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Optimization of magneto rheological fluid assisted cylindrical surface finishing parameters for machining AISI 304L austenitic stainless steel

[1]Anandan K and [2]Suresh prabhu P

[1]*Research Scholar, Department of Mechanical Engineering, P.S.V. College Of Engineering and Technology, Krishnagiri, India.*
[2]*Professor and Director Research, Department of Mechanical Engineering, Karpagam Academy of Higher Education, Coimbatore, India.*

Address For Correspondence:
Anandan K, Research Scholar, Department of Mechanical Engineering, P.S.V. College Of Engineering and Technology, Krishnagiri, India.
E-mail: anandan.phd2015@gmail.com; Mobile No: +91-9843436068

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ABSTRACT

Magneto rheological abrasive flow finishing process provides better control over rheological properties of abrasive-laden finishing medium that exhibits changes in rheological behaviour in the presence of external magnetic field. The finishing fluid used in this study contains SiC and iron particles with a combination of specific volume percentage of silicon oils. The smart characteristics of magneto-rheological fluid are utilized to precisely control finishing forces to control surface quality. Experiments were conducted on austenitic stainless steel AISI 304 L and it is observed that by decreasing magnetic field strength, the surface roughness decreases. Besides, with increase in abrasive particle mesh number, surface roughness tends to be higher. However, there is a slight difference observed through different finishing cycle times. An approach for the optimization of machining parameters on finishing cylindrical surface of 304L stainless steel through magneto rheological fluid with multiple responses based on artificial neural network and response surface methodology. In the present work, parameters such as working gap, workpiece speed, wheel speed and feed rate are optimized considering the responses such as normal force (F_N), surface roughness (Ra) and material removal rate (MRR). Optimized process parameters can be determined by statistical methods and the experimental values were correlated with statistical parameters values.

INTRODUCTION

The conventional finishing process required a long processing time and expensive equipments to achieve the desired surface finish characteristics these factors lead to economically ineffectual. The surface of the materials is generally produced by different material removal process. For most of the industrial components, surface finish plays a crucial role in the service life of the component. It is a well-established fact that the fatigue life is strongly influenced by the surface polish and surface treatment. Fatigue failures generally nucleate at the surface defects of engineering parts. Therefore, surface conditions become a major factor to influencing the fatigue strength of the component. As the surface roughness increases, problems such as fluid flow resistance and optical loss increase resulting in poor efficiency. AISI 304L stainless steel has the extensive properties like better corrosion resistance than 302 type SS, high ductility, excellent drawing, forming and spinning. Essentially non-magnetic, becomes slightly magnetic when cold worked. Low carbon content means less carbide participation in the heat affected zone during welding and lower susceptibility to inter granular corrosion. Magneto rheological finishing process is an advanced precision finishing process technology used for finishing material surfaces up to Nano level. Lohithaksha *et al.* (2013) investigated the parameter optimization of end milling operation for Inconel 718 super alloy with multi-response criteria based on the Taguchi orthogonal array with the grey relational analysis. Jayaraman & Mahesh kumar (2014) presented a novel approach for the

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optimization of machining parameters on turning on AA 6063 T6 aluminium alloy with multiple responses based on orthogonal arrays with grey relational analysis. Khan *et al.* (2014) investigated the effect of WEDM process parameters on the surface roughness average and the kerf width of the stainless steel 304L. Saedon *et al.* (2014) studied the effects of the process parameters on different responses such as surface roughness (Ra), cutting rate and the material removal rate (MRR) on wire electro discharge machining (WEDM) operations and they proposed that an optimal combination of process parameters in the machining of titanium alloy in order to achieve minimum surface roughness. Sunil Jha *et al.* (2007) studied the effect of extrusion pressure and a number of finishing cycles on surface roughness in magneto rheological abrasive flow finishing (MRAFF) process. Ajay Sidpara & Jain (2012) proposed a theoretical model of the normal and tangential forces acting on the workpiece to improve the in-depth understanding of the mechanism of material removal during MR fluid based finishing process. Ajay Sidpara & Jain (2012) conducted an experimental study to predict the effect of process parameters (concentration of magnetic particles and abrasive particles, carrier wheel speed, and initial surface roughness) on surface finish and the material removal rate in MRF of single crystal silicon blank and reported that the final surface roughness value in terms of arithmetical mean roughness (Ra) obtained is as low as 8 nm. Shafrir *et al.* (2007) studied precision micro ground surfaces of tungsten carbides with aid of magneto rheological finishing (MRF) and found that peak-to-valley (p–v) micro roughness of the surface after micro grinding with rough or medium abrasive size tools gives a measure of the deformed layer depth. Kyung-In Jang *et al.* (2012) proposed a new de-burring process utilizing a magneto rheological fluid. Cheng *et al.* (2009) studied fabrication process ability aspect of the RB-SiC components, and investigates the results obtained by magneto rheological finishing (MRF) of RB-SiC mirror. They stated features of different polishing fluids and the characteristics of relative removal rates, analyses the processing limitations of the normal processing techniques and studies the effects of certain processing parameters on surface accuracy. Cheng *et al.* (2009) conducted an experimental investigation on optical aspheric components with assist of MR fluid using a 2-axis wheel tool and shown that surface roughness can be reduced from an initial value of 3.8–1.2 nm after 10 min of polishing. Jain *et al.* (2010) developed a new finishing process, namely, chemo-mechanical magneto-rheological finishing (CMMRF) for polishing silicon blanks that combines the beneficial features of chemical mechanical polishing (CMP) and magneto-rheological finishing (MRF) without the detrimental effects of either process involved. Tsai *et al.* (2008) performed an experimental investigation to obtain optimal processing conditions for the abrasive jet polishing of SKD61 mold steel. Jae-SeobKwak (2009) increased the magnetic flux density for non-ferrous materials through an installation of a permanent magnet on the opposite side of the workpiece to be machined was proposed and evaluated by computer simulation and experimental verification. Ajay Sidpara & Jain (2011) performed an experimental investigation into forces during magneto rheological fluid based finishing process that has been applied to a large variety of brittle materials, ranging from optical glasses to hard crystals. They also studied on-line monitoring of normal force and tangential force acting on the workpiece through the magneto rheological (MR) fluid and reported that maximum contribution was made by a working gap on the forces developed on the workpiece surface followed by CIP concentration while the least contribution is noticed by the wheel speed. Senthilkumar *et al.* (2014) investigated machining parameters cutting insert shape, relief angle and nose radius, using Taguchi based grey relational analysis. Performance measures viz., flank wear, surface roughness and material removal rate (MRR) were optimized using grey relational grade and ANOVA shows that cutting insert shape is the prominent parameter followed by feed rate and depth of cut that contributes towards output responses. An experiment conducted with the identified optimum condition shows a lower flank wear and surface roughness with higher MRR. Sadiq & Shunmugam (2010) proposed a novel method to improve the finish on non-magnetic surfaces in magneto-rheological abrasive honing process. Mamilla Ravi Sankar *et al.* (2009) performed an experimental investigation and mechanism of material removal in Nano finishing of MMCs using abrasive flow finishing (AFF) process. sidpara & Jain (2012) conducted an experimental study to predict the effect of process parameters (concentration of magnetic particles and abrasive particles, carrier wheel speed, and initial surface roughness) on surface finish and the material removal rate in MRF of single crystal silicon blank. In this present study, the effect of various process parameters of cylindrical surface finishing process with aid of Magneto-rheological fluid is proposed. Working gap, workpiece speed, wheel speed and feed rate were selected as input parameters and corresponding outputs are normal force, surface roughness and material removal rate were studied. Based on the parameter study optimal combination of process parameters is identified using the method of simultaneous optimization of multiple response variables.

Experimental Procedure:

Material selection:

Austenite stainless steel (AISI 304L) cylindrical pipe of 160 mm outer diameter; 8 mm thickness and 265 mm length workpiece material were used for this magneto rheological fluid assisted cylindrical surface finishing study. The chemical composition of the workpiece material is shown in **Table. 1.**

Table 1: Chemical composition of workpiece material (SS 304L)

Material	C	Mn	P	S	Si	Cr	Ni	Al	Fe
SS 304L	0.03	2	0.045	0.03	0.75	20	12	0.1	Balance

Table 2. Parameters and their selected levels

Parameters	Levels				
Working gap (mm)	0.25	0.5	0.75	1	1.25
Workpiece rotation (rpm)	200	250	300	350	400
Wheel speed (rpm)	150	200	250	300	350
Feed rate (mm/rev)	0.05	0.1	0.15	0.2	0.25

Cylindrical surface machining:

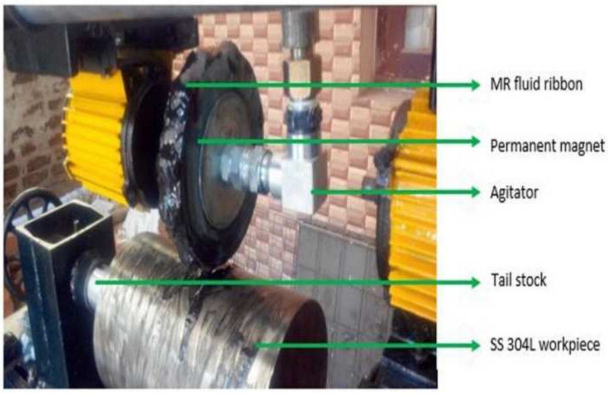

Fig. 1: MR fluid cylindrical surface machining of AISI 304L stainless steel

The cylindrical surface finishing experiments is carried out to finish the final surface of the object with the aid of magneto rheological (MR) fluid. The experimental setup of the cylindrical finishing machine is shown in **Fig. 1.** Magneto rheological fluid composed of silicon oil with grease, CIPs and Si-C (silicon carbide). Wheel type rotating magnetic tool of 25 mm thickness consist of a number of tiny holes of 3-5 mm diameter on the outer surface of the circular to for MR fluid passage. MR fluid is deposited by a hydraulic pumping system on the circular surface of a rotating magnetic tool, which transports the fluid to the work zone surface. Initially, the work specimen is finished with conventional grinding. Experiments were conducted at different levels of feed rate, Rotation of wheel speed, work piece rotation and the output response of normal and tangential force acting along the workpiece were measured through tool dynamometer. Selected levels of process parameters are shown in **Table. 2**. Each experiments was performed in the period of 12-15 minutes to obtain the best finish.

RESULTS AND DISCUSSION

The results of ANN to predict and optimize the force, surface roughness and material removal rate based on input machining parameters in cylindrical surface machining are shown and discussed below.

Prediction of output responses by ANN:

In this research, a multi-layer back propagation network was employed as a tool for mapping the complex and highly interactive process parameters such as working gap, workpiece speed, wheel speed and feed rate to predict the optimal force, surface roughness and material removal rate.

A three layer feed-forward network is constructed with four input neurons in the input layer and three neurons in the output layer to map the output like force, surface roughness and material removal rate to four input variables. In the developing stages of the neural network, initialization of weights, selection of the activation function and selection of the number of neurons to be used in the hidden layer are considered as the learning factors. In this work, the number of neurons in the hidden layer is determined by the trial and error approach. The number of neurons within the hidden layer is selected based on the accuracy of the prediction. After a number of trails it was found that the neural network structure 4-10-3 designed using Matlab Neural Network Toolbox leads to the best results. **Table. 3** shows the experimental data as utilized as a training data for ANN. The available experimental sample size of 30 and it consist of number of training and testing samples are 25 and 5 respectively. The performance plot and regression plots of F_n, R_a and MRR are shown in **Fig. 2 and Fig. 3.** A successful training is achieved after 6 iteration with MSE error of 4.5763 and 2 validating checks. The R-value for the training data is at 0.99291, the R-value for the validation data is 0.98646 and the R-value for the testing data is 0.96355 for cylindrical finishing operation. comparison of the measured and predicted values for force, surface roughness and MRR using the ANN model are given in **Table 4.**

Table 3: Parameters of artificial neural network process for F_n, R_a and MRR

Name	ANN model
Network type	FFBP model
No of hidden layers	2
Transfer function	PURELIN
Training function	TRAINLM
Learning function	LEARNGDM
Performance function	Mean square error
Number of neurons	4
Sum of squared error	0.00073676
Number of epochs	6
Validation checks	2
Learning factor	0.6

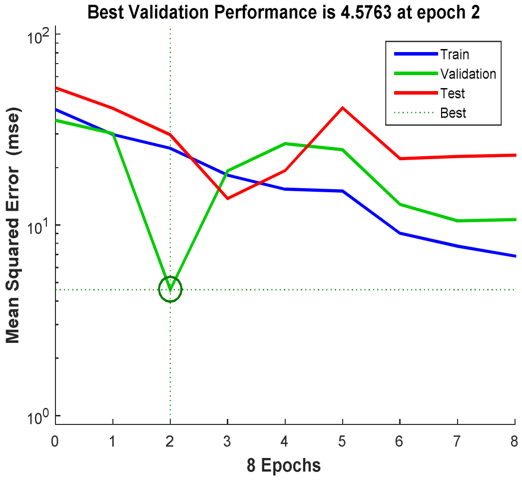

Fig. 2: ANN performance plot for F_n, R_a and MRR

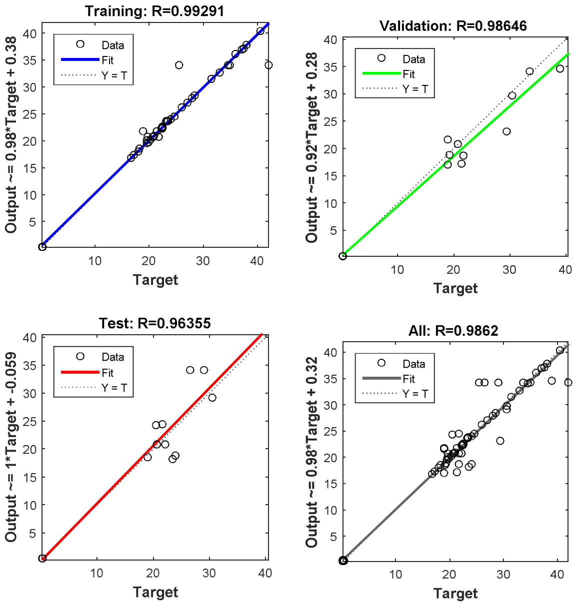

Fig. 3: ANN regression plot for F_n, R_a and MRR

Table 4: Comparison of experimental value with ANN predicted values.

parameters				Experimental value			ANN predicted			% Error deviation (%)		
A	B	C	D	Fn	Ra	MRR	Fn	Ra	MRR	Fn	Ra	MRR
0.5	350	200	0.2	23.37	26	0.267	23.744	26.239	0.289	-1.601	-0.920	-8.240
0.5	250	200	0.1	23.41	18	0.314	23.698	18.104	0.356	-1.230	-0.575	-13.217
0.5	250	300	0.2	24.62	24	0.343	24.461	24.059	0.320	0.646	-0.245	6.706
1	250	200	0.2	19.28	30.5	0.195	18.856	29.720	0.210	2.199	2.557	-7.692
0.75	300	250	0.15	20.74	37	0.357	20.832	34.150	0.355	-0.443	7.702	0.487
1	250	200	0.1	22.69	20	0.2	24.503	18.757	0.210	-7.988	6.215	-5.000
0.5	250	200	0.2	20.41	27	0.238	21.755	27.118	0.255	-6.590	-0.438	-6.934
1	250	300	0.1	20.24	33	0.305	20.253	32.686	0.356	-0.066	0.950	-16.809
0.5	350	300	0.2	22.35	40.5	0.333	22.336	40.447	0.346	0.065	0.132	-3.787
1	250	300	0.2	16.75	38	0.248	16.890	37.835	0.260	-0.835	0.433	-4.839
0.5	350	300	0.1	17.24	22.5	0.205	17.329	22.565	0.230	-0.519	-0.287	-12.195
1	350	200	0.2	19.52	21	0.29	19.484	20.999	0.310	0.183	0.006	-6.897
0.5	350	200	0.1	18.27	37.5	0.219	18.463	37.058	0.200	-1.055	1.180	8.676
1	350	300	0.2	18.92	36	0.267	16.988	34.547	0.260	10.210	4.035	2.622
0.75	300	250	0.15	19.68	25.5	0.248	20.832	27.412	0.230	-5.853	-7.498	7.258
1	350	300	0.1	19.05	30.5	0.186	18.478	29.193	0.192	3.003	4.284	-3.226
0.75	300	250	0.15	20.59	32	0.224	20.832	34.150	0.210	-1.175	-6.719	6.250
0.75	300	250	0.15	22.16	31.5	0.262	20.832	34.150	0.270	5.993	-8.413	-3.053
0.5	250	300	0.1	19.57	36	0.219	20.023	36.048	0.200	-2.315	-0.134	8.676
1	350	200	0.1	22.42	28.5	0.245	22.319	28.372	0.240	0.450	0.450	2.041
1.25	300	250	0.15	20.61	19	0.268	18.625	21.674	0.280	9.630	-14.073	-4.478
0.75	300	350	0.15	20.68	22.5	0.257	20.742	22.439	0.280	-0.298	0.273	-8.949
0.75	300	250	0.15	21.75	35	0.239	20.832	34.150	0.250	4.221	2.428	-4.603
0.25	300	250	0.15	23.15	31.5	0.305	23.676	31.535	0.351	-2.273	-0.111	-15.007
0.75	300	150	0.15	22.81	21	0.285	24.342	18.259	0.290	-6.717	13.052	-1.754
0.75	300	250	0.05	19.84	34.5	0.291	19.772	34.060	0.310	0.344	1.276	-6.529
0.75	200	250	0.15	21.43	28	0.246	21.836	27.958	0.260	-1.896	0.152	-5.691
0.75	300	250	0.15	20.81	33.6	0.261	20.832	34.150	0.240	-0.105	-1.638	8.046
0.75	400	250	0.15	18.69	26.2	0.274	17.247	23.092	0.290	7.718	11.864	-5.839
0.75	300	250	0.25	22.26	37.1	0.259	22.292	37.045	0.262	-0.143	0.147	-1.078

Optimal parameters:

The optimal machining parametric combinations of the cylindrical surface finishing process for achieving maximum normal force, minimum surface roughness and maximum MRR achieved by adopting a multi-objective optimization procedure through response surface methodology. The optimization was carried out using Minitab, with multiple objectives viz. As the composite desirability is close to 1, it can be concluded that the parameters are within their working range. Optimization plot for the responses is shown **Fig. 4.** The optimized values of machining parameters are *A*= 0.5 mm, *B* = 200 rpm and *C*= 150 rpm and D = 0.05 mm/rev, Machining with optimum parametric combination, F_n can be achieved as high as 24.5665, R_a can be achieved as low as 13.293 and MRR can be achieved as high as 0.3199 g/min.

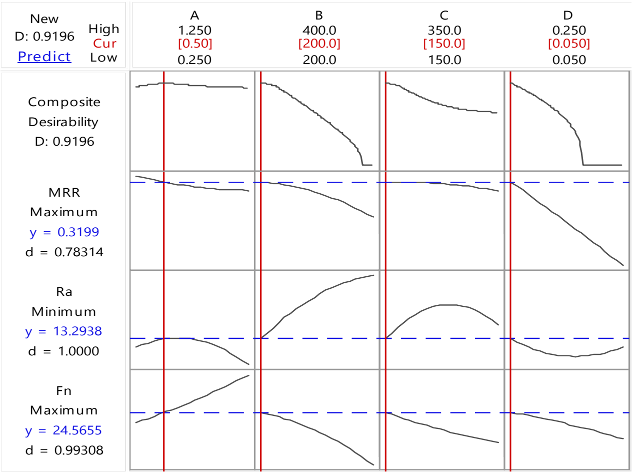

Fig. 4: optimization plot.

Scanning electron microscopic study:

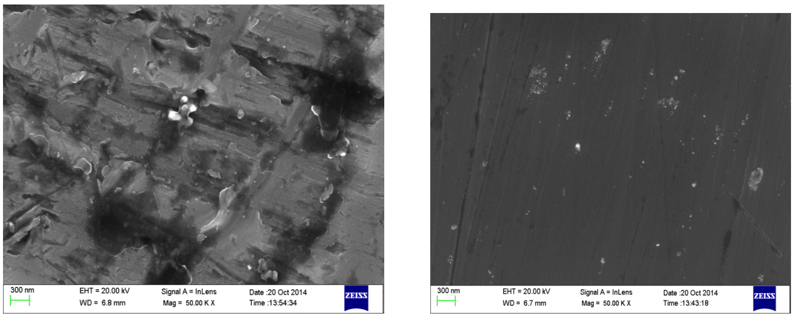

Fig. 5: Scanning electron microscope image (SEM) (a) without MR fluid finished workpiece at 300 nm level. (b) MR fluid finihsed workpiece at 300 nm level.

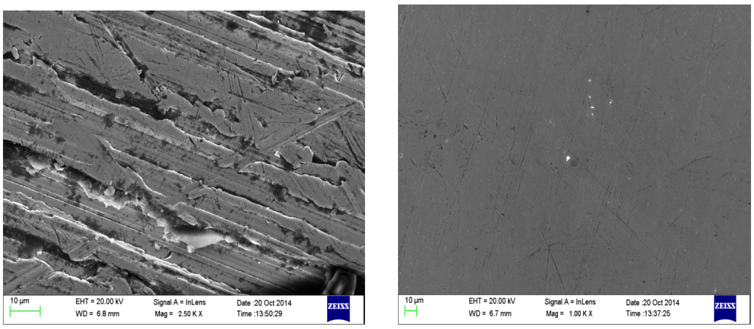

Fig. 6: scanning electron microscope (SEM) image (a). without MR fluid finished workpiece at 10 µm level. (b). MR fluid finihsed workpiece at 10 µm level.

Atomic force microscopic study:

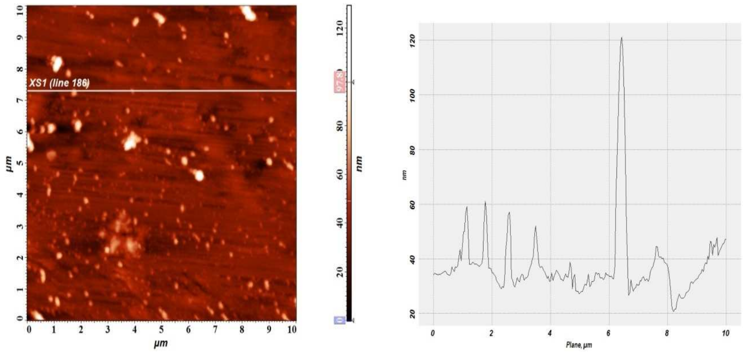

Fig. 7: Atomic force microscopic image of (a) 304L stainless steel without MR fluid finished surface (b) Cross sectional view.

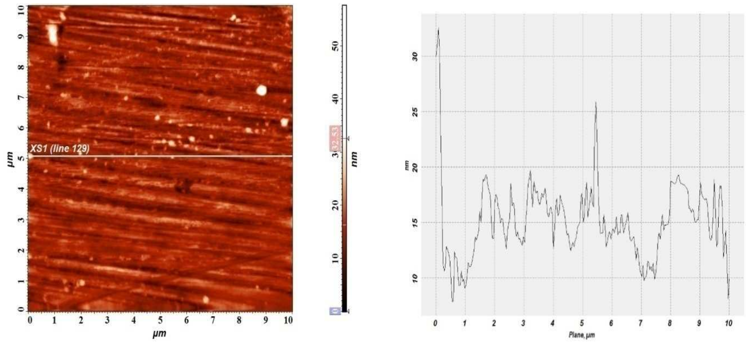

Fig. 8: The atomic force microscope image of (a) 304L stainless steel with MR fluid finished surface. (b) Cross sectional view.

Magneto rheological fluid assisted cylindrical surface finishing of 304L stainless steel material is evaluated and micro structural examination done under the standard metallographic procedure is shown in **Fig. 5, Fig. 6, Fig. 7 and Fig. 8**

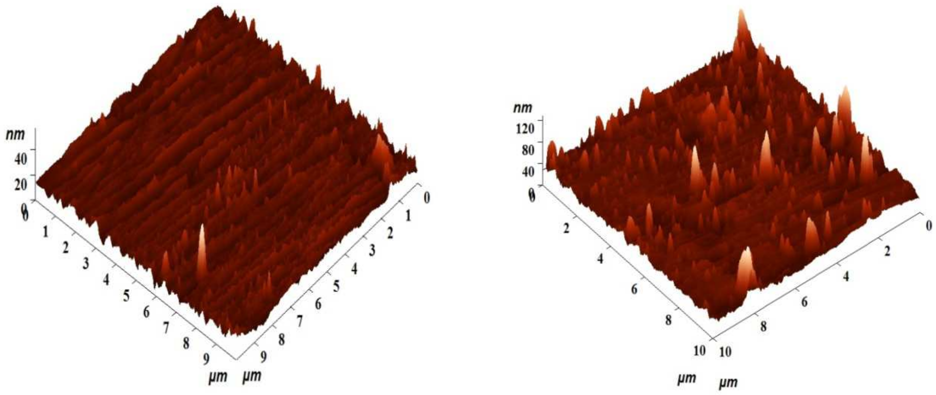

Fig. 9: Topography of (a) MR fluid finished surface (b) without MR fluid finished surface.

Fig. 9 (a) and (b) shows the 3D topography of final surfaces of cylindrical finishing process. One of the surface roughness values of Exp. No. 2 is obtained as low as 18 nm. It clearly shows that MRF process can finish AISI 304L stainless steel by proper combination of process parameters. Furthermore, surface roughness of 304L SS without MR fluid is around 100 nm (average initial value) to 50–120 nm (average final value). Therefore, significant reduction in the surface roughness has been achieved in the present study.

Conclusion:

An experimental investigation is performed to observe the effects of process parameters for finishing 304L austenitic stainless steel by cylindrical magneto rheological fluid finishing operation. Surface roughness is significantly affected by feed rate and least affected by workpiece speed. Material removal rate increases with an increase in CIPs concentration and wheel speed while it decreases with increasing the concentration of abrasive beyond an optimum condition. An artificial neural network technique coupled with response surface methodology for the prediction and optimization of machining parameters leading to maximum normal force, minimum surface roughness and maximum material removal rate. The predicted results are found to be close to the experimental values. The mean relative error are 0.119 %, 0.536 % and -3.169 % respectively which shows that the developed model has good accuracy in predicting the output values. The ANN model coupled with RSM leads to maximum normal force value of 24.5665 N, minimum surface roughness value of 13.293 μm and maximum MRR value of 0.3199 g/min corresponding to optimum machining parameters 0.5 mm of working gap, 200 rpm of workpiece speed, 150 rpm of wheel speed and 0.05 mm/rev of feed rate.

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