PREDICTION OF MULTI RESPONSES IN RADIAL DRILLING PROCESS USING MAMDANI FUZZY INFERENCE SYSTEM

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CERTIFICATE

This is to certify that the thesis entitled "**PREDICTION OF MULTI RESPONSES IN RADIAL DRILLING PROCESS USING MAMDANI FUZZY INFERENCE SYSTEM**" submitted by Debraj Chatterjee in partial fulfilment of the requirements for the award of Bachelor of Technology Degree in Mechanical Engineering at the **NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA** (Deemed University) is an authentic work carried out by him under my guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University / Institute for the award of any Degree or Diploma.

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Abstract

Engineering problems often embody many characteristics of a multi-response optimization problem, and these responses are often conflicting in nature. To address this issue, the present work uses Grey- based Taguchi method to express surface roughness of drilled holes and drill flank wear into an equivalent single response grey relational grade. Experiments have been conducted in a radial drilling machine with five input parameters using L_{27} orthogonal array. It has been observed that combined response of flank wear and surface roughness is affected by almost all input parameters; however, drill diameter is statistically most significant one whereas Spindle speed is least significant input parameter. The prediction results were obtained via. Mamdani fuzzy logic model and BPNN and the corresponding results were compared. It is observed that Mamdani produces better result compared to BPNN in predicting the equivalent response grey relational grade. The advantage of mamdani fuzzy logic lies in the fact that it can take into account the uncertainty and impreciseness involved during experimentation. It is usually convenient for the practitioners to express model inputs in linguistic terms such as high, low, medium rather than expressing in quantifiable terms. The extraction of linguistic terms can largely reduce the chances of error, which is a constriction experienced in case of crisp values used in neural networks.

CHAPTER1

INTRODUCTION

Introduction

DRILLING

Making round holes in metal pieces is known as drilling. In drilling operation the metal is removed by shearing and extrusion. The drilling is done with a drilling machine.

Types of drilling machines:

1.Portable drilling machine

2.Sensitive drilling machine

3.Radial drilling machine

4.Gang drilling machine

5.Multiple drilling machine

6.Multiple spindle drilling machine

7.Deep hole drilling machine

Drilling tools

Flat drill- It is a simple type drill with cutting edges bevelled at 60.

Straight fluted drill- It is considered as a cutting tool having zero rake.

Twist drill- It is an end cutting tool with two three or four cutting lips. It has a cylindrical body in which grooves are cut. These grooves are called flutes. During drilling the drill is held by the shank. The shank is either parallel or tapered. The parallel shank is provided on small sized drills. The tapered shank drills are called morse taper. The twist drills are either carbon steel or high speed drills.

Parameters used in drilling

1.Point angle

2.Lip relief angle

3.Chisel edge angle

4.Helix or rake angle

Operations performed on a drilling machine:

Boring- It is used to enlarge a hole that has already been drilled.

Reaming- It is used to both enlarge a hole and give it a smooth finish.

Tapping- A tap has basically three parts the taper tap which consists of eighty to ten threads then an intermediate tap with two to three threads and lastly a bottoming or plug tap at the extreme end. It is used to produce internal threads in a hole. The size of the hole in which taps are to be produced are less than two times the size of the thread that is being obtained.

Counterboring – It is used for increasing the hole so that bolt heads can be fixed.

Spot facing- It is used for providing a smooth surface around a hole.

Countersinking- It is used to make a cone shaped enlargement at the end of a hole

Lapping- It is used to finish a small diameter hole

Trepanning- In this operation metal is removed along the circumference of a tool thereby producing a hole

Fig1

Radial arm drill press controls

CHAPTER 2

LITERATURE REVIEW

2 Literature review

Tool failure

By plastic deformation when the form of the tool is lost. The tool is normally hard but under cutting conditions when the temperature or the stresses is high plastic deformation causes loss of form stability that is cutting ability of tool.

By a process of mechanical breakage if the cutting force is very high or developing fatigue cracks under chatter conditions.

By a process of gradual wear which takes place due to interaction between the work and tool material.

Types of tool wear

Wear can be defined as total loss in weight or mass of the sliding pairs accompanying friction. The wear between the rubbing surfaces occurs due to

1 Macrotransfer type mechanical wear process like abrasion and adhesion

2 Microtransfer type thermochemical process like diffusion

3 Electrochemical process like localised galvanic action or oxidation

Abrasion wear

It is because of ploughing by hard constituents including fragments of built up edge formationas they are swept over the tool surface. Such wear is common in the tool flank because of the nature of contact.

Adhesion wear

When the metallic surfaces are brought into close contact under moderate loads a metallic bond between adjoining materials take place . This occurence is known as adhesion.The strength of the points of adhesion is so great that while attempting to free the surfaces separation takes place not only along the interface but in one of the material itself transferring and removing materials often with sliding member of the pair. Quantity of material transferred is proportional to the real area of contact as well as the hardness of the mating pair under likewise environment

Chemical wear

Chemical wear is due to interaction between tool and work material in the cutting fluid . If the fluid is active then the tool wear may be greatly increased by chemical reaction. Frequently sharp tool forces are lower and the surface finish greater with such fluids but wear rate is greater.the results are less friction and better finish.

Diffusion wear

The diffusion wear occurs when temperature is very high , large deformation takes place and a high strain rate is common at the chip tool interface

Radial arm press drill controls

Fig 2

Radial drilling machine

The metal cutting process involves plastic deformation, fracture, impact continuous and intermittent multi contact points and friction. Direct visual inspection is never possible since workpiece and chip obstruct the view therefore sensors are used to observe the failure. To get desired quality cutting parameters should be selected in a proper way. Wardany et al. (1996) reported that drilling is a complex operation when compared to other machining operation as the two points of the drill wear alternately till they both have zero clearance at the margin, and become lodged within work piece. Kanai and Kanda (1978) suggested that different types of drill wear could be recognized as outer corner wear, flank wear, margin wear, crater wear, chisel wear and chipping at the lip. Bonifacio and Dinz (1994), Rao (1986) suggested that the wide tool failure modes are flank wear, fracture, crater wear and plastic deformation . Nouari et al. (2003) provided necessary information about the main factors affecting the hole quality i.e. cutting speed, temperature, feed rate, geometrical parameters as well as the influence of the cutting conditions and the temperature on the tool life in drilling. They suggested that improvement of surface quality and dimensional accuracy of the holes can be got at large cutting speed and a weak feed rate.

Surface rougness is a major matter of concern over the last few years as industries desperately try to excel in quality and reduce the price simultaneously. It is indicated as an important design feature in many situations such as parts subject to fatigue loads, precision fits, and aesthetic requirements. In addition to tolerances, surface roughness imposes one of the most critical constraints for the selection of machines and cutting parameters in process planning. Drill wear is an important issue since wear on drill affects the whole quality and tool life of the drill. Direct visual inspection of cutting edge of tool and measurement of roughness of the drilled hole in a transfer line is not feasible and therefore indirect methods using sensory feed back during drilling have been is use to compute the roughness of drilled hole and the wear of the drill

Standardised methods were suggested by DOE for each of steps which has been used comprehensively in this work to significantly reduce the the number of experiments and form the rule box. As there are five input parameters thus there should have been around two hundred and forty three rules which has been reduced to only twenty seven rules. The degree of significance of each of the factors on the process response has been deduced by using ANOVA

CHAPTER 3

METHODOLOGY

3 METHODOLOGY

3.1 PARAMETRIC OPTIMISATION

Taguchi method, tool for parameter design of the performance characteristics has been used to determine optimal machining parameters for minimization of flank wear and surface roughness. The predicted data got from mathematical models can be converted into a signal-to-noise (S/N) ratio. The feature that lower value represents better machining performance, such as surface roughness and flank wear is called 'lower-the-better', L_{LB}.

$$L_{LB} = \frac{1}{n}\sum_{i=1}^{n} y2$$

where y is the experimental response (surface roughness or flank wear) and n is the number of observations.

S/N ratio for SF = $-10\log_{10}(L_{LB})$

3.2 GREY RELATIONAL ANALYSIS

Experimental data are normalized ranging from zero to one. The process is known as Grey relational generation. Next, from the normalized experimental data, Grey relational coefficient is got to represent the correlation between the desired and actual experimental data. Then overall Grey relational grade is determined by getting the average of the Grey relational coefficient according to selected responses. The overall performance characteristic of the multiple response process is dependent on the calculated Grey relational grade. This converts a multiple response process optimization problem into a single response optimization situation where the objective function is overall Grey relational grade. The optimal parametric combination is then calculated which would give highest Grey relational grade. The optimal factor setting for maximizing overall Grey relational grade can be done by Taguchi method. In Grey relational generation, the normalized data i.e. surface finish and flank wear corresponding to lower-the-better (LB) criterion is

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)}$$

Where $x_i(k)$ is the value after Grey relational generation, min $y_i(k)$ is the smallest value of $y_i(k)$ for the k_{th} response, and max $y_i(k)$ is the largest value of $y_i(k)$ for the k_{th} response. The sequence is $x_0(k)$ (k=1,2....27) for the responses. Grey relational grade says about the degree of relation between the 27 sequences $x_0(k)$ and $x_i(k)$, (k=1,2,3...27). The Grey relational coefficient $\xi_i(k)$ is can be got as:

$$\xi_i(k) = \frac{\Delta\min + \Psi\Delta\max}{\Delta oi(k) + \Psi\Delta\max}$$

Where $\Delta_{oi} = \| x_0(k) - x_i(k)\|$ difference of absolute value $x_o(k)$ and $x_i(k)$; Ψ is the distinguishing coefficient $0 \le \Psi \le 1$; $\Delta_{min} = \forall j^{min} \in i \forall k^{min} \| x_0(k) - xj(k)$□ = the smallest value of Δ_{oi}; and $\Delta_{max} = \forall j^{max} \in i \forall k^{max} \| x_o(k) - xj(k)\|$ = the largest value of Δ_{oi} .The grey relational grade is calculated as the average of the grey relational coefficients. The grey relational grade is denoted by γ_i

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi i(k)$$

where *n* is the number of process responses.

A high value of grey relational grade tells that degree of relation between the reference sequence $x_o(k)$ and the given sequence $x_i(k)$ is very high. The reference sequence $x_o(k)$ represents the best process sequence; therefore, higher Grey relational grade means that parameter combination is nearer to the optimal.The grand mean and the main effect plot of Grey relational grade are used to calculate the optimal process condition. We see the levels at which it is highest and then decide the optimal condition.

3.3 ANOVA

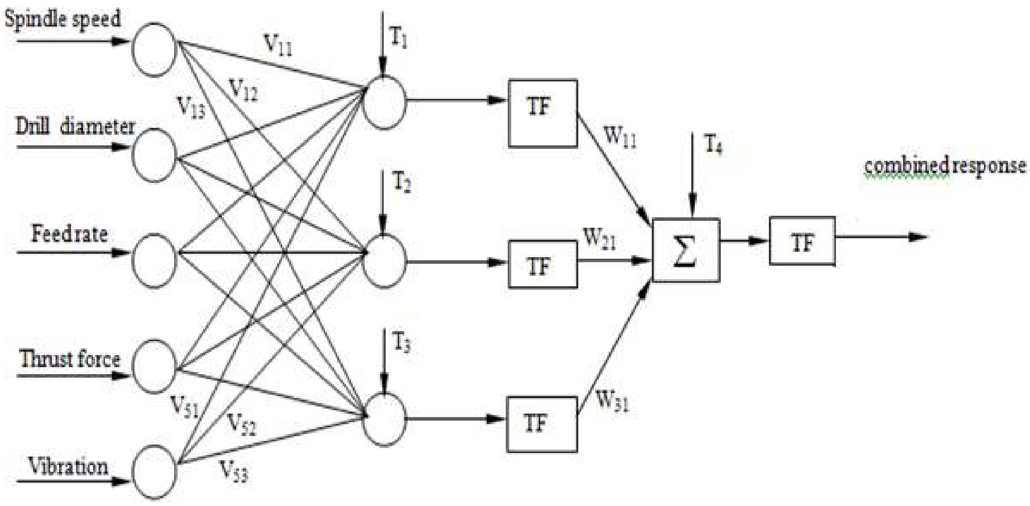
The degree of significance of the factors were deduced by using ANOVA.

3.4 BACK PROPAGATION NEURAL NETWORK

Back propagation neural network (BPNN) is a three-layered feed forward architecture. The three layers are input layer, hidden layer and output layer respectively. Back propagation proceeds in three stages learning or training and testing or inferences. In the figure1 given below there are A input neurons B hidden neurons and C output neurons . Input layer gets information from the external sources and transmits this information to the network for processing. Hidden layer gets information from the input layer, and does all the information processing, and output layer gets processed information from the network, and transmits the results out to an external receptor. The input signals are modified by interconnection weight, known as weight factor w_{ji}, that indicates the interconnection of i^{th} node of the first layer to j^{th} node of the second layer. The sum of modified signals (total activation) is then modified by a sigmoid transfer function (f). Likewise outputs signal of hidden layer are modified by interconnection weight (w_{kj}) of k^{th} node of output layer to j^{th} node of hidden layer. The summation of all the modified signal is then modified by sigmoid transfer (f) function and output is collected at the output layer.

FIG 3 NETWORK ARCHITECTURE

Fig3



Let $I_p =$ = be the p^{th} pattern among N input patterns. Where W_{ji} and W_{kj} are connection weights between i^{th} input neuron to j^{th} hidden neuron, and j^{th} hidden neuron to k^{th} output neuron, respectively.

Output from a neuron in the input layer is,

$O_{pi} = I_{pi}$ i=1, 2............A

Output from a neuron in the hidden layer is

$O_{pj} = f(NET_{pj}) = f(\sum_{i=0}^{A} Wji\ Opi)$, j=1,2........B

,

Output from a neuron in the output layer is

$O_{pk} = f(NET_{pk}) = f(\sum_{j=0}^{B} WkjOpj)$, k= 1,2..........C

Sigmoid transfer function f : a bounded, monotonic, non-decreasing, S-shaped function that provide a graded nonlinear response. The logistic sigmoid function

$$f(x)= \frac{1}{1+ e^{-x}}$$

Training in back propagation neural network

In training, the predicted output is compared with the desired output, and the mean square error can be got. If the mean square error is more than a particular limiting value, it is back propagated from output to input, and weights are further changed till the error or number of iterations is within a sustainable limit.

Mean square error, E_p for pattern p is defined as

$$E_p = \sum_{i=1}^{n} \frac{1}{2}(Dpi - Opi)2$$

where, D_{pi} is the target output, and O_{pi} is the computed output for the i^{th} pattern. The method requires the computation of local error gradients in order to determine the appropriate weight corrections to reduce error. The synaptic weights are updated according to following equation.

$$W_{ji}(t+1) = W_{ji}(t) + \Delta W_{ji}(t+1)$$

$$\Delta W_{ji}(t+1) = \alpha\, \Delta W_{ji}(t) + \eta\, \delta_j^{\{lay\}}\, y_i^{\{lay-1\}}$$

α = momentum coefficient

η =learning rate

Testing of back propagation neural network:

Data set is divided into training set and testing set. The error on the testing set is observed during the training process. The testing error will lessen during the initial phase of training, as does the training set error. But when data over feeds into the network , the error on the testing set will rise. When the testing error starts to increase for a given number of iterations, the training is stopped; and the weights at the minimum value of the testing error are restored. The testing data is then put into the trained network to evaluate the percentage variation of predicted output in comparison to the actual output.

Learning parameter and training parameter

In the backpropagation neural network technique learning parameters and momentum parameters are used . the learning parameter decides how quickly a network is going to get trained, while the momentum parameter pevents the prediction to get limited to lower and local values.

3.5 .Prediction using mamdani fuzzy logic model

The various operations, laws and properties of fuzzy sets are introduced along with that of the classical sets. The classical set being dealt with is defined by means of the crisp boundaries. This means that there is no uncertainty involved in the location of the boundaries for these sets. But the fuzzy set, on the other hand is defined by its vague properties.. The crisp sets are sets not having ambiguity in their membership. The fuzzy set theory is a very efficient theory in dealing with the concepts of ambiguity. The fuzzy sets are handled after reviewing the concepts of the classical or crisp sets.

Fuzzy Inference Methods:

The two types of fuzzy inference method are Mamdani’s fuzzy inference method, which is the most commonly seen inference method. This method was introduced by Mamdani and Assilian (1975). Another inference method is the so-called Sugeno or Takagi–Sugeno–Kang method of fuzzy inference process. This method was introduced by Sugeno (1985). This method is also called as TS method. The difference between the two methods lies in the consequent of fuzzy rules. Mamdani fuzzy systems use fuzzy sets as rule consequent whereas TS fuzzy systems use linear functions of input variables as rule consequent. All the present results on fuzzy systems as universal approximators deal with Mamdani fuzzy system and no result is available for TS fuzzy systems with linear rule consequent.

Mamdani’s Fuzzy Inference Method

Mamdani’s fuzzy inference method is the most common fuzzy methodology. Mamdani’s method was among the first control systems built using fuzzy set theory. It was proposed by Mamdani (1975) as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani’s efforts were based on Zadeh’s (1973) paper on fuzzy algorithms for complex systems and decision processes. Mamdani type inference, as defined it for the Fuzzy Logic Toolbox, suggests that the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. It is possible, and in many cases much more useful, to use a single spike as the output membership function rather than a distributed fuzzy set. This is sometimes known as a *singleton* output membership function, and it can be thought of as a pre-defuzzified fuzzy set. It increases the efficiency of the defuzzification process because it greatly simplifies the computation required by the more general Mamdani method, which calculates the centroid of a two-dimensional function. Rather than integrating across the two-dimensional function to find the centroid, the weighted average of a few data points can be calculated. Sugeno type systems support this type of model. In general, Sugeno type systems could be used to model any inference system in which the output membership functions can be linear or constant.

1. Determining a set of fuzzy rules

2. Fuzzifying the inputs by using the input membership functions

3. Combining the fuzzified inputs according to the fuzzy rules to make a rule strength

4. Finding the result of the rule by combining the rule strength and the output membership function

5. Combining the consequences to get an output distribution

6. Defuzzifying the output distribution (this step is if a crisp output (class) is needed).

Construction and Working of Inference System

Fuzzy inference system contains a fuzzification interface, a rule base, a database, a decision-making unit, and finally a defuzzification interface. A FIS with five functional block described in Fig.4. The function of each block is as follows:

– rule base consisting a number of fuzzy IF–THEN rules;

– database which defines the membership functions of the fuzzy sets used in the fuzzy rules;

– decision-making unit which performs the inference operations on the rules;

– a fuzzification interface which converts the crisp inputs into degrees of match with linguistic values

– a defuzzification interface which converts the fuzzy results of the inference into a crisp output.

The working of FIS can be described as below. The crisp input is transformed in to fuzzy by the fuzzification method. After fuzzification the rule base is made. The rule base and the database are together referred to as the knowledge base. Defuzzification is used to transform fuzzy value to the real world value which is actually the output. The steps of fuzzy reasoning (inference operations upon fuzzy IF−THEN

rules) performed by FISs are:

1. The input variables are compared with the membership functions on the antecedent part to get the membership values of the linguistic labels.

(this step is called fuzzification.)

2. The membership values on the premise part are combined(through a specific t-norm operator, usually multiplication or min) to get firing strength

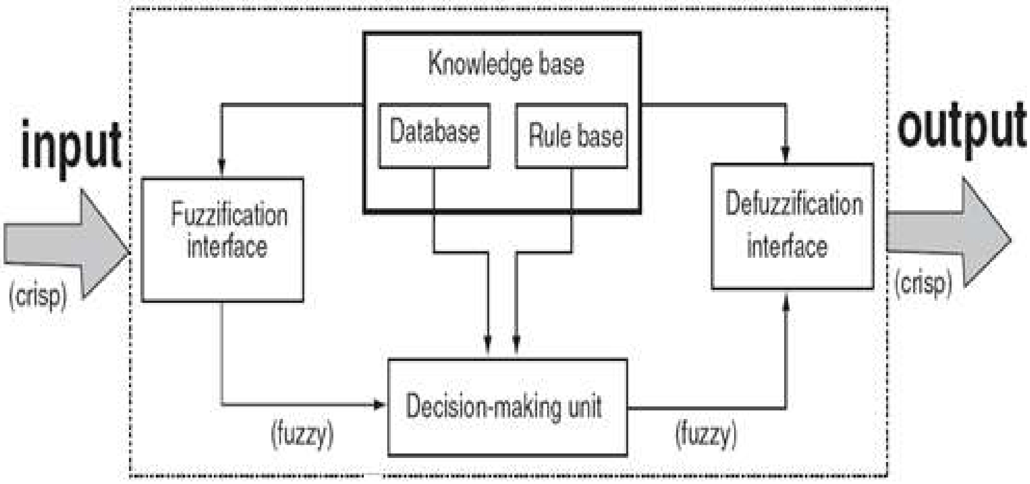
(weight) of each rule.

3. The qualified consequents (either fuzzy or crisp) of each rule are generated

depending on the firing strength.

4. The qualified consequents are aggregated to produce a crisp output. (This

is called defuzzification.)



Fuzzy inference system

FIG 4

Membership Functions

Fuzziness in a fuzzy set is characterized by its membership functions. It classifies the element in the set, for both discrete and continuous. The membership functions can also be got by graphical representations. The graphical representations includes different shapes. There are certain restrictions with regard to the shapes used. The rules formulated to represent the fuzziness in an application are also fuzzy. The "shape" of the membership function is an important criterion that is to be considered. There are different techniques to form membership functions. This work discusses on the features and the various techniques of arriving membership functions

.

Features of Membership Function

The feature of the membership function is defined by three properties. They are:

(1) Core

(2) Support

(3) Boundary

Fuzzification

Fuzzification is an important aspect in the fuzzy logic theory. Fuzzification is the method where the crisp quantities are transformed to fuzzy (crisp to fuzzy). By identifying some of the uncertainties present in the crisp values, we formulate the fuzzy values. The transformattion of fuzzy values is represented by the membership functions. In practical applications, in industries, etc., measurement of voltage, current, temperature, etc., there may be a negligible error. This causes imprecisiness in the data. This imprecisiness can be represented by the membership functions. Hence fuzzification is done. Thus fuzzification process involves assignment of membership values for the crisp quantities.

Fuzzy Inference System

Fuzzy inference systems (FISs) can be called as fuzzy rule-based systems, fuzzy model, fuzzy expert system, and fuzzy associative memory. This is a important unit of a fuzzy logic system. The decision-making is a major part in the entire system. The FIS forms suitable rules and based upon those rules the decision is made. This is based on the concepts of the fuzzy set theory, fuzzy IF–THEN rules, and fuzzy reasoning. FIS uses "IF. . . THEN. . . " statements, and the connectors used in the rule statement are "OR" or "AND" to formulate the necessary decision rules. The basic FIS can accept either fuzzy inputs or crisp inputs, but the outputs it produces are always fuzzy sets. When the FIS is used as a controller, it is deemed necessary to have a crisp output. Therefore in this case defuzzification method is used to extract a crisp value that best represents a fuzzy set.

RULE BOX OF THE MAMDANI FUZZY LOGIC MODEL:-

In fuzzy logic the basis for obtaining fuzzy output are the rules. The rulebased system is different from the expert system in the fact that the rules comprising the rule-based system originates from sources other than that of human experts .The rule-based form uses linguistic variables as its antecedents and consequents. The antecedent expresses an inference or the inequality, which should be satisfied. The consequents are those, which we can conclude, and is the output if the antecedent inequality is satisfied. The fuzzy rule-based system uses IF–THEN rule-based system, given by, IF antecedent, THEN consequent.

Formation of Rules

The formation of rules is in general the canonical rule formation. For any linguistic variable, there are three general forms in which the canonical rules can be formed. They are:

(1) Assignment statements

(2) Conditional statements

(3) Unconditional statement

DEFUZZIFICATION

The conversion of fuzzy to crisp values is defuzzification. The fuzzy results obtained cannot be used as such to the applications, and thus it is necessary to transform the fuzzy quantities into crisp quantities for further processing. This can be done by using defuzzification process. The defuzzification can reduce a fuzzy to a crisp single-valued quantity or as a set, or convert to the form in which fuzzy quantity is present. Defuzzification is also known as “rounding off” method. Defuzzification reduces the collection of membership function values to a single scaler quantity.

Defuzzification Methods

Apart from the lambda cut sets and relations which transform fuzzy sets or relations into crisp sets or relations, there are other varied defuzzification methods used to transform the fuzzy quantities into crisp quantities. The output of an entire fuzzy method can be an union of two or more fuzzy membership functions.

There are seven methods used for defuzzifying the fuzzy output functions.

They are:

(1) Max-membership principle,

(2) Centroid method,

(3) Weighted average method,

(4) Mean–max membership,

(5) Centre of sums,

(6) Centre of largest area, and

(7) First of maxima or last of maxima

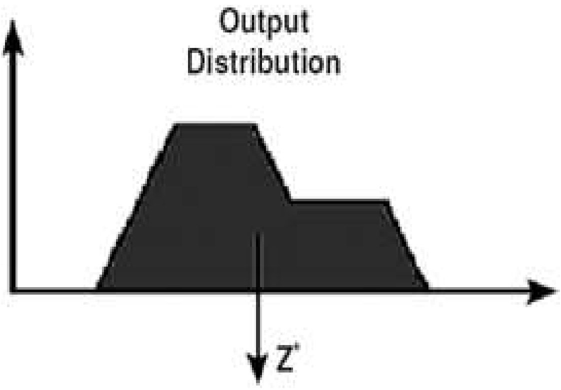
In many examples, it is desired to come up with a single crisp output from an FIS.. This crisp number is obtained in a process known as defuzzification. There are two common techniques for defuzzifying:

Center of mass. This method is used to take the output distribution and center of mass is found out to get a crisp number. It is calculated as shown I fig 5

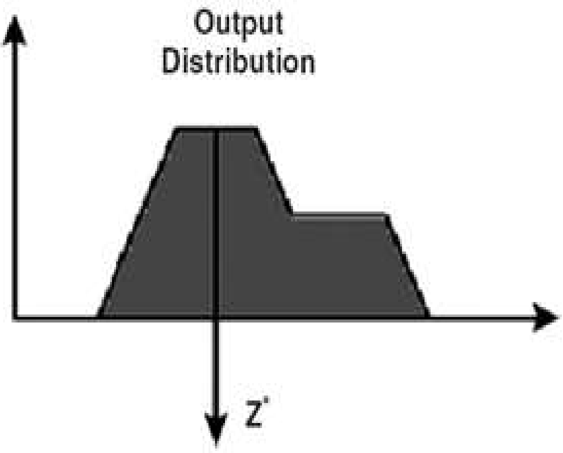
$$Z = \frac{\sum_{j=1}^{q} Zj\ uc(Zj)}{\sum_{j=1}^{q} uc(Zj)}$$

Mean of maximum. This method is used to take the output distribution and its mean of maxima is found out to get one crisp number. It is calculated as shown in figure 5

$$Z = \sum_{J=1}^{L} \frac{Zj}{L}$$



Defuzzification using the center of mass



Defuzzification using the mean of maximum

Fig5

Graphs were plotted between the mamdani fuzzy logic results and the experimental results.The neural network results were also plotted with the experimental results. Correlation coefficient was calculated for each of the graphs and a nearly linear relationship was found.

CHAPTER 4

EXPERIMENTAL SETUP

4 EXPERIMENTAL SETUP

A radial drilling machine (Batliboi Limited, BR618 model) was used for the drilling operation and Figure 4 shows the schematic diagram of the present experimental setup. Details of the equipment, sensors and the cutting conditions for the drilling operation performed is illustrated in Table 1. Table 2 and 3 give properties of the drill and work piece material respectively used in the present study. In all the drilling operations performed, no coolant was used. Root mean square (RMS) values of thrust force is recorded through a piezo-electric dynamometer. Signals from the dynamometer were passed through low-pass filter with a cut off frequency 10 Hz and is amplified through charge amplifier and stored in the computer through a data acquisition system. A piezo-electric accelerometer was used to capture feed vibration signal that was attached on the top surface of the mild steel specimen. Signal from the accelerometer was passed through vibration analyzer and cut off frequency of low-pass filter of vibration signals was maintained at 7 Hz. RMS values of amplitude of vibration was collected through Bruel & Kjaer software (Pulse, version 7), and was stored in the computer through data acquisition system. Flank wear of the drill was measured with the help of the reflected light optical microscope. Charge couple display (CCD) color camera was attached to capture the image. The maximum depth of flank wear was used as the criterion to characterize the drill condition, and was got by measuring the wear at different points on each of the flank side of cutting edges.

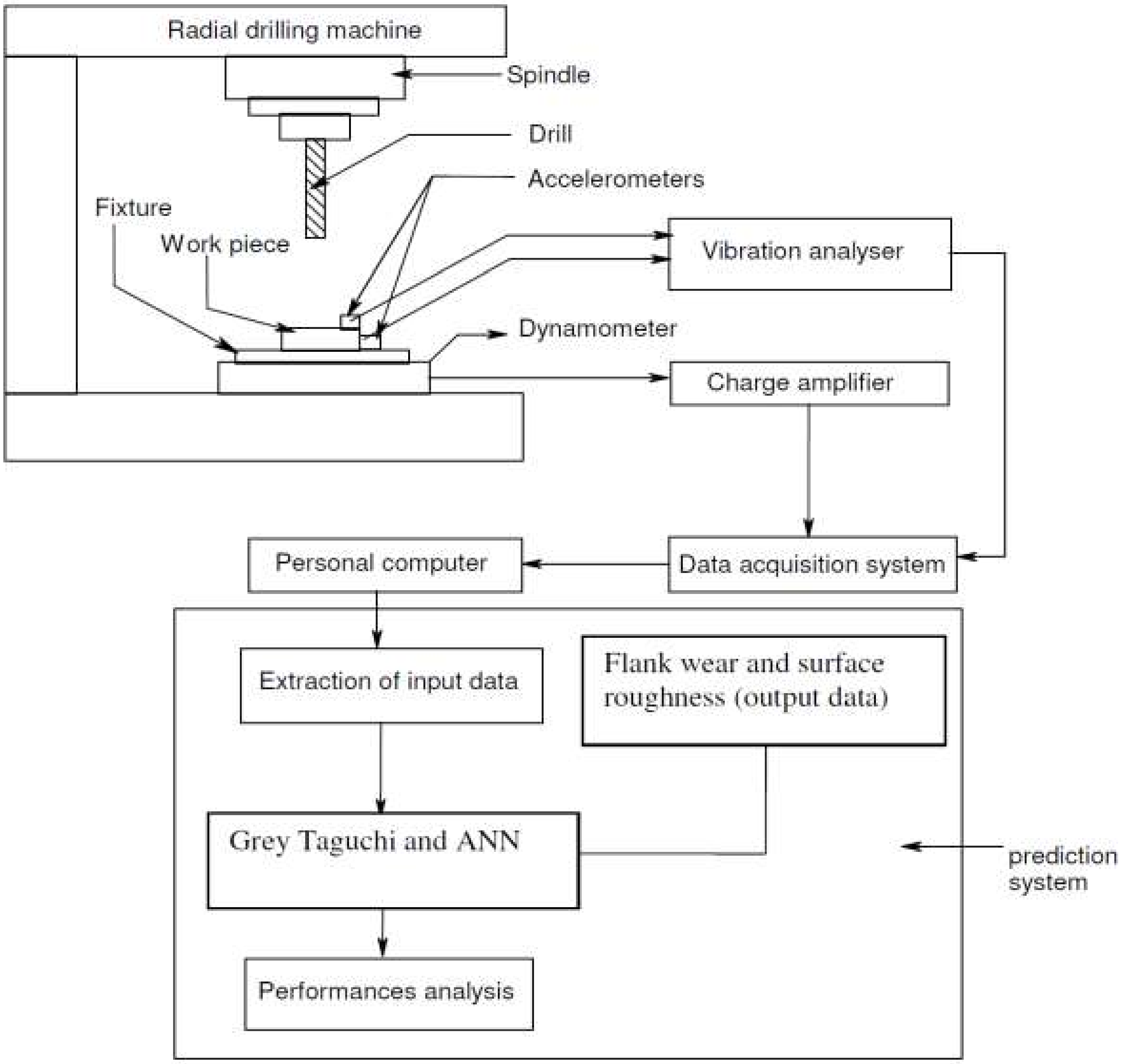


Fig 6 experimental setup

Table 1 Details of the cutting conditions and experimental set up

Range of spindle speed (rpm)	***Range of feed rate mm/rev***	***Range of drill dia(mm)***	***Experimental set up***	***Features collected***	***Specifications***
			Radial drilling machine(batliboi limited,BR618 model)		***50-1600 rpm in 16 steps, 0.13-1.4 mm/rev in 8 steps***
			Dynamometer(Kistler type 9272)	***Thrust force***	***Sensitivity 3.8 Pc/N and -1.6 Pc/N-cm***
			Charge amplifier(Kistler type,5015)		***25Khz sampling rate, 1000N/v and 10Nm/v***
			Data acquisition system for cutting force signals(Advantech,PCL818HG,16 channel A/D)		***10 Khz sampling rate***
			Accelerometer probes(Bruel and Kjaer4396)	***Feed vibrations***	***25.6 Khz frequency range***
			Vibration analyser(Bruel and Kjaer3560D)		***7 Hz-25.6 Khz***
325,650, 975	***0.13,0.25,0.37***	***9.5,10.5,11.5***	***Data acquisition systemfor vibration signal(Bruel and Kjaer7701)***		***65.5 kHz***
			Optical microscope(Carlzeiss axiotech)	***Flank wear***	$25\times$ ***mm travel range, height of 440 mm with a 30° viewing angle***
			CCD camera(WAT201A		***280 K pixel and 20***

			model)		***magnification***
			Surface rougness tester	***Drilled hole roughness***	***Average surface roughness (0.2 μι-25.2 μι)***
			Scanning electron microscope	***Compositio n study***	***Resolution 4 nm, Accelerating Voltage 0.5 to 30 kV, Magnification x15 to 200,000***
			Brinnel hardness tester	***Hardness of HSS drill and work piece***	***Hydraulic, 1500-3000 kgf load range, 450 mm throat depth***
			Tool makers microscope	***Geometry of HSS drill***	***Geometry of HSS drill***

Table 2 HSS drill geometry and chemical composition has been described below:

(a) Geometry of HSS drill bit (long series)

Tool Dia (mm)	*Flute Length (mm)*	*Total length (mm)*	*Point Angle (degrees)*	*Helix Angle (degrees)*
9.5	*115*	*175*	*118*	*30*
10.5	*121*	*184*	*118*	*30*
11.5	*128*	*195*	*118*	*30*

Flute 2 Flutes

Flute type parabolic

Shank type straight cylindrical

No coating

(b) Chemical Composition of HSS drill materials (weight%) have been described below:

Tungsten	*Chromium*	*Vanadium*	*Cobalt*	*Molybdenum*	*Carbon*	*Hardness*
18	*4.3*	*1.1*	*5*	*0.65*	*0.75*	*290 BHN*

BHN indicates brinnel hardness number

Table 3 *Mild steel chemical composition and mechanical properties has been described below*

(a) Chemical composition (weight %)

Carbon	*Manganese*	*Silicon*	*Sulphur*	*Phosphorous*	*Others*	*Rest*
0.07	*1.1*	*0.5*	*0.035*	*0.025*	*0.08 Ti* *0.07 Zr*	*Iron (Fe)*

(b) Mechanical properties

Ultimate tensile stress (MN/m2)	*Yield stress (MN/m2)*	*Density (Kg/m3)*	*Elongation (%)*	*Vicker's Hardness*
300	*170*	*7850*	*42*	*140*

CHAPTER 5

RESULTS AND DISCUSSION

5 RESULTS AND DISCUSSION

Table 4 Experimental Results (L_{27} OA)

Experiment No.	Diameter, L (mm)	Speed, M (RPM)	Feed rate, N (mm/rev)	Thrust force, D F	Feed Vibration, K (m/s^2)	Average Roughness R_a (μ ι)	Flank wear W (μ ι)
1	9.5	325	0.13	1566	8	2.7093	133.7761
2	9.5	325	0.25	2900	19	1.122614	109.5114
3	9.5	325	0.37	4234	30	0.808594	98.34312
4	9.5	650	0.13	2900	30	2.437704	199.2778
5	9.5	650	0.25	4234	8	0.782813	172.3982
6	9.5	650	0.37	1566	19	0.491415	88.67653
7	9.5	975	0.13	4234	19	0.657731	88.60489
8	9.5	975	0.25	1566	30	0.731915	20.73748
9	9.5	975	0.37	2900	8	3.228649	227.6959
10	10.5	325	0.13	2900	19	2.019085	134.0201
11	10.5	325	0.25	4234	30	0.906612	99.22988
12	10.5	325	0.37	1566	8	0.821605	91.98041
13	10.5	650	0.13	4234	8	2.173356	194.3373
14	10.5	650	0.25	1566	19	0.535945	188.4641
15	10.5	650	0.37	2900	30	0.497471	82.29112

16	10.5	975	0.13	1566	30	0.654535	90.58278
17	10.5	975	0.25	2900	8	0.729283	22.78724
18	10.5	975	0.37	4234	19	2.466166	199.2513
19	11.5	325	0.13	4234	30	1.69614	114.839
20	11.5	325	0.25	1566	8	2.479666	127.808
21	11.5	325	0.37	2900	19	3.075034	130.8547
22	11.5	650	0.13	1566	19	2.829449	146.4621
23	11.5	650	0.25	2900	30	3.363978	149.4249
24	11.5	650	0.37	4234	8	2.020526	138.9131
25	11.5	975	0.13	2900	8	3.598331	167.1992
26	11.5	975	0.25	4234	19	2.356883	156.7149
27	11.5	975	0.37	1566	30	3.134449	164.3919

The data has been set at three different levels signifying the domain of the experiments

TABLE 5

	Levels		
Parameter	1	2	3
Diameter, L (mm)	9.5	10.5	11.5
Speed, M (rpm)	325	650	975
Feed rate, N (mm/rev)	0.13	0.25	0.37
Thrust force, D (N)	1566	2900	4234
Feed vibration, K (m/s^2)	8	19	30

Grey relational analysis was done on the experimental data. At first the values were normalised and grey relational generation was done the values for which are provided in the table 6. Then grey relational coefficients were calculated whose values have been furnished in table7. Finally grey relational grade was calculated which are given in table8. According to the grey relational grade the experiments were ranked and the corresponding orders has been provided as well.

Table 6

The Δ_{oi} was calculated for each of the following responses

Experiment Number	Surface roughness	Flank wear
X0	1.00000	1.00000
1	0.85746	0.77804
2	0.41494	0.69451
3	0.25014	0.64962
4	0.80441	0.94436
5	0.23386	0.88389
6	0.00000	0.60643
7	0.14642	0.60610
8	0.20009	0.00000
9	0.94555	1.00000
10	0.70977	0.7788
11	0.30760	0.65336
12	0.25816	0.62170
13	0.74675	0.93388
14	0.04357	0.92108
15	0.00615	0.57525
16	0.14397	0.61531
17	0.19828	0.03934

18	0.81024	0.94431
19	0.62223	0.71433
20	0.81298	0.75899
21	0.92107	0.76882
22	0.87926	0.81585
23	0.96618	0.82421
24	0.71013	0.79376
25	1.00000	0.87111
26	0.78748	0.84409
27	0.93068	0.86405

Table 7

Grey relational coefficient of each performance characteristics was taken as : (Ψ=0.5)

Experiment number	Surface roughness	Flank wear
X0	1.00000	1.00000
1	0.77817	0.69256
2	0.46081	0.62074
3	0.40004	0.58797
4	0.71881	0.89987
5	0.39490	0.81155

6	0.33333	0.55956
7	0.36939	0.55935
8	0.38464	0.33333
9	0.9018	1.00000
10	0.63273	0.69329
11	0.41932	0.59057
12	0.40263	0.56928
13	0.66379	0.88321
14	0.34330	0.86368
15	0.33471	0.54068
16	0.36872	0.56517
17	0.38411	0.34231
18	0.72489	0.89978
19	0.56962	0.63640
20	0.72778	0.67476
21	0.86366	0.68383
22	0.80549	0.73083
23	0.93664	0.73987
24	0.63302	0.70798
25	1.00000	0.79506
26	0.70173	0.76229
27	0.87824	0.78622

Table 8

Overall grey relational grade has been calculated by giving same weightage to responses

Experiment Number	Overall grey relational grade	Order
1	0.735360	10
2	0.540772	18
3	0.494006	20
4	0.809340	6
5	0.603225	16
6	0.446444	24
7	0.464368	23
8	0.358988	27
9	**0.950897**	**1**
10	0.663007	14
11	0.504946	19
12	0.485954	21
13	0.773502	8
14	0.603490	15
15	0.437695	25
16	0.466946	22
17	0.363209	26
18	0.812330	5
19	0.603013	17

20	0.701269	12
21	0.773742	7
22	0.768159	9
23	0.838256	3
24	0.670497	13
25	0.897528	2
26	0.732012	11
27	0.832228	4

ANOVA was used to determine the significance of each of the factors.

TABLE 9

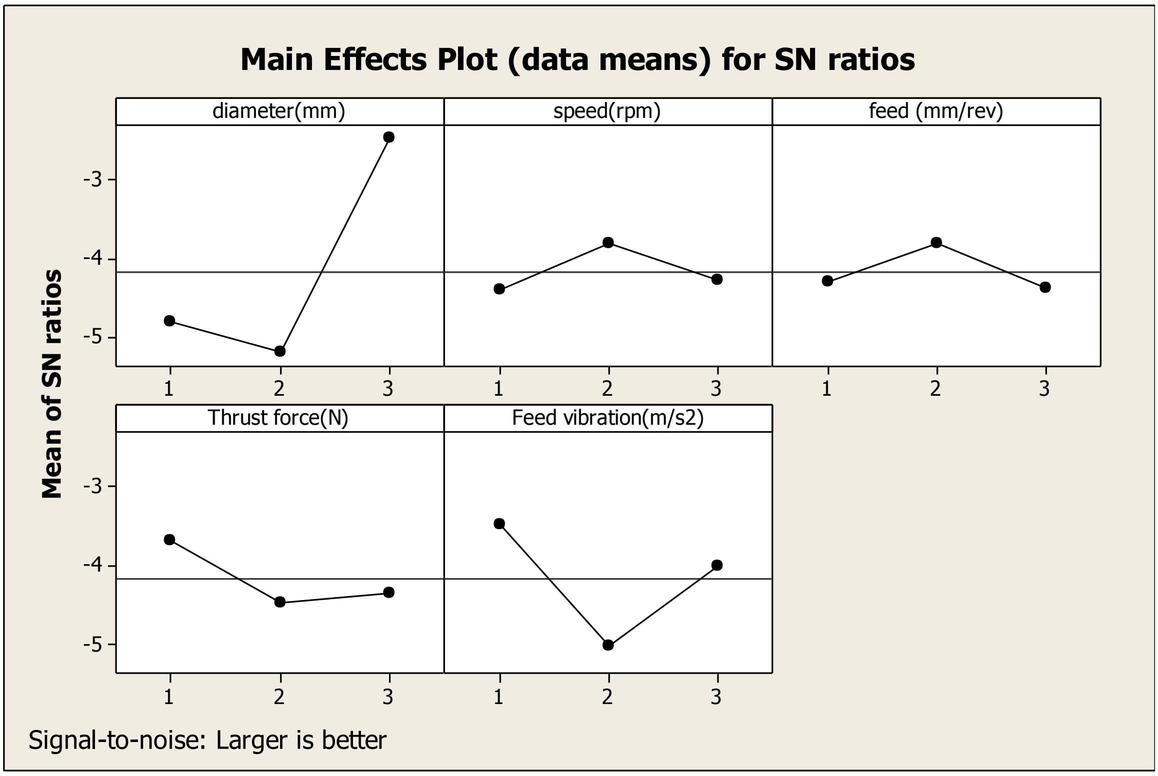
SOURCE	SUM OF SQUARES	DEGREE OF FREEDOM	MEAN SQUARE	F-value	Probability
L	.212	2	.106	4.336	.031
M	.008	2	.004	.173	.843
N	.038	2	.019	.779	.476
D	.051	2	.026	1.053	.372
K	.026	2	.013	.526	.601
ERROR	.391	16	.024		

From there the factors were ranked and it is found that the most significant factor was the L that is the drill diameter and the least significant factor was M that is spindle speed.

TABLE10

FACTORS	Percentage contribution	RANKING
DIAMETER	63.4%	1
THRUST FORCE	15.23%	2
FEED RATE	11.3%	3
FEED VIBRATION	7.7%	4
SPEED	2.4%	5

The optimal parameter setting was got from the combination of L_3 M_2 N_2 D_1 K_1 for the ninth experiment having highest performance .this is observed in figure7



Best multiple performance characterizes and the optimal parameter setting was obtained by carrying out sensitive analysis at different value of Ψ . It is seen from table 11 and figure 7, that the ninth experiment has the highest grey relational grade, which indicates that the best multiple performance characteristics were got with the combination of $L_3M_2N_2D_1K_1$ for varied ranges of grey relational coefficient (0-1).

Table 11 Overall grey relational grade at different value of Ψ was calculated and has been given below:

	Overall grey relational grade				
Expt. no	Ψ=.5	Ψ=.1	Ψ=.3	Ψ=.7	Ψ=.9
1	0.735360	0.361451	0.626331	0.795036	0.832722
2	0.540772	0.196294	0.417213	0.620450	0.676310
3	0.494006	0.169849	0.373509	0.574613	0.632639
4	0.809340	0.490413	0.724447	0.853988	0.881627
5	0.603225	0.289096	0.501180	0.667589	0.712953
6	0.446444	0.146758	0.331658	0.525936	0.584718
7	0.464368	0.153668	0.346198	0.545241	0.604403
8	0.358988	0.101016	0.251760	0.439230	0.501562
9	**0.950897**	**0.823730**	**0.923191**	**0.963914**	**0.971476**
10	0.663007	0.283795	0.541935	0.733392	0.779433
11	0.504946	0.175046	0.383117	0.585768	0.643563
12	0.485954	0.163930	0.365116	0.567329	0.626112
13	0.773502	0.442539	0.680833	0.824016	0.855985
14	0.603490	0.326782	0.515247	0.660637	0.702090

15	0.437695	0.140993	0.322900	0.517809	0.577297
16	0.466946	0.155458	0.348831	0.547604	0.606539
17	0.363209	0.102590	0.255136	0.443826	0.506288
18	0.812330	0.493697	0.727981	0.856513	0.883795
19	0.603013	0.234298	0.477432	0.679834	0.731709
20	0.701269	0.320828	0.585256	0.766521	0.808364
21	0.773742	0.430409	0.678238	0.825200	0.857499
22	0.768159	0.402470	0.666332	0.822302	0.855926
23	0.838256	0.554924	0.764603	0.876592	0.900186
24	0.670497	0.291521	0.550598	0.739795	0.784978
25	0.897528	0.718448	0.849742	0.922253	0.937366
26	0.732012	0.355365	0.621677	0.792470	0.830656
27	0.832228	0.507199	0.750221	0.873628	0.898623

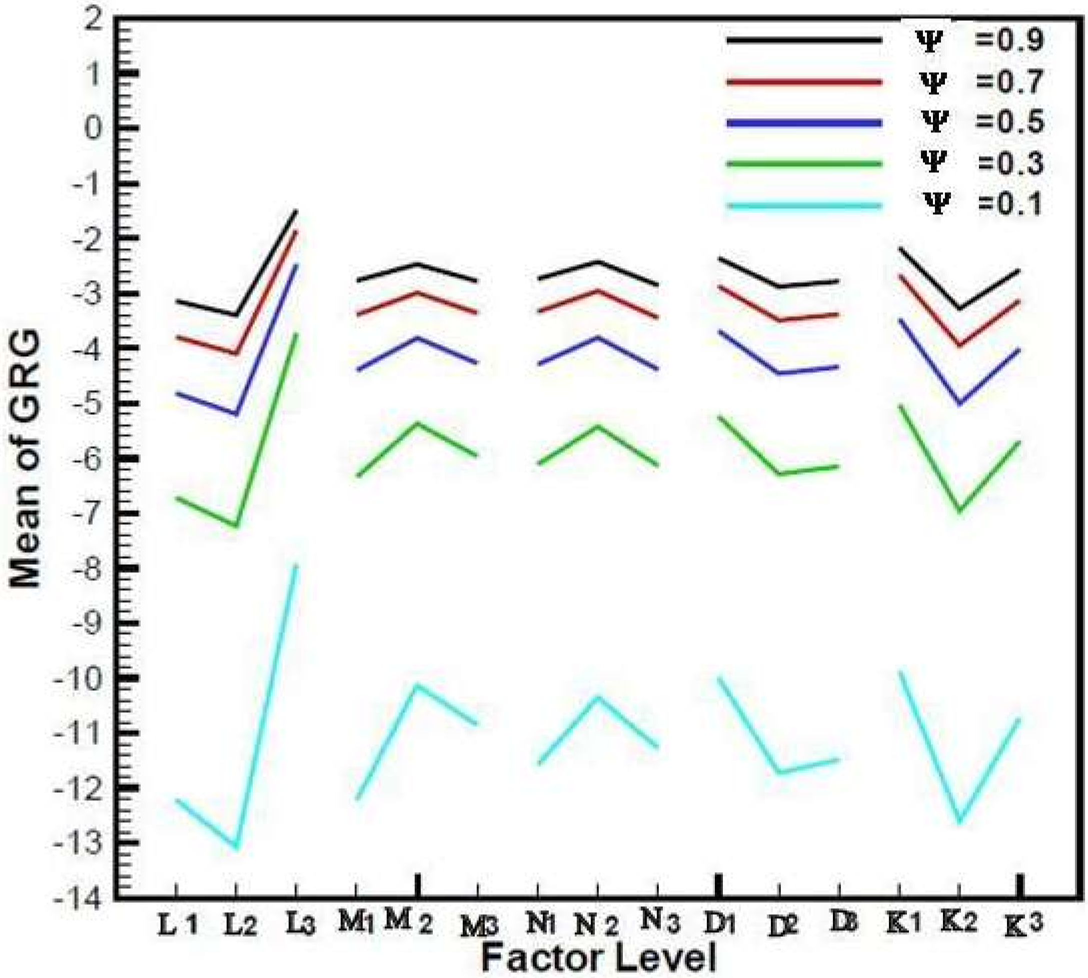


Figure 8 Sensitivity analysis

A linear predictive equation can be formulated based on Taguchi analysis. For optimal factor combination the predictive equation is as follows:

$\bar{\eta} = \bar{T} + (\bar{L}_3 - \bar{T}) + (\bar{M}_2 - \bar{T}) + (\bar{N}_2 - \bar{T}) + (\bar{D}_1 - \bar{T}) + (\bar{K}_1 - \bar{T})$

where,

$\bar{\eta}$ is the predicted average for the process

$\bar{T}$ is the overall experimental average for this process

$\bar{L_3}$ $\bar{M_2}$ $\bar{N_2}$ $\bar{D_1}$ $\bar{K_1}$ are considered as the Mean response for factors at given levels.

The predicted average for other factor combinations can also be got and if the error is within controllable limits such as 3% then prediction is correct.

Prediction results using back propagation neural network.

A neural network was simulated and the predicted results are as given below in table 12

The learning parameter(lr) and Momentum parameter(mr) are given below :

Learning parameter =0.05

Momemtum parameter= 0.9

Table 12

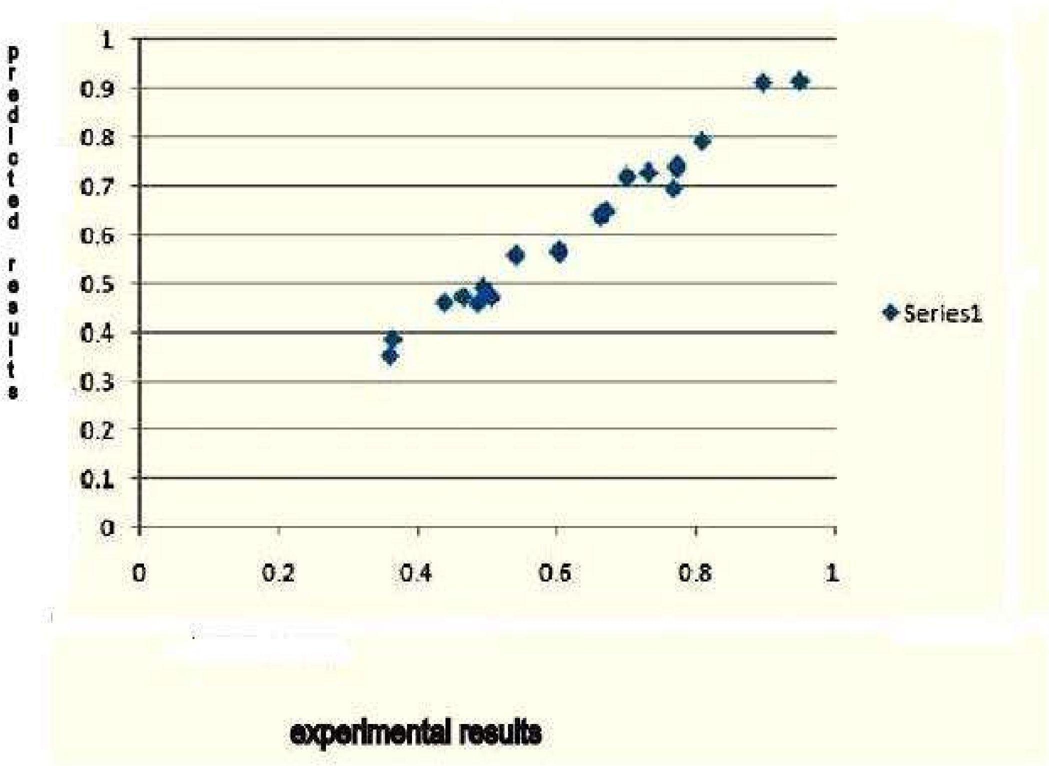
Diameter ,L (mm)	Speed,M (RPM)	Feed rate N (mm/rev)	Thrust force,D (N)	Feed Vibration K, (m/s^2)	Output	Error
9.5	325	0.25	2900	19	0.5578	3.16
9.5	325	0.37	4234	30	0.4932	0.16
9.5	650	0.13	2900	30	0.7904	2.33
9.5	650	0.25	4234	8	0.564	6.49
9.5	975	0.13	4234	19	0.4739	2.06
9.5	975	0.25	1566	30	0.3532	1.5
9.5	975	0.37	2900	8	0.9139	3.88
10.5	325	0.13	2900	19	0.64	3.46
10.5	325	0.25	4234	30	0.4733	6.25
10.5	325	0.37	1566	8	0.4602	5.28
10.5	650	0.13	4234	8	0.7363	4.8
10.5	650	0.25	1566	19	0.5622	6.82
10.5	650	0.37	2900	30	0.4617	5.5
10.5	975	0.25	2900	8	0.3877	6.74
11.5	325	0.13	4234	30	0.5695	5.55
11.5	325	0.25	1566	8	0.72	2.68
11.5	325	0.37	2900	19	0.741	4.22
11.5	650	0.13	1566	19	0.6942	9.62
11.5	650	0.37	4234	8	0.6476	3.4
11.5	975	0.13	2900	8	0.9112	1.52
11.5	975	0.25	4234	19	0.7277	0.58

The Maximum error found in above method is 9.62%.

The correlation coefficient was found to be .9875.

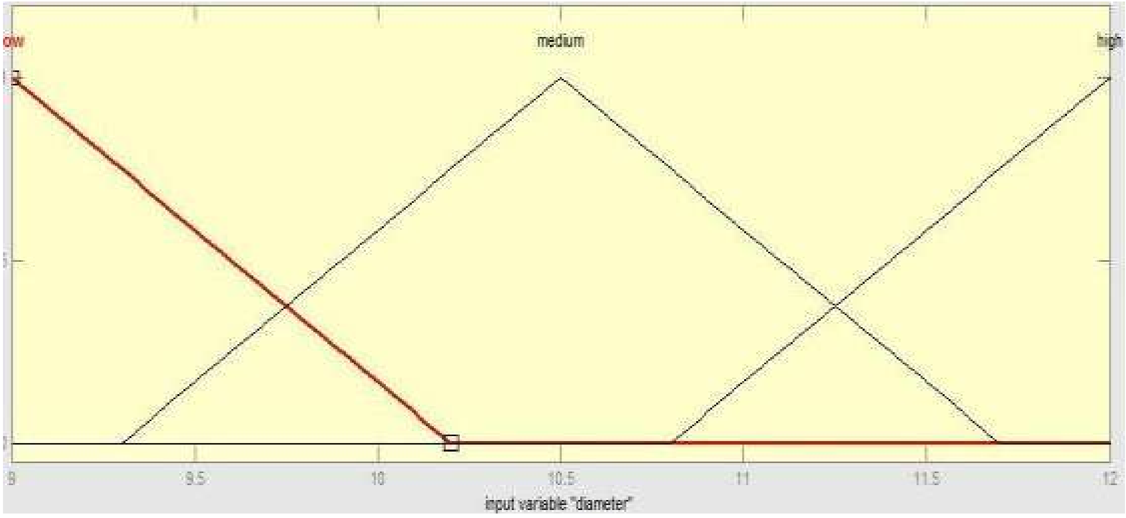
Results of neural network had been plotted with actual experimental output in fig9

Fig 9.

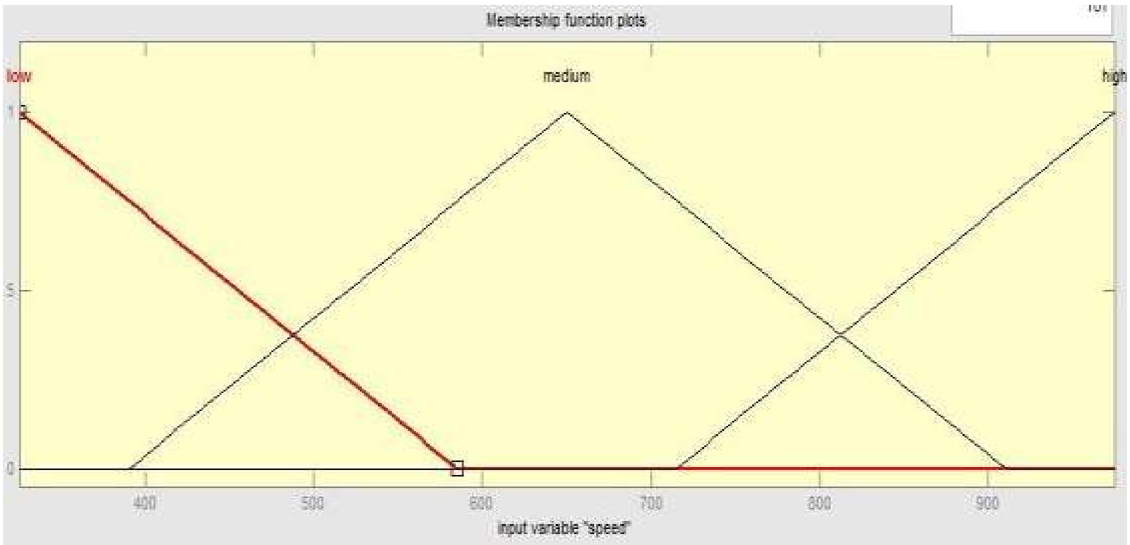


Prediction results using mamdani fuzzy logic model

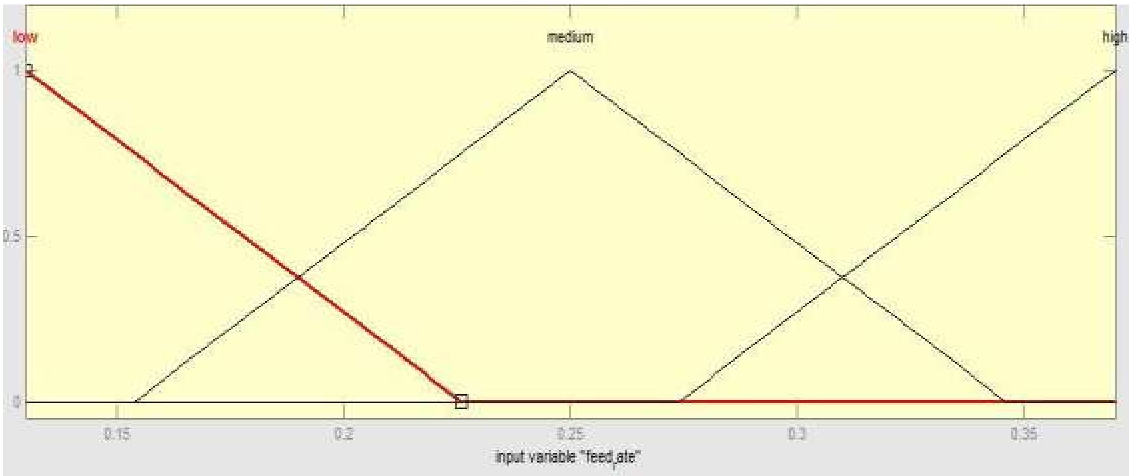
INPUT MEMBERSHIP FUNCTIONS



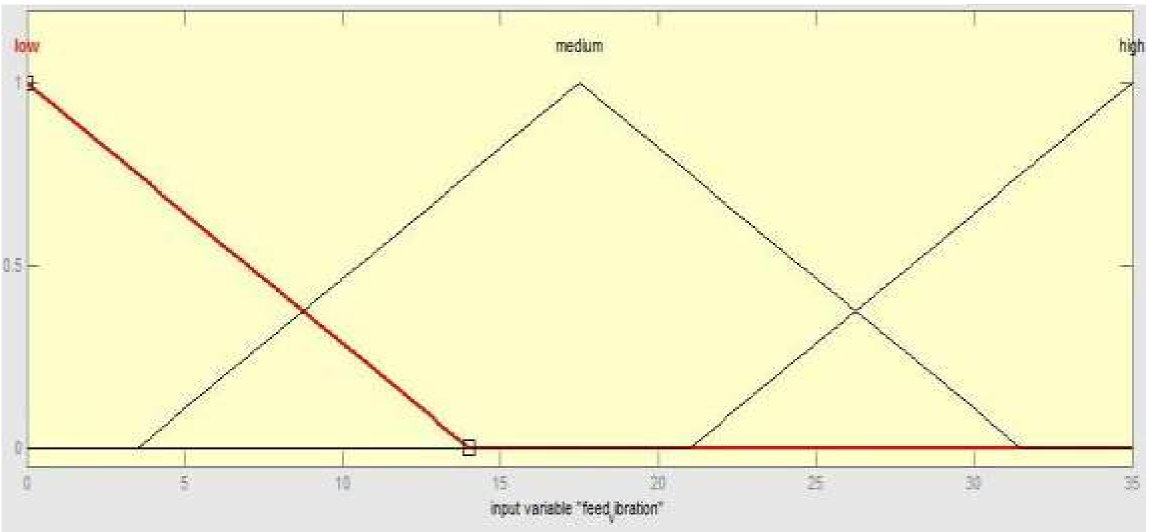
DIAMETER FIG 10



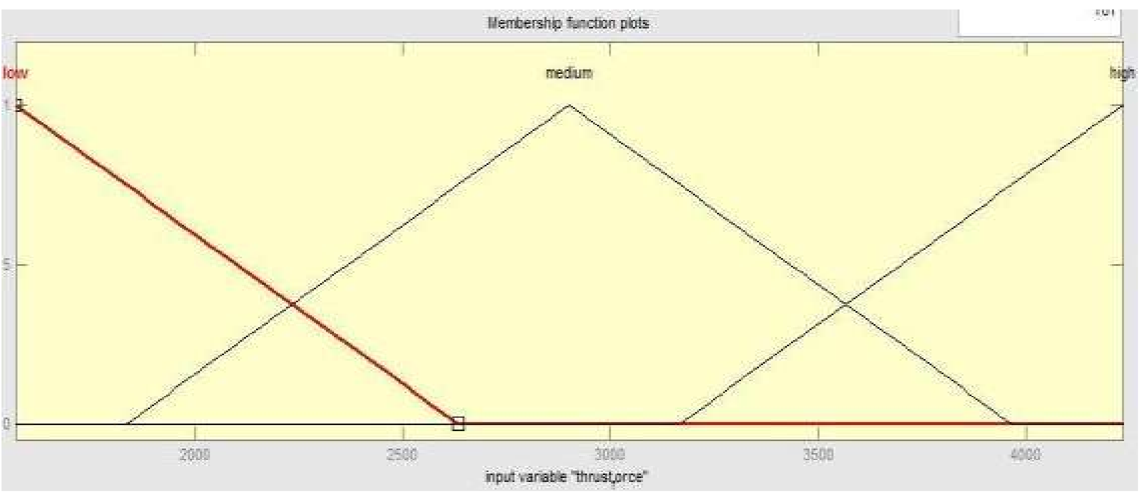
SPEED FIG 11



FEED RATE FIG12

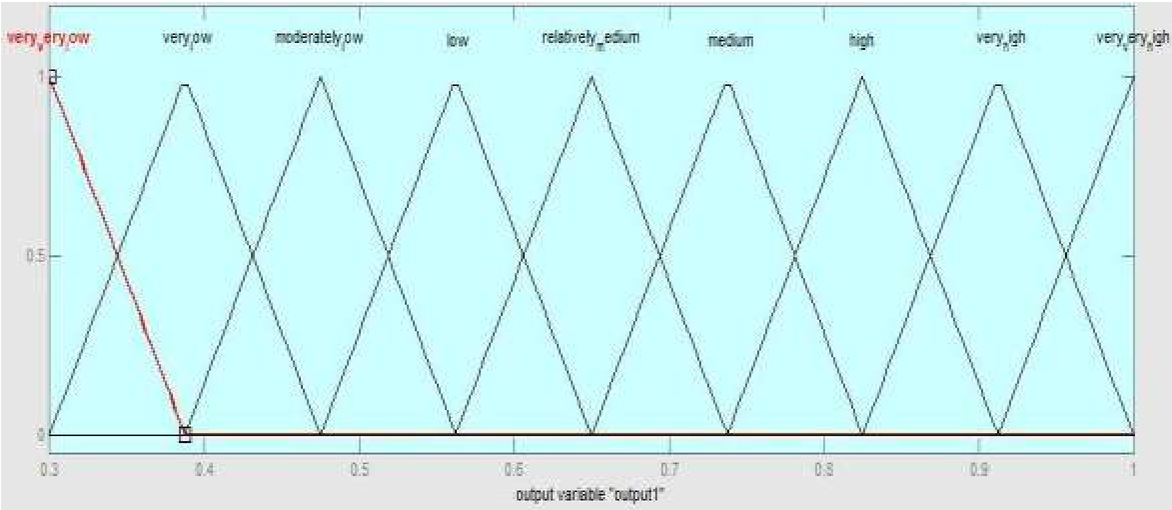


FEED VIBRATION FIG 13



THRUST FORCE FIG 14

OUTPUT MEMBERSHIP FUNCTION FIG15



RULE BOX OF THE MAMDANI FUZZY INFERENCE SYSTEM

1. If (input1 is low) and (input2 is low) and (input3 is low) and (input4 is low) and (input5 is low) then (output1 is medium) (1)

2. If (input1 is low) and (input2 is low) and (input3 is medium) and (input4 is medium) and (input5 is medium) then (output1 is low) (1)

3. If (input1 is low) and (input2 is low) and (input3 is high) and (input4 is high) and (input5 is high) then (output1 is moderately low) (1)

4. If (input1 is low) and (input2 is medium) and (input3 is low) and (input4 is medium) and (input5 is high) then (output1 is high) (1)

5. If (input1 is low) and (input2 is medium) and (input3 is medium) and (input4 is high) and (input5 is low) then (output1 is low) (1)

6. If (input1 is low) and (input2 is medium) and (input3 is high) and (input4 is medium) and (input5 is medium) then (output1 is moderately low) (1)

7. If (input1 is low) and (input2 is high) and (input3 is low) and (input4 is high) and (input5 is medium) then (output1 is moderately_low) (1)

8. If (input1 is low) and (input2 is high) and (input3 is medium) and (input4 is low) and (input5 is high) then (output1 is very low) (1)

9. If (input1 is low) and (input2 is high) and (input3 is high) and (input4 is medium) and (input5 is low) then (output1 is very_very_high) (1)

10. If (input1 is medium) and (input2 is low) and (input3 is low) and (input4 is medium) and (input5 is medium) then (output1 is relatively_medium) (1)

11. If (input1 is medium) and (input2 is low) and (input3 is medium) and (input4 is high) and (input5 is high) then (output1 is moderately_low) (1)

12. If (input1 is medium) and (input2 is low) and (input3 is high) and (input4 is low) and (input5 is low) then (output1 is moderately_low) (1)

13. If (input1 is medium) and (input2 is medium) and (input3 is low) and (input4 is high) and (input5 is low) then (output1 is medium) (1)

14. If (input1 is medium) and (input2 is medium) and (input3 is medium) and (input4 is low) and (input5 is medium) then (output1 is low) (1)

15. If (input1 is medium) and (input2 is medium) and (input3 is high) and (input4 is medium) and (input5 is high) then (output1 is moderately_low) (1)

16. If (input1 is medium) and (input2 is high) and (input3 is low) and (input4 is medium) and (input5 is high) then (output1 is moderately_low) (1)

17. If (input1 is medium) and (input2 is high) and (input3 is medium) and (input4 is medium) and (input5 is low) then (output1 is very_low) (1)

18. If (input1 is medium) and (input2 is high) and (input3 is high) and (input4 is high) and (input5 is medium) then (output1 is very very low) (1)

19. If (input1 is high) and (input2 is low) and (input3 is low) and (input4 is high) and (input5 is high) then (output1 is low) (1)

20. If (input1 is high) and (input2 is low) and (input3 is medium) and (input4 is low) and (input5 is low) then (output1 is medium) (1)

21. If (input1 is high) and (input2 is low) and (input3 is high) and (input4 is medium) and (input5 is medium) then (output1 is medium) (1)

22. If (input1 is high) and (input2 is medium) and (input3 is low) and (input4 is low) and (input5 is medium) then (output1 is medium) (1)

23. If (input1 is high) and (input2 is medium) and (input3 is medium) and (input4 is medium) and (input5 is high) then (output1 is high) (1)

24. If (input1 is high) and (input2 is medium) and (input3 is high) and (input4 is high) and (input5 is low) then (output1 is relatively medium) (1)

25. If (input1 is high) and (input2 is high) and (input3 is low) and (input4 is medium) and (input5 is low) then (output1 is very high) (1)

26. If (input1 is high) and (input2 is high) and (input3 is medium) and (input4 is high) and (input5 is medium) then (output1 is medium) (1)

27. If (input1 is high) and (input2 is high) and (input3 is high) and (input4 is low) and (input5 is high) then (output1 is medium) (1)

Program for obtaining the output

```
>> a= readfis ('tool real');

>> evalfis ([ 9.5 325 .13 1566 8; 9.5 325 .25 2900 19; 9.5 325 .37 4234 30], a)

ans =
```

0.7375

0.5625

0.4750

```
>> a= readfis ('tool real');
>> evalfis([9.5 650 .13 2900 30; 9.5 650 .25 4234 8; 9.5 650 .37 1566 19; 9.5
975 .13 4234 19; 9.5 975 .25 1566 30; 9.5 975 .37 2900 8], a)
```

ans =

0.8250

0.5625

0.6500

0.4750

0.3875

0.9665

```
>> a=readfis ('tool real');
>> evalfis([10.5 325 .13 2900 19; 10.5 325 .25 4234 30; 10.5 325 .37 1566 8;
10.5 650 .13 4234 8; 10.5 650 .25 1566 19; 10.5 650 .37 2900 30; 10.5 975 .13
1566 30; 10.5 975 .25 2900 8; 10.5 975 .37 4234 19],a)
```

ans =

0.6500

0.4750

0.4750

0.7375

0.5625

0.4750

0.6500

0.3875

0.3274

>> a=readfis ('tool real');

>> evalfis([11.5 325 .13 4234 30; 11.5 325 .25 1566 8; 11.5 325 .37 2900 19; 11.5 650 .13 1566 19; 11.5 650 .25 2900 30; 11.5 650 .37 4234 8; 11.5 975 .13 2900 8; 11.5 975 .25 4234 19; 11.5 975 .37 1566 30], a)

ans =

0.5625

0.7375

0.7375

0.7375

0.8250

0.6500

0.9125

0.7375

0.7375

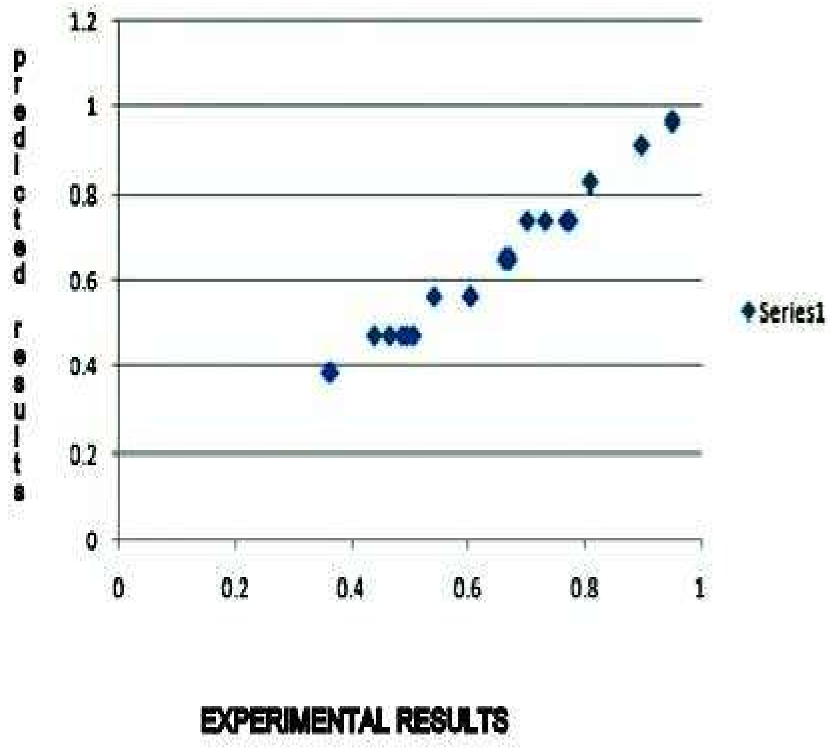
RESULTS WERE PREDICTED USING MAMDANI FUZZY LOGIC MODEL IN TABLE 13

Table 13

Diameter A,(mm)	Speed,B (RPM)	Feed rate,C (mm/rev)	Thrust force,D (N)	Feed Vibration E,(m/s^2)	Output	ERROR
9.5	325	0.25	2900	19	0.5625	4.03
9.5	325	0.37	4234	30	0.475	3.84
9.5	650	0.13	2900	30	0.825	1.97
9.5	650	0.25	4234	8	0.5625	6.74
9.5	975	0.13	4234	19	0.475	2.1
9.5	975	0.25	1566	30	0.3875	7.96
9.5	975	0.37	2900	8	0.9665	1.64
10.5	325	0.13	2900	19	0.65	1.96
10.5	325	0.25	4234	30	0.475	5.9
10.5	325	0.37	1566	8	0.475	2.24
10.5	650	0.13	4234	8	0.7375	4.654
10.5	650	0.25	1566	19	0.5625	6.7
10.5	650	0.37	2900	30	0.475	8.54
10.5	975	0.25	2900	8	0.3875	6.69
11.5	325	0.13	4234	30	0.5625	6.71
11.5	325	0.25	1566	8	0.7375	5.17
11.5	325	0.37	2900	19	0.7375	4.67
11.5	650	0.13	1566	19	0.7375	3.9
11.5	650	0.37	4234	8	0.65	3.09
11.5	975	0.13	2900	8	0.9125	1.67
11.5	975	0.25	4234	19	0.7375	0.75

The maximum error found in above method is 8.54

GRAPH IS PLOTTED BETWEEN EXPERIMENTAL RESULTS AND MAMDANI FUZZY OUTPUT IN FIG16



The correlation coefficient was found out to be .9861

Now some random inputs were inserted and the results of mamdani fuzzy inference and neural network were compared

RESULTS OF RANDOM INPUTS USING FUZZY LOGIC IN TABLE 14

TABLE 14.

Serial no	Diameter A(mm)	Speed B(rpm)	Feed rate C(mm/rev)	Thrust force D(N)	Feed vibration E(m/s^2)	Output
1	9.6	335	.14	1580	10	0.7375
2	10.8	650	0.27	3000	21	0.6523
3	11.3	960	0.36	4200	29	0.3383
4	9.7	350	0.15	1600	22	0.6578
5	10.9	675	0.29	3200	12	0.6543

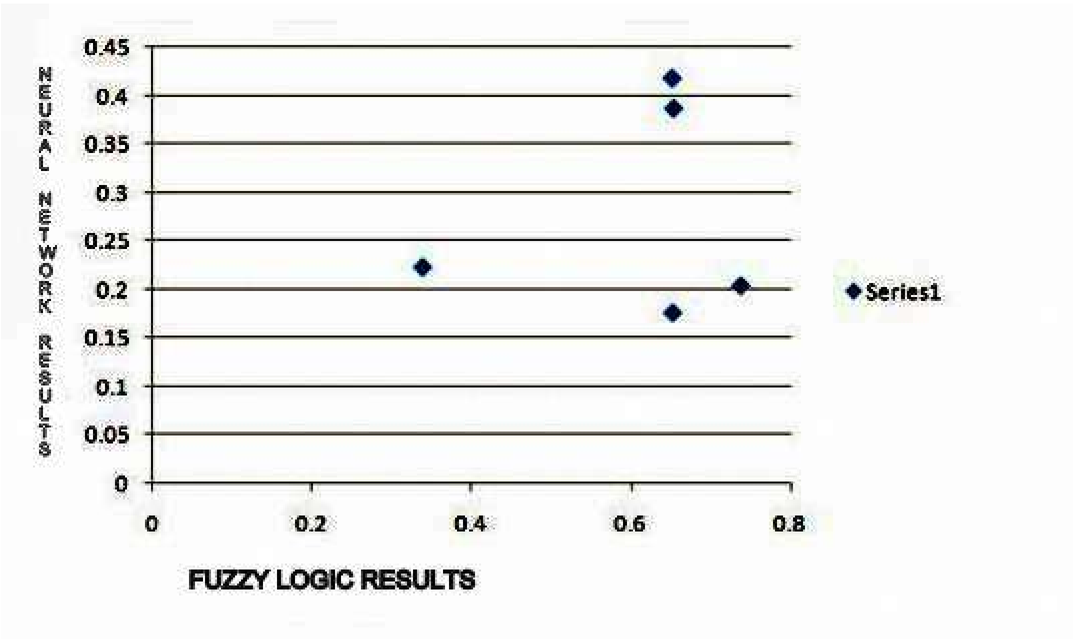
RESULTS OF RANDOM INPUTS USING NEURAL NETWORK IN TABLE 15

TABLE 15.

Serial no	Diameter A(mm)	Speed B (Rpm)	Feed rate C (mm/rev)	Thrust Force D(N)	Feed vibration E(m/s^2)	Output
1	9.6	335	.14	1580	10	.2033
2	10.8	650	.27	3000	21	.4178
3	11.3	960	.36	4200	29	.2225
4	9.7	350	.15	1600	22	.1755
5	10.9	675	.29	3200	12	.3867

GRAPH WAS PLOTTED BETWEEN THE RESULTS OF NEURAL NETWORK AND MAMDANI FUZZY INFERENCE METHOD FIG 12

FIG17



Chapter 6

CONCLUSION

6 CONCLUSIONS

Anova was used to determine the significance of each of the factors and it was found that the most significant factor was the drill diameter and the least significant factor was spindle speed

For improving the tool life, machining cost and quality of the manufactured items online monitoring of tool life and surface roughness is important. Design of experiments (DOE) was used to remove the unnecessary experiments and obtain the rule box. Prediction results suggest that Mamdani inference method predictions are better than neural network .Inference was based on maximum error calculated.

As mamdani inference method takes in fuzzy inputs, it has more accuracy than BPNN which takes in crisp inputs.

In context of shop floor, inefficient workers perceived linguistic variables much easily than crisp variables which are used in neural network. Thus mamdani inference method has widest scope of application.

It can be concluded from sensitivity analysis that on changing the grey relational coefficient the optimal parameter setting of the experiment does not alter.

CHAPTER 7

LIMITATION AND SCOPE OF WORK

Limitation and scope of work

Here grey taguchi method was used to convert multiresponse optimisation problem into a single response optimisation problem, .thus more than one model has been used but that procedure can be accomplished by mamdani fuzzy inference method itself thereby limiting it to the use of only one model which is very time efficient

Feed vibration in only one direction has been taken thus feed vibrations in all the three directions can be taken as inputs.

In this work average roughness and flank wear are taken as responses dimensional accuracy can be considered as an response as well.

CHAPTER 8

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8 BIBLIOGRAPHY

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