MODELLING & OPTIMIZATION OF MACHINING PARAMETERS FOR MICRO-TEXTURED CUTTING TOOLS

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Contents

- Introduction
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- Research objective and methodology
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- Conclusion and Future work
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1. INTRODUCTION

- Optimization is a method through which we can obtain a desirable maximum or minimum of an objective function , using a set of decision variables and under a set of given constraint equalities and inequalities. optimization plays a big role to make products , devices or services available to everyone and still make an efficient, profitable, useful machines.

- Isaac newton (1642-1727) : the development of differential calculus method of optimization.

- Joseph-louis LaGrange (1736- 1813) : calculus of variations, minimizations of functionals method of optimization for constrained problems.

- Augustin-louis Cauchy (1789-1857) : solution by direct substitution, steepest descent method for unconstrained optimization.

- George Bernard Dantzig (1914- 2005) : linear programming and simplex method.

- Albert William tucker (1905-1995) : necessary and sufficient conditions for the optimal solution of programming problems, non linear programming.

- Evolutionary computation, describes the field of investigation that concerns all evolutionary algorithms and offers practical advantages to several optimization problems. key advantage of evolutionary computation is that it is conceptually simple Evolutionary algorithms can be applied to any problems that can be formulated as function optimization problems. Evolutionary algorithms can be combined with more traditional optimization techniques. Evolution is a highly parallel process.

Classiffication of Optimization Techniques

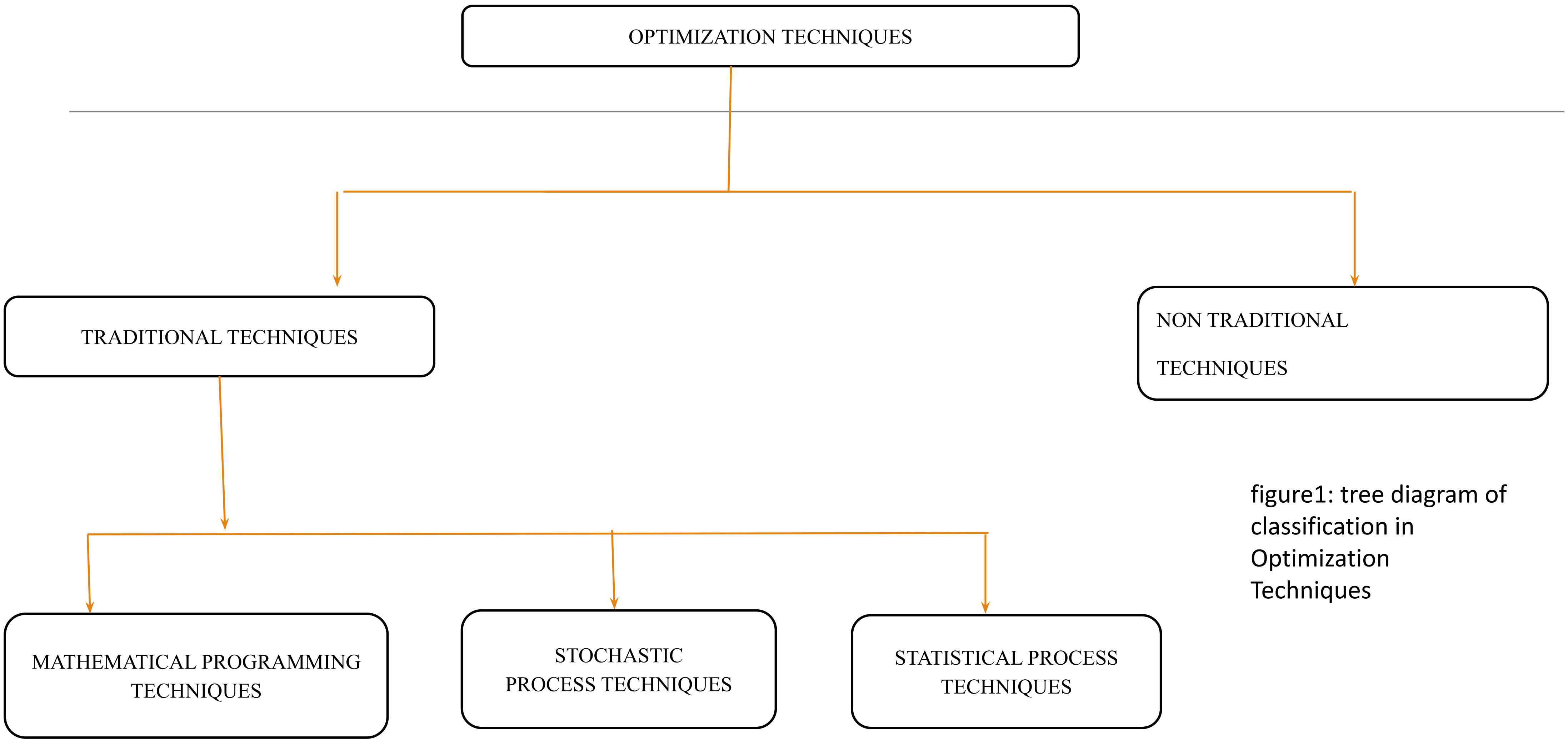


figure1: tree diagram of classification in Optimization Techniques

LITERATURE REVIEW

Table1:Literature Review of work done on genetic algorithm

Auther/Journal	Literature Review	Date
Lingxuan Zhang et. al.	“A hybrid model using supporting vector machine and multi–objective genetic algorithm for processing parameters optimization in micro-EDM”	2010
Wang et al.	“ Optimization of multi-pass milling using genetic simulated annealing”.	2005
Rituparna Dutta et al.	“A classical-cum-Evolutionary Multi-Objective Optimization for Optimal Machining Parameters”	2009
U. Deepak et.al.	“Optimization of milling operation using genetic and PSO algorithm.”	2018
K.Kalita et. al.,	“Optimizing Drilling Induced Delamination in GFRP Composites using Genetic Algorithm& Particle Swarm Optimisation”	2009
D. Venkatesan et al.,	“Genetic Algorithm based Artificial Neural Network model for optimization of machining processes”	2013
Kulankara Krishnakumar et al	“Machining fixture layout Optimization using Genetic Algorithm”	2015
Girish Kant et al	“Predictive modelling and optimization of machining parameters to minimise surface roughness using Artificial Neural Network coupled with Genetic Algorithm”	2013
Pavel A Borisovsky et al.,	“Genetic algorithm for balancing reconfigurable machining lines”	

LITERATURE REVIEW

Table2: Literature review of work done in WEDM process

Auther/Journal	Literature Review
G C Onwubolu et al.	“Multi pass turning operations optimization based on genetic algorithm”
S. Marichamy et al.,	“Artificial Neural Network model and Genetic Algorithm based optimization during Electric Discharging Machining of ἀ- □ brass”
V.N. Gaitonde et al.,	“Genetic Algorithm- based burr size minimization in drilling of AISI 316L stainless steel”
Yanming Liu et al.	“A Modified Genetic Algorithm Based Optimisation of Milling Parameters”
Doriana M et al.,	“Genetic algorithm-based optimization of cutting parameters in turning processes”
S. Ujjaini Kumar et al.,	“Multi Objective Optimization of wire-electrical discharge machining of satellite using Taguchi – Grey approach”
Urgasen Ga et al	“ Optimization of Process Parameters for SS304 in Wire Electrical Discharge Machining using Taguchi’s method”
Ranjan et.al	“Multi-objective Optimization of a Hybrid Machining Process Abrasive Powder Mixed WEDM of Inconel 718 using Particle Swarm Optimization Technique.”
M. Satheesh et.al.,	“Multi Objective Optimization of Weld Parameters of Boiler Steel Using Fuzzy Based Desirability Function”.

Date
2010
2005
2009
2018
2009
2013
2015
2013

LITERATURE REVIEW

Table3: Literature review of work done in WEDM process

Auther/Journal	Literature Review	Date
Himadri Majumder et al.,	"MULTI-RESPONSE OPTIMIZATION OF WEDM PROCESS PARAMETERS USING TAGUCHI BASED DESIRABILITY FUNCTION ANALYSIS".	2018
Arun Pratap Singh et al.,	"Multi response optimization for micro-EDM machining of AISI D2 die steel using RSM and neural network".	2021
Gurudev Singha et al.,	"Optimization of EN24 Steel on EDM Machine using Taguchi & ANOVA Technique"	2018
Rafał Swiercz et.al.,	"Multi-Response Optimization of Electrical Discharge Machining Using the Desirability Function".	2019
Prosum Mandal et al	"Multi-objective optimization of Cu-MWCNT composite electrode in electro discharge machining using MOPSO-TOPSIS"	2021
Ali R. Yildiz et al.,	"Cuckoo search algorithm for the selection of optimal machining parameters in milling operations"	2013
Dun Liu et al	"Modelling and optimization of operating parameters for abrasive waterjet turning alumina ceramics using response surface methodology combined with BOX-BEHNKEN design"	2014
Deepak Kumar Naik el. al.	" Application of desirability function based response surface methodology (DRSM) for investigating the plasma arc cutting process of Saihard steel".	2018
Ram Singh et.al.,	"Optimization of machining process parameters in conventional turning operation of Al5083/B4C composite under dry condition".	2018

Research Objectives

Objective 1: Study and compare the mathematical predictions of ANN, RSM and Fuzzy logic models.

Objective 2:Use the values predicted by the above three models, compute their error percentage and select the one with the least error percentage.

Methodology (flow diagram)

Obtain experimental output values for given inputs of textured coating and tabulate them

↓

Perform various mathematical modelling using the experimental process parameters & output values.

↓

Compare and conclude about the importance of each of the mathematical model results

Experimental details

- Three different textures created on the HSS cutting tools using WEDM

(a) Inclined texture

(b) Cross texture

(c) parallel texture

Figure 2:textures obtained by wedm process

- The material removal rate (MRR) is expressed as: $MRR = \frac{\frac{\pi}{4}(Di^2 - Df^2)L}{Machining\ time}$
- The tool wear rate during machining can be investigated using the expression:

$$Tool\ wear\ rate = \frac{Wi - Wf}{tm\rho}$$

where, Wi = Initial Weight of the cutting tool insert (g)

Wf = Final Weight measured of the cutting tool insert (g)

ρ = Density of the cutting tool materials (g/mm3)

tm = Machining time in minute

DESIGN OF EXPERIMENTS (DOE)

Response surface methodology is used in order to minimize the tool wear rate (TWR) and material removal rate (MRR).

Table 4: Input process parameters and their levels for machining investigation.

Factors	Parameters	Levels		
		Level 1	Level 2	Level 3
A	Spindle Speed (rpm)	290	480	700
B	Feed rate (mm/rev)	0.06	0.14	0.2
C	Depth of cut (mm)	0.2	0.4	0.6

Table 5: Process parameters and Output values for inclined texture

Exp. No.	A	B	C	MRR (mm^3/min)	TWR (mm^3/min)
1	290	0.06	0.2	341.969	1.838
2	290	0.14	0.4	1259.020	5.551
3	290	0.2	0.6	2213.422	0.365
4	480	0.06	0.4	1075.367	1.528
5	480	0.14	0.6	3553.508	0.271
6	480	0.2	0.2	1048.185	1.190
7	700	0.06	0.6	2306.153	0.838
8	700	0.14	0.2	882.283	1.435
9	700	0.2	0.4	1349.831	1.682

Experimental output values for each texture

Table 6: Process parameters and Output values for cross texture

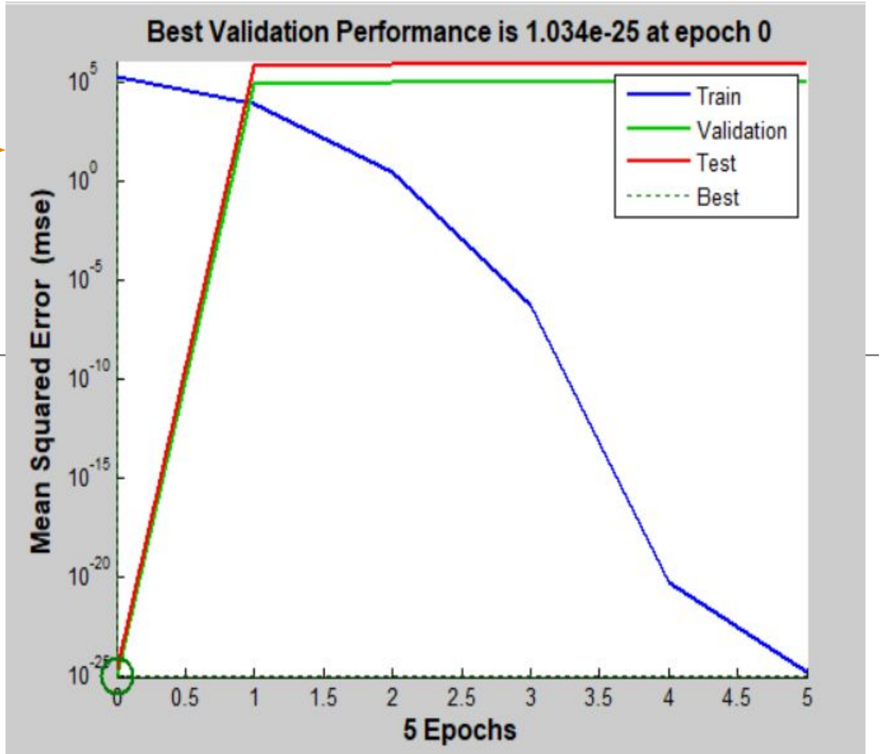
Exp. No.	A	B	C	MRR (mm^3/min)	TWR (mm^3/min)
1	290	0.06	0.2	178.807	0.467
2	290	0.14	0.4	1305.028	0.222
3	290	0.2	0.6	2486.410	0.417
4	480	0.06	0.4	346.410	2.908
5	480	0.14	0.6	3747.222	0.205
6	480	0.2	0.2	721.369	0.427
7	700	0.06	0.6	1819.608	1.079
8	700	0.14	0.2	1243.571	2.946
9	700	0.2	0.4	2388.573	2.323

Table 7: Process parameters and Output values for parallel texture

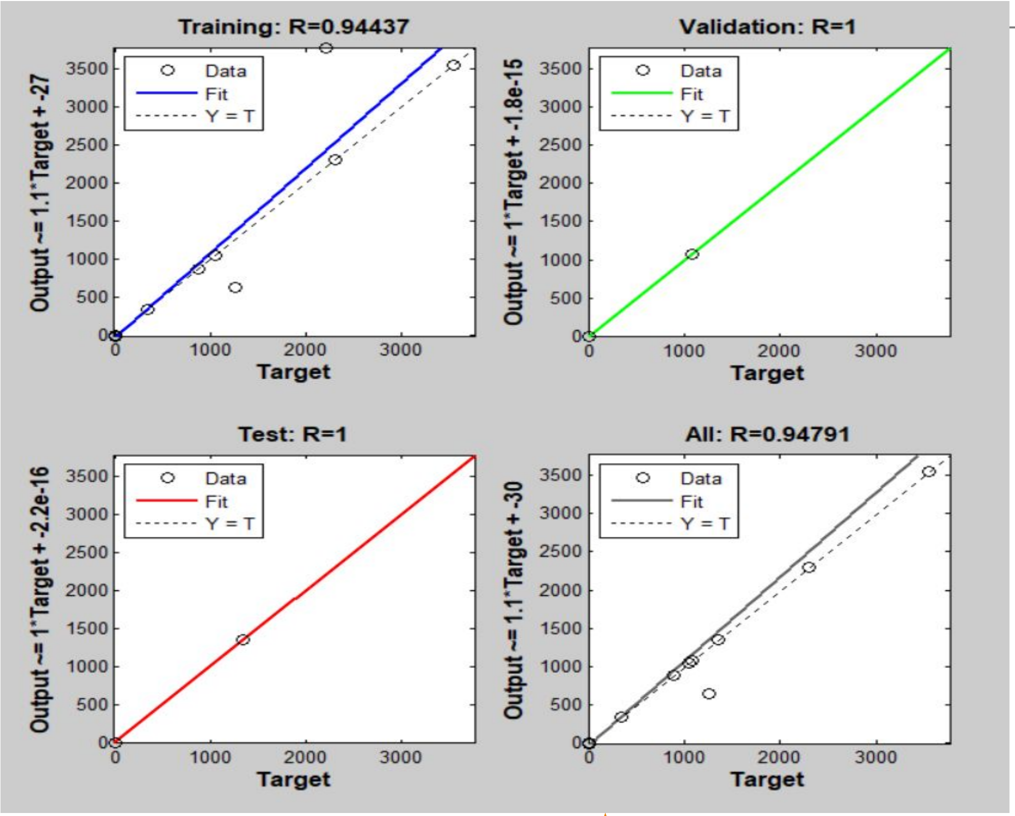
Exp. No.	A	B	C	MRR (mm^3/min)	TWR (mm^3/min)
1	290	0.06	0.2	366.186	1.648
2	290	0.14	0.4	913.310	0.347
3	290	0.2	0.6	2566.085	2.814
4	480	0.06	0.4	760.567	3.489
5	480	0.14	0.6	2147.719	1.869
6	480	0.2	0.2	666.475	2.269
7	700	0.06	0.6	1509.957	0.243
8	700	0.14	0.2	808.617	1.178
9	700	0.2	0.4	2124.118	0.901

- **ANALYSIS AND MODELLING from next slide**

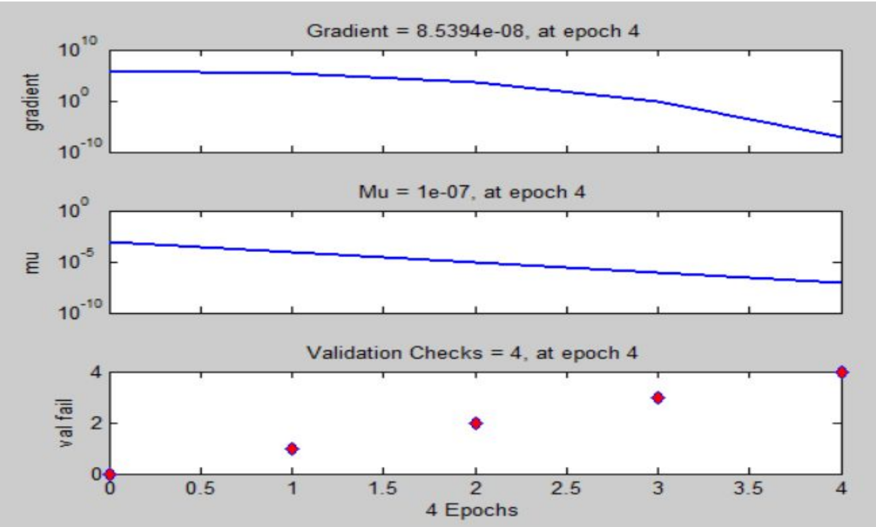
Inclined texture ANN models and prediction



Performance curve



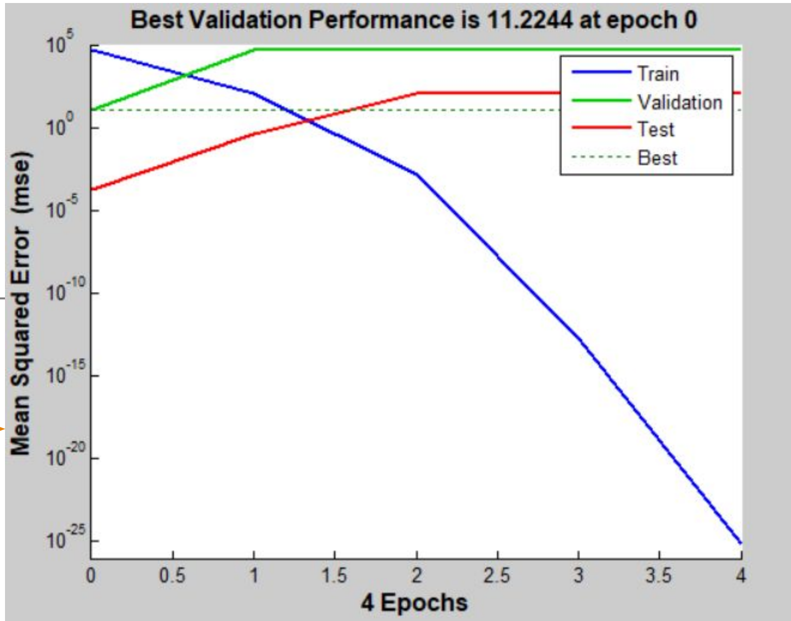
Regression plots

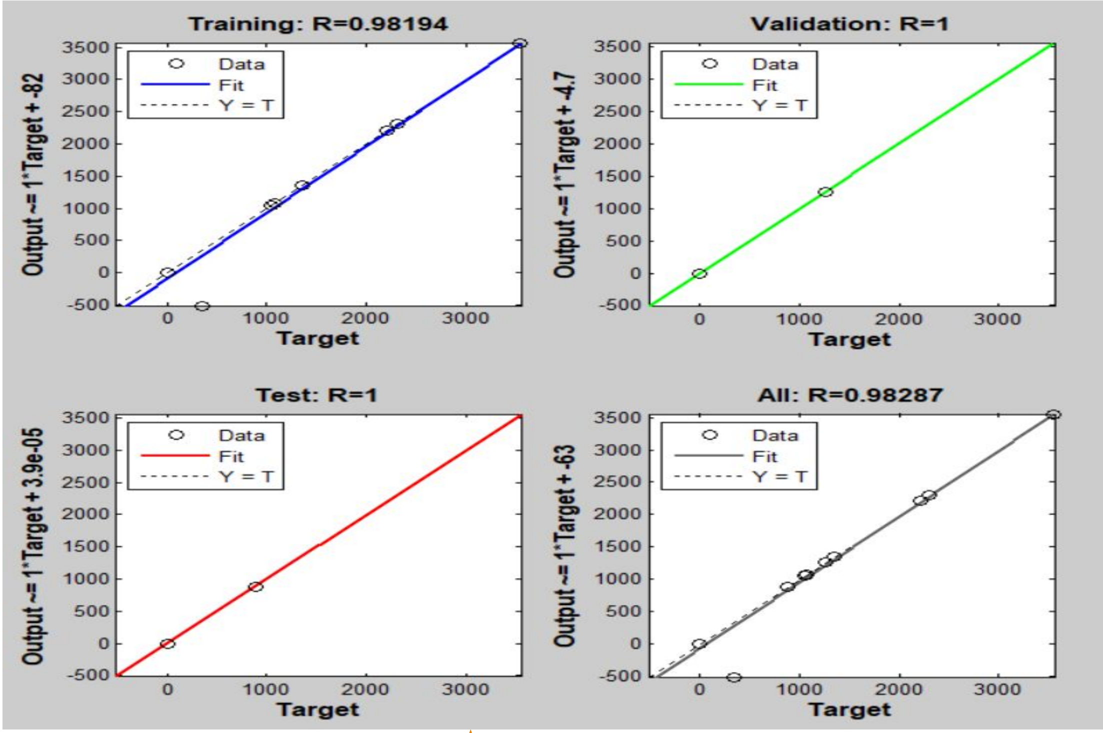


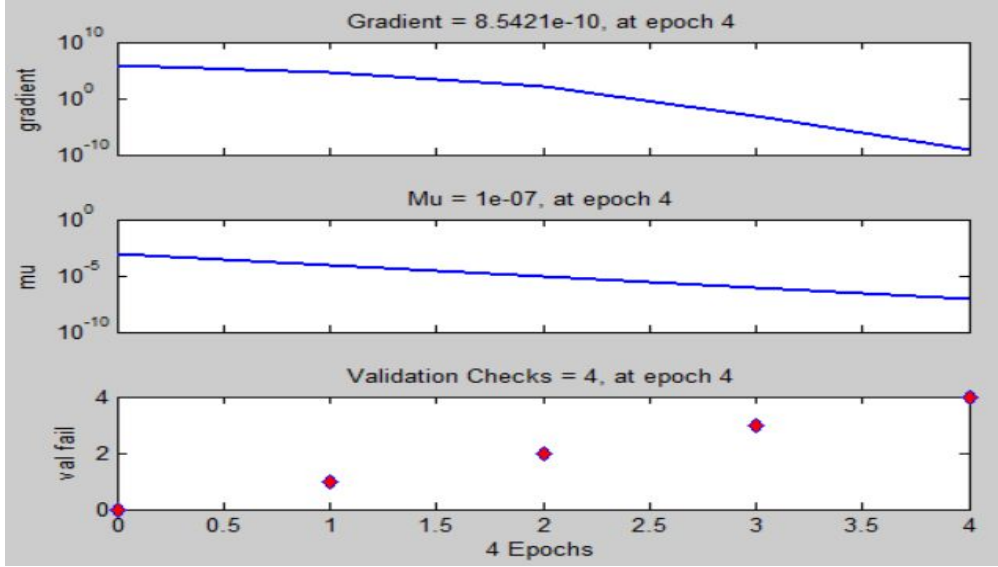
Training state

Parallel textured ANN models

Performance curve





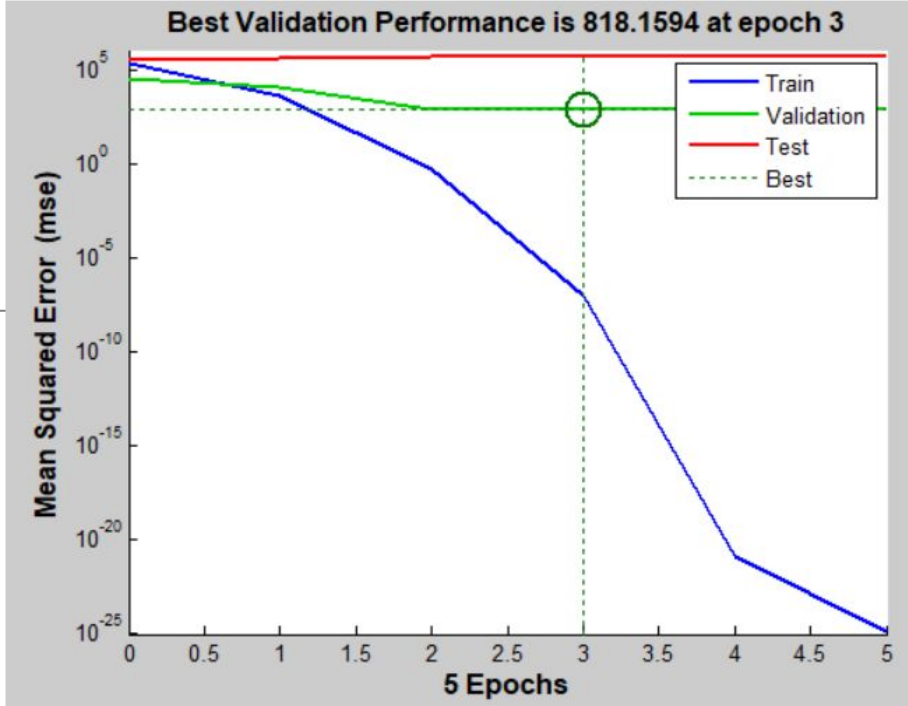


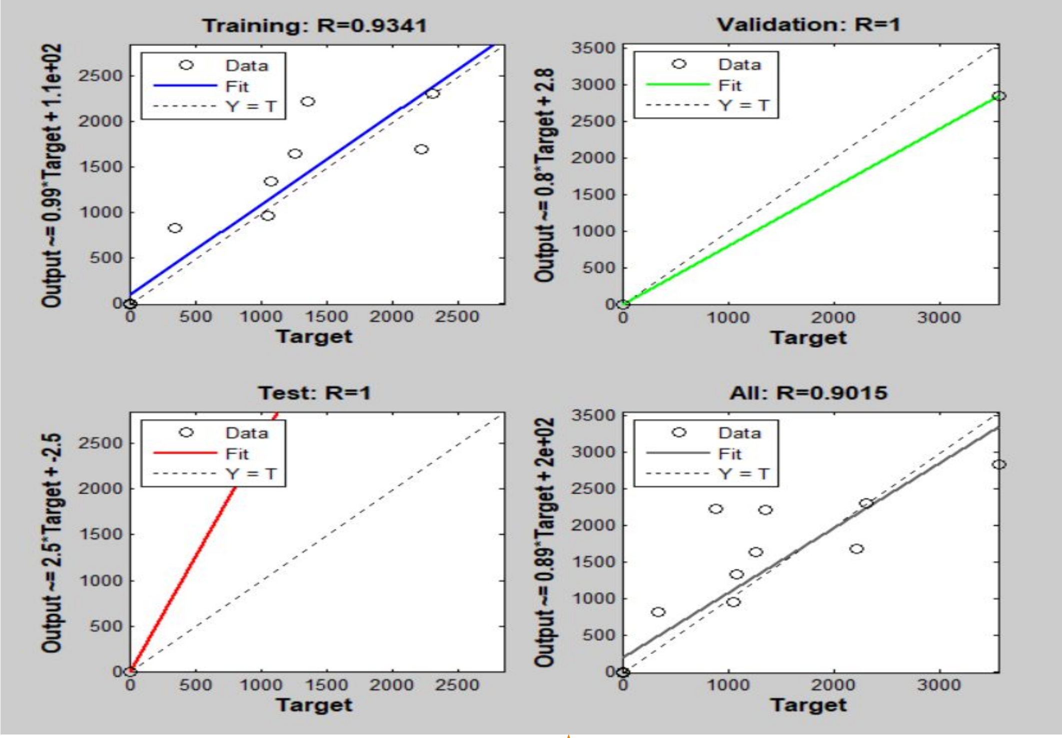
Training state

Regression plots

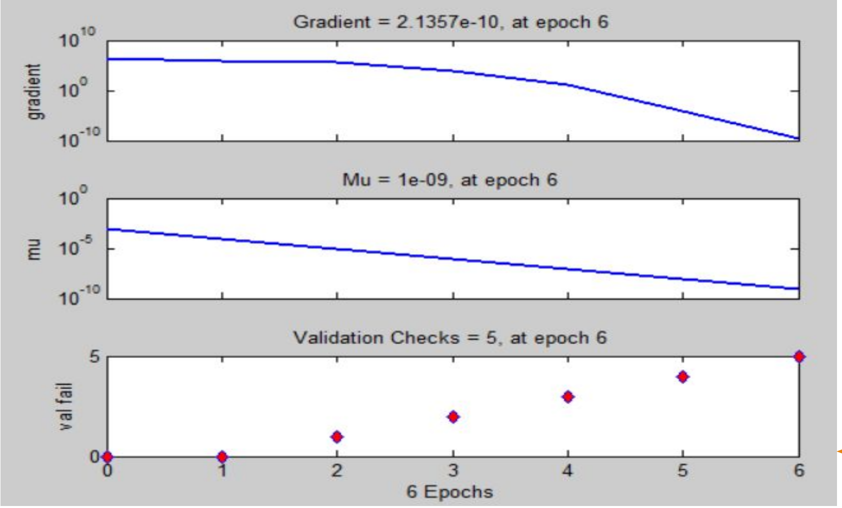
Cross textured models

Performance curve





Regression plots



Training state

cross
textured coatings

Table 5: predicted values of MRR &TWR for different configured textures

MRR	TWR
341.9690	1.8380
640.5395	2.8829
3.7658e+03	-0.9166
1.0754e+03	1.5280
3.5535e+03	0.2710
1.0482e+03	1.1900
2.3062e+03	0.8380
882.2830	1.4350
1.3498e+03	1.6820

a)Inclined textured predicted values

MRR	TWR
-508.7066	2.0981
1.2593e+03	0.8238
2.2134e+03	0.3652
1.0754e+03	1.5273
3.5536e+03	0.2710
1.0479e+03	1.1903
2.3059e+03	0.8382
882.2635	1.4350
1.3498e+03	1.6820

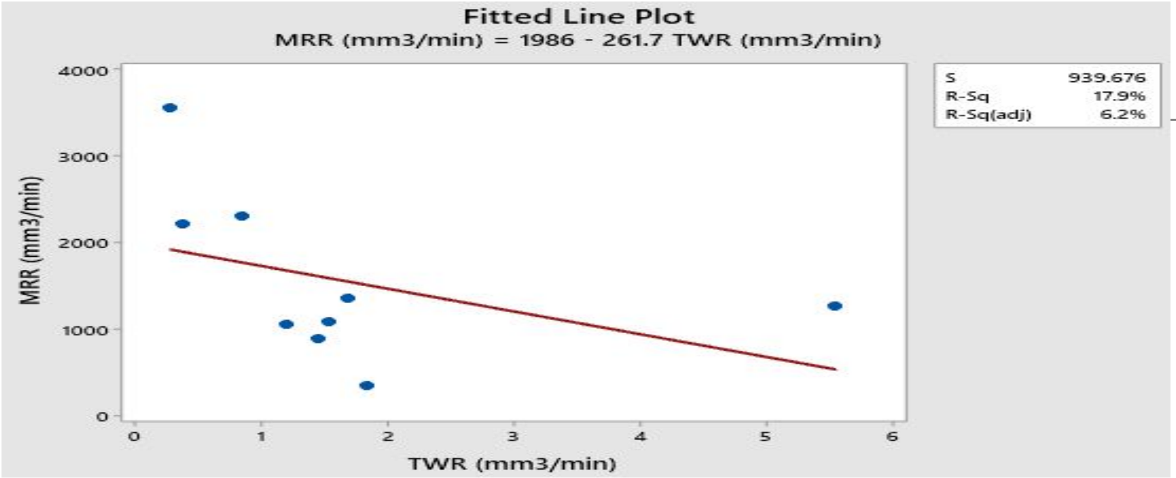
b)Parallel textured predicted values

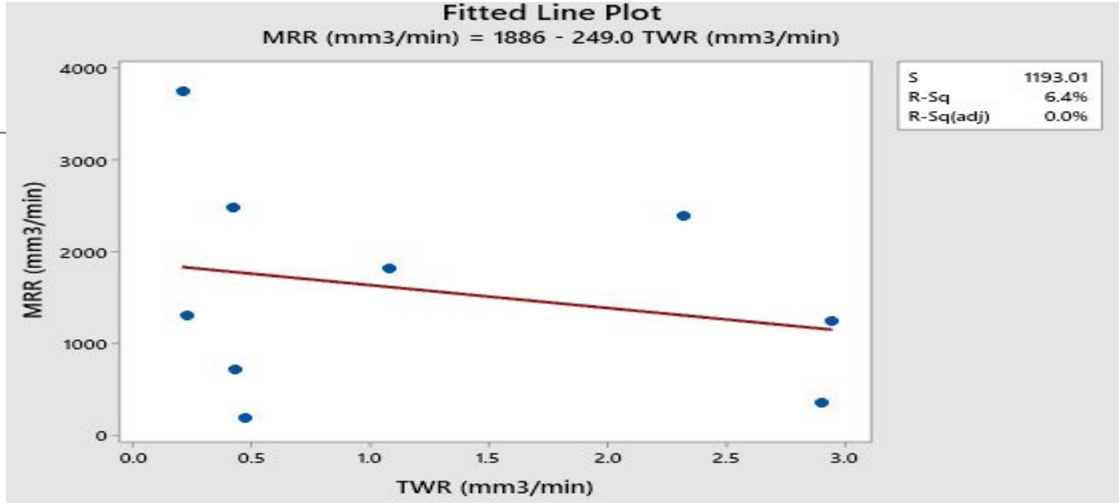
MRR	TWR
825.7180	1.7633
1.6466e+03	5.4205
1.6884e+03	2.0705
1.3409e+03	2.2086
2.8410e+03	3.0059
964.8414	1.4115
2.3007e+03	1.0522
2.2316e+03	1.1633
2.2115e+03	-0.0495

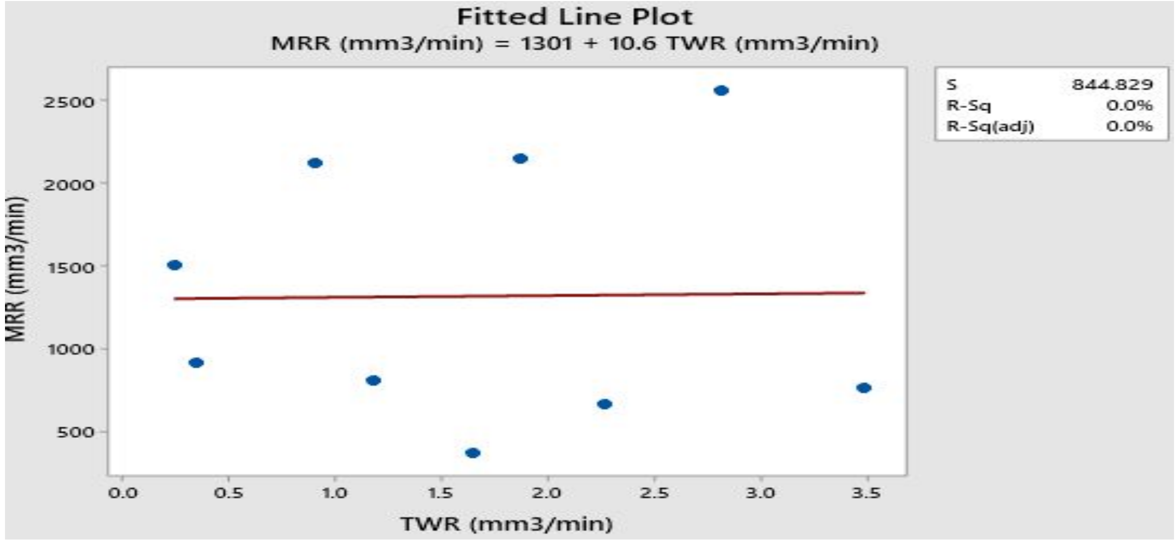
c)Cross textured predicted values

Optimization using RSM

analysis : MRR (mm3/min) versus TWR (mm3/min)







Optimization using RSM

- Equations of MRR and TWR for HSS cutting tools with inclined texture

Regression Equation in Uncoded Units

MRR (mm3/min) = -1837 + 9.055 Spindle Speed (rpm) + 27118 Feed rate (mm/rev)
- 8543 Depth of cut (mm) - 0.01218 Spindle Speed (rpm)*Spindle Speed (rpm)
- 118464 Feed rate (mm/rev)*Feed rate (mm/rev)
+ 14798 Depth of cut (mm)*Depth of cut (mm)
+ 14.29 Spindle Speed (rpm)*Feed rate (mm/rev)
+ 4.213 Spindle Speed (rpm)*Depth of cut (mm)

Regression Equation in Uncoded Units

TWR (mm3/min) = -2.818 - 0.02830 Spindle Speed (rpm) + 140.8 Feed rate (mm/rev)
+ 29.11 Depth of cut (mm) + 0.000024 Spindle Speed (rpm)*Spindle Speed (rpm)
- 369.5 Feed rate (mm/rev)*Feed rate (mm/rev)
- 61.41 Depth of cut (mm)*Depth of cut (mm)
- 0.07845 Spindle Speed (rpm)*Feed rate (mm/rev)
+ 0.02988 Spindle Speed (rpm)*Depth of cut (mm)

- Equations of MRR and TWR for HSS cutting tools with cross texture

Regression Equation in Uncoded Units

MRR (mm3/min) = 921.8 - 5.043 Spindle Speed (rpm) + 20265 Feed rate (mm/rev)
- 7757 Depth of cut (mm) - 0.001262 Spindle Speed (rpm)*Spindle Speed (rpm)
- 148606 Feed rate (mm/rev)*Feed rate (mm/rev)
+ 17827 Depth of cut (mm)*Depth of cut (mm)
+ 53.77 Spindle Speed (rpm)*Feed rate (mm/rev)
+ 0.8175 Spindle Speed (rpm)*Depth of cut (mm)

Regression Equation in Uncoded Units

TWR (mm3/min) = -4.351 + 0.01520 Spindle Speed (rpm) - 66.76 Feed rate (mm/rev)
+ 30.98 Depth of cut (mm) - 0.000000 Spindle Speed (rpm)*Spindle Speed (rpm)
+ 163.3 Feed rate (mm/rev)*Feed rate (mm/rev)
- 18.50 Depth of cut (mm)*Depth of cut (mm)
+ 0.02299 Spindle Speed (rpm)*Feed rate (mm/rev)
- 0.03492 Spindle Speed (rpm)*Depth of cut (mm)

- Equations of MRR and TWR for HSS cutting tools with parallel texture

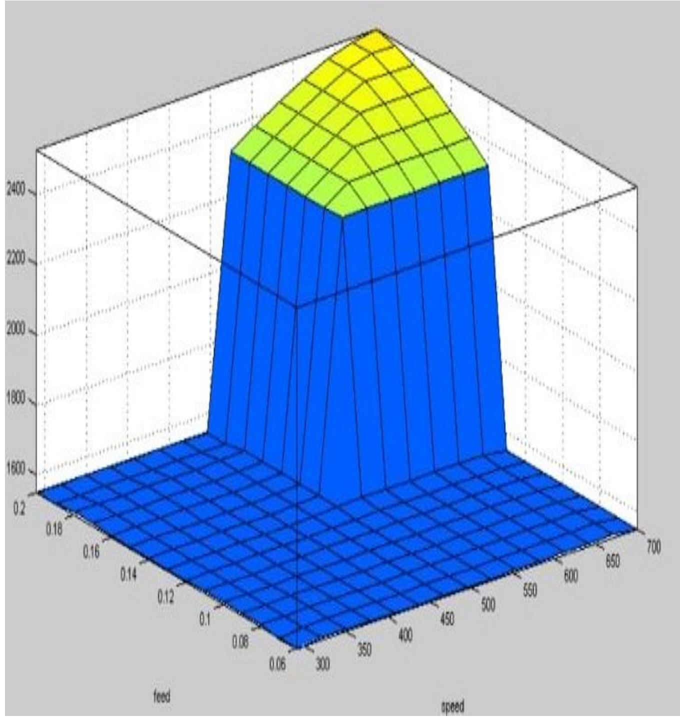
Regression Equation in Uncoded Units

MRR (mm3/min) = 1965 - 5.535 Spindle Speed (rpm) - 24232 Feed rate (mm/rev)
+ 2178 Depth of cut (mm) + 0.004366 Spindle Speed (rpm)*Spindle Speed (rpm)
+ 48973 Feed rate (mm/rev)*Feed rate (mm/rev)
+ 7446 Depth of cut (mm)*Depth of cut (mm)
+ 32.79 Spindle Speed (rpm)*Feed rate (mm/rev)
- 6.685 Spindle Speed (rpm)*Depth of cut (mm)

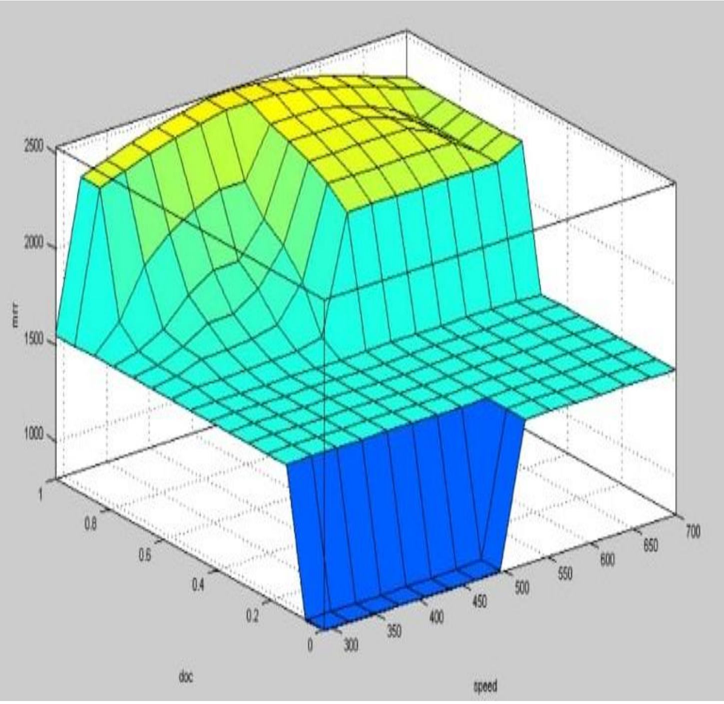
Regression Equation in Uncoded Units

TWR (mm3/min) = -3.385 + 0.03951 Spindle Speed (rpm) - 101.6 Feed rate (mm/rev)
+ 12.46 Depth of cut (mm) - 0.000032 Spindle Speed (rpm)*Spindle Speed (rpm)
+ 302.4 Feed rate (mm/rev)*Feed rate (mm/rev)
+ 7.186 Depth of cut (mm)*Depth of cut (mm)
+ 0.02929 Spindle Speed (rpm)*Feed rate (mm/rev)
- 0.03524 Spindle Speed (rpm)*Depth of cut (mm)

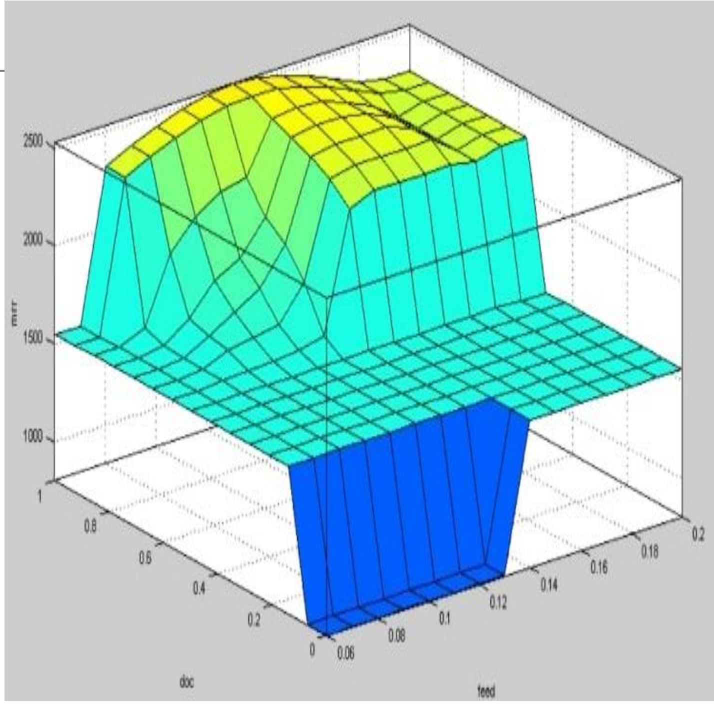
Fuzzy optimization models



Inclined MRR Plot



Cross MRR Plot



Parallel MRR Plot

FUZZY TABLE

TABLE 6: Fuzzy logic table describing degree of truth with three levels

Input values | Output values

S.No.	SPEED	FEED	DEPTH OF CUT(DOC)	MRR	TWR
1.	L	L	L	L	L
2.	L	M	M	L	L
3.	L	H	H	H	H
4.	M	L	M	M	M
5.	M	M	H	H	H
6.	M	H	L	H	M
7.	H	L	H	M	H
8.	H	M	L	M	M
9.	H	H	M	H	M

- **L=LOW**
  M=MEDIUM
  H=HIGH

Conclusion

• The results obtained by fuzzy logic are linguistic and they give the extent to which a value obeys. Therefore, fuzzy logic is a qualitative mathematical model. It specifies a range of values.

• The results obtained by RSM models give the curvature of the plot that can be obtained for the

Given data of experiments. We also obtained a function which can be further used to optimize the machining parameters and give the best working condition.

• The results obtained by ANN models can use the experimental data to create a black box and predict values with minimum errors. Although, its parameterization is still the work of user and its efficiency depends on the users skill.

• Overall, these models have their own unique advantages and can be used according to the context and requirements.

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Thank you!!