

EXPERIMENTAL STUDY of PROCESS PARAMETERS IN MILLING USING FUZZY LOGIC AND REGRESSION ANALYSIS APPROACH

A Thesis

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Degree of*

**MASTER OF ENGINEERING
IN
CAD/CAM & ROBOTICS**

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CERTIFICATE

I hereby declare that the work which is being presented in the dissertation work entitled, "Experimental study of Process parameters in milling using Fuzzy Logic and Regression analysis approach", in partial fulfillment of the requirements for the award of degree of Master of Engineering in Mechanical Engineering in CAD/CAM & ROBOTICS submitted in Mechanical Engineering Department, Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of Dr.V.K.Singla refers other researchers work which are duly listed in the reference section.

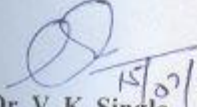
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ABSTRACT

Milling is a machining operation in which a workpiece is fed past under a rotating cylindrical tool with multiple cutting edges. The axis of rotation of the tool is perpendicular to the feed direction. The tool is called the milling cutter and the cutting edges are called teeth. Mostly plane surfaces are created through milling. It's an interrupted cutting operation; the teeth of milling cutter enter and exit workpiece during each revolution. The cutting forces exerted by the cutting tool on the work piece during a machining action to be identified in order to control the tool wear and occurrence of vibration, thus to improve tool-life. Modeling of cutting forces in milling is often needed in machining automation.

In the present study the comparison has been made between data for experimental study and software study comparing the data for variation of tool wear rate, Material removal rate and Surface hardness using MATLAB software. The objective of this study is to predict the effects of cutting parameters on the variations of cutting forces during end milling operation on vertical milling machine.

A number of tests were performed with different cutting speed and feed rates. The cutting force has been measured using the piezoelectric dynamometer for varying feed rate, speed and depth of cut. The different values of cutting speed, feed and depth of cut evaluated were used as input for obtaining MRR, TWR, and Surface hardness in MATLAB 7.0 Software. Thus, Using from experimental results of cutting parameters and wear values of analytical model, fuzzy logic capabilities have been used to predict the wear rate as the force values increase. The simulation results presented with MATLAB software show the effectiveness of proposed system for tool and material wear in Milling operation. This model and analysis are useful not only for predicting the tool wear but also for selecting optimum process parameters for achieving the stability of the end milling process.

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CHAPTER 1

INTRODUCTION

1.1 MILLING MACHINE

Milling machines were first invented and developed by Eli Whitney to mass produce interchangeable musket parts. Development and improvements of the milling machine and components continued, which resulted in the manufacturing of heavier arbors and high speed steel and carbide cutters. These components allowed the operator to remove metal faster, and with more accuracy, than previous machines. Variations of milling machines were also developed to perform special milling operations. During this era, computerized machines have been developed to alleviate errors and provide better quality in the finished product. Milling is the process of removing material from a work piece by moving the work piece (fixed to the table/bed) past a fixed position, rotating multi or single tooth/flute milling cutter (tool bit). The cutting action of teeth around the center axis of the milling cutter provides a fastest and accurate approach to machining. The machined surface may be flat, angular, or a multi dimensional curve or curve surface. The adjoining surfaces or edges (features) may also be milled to produce any combination of shapes and contours. The machine used for these applications is properly referred to as a milling machine tool or a machining center.

1.2 Classification

Milling operations are classified into two major categories:

- Peripheral (side)
 - » Generally in a plane parallel to the axis of the cutter
 - » Cross section of the milled surface corresponds to the contour of the cutter
- Face
 - » Generally at right angles to the axis of rotation of the cutter
 - » Milled surface is flat and has no relationship to the contour of the cutter
 - » Combined cutting action of the side and face of the milling cutter
- Thread milling - milling treads using the capability of a three axis contouring CNC machine.

Two Major Classifications - Knee & Column and Bed

- Knee & Column (Bridgeport type)
 - » Basic job shop type mill
 - » Column mounted to the base which is the major support frame.
 - » Construction provides controlled motion of the worktable in three mutual perpendicular directions.

- » Knee moves vertically on the ways in the front of the machine
 - » Table moves longitudinally on the ways on the saddle
 - » Saddle moves transversely on the ways on the knee
 - » Quill moves parallel in Z axis or, if head is rotated, X axis
 - » Versatile general purpose machine
- Bed
- » Used extensively in production milling operations
 - » Rigid construction capable of heavy cuts
 - » Table is mounted directly to the bed
 - » Spindle head moves vertically to set depth of cut
 - » Head locks into position for cut
 - » Base of machine functions as a coolant reservoir

1.3 Type of milling machine

A wide variety of milling machines are manufactured and may be classified as horizontal and vertical, low, intermediate, and high production and special purpose.

1.3.1 Horizontal milling machine

The horizontal milling machine shown in Fig 1.1 is so called because the milling cutter is held in a horizontal position. It is also called a column and knee machine because they make up the main structure members. Although the machine shown is very versatile, it is limited to low production. Horizontal machine tend to be advantageous for heavy, box-shaped parts, such as gear housing, they have many feature that need to be machined on the side faces, the horizontal machine easily supports heavy work piece of this type. The chips drop out of the way during machine. Pallet system used to shuttle pieces in and out of the work station to be easier to design for a horizontal machine. Where everything in front of the main column is open and accessible.



Figure 1.1 Horizontal milling machine

1.3.2 Vertical milling machine

The vertical milling machine as shown in Fig 1.2 has the cutting tool held in a vertical position. This machine can also be classified as a column and knee type since they represented the main structure member. The CNC control shown makes this machine extremely versatile and of intermediate production.

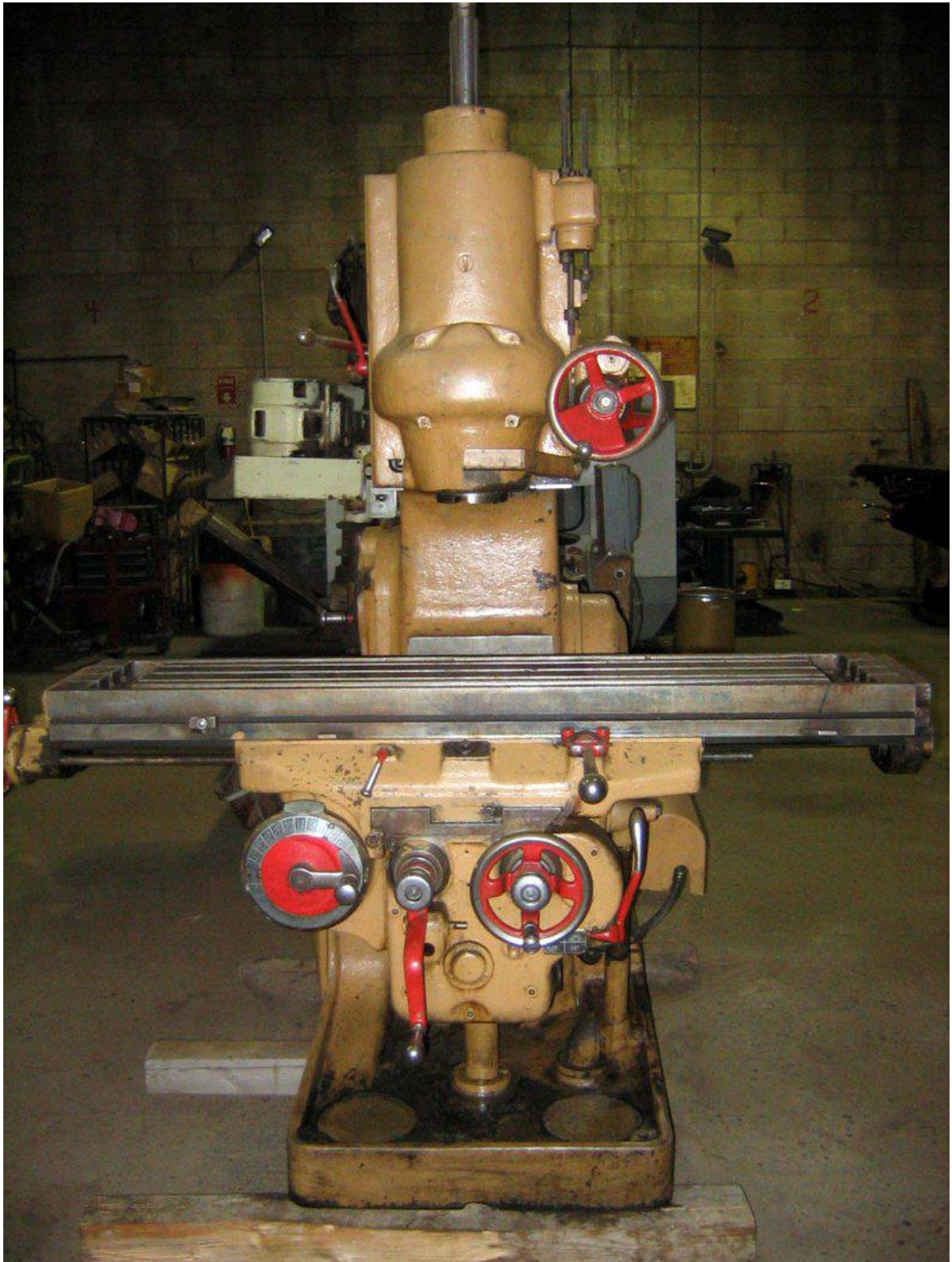


Figure 1.2 Vertical milling machine

1.3.3 Planer milling machine

The larger milling machine is equipped with two cutting heads of 250hp each. The cuts are made by the rotating milling cutters as the table reciprocates back and forth. The cutters can be made to cut either on the top surface or on the edge of the stock.

1.4 Major components

Keep in mind that although we are discussing a knee and a column milling machine, this information can be applied to other types.

(1) Column

The column, including the base, is the main casting which supports all other parts of the machine, an oil reservoir and a pump in the column keeps the spindle lubricated. The column rests on a base that contains a coolant reservoir and a pump that can be used when performing any Machining operation that requires a coolant.

(2) Knee

The knee is the casting that supports the table and the saddle. The feed change gearing is enclosed within the knee. It is supported and can be adjusted by the elevating screw. The knee is fastened to the column by dovetail ways. The lever can be raised or lowered either by hand or power feed. The hand feed is usually used to take the depth of cut or to position the work, and the power feed to move the work during the machining operation.

(3) Saddle and Swivel Table

The saddle slides on a horizontal dovetail, parallel to the axis of the spindle, on the knee. The swivel table (on universal machines only) is attached to the saddle and can be swiveled approximately 45° in either direction.

(4) Power Feed Mechanism

The power feed mechanism is contained in the knee and controls the longitudinal, transverse (in and out) and vertical feeds. The desired rate of feed can be obtained on the machine by positioning the feed selection levers as indicated on the feed selection plates. Most milling machines have a rapid traverse lever that can be engaged when a temporary increase in speed of the longitudinal, transverse, or vertical feeds are required. For safety reasons, extreme caution should be exercised while using the rapid traverse controls.

(5) Table

The table is the rectangular casting located on top of the saddle. It contains several T-slots for fastening the work or work holding devices. The table can be moved by hand or by power. To move the table by hand, engage and turn the longitudinal hand crank. To move it by power, engage the longitudinal directional feed control lever. The longitudinal directional control lever can be positioned to the left, to the right, or in the center. Place the end of the directional feed control lever to the left to feed the table to the left. Place it to the right to feed the table to the right places it in the center position to disengage the power feed, or to feed the table by hand.

(6) Spindle

The spindle holds and drives the various cutting tools. It is a shaft, mounted on bearings supported by the column. The spindle is driven by an electric motor through a train of gears, all mounted within the column. The front end of the spindle, which is near the table, has an internal taper machined on it. Two keys, located on the face of the spindle, provide a positive drive for the cutter holder, or arbor.

(7) Over arm

The over arm is the horizontal beam to which the arbor support is fastened. The over arm, may be a single casting that slides in the dovetail ways on the top of the column. It may consist of one or two cylindrical bars that slide through the holes in the column. On some Machines to position the over arm, first unclamp the locknuts and then extend the over arm by turning a crank. On others, the over arm is moved by merely pushing on it. The over arm should only be extended far enough to so position the arbor support as to make the setup as rigid as possible.

(8) Arbor Support

The arbor support is a casting containing a bearing which aligns the outer end of the arbor with the spindle. This helps to keep the arbor from springing during cutting operations. Two types of arbor supports are commonly used. One type has a small diameter bearing hole, usually 1-inch maximum in diameter. The other type has a large diameter bearing hole, usually up to 2 3/4 inches, an oil reservoir in the arbor support keeps the bearing surfaces lubricated. An arbor support can be clamped anywhere on the over arm.

1.5 Special type of milling machines

Many types of special milling machines are to accomplish specific kind of work more easily than the standard types. Most of these machines are vertical mills that have been adapted to reproduce accurately. Automatics machines are made to traverse the pattern either electrically or hydraulically.

1.5.1 Vertical Machining center

The most versatile milling machine is now the machining center; machining centers are designed and built to provide for flexible manufacturing (FM). Therefore, they can be used for wide range from a just few part to production quantities. Programming can be relatively simple. An NC machining center by definition is able to perform milling, drilling, and boring cuts and has either indexing turret tool holder or provides for automatics tool change. Machining centers are built in either the horizontal or vertical configuration; the relative merits of each will be discussed briefly.

Vertical machining centers are often preferred for flat parts that must have through holes. Fixture for these parts are more easily designed and built for a vertical spindle. Also, the thrust of cut developed in drilling or in milling pockets can be absorbed directly by the bed of the machine. The vertical machine is preferred where three-axis work is done on a single face, as in mold and die work. The weight of a vertical machine as it extends away from the column, particularly on larger machines, can be a factor in maintaining accuracy.



Figure 1.3 Vertical milling center (machine tool lab)

1.6 Milling machining study

Today live tooling lathes can now duplicate some of these operations. Eliminating the need for multiple set-ups, the shop has both CNC and manual vertical mills, Precision ± 0.0005 or $\pm 0.013\text{mm}$, these tolerances are operation and operator dependent and under ideal new equipment conditions. Today milling machines are also used for drilling, reaming, boring, counter boring, counter sinking, tapping, grooving and chamfering holes.

Milling is one of the basic machining processes. Milling is a very versatile process Capable of producing simple two dimensional flat shapes to complex three dimensional interlaced surface configurations. Cutting tools for this process are called milling cutters

The milling process:

- Typically uses a multi-tooth cutter
- Work is fed into the rotating cutter
- Capable of high MRR
- Well suited for mass production applications
- Highly versatile machining operation
- Multitooth tool that produces a number of chips in one revolution

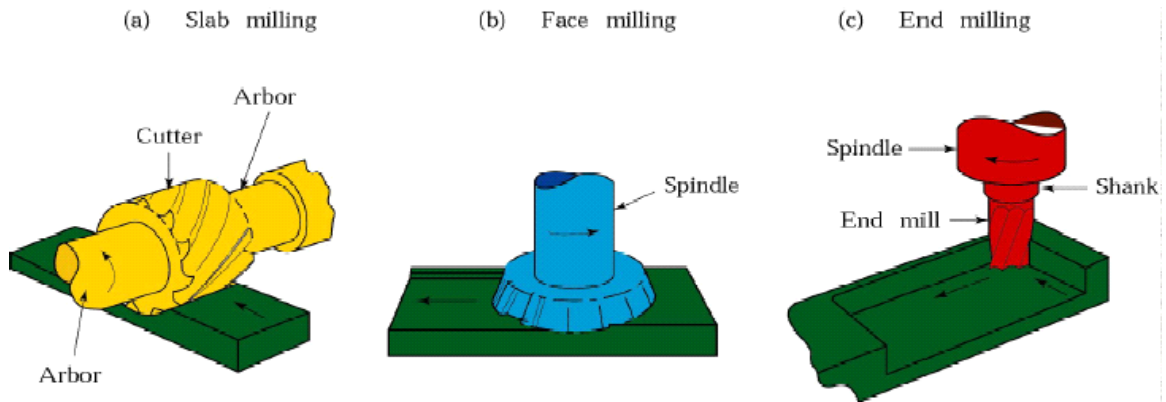


Fig 1.4: Some of the basic type milling cutters and milling operations.

a) Slab Milling

- Slab milling also called as peripheral milling
- Cutters have straight or helical teeth resulting in orthogonal or oblique cutting action.

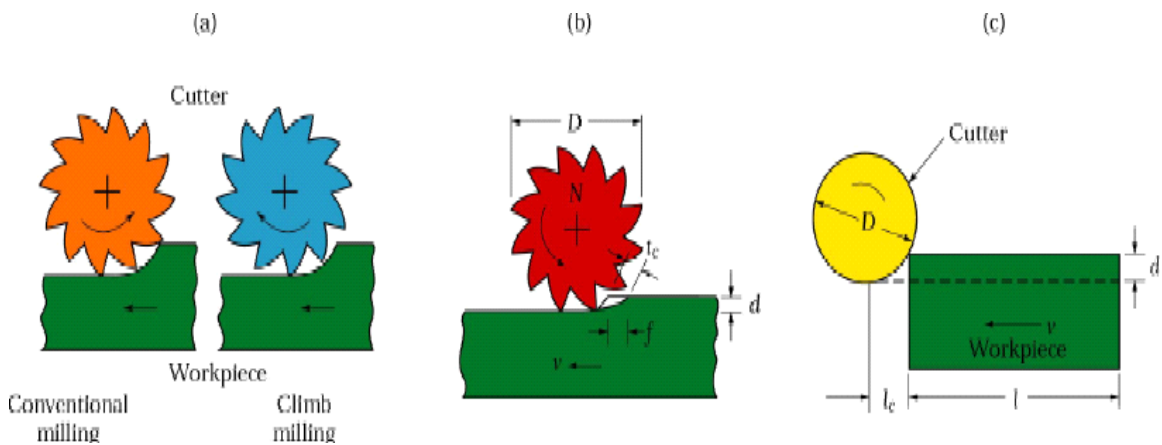


Fig 1.5: (a) Conventional milling and climb milling (b) Slab milling operation, showing depth of cut, d , feed per tooth, f , chip depth of cut, t_c , and workpiece speed, v . (c) cutter travel distance l_c to reach full depth of cut.

b) Face Milling

- The cutter is mounted on a spindle having an axis of rotation perpendicular to the workpiece surface.

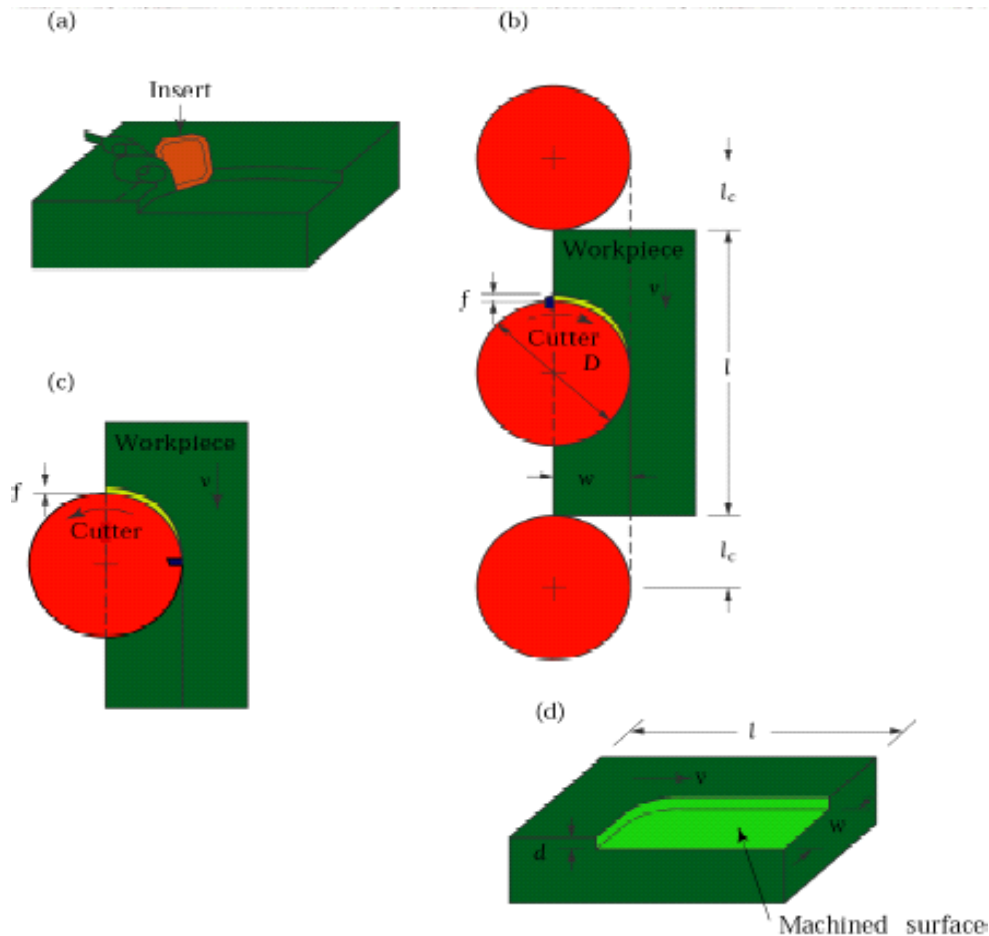


Fig1.6: Face milling operation showing (a) action of an insert in face milling; (b) climb milling; (c) conventional milling d) dimensions in face milling. The width of cut, w , is not necessarily the same as the cutter radius Fig:A face milling cutter with indexable inserts.

c) End Milling The cutter in end milling generally rotates on an axis vertical to the workpiece. Cutting teeth are located on both the end face of the cutter and the periphery of the cutter body.

1.7 MILLING PROCESS PARAMETERS

Milling cutting geometry

1) True rake

True rake is the slope of the tooth face with respect to a radial reference plane through the nose of the cutting edge and is the resultant of the axial, radial, and angles, it is measured in the perpendicular to the surface generated by the cutting edge, the true rake of a given axial and radial combination becomes more positive as the lead angle increases, which offers freer cutting and lower horsepower consumption.

2) Angle of inclination

The same angles used to determine true rake are also used to measure inclination angles, as shown in fig. the plane of measurement differs, however; measurement is made from the plane generated by the cutting edge rather than perpendicular to it.

3) Cutter effect on surface finish

A number of variables affect the surface finish produced by a cutter, such as machine rigidity, work material, fixturing and feed rate. Once methods of improving the surface finish is by using an insert that has a wiper flat, to be effective, the wiper flat should be approximately 25% longer than the feed per revolution in order to wipe out any high points left by the preceding insert.

Speed computation

The formula for calculating spindle speed in revolutions per minute

Is as follows

$$\text{Rpm} = (\text{C.S.} \times 4 / D) \dots\dots\dots (1)$$

Where, rpm = spindle speed (in revolution per minute)

C.S = cutting speed of milling cutter (in surface mm per minute)

D = diameter of milling cutter (in mm)

Feeds for milling

General

The rate of feed, or the speed at which the work piece passes the cutter, determines the time required for cutting a job. In selecting the feed, there are several factors which should be considered.

These factors are:

1. Forces are exerted against the work piece, the cutter, and their holding devices during the cutting process. The force exerted varies directly with the amount of metal removed and can be regulated by the feed and the depth of cut. Therefore, the correct amount of feed and depth of cut are interrelated, and in turn are dependent upon the rigidity and power of the machine. Milling machines are limited by the power that they can develop to turn the cutter and the amount of vibration they can resist when using coarse feeds and deep cuts.
2. The feed and depth of cut also depend upon the type of milling cutter being used. For example, deep cuts or coarse feeds should not be attempted when using a small diameter end milling cutter, as such an attempt would spring or break the cutter. Coarse cutters with

strong cutting teeth can be fed at a faster rate because the chips may be washed out more easily by the cutting oil.

3. Coarse feeds and deep cuts should not be used on a frail work piece, or on a piece that is mounted in such a way that its holding device is not able to prevent springing or bending.

4. The degree of finish required often determines the amount of feed. Using a coarse feed, the metal is removed more rapidly but the appearance and accuracy of the surface produced may not reach the standard desired for the finished product. Because of this, finer feeds and increased speeds are used for finer, more accurate finishes.

Horsepower at the motor is

$$HP_m = (Q \cdot P) / E \dots\dots\dots (4)$$

Where E is the efficiency of the machine, normally 20% of the motor efficiency is lost through the gear train.

Cutting speed

To determine the proper speed for milling,

$$Rpm = 3.82 \cdot V_c / D_c \dots\dots\dots (5)$$

Where V_c = cutting velocity (mm/m)

D_c = cutter diameter (mm)

Feed rate

The milling cutter rate is

$$f_m = f_z \cdot n \cdot rpm \dots\dots\dots (6)$$

Where f_z = mm per tooth, at least two or three teeth should be in the cut at one time to reduce vibration, cutter deflection, and insert chipping.

N = number of teeth in the cutter

Cutting time

The time required to make a cut is based on the length of the cut plus the cutter approach and over travel of the cutter divided by the feed rate;

$$Time = (L + dL) / f_m \dots\dots\dots (7)$$

Where

L = length of stroke,

dL = cutter approach to the work; an approximation for the cutter approach can be taken as one-half the diameter of the cutter,

f_m = feed rate (mm/min)

1.8 Effect of work material properties

Mild steel is the most common form of steel because its price is relatively low while it provides material properties that are acceptable for many applications. Low carbon steel contains approximately 0.05–0.15% carbon and mild steel contains 0.16–0.29% carbon, therefore it is neither brittle nor ductile. Mild steel has a relatively low tensile strength, but it is cheap and malleable; surface hardness can be increased through carburizing. It is often used when large quantities of steel are needed, for example as structural steel. The density of mild steel is approximately 7.85 g/cm^3 (0.284 lb/in^3) and the Young's modulus is 210,000 MPa (30,000,000 psi).

Low carbon steels suffer from *yield-point run out* where the material has two yield points. The first yield point (or upper yield point) is higher than the second and the yield drops dramatically after the upper yield point. If a low carbon steel is only stressed to some point between the upper and lower yield point then the surface may develop Lüder bands

Mild Steel Properties

This article is aimed at explaining what is mild steel and discuss some facts related to it. Keep reading to know about various mild steel properties and understand the role it plays in manufacture of metal items.

➤ **Table1.1: Hardness Testing of Mild Steel on Scale B**

Sr. NO	Brinell Hardness Testing on Scale B
1	93
2	94
3	94
Average	93.6

Mild steel is the type of steel, which is used in 85% of all steel applications in the United States of America. Steel is any alloy of iron, consisting of 0.2% to 2.1% of carbon, as a hardening agent. Besides carbon, there are many metal elements that are a part of steel

alloys. The elements other than iron and carbon, used in steel are chromium, manganese, tungsten and vanadium. All these elements along with carbon, act as hardening agents. That is, they prevent dislocations from occurring inside the iron crystals and prevent the lattice layers from sliding past each other. This is what makes steel harder than iron.

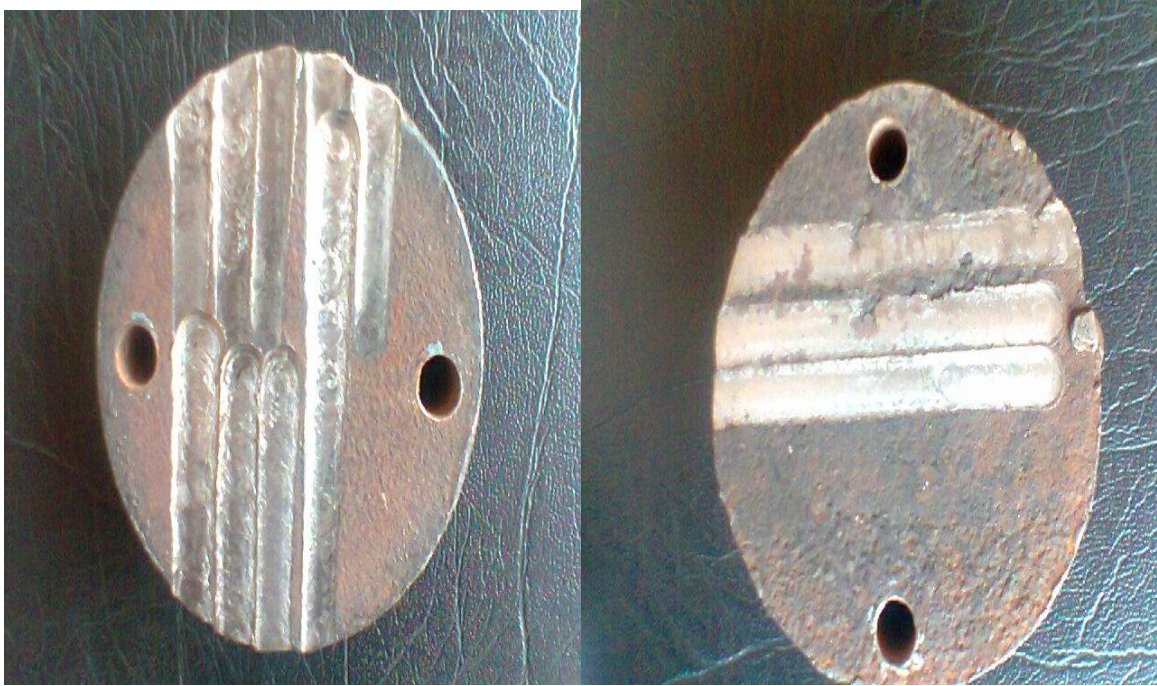


Figure 1.7 Mild steel workpiece

Varying the amounts of these hardening agents, creates different grades of steel. The ductility, hardness and mild steel tensile strength are a function of the amount of carbon and other hardening agents, present in the alloy. The amount of carbon is a deciding factor, which decides hardness of the steel alloy. A steel alloy with a high carbon content is mild steel, which is in fact much harder and stronger than iron. Though, increased carbon content increases the hardness of the steel alloy, it causes a decrease in its ductility. Read more on 'Physical Properties of Steel. Mild steel can also be described as steel which is not stainless steel. Mild steel differs from stainless steel in its chromium content.

Mild Steel Properties and Uses

Here is a compilation of mild steel properties and its uses in various fields of technology.

- Let us see, what makes the mild steel composition. Other than maximum limit of 2 % carbon in the manufacture of carbon steel, the proportions of manganese (1.65%), copper (0.6%) and silicon (0.6%) are fixed, while the proportions of cobalt, chromium, niobium, molybdenum, titanium, nickel, tungsten, vanadium and zirconium are not.
- A high amount of carbon makes mild steel different from other types of steel. Carbon makes mild steel stronger and stiffer than other type of steel. However, the hardness comes at the price of a decrease in the ductility of this alloy. Carbon atoms get affixed in the interstitial sites of the iron lattice and make it stronger.
- What is called as mildest grade of carbon steel or 'mild steel' is typically carbon steel, with a comparatively mild amount of carbon (0.16% to 0.19%). It has ferromagnetic properties, which make it ideal for manufacture of electrical devices and motors.
- The calculated average industry grade mild steel density is 7.85 gm/cm^3 . Its Young's modulus, which is a measure of its stiffness is around 210,000 Mpa.
- Mild steel is the cheapest and most versatile form of steel and serves every application which requires a bulk amount of steel.
- The high amount of carbon, also makes mild steel vulnerable to rust. Naturally, people prefer stainless steel over mild steel, when they want a rust free technology. Mild steel is also used in construction as structural steel. It is also widely used in the car manufacturing industry.

1.9 TOOL WEAR MONITORING

Tool wear monitoring/sensing should be one of the primary objectives in order to produce the required end products in an automated industry so that a new tool may be introduced at the instant at which the existing tool has worn out, thus preventing any hazards occurring to the machine or deterioration of the surface finish. Cutting tools may fail due to the plastic deformation, mechanical breakage, cutting edge blunting, and tool brittle fracture or due to the rise in the interface temperatures. Throughout the world today, there is a continuous struggle for cheaper production with better quality. This can be achieved only through optimal utilization of both material and human resources. Tool wear influences

cutting power, machining quality, tool life and machining cost. When tool wear reaches a certain value, increasing cutting force, vibration and cutting temperature cause surface integrity deteriorated and dimension error greater than tolerance. The life of the cutting tool comes to an end. Then the cutting tool must be replaced or ground and the cutting process is interrupted. The cost and time for tool replacement and adjusting machine tool increases cost and decreases the productivity. Hence tool wear relates to the economic of machining and prediction of tool wear is of great significance for the optimization of cutting process.

Tool material: The tool material used should be capable of high speed machining with dry cutting conditions. In present investigation HSS was used for performing the experiments.

Tool geometries:

a) Tool length: 10mm

b) Cutter diameter: 8 mm

TOOL WEAR: Cutting tools are subjected to an extremely severe rubbing process. They are in metal-to-metal contact, between the chip and work piece, under conditions of very high stress at high temperature. The situation is further aggravated due to the existence of extreme stress and temperature gradients near the surface of the tool. However, wears are occurring during the cutting action, and it will result in the failure of the cutting tool. When the tool wear reach certain extent, the tool or edge change has to be replaced to guarantee the ordinary cutting action. Under high temperature, high pressure, high sliding velocity and mechanical or thermal shock in cutting area, cutting tool has normally complex wear appearance, which consists of some basic wear types such as crater wear, flank wear, thermal crack, brittle crack, fatigue crack, insert breakage, plastic deformation and build-up edge. The dominating basic wear types vary with the change of cutting conditions.

1.9.1 TOOL WEAR MECHANISM

In order to find out suitable way to slow down the wear process, many research works are carried out to analyze the wear mechanism in metal cutting. It is found that tool wear is not formed by a unique tool wear mechanism but a combination of several tool wear mechanisms.

Abrasive wear Abrasive wear is mainly caused by the impurities within the workpiece material, such as carbon, nitride and oxide compounds, as well as the built-up fragments. This is a mechanical wear, and it is the main cause of the tool wear at low cutting speed.

Adhesive wear The simple mechanism of friction and wear proposed by Bowden and Tabor is based on the concept of the formation of welded junctions and subsequent destruction of these. Due to the high pressure and temperature, welding occurs between the fresh surface of the chip and rake face because of the chip flowing on the rake face results in chemically clean surface. Severe wear is characterized by considerable welding and tearing of the softer rubbing surface at high wear rate, and the formation of relatively large wear particles. Adhesion wear occurs mainly at low machining temperatures on tool rake face, such built up edge (BUE). Under mild wear conditions, the surface finish of the sliding surfaces improves.

Diffusion wear Wear is a process of atomic transfer at contacting asperities. A number of workers have considered that the mechanism of tool wear must involve chemical action and diffusion. They have demonstrated welding and preferred chemical attack of (W) tungsten carbide in (W-Ti) tungsten-titanium carbides. There are several ways in which the wear may be dependent on the diffusion mechanism.

(i) Gross softening of the tool: Diffusion of carbon in a relatively deep surface layer of the tool may cause softening and subsequent plastic flow of the tool. This flow may produce major changes in the tool geometry, which result in high forces and a sudden complete failure of the tool.

(ii) Diffusion of major tool constituents into the work (Chemical element loss): The tool matrix or a major strengthening constituent may be dissolved into the work and chip surfaces as they pass the tool. In cast alloy, carbide or ceramic tools, this may be the prime wear phenomenon. With HSS tools, iron diffusion is possible, but it seems unlikely to be the predominant wear process. Diamond tool – cutting iron and steel is the typical example of diffusion wear.

(iii) Diffusion of a work-material component into the tool: A constituent of the work material diffusing into the tool may alter the physical properties of a surface layer of the tool. For example, the diffusion of lead into the tool may produce a thin brittle surface layer, this thin layer can be removed by fracture or chipping.

Oxidation wear High temperatures and the presence of air mean oxidation for most metals. A slight oxidation of tool face is helpful to reduce the tool wear. It reduces adhesion, diffusion and current by isolating the tool and the workpiece. But at high temperature soft oxide layers, for example WO_3 , TiO_2 , are formed rapidly, and then taken away by the chip and the workpiece. This results in a rapid tool material loss, which is oxidation wear.

Chemical wear Corrosive wear (due to chemical attack of a surface)

Fatigue wear Fatigue wear is often a thermo-mechanical combination. Temperature fluctuations and the loading and unloading of cutting forces can lead to cutting edge cracking and breaking. Intermittent cutting action leads to continual generation of heat and cooling as well as shocks of cutting edge engagement. According to the temperature distribution on the tool face, it is assumed that crater wear is mainly caused by abrasive wear, diffusion wear and oxidation wear, but flank wear mainly dominated by abrasive wear due to hard second phase in the workpiece material.

1.9.2 PREDICTION OF TOOL WEAR

Prediction of tool wear is complex because of the complexity of machining system. Tool wear in cutting process is produced by the contact and relative sliding between the cutting tool and the work piece and between the cutting tool and the chip under the extreme conditions of cutting area; temperature at the cutting edge can exceed 530°C and pressure is greater than 13.79 N/mm^2 . Any element changing contact conditions in cutting area affects tool wear.

Figure 1.10 shows influencing elements of the tool wear. These elements come from the whole machining system comprising workpiece, tool, interface and machine tool.



Fig. 1.8 Influencing elements of tool wear

1.9.3 EFFECT OF TOOL WEAR ON TECHNOLOGICAL PERFORMANCE

Influence on cutting forces Flank wear (or wear-land formation) and chipping of the cutting edge affect the performance of the cutting tool in various ways. The cutting forces are normally increased by wear of the tool.

Surface finish (roughness) produced in a machining operation usually deteriorates as the tool wears. This is particularly true of a tool worn by chipping and generally the case for a tool with flank-land wear although there are circumstances in which a wear land may burnish (polish) the workpiece and produces a good finish.

Dimension accuracy Flank wear influences the plan geometry of a tool this may affect the dimensions or shape of the components.

Vibration or chatter The vibration is another aspect of the cutting process which may be influenced by flank wear. A wear land increases the tendency of a tool to dynamic instability. A cutting operation which is quite free of vibration when the tool is sharp may be subjected to an unacceptable chatter mode when the tool wears.

1.9.4 CONSEQUENCES OF TOOL WEAR

- Decrease the dimension accuracy, production efficiency, and component
- Increase the surface roughness, cutting force, temperature, and cost
- Likely cause vibration.

CHAPTER 2

LITERATURE REVIEW

2.1 Application of fuzzy logic approach to milling operation

J. C. Chen et al. ¹(2001) described a fuzzy-nets approach for a multilevel in-process **surface roughness** recognition system in **milling operations**, the goal of which was to predict surface roughness (Ra) under multiple cutting conditions determined by tool material, workpiece material, tool size, etc. Surface roughness was measured indirectly by extrapolation from vibration signal and cutting condition data, which were collected in real-time by an accelerometer sensor. Experimental results showed that parameters of spindle speed, feedrate, depth of cut, and vibration variables could predict surface roughness (Ra) under eight different combinations of tool and workpiece characteristics. This neural fuzzy system was shown to predict surface roughness (Ra) with 90% prediction accuracy during a milling operation.

V. Susanto et al. ²(2003) demonstrated a fuzzy logic based in-process **tool-wear** monitoring System in **face milling operations**. The fuzzy membership function and rule bank were based on observations during cutting experiments using artificial tool-wear inserts in face milling operations. Maximum resultant force and cutting parameters (feedrate and depth of cut) were used as independent variables, and the system was verified using 25 test experimental runs. A t-test using an alpha value of 0.05 demonstrated that the system had greater than 90% accuracy when predicting tool-wear magnitude on-line. Decision-making methods, such as fuzzy logic (FL) model had been employed along with Acoustic emission (AE) sensors to monitor tool-wear during machining processes. The system employs a dynamometer to collect cutting force data, and FL was used to make decisions based on signals received from the dynamometer and the machine controller.

Joseph C. Chen et al. ³(2000) described that fuzzy logic and the neural networks systems were very effective in detecting the **breakage of cutting tools** during machining processes like **milling**. In the present study, a fuzzy-nets training procedure was developed to build the rule banks to meet the dynamic requirements of machining processes. Furthermore, two fuzzy-nets systems were combined to serve as a tool breakage detection system for an end milling operation. The system was capable of responding and adapting in "real-time" to either shut down the machine when a tool fracture occurs or tune the process parameters "on-line". When machining tools were capable of detecting tool breakage, the machine tool-life increases, a zero defect rate was approachable. The major goal of the current research was to propose a fuzzy-nets training scheme that provided adaptive control capabilities in machining process control, particularly for a tool breakage detection system.

F. Ismail et al. ⁴(1995) investigated the potential of employing the spindle speed modulation method for real-time control of **chatter in peripheral milling**. The main objective of the current work was to develop a chatter indicator that was suitable as a feedback signal for the relative vibration suppression properties of various speed modulation parameters. Experimental and simulation runs had shown that this indicator provided a well estimate of the relative cutting condition. The data (in terms of spindle

speed modulation parameters in relation to cutting stability) will further be used into develop a fuzzy logic controller for active chatter suppression.. The milling model was first described to illustrate how the dynamic and static force components were computed . Subsequently, these components were used to construct the chatter indicator.

W .Hsiang Lai ⁵(2000), According to previous research of dynamic end milling models, the instantaneous dynamic radii on every cutting position affects the cutting forces directly since the simulated forces are proportional to the chip thickness, and the chip thickness is a function of dynamic radii and federates. With the concept of flute engagement introduced, it is important to discuss it with respect to radial and axial depths of cut because the length of the engaged flutes is affected by factors in the axial feed and rotational directions. Radial and axial depths of cut affect the “contact area”, which is the area that a cutter contacts with the work piece. When radial and axial depths of cut increase, the cutting forces also increase since the engaged flute lengths are increased.

Y. Li et al ⁶(1999), proposed a method for predicting **transient state forces in milling processes** as the cutter engages with and disengages from a work piece. Analysis of this nature can contribute to the fundamental understanding of forced vibrations, deflections, and dynamic stability of multi-flute milling systems at the start and end of a cutting pass, thereby facilitating process planning, tool geometry optimization, and online diagnostics. The calculation of transient cutting forces is commonly performed with the determination of local forces and numerical integration along cutting edges. The resulting milling forces in axial, feed, and cross-feed directions are expressed explicitly in terms of work piece material properties, tool geometry, cutting parameters and process configuration.

Chang Ching-Kao et al. ⁷(2007) presented an **optimal cutting-parameter** design of heavy cutting in **side milling for SUS304 stainless steel**. The orthogonal array with grey-fuzzy logics was applied to optimize the side milling process with multiple performance characteristics. A grey-fuzzy reasoning grade obtained from the grey-fuzzy logics analysis was used as a performance index to determine the optimal cutting parameters. The selected cutting parameters were spindle speed, feed per tooth, axial depth of cut and radial depth of cut, while the considered performance characteristics were tool life and metal removal rate. The results of confirmation experiments reveal that grey-fuzzy logics can effectively acquire an optimal combination of the cutting parameters, which can further effectively improve tool life and metal removal rate. Hence, performance in the side milling process for heavy cutting can be significantly improved through this approach.

B. Ganesh babu et al. ⁸(2008) predicted the effects of cutting parameters on the variations of cutting forces during end milling operation of Al SiC metal matrix composite material. Cutting forces were measured for varying feed rates. In this study Response Surface Methodology was used by designing four factors, five level central composite rotatable design matrixes with full replication; for planning, conduction, execution and development of mathematical models. The average cutting forces were determined at different feed rates in tangential, radial, and axial directions per tooth period by keeping immersion and axial depth of cut as constant. A comparison between modeling and experiment was presented. This model and analysis were useful not only for predicting the tool wear but also for selecting optimum process parameters for achieving the stability of

the end milling process. Thus, cutting forces exerted by the cutting tool on the work piece during a machining action were identified in order to control the tool wear and occurrence of vibration, thus to improve tool-life.

Jaharah A. Ghani et al. ⁹(2006) described the tool life prediction model when end milling AISI H13 tool steel using P10 TiN coated carbide tool. The development of the model utilized the data set from the Taguchi method design of experiment with L18(21x37) orthogonal array. The effects of cutting speed, feed rate and depth of cut on tool life of P10 were discussed. A prediction model for speed within the region of 224 m/min to 355 m/min, feed rate of 0.1 mm/tooth to 0.25 mm/tooth, and depth of cut of 0.3 mm to 0.8 mm were presented. The adequacy of the predicted model after performing multiple regression analysis gave 95% confidence interval with coefficient of multiple determination(R^2) of 0.845. Whereas from average percentage deviation (ϕ) calculated, it showed that the accuracy of the predicted model was only 23%. This showed that the accuracy of the predicted model could not depend solely on the analysis performed using SPSS alone. Other methods to check the model accuracy such as average percentage deviation (ϕ) were also important.

Turnad Lenggo Ginta et al. ¹⁰(2010) presented the results of an investigation of machinability improvement in end-milling of Titanium Alloy Ti-6Al-4V as workpiece. End milling tests were conducted on the Vertical Machining Centre with full immersion cutting. Machining was performed with a 20 mm diameter end-mill tool holder fitted with one uncoated WC-Co carbide inserts. The range which was used for cutting speed, axial depth of cut, and feed, are 80.5 – 200 m/min, 0.5 – 2.0 mm, and 0.05 – 0.15 mm/tooth, respectively. Induction coil heating was utilized during end milling under preheated conditions at 315, 450, and 650°C. Flank wear had been considered as the criterion for tool failure and the wear was measured using a Scanning electron microscope (SEM). Tests were conducted until an insert was rejected when an average flank wear greater than 0.30 mm was recorded. Cutting force and torque measurements were conducted using the Kistler Rotating Cutting Force Dynamometer. Vibration during cutting was captured using an online vibration monitoring system. The results lead to the conclusion that workpiece preheating significantly increased the tool life of uncoated WC-Co carbide inserts in end-milling of Titanium Alloy Ti-6Al-4V.

M.A. Lajis et al. ¹¹(2008) developed a tool life model in end milling of hardened steel AISI D2 using PVD TiAlN coated carbide cutting tool. The hardness of AISI D2 tool lies within the range of 56-58 HRC. The independent variables or the primary machining parameters selected for this experiment were the cutting speed, feed, and depth of cut. First and second order models were developed using Response Surface Methodology (RSM). Experiments were conducted within specified ranges of the parameters. Design-Expert 6.0 software was used to develop the tool life equations as the predictive models. The predicted tool life results are presented in terms of both 1st and 2nd order equations with the aid of a statistical design of experiment software called Design-Expert version 6.0. Analysis of variance (ANOVA) had indicated that both models were valid in predicting the tool life of the part machined under specified condition and the prediction of average error was less than 10%.

2.2 Application of fuzzy logic approach to turning operation

Basim A. Khidhir et al.¹²(2010) described a modification approach applied to a fuzzy logic based model for **predicting cutting force When Machining Nickel Based Hastelloy C-276 in turning operations** where the machining parameters for cutting speed ranges, feed rate, depth of cut and approach angle were not overlapping. For this study, data were selected depending on the design of experiments. Response surface methodology was applied to predict the cutting force and to examine the fuzzy logic based model. Most Nickel based Hastelloy C-276 was a difficult-to-machine material because of its low thermal diffusive property and high strength at high temperature. Machinability consideration of nickel based Hastelloy C-276 in turning operations had been carried out using ceramic inserts under dry conditions. . Response Surface Methodology (RSM) was a combination of experimental and regression analysis and statistical inferences.

Y. H. Lee et al.¹³(1999) described a **computer-aided approach for the optimum selection of cutting conditions for a turning process**. The approach included a fuzzy non-linear Programming and neural network model. In this paper, the fuzzy non-linear programming was employed to predict optimum cutting conditions in uncertain, ill-defined and vague situations of machining operations. The fuzzy non-linear programming provides ease of implementation, flexibility and a tolerant nature to arbitrary complexity in machining operations. In addition, in this paper, the output from the fuzzy non-linear programming model was also utilized to develop a neural network model for machinability assessment. Fuzzy logic had also been applied in mathematical programming models to enhance flexibility in providing feasible solutions.

2.3 Application of fuzzy logic approach to drilling operation

Aidin Salimi et al.¹⁴(2009) proposed an intelligent system for **tool wear** monitoring in **drilling**. Experimental results of cutting and thrust forces were measured by a dynamometer and then the tool wear rates obtained for different values of forces from an analytical model. Using from experimental results of force and wear values of analytical model, fuzzy logic capabilities had been used to predict the wear rate as the force values increase. The simulation results presented with MATLAB software show the effectiveness of proposed system for on-line tool wear in drilling Operation.

Simranpreet Singh Gill et al.¹⁵(2010) described a precise fuzzy model approach required to simulate the **material removal of hard and brittle ceramics by ultrasonic drilling**. Depth of penetration, time for penetration and penetration rate were taken as model's input features. The model combined modeling function of fuzzy inference with the learning ability of artificial neural network; and a set of rules had been generated directly from experimental data. The proposed modeling approach was verified by comparing the predicted results with the actual practical results obtained by conducting the confirmation experiments.

Sivarao et al.¹⁶(2002) identified the parameters which enable the prediction of **surface roughness in drilling**. Two expert systems were used to analyze the best fit model in predicting the output of surface roughness for this specific drill job. The prediction accuracy was then compared to analyze which model could give better results so that it

can be recommended for machine learning and future work. Both had their own ability in determining the output and decision making in tool condition monitoring which determines and maintain the quality of drilled surface to its highest standard of the end product. Finally, the best Expert System was to be recommended for this specific drill job as per their limitations and advantageous upon carrying out the comparative analysis among the expert systems within the range of experimental values. From the findings, it was found that Sugeno Fuzzy model gives better the closest values as compared to the ANN model. Thus, the work conditions and Fuzzy environment was selected for predictions of surface roughness in drilling.

X. Li et al.¹⁷(2000) presented a **hybrid learning method to map the relationship between the features of cutting vibration and the tool wear condition in drilling**. The alternating direction of cutting force leads to vibrations of the machine structure. These vibrations change owing to the tool wear conditions. A neural network model with fuzzy logic (FNN), responding to learning algorithms, was presented. It had many advantageous features, such as less computation and ability to learn fast. The experimental results demonstrated the feasibility of using vibration signals to monitor the drill wear condition.

Erkki Jantunen¹⁸(2000) presented Automatic diagnosis of tool wear for unmanned use of flexible manufacturing systems and machine tools. The paper dealt with the use of regression analysis techniques together with fuzzy logic in order to overcome the challenges in tool wear monitoring. Regression analysis, based on a higher order polynomial function that emphasizes the most recent measured data and has a limited number of terms, can very well follow and give prognosis of the development of the monitored parameters from such signals as vibration, sound and acoustic emission. The use of fuzzy logic made it possible to automatically define limits for the monitored parameters and to combine the information from a number of signals. The proposed approach is tested with data from drilling tests.

Byeong-Mook Chung¹⁹(2010) described the importance to minimize or reduce occurrences of delaminations in drilling of composite laminates. In particular, a peel-up delamination at entrance and pushout delamination at exit are common. Delaminations may be avoided by regulating the drill thrust force can be controlled by adjusting the feedrate of the drill. Dynamics involved in drilling of composite laminates is time varying and nonlinear. In this paper, a fuzzy logic model and control strategy are proposed. Simulation results show that the fuzzy model can describe the nonlinear time-varying process well. The fuzzy controller realizes a fast rise time and a little overshoot of drilling force.

2.4 Study of fuzzy logic and Regression analysis in EDM operation

C. L. Lin et al.²⁰(2002) used the fuzzy logic analysis with orthogonal array and grey relational analysis method in carrying out experiments for **solving the multiple responses in the electrical discharge machining (EDM)** process. Experimental results had shown that both approaches can optimize the machining parameters (pulse on time, duty factor, and discharge current) with considerations of the multiple responses (electrode wear ratio, material removal rate, and surface roughness) effectively. Fuzzy logic analysis including the max–min fuzzy inference method was applied to deal with multiple responses using

the fuzziness of human concepts. As a result, the complicated interrelationships among the multiple responses can also be solved by the fuzzy-based approach

P. Srinivasa Rao et al. ²¹(2010) attempted to develop the mathematical model for predicting die-sinking electrical discharge machining of AISI 304 stainless steel characteristics such as the metal removal rate (MRR), the tool wear rate (TWR), the surface roughness (Ra value) and the hardness(HRB) using fuzzy mathematical method. The process parameters taken into consideration were the current (I), the open-circuit voltage (V), the servo (SV) and the dutycycle (η). A fuzzy rule base characterizing the relationship between input and output parameters was built through experiments. The design of experiments technique had been used to conduct the experiments, which in turn reduced the number of experiments. The predicted results were analyzed through experimental verification. The model predicted values and measured values were fairly close to each other. A regression analysis of experimental and predicted outputs was performed to investigate the model. It was found that the R2 values are 0.978, 0.91, 0.992 and 0.979 for the metal removal rate, the tool wear rate, the surface roughness and the hardness, respectively.

M. M. Rahman et al. ²²(2010), dealt with optimized model to investigate the effects of peak current, pulse on time and pulse off time in EDM performance on material removal rate of titanium alloy utilizing copper tungsten as electrode and positive polarity of the electrode. The experiments were carried out on Ti6Al4V by varying the peak current, pulse on time and pulse off time. A mathematical model was developed to correlate the influences of these variables and material removal rate of workpiece. Design of experiments (DOE) method and response surface methodology (RSM) techniques were implemented. The validity test of the fit and adequacy of the proposed models had been carried out through analysis of variance (ANOVA). The obtained results gave the evidence that as the material removal rate increases, the peak current and pulse on time increased. The effect of pulse off time on MRR changed with peak ampere. The optimum machining conditions in favor of material removal rate were estimated and verified with proposed optimized results. It was observed that the developed model was within the limits of the agreeable error (about 4%) when compared to experimental results. This result lead to desirable material removal rate and economical industrial machining to optimize the input parameters.

Y.M.Puri ²³(2010) presented the use of fuzzy logic in the Taguchi method to optimize Electro Discharge Machining (EDM) process with multiple quality characteristics. Electronica EZEECUT-WEDM setup was used as an experimental machine. The work-piece material used was High-Chromium-High-Carbon die steel. Rough machining with EDM gives poor surface finish and has micro cracks and pores. Finish machining gives better surface finish but with very poor machining speed (MRR). Hence achieving higher cutting speed along with better surface finish can be considered as a multi-objective optimization problem. Taguchi method has become a powerful tool in the design of experiments as it improves performance characteristics by optimizing the process parameters and reduces sensitivity of the system performance to noise. Thus, experimental results are then transformed into a signal-to-noise (S/N) ratio. The S/N ratio can be used to measure the deviation of the performance characteristics from the desired values. However, Taguchi method can optimize single performance characteristics at a time.

Hence Taguchi approach was coupled with fuzzy logic for optimization of multiple quality characteristics. Furthermore, a statistical analysis of variance (ANOVA) is performed to identify the process parameters that are statistically significant. The optimal combination of the process parameters can then be predicted based on the above analysis. Experimental results confirm that this approach was simple, effective and efficient for simultaneous optimization of multiple quality characteristics i.e. MRR and surface finish in EDM.

CHAPTER 3

FUZZY LOGIC APPROACH

3.1 Fuzzy Logic (FL) and related terms

Logic started as the study of language in arguments and persuasions, and it may be used to judge the correctness of a chain of reasoning, in a mathematical proof for example. In two valued logic a proposition is either truth or false, but not both. The "truth" or "falsity" which is assigned to a statement is its truth-value. In Fuzzy Logic, a proposition may be true or false or have an intermediate truth-value, such as may be true. The sentence level is high an example of such a proposition in a fuzzy controller. 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; in that case we are dealing with multi-valued logic. In practice a finer subdivision of the unit interval may be more appropriate.

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. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions. Fuzzy logic emerged as a consequence of the 1965 proposal of fuzzy set theory by Lotfi Zadeh. 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), probability theory uses the concept of subjective probability (i.e., how probable do I think that a variable is in a set).

1) Fuzzy sets are a further development of the mathematical concept of a set. Sets were first studied formally by the German mathematician Georg Cantor (1845-1918). His theory of sets met much resistance during his lifetime, but nowadays most mathematicians believe it is possible to express most, if not all, of mathematics in the language of set theory. Many researchers are looking at the consequences of 'fuzzifying' set theory, and much mathematical literature is the result. For control engineers, fuzzy logic and fuzzy relations are the most important in order to understand how fuzzy rules work.

2) Conventional set is a collection of objects which can be treated as a whole. Cantor described a set by its members, such that an item from a given universe is either a member or not. The terms set, collection and class are synonyms, just as the terms *item*, *element* and *member*. Almost anything called a set in ordinary conversation is an acceptable set in the mathematical sense.

3) Universe: Elements of a fuzzy set are taken from a Universe of discourse or Universe for short. The universe contains all elements that can come into consideration. Even the universe depends on the context.

4) Membership Function: Every element in the universe of discourse is a member of the fuzzy set to some grade, maybe even zero. The set of elements that have a non-zero membership is called the Support of the fuzzy set. The function that ties a number to each element x of the universe is called the Membership Function.

5) Normalisation: A fuzzy set is normalised if its largest membership value =1. You normalise by dividing each membership value by the largest membership in the set, $a/\max(a)$.

6) Linguistic Variables: Just like an algebraic variable takes numbers as values, a Linguistic Variable takes words or sentences as values. The set of values that it can take is called its term set. Each value in the term set is a Fuzzy Variable defined over a base variable. The base variable defines the universe of discourse for all the fuzzy variables in the term set. In short, the hierarchy is as follows linguistic variable to fuzzy variable to base variable.

7) Inference: In order to draw conclusions from a rule base we need a mechanism that can produce an output from a collection of if *then* rules. This is done using the compositional rule of inference (CROI). The verb to infer means to conclude from evidence, deduce, or to have as a logical consequence – do not confuse 'inference' with 'interference'. To understand the concept, it is useful to think of a function $y=f(x)$, where f is a given function, x is the independent variable, and y the result; a value y_0 is inferred from x_0 given f .

3.2 Why to choose fuzzy logic

1. Because of rule base operation any reasonable number of inputs can be processed and the numerous outputs can be generated.
2. FL is inherently robust and don't require precise.
3. FL can control non linear systems that would be difficult are impossible to model mathematically.
4. FL can give accurate result.
5. Since FL control processes user defined rules governing the target control system. It may be modified easily to improve performance.

Fuzzy logic deals with uncertainty in engineering by attaching degrees of certainty to the answer to a logical question. Why should this be useful? The answer is commercial and practical. Commercially, fuzzy logic has been used with great success to control machines and consumer products. In the right applications fuzzy logic systems are simple to design, and can be understood and implemented by non-specialists in control theory. In most cases someone with an intermediate technical background can design a fuzzy logic controller. The control system will not be optimal but it can be acceptable. Control engineers also use it in applications where the on-board computing is very limited and adequate control is enough. Fuzzy logic is not the answer to all technical problems, but for control problems where simplicity and speed of implementation is important then fuzzy logic is a strong candidate. Fuzzy technologies and devices can be applied successfully in areas such as robotics and motion control, evaluation of design alternatives, decision making, and the design of intelligent systems, in materials selection involving multi-criteria, image processing and machine vision.

3.3 A cross section of applications that have successfully used fuzzy control includes

- Air Conditioners, Humidifiers
- Washing Machines/Dryers, Vacuum Cleaners, Toasters, Microwave Ovens, Refrigerators
- Television, Photocopiers, Still and Video Cameras, Hi-Fi Systems
- Vehicle Climate Control, Automatic Gearboxes, Four – Wheel Steering, Seat/Mirror Control Systems

3.4 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.

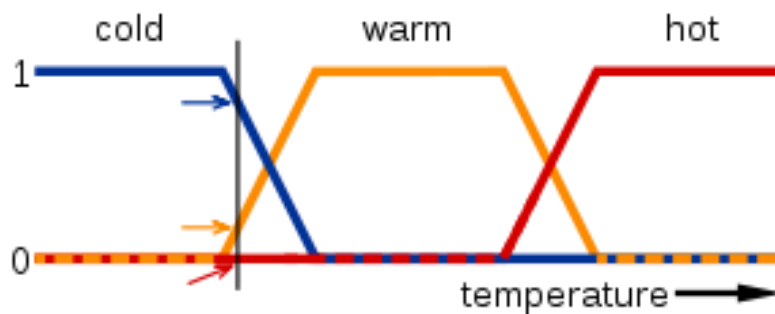


Fig 3.1: Fuzzy logic temperature

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".

3.5 A Fuzzy Logic System

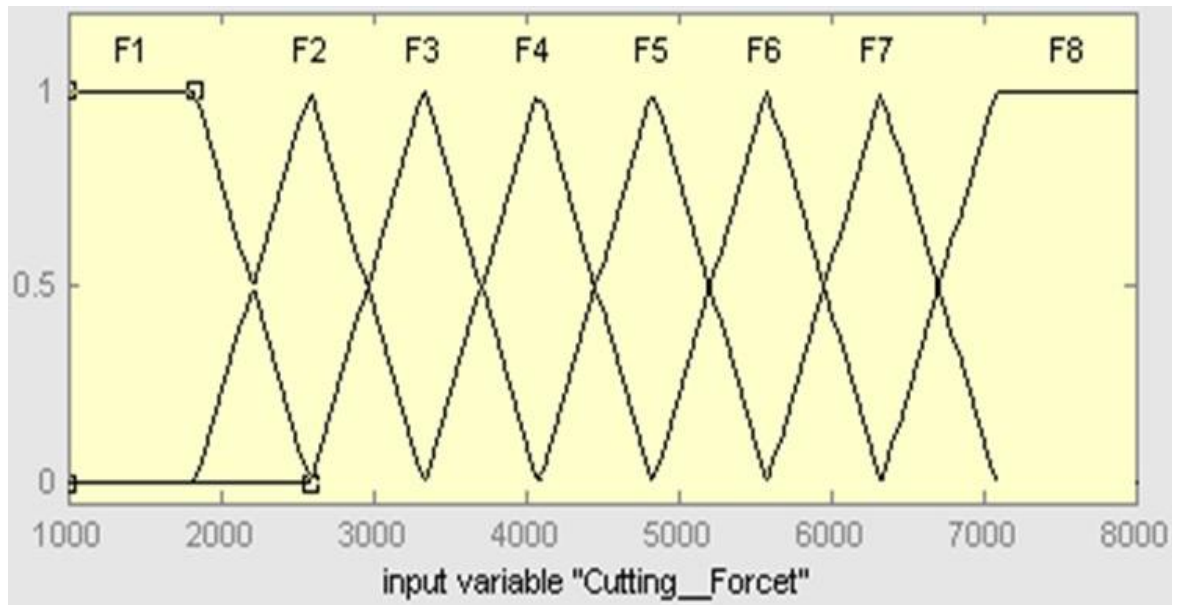


Fig 3.2: Input Membership Function-Cutting force

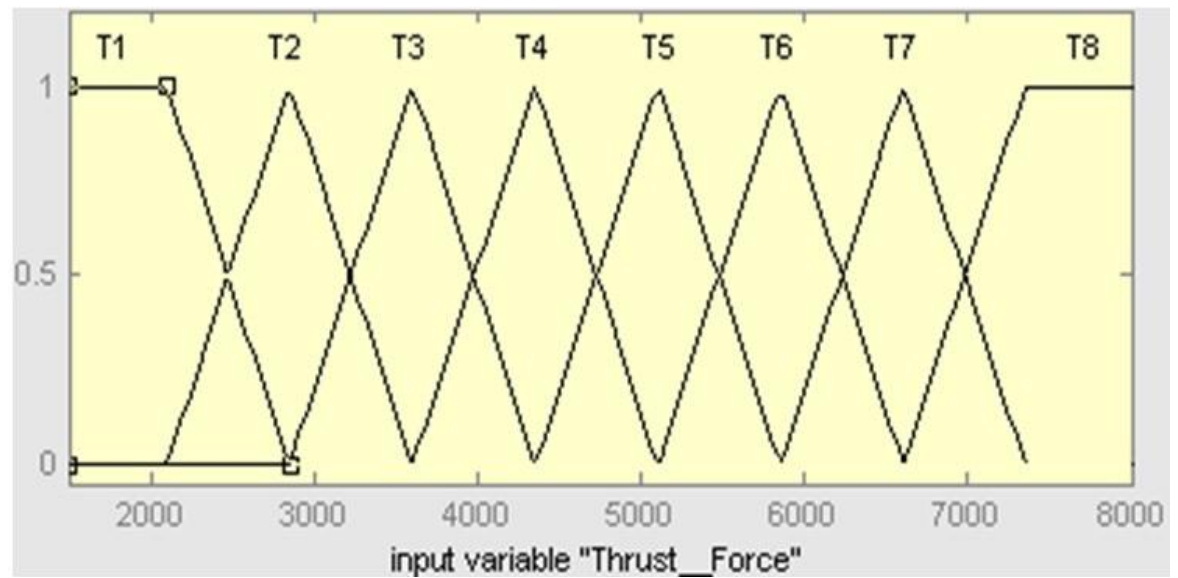


Fig 3.3: Input Membership Function-Thrust force

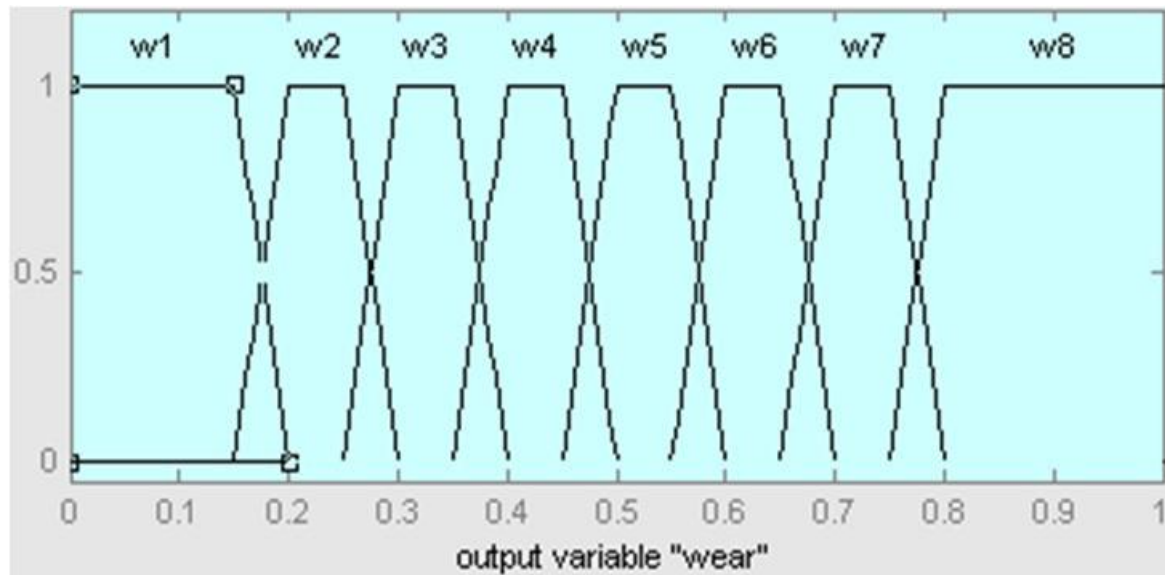


Fig 3.4: Output Member Function-Wear

1. If (Cutting_Forcet is F1) and (Thrust_Force is T1) then (wear is w1) (1)
2. If (Cutting_Forcet is F1) and (Thrust_Force is T2) then (wear is w1) (1)
3. If (Cutting_Forcet is F2) and (Thrust_Force is T1) then (wear is w1) (1)
4. If (Cutting_Forcet is F2) and (Thrust_Force is T2) then (wear is w2) (1)
5. If (Cutting_Forcet is F2) and (Thrust_Force is T1) then (wear is w2) (1)
6. If (Cutting_Forcet is F1) and (Thrust_Force is T2) then (wear is w2) (1)
7. If (Cutting_Forcet is F2) and (Thrust_Force is T3) then (wear is w2) (1)
8. If (Cutting_Forcet is F3) and (Thrust_Force is T2) then (wear is w2) (1)
9. If (Cutting_Forcet is F3) and (Thrust_Force is T3) then (wear is w3) (1)
10. If (Cutting_Forcet is F3) and (Thrust_Force is T2) then (wear is w3) (1)
11. If (Cutting_Forcet is F3) and (Thrust_Force is T4) then (wear is w3) (1)
12. If (Cutting_Forcet is F4) and (Thrust_Force is T3) then (wear is w3) (1)
13. If (Cutting_Forcet is F2) and (Thrust_Force is T3) then (wear is w3) (1)
14. If (Cutting_Forcet is F4) and (Thrust_Force is T4) then (wear is w4) (1)
15. If (Cutting_Forcet is F4) and (Thrust_Force is T5) then (wear is w4) (1)
16. If (Cutting_Forcet is F5) and (Thrust_Force is T4) then (wear is w4) (1)
17. If (Cutting_Forcet is F3) and (Thrust_Force is T4) then (wear is w4) (1)
18. If (Cutting_Forcet is F4) and (Thrust_Force is T3) then (wear is w4) (1)
19. If (Cutting_Forcet is F5) and (Thrust_Force is T5) then (wear is w5) (1)
20. If (Cutting_Forcet is F5) and (Thrust_Force is T4) then (wear is w5) (1)
21. If (Cutting_Forcet is F4) and (Thrust_Force is T5) then (wear is w5) (1)
22. If (Cutting_Forcet is F5) and (Thrust_Force is T6) then (wear is w5) (1)
23. If (Cutting_Forcet is F6) and (Thrust_Force is T5) then (wear is w5) (1)
24. If (Cutting_Forcet is F6) and (Thrust_Force is T6) then (wear is w6) (1)
25. If (Cutting_Forcet is F7) and (Thrust_Force is T6) then (wear is w6) (1)
26. If (Cutting_Forcet is F6) and (Thrust_Force is T7) then (wear is w6) (1)
27. If (Cutting_Forcet is F5) and (Thrust_Force is T6) then (wear is w6) (1)
28. If (Cutting_Forcet is F6) and (Thrust_Force is T5) then (wear is w6) (1)
29. If (Cutting_Forcet is F7) and (Thrust_Force is T7) then (wear is w7) (1)
30. If (Cutting_Forcet is F8) and (Thrust_Force is T7) then (wear is w7) (1)
31. If (Cutting_Forcet is F7) and (Thrust_Force is T8) then (wear is w7) (1)
32. If (Cutting_Forcet is F7) and (Thrust_Force is T6) then (wear is w7) (1)
33. If (Cutting_Forcet is F6) and (Thrust_Force is T7) then (wear is w7) (1)
34. If (Cutting_Forcet is F8) and (Thrust_Force is T8) then (wear is w8) (1)
35. If (Cutting_Forcet is F8) and (Thrust_Force is T7) then (wear is w8) (1)
36. If (Cutting_Forcet is F7) and (Thrust_Force is T8) then (wear is w8) (1)

Fig 3.5: 36 rules which applied to Sugeno fuzzy system

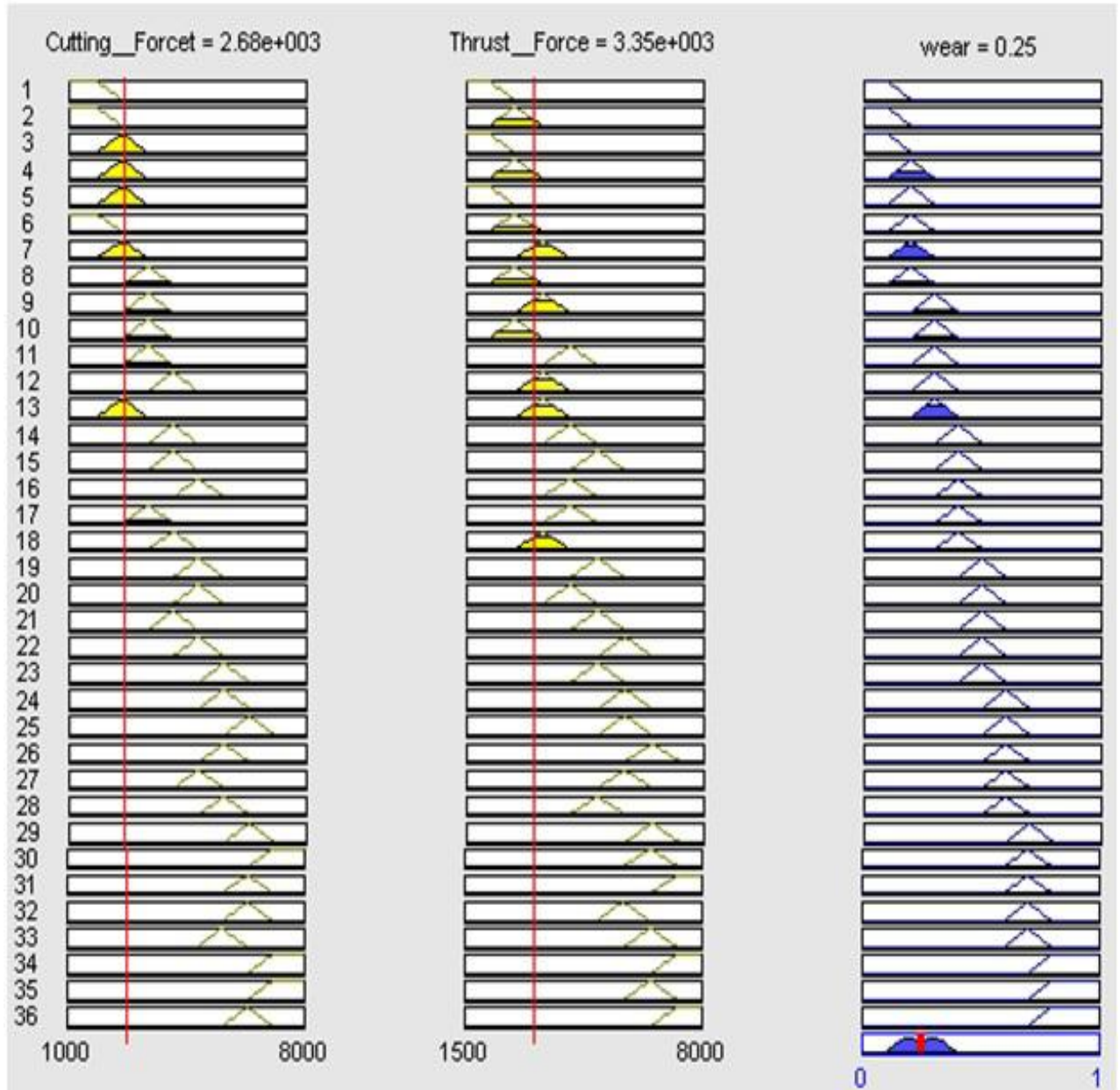


Fig 3.6: FUZZY RULE BASE SYSTEM

The rule view window allows direct simulation of the input to the FIS showing the resulting input and output membership functions. The graphs on the left correspond to the input membership functions; the red line indicates the current input value. It can be moved to simulate different input values. Where this line crosses the membership functions are the values which represent the degree to which the input is believed to belong to that particular membership. The graphs on the right are the output membership functions. Notice that they have been AND with the value of the input membership function. The bottom right output function represents the output of the FIS. The red bar on this graph indicates where the estimated value for the output variable lies. Experiment with the FIS to see how the value of the input function effects the output.

CHAPTER 4

PROBLEM FORMULATION

4.1 INTRODUCTION

The objective of this study is to predict the effects of cutting parameters on the variations of cutting forces during end milling operation on vertical milling machine. The cutting forces will be measured using the dynamometer for varying the feed rate, speed and depth of cut. The different values of cutting forces evaluated were used as input for obtaining tool wear rates in MATLAB 7.0 Software. Thus, Using from experimental results of force and wear values of analytical model, fuzzy logic capabilities have been used to predict the wear rate as the force values increase. In the present study the comparison will be made between data for experimental study and software study comparing the data for variation of Tool Wear Rates in MATLAB software. This model and analysis are useful not only for predicting the tool wear but also for selecting optimum process parameters for achieving the stability of the end milling process. To reduce the total number of experiments and to obtain data uniformly from all the regions of the selected working area, a Taguchi design procedure has been adopted

The key factor in Problem formulation is to obtain sufficient experimental data simulating the working environment in the laboratory. Five independently controllable factors affecting the wear performance will be identified as the Depth of cut (d), Feed rate (F), Cutting speed, cutting and thrust forces. To reduce the total number of experiments, the secondary parameters that will be kept constant during the machining process will be tool geometry and the tool height. In order to develop this system, a metal cutting experiment on a vertical milling machine (VMC) is required. A dynamometer will be mounted on the worktable and a work piece on the top of the dynamometer. Cutting force signals should be transmitted from the table mount dynamometer to the amplifier to the system. The fuzzy membership functions and rule bank will be based on observations during cutting experiment.

4.2 INPUT PROCESS PARAMETERS

D - Diameter of milling cutter (in mm)
F – Feed rate (mm/min)
f – Feed rate (mm/tooth)
N - Number of teeth in the cutter
C.S.-Cutting speed of milling cutter (in surface mm per minute)
P – Power required for the operation (KW)
d- Depth of cut (mm)

4.3 OUTPUT PROCESS PARAMETERS

Material Removal Rate
Tool wear rate
Surface Hardness

4.4 SPECIFICATIONS OF VERTICAL MACHINING CENTER

1. Machine Number 883/2/90
2. Machine type VM-25-A
3. Manufacturers New Bharat engineering works(Jamnagar) Private Ltd
4. Motor number 807 (3- phase)
5. Horse power of driving motor 0.75/1 HP
6. Voltage 415 volts
7. Current 1.3/1.9 Amps
8. RPM 1400/2800 rpm
9. Cycles 50

10. Cutting Speeds on VMC (in m/min.):

A	102	204	340	450
B	680	900	1450	2900

11. Depth of cuts (in mm) 0, 0.25, 0.50, 0.75, 1, 1.25

12. Feed (in mm/min)

A	20	35	65
B	100	175	315

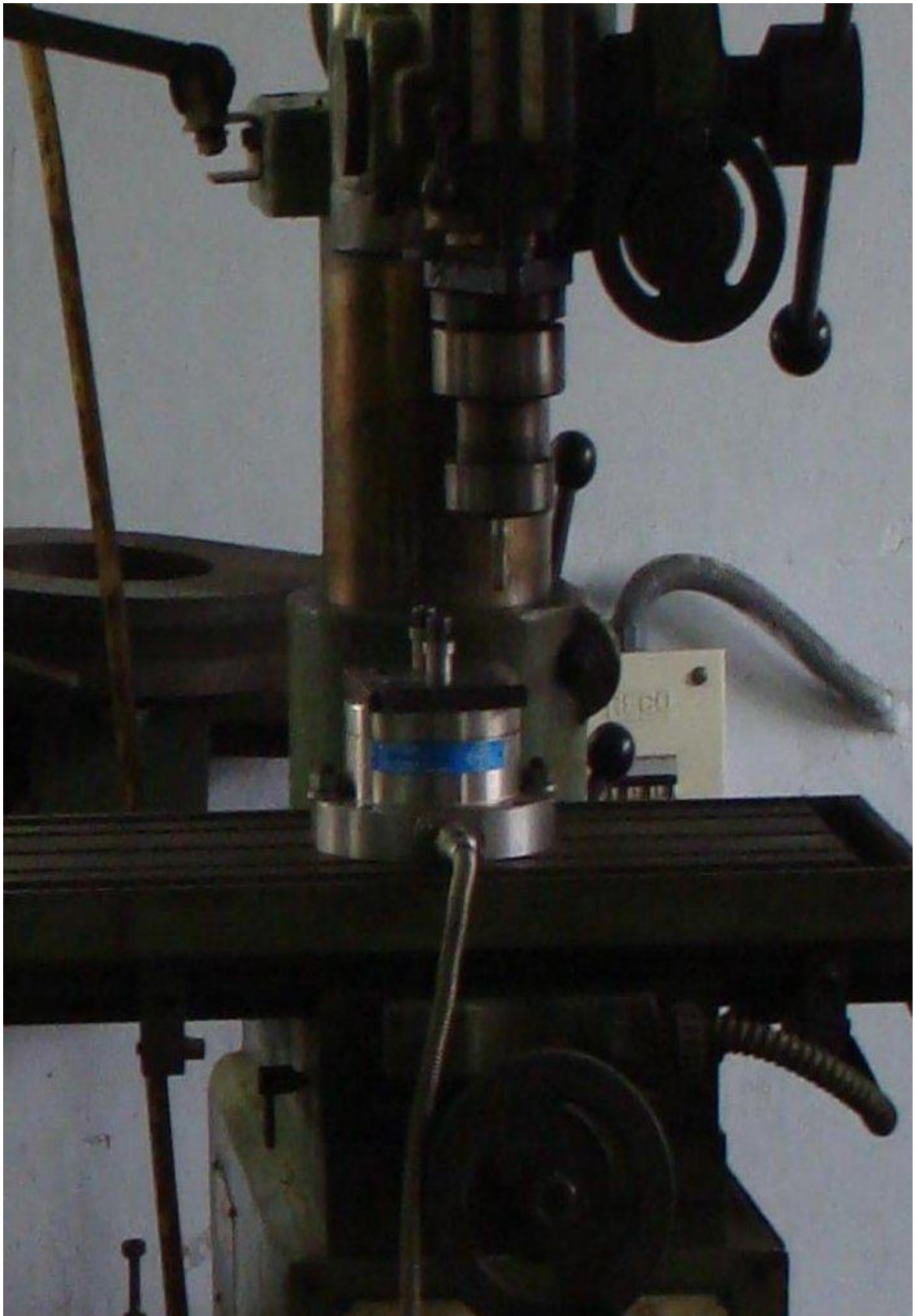


Fig 4.1: Proposed Machine Piezo-electric three-component dynamometer (Kistler, Type 5070A)

4.5 Dynamometer

A dynamometer is a device used for measuring force, moment of force (torque), or power. For example, the power produced by an engine, motor or other rotating prime mover can be calculated by simultaneously measuring torque and rotational speed(rpm). A dynamometer can also be used to determine the torque and power required to operate a driven machine such as a pump. In that case, A *motoring or driving* dynamometer is used. A dynamometer that is designed to be driven is called an absorption or passive dynamometer. A dynamometer that can either drive or absorb is called a universal or active dynamometer.



Figure 4.2:- Work piece mounted on dynamometer

- **Principle of Absorbing Dynamometer**

An absorbing dynamometer acts as a load that is driven by the prime mover that is under test. The dynamometer must be able to operate at any speed and load to any level of torque that the test requires. Absorbing dynamometers are not to be confused with "inertia" dynamometers, which calculate power solely by measuring power required to accelerate a known mass drive roller and provide no variable load to the prime mover. An Absorption dynamometer is usually equipped with some means of measuring the operating torque and speed. In most dynamometers power (P) is not measured directly; it must be calculated from torque (τ) and angular velocity (ω) values or force (F) and linear velocity (v).

$$P = \tau \cdot \omega$$

or

$$P = F \cdot v$$

Table 4.1 Specifications Of Dynamometer

Calibration			Calibrated
Measuring Range	Fx, Fy, Fz	KN	± 5
Sensitivity	Fx, Fy	pC/N	≈ 7.5
	Fz	pC/N	≈ 3.7
Natural Frequency	Fnx	KHz	≈ 2.3
	Fny	KHz	≈ 3.5
Operating temperature range		$^{\circ}\text{C}$	0...70
Length		Mm	≈ 170
Width		Mm	≈ 100
Height		Mm	≈ 60

A two component cutting force dynamometer of cantilever type is used in the present work. The dynamometer structure is made of aluminum. The dynamometer is mounted on the table with the help of fasteners which are further tightened on T- slots. The work piece is mounted on a dynamometer (Kistler 9257A) linked to an acquisition data system in order to measure also the loads during milling. The action of the forces is to bend the structure. The axial cutting force bends the structure about the one axis and the tangential feed force bends the structure about another axis. The force is displayed on the display meter which is connected with the dynamometer.

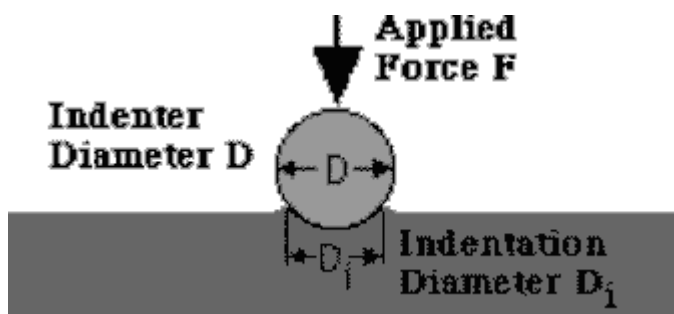
4.6 The Brinell Hardness Test

The Brinell hardness test consists of indenting the test material with a 10 mm diameter hardened steel or carbide ball subjected to a load of 3000 kg. For softer materials the load can be reduced to 1500 kg or 500 kg to avoid excessive indentation. The full load is normally applied for 10 to 15 seconds in the case of iron and steel and for at least 30 seconds in the case of other metals.



Figure 4.3: Brinell Hardness Testing Machine

The Brinell hardness number is calculated by dividing the load applied by the surface area of the indentation.



$$\text{BHN} = \frac{F}{\frac{\pi}{2} D \cdot (D - \sqrt{D^2 - D_i^2})}$$

where:

F = applied force ([kgf](#))

D = diameter of indenter (mm)

D_i = diameter of indentation (mm)

A well structured Brinell hardness number reveals the test conditions, and looks like this, "75 HB 10/500/30" which means that a Brinell Hardness of 75 was obtained using a 10mm diameter hardened steel with a 500 kilogram load applied for a period of 30 seconds.

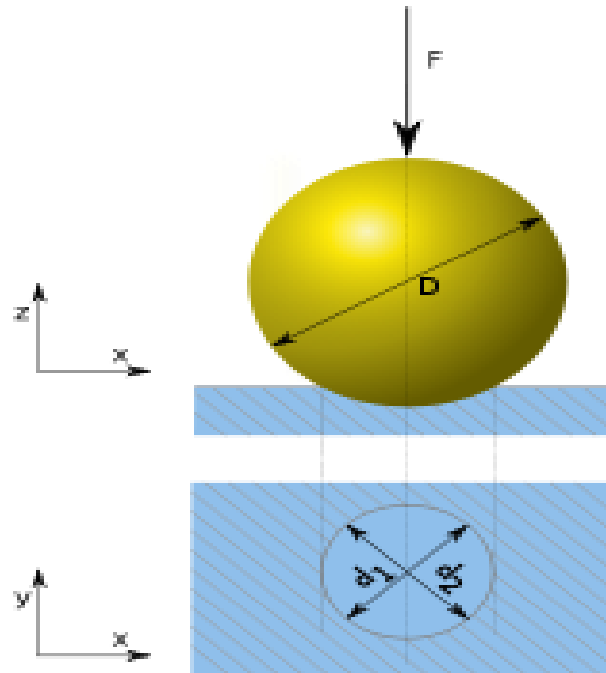


Fig 4.4: Force diagram

The **Brinell scale** characterizes the indentation hardness of materials through the scale of penetration of an indenter, loaded on a material test-piece. It is one of several definitions of hardness in materials science. Proposed by Swedish engineer Johan August Brinell in 1900, it was the first widely used and standardised hardness test in engineering and metallurgy. For softer materials, a smaller force is used; for harder materials, a tungsten carbide ball is substituted for the steel ball.

CHAPTER 5

EXPERIMENTAL SETUP, DESIGN AND ANALYSIS OF DATA

An experimental set-up is developed for the measurement of forces during the milling process.

5.1 OUTLINE OF THESIS WORK

The recent study consists of experimentations, parametric analysis using MATLAB 7.0 software and finally theoretical modeling using MINITAB software. The Experiment has been conducted by milling the Mild steel material, using HSS end mill cutter with 8mm diameter and four tooth tool in a vertical Milling machine. Experiments were carried out under various cutting conditions. The cutting force components in feed, tangential, and radial directions have been measured with a Piezo-electric three component dynamometer (Kistler, Type 5070A), a multi channel charge amplifier (Kistler, Type 5070A) and a data acquisition system. Once forces are known in 3-D space, these are fed into MATLAB input table and we can compare the fuzzy result and the wear simulation result by the model. For validation of experiment results we need theoretical method, for that purpose 1st order mathematical equation is used and its coefficients are calculated using MINITAB. Once we have a valid mathematical model compatible with experimentation we don't need to repeat experiments for large number of time. Here we can feed the parameters and we will get the desirable forces thus saving lot of effort and time.

For experimentation a KISTLER DYNO WARE is installed on the machine bed. According to the design of experiment input variables are varied while in the end milling the forces on the work pieces are calculated by dynamometer, which was coupled with CPU for each set of reading 100 sec time duration. Next section gives the detailed study of force reading given by dynamometer for specified duration of time. Test conditions leading to various components of cutting force in Mild Steel material were chosen. To reduce the total number of experiments and to obtain data uniformly from all the regions of the selected working area, a Taguchi design procedure has been adopted.

5.2 TAGUCHI DESIGN

Dr. Genichi Taguchi is regarded as the foremost proponent of robust parameter design. Taguchi techniques have been used widely in engineering design [Ross (1996) and Phadke (1989)]. In particular, it is recommended for analyzing metal cutting problems for finding the optimal combination of parameters. It mainly uses the parameter design, which is an engineering method for product or process design that focuses on determining the parameter(factor) settings producing the best levels of a quality characteristic (performance measure) with minimum variation. Taguchi designs provide a powerful and efficient method for designing processes that operate consistently and optimally over a variety of conditions. To determine the best design requires the use of a strategically designed experiment which exposes the process to various levels of design parameters. Taguchi's approach to design of experiments is easy to adopt and apply for users with limited knowledge of statistics; hence it has gained a wide popularity in the engineering and scientific community.

Further, depending on the number of factors, interactions and their level, an orthogonal array is selected by user. Taguchi has used signal-noise (S/N) ratio as the **quality characteristic of choice**. Signal represents the desirable value and Noise represents the Undesirable value. Objective of using S/N Ratio is a measure of performance to develop products and processes insensitive to noise factors. So, S/N ration indicates the degree of predictable performance of a product or process in presence of noise factors.

1) $S/N = 10 \log [(average \text{ of observed data e.g., MRR}) / (square \text{ of Variation of observed data})]$

2) $S/N = -10 \log [(summation \text{ of square of observed data}) / (number \text{ of observations})]$

3) $S/N = -\log [summation \text{ of } (1/square \text{ of observed data}) / (number \text{ of observations})]$

Smaller is the best characteristic, larger the better characteristic and largest is a good characteristic.

Taguchi Orthogonal Array Design

L9 (3**3)

Factors: 3, Runs: 9

Table 5.1: Columns of L9 (34) Array using 1 2 3 as factor levels**

A	B	C
1	1	1
1	2	2
1	3	3
2	1	2
2	2	3
2	3	1
3	1	3
3	2	1
3	3	2

Table 5.2: Factor and their levels

S.No.	Machining Parameters	Unit	Notation	Factor Levels		
				1(low)	2(center)	3(high)
1	Feed Rate	mm/min	F	100	175	315
2	Cutting Speed	m/min	V	204	450	680
3	Depth of cut	mm	A	0.25	0.50	0.75

5.3 DEVELOPMENT OF REGRESSION ANALYSIS USING MINITAB- 15

The response function representing the output performance can be expressed as:

$$Y=f(V, F, A)$$

Where Y = the response or yield.

The values of the coefficients of the polynomial were calculated by regression method. The magnitude of the regression co-efficient is a good indication of the significance of the parameters. A statistical analysis software package **MINITAB-15** was used to calculate the values of these coefficients and also to determine the significant direct and interaction effects precisely. For the required response, all of the 9 observed values are given to the software as input. The significance of the coefficients was evaluated and insignificant coefficients are not included in the model.

The adequacy of the model was tested using the analysis of variance technique. As per this technique, the calculated value of the F-ratio of the model developed does not exceed the standard tabulated value of F-Ratio for a desired level of confidence say 95 %.

5.3.1 Regression Analysis using MINITAB: MRR (Material removal rate) versus Speed, Feed, D.O.C (depth of cut)

Speed	Feed	D.O.C	MRR	RESI1	SRES1	COEF1	FITS1
204	100	0.25	2.40	-0.39678	-0.55169	-4.94803	2.7968
204	175	0.50	4.30	0.65362	0.76376	0.02640	3.6464
204	315	0.75	7.96	0.18004	0.30624	0.01775	7.7800
450	100	0.50	9.72	-0.15543	-0.16727	2.33333	9.8754
450	175	0.75	12.31	0.51989	0.58366		11.7901
450	315	0.25	11.84	-1.26861	-1.67645		13.1086
680	100	0.75	15.36	-1.17163	-1.70325		16.5316
680	175	0.25	17.89	1.19370	1.53071		16.6963
680	315	0.50	20.21	0.44520	0.56974		19.7648

Where RESI = residual, SRES1= standardized residual,

COEF1= coefficients, FITS1= Fitted values or predicted values.

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The regression equation is

$$\text{MRR} = -4.95 + 0.0264 \text{ Speed} + 0.0178 \text{ Feed} + 2.33 \text{ D.O.C}$$

Predictor	Coef	SE Coef	T	P	VIF
Constant	-4.948	1.386	-3.57	0.016	
Speed	0.026404	0.001809	14.60	0.000	1.008
Feed	0.017751	0.003794	4.68	0.005	1.008
D.O.C	2.333	1.715	1.36	0.232	1.000

S = 1.05040, R-Sq = 98.0%, R-Sq (adj) = 96.9%,
PRESS = 21.3544, R-Sq (pred) = 92.44%

Where SE coef= Standard error of coefficient, T= t-test, P= P-value,
VIF= Variance inflation factor, S= Standard deviation,
R-Sq= R^2 (R-squared), R-Sq (adj) = adjustable R^2 ,
PRESS = Prediction sum of squares, R-Sq (pred) = predicted R^2

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	3	276.947	92.316	83.67	0.000
Residual Error	5	5.517	1.103		
Total	8	282.464			

Source	DF	Seq SS
Speed	1	250.757
Feed	1	24.149
D.O.C	1	2.042

Where DF= Degree of freedom, SS= Sum of squares, MS= Mean squares,
F= F-test, P= P-value, Seq SS= Sequential Sum of squares

 **Regression analysis** generates an equation to describe the statistical relationship between one or more predictors and the response variable and to predict new observations. Regression generally uses the ordinary least squares method which derives the equation by minimizing the sum of the squared residuals. Regression results indicate the direction, size, and statistical significance of the relationship between a predictor and response.

Analysis of Variance (ANOVA) is similar to regression  in that it is used to investigate and model the relationship between a response variable  and one or more predictor variables . However, analysis of variance differs from regression in two ways: the predictor variables are qualitative (categorical ), and no assumption is made about the nature of the relationship (that is, the model does not include coefficients for variables).

Residual is the difference between an observed value (y) and its corresponding fitted value ($\hat{y}$). Residual values are especially useful in regression and ANOVA procedures because they indicate the extent to which a model accounts for the variation in the observed data.

Standardized residuals (or internally Studentized residuals) equals the value of a residual, e.g., divided by an estimate of its standard deviation.

Coefficients (Coef): The numbers by which the variables in an equation are multiplied. For example, in the equation $y = -3.6 + 5.0X_1 - 1.8X_2$, the variables X_1 and X_2 are multiplied by 5.0 and -1.8, respectively, so the coefficients are 5.0 and -1.8.

P-value for each coefficient tests the null hypothesis that the coefficient is equal to zero (no effect). Therefore, low p-values suggest the predictor is a meaningful addition to your model. Determines the appropriateness of rejecting the null hypothesis in a hypothesis test. P-values range from 0 to 1. The smaller the p-value, the smaller the probability that rejecting the null hypothesis is a mistake.

Variance inflation factor (VIF) indicates the extent to which multicollinearity (correlation among predictors) is present in a regression analysis. Multicollinearity is problematic because it can increase the variance of the regression coefficients, making them unstable and difficult to interpret.

R^2 (R-squared) is the Percentage of response variable variation that is explained by its relationship with one or more predictor variables. In general, the higher the R^2 , the better the model fits your data. R^2 is always between 0 and 100%. It is also known as the coefficient of determination or multiple determinations (in multiple regression).

Sum of squares (SS) represents a measure of variation or deviation from the mean. It is calculated as a summation of the squares of the differences from the mean. In ANOVA, the total sum of squares helps express the total variation that can be attributed to various factors

Sequential sum of squares (Seq SS) depends on the order the factors are entered into the model. For example, if you have a model with three factors, X1, X2, and X3, the sequential sum of squares for X2 shows how much of the remaining variation X2 explains, given that X1 is already in the model.

Standard error of coefficient: The standard deviation of the estimate of a regression coefficient. It measures how precisely your data can estimate the coefficient's unknown value. Its value is always positive, and smaller values indicate a more precise estimate.

t-test: A hypothesis test of the mean of one or two normally distributed populations. t-test in regression output whether the values of coefficients in the regression equation differ significantly from zero.

Prediction sum of squares (PRESS) is used to calculate the predicted R^2 which is generally more intuitive to interpret. In general, the smaller the PRESS value, the better the model's predictive ability.

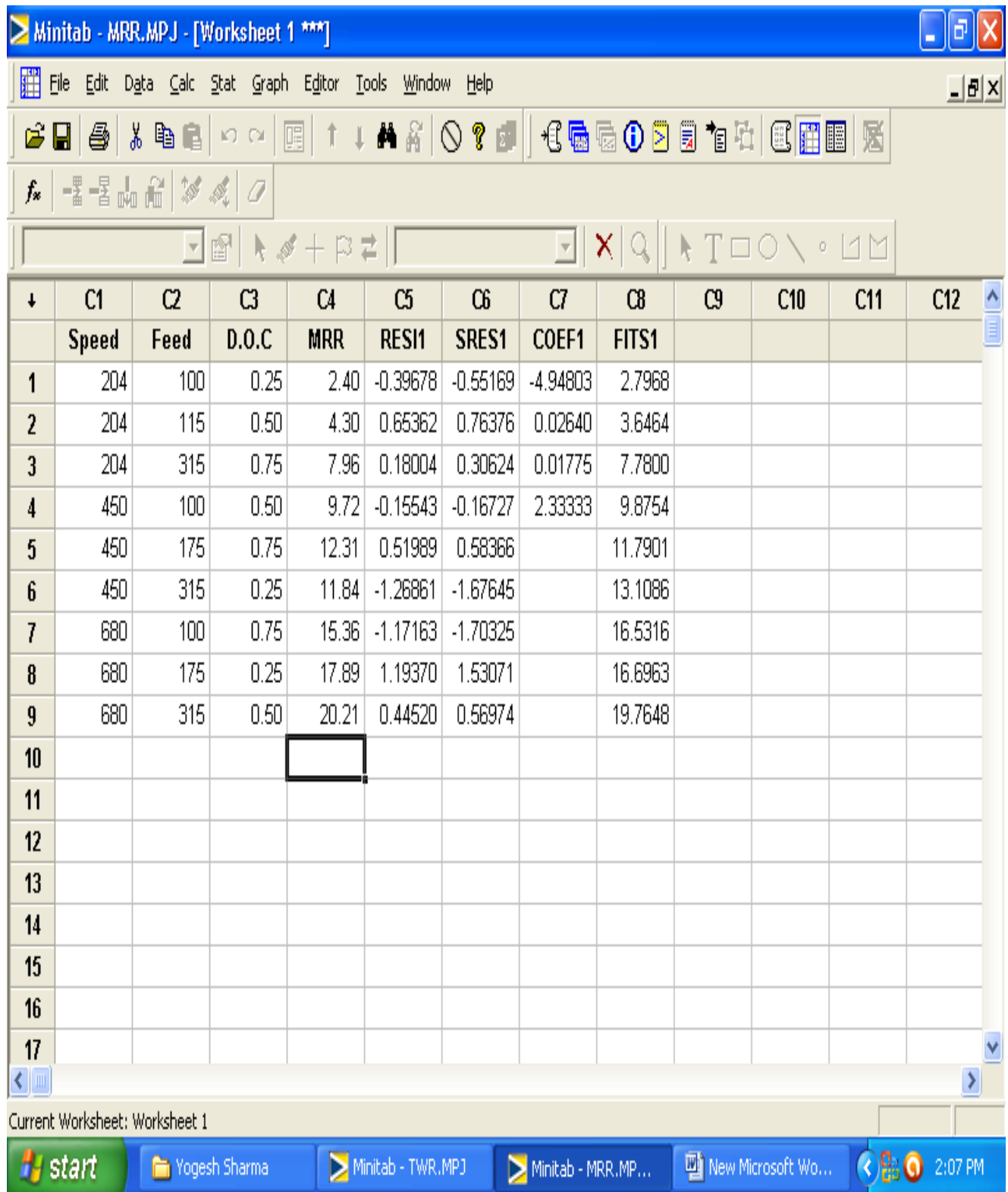
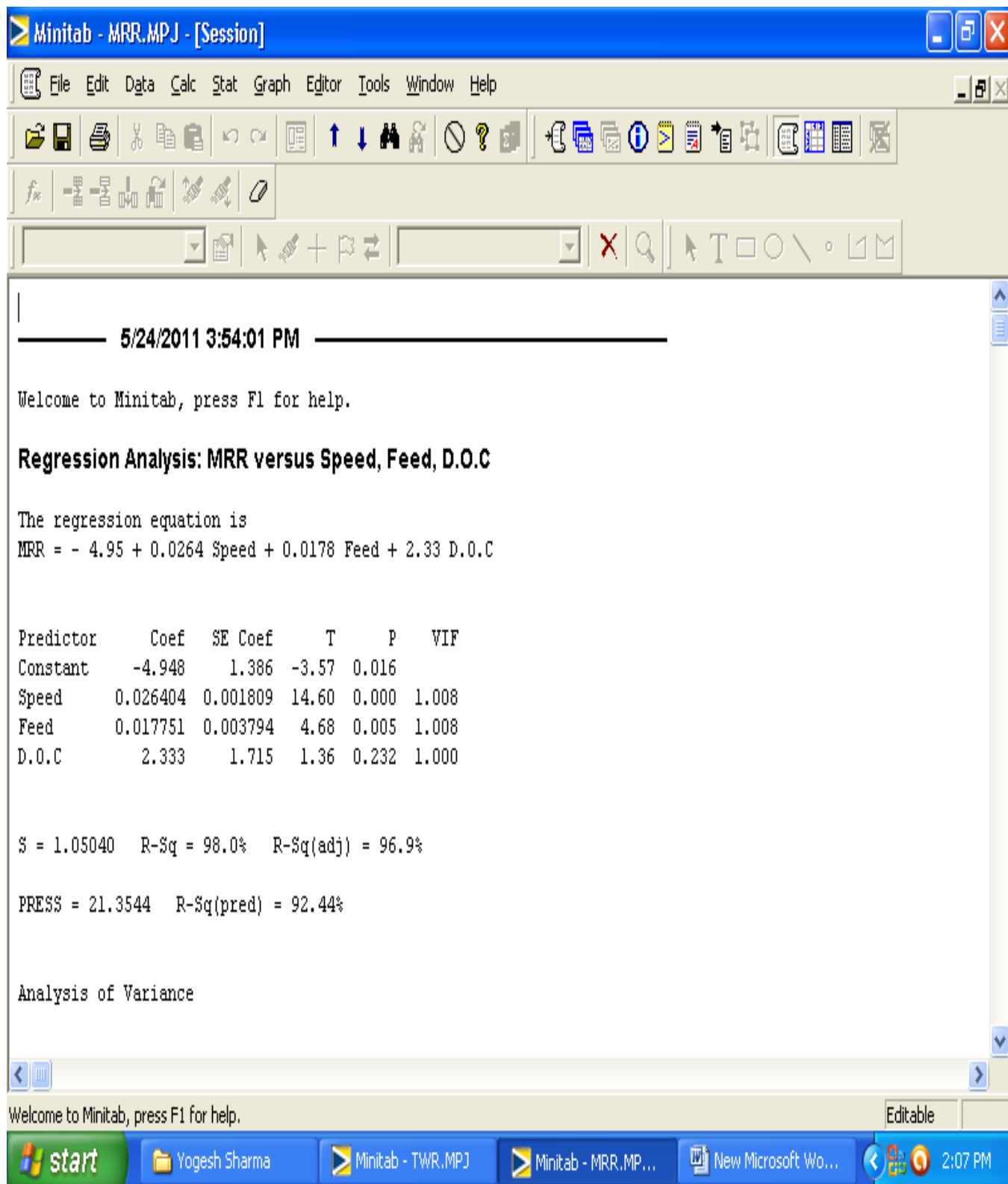
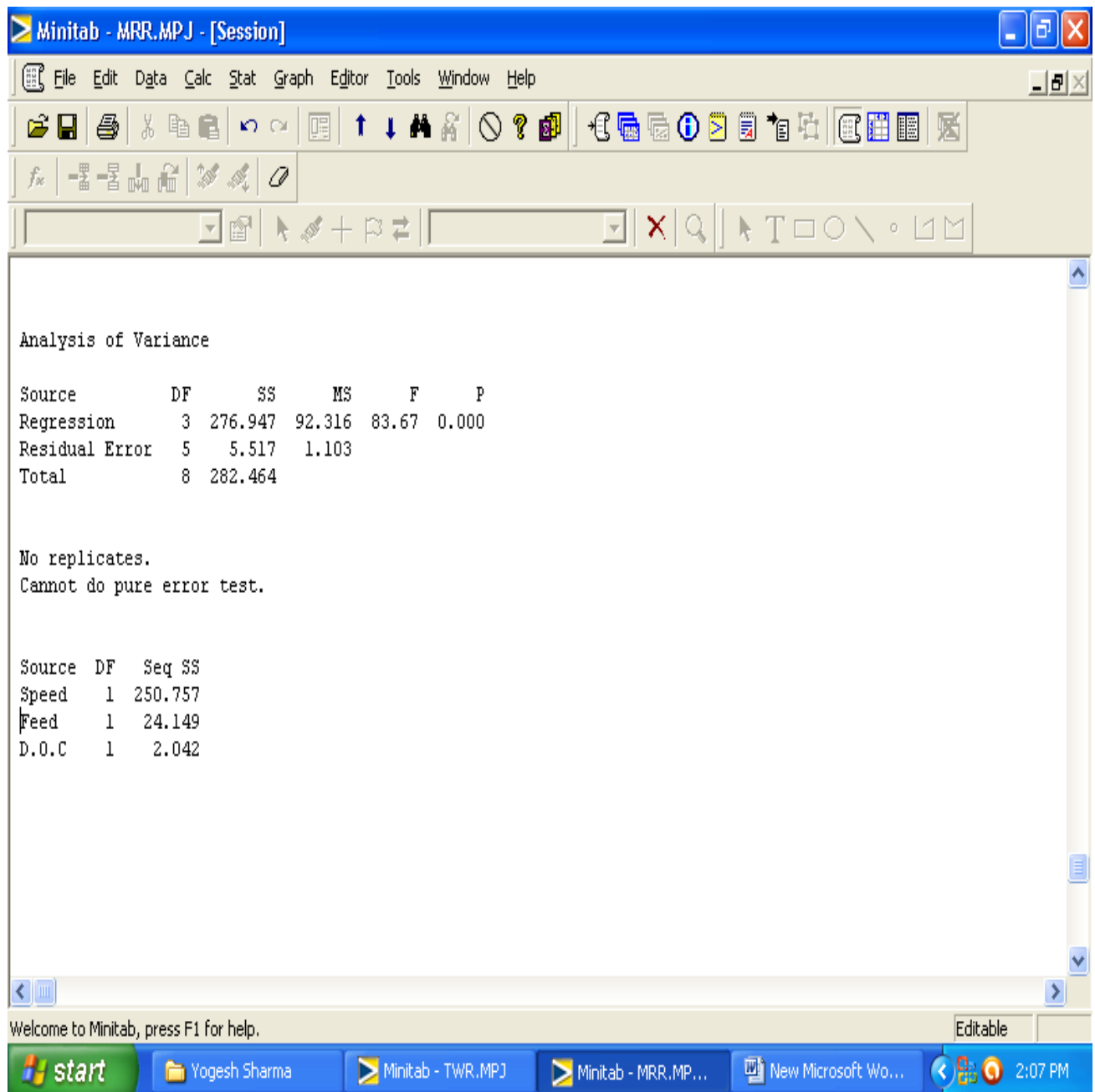


**Fig 5.1: Pictorial presentation of Regression Analysis:
MRR vs Speed, Feed, D.O.C**



**Continue.....Fig 5.1: Pictorial presentation of Regression Analysis:
MRR vs Speed, Feed, D.O.C**



**Continue.....Fig 5.1: Pictorial presentation of Regression Analysis:
MRR vs Speed, Feed, D.O.C**

$$S/N = 10 \log [11.332 / (17.81 \times 17.81)] = 10 \log (.036) = -14.51$$

$$S/N = -10 \log [1438.24 / 9] = -22.04 \Rightarrow \text{Best S/N ratio}$$

$$S/N = -\log [0.28 / 9] = 1.51$$

5.3.2 Regression Analysis using MINITAB: TWR versus Speed, Feed, D.O.C

Speed	Feed	D.O.C	TWR	RESI4	SRES4	COEF4	FITS4
204	100	0.25	0.0009	0.0001735	0.34240	-0.0026075	0.0007265
204	175	0.50	0.0014	0.0007539	1.25011	0.000013	0.0006461
204	315	0.75	0.0022	-0.0000469	-0.11321	0.0000091	0.0022469
450	100	0.50	0.0030	0.0006957	-1.06239	-0.0008667	0.0036957
450	175	0.75	0.0039	0.0002605	-0.41507		0.0041605
450	315	0.25	0.0050	-0.0008661	-1.62419		0.0058661
680	100	0.75	0.0063	-0.0001576	-0.32521		0.0064576
680	175	0.25	0.0078	0.0002275	0.41395		0.0075725
680	315	0.50	0.0095	0.0008719	1.58346		0.0086281

Where RES4 = residual,

SRES4= standardized residual,

COEF4= coefficients,

FITS4= Fitted values or predicted values.

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The regression equation is

TWR = - 0.0544 + 0.000428 Speed + 0.000329 Feed + 0.0160 D.O.C

Predictor	Coef	SE Coef	T	P	VIF
Constant	-0.05444	0.01759		-3.09	0.027
Speed	0.00042784	0.00002296	18.64	0.000	1.008
Feed	0.0003285	0.00004816	6.82	0.001	1.008
D.O.C	0.016	0.02177	0.73	0.495	1.000

S = 0.0133326, R-Sq = 98.8%, R-Sq(adj) = 98.1%,

PRESS = 0.00329562, R-Sq(pred) = 95.64%

Where SE coef= Standard error of coefficient,

T= t-test, P= P-value,

VIF= Variance inflation factor,

S= Standard deviation,

R-Sq= R^2 (R-squared),

R-Sq (adj) = adjustable R^2 ,

PRESS = Prediction sum of squares,

R-Sq (pred) = predicted R^2

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	3	0.074727	0.024909	140.13	0.000
Residual Error	5	0.000889	0.000178		
Total	8	0.075616			

Source	DF	Seq SS
Speed	1	0.066361

Feed	1	0.008270
D.O.C	1	0.000096

Where DF= Degree of freedom, SS= Sum of squares, MS= Mean squares,
F= F-test, P= P-value, Seq SS= Sequential Sum of squares

Unusual Observations

Obs	Speed	TWR	Fit	SE Fit	Residual	St Resid
1	204	0.05000	0.06969	0.00972	-0.01969	-2.16R

R denotes an observation with a large standardized residual.

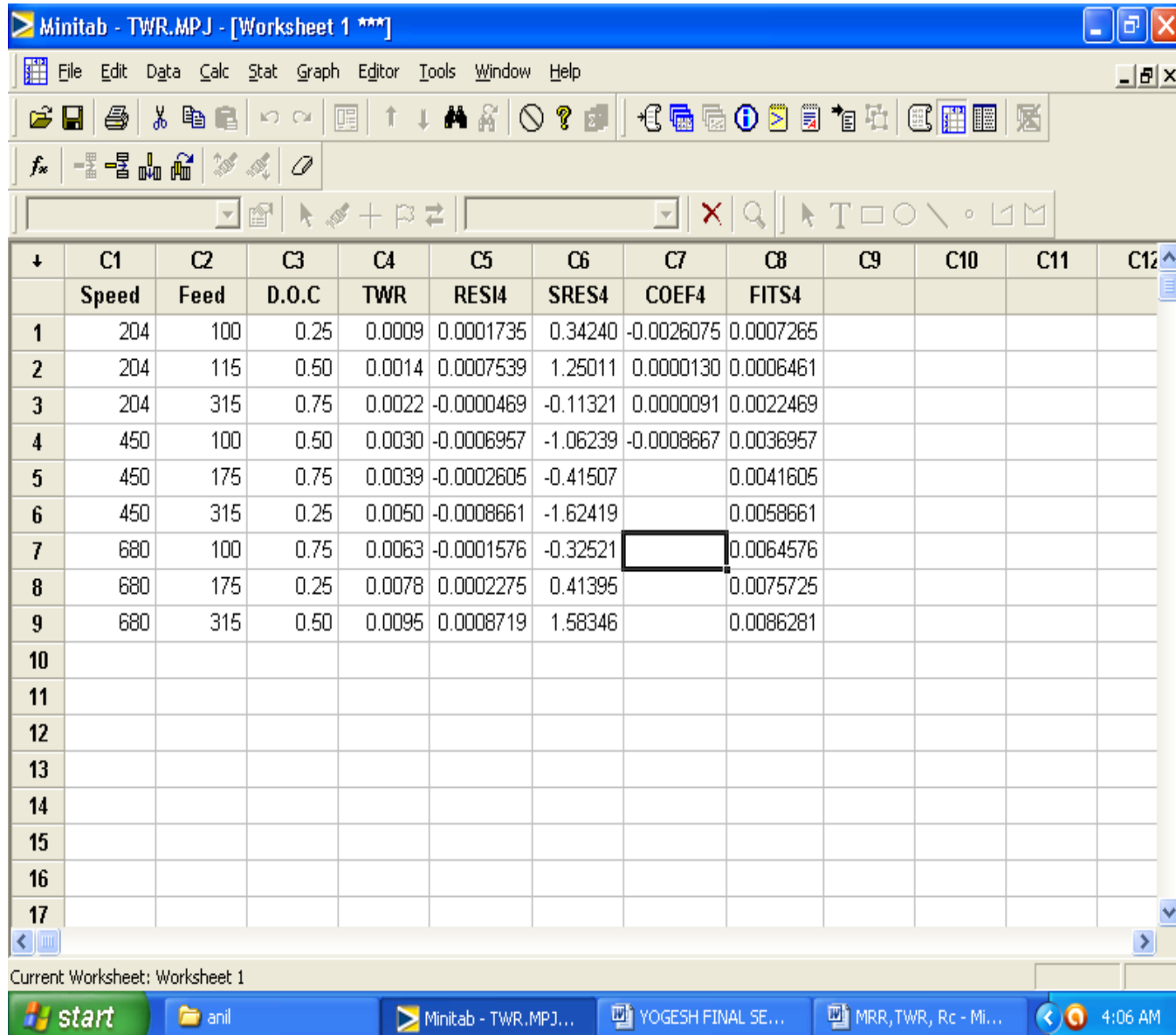
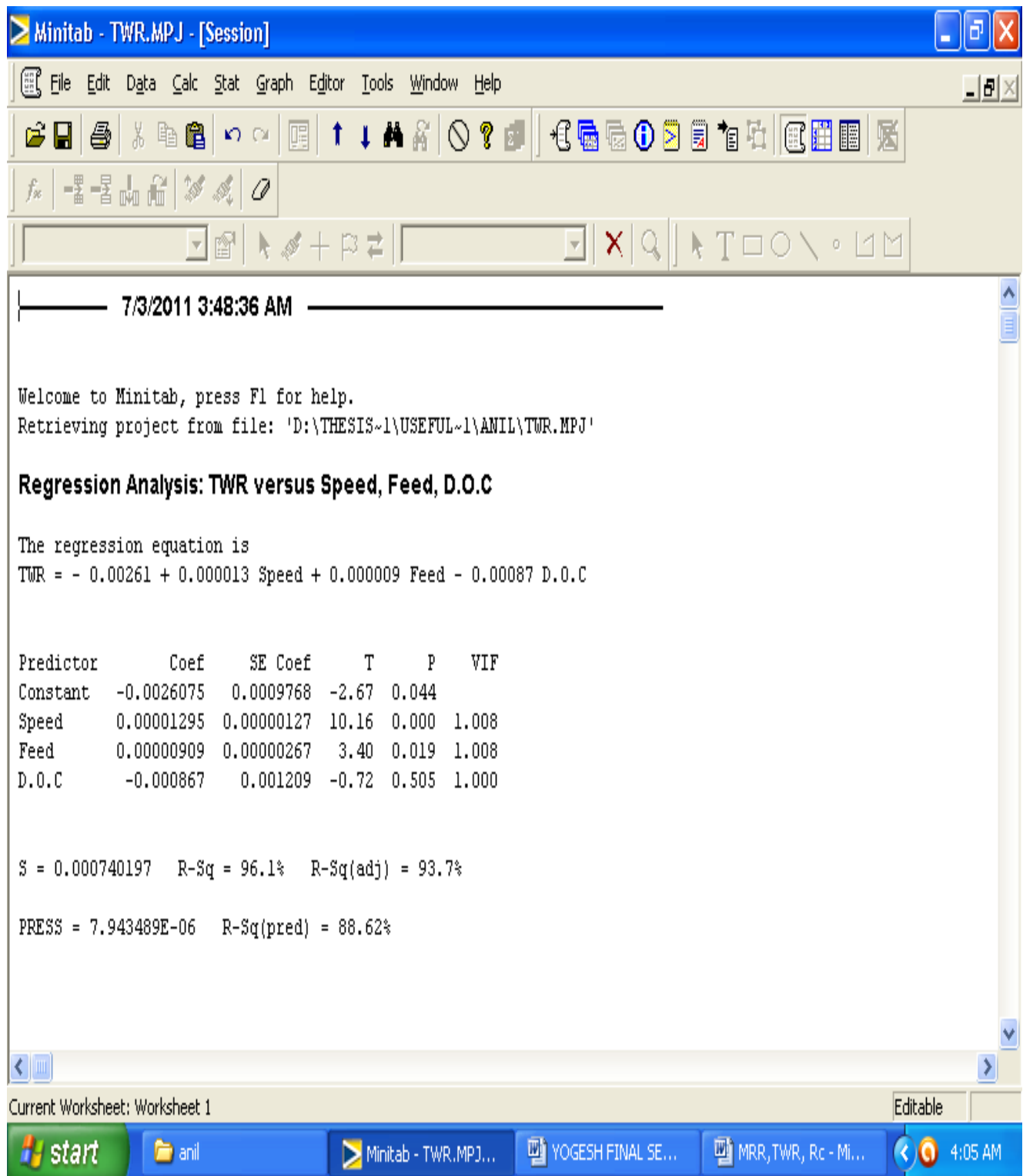
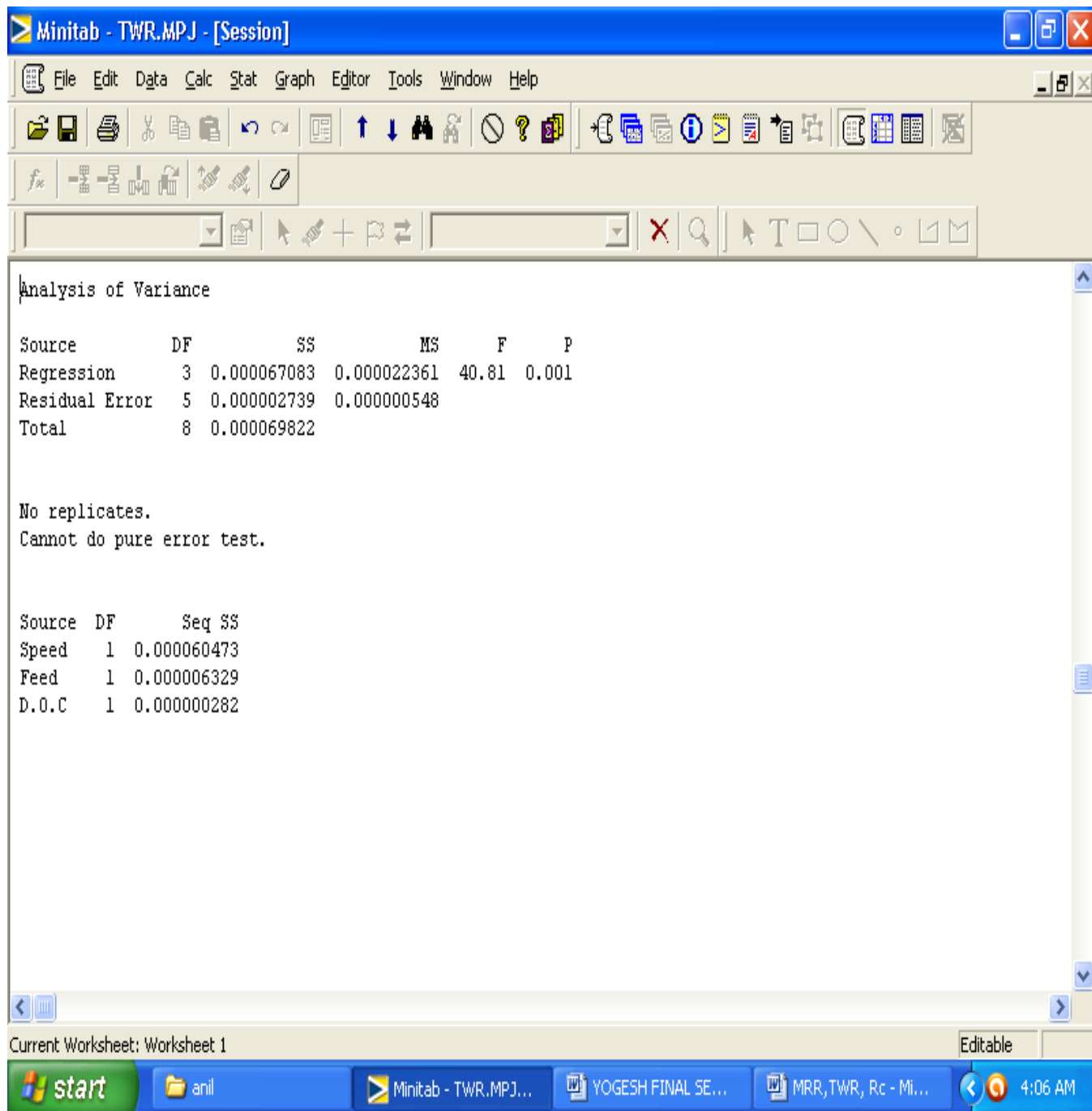


**Fig 5.2: Pictorial presentation of Regression Analysis:
TWR vs Speed, Feed, D.O.C**



**Continue.....Fig 5.2: Pictorial presentation of Regression Analysis:
TWR vs Speed, Feed, D.O.C**



**Continue.....Fig 5.2: Pictorial presentation of Regression Analysis:
TWR vs Speed, Feed, D.O.C**

$$S/N = 10 \log [(0.0044) / (0.004 * 0.004)] = 24.39$$

$$S/N = -10 \log [0.0002476 / 9] = 45.61$$

$$S/N = -\log [1710749.956 / 9] = -5.28 \Rightarrow \text{Best S/N ratio}$$

5.3.3 Regression Analysis using MINITAB: Hardness (HRB) versus Cutting Speed, Feed, D.O.C

Speed	Feed	D.O.C	HRB	RESI4	SRES4	COEF4	FITS4
204	100	0.25	111	0.459339	0.89004	112.544	110.541
204	175	0.50	110	-0.626388	-1.00914	-0.013	110.626
204	315	0.75	112	-0.122348	0.29451	0.006	110.878
450	100	0.50	108	0.632534	0.93007	-0.035	110.367
450	175	0.75	107	-0.831205	-1.26707		110.831
450	315	0.25	109	0.269215	0.49100		110.731
680	100	0.75	105	0.599914	1.16630		110.400
680	175	0.25	104	-0.890154	-1.51435		110.890
680	315	0.50	106	0.236594	0.40789		110.763

Where RES4 = residual,

SRES4= standardized residual,

COEF4= coefficients,

FITS4= Fitted values or predicted values.

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Welcome to Minitab, press F1 for help.

The regression equation is

HRB = 113 - 0.0129 Speed + 0.00630 Feed - 0.04 D.O.C

Predictor	Coef	SE Coef	T	P	VIF
Constant	112.544	1.008		111.65	0.027
Speed	-0.012863	0.001324	-9.71	0.000	1.008
Feed	0.006300	0.002769	2.28	0.0072	1.008
D.O.C	-0.035	1.256	-0.03	0.979	1.000

S = 7.99279 R-Sq = 95.1% R-Sq(adj) = 92.1%

PRESS = 321.729 R-Sq(pred) = 95.03%

Where SE coef= Standard error of coefficient,

T= t-test, P= P-value,

VIF= Variance inflation factor,

S= Standard deviation,

R-Sq= R^2 (R-squared),

R-Sq (adj) = adjustable R^2 ,

PRESS = Prediction sum of squares,

R-Sq (pred) = predicted R^2

Analysis of Variance

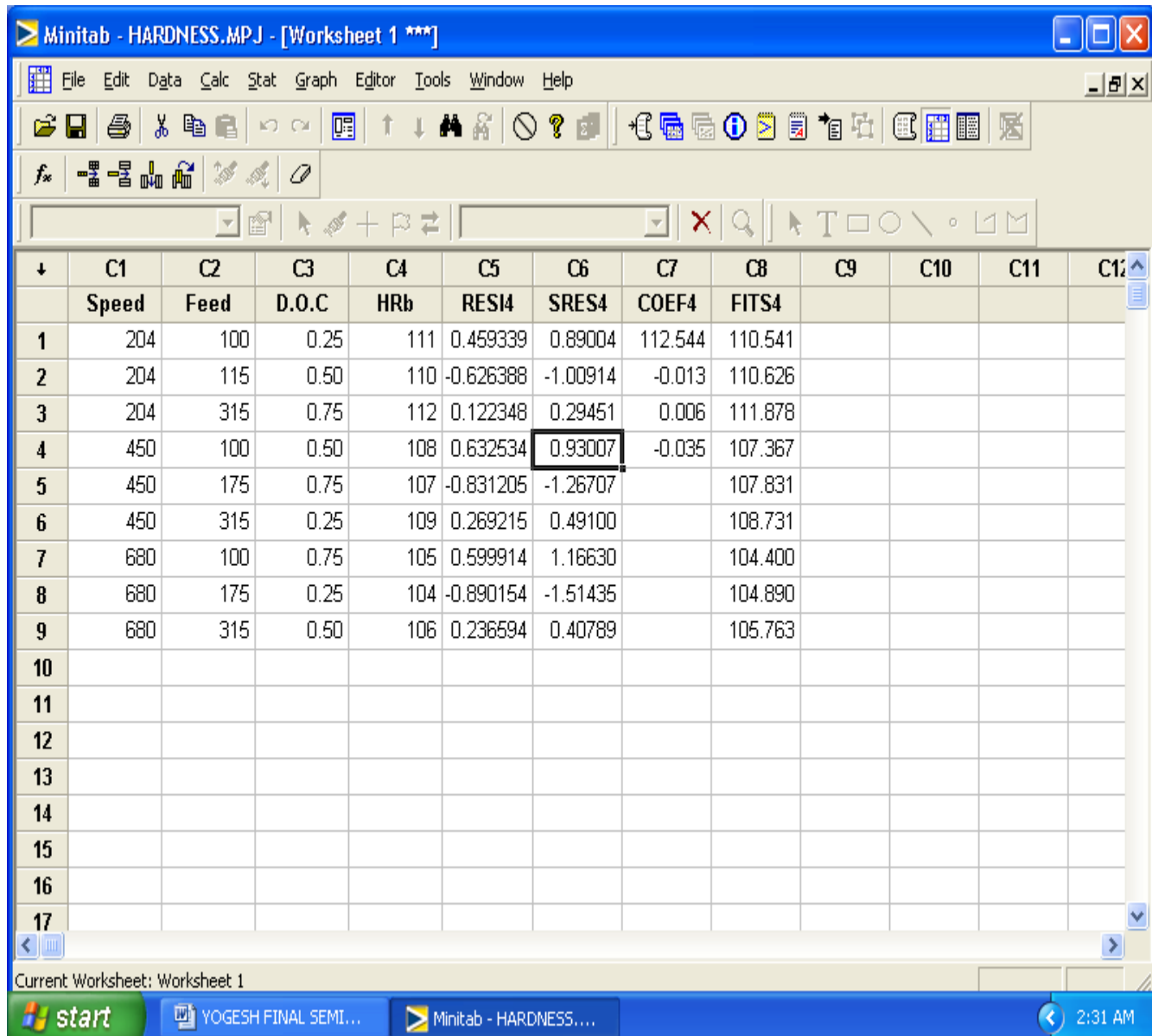
Source	DF	SS	MS	F	P
Regression	3	6156.9	2052.3	32.12	0.001
Residual Error	5	319.4	63.9		
Total	8	6476.3			

Source	DF	Seq SS
Speed	1	5826.1
Feed	1	330.7
D.O.C	1	0.0

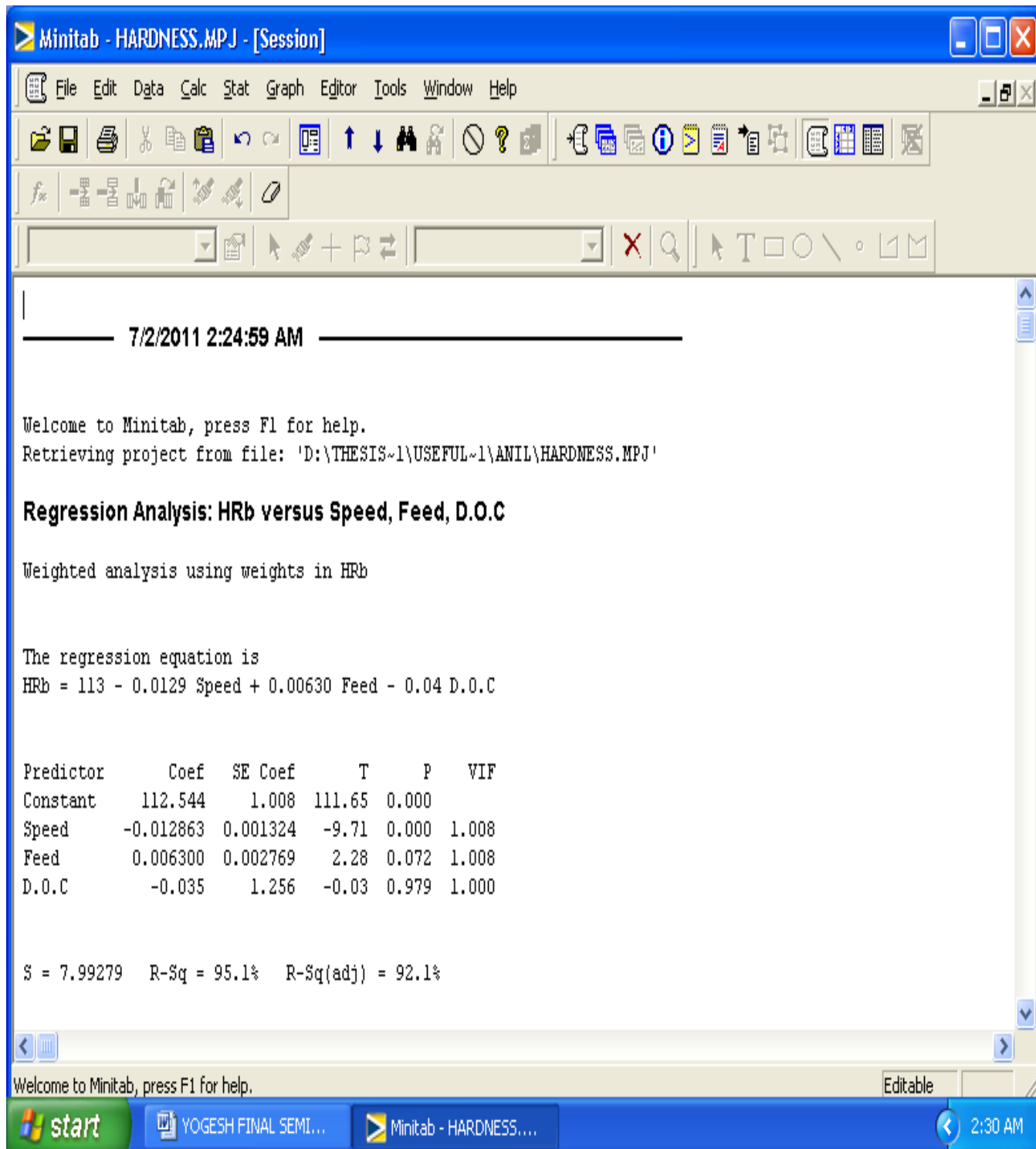
No evidence of lack of fit ($P \geq 0.1$).

Where DF= Degree of freedom, SS= Sum of squares, MS= Mean squares,

F= F-test, P= P-value, Seq SS= Sequential Sum of squares



Continue.....Fig 5.3: Pictorial presentation of Regression Analysis:
HRB vs Speed, Feed, D.O.C



Continue.....Fig 5.3: Pictorial presentation of Regression Analysis:
HRB vs Speed, Feed, D.O.C

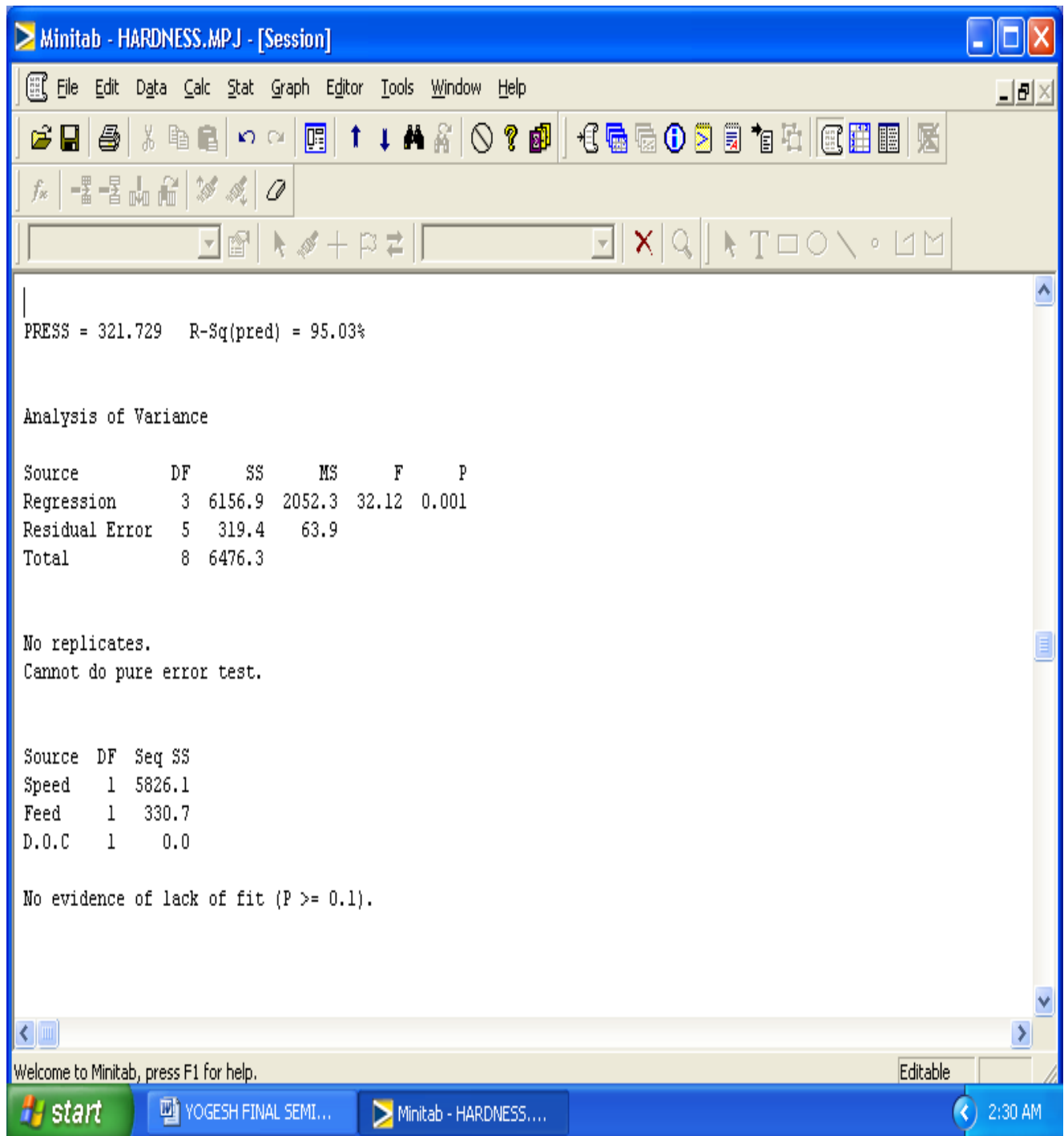


Fig 5.3: Pictorial presentation of Regression Analysis: HRB vs Speed, Feed, D.O.C

$$S/N = 10 \log [108 / 60] = 2.552$$

$$S/N = -10 \log [105036 / 9] = -4.067 \Rightarrow \text{Best S/N ratio}$$

$$S/N = -\log [0.000773 / 9] = 4.066$$

5.4 FUZZY LOGIC using MATLAB

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 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), probability theory uses the concept of subjective probability (i.e., how probable do I think that a variable is in a set).

5.4.1 FUZZY LOGIC using MATLAB: MRR vs. Cutting Speed, Feed, D.O.C.

Note that the Inputs 1, 2, 3 and Rule editor are the same for subsections 5.4.1, 5.4.2, 5.4.3, but the Output and Rule viewer are different for subsections 5.4.1, 5.4.2, and 5.4.3.

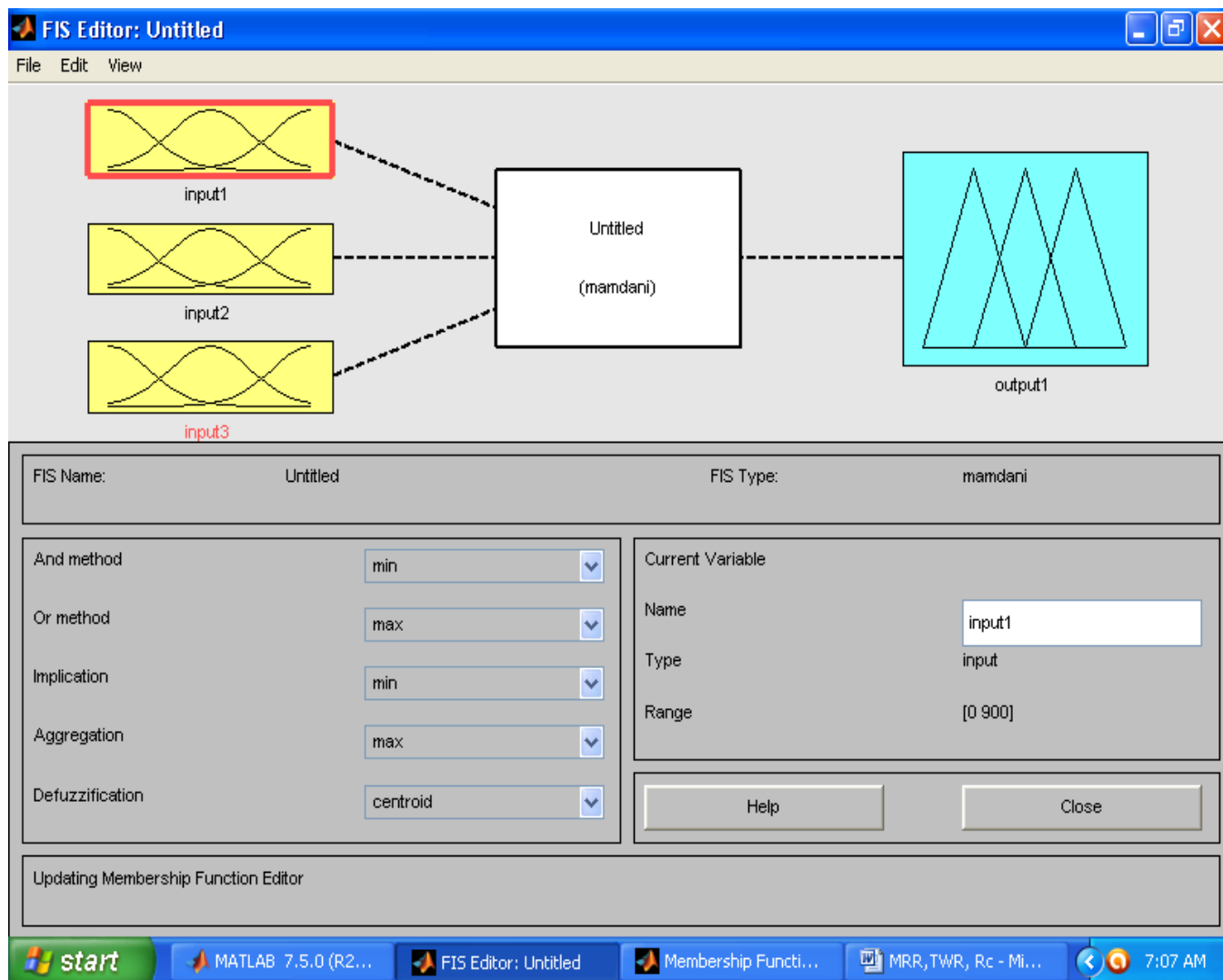


Fig 5.4: Pictorial presentation of Fuzzy Inference system (FIS)

There are many membership functions based on their input and output transition behavior. In this paper, we used triangular and trapezoid model for input and trapezoid for output. Figures (5.5,5.6,5.7) respectively show the membership function of cutting speed, feed and depth of cut as inputs and MRR as output.

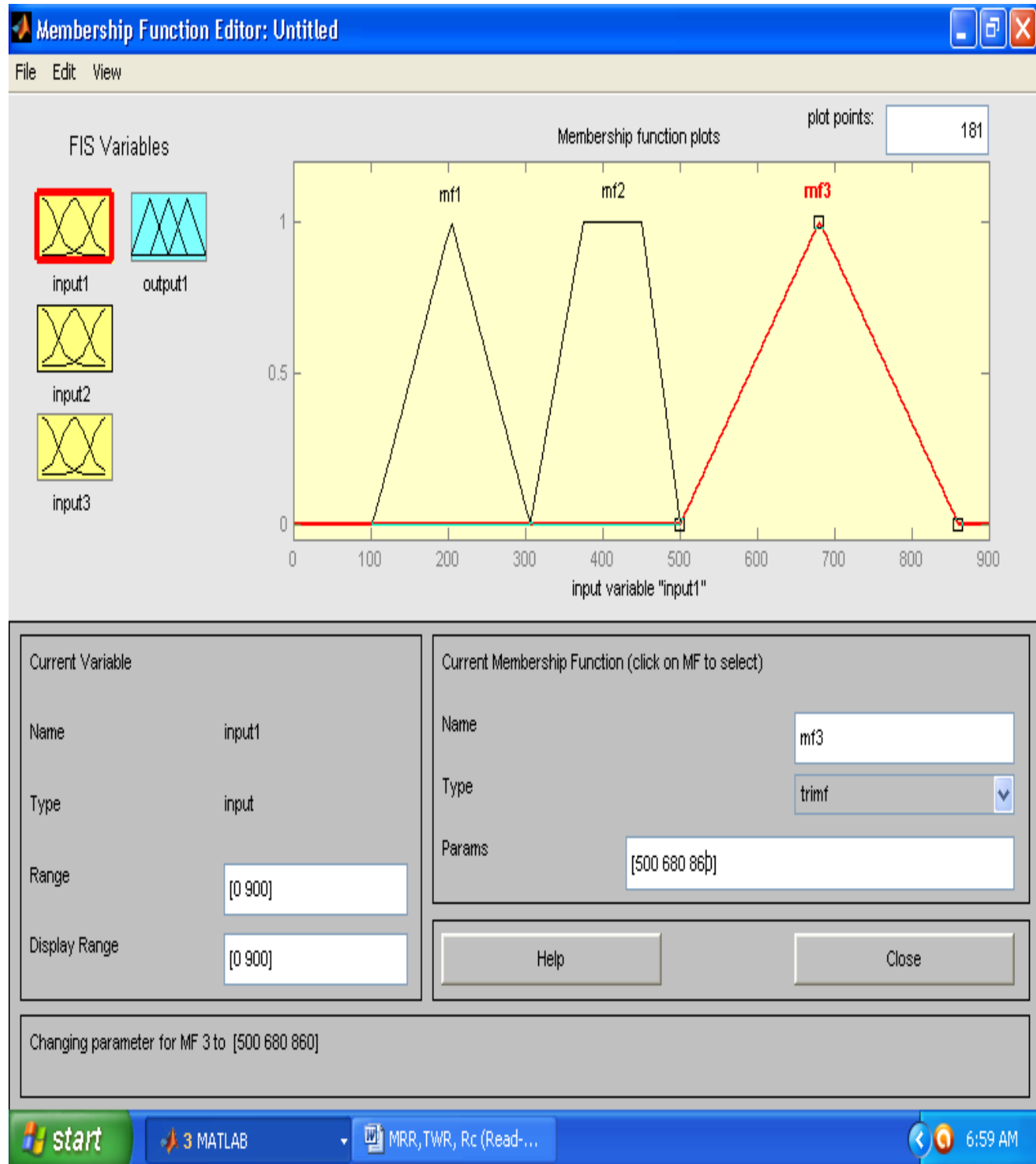


Fig 5.5: Cutting Speed membership function (Input-1)

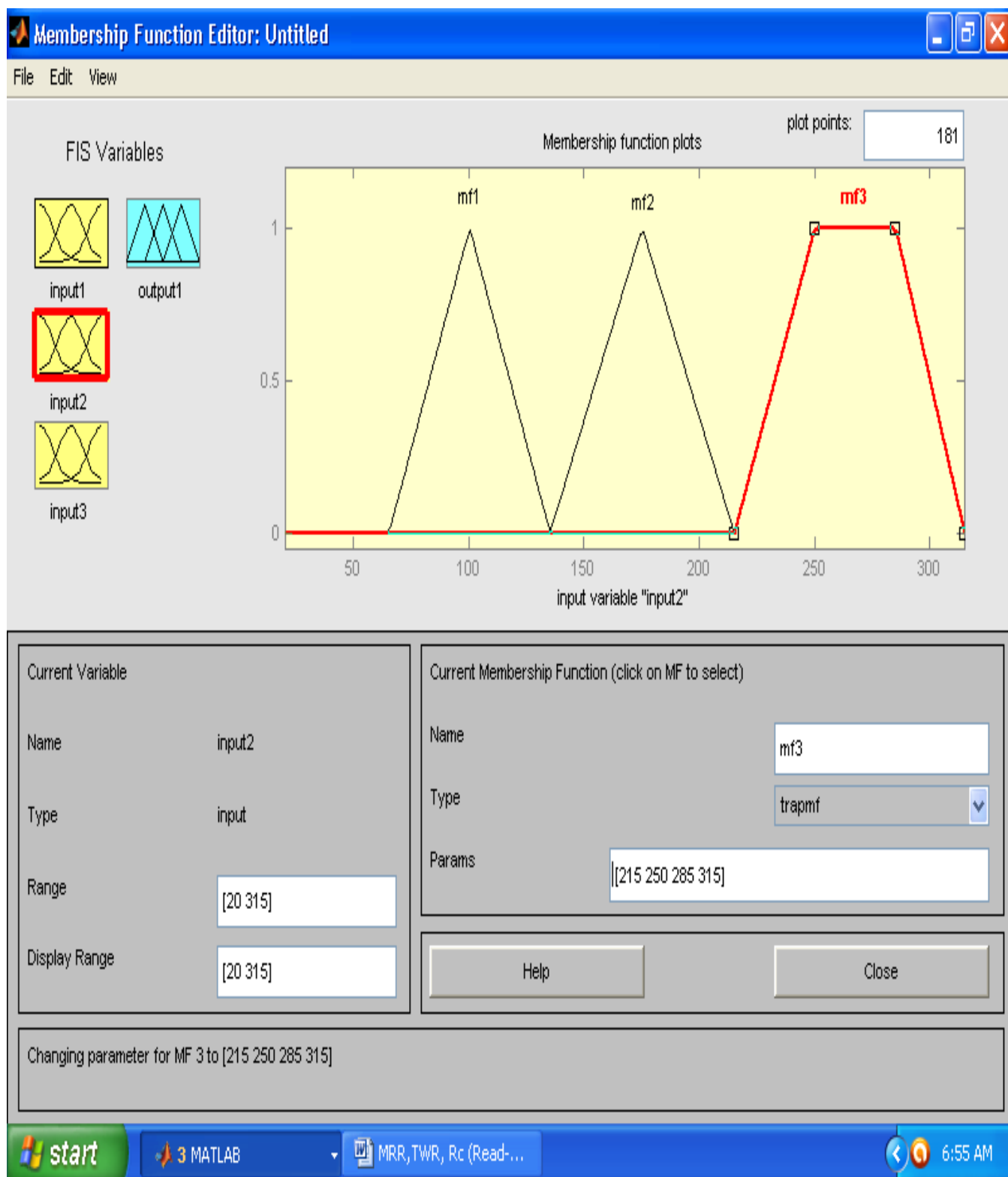


Fig 5.6: Feed membership function (Input-2)

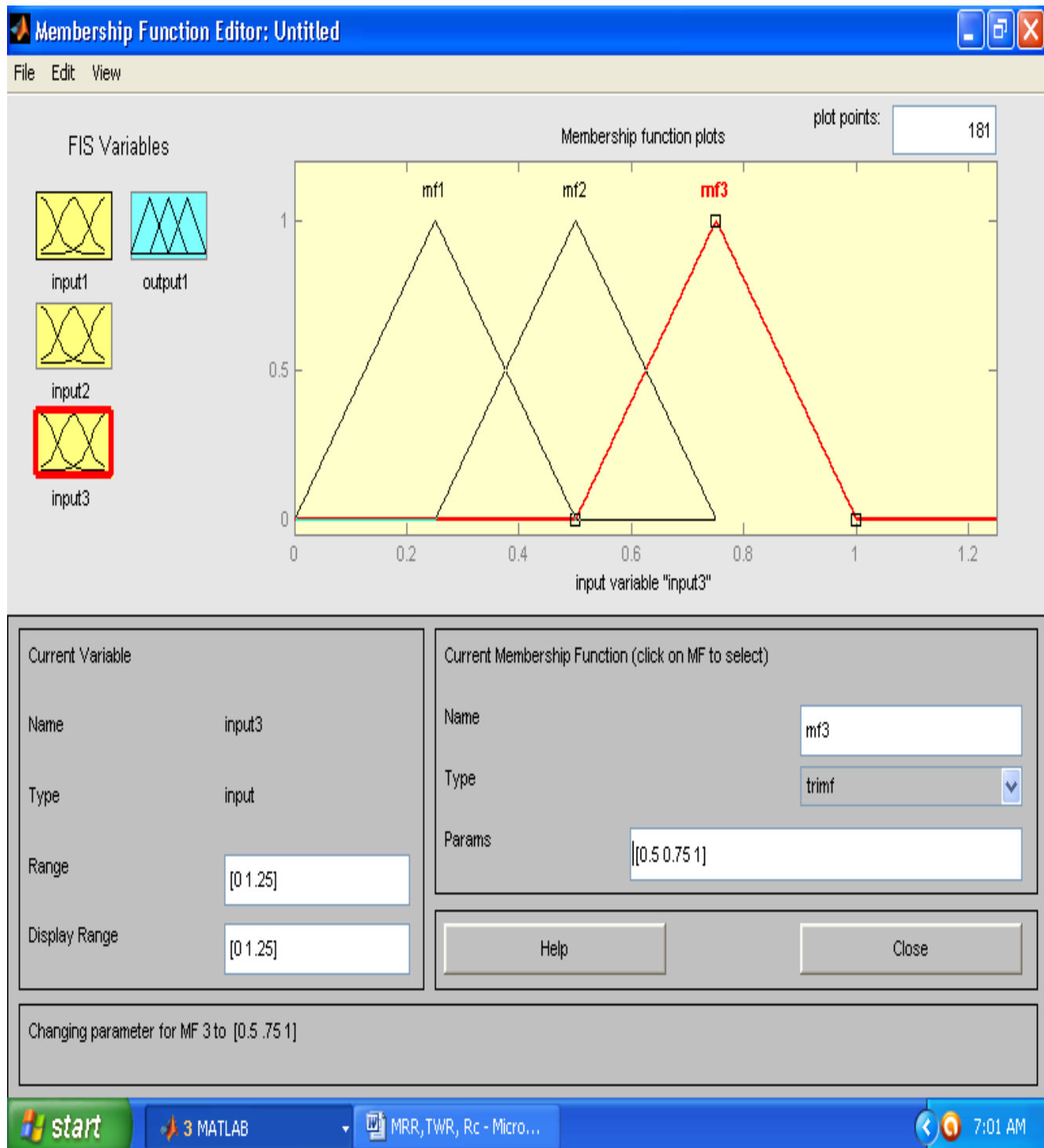


Fig 5.7: Depth of Cut membership function (Input-3)

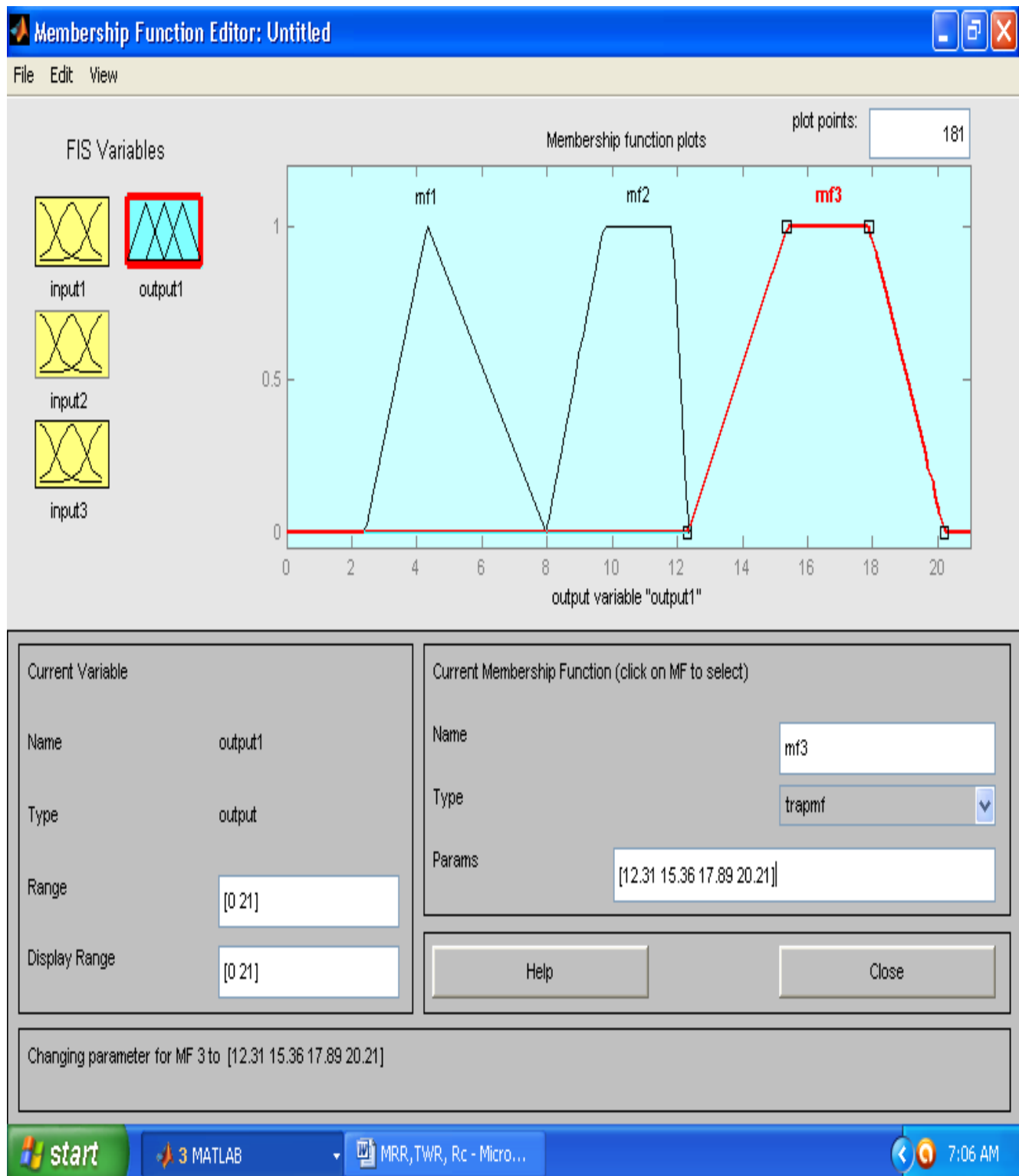


Fig 5.8: Material Removal Rate (MRR) membership function (as an Output)

Number of rules applied for this systems are 81. Their values are estimated by results of simulation. Number of rules is based on accuracy of work, data collection possibility and determining the type of membership function. The rules used in this system have been shown in fig. 5.9.

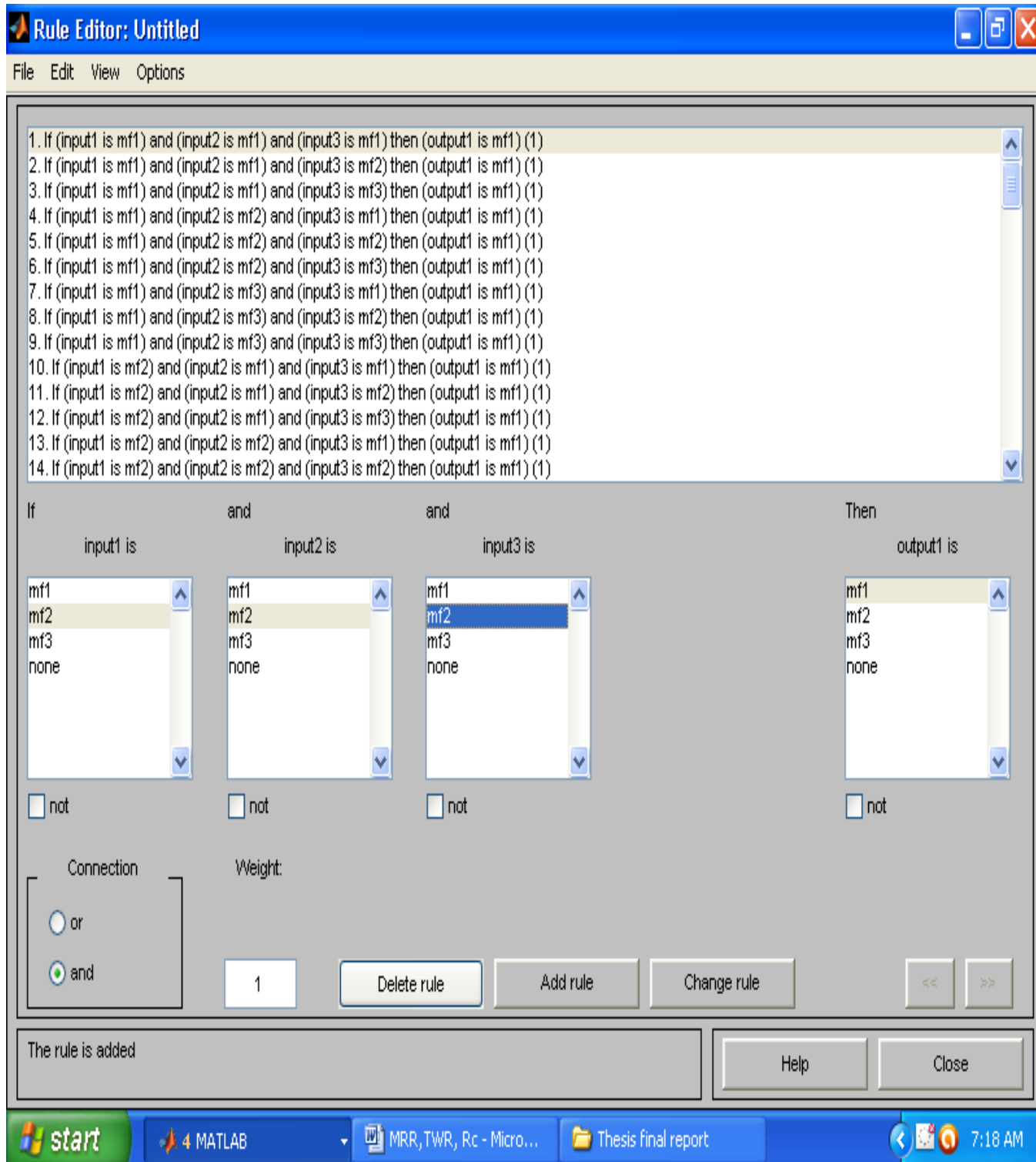
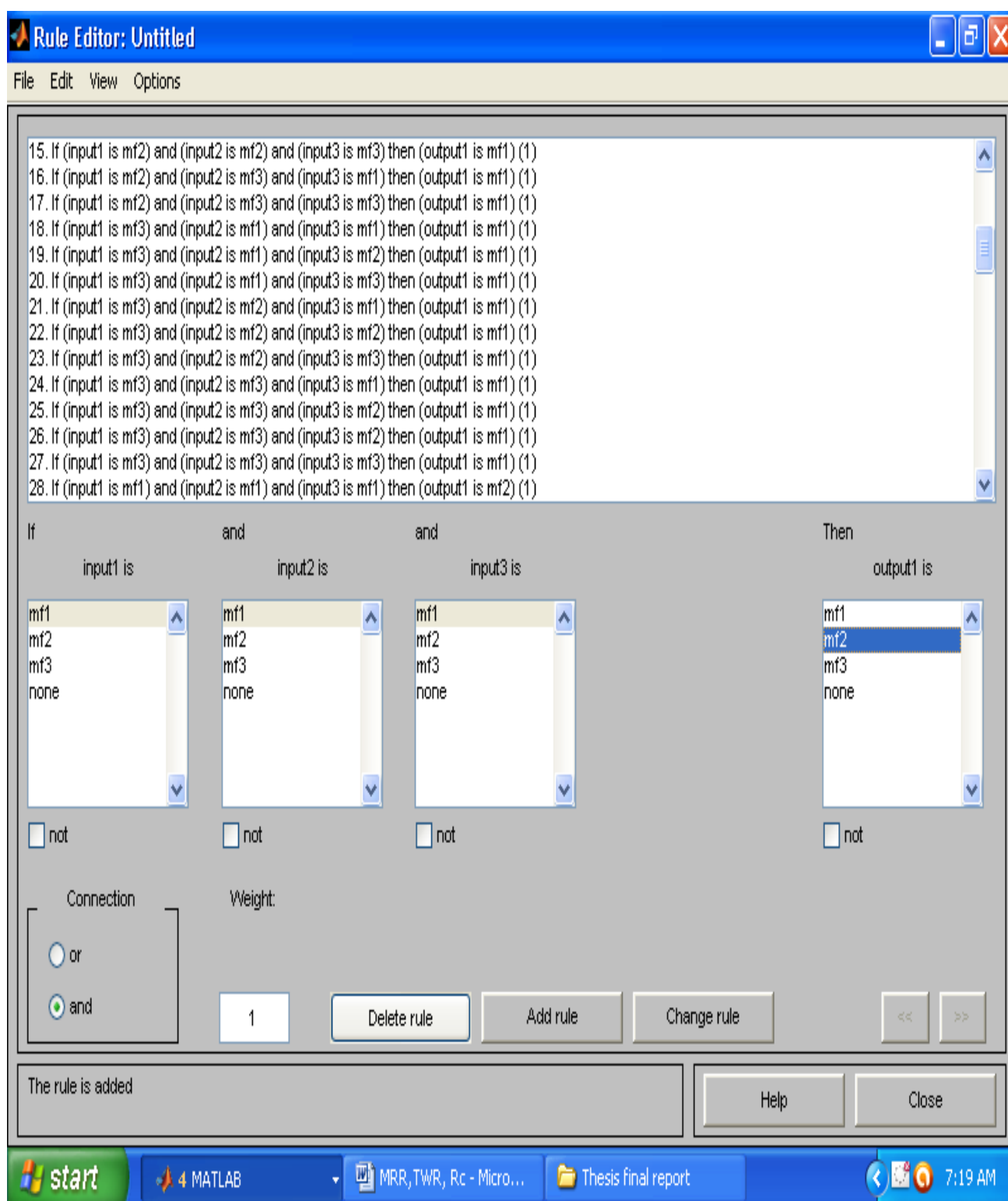
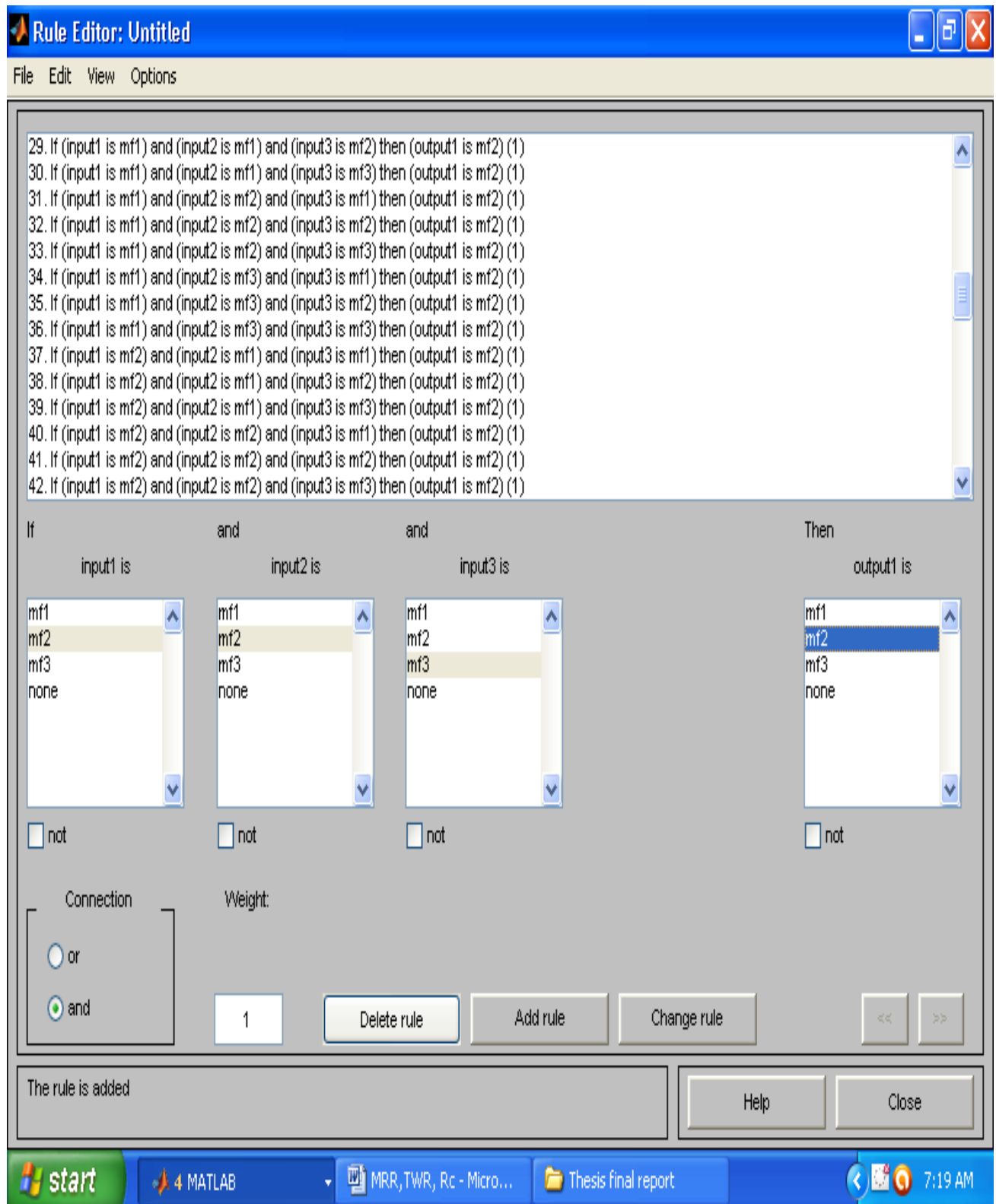


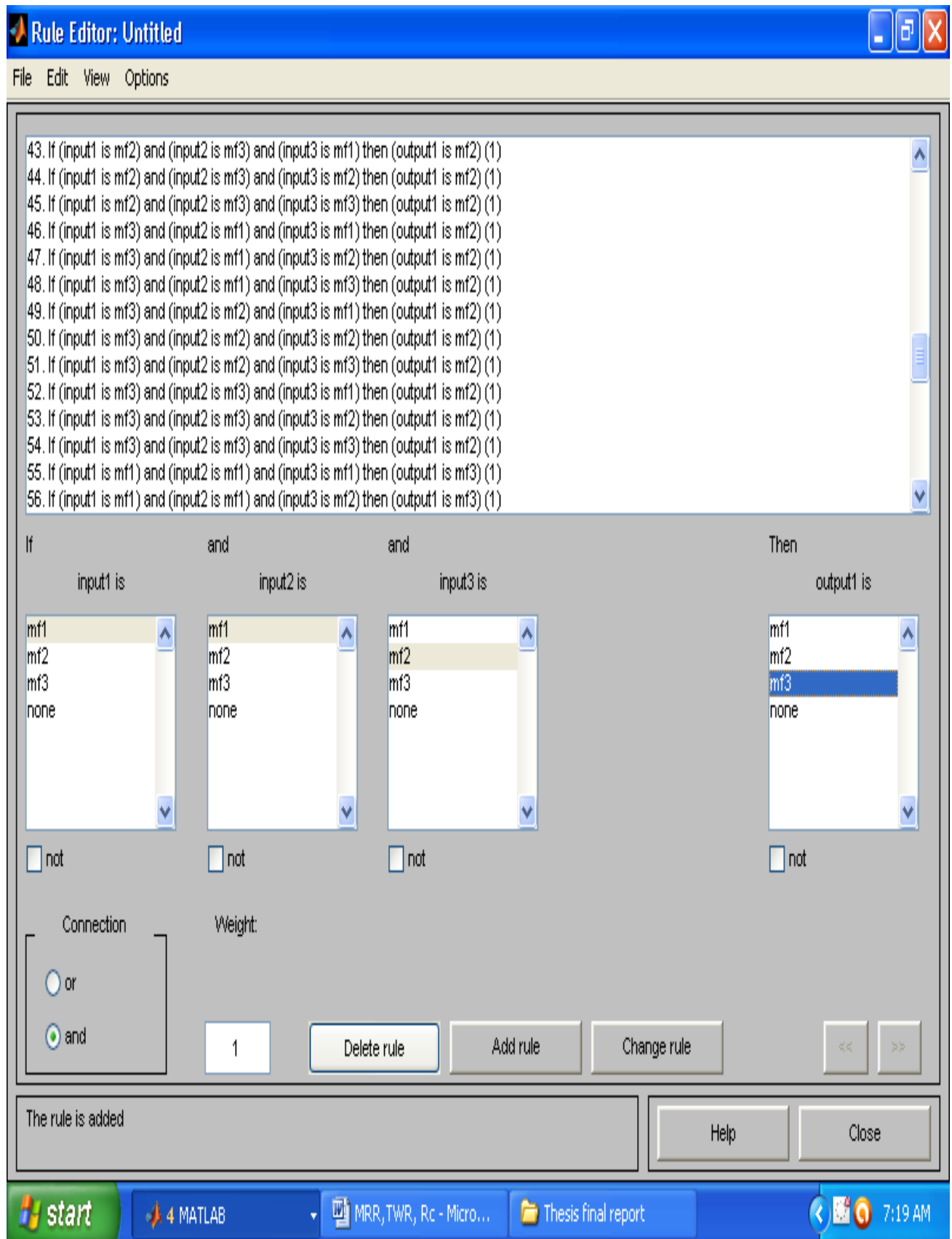
Fig 5.9: Rules of fuzzy system



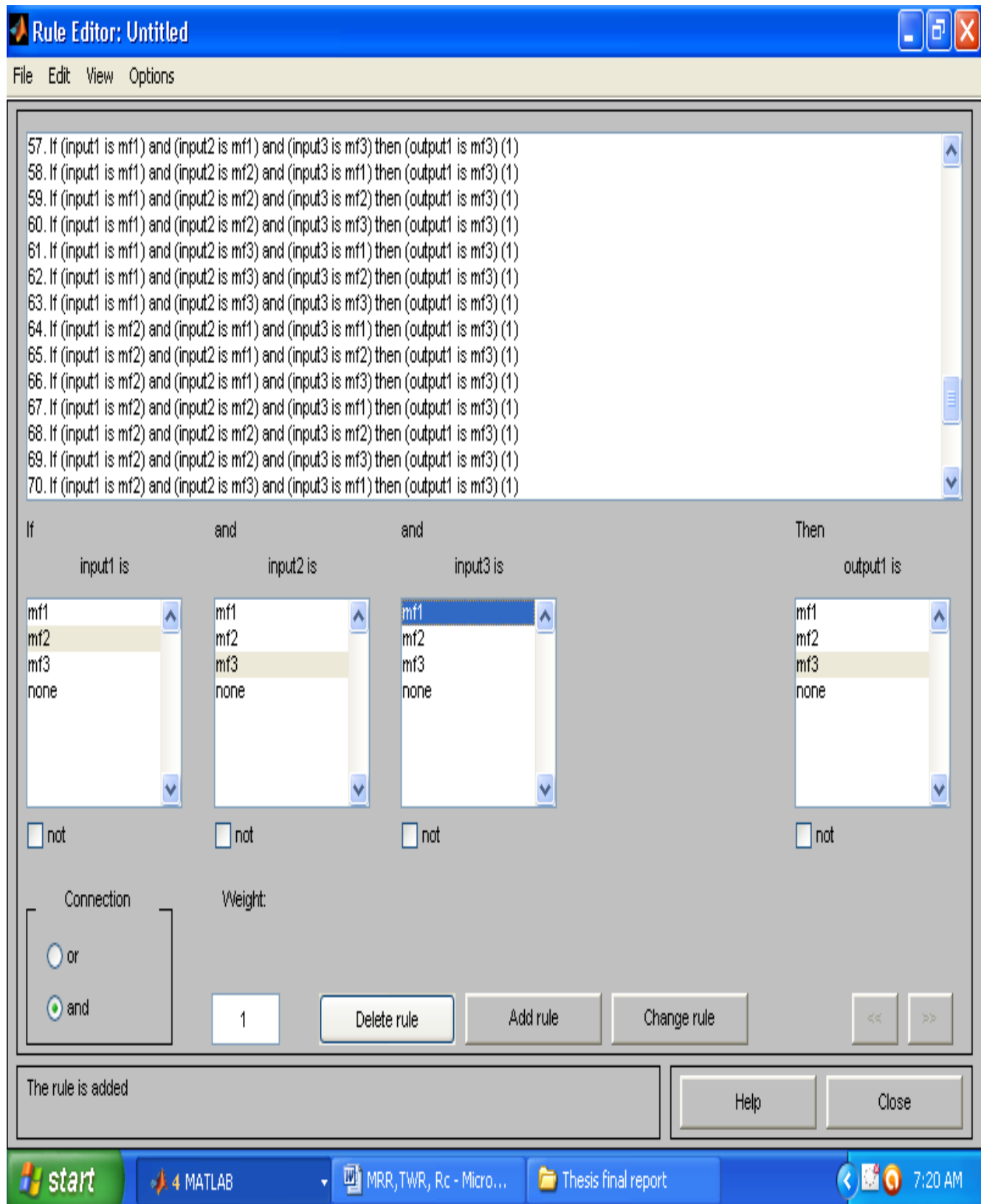
Continue.....Fig 5.9: Rules of fuzzy system



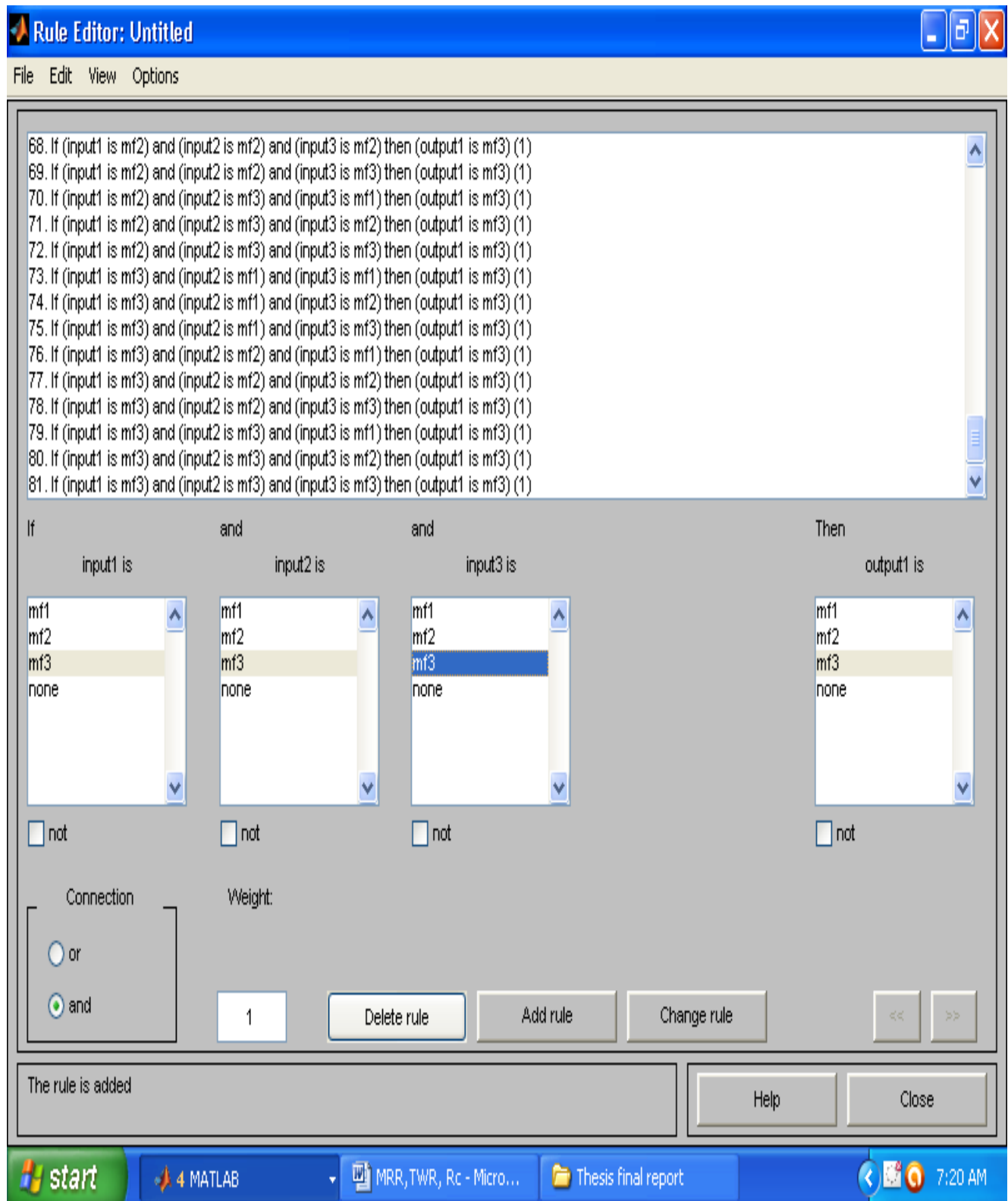
Continue.....Fig 5.9: Rules of fuzzy system



Continue.....Fig 5.9: Rules of fuzzy system



Continue.....Fig 5.9: Rules of fuzzy system



Continue.....Fig 5.9: Rules of fuzzy system

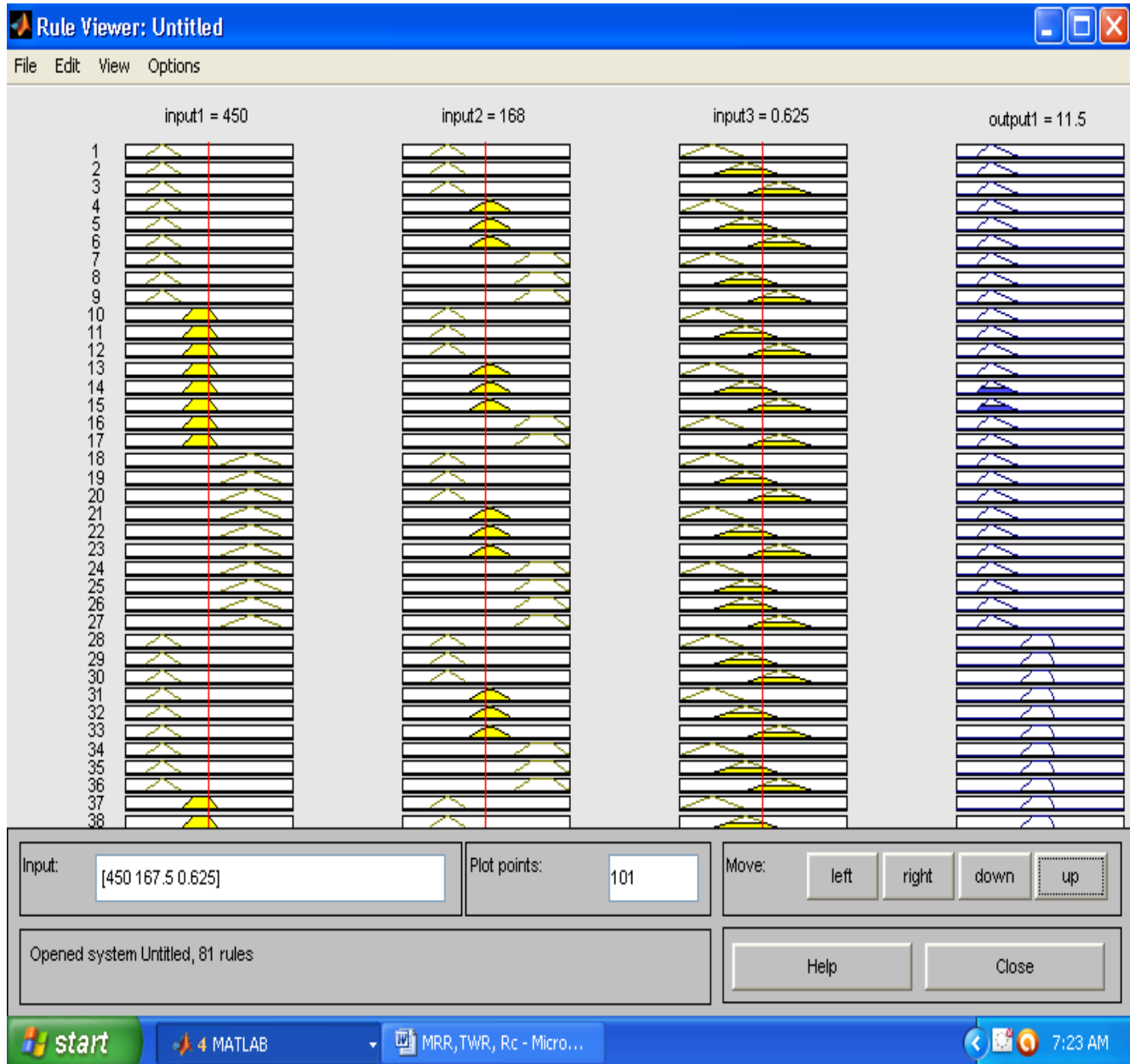
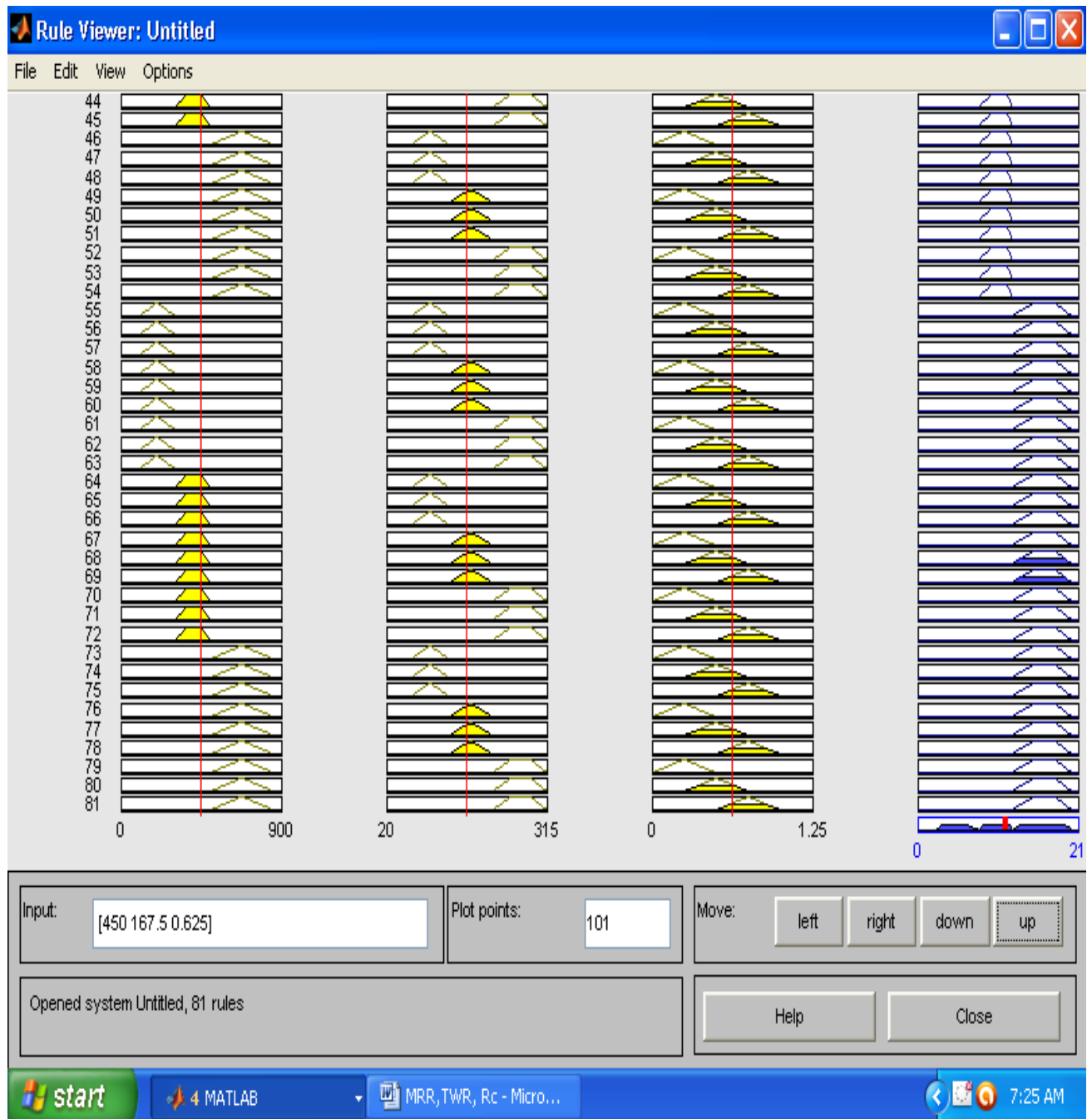


Fig 5.10: Pictorial presentation of Fuzzy rule base system for MRR vs Cutting Speed, Feed, D.O.C

After writing the rules, we can see the rules firing by selecting different inputs. We can see the values of fuzzy outputs and compare it with real values. Therefore by selecting value of rules we can be sure of system accuracy. This operation is done by selecting numerical values too or by moving pilot through the value of forces and understanding the wear proportion. Figure 5.10 shows the fuzzy rule base system. In this paper we suppose that the value of MRR for tool changing is 11.5 mm but for a real tool it must be estimated and substituted in this system. The relationship between simulation results of fuzzy systems and the real results obtained from model will be shown while simulation progress. In simulation process ongoing, when the value of MRR reaches to 11.5mm, the process is stopped.



Continue..... Fig 5.10: Pictorial presentation of Fuzzy rule base system for MRR vs Cutting Speed, Feed, D.O.C

The graphs on the left correspond to the input membership functions; the red line indicates the current input value. It can be moved to simulate different input values. Where this line crosses the membership functions are the values which represent the degree to which the input is believed to belong to that particular membership. The graphs on the right are the output membership functions. Notice that they have been AND with the value of the input membership function. The bottom right output function represents the output of the FIS. The red bar on this graph indicates where the estimated value for the output variable lies.

5.4.2 FUZZY LOGIC using MATLAB: TWR vs. Cutting Speed, Feed, D.O.C

Note that the Inputs 1, 2, 3 and Rule editor are the same for subsections 5.4.1, 5.4.2, 5.4.3, but the Output and Rule viewer are different for subsections 5.4.1, 5.4.2, and 5.4.3.

The minimum value of wear in rule writing process, has been shown by, mf1 and the maximum value of wear that, the tool is worn out and breakage probability is very high, been shown by mf3.

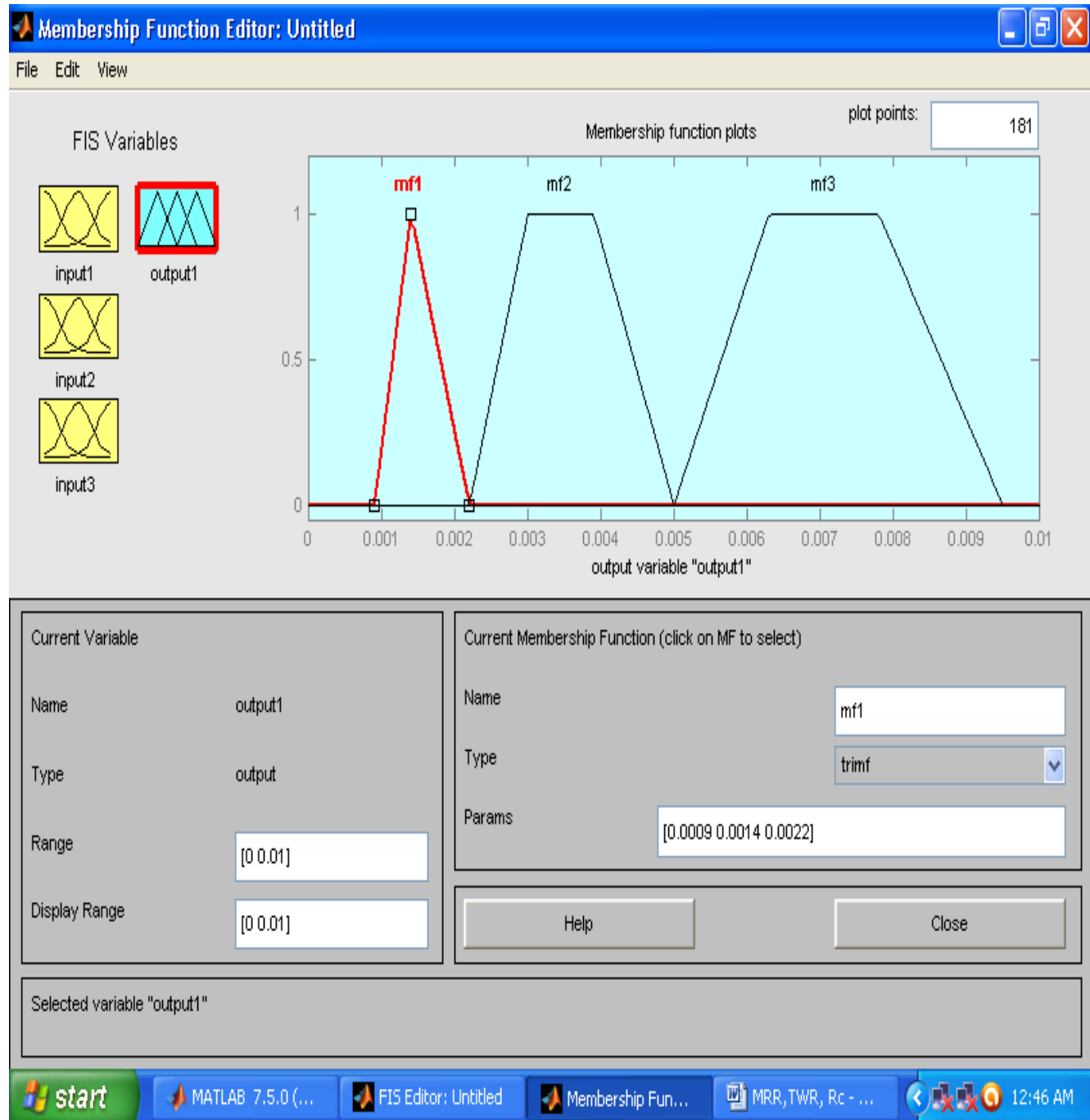


Fig 5.11: Tool Wear Rate (TWR) membership function (as an output)

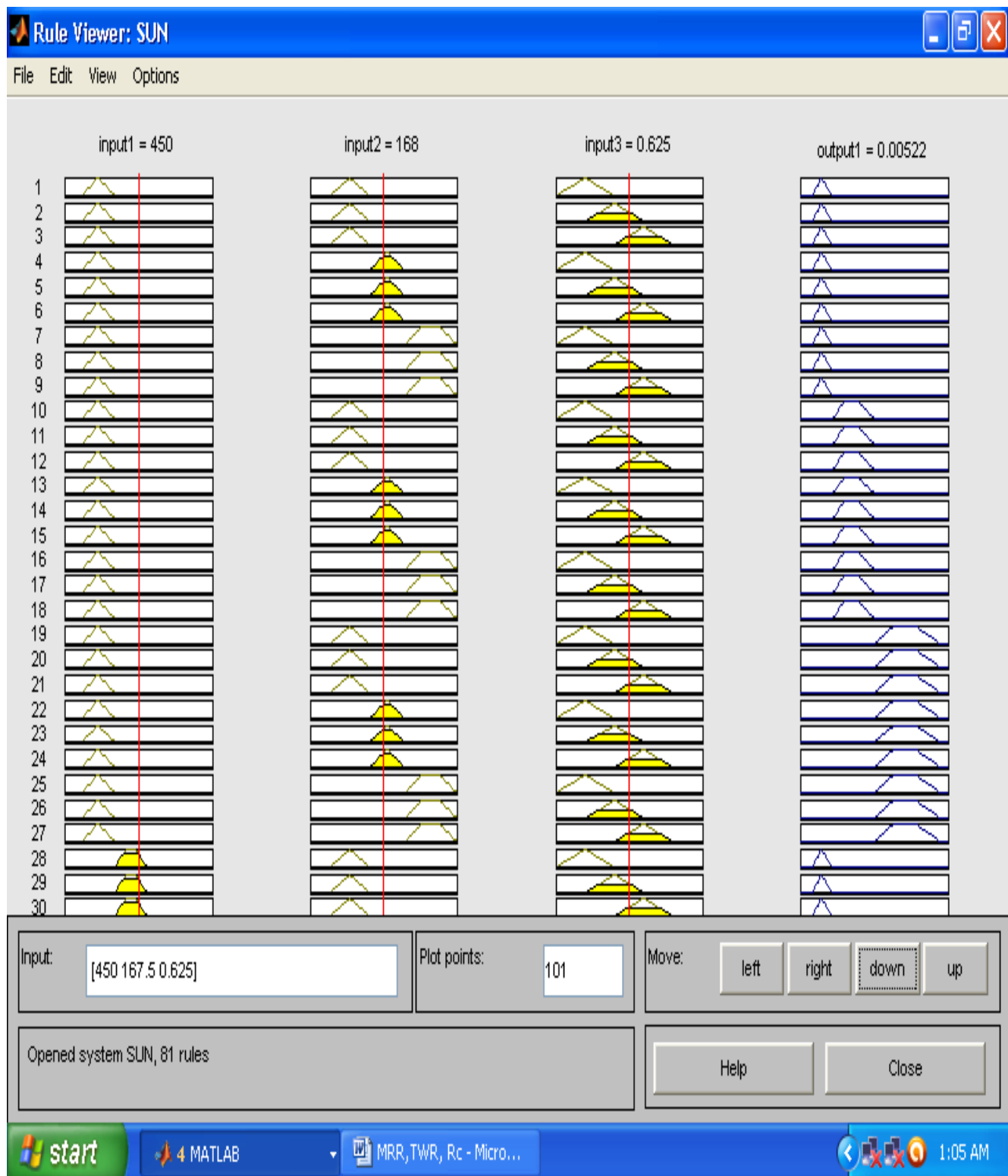
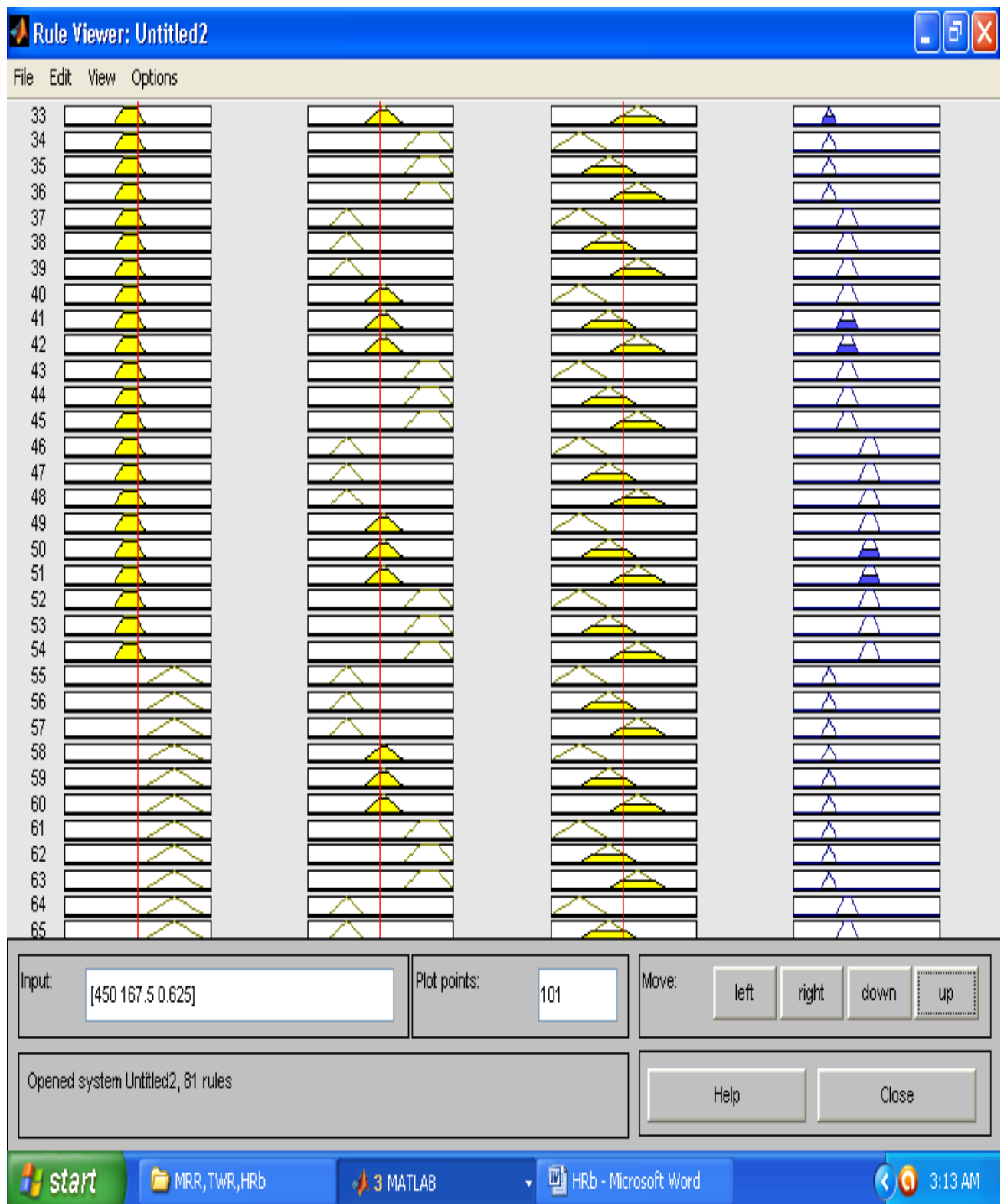
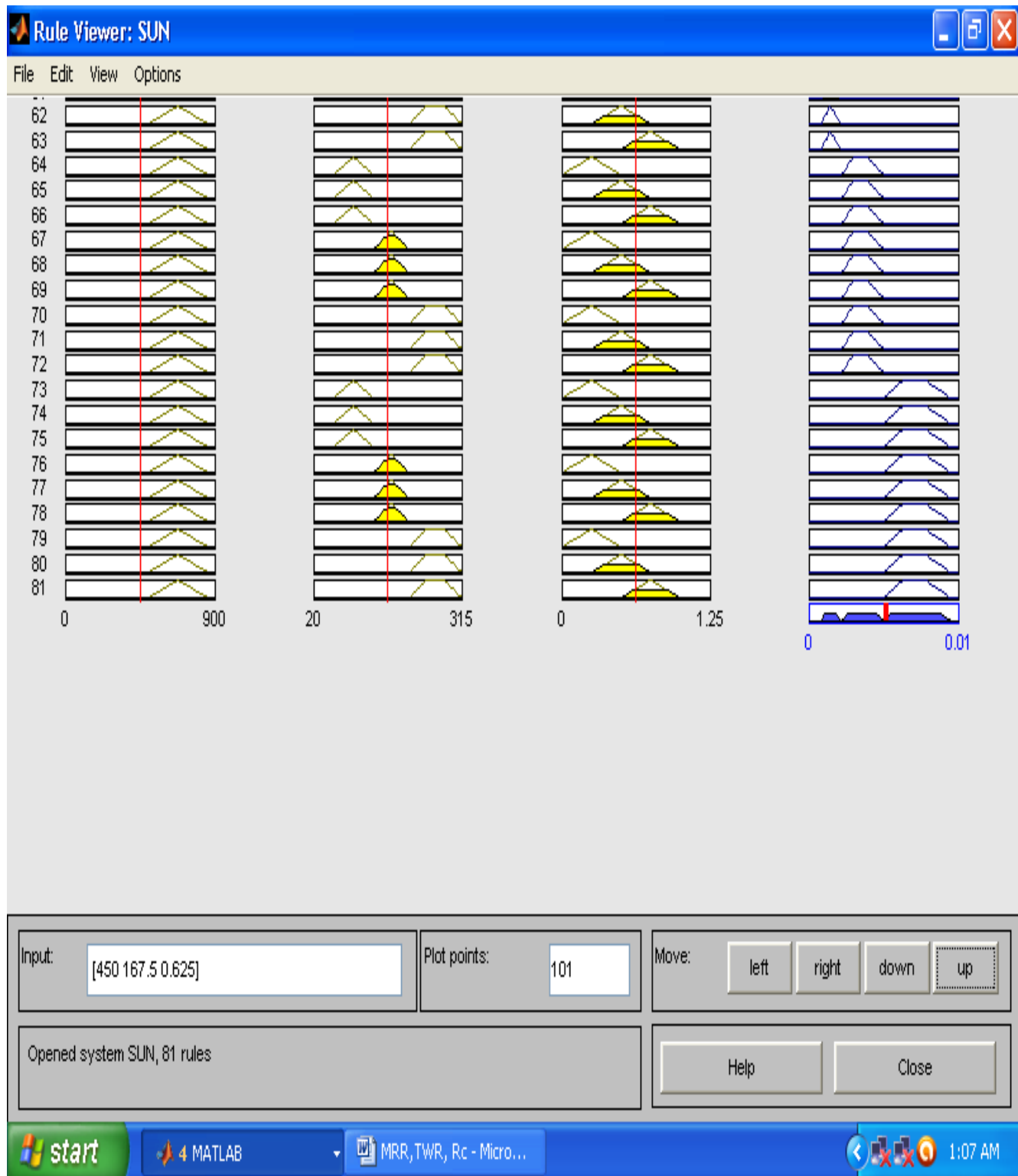


Fig 5.12: Pictorial presentation of Fuzzy rule base system for TWR vs Cutting Speed, Feed, D.O.C



Continue..... Fig 5.12: Pictorial presentation of Fuzzy rule base system for TWR vs Cutting Speed, Feed, D.O.C



Continue..... Fig 5.12: Pictorial presentation of Fuzzy rule base system for TWR vs Cutting Speed, Feed, D.O.C

5.4.3 FUZZY LOGIC using MATLAB: Hardness (HRB) vs. Speed, Feed, D.O.C

Note that the Inputs 1, 2, 3 and Rule editor are the same for subsections 5.4.1, 5.4.2, 5.4.3, but the Output and Rule viewer are different for subsections 5.4.1, 5.4.2, and 5.4.3.

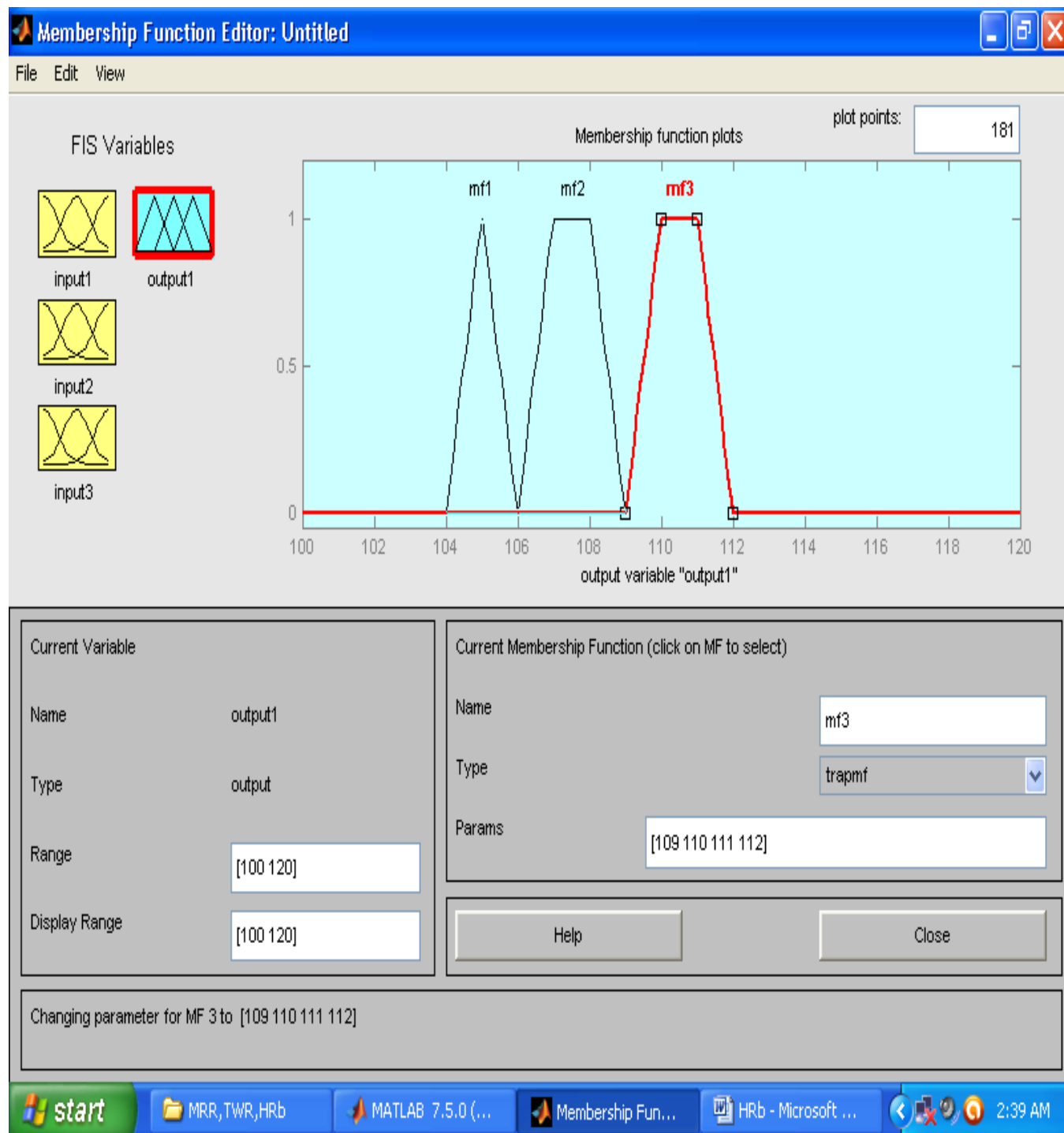


Fig 5.13: Hardness (HRB) membership function (as an output)

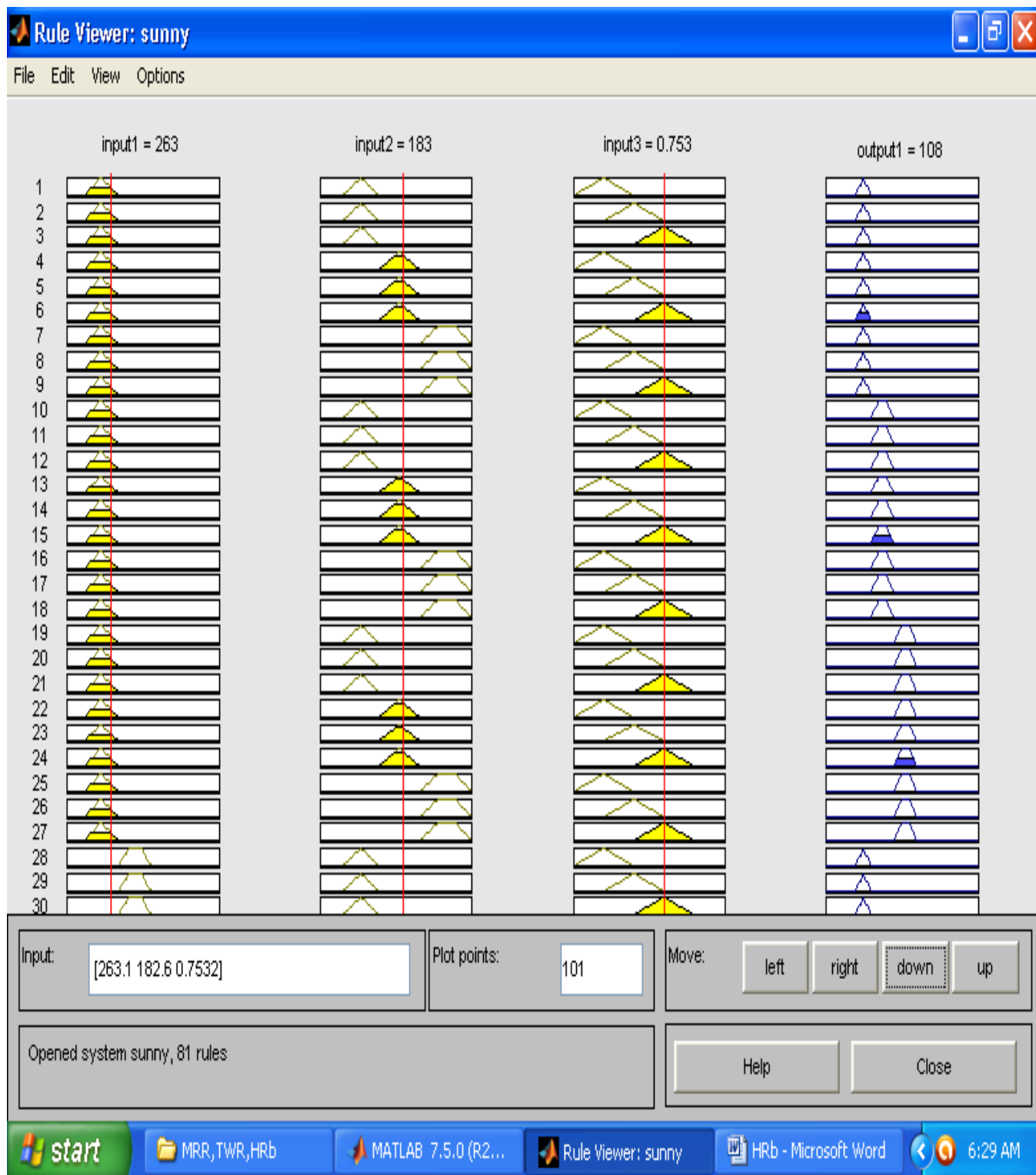
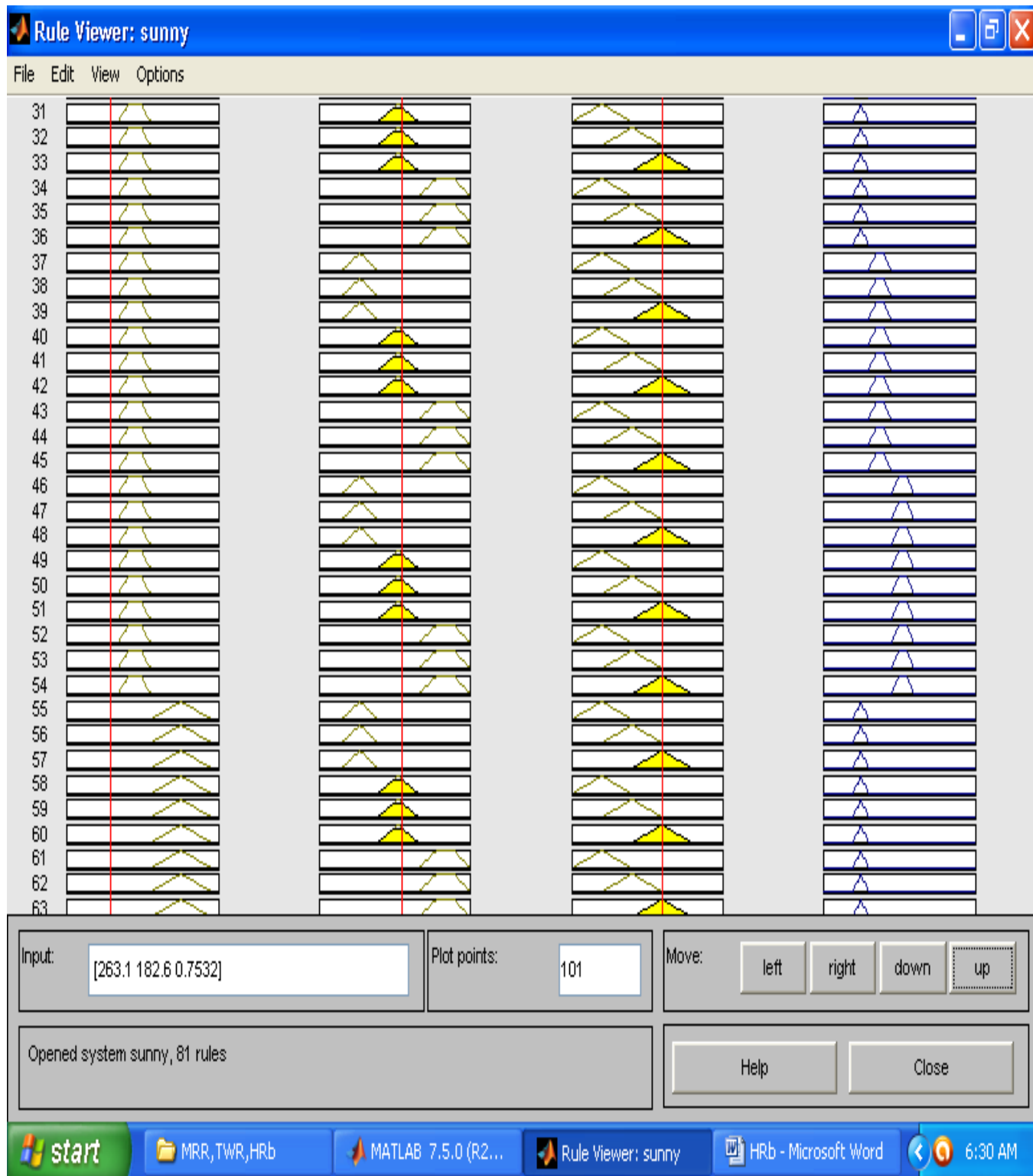
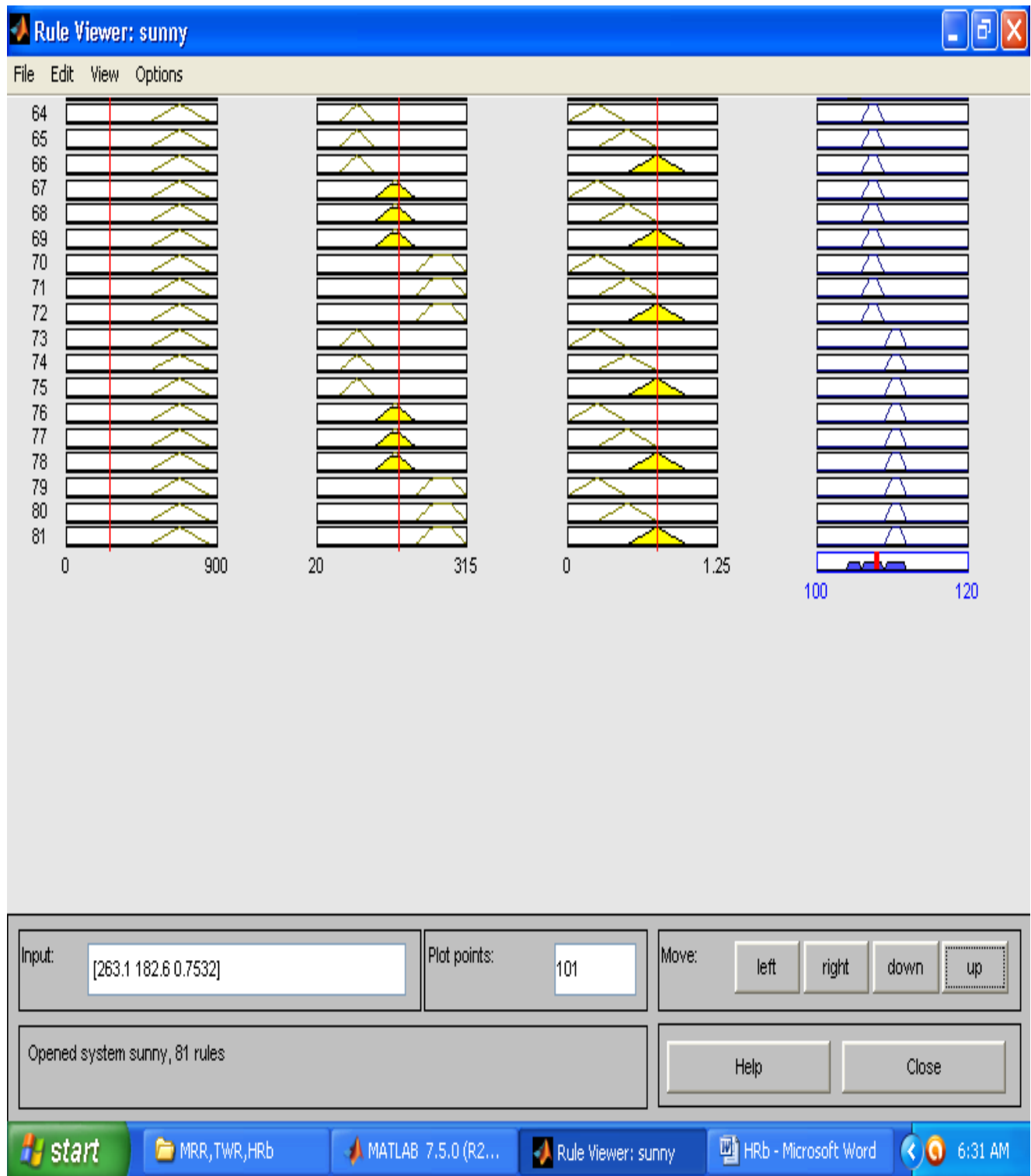


Fig 5.14: Pictorial presentation of Fuzzy rule base system for HRB vs Cutting Speed, Feed, D.O.C



Continues.....Fig 5.14: Pictorial presentation of Fuzzy rule base system for HRB vs Cutting Speed, Feed, D.O.C



Continues.....Fig 5.14: Pictorial presentation of Fuzzy rule base system for HRB vs Cutting Speed, Feed, D.O.C

5.5 Data Recording by DYNAMOMETER(Kistler/DynoWare):

For DATA Recording, a KISTLER DYNO WARE is installed on the machine bed. According to the design of experiment input variables are varied while in the end milling the forces on the work pieces are calculated by dynamometer, which was coupled with CPU for each set of reading 100 sec time duration. Next section gives the detailed study of force reading given by dynamometer for specified duration of time. Test conditions leading to various components of cutting force in Mild Steel material were chosen.

**Table 5.3: Experimental Results of measured parameters against known parameters
Cutting speed, feed and depth of cut**

S.No.	Cutting Speed, v(rpm)	Feed, f(mm/rev)	Depth of cut, d(mm)	F _x (N), Tangential cutting force	F _y (N), Radial cutting Force	F _z (N), Axial cutting force
1	204	100	0.25	-280	-125	-275
2	204	175	0.50	-50	120	-80
3	204	315	0.75	25	170	-10
4	450	100	0.50	10	320	220
5	450	175	0.75	10	340	150
6	450	315	0.25	-140	285	10
7	680	100	0.75	200	310	40
8	680	175	0.25	-290	100	-160
9	680	315	0.50	-160	450	50

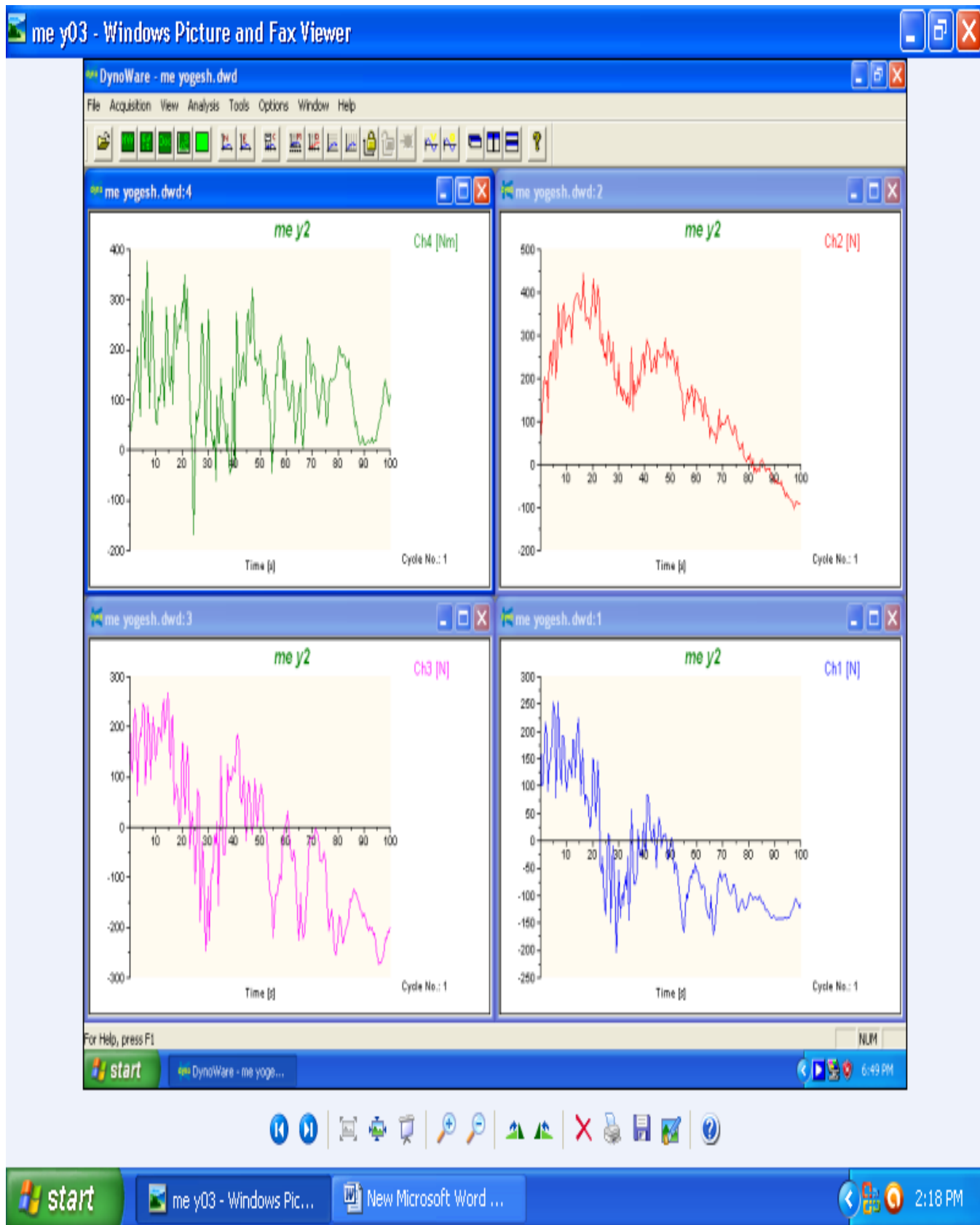


Figure 5.15: Graphical representation of Force Variations at Cutting Speed= 204 m/min, Feed= 315 mm/min, Depth of cut= 0.75 mm

CHAPTER-6

RESULTS AND SCOPE FOR FUTURE WORK

6.1 RESULTS AND DISCUSSIONS

The aim of study is to predict the effects of cutting parameters on the variations of MRR, TWR, Hardness, Cutting forces during end milling operation of MILD steel alloy materials. The number of experiments has been conducted on MS specimen to find out the MRR, TWR, and Hardness of the tool, at varying machining parameters, which are cutting speed (v), cutting feed (f) and depth of cut (d). In order to check the validity of the results various graphs are plotted between Input and output components. On the basis of present study following conclusions can be drawn:

1. This research work was undertaken to develop a mathematical relationship between the MRR, TWR, HRB in end milling of mild steel and the machining variables by using the experimental results obtained through use of the concept of Taguchi design. It has been possible to develop the first order (linear model). Adequacy or validity of the models has been evaluated by ANOVA which indicates that the models are reliable. Linear model (1st order) has shown that the cutting speed has the most significant influence on MRR followed by feed and depth of cut. Hence, the percentage average of error between the predicted and measured tool life of both models is less than 5%.
2. Statistical analysis has been conducted to determine the effectiveness of using different defuzzification methodologies and membership functions. These factors impact the training speed and accuracy significantly. It has been found that results generated by the designed fuzzy model are close to the experimental results with 96.55% accuracy.
3. After investigating the significance of developed model, it has been concluded that the probability of the model to predict accurate results is 98.3% as validated by the application of F-test and T-test. This test is used for test of goodness of fit, comparison of a number of frequency distribution and finding association and relationship between attributes. With this much accuracy, model can be used by the practicing engineer who would like to get quick answers for on-line intelligent control and/or optimization.
4. Sugeno-Fuzzy has shown the capability of generalization and prediction of MRR, TWR, and Hardness in milling within the range of experimental data.
5. The maximum deviation observed and estimated by Fuzzy is very minimal and within the recommended regions of MRR, TWR, Hardness analysis in Milling.
6. The predicted values of Fuzzy output can be further precisely predicted with the change of structure and the weights to the system by increasing the number of experiments.
7. The tool wear rate equation shows that the depth of cut is the main factor affecting the tool wear rate, followed by the feed rate. On the other hand, cutting speed effect is less significant within the testing region of cutting speed, feed rate and depth of cut.

6.2 SCOPE FOR FUTURE WORK

With increasing competitiveness as observed in the recent times, manufacturing systems in the industry are being driven more and more aggressively. So there is always need for Perpetual improvements. Thus for getting still more accurate results we can take into account few more parameters as given below:

1. CNC machines can be used for the experimentation to have the better control of the process variables and also parameters can be set to the desired accuracy.
2. The present work can be extended with different diameter of MILLING tools, process parameters, material thickness, other combinations of machine and type to test the ability of the expert systems in prediction of the output which the findings can be applied for indirect tool condition monitoring in unmanned manufacturing system.
3. The experiments can be conducted for constant time period instead of constant volume.
4. Further research can be extended on temperature measurements.
5. In the present work the material used is Mild Steel. Choose materials like CBN and alloys which are in use on the same VMC and verify the results.
6. The usage of fuzzy logic in machining processes could be extended to include a larger scale of feed rate and depth of cut, in addition to including more variables, such as material types for the tool and workpiece, and the size of end mills. By including these directions in future study, an adaptive control module in machining.
7. The force signal generated in the present research was collected by a dynamometer, which is relatively expensive and usually inconvenient for industrial applications. Other types of sensors, particularly accelerometers, may potentially replace the dynamometer for the fuzzy-nets-based system, due to their lower cost and easy installation.

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APPENDIX

Sr. no	Speed	Feed	Depth of Cut	Time	Torque(Nm)		MRR	TWR	Hardness
	(m/min)	(mm/min)	(mm)	(sec)	Max (+ve)	Min (-ve)	(mm3/min)	(mm3/min)	HRB
1	204	100	0.25	100	530	10	2.40	0.0009	111
2	204	175	0.50	100	275	120	4.30	0.0014	110
3	204	315	0.75	100	545	472	7.96	0.0022	112
4	450	100	0.50	100	694	82	9.72	0.0030	108
5	450	175	0.75	100	564	190	12.31	0.0039	107
6	450	315	0.25	100	455	148	11.84	0.0050	109
7	680	100	0.75	100	361	320	15.36	0.0063	105
8	680	175	0.25	100	419	268	17.89	0.0078	104
9	680	315	0.50	100	468	121	20.21	0.0095	106