise ratio (S/N Ratio).

The various data for each factor and their interaction was P value find for the significant of each. The principal of the P value is that the value less than 0.05 that factors or interactions are significant if value is more than 0.05 then that factors or interactions are insignificant. From the ANOVA table for mean we see it Power Rate P value is 0.001, Abrasive slurry P value is 0.000 and Concentration P value is 0.002 these factors are significant. Grit Size P value is 0.797 and same Power rate and Abrasive slurry interaction P value is more than 0.05 so that these are insignificant. In the table 5.3.3, the ranks are show for the different factor. 1st rank is given to the Abrasive slurry that mean Abrasive slurry has the highest contribution to MRR. 2nd rank is give to the type of power rate (%), 3rd rank is given to the slurry concentration and the 4th rank is given to the Grit size that means Grit size have the minimum contribution to the MRR.

Highest MRR was observed when Work-piece is machined on Power Rate 60, Abrasive slurry Silicon Carbide and Slurry concentration 30%. It also observes that the interaction AxB is not any effect on the MRR. The best MRR value was compromised to get best results. MRR Assumed to be achieved best result if GFRP work piece is machined at Power Rate 60, Abrasive slurry Silicon Carbide and Slurry concentration 30%. With 95% confidence interval mean value of MRR was found to be 10.87±1.15 mm^3/min.

11.1.2 TOOL WEAR RATE

The effect of parameters i.e, power rate, abrasive slurry, slurry concentration and grit size and some other interaction were evaluated using ANOVA and factorial design analysis. A confidence interval of 95.0% has been used for the analysis. One repetition for each 18 trails was completed to measure the Signal to Noise ratio (S/N Ratio).

The various data for each factor and their interaction was P value find for the significant of each. The principal of the P value is that the value less than 0.05 that factors or interactions are significant if value is more than 0.05 then that factors or interactions are insignificant. From the ANOVA table for mean we see it Power Rate P value is 0.000, Abrasive slurry P value is 0.047 and Grit Size P value is 0.010 these factors are significant. Slurry concentration P value is 0.142 and same Power rate and Abrasive slurry interaction P value is more than 0.05 so that these are insignificant. In the table 5.4.3, the ranks are show for the different factor. 1st rank is given to the power rate (%) that mean power rate has the highest contribution to TWR. 2nd rank is give to the type of Grit size, 3rd rank is given to the Abrasive slurry and the 4th rank is given to the Slurry concentration that means Slurry concentration have the minimum contribution to the TWR.

Lowest TWR was observed when Work-piece is machined on Power Rate 20, Abrasive slurry Silicon Carbide + Aluminum oxide and Grit size 600. It also observes that the interaction AxB is not any effect on the TWR. The best TWR value was compromised to get best results. TWR Assumed to be achieved best result if GFRP work piece is machined at Power Rate 20, Abrasive slurry Silicon Carbide + Aluminum oxide and Grit size 600. With 95% confidence interval mean value of TWR was found to be 0.2144±0.0137 mm^3/min.

11.1.3 SURFACE ROUGHNESS

The effect of parameters i.e, power rate, abrasive slurry, slurry concentration and grit size and some other interaction were evaluated using ANOVA and factorial design analysis. A confidence interval of 95.0% has been used for the analysis. One repetition for each 18 trails was completed to measure the Signal to Noise ratio (S/N Ratio).

The various data for each factor and their interaction was P value find for the significant of each. The principal of the P value is that the value less than 0.05 that factors or interactions are significant if value is more than 0.05 then that factors or interactions are insignificant. From the ANOVA table for mean we see it Power Rate P value is 0.000, Abrasive slurry P value is 0.002 and Slurry concentration P value is 0.036 these factors are significant. Grit Size P value is 0.409 and same Power rate and Abrasive slurry interaction P value is more than 0.05 so that these are insignificant. In the table 5.5.3, the ranks are show for the different factor. 1st rank is given to the power rate (%) that mean power rate (%) has the highest contribution to SR. 2nd rank is give to the Abrasive slurry, 3rd rank is given to the slurry concentration and the 4th rank is given to the Grit size that means Grit size have the minimum contribution to the SR.

Lowest SR was observed when Work-piece is machined on Power Rate 20, Abrasive slurry Silicon Carbide and Slurry concentration 30%. It also observes that the interaction AxB is not any effect on the SR. The best SR value was compromised to get best results. SR Assumed to be achieved best result if GFRP work piece is machined at Power Rate 20, Abrasive slurry Silicon Carbide and Slurry concentration 30%. With 95% confidence interval mean value of SR was found to be 0.4479±0.137 μm.

11.1.4 HARDNESS

The effect of parameters i.e, power rate, abrasive slurry, slurry concentration and grit size and some other interaction were evaluated using ANOVA and factorial design analysis. A confidence interval of 95.0% has been used for the analysis. One repetition for each 18 trails was completed to measure the Signal to Noise ratio (S/N Ratio).

The various data for each factor and their interaction was P value find for the significant of each. The principal of the P value is that the value less than 0.05 that factors or interactions are significant if value is more than 0.05 then that factors or interactions are insignificant. From the ANOVA table for mean we see it Power Rate P value is 0.000, Abrasive slurry P value is 0.000 and Grit Size P value is 0.004 these factors are significant. Slurry concentration P value is 0.586 and same Power rate and Abrasive slurry interaction P value is more than 0.05 so that these are insignificant. In the table 5.6.3, the ranks are show for the different factor. 1st rank is given to the Abrasive slurry that mean Abrasive slurry has the highest contribution to Hardness. 2nd rank is give to the type of power rate (%), 3rd rank is given to the Grit size and the 4th rank is given to the Slurry concentration that means Slurry concentration have the minimum contribution to the Hardness.

Highest hardness was observed when Work-piece is machined on Power Rate 60, Abrasive slurry Silicon Carbide + Aluminum oxide (MIX) and Grit size 600. It also observes that the interaction AxB is not any effect on the Hardness. The best hardness value was compromised to get best results. Hardness Assumed to be achieved best result if GFRP work piece is machined at Power Rate 60, Abrasive slurry Silicon Carbide + Aluminum oxide (MIX) and Grit size 600. With 95% confidence interval mean value of Hardness was found to be 76.76±0.60 HRB.

11.2 **CONCLUSIONS**

The present study was carried out to study the effect of input parameters Power Rate (%) Type of Abrasive slurry, Slurry concentration and Grit Size and the interaction between Power Rate and Abrasive slurry (AxB) on the MRR, TWR, Surface Roughness and Rockwell Hardness. The following conclusions have been drawn from the study:

- The MRR mainly affected by the Power rate (%) and Abrasive slurry.
- Maximum MRR Obtained at Power Rate 60, Abrasive slurry Silicon carbide and slurry concentration 30%.
- Higher slurry concentration gives the high MRR.
- The TWR mainly affected by the Power rate (%) and Grit size.
- Lowest tool wear rate occurs when slurry Concentration 20%, abrasive slurry Silicon Carbide+Aluminum oxide (MIX) and Grit size 600.
- High Power rate gives high MRR and TWR.
- Maximum TWR occurs due to power and grit size.
- Minimum surface roughness occurs when Power Rate 20%, Abrasive slurry Silicon Carbide and Slurry concentration 30%.
- Maximum effect on machined surface finish is due to type of Abrasive slurry and power rate.
- Maximum effect on the Hardness is due to Power 60, Abrasive slurry Mixture (Aluminium Oxide and Silicon Carbide) and Grit size 600.
- Maximum Rockwell Hardness is obtained by Mixture Slurry (Aluminium Oxide and Silicon Carbide) of power 60.
- Mamdani-Fuzzy has shown the capabilities of generalization and prediction of MRR, TWR, Surface roughness and hardness in USM within the range of experimental data.
- The maximum deviation observed and estimated by fuzzy is very minimal.

- The predicted value of fuzzy output can be further precisely predicted with the change of input parameter values.

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