

Optimization of Duplex Stainless Steel in End Milling Process

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ABSTRACT: The main objective of this project is to find out the optimum cutting parameters during end milling operation of ASTM grade 4A Duplex stainless steel using TiNi coated carbide tools. The influence of cutting speed, feed rate and depth of cut on surface roughness, cutting force are to be observed and noted. In this study, the Taguchi method is used to find out the optimal cutting parameters for surface roughness, cutting force, tool temperature and tool wear in milling. The L27 orthogonal array is employed to study the performance and characteristics in milling operations. Three factors namely, cutting speed, feed rate and depth of cut are used as the input parameter. Three levels of spindle speeds(500,710,1000rpm),three levels of feed rate(40,63,100mm/min)and three levels of depth of cut(0.4,0.7,1.0mm) are employed. Experimental results are provided to illustrate the effectiveness of this approach.

KEYWORDS: Self curing concrete, Internal curing, Poly Ethylene Glycol

I. INTRODUCTION

During the last 30 years, the usage of stainless steel material increased dramatically. The attractive combination of excellent corrosion resistance, a wide range of strength levels including Strength retention at cryogenic and elevated temperature, good formability and an aesthetically pleasing appearance have made stainless steel materials of choice for a diverse range of application ,from critical piping components in boiling water nuclear reactors to the ubiquitous kitchen sink.

This work is carried out to find out the optimum cutting conditions. This work is carried out also to find out the influence of the cutting parameters such as cutting speed, feed rate and depth of cut on the surface finish, cutting force, tool wear and tool temperature using design of experiment method .Use of design of experiment method is economical and efficient in optimization of process parameters. The work is also carried out to predict the surface roughness using ANN. The usage of ANN gives almost accurate prediction values.

It is difficult to develop a precise mathematical model for a dry milling process as it is very complex. A non linear relationship between performance parameters and operating parameters exists in this process. Mathematical model like linear and non-linear regression models may not be able to capture those non linear correlations.ANN has the ability to correlate the input and output parameters are used for modeling in this process.ANN is characterized by topology, learning rule and activation function used. Domain knowledge from examples can be captured by neural networking and do not archive knowledge in an explicit form such as rules or database. Yet they can readily handle both continuous and discrete data and have a good generalization capability. Neural network can be used as mapping devices and pattern classifiers. In the manufacturing field they are used as optimization, modeling, prediction, control, classification and pattern recognition in the data association, clustering and signal processing

II. RELATED WORK

The duplex stainless steel is allowed for the end milling process. We are considering mainly three input parameters and two output parameters. Speed, feed rate and depth of cut are the input parameters and surface roughness and cutting force are the output parameters.

The equipments used for the output parameters measurement are surface roughness meter and kistler dynamometer respectively.



Fig 1 Stainless steel work piece



Fig 2 surface roughness measurement



Fig 3 Milling operation

Table 1 Material specification

Sl.No	Properties	
1.	Tensile strength (Mpa)	741
2.	Yield strength (Mpa)	546
3.	Elongation (%)	32.2
4.	Hardness (BHN)	223

Software used

An artificial neural network (ANN), usually called neural network (NN) is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data.

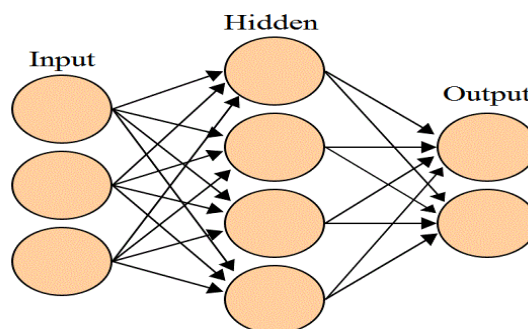


Fig 3 Text inpainting

Matlab program to predict the Cutting force

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p = [500 40 0.4; 500 63 0.4;500 100 0.4;
710 40 0.4;710 63 0.4;710 100 0.4;
1000 40 0.4;1000 63 0.4;1000 100 0.4;
500 40 0.7;500 63 0.7;500 100 0.7;
710 40 0.7;710 63 0.7;710 100 0.7;
1000 40 0.7;1000 63 0.7;1000 100 0.7;
500 40 1.0;500 63 1.0;500 100 1.0;
710 40 1.0;710 63 1.0;710 100 1.0;
1000 40 1.0;1000 63 1.0;1000 100 1.0]';
t=[281.65;179.77;397.15;195.52;240.52;270.30;38.98;121.0;150.41;
201.0;555.65;375.76;159.48;243.76;332.98;179.64;132.31;221.43;
259.02;319.15;335.35;236.88;187.32;320.49;142.22;384.46;226.17]';
plot(p,t,'o')
net = newff(p,t,10);
y1 = sim(net,p)
plot(p,t,'o',p,y1,'x')

net.trainParam.epochs = 1000;
net.trainParam.goal = 0.001;
net = train(net,p,t);
r=[0.16 283 .5]';
y2 = sim(net,r)
    
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III. EXPERIMENTAL RESULTS

Table 2 Response table for cutting force

Standard Order Trial No	Response Value	Speed (rpm)			Feed(mm/min)			Depth Of Cut(mm)		
		N1	N2	N3	F1	F2	F3	d1	d2	d3
		500	710	1000	40	63	100	0.4	0.7	1.0
1	281.65	281.65			281.65			281.65		
2	179.77					179.77		179.77		
3	397.15	397.15					397.15	397.15		
4	195.52		195.52		195.52			195.52		
5	240.52		240.52			240.52		240.52		
6	270.30		270.30				270.30	270.30		
7	138.98			138.98	138.98			138.98		
8	121.00			121.00		121.00		121.00		
9	150.41			150.41			150.41	150.41		
10	201.00	201.00			201.00				201.00	
11	555.65	555.65				555.65			555.65	
12	375.76	375.76					375.76		375.76	
13	159.76		159.76		159.76			159.76		
14	243.76		243.76			159.76		243.76		
15	332.98		332.98				159.76	332.98		
16	179.64			179.64	179.64			179.64		
17	132.31			132.31		132.31		132.31		
18	221.43			221.43			221.43		221.43	
19	259.02	259.02			259.02					259.02
20	319.15	319.15				319.15				319.15
21	335.35	335.35					335.35			335.35
22	236.80		236.80		236.80					236.80
23	187.32		187.32			187.32				187.32
24	320.49		320.49				320.49			320.49
25	140.22			140.22	140.22					140.22
26	384.40			384.40		384.40				384.40
27	226.17			226.17			226.17			226.17
Total	6786.6	2902.4	2187.2	1694.4	1792.4	2363.7	2629.5	1975.1	2401.9	2408.7
No Of Values	27	9	9	9	9	9	9	9	9	9
Average	251.3	322.5	243.1	188.3	199.2	262.6	292.2	219.4	266.8	267.6
Effect		134.24				93.01		48.19		

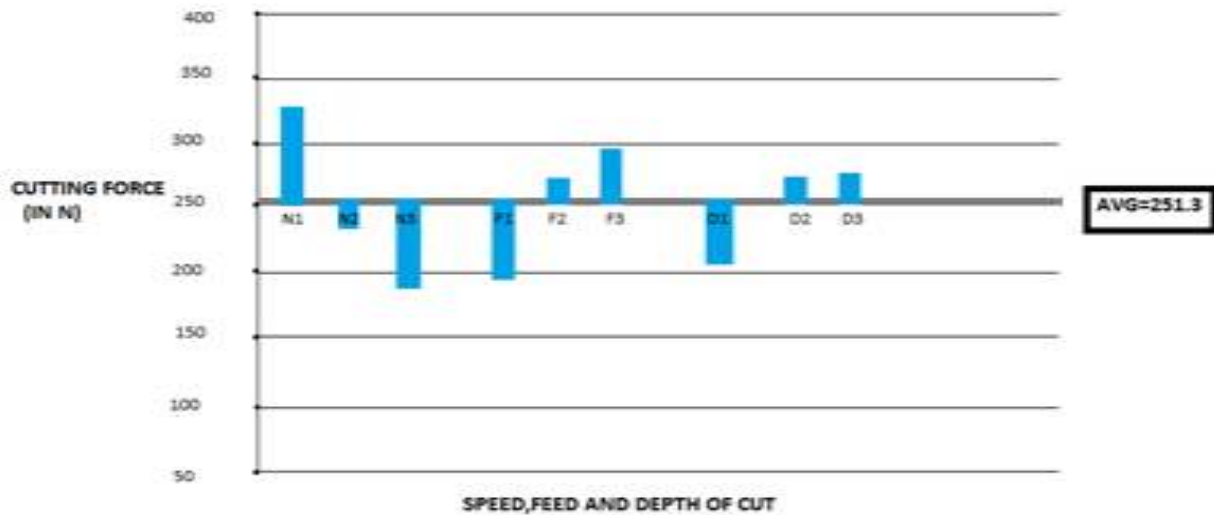


Fig4. Response graph for cutting force

Table 3 Response table for surface roughness

Standard Order Trial No	Response Value	Speed (rpm)			Feed(mm/min)			Depth Of Cut(mm)		
		N1	N2	N3	F1	F2	F3	d1	d2	d3
		500	710	1000	40	63	100	0.4	0.7	1.0
1	0.72	0.72			0.72			0.72		
2	0.77	0.77				0.77		0.77		
3	0.85	0.85					0.85	0.85		
4	0.8		0.8		0.8			0.8		
5	0.88		0.88			0.88		0.88		
6	0.75		0.75				0.75	0.75		
7	0.59			0.59	0.59			0.59		
8	0.46			0.46		0.46		0.46		
9	0.67			0.67			0.67	0.67		
10	1.08	1.08			1.08				1.08	
11	0.6	0.6				0.6			0.6	
12	1.16	1.16					1.16		1.16	
13	0.88		0.88		0.88				0.88	
14	1.06		1.06			1.06			1.06	
15	1.02		1.02				1.02		1.02	
16	0.61			0.61	0.61				0.61	
17	0.69			0.69		0.69			0.69	
18	0.61			0.61			0.61		0.61	
19	0.99	0.99			0.99					0.99
20	0.88	0.88				0.88				0.88
21	0.65	0.65					0.65			0.65
22	1.18		1.18		1.18					1.18
23	1.21		1.21			1.21				1.21
24	2.2		2.2				2.2			2.2
25	1.81			1.81	1.81					1.81
26	1.74			1.74		1.74				1.74
27	1.32			1.32			1.32			1.32
Total	25.58	7.64	9.98	8.5	8.68	8.23	9.23	6.49	7.71	11.92
No Of Values	27	9	9	9	9	9	9	9	9	9
Average	0.94	0.84	1.10	0.95	0.96	0.91	1.02	0.72	0.86	1.32
Effect		0.26			0.11			0.6		

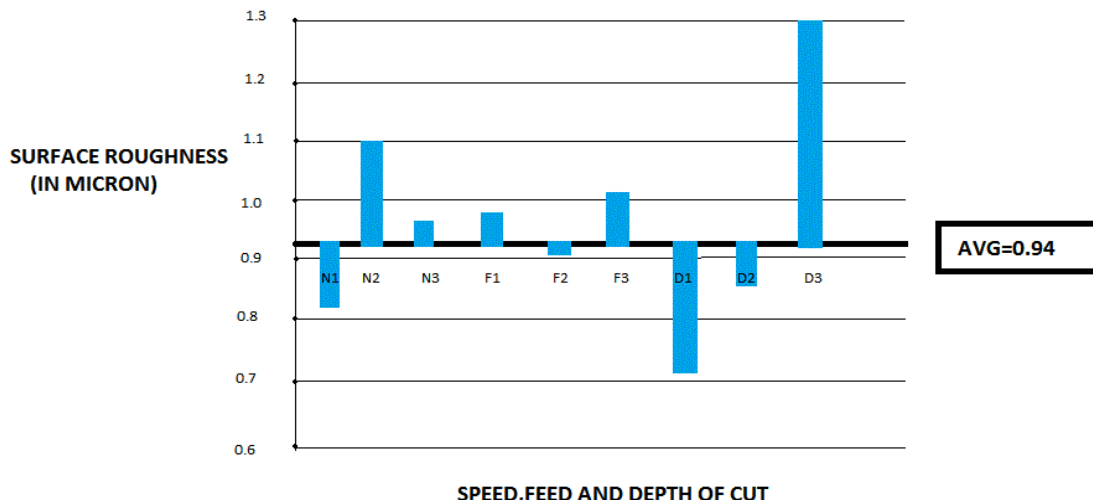


Fig. 5. Response graph for cutting force

Table 4 Prediction Results

S.n	Spindle Speed (rpm)	Feed Rate (mm/min)	Depth of Cut(mm)	Predictd Cutting Force(N)	Experimental Cutting Force(N)
1	355	40	0.5	219.07	221.59
2	500	63	0.5	169.36	170.54
3	1000	100	0.5	130.92	125.43

The experimental data of measured Cutting force are utilised to train the neural network model .Trained neural network models are used in predicting cutting force for various different cutting conditions .The developed prediction system is found to be capable of accurate cutting force prediction for the range it has been trained .The predicted values of the ANN were found to be very close to the experiment values.

Three experiments were carried out to validate the ANN prediction,from this we found that ann prediction gives 80% nearer to the experimental values.From this I came to the conclusion that, the ANN predicted values are more accurate and precise.

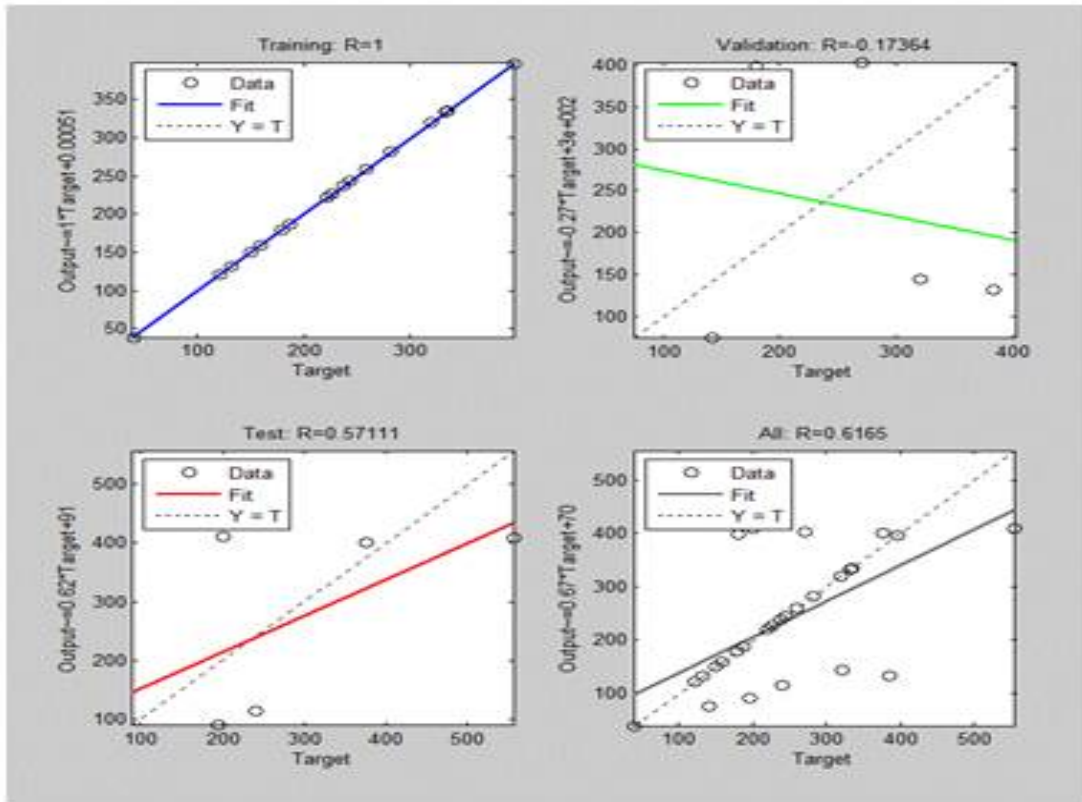


Fig 6 Regression result from ANN model: Output Vs Target

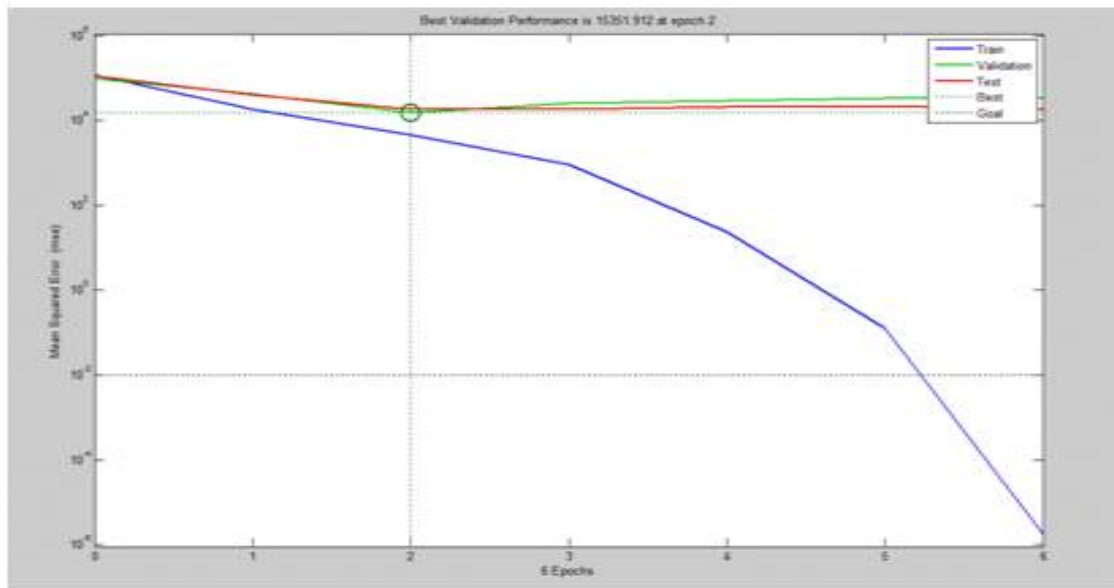


Fig 6 Performance Graph MSE Vs Epochs

IV. CONCLUSION

The optimization of cutting parameters during milling of stainless steel using coated carbide tools has been carried out. Design of experiment (DOE) method was used to find out the influence of input cutting parameters cutting speed, feed rate and depth of cut on the output parameters surface roughness, cutting force, tool wear and tool temperature. L27 orthogonal array with three factors and three levels were used. The three levels of Spindle speed were 500, 710 and 1000 rpm. The three levels of feed were 40, 63 and 100 mm/min. The three levels of depth of cut were 0.4, 0.7 and 1 mm. Dry milling process has been eliminated the cutting fluid disposal problem and environmental hazards in the shop floor. From the analysis of result in end milling using Taguchi method, the following can be concluded from the present study:

1. Taguchi's robust design method is suitable to analyse the metal cutting problems..

2. Low feed rate (40mm per min) , low depth of cut (0.4 mm) and cutting speed of (1000 rpm) lead to smaller value of resultant cutting force for the specific test range.
3. In end milling, use of high cutting speed (1000 rpm), low feed rate (40mm per min) and low depth of cut (0.4 mm) are recommended to obtain better surface finish for the specific test range.
4. Artificial Neural Network (ANN) was used to predict the cutting force. The predicted values of the ANN were found to be very close to the experimental values.

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