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RESEARCH ARTICLE

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Modelling and optimization of Nd:YAG laser micro-turning process during machining of aluminum oxide (Al_2O_3) ceramics using response surface methodology and artificial neural network

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Abstract – Pulsed Nd:YAG laser has high intensity and high quality beam characteristics, which can be used to produce micro-grooves and micro-turning surface on advanced engineering ceramics. The present research attempts to develop mathematical models by using response surface methodology approach for correlating the machining process parameters and the process responses during laser micro-turning of aluminum oxide (Al_2O_3) ceramics. The process parameters such as laser average power, pulse frequency, workpiece rotating speed, assist air pressure and *Y* feed rate were varied during experimentation. The rotatable central composite design experimental planning has been used to design the experimentation. The performance measures considered are surface roughness (*Ra*) and micro-turning depth deviation. Multi-objective optimization has been carried out for achieving the desired surface roughness as well as minimum depth deviation during laser micro-turning operation. Further, an artificial neural network (ANN) model has been developed to predict the process criteria. Levenberg-Marquadt training algorithm is used for multilayer feed forward backpropagation neural network. The developed ANN model has 5-10-2 feed forward network. There are 5 neurons in the input layer, 10 neurons in the hidden layer and 2 neurons in the output layers corresponding to two output responses, respectively. The developed ANN model has been validated using data obtained by conducting additional set of experiments. It was found that the developed ANN model can predict the process criteria more accurately than response surface methodology (RSM) based developed models.

Key words: Laser micro-turning, Nd:YAG laser, Alumina, Surface roughness, Depth deviation, Response surface methodology, Artificial neural network

1. Introduction

Aluminium oxide (Al_2O_3) finds potential use in probably the broadest number of engineering applications such as automobile, aerospace, biomedical, etc. due to its extreme hardness, strength, stability in high temperature and high degree of resistance to wear and corrosion. Owing to these outstanding mechanical, thermal as well as chemical properties of alumina ceramics, conventional machining processes find poor machinability and uneconomical productivity [1]. Moreover, the optical and physical properties of the advanced ceramic materials to be machined provide significant variations in the quality characteristics during micromachining of engineering ceramics. To overcome the problems involved during machining of advaced ceramics, several advanced machining processes (AMPs) have been developed and implemented in macro as well as micro-manufacturing industries. Laser beam machining (LBM) is one of them which is basically accomplished by precisely manipulating a beam of coherent light to vaporize unwanted portion of material from work samples. At present, laser materials processing technologies such as laser micro-cutting, micro-drilling, micro-grooving, etc. find a wide and diversified range of successful applications in various microengineering fields due to several machining features such as machinability of difficult-to-process materials, advanced ceramics and composites, high productivity, non-contact processing, elimination of finishing operations, adaptability to automation, reduced processing cost, improved product quality, greater material utilization, minimal heat-affected zone (HAZ) and green manufacturing [2, 3].

Micro-turning process with a single laser beam is one of the new laser materials processing technologies [4]. This process is

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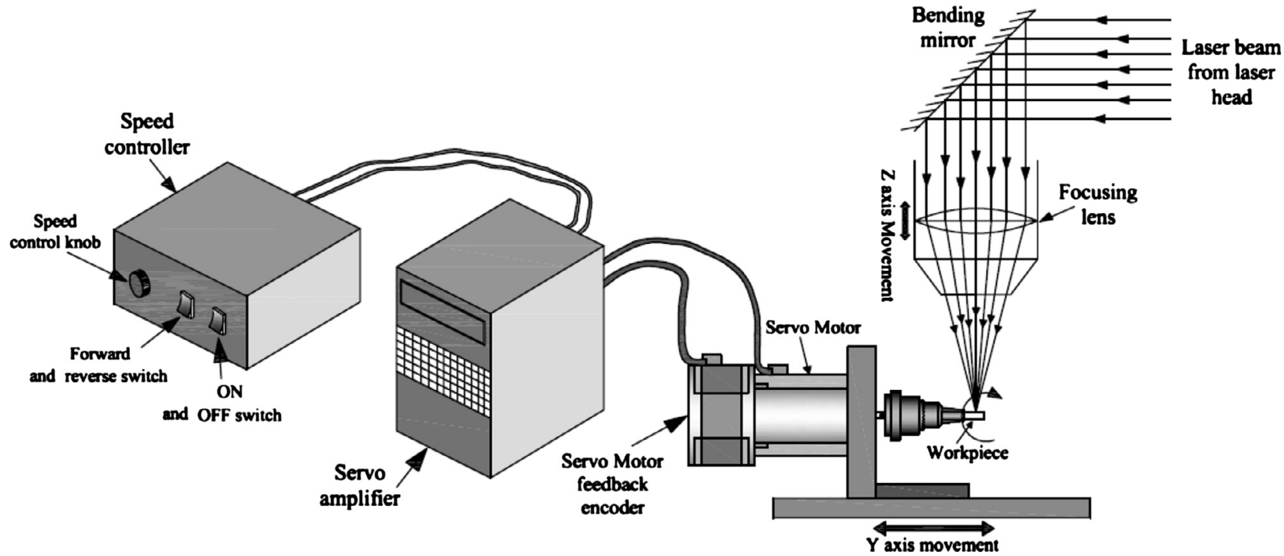

Figure 1. Schematic view of the workpiece rotating system including servo motor and amplifier.

used to produce quality surface with intricate depth dimensions on cylindrical shaped components of advanced materials like ceramics. Laser micro-turning process deals with the layer-by-layer material removal from rotating cylindrical material by irradiation of high-intense laser beam for specific length of turn along the cylindrical axis of the workpiece by controlling its rotating speed as well as the continuous axial feed movement simultaneously. However, to produce accurate dimensional micro-turned depth with quality surface features in laser micro-turning operation, one must find a set of process parameters, which gives the desired performances or criteria under particular processing constraints. The various process parameters involved in laser micro-turning operation are laser beam parameters (pulse energy, pulse frequency, pulse duration), workpiece motion parameters (axial feed rate, rotating speed), assist gas parameters (assist-gas pressure, types of gas, types of nozzle), etc. These process parameters play dynamic role during laser micro-turning operation of engineering ceramic materials. Moreover, it is very difficult to control precisely such a large number of process parameters during laser machining operation, especially during laser micro-turning of cylindrical components with specific length and depth of turn within tight tolerance.

In the past literature, it is found that there are very few researches on laser micro-turning process of advanced ceramics [4–6]. However, these researches represented basic experimental studies to appraise the capability of laser beam for micro-turning operation. Experimentation for laser micro-turning process based on design of experiments (DoE) still has not been carried out. Moreover, there is a need of developing empirical relationship between the process parameters and the performance measures for laser micro-turning process. Furthermore, multi-response optimization process parametric setting must be searched out to get desired accurate dimensional features in different components. With these intentions, in the present research, an attempt has been made to design and develop a model using a combined approach of response surface methodology (RSM) and artificial neural network (ANN) for predicting the desired response values within the considered range of process parameters during laser micro-turning of alumina (Al_2O_3) ceramic with pulsed Nd:YAG laser system. Further, the ANN model has been used to predict the multi-optimization parametric setting to achieve desired responses during laser micro-turning operation with pulsed Nd:YAG laser.

2. Details of experimental set-up with the developed workpiece rotating system

The present experimentation has been conducted on a computer numerical control (CNC) pulsed Nd:YAG laser micro-machining system (model: Series 2000, make: Sahajanand Laser Technology Ltd., India). The machining system has several subsystems, which include laser generating unit (Nd:YAG rod, krypton arc flash lamp, elliptical cavity, safety shutter, fully and partially reflective mirrors, Q-switch), beam delivery unit (bending mirror, focusing lens, lens protector), power supply unit, CNC controller (X, Y and Z axes controllers), cooling unit (heat exchanger, internal and external chilling unit) and pressurized air/gas delivery unit. The laser beam micro-machining set-up with its various units mentioned above is shown and described in [7]. The movement of the three axes (X, Y and Z) is controlled by Panasonic servo controller and a personal computer attached with it. The chilling units and heat exchanger circulates deionized water through the laser head and Q-switch to protect the Nd:YAG rod and krypton lamp being damaged.

To rotate the work sample in a particular speed, a workpiece rotating system has been developed indigenously. The details of workpiece holding and rotating system are described in [8]. In Figure 1, the schematic view of the workpiece rotating system including servo motor and amplifier is shown. The Y feed movement of CNC work table was provided by a PC connected to Nd:YAG laser system. After removal of a micro-layer from work surface, the focused lens was moved down by Z-axis

Table 1. Compositions and properties of Alumina (Al_2O_3) ceramic used for experimentation.

Material type	Recrystalised Alumina
Percentages of compositions	
Alumina (Al_2O_3)	99
Silica (SiO_2)	0.7
Magnesia (MgO)	0.07
Iron oxide (Fe_2O_3)	0.07
Sodium oxide, Calcia	Rest
Volume density gm/cc	3.85
Apparent porosity %	Nil – 0.1
Expansion coefficient 20–1000 °C	8.4×10^{-6}/°C
Melting point	2000 °C
Limit of use	1900 °C

motion, so as to focus the laser beam on the previous completed laser scans. Finally, laser micro-turning surface was achieved on cylindrical samples of desired length of turn as well as desired depth.

3. Experimental planning based on response surface methodology

The present experimentation of laser micro-turning operation of alumina (Al_2O_3) work sample of 10 mm diameter has been conducted based on the central composite rotatable second-order design of RSM [6]. The compositions as well as the major properties of Aluminum Oxide (Al_2O_3) ceramic are listed in Table 1. The schematic view of desired depth to be machined by laser micro-turning operation on work sample is shown in [8]. The input process parameters considered during experimentations are laser average power, pulse frequency, sample rotational speed, assist air pressure and *Y* feed rate. In [8], the coded as well as uncoded values of the considered process parameters are enlisted. The selection of the ranges of various process parameters has been done after performing a lot of trial experimentations.

Empirical models using second-order polynomial equations have been developed based on response surface methodology (RSM) design to establish the mathematical relationship between the predominant process parameters and the measured responses. The general second-order polynomial equation is described in [8]. The experimentation consists of 32 experiments and all the experiments have been carried out randomly to minimize the error due to repetition of set of process parameters at central point. The details of process parametric settings and corresponding experimental results for all 32 experimental runs are shown in [8]. Surface roughness (*Ra*) and laser micro-turning depth deviation have been measured for each of the experimental runs. SURFCOM 120A-TSK roughness measuring instrument was used to measure the surface roughness of each work sample. Roughness of each experiment was measured six times by rotating the workpiece at 60°. The cut-off length was 0.25 mm and total length of measurement (*L*) was 2.5 mm. The micro-turned depth was measured using a 10× magnification lens attached with an optical measuring microscope (Olympus STM6). The target micro-turning depth was 100 μm and the depth deviation was calculated as described in [8]. The schemes of the surface roughness and micro-turning depth measurements are shown in [8]. The experimental results obtained for both the responses i.e. surface roughness (*Ra*) and micro-turning depth deviation were used to develop mathematical models by using MINITAB™ software. Multi-objective optimization has been done using RSM based approach to obtain the process parametric setting to obtain the desired process criteria. The experimentally observed data were also used to develop an ANN model.

4. Modelling of laser micro-turning process through RSM

The mathematical models, which correlate the considered input process parameters and the measured responses, have been developed for each of the responses based on the response surface methodology (RSM) and shown in [8]. For surface roughness criterion, the standard *F*-value for lack-of-fit is 4.06 for 95% confidence level. However, the calculated *F*-value is 1.18 which is far lower than the standard *F*-value. This implies that the developed mathematical model is adequate at 95% confidence level. The values of adjusted R^2(*R*-Sq(adj)) is 86.90% and error term (*S*) is 0.00345854 indicate the accuracy of the developed model. However, for micro-turning depth deviation, the standard *F*-value for lack-of-fit is 4.06 for 95% confidence level. However, the calculated *F*-value is 3.11, which is lower than the standard *F*-value. This implies that the developed mathematical model is adequate at 95% confidence level. The values of adjusted R^2(*R*-Sq(adj)) is 87.07% and error term (*S*) is 0.00071345 indicate the accuracy of the model. Based on the models developed for the responses, validity of these models was checked through six confirmation experiments. Table 2 shows the process parametric settings with the RSM predicted results of the responses. Experimentation has been conducted in these process parametric combinations and the experimental results have been compared with the RSM predicted results. It is observed in Table 2 that the developed RSM models have predicted the responses satisfactorily as average percentage of prediction errors for surface roughness and micro-turning depth deviation are 3.63% and 3.92% and overall prediction error is 3.78%.

5. Development of ANN model to predict process responses

An artificial neural network (ANN) is a computational model that is being inspired by biological nervous systems. A neural network consists of an interconnected group of artificial neurons working in unison to solve specific problems. ANN has the capability of learning and thereby acquiring knowledge and makes it available for further use to predict specific data [9, 10]. The multilayered ANN model which has the computational ability of non-linear problems can be used to predict and optimize the laser micro-turning process using pulsed Nd:YAG laser machining system. Among the developed ANN models, feed-forward back-propagation neural network is

Table 2. Validation experimentation of developed empirical models based on RSM.

Expt. no.	Coded values of process parameters					Responses				Percentage of error (%)	
						Experimental results		RSM predicted results			
	X_1	X_2	X_3	X_4	X_5	Surface roughness (Ra), µm	Depth deviation mm	Surface roughness (Ra), µm	Depth deviation mm	Surface roughness (Ra)	Depth deviation
1	−2	−1	−1	0.2	−1.2	6.77	0.05696	6.47	0.05478	4.36	3.83
2	0	−1	1.8	1.2	0.1	6.11	0.02467	5.88	0.02341	3.81	5.11
3	2	0.6	0	−0.6	1.2	6.19	0.02799	6.03	0.02698	2.56	3.62
4	−1	0.2	1	1.8	0.8	6.80	0.06392	6.60	0.06138	3.01	3.97
5	1	1.4	0.2	−0.2	−0.8	5.65	0.09828	5.46	0.09516	3.44	3.17
6	−1	−1.2	−0.8	−0.8	1.1	5.86	0.04532	5.59	0.04358	4.58	3.83
Average percentage of prediction error										3.63	3.92
Overall percentage of prediction error										3.78	

X_1: Average power, X_2: Pulse frequency, X_3: Rotational speed, X_4: Air pressure, X_5: Y feed rate.

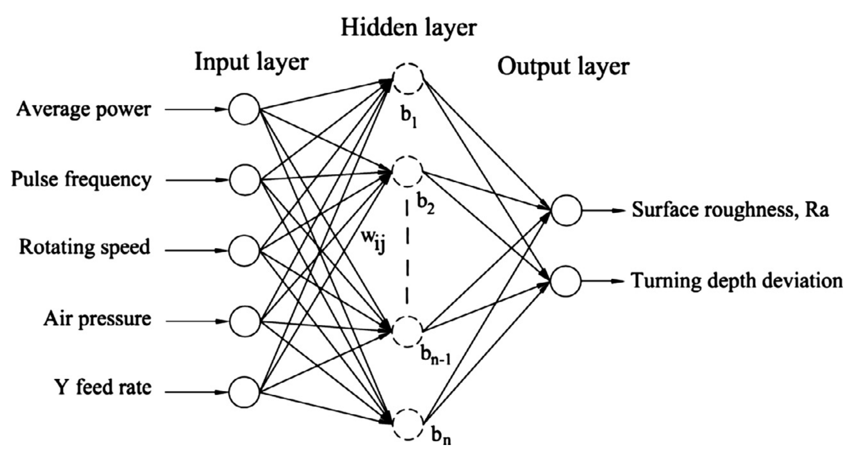

Figure 2. Network architecture of the developed ANN model.

widely used for prediction and optimization of various machining processes [11–13]. The back-propagation algorithm has been developed based on gradient descent learning and the weights of connections between different neurons are calculated based on equation (1):

$$\Delta W_{ij} = \eta \frac{\delta E}{\delta W_{ij}}, \quad (1)$$

where, ΔW_{ij} is the weight update of the line connecting ith and jth neuron of the two neigbouring layers, η is the learning rate and dE/dW_{ij} is the error gradient corresponding to the weight W_{ij}.

Neural Network Toolbox™ of version R2009b is used to design the feed-forward network for developing the ANN model for the present experimentation. The architecture of the feed-forward ANN model is shown in Figure 2. The figure shows a multilayer feed-forward neural network, which has one input layer, one hidden layer and one output layer. Each of these layers includes a number of processing units, which is termed as "neuron". In the input layer, there are five neurons, which are corresponds to five input process parameters that have been already enlisted in Table 1 in reference [8]. The output layer consists of two neurons, which corresponds to the output responses namely surface roughness (Ra) and micro-turning depth deviation. One of the important tasks in developing the ANN models is to choose the number of neurons in the hidden layer and this number should be carefully selected to reach the desired goal with least number of iterations for obtaining the desired output results at minimum possible time. Several training operation has been conducted by feeding the input and output data to search out the optimal number of neurons. It is observed that using 10 numbers of neurons in the hidden layer results least overall mean percentage of prediction error for the ANN model. The percentage of prediction error for each machining setting has been calculated as per equation (5) as in reference [8]. The variation of overall percentage of prediction error with different numbers of neurons is shown in Figure 3, from which it is can be concluded that 10 numbers of neurons in the hidden layer would provide the best output results in shortest time for the present ANN model. Hence, a multi-layered feed-forward backpropagation network of 5-10-2 neurons is used for developing the ANN model in the present research investigation.

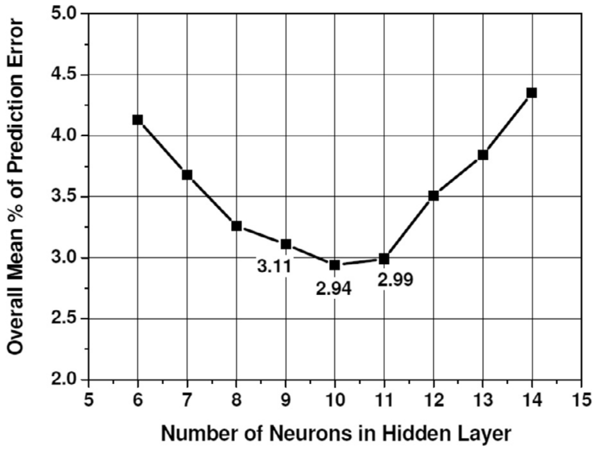

Figure 3. Plot of overall mean percentage prediction error at different number of neurons in the hidden layer.

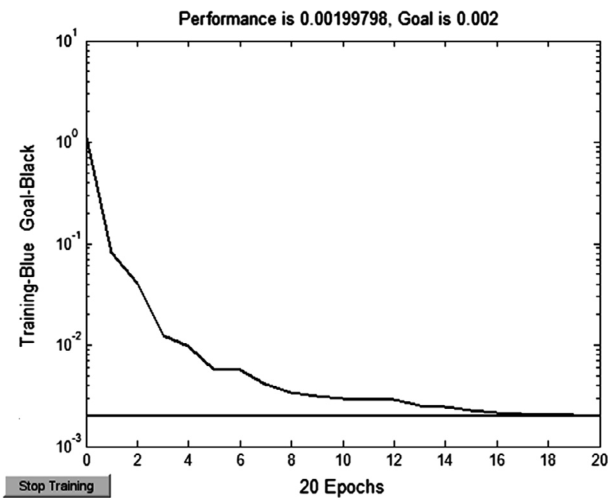

Figure 4. The training curve generated at the end of training session.

Table 3. Comparison between experimental and ANN predicted results of test data.

Expt No.	Experimental results		ANN predicted results		% of prediction error	
	Surface roughness *Ra* (μm)	Turning depth deviation (mm)	Surface roughness *Ra* (μm)	Turning depth deviation (mm)	Surface roughness *Ra*	Turning depth deviation
1	6.77	0.05696	6.52	0.05544	3.63	2.67
2	6.11	0.02467	5.96	0.02370	2.52	3.95
3	6.19	0.02799	6.04	0.02742	2.42	2.03
4	6.80	0.06392	6.62	0.06177	2.67	3.37
5	5.65	0.09828	5.46	0.09621	3.29	2.11
6	5.86	0.04532	5.64	0.04403	3.78	2.84
Average percentage of prediction error					3.05	2.83
Overall percentage of prediction error					2.94	

6. Results and analysis based on developed ANN model

The neural network model has been developed with multi-layered feed-forward backpropagation network of 5-10-2 neurons based on the input data and output results of 32 experimental settings as shown in Table 2 in reference [8]. Figure 4 shows the training plot which was generated at the end of training session. After the performance goal was met during training of the network, a set of separate experimentations have been conducted and the data are utilized to test and validate the developed ANN model. The validation experimentation for the developed ANN model consists of six experiments as shown in Table 2. The ANN model predicted results in these six experiments were compared with the results of responses obtained during actual experimentation. Table 3 shows the comparative results of prediction errors for experimental results and ANN predicted results. It is observed from Table 3 that the results predicted by the developed ANN model are very close to the experimentally obtained results and overall percentage of prediction error for the responses is 2.94, which is acceptable. The comparative plots of ANN model predicted results with 32 settings of experimental results for surface roughness (*Ra*) and micro-turning depth deviation are shown in Figures 5 and 6, respectively. In Table 4, the comparison of prediction errors for RSM and ANN models has been shown for the six experiments mentioned above. It is observed from the percentage errors that ANN model can predict (overall percentage of prediction error = 2.94%) the responses more adequately and accurately than the RSM model (overall mean of percentage prediction error = 4.76). Figures 7 and 8 compare the results of surface roughness (*Ra*) and micro-turning depth deviation, respectively for experimentally observed data, RSM model predicted data and ANN model predicted data.

7. Comparison of multi-objective optimization based on RSM and ANN model

Multi-objective optimization based on RSM approach has been carried out using MINITAB software to achieve the minimum response values i.e. least surface roughness (*Ra*) as well as micro-turning depth deviation. The optimal process parametric combination with the minimum achievable response values

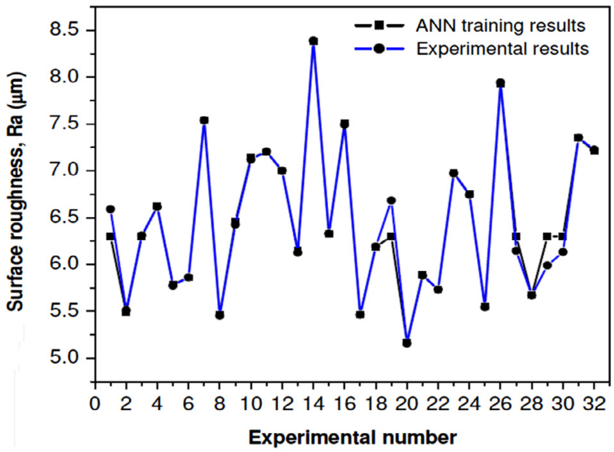

Figure 5. Comparison of ANN predictive results with experimental obtained results for surface roughness, *Ra*.

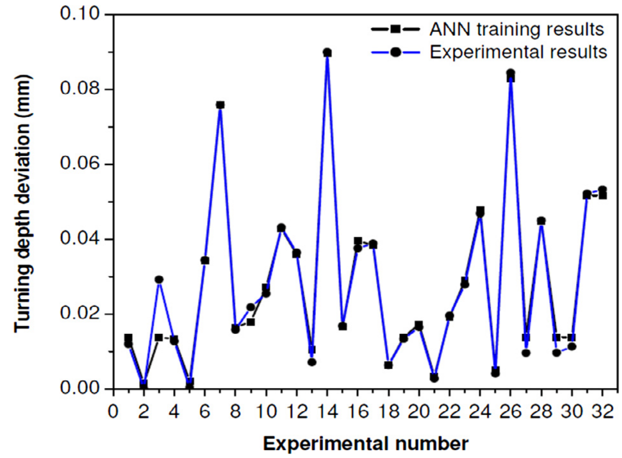

Figure 6. Comparison of ANN predictive results with experimental obtained results for micro-turning depth deviation.

Table 4. Comparison of prediction error of RSM model estimated and ANN model predicted results of test data.

Expt. No	% of estimation error of RSM model		% of prediction error of ANN model	
	Surface roughness, *Ra*	Turning depth deviation	Surface roughness, *Ra*	Turning depth deviation
1	4.36	3.83	3.63	2.67
2	3.81	5.11	2.52	3.95
3	2.56	3.62	2.42	2.03
4	3.01	3.97	2.67	3.37
5	3.44	3.17	3.29	2.11
6	4.58	3.83	3.78	2.84
Average percentage of prediction error	3.63	3.92	3.05	2.83
Overall percentage of prediction error	3.78		2.94	

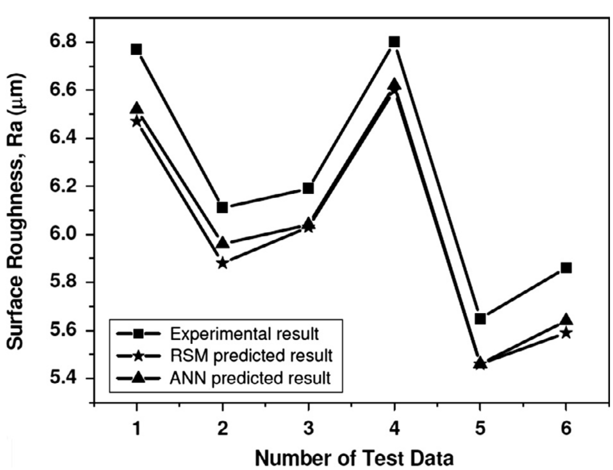

Figure 7. Comparative plot of experimental, RSM predicted results and ANN predicted results for surface roughness (*Ra*).

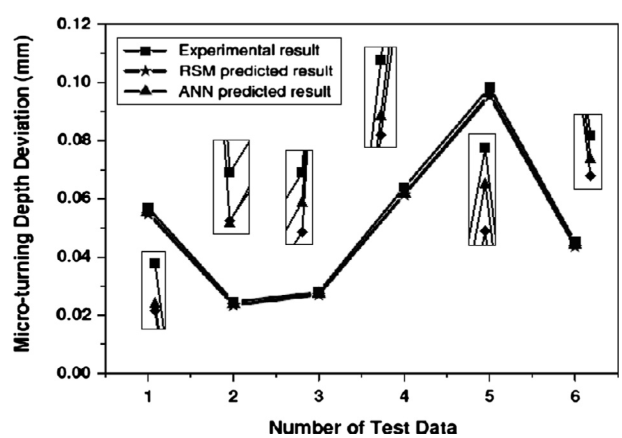

Figure 8. Comparative plot of experimental, RSM predicted results and ANN predicted results for micro-turning depth deviation.

generated through developed mathematical models using MINITAB software is shown in reference [8]. The minimum response values obtained as surface roughness (*Ra*) of 5.63 µm and turning depth deviation of −0.00020 mm at an optimal process parametric combination of laser average power at 7.81 Watt, pulse frequency at 5601.59 Hz, workpiece rotational speed at 435.60 rpm, assist air pressure at 0.30 kgf/cm^2 and *Y* feed rate at 0.4434 mm/s. Due to machine constraints in one hand and non-rounded off figure of process parametric setting in the other hand, experiment has been carried out at

Table 5. Comparison of RSM-predicted, ANN predicted and experimental results at RSM-based optimal parametric setting.

Expt.	Experimental results	RSM predicted results	ANN predicted results	Percentage of prediction error in RSM approach	Percentage of prediction error in ANN approach
Nearer feasible setting of RSM predicted optimal parametric setting (Avg. power = 7.81 watt; Pulse Freq. = 5600 Hz; Rotating sp. = 436 rpm; Air press. = 0.30 kg-cm^{-2}; *Y* feed rate = 0.443 mm/s)	Surface roughness, *Ra* = 5.91 µm	Surface roughness, *Ra* = 5.63 µm	Surface roughness, *Ra* = 5.72 µm	4.74	3.21
	Turning depth deviation = 0.00021 mm	Turning depth deviation = −0.00020 mm	Turning depth deviation = 0.000203 mm	4.76	3.33

the nearer feasible setting of optimal parametric combination achieved at RSM based multi-response optimization and the process responses were compared. In Table 5, the optimal response values of RSM predicted and experimentally observed results are shown. It is observed from Table 5 that RSM predicted results are in close agreement with experimentally observed results as the percentage of prediction errors for both the responses are 4.74 and 4.76, respectively, which are in acceptable range. These results corroborate the optimality of RSM based approach for laser micro-turning operation.

Multi-objective optimization results have also been predicted using developed ANN model at the RSM predicted optimal parametric combination as surface roughness (*Ra*) of 5.72 µm and micro-turning depth deviation of 0.000203 mm. Percentage of prediction errors for ANN model have been calculated and enlisted in Table 5. It is observed from Table 5 that the developed ANN model has predicted response results very nearer to the results obtained in actual experimentation and the percentage of prediction errors obtained as 3.21 and 3.33, respectively, which are acceptable. Therefore, it is confirmed that the developed ANN model can predict better results than the RSM predicted results.

8. Conclusions

In the present research study, laser micro-turning of cylindrical alumina ceramic material has been carried out based on response surface methodology (RSM) design of experiments (DoE). Mathematical modelling of surface roughness (*Ra*) and micro-turning depth deviation were successfully developed to correlate these process criteria with various process parameters considered during experimentations. The major conclusions that can be drawn from the present research study are as follows:

(i) Experimentations have been successfully conducted using central composite design (CCD) based on RSM. The experimental results are used to develop the mathematical models for surface roughness and micro-turning depth deviation. To check the validity of the developed models, confirmation experiments have been conducted and it was found that the RSM based model predicted results are close to the experimentally obtained results and the calculated overall percentage of prediction error is 3.78, which is acceptable.

(ii) The experimental results were used to develop a multilayer feed-forward back propagation neural network (BPNN). To train the network, a large number of training sessions have been conducted by changing the number of neurons in the hidden layer and it was found that 10 numbers of neurons in the hidden layer predicted the response results quite satisfactorily with least overall prediction error. Hence, feed-forward back propagation neural network of 5-10-2 was adopted and the ANN model was successfully developed to predict the process performances of laser micro-turning process.

(iii) To validate the developed ANN model, another set of experiments have been carried out at those process parametric combinations that were used for testing the validity of the RSM mathematical models. It was found that ANN model predicted the process criteria quite close to the results obtained in experiments in those experimental combinations. The overall percentage of prediction error for the developed ANN model was calculated as 2.94. It is also confirmed that the developed ANN model has predicted process responses more adequately and accurately than the RSM model predicted results.

(iv) Based on the RSM developed models, multi-objective optimization of the process parameters was carried out to achieve the desired surface roughness and minimum micro-turning depth deviation. The responses were also predicted using developed ANN model at the RSM based multi-objective parametric combination. Experiment was carried out at very near to the feasible parametric setting of multi-objective optimization and the prediction errors were calculated both for RSM as well as ANN model. It was found that ANN model has predicted relatively closed response results to the experimentally obtained results than RSM based developed mathematical models.

The research findings obtained in the present study will be an effective tool to predict the desired responses during laser micro-turning operation of cylindrical alumina ceramic materials. Furthermore, the successfully developed RSM and ANN models can be effectual technological guidelines to produce desired surface quality on various cylindrical ceramic components or parts.

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