OPTIMIZATION OF PROCESS PARAMETERS IN LASER MICROGROOVING OF ALUMINA CERAMIC USING GENETIC ALGORITHM

Debabrata DHUPAL[1], Salila RANJAN DIXIT[2], Sudhansu Ranjan DAS[3]

Requirement of micromachining of advance engineering materials are extremely demand in present day precision industries as it has extensive application in diverse domain like automobile, electronic, biomedical, and aerospace engineering. The present paper addresses the modeling and optimization study on dimensional deviations of square shaped microgroove in laser micromachining of aluminum oxide ceramic material with pulsed Nd:YAG laser by considering air pressure, lamp current, pulse frequency, pulse width and cutting speed as process parameters. Thirty two sets of laser microgrooving trials based on central composite design of experiments are performed and response surface method, artificial neural network and genetic algorithm are subsequently applied for mathematical modeling and multi response optimization. The performance of the predictive ANN model based on 5-8-8-3 architecture, gave the minimum error (MSE=0.000099) and presented highly promising to confidence with percentage of error less than 3% while compared it with experimental result data set. The ANN model combined with GA leads to minimum dimensional deviations corresponding to optimum laser microgrooving process parameters 1.2 kgf/cm^2 of air pressure, 19.5 A of lamp current, 4 kHz of pulse frequency, 6% of pulse width, and 24 mm/s of cutting speed. Finally, the results have verified by performing further confirmation experiment.

Keywords: Laser microgrooving, Aluminum oxide, RSM, ANN, GA.

1. Introduction

Advanced engineering ceramics have been widely used in industries because of their superior characteristics such as electrical insulation, high hardness, low thermal expansion coefficient, corrosion resistance, high temperature resistance and low weight-to-strength ratio [1] and particularly these are extremely hard-to-cut materials due to extreme brittleness. Owing to these complexities, the task to machine a component with deterministic precision becomes challenging. In recent past, laser beam machining (LBM) has been explored as an effective and emerging process for shaping ceramic materials. Pulsed laser is efficient for micromachining of hard-to-cut material because of low pulse width with high peak power. Nd:YAG laser beam emit light or photons of shorter wavelength generating high power densities and small focused spot diameter better than benefits offered by conventional CO_2 laser. Laser microgrooving operation considers various

[1] Veer Surendra Sai University of Technology, India, e-mail; debabratadhupal@gmail.com
[2] Veer Surendra Sai University of Technology, India, e-mail: salila.simple@gmail.com
[3] Veer Surendra Sai University of Technology, India, e-mail: das.sudhansu83@gmail.com

micromachining input process parameters like laser power, pulse width, spot size and cutting speed were quite compatible as well as close agreement with derived energy equation of heat transfer [2,3]. Apart, assist gas pressure substantially affects the shape, geometry and dimension of cut during laser micromachining operation [4,5]. The present work dealt with microgrooves produced on aluminum oxide (Al_2O_3) flat workpiece by Nd:YAG laser treatment emphasizing explication of square microgroove dimension and geometry of the machined quality. During square microgrooving operation maintaining of squareness and depth are essential owing to implicit focusing quality of the laser machining process.

When the manufactures are dealing with multiple conflicting objectives, modeling technique helps in enhancing the efficacy of machining process. Although some theoretical models require simplifications, assumptions and approximations for approaching real machining process, don't consider any undesirable deficiency in the process. Therefore, analytical solutions cannot be easily extended to practical usage [6], and for this reason adequate modelling is essential to do quality predictions in a function of operating conditions. The model development by RSM and ANN are convenient methods for product as well as process improvement and have received considerable attention by the researchers in the last two decades. Moreover, owing to the complicated behavior of the machining processes, where a few distinctive and opposing goals must be optimized, at the same time the mono-objective optimization techniques don't allow to find the comprehensive ideal cutting conditions value which fulfills all the execution attributes in machining; hence the multi-objective optimization has turned into an undeniably vital and challenging assignment [7,8]. For sure, it offers most prominent measure of data with a specific end goal to settle on a choice on choosing process parameters in machining process. Amid all the optimization techniques, the genetic algorithm (GA) has explored as an effective and reliable tool in advanced computing technology for the outline of high-quality frameworks as it gives a straightforward, proficient, and well-organized way to optimize output, for example, performance, cost, and quality.

Various researchers have employed methods which include statistical and analytical approach using RSM [9-15] and ANN [16-21] for mathematical modeling in order to predict the responses and GA [22-24] for multi response optimization in order to control the process parameters during laser micromachining process. The appropriate combination and utilization, along with proper adjustment of pre-cited machining parameters are of prime importance for acquiring good grade of microgrooving, which generally consumes precious time and effort due to the dynamic behavior of the laser micromachining process. Yet almost no systematic study has been reported in laser microgrooving operation that ensured scope for researchers and also no method currently results in same level of efficiency for all process. The novelty of the present study focuses on development of computational as well as empirical models and multi-response parametric optimization in microgrooving of aluminum oxide (Al_2O_3) ceramic material through Nd:YAG laser treatment. Particularly, design of experiments (DOEs), response surface methodology (RSM), artificial neural network (ANN) and genetic algorithm (GA) have been applied for process improvement. The following dimensional deviations of the microgroove are addressed; upper width deviation, lower width deviation and depth deviation.

2. Experimental setup and procedure

Microgrooving experiments were performed on TEM_{00} operating mode using computer numerical control (CNC) pulsed Nd:YAG laser machining system (model: SLT-SP2000, make: SLT ltd.) consists of various subsystems. For experimentation, the laser beam (focused by the lens with focal length of 50 mm) was set at workpiece surface as the focal plane which resulted in laser beam spot size of nearly 0.1 mm. Al_2O_3 flat workpiece was subjected to microgrooving by multiple laser pulses using Nd:YAG laser treatment with actual peak power move between 0.7 to 5 kW. The compressed as well as regulated gas (here, air) is supplied into a fine co-axial nozzle to allow the grooving as per the experimental design. The movement of lens is controlled by the CNC Z-axis controller unit for to attain the desired height (here, depth) of the microgroove. Multi sawing software is used to generate square microgroove of size 200x200x200 micron by setting zero taper angle. Prior to machining, the location of workpiece and focusing condition on workpiece surface was observed as well as cheeked by CCD camera including CCTV monitor in order to govern the position of laser beam spot precisely.

Table 1

Properties of workpiece material (alumina, Al_2O_3)

Properties	Units	Value
Density	g/c^3	3.96
Specific heat	J/kgK	775
Thermal conductivity	(cal/s)/(cm^{2}C/cm)	0.072 to 100ºC
		0.15 to 1000ºC
Compressive strength	MPa	2500
Modulus of elasticity	GPa	393
Hardness	GPa	1800, HB-30
Fracture toughness	MPa-√m	4
Sintering temperature	ºC	1600
Melting temperature	ºC	2050

In the present work response surface methodology (RSM) as well as artificial neural network (ANN) were considered for mathematical modelling and genetic algorithm (GA) for multi-objective optimization by utilizing the observational data based on design of experiments (DOEs). Aluminum oxide

(Al_2O_3) plate of size 30 mm x 30 mm was chosen as workpiece material for the experimentation. The various leading properties of aluminum oxide are presented in Table 1.

Table 2

Process parameters and levels

Parameters	Unit	Levels				
		-2	-1	0	1	2
Air pressure (X_1)	kgf/cm^2	0.4	0.8	1.2	1.6	2.0
Lamp current (X_2)	A	14.5	17	19.5	22	24.5
Pulse frequency (X_3)	kHz	1	2	3	4	5
Pulse width (X_4)	%	0	2	4	6	8
Cutting speed (X_5)	mm/s	12	16	20	24	28

Table 3

Design of experimental plan and experimental results

Test no.	Actual setting of parameters					Dimensions of microgroove (mm)			Dimensional deviations of microgroove (mm)		
	X_1	X_2	X_3	X_4	X_5	Upper width	Lower width	Depth	Upper width deviation	Lower width deviation	Depth deviation
1	1.6	17.0	2	2	16	0.1967	0.1390	0.160	-0.003	-0.061	-0.040
2	0.8	22.0	2	2	16	0.2210	0.2020	0.200	0.021	0.002	0.000
3	1.6	17.0	4	6	16	0.1840	0.1550	0.168	-0.016	-0.045	-0.032
4	1.6	22.0	4	6	24	0.2154	0.1910	0.212	0.0154	-0.009	0.012
5	0.8	17.0	4	2	16	0.1930	0.1280	0.162	-0.007	-0.072	-0.038
6	1.2	24.5	3	4	20	0.2330	0.2005	0.234	0.033	0.001	0.034
7	1.2	19.5	3	4	28	0.2490	0.1620	0.209	0.049	-0.038	0.009
8	1.2	19.5	3	4	20	0.2210	0.1355	0.165	0.011	-0.064	-0.035
9	1.2	19.5	3	4	20	0.2054	0.1525	0.176	0.005	-0.047	-0.024
10	1.2	19.5	3	0	20	0.2137	0.1565	0.142	0.013	-0.043	-0.058
11	1.6	22.0	4	2	16	0.2062	0.1495	0.164	0.006	-0.050	-0.036
12	1.2	19.5	3	4	20	0.1950	0.1350	0.202	-0.005	-0.065	0.002
13	0.4	19.5	3	4	20	0.1853	0.1295	0.164	-0.014	-0.070	-0.036
14	1.2	19.5	3	8	20	0.1792	0.1295	0.149	-0.021	-0.070	-0.051
15	0.8	22.0	4	2	24	0.1915	0.1365	0.185	-0.008	-0.063	-0.015
16	1.2	19.5	3	4	12	0.2090	0.1265	0.189	0.009	-0.073	-0.011
17	0.8	17.0	4	6	24	0.2040	0.1135	0.159	0.004	-0.086	-0.041
18	0.8	17.0	2	6	16	0.1956	0.1255	0.136	-0.004	-0.074	-0.063
19	1.6	22.0	2	6	16	0.1915	0.1745	0.193	-0.008	-0.025	-0.006
20	1.2	19.5	5	4	20	0.1996	0.1700	0.163	-0.001	-0.030	-0.037
21	1.2	19.5	3	4	20	0.2060	0.1430	0.155	0.006	-0.057	-0.045
22	2.0	19.5	3	4	20	0.1995	0.1470	0.142	-0.001	-0.053	-0.058
23	1.2	19.5	3	4	20	0.1992	0.1420	0.142	-0.001	-0.058	-0.057
24	0.8	17.0	2	2	24	0.2040	0.1440	0.132	0.004	-0.056	-0.067
25	0.8	22.0	4	6	16	0.2050	0.1425	0.228	0.005	-0.057	0.028
26	0.8	22.0	2	6	24	0.2370	0.1735	0.183	0.037	-0.026	-0.016
27	1.6	22.0	2	2	24	0.2316	0.1700	0.205	0.032	-0.030	0.005
28	1.2	14.5	3	4	20	0.1940	0.1190	0.117	-0.006	-0.081	-0.083
29	1.6	17.0	2	6	24	0.1907	0.1255	0.120	-0.009	-0.074	-0.080

30	1.6	17.0	4	2	24	0.2160	0.1535	0.126	0.016	-0.046	-0.074
31	1.2	19.5	1	4	20	0.2125	0.2091	0.170	0.012	0.009	-0.030
32	1.2	19.5	3	4	20	0.2067	0.1630	0.168	0.006	-0.037	-0.032

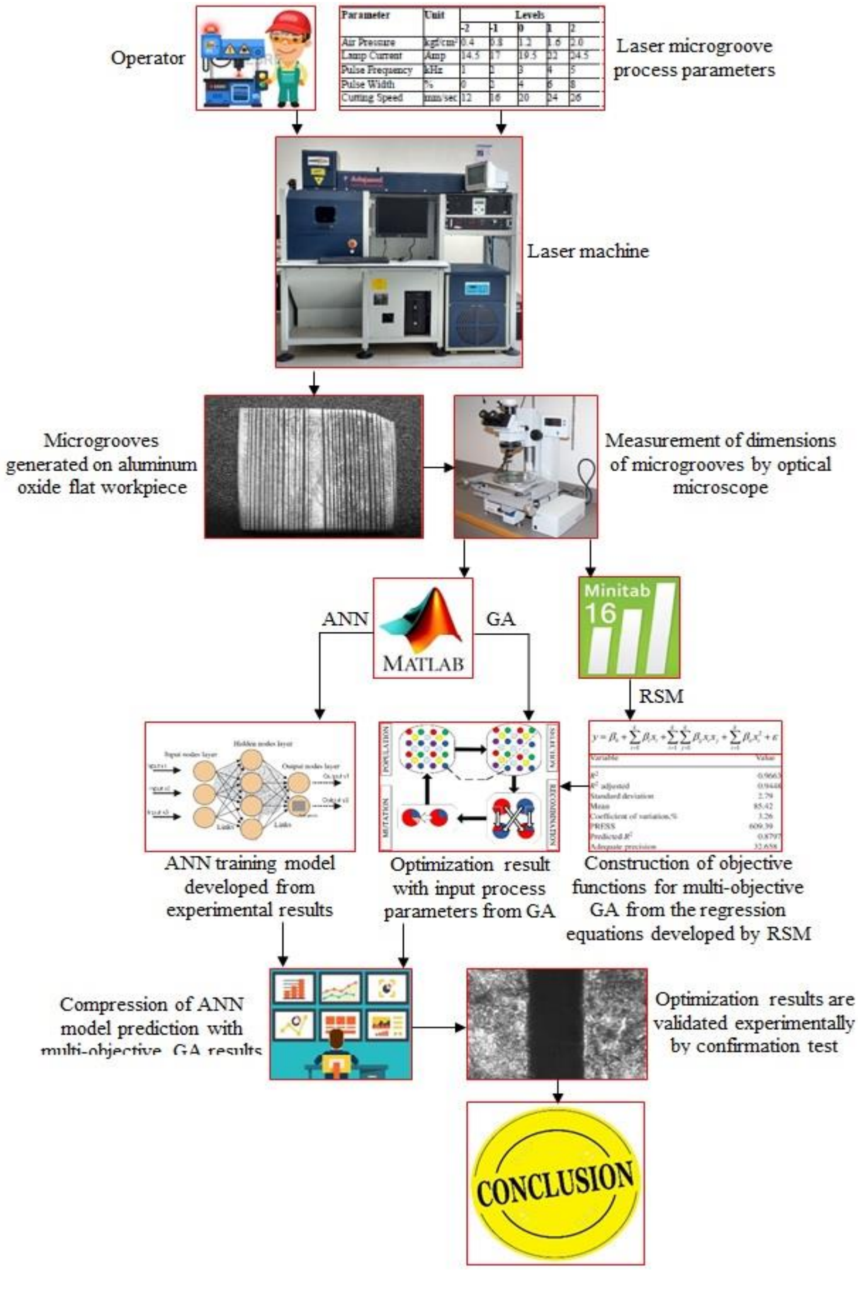

Fig. 1 Schematic of experimental setup and methodology presented

In the current investigation air pressure, lamp current, pulse frequency, pulse width and cutting speed are considered to be the process parameters which affect the response of interest in laser microgrooving operation namely upper width deviation, lower width deviation and depth deviation. The identified process parameters and their associated levels are presented in Table 2. Using the selected factors (five) and parameters levels (five), a design matrix was formulated in conformance with central composite design (CCD) design of experiments (DOEs) associated with thirty two (32) experimental runs. Design of experimental plan with actual value of process parameters, measured responses and estimated deviation parameters are presented in Table 3. The different dimensional deviations (responses) of machined micro-groove were measured by utilizing optical microscope (model: STM6, make: Olympus) at the magnification level of 10X. Figure 1 shows the schematic layout of the experimental setup for Nd:YAG laser machining unit with methodology followed in the current study.

The various dimensional deviations like: (i) upper width deviation (Y_{UWD}) is calculated by taking the difference between actual upper width (Y_{AUW}) and target upper width (Y_{TUW}), (ii) for lower width deviation (Y_{LWD}) is calculated by considering the variation between actual lower with (Y_{ALW}) and target lower width (Y_{TLW}), and (iii) in case of depth deviation (Y_{DD}) is similarly estimated by subtracting target depth (Y_{TD}) from actual depth (Y_{AD}).

3. Results and Discussion

3.1 Model prediction using response surface methodology

Response surface methodology is an integration of mathematical as well as statistical technique, useful for modeling [25] in various fields of engineering. In RSM, the second-order quadratic equation is the most common response model and the approximation of the response function is obtained in the form of predictive variables by establishing the relationship between input parameters and desired responses (output).This is usually expressed in following equation,

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_{ii} X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i\cdot} \sum_{j} \beta_{ij} X_i X_j, \quad (1)$$

where Y is the estimated response, β_0 is the constant, β_i , β_{ii} and β_{ij} represents the coefficients of linear, quadratic and cross-product terms respectively. X reveals the coded variables that correspond to the studied process parameters.

The empirical models in the form of quadratic regression equations to predict the various dimensional deviations of microgroove (Y_{UWD}, Y_{LWD}, and Y_{DD}) with air pressure (X_1), lamp current (X_2), pulse frequency (X_3), pulse width (X_4) and cutting speed (X_5) are given below. Later these proposed regression models are employed as objective functions for multi response optimization via genetic algorithm (GA). The upper width deviation (Y_{UWD}) is presented in Eq. (2). Its coefficients of determination (experimental and adjusted) are R^2 = 89.1%, R^2 (adj.) = 87%, respectively.

$$Y_{UWD} = 0.00448 + 0.01610X_1 - 0.00657X_2 - 0.00882X_3 + 0.01477X_4 + 0.00079X_5 + 0.007279X_1^2 - 0.00016X_2^2 - 0.00971X_3^2 + 0.02279X_4^2 - 0.01381X_5^2 - 0.01822X_1X_2 + 0.00848X_1X_3 + 0.00157X_1X_4 - 0.00015X_1X_5 + 0.01003X_2X_3 - 0.00497X_2X_4 - 0.01880X_2X_5 + 0.01123X_3X_4 - 0.02525X_3X_5 + 0.01335X_4X_5, \quad (2)$$

The lower width deviation (Y_{LWD}) is presented in Eq. (3). Its coefficients of determination (experimental and adjusted) are R^2 = 91.7%, R^2 (adj.) = 90.1%, respectively.

$$Y_{LWD} = -0.05375 + 0.03488X_1 - 0.01356X_2 - 0.00629X_3 + 0.00521X_4 + 0.01063X_5 + 0.01026X_1^2 + 0.04006X_2^2 - 0.0649X_3^2 - 0.00524X_4^2 - 0.01124X_5^2 + 0.029121X_1X_2 + 0.01713X_1X_3 + 0.00338X_1X_4 - 0.00788X_1X_5 + 0.02262X_2X_3 + 0.01188X_2X_4 + 0.04113X_2X_5 + 0.00513X_3X_4 + 0.02237X_3X_5 + 0.01313X_4X_5, \quad (3)$$

The depth deviation (Y_{DD}) is presented in Eq. (4). Its coefficients of determination (experimental and adjusted) are R^2 = 89.4%, R^2 (adj.) = 87.4%, respectively.

$$Y_{DD} = -0.03239 + 0.05355X_1 + 0.00489X_2 + 0.00675X_3 - 0.00405X_4 - 0.00671X_5 + 0.00972X_1^2 + 0.00057X_2^2 - 0.02018X_3^2 + 0.03322X_4^2 - 0.01293X_5^2 - 0.01464X_1X_2 + 0.01499X_1X_3 + 0.02249X_1X_4 - 0.00094X_1X_5 + 0.04886X_2X_3 + 0.00236X_2X_4 - 0.02251X_2X_5 - 0.00371X_3X_4 + 0.00236X_3X_5 + 0.01136X_4X_5. \quad (4)$$

3.2 Model prediction using artificial neural network

Artificial neural network has been turned into designed to mimic the linear order characteristics of structure inter-linked nerve cells of human brain called biological neurons. Briefly, a group of certain inputs are mostly employed, every of one which designate the output of any other neuron. Every input is multiplied by an associated weight corresponding a synaptic connection, and these are summed up to establish the actuation standard of the neuron.

In this work, artificial neural network is applied to propose a model to train in order that a set of inputs to return the appropriated or useful set of outputs. ANN uses milti-layer architecture consisting of different layers (input, hidden and output) for solving the non-linear and complex problems with the help of feed-forward back-propagation training algorithm [26]. Usually, in back propagation NN, the net input is expressed as follows:

$$Y_j = \sum_{i=1}^{i=n} w_{ij} x_i, \quad (5)$$

And the network output (***Z_j***) of each neuron ***i*** is obtained by processing the net input via an activation or transfer function (here, tangent hyperbolic type***)*** as follows:

$$Z_j = f(Y_j) = \frac{1-e^{-Y_j}}{1+e^{-Y_j}}. \quad (6)$$

where $\boldsymbol{Y_j}$ net input considered as linear combination of input variables in terms of weights, ***j*** number of neurons, ***n*** is the input parameters, $\boldsymbol{x_i}$ is the input parameter ***i*** of the network, $\boldsymbol{w_{ij}}$ represents the synaptic weight to $\boldsymbol{j^{th}}$ neuron in the output layer from the $\boldsymbol{i^{th}}$ neuron in the previous layer.

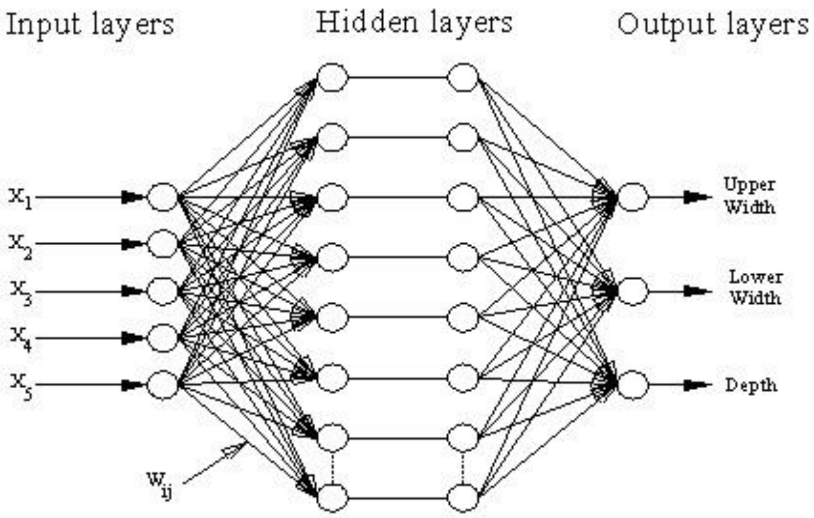

Fig. 4 Developed 5-8-8-3 ANN architecture

In this study, many network architectures were tried, prior to use the optimal neural network architecture of 5-8-8-3 (with the lowest MSE), which is shown in Fig. 4. The network consist of one input layer which have five neuron, two hidden layer which have eight neuron each and there output layer which have three neuron severally. For calculation of connection weights requires a set of desired network output values which are occasionally referred as training data set. The desired output values are generated utilizing experimental data set, as reflected in Table 3. The Matlab function TRAINGD was used for reforming the data of the network which functions on the back propagation algorithm [27]. TRAINGD is a network training function which works in accordance to gradient descent method which is used to update the weight variable repetitively and also to reduce the mean-square-error (MSE) between expected data and training data set. The change in weight variables is given in Eq. (7).

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} Z_j; \quad (7)$$

where $\boldsymbol{E}$ is the mean-square-error estimating the gradient of the error, η is the learning rate parameter generally control the stability and rate of convergence of the ANN model. η is considered as 0.0001 which is the constant value of learning rate. The MSE value calculated from the ANN is found to be 0.000099. Figure 5 shows the data observed based on experiment of ANN training by means of MATLAB.

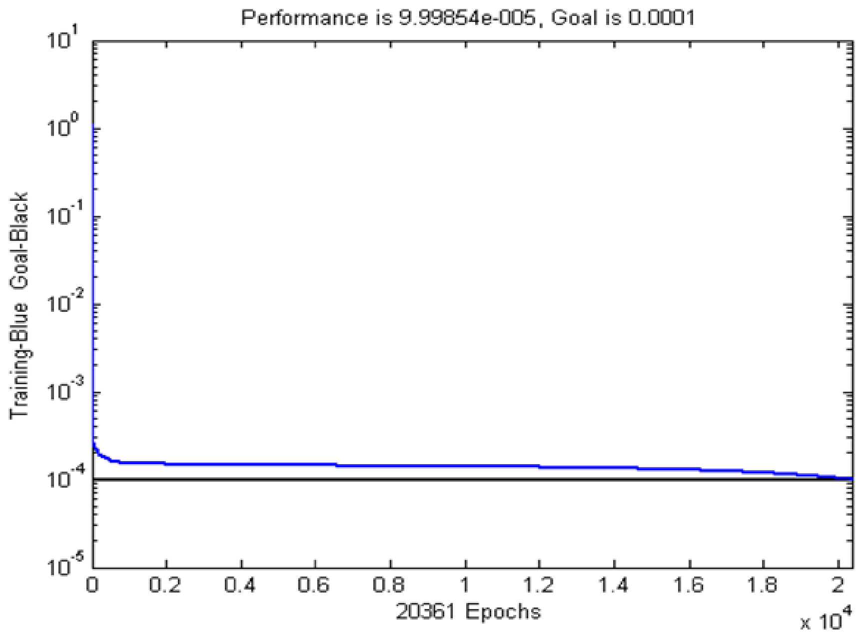

Fig. 5 Generation curve: MSE versus epochs during training and validation session

The results data obtained from experimentation and predicted data received by neural network were compared. Out of the 32 experimental data received in accordance with DOEs, 29 data was performed for training of the neural network model. Subsequently, the remaining three (32-29) experimental results (check data) were compared with trained ANN model. Tables 4 and 5 showed the comparison results between the experimental and ANN for 3 check data set and 29 training set, respectively. It can be seen that, a close agreement between the ANN prediction and the experimental results. Figures 6-8 compare the ANN prediction results for upper width, lower width and depth with the results of experiment for training and check data set. It is observed that the variation in ANN and experimental result is under 3%, which avoids the misleading conclusion to consider reliable model, particularly ANN for predicting the responses satisfactorily under pre-cited process parameters in laser microgrooving operations.

Table 4

Check data set for testing ANN model and comparison results of predicted and measured dimensions of microgroove

Test No.	Responses in mm					
	Upper width		Lower width		Depth	
	ANN pred.	Experimental result	ANN pred.	Experimental result	ANN pred.	Experimental result
1	0.18640	0.1840	0.1979	0.202	0.2130	0.2127
2	0.2142	0.21375	0.1499	0.1525	0.1640	0.1621
3	0.2031	0.2050	0.1279	0.1255	0.1168	0.12

Table 5

Training data set for testing ANN model and comparison results of predicted and measured dimensions of microgroove

Sl. No.	Responses in mm					
	Upper width		Lower width		Depth	
	ANN pred.	Experimental result	ANN pred.	Experimental result	ANN pred.	Experimental result
1	0.1958	0.1967	0.1341	0.1390	0.1601	0.1600
2	0.2215	0.2210	0.1534	0.1550	0.1932	0.2000
3	0.2163	0.2154	0.1715	0.1910	0.1667	0.1680
4	0.1206	0.1930	0.1262	0.1280	0.1524	0.1620
5	0.2327	0.2330	0.1931	0.2005	0.2323	0.2343
6	0.2131	0.2490	0.1515	0.1620	0.1688	0.2090
7	0.2003	0.2210	0.1468	0.1355	0.1669	0.1650
8	0.2003	0.2054	0.1534	0.1565	0.1758	0.1760
9	0.2073	0.2062	0.1479	0.1495	0.1522	0.1420
10	0.2003	0.1950	0.1468	0.1350	0.1609	0.1640
11	0.2035	0.1853	0.1297	0.1295	0.1636	0.1640
12	0.1789	0.1792	0.1348	0.1295	0.1517	0.1495
13	0.2131	0.1915	0.1516	0.1365	0.1819	0.1850
14	0.209	0.2090	0.1292	0.1265	0.1898	0.1893
15	0.2039	0.2040	0.1114	0.1135	0.1605	0.1590
16	0.1957	0.1956	0.1242	0.1255	0.1407	0.1367
17	0.1918	0.1915	0.1714	0.1745	0.1946	0.1937
18	0.1996	0.1996	0.1659	0.1700	0.1685	0.1630
19	0.2003	0.2060	0.1468	0.1430	0.1669	0.1550
20	0.2024	0.1995	0.1569	0.1470	0.1305	0.1420
21	0.2003	0.1992	0.1468	0.1420	0.1669	0.1427
22	0.2124	0.2040	0.1371	0.1440	0.1336	0.1327
23	0.2371	0.2370	0.1396	0.1425	0.2295	0.2280
24	0.2316	0.2316	0.1853	0.1735	0.1909	0.1832
25	0.1937	0.1940	0.194	0.1700	0.2058	0.2057
26	0.2035	0.1907	0.1234	0.1190	0.1229	0.1170
27	0.215	0.2160	0.1589	0.1535	0.127	0.1260
28	0.2151	0.2125	0.1861	0.2091	0.1698	0.1700
29	0.2003	0.2067	0.1468	0.1630	0.1669	0.1683

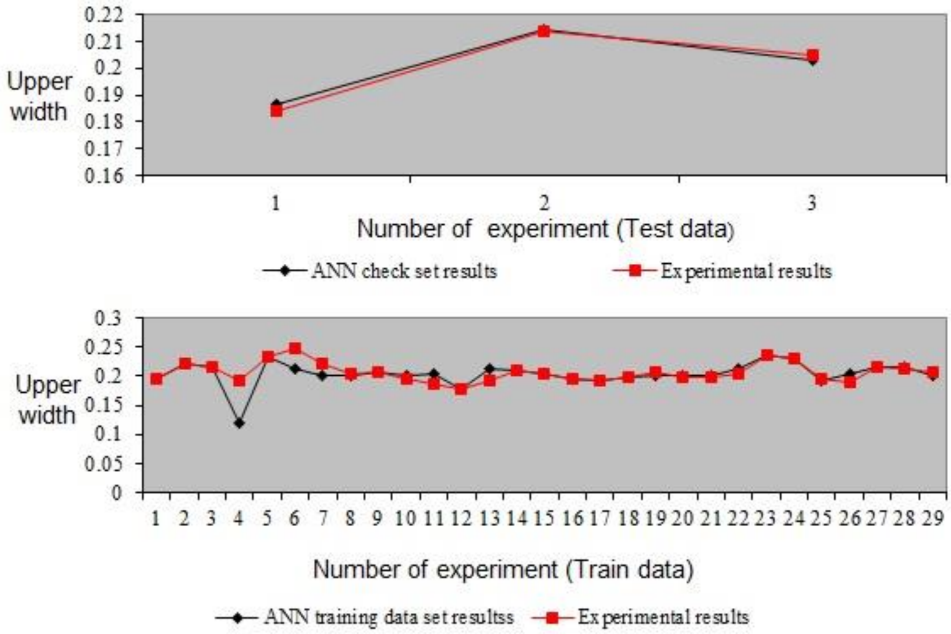

Fig. 6 Graphical comparison of predicted ANN with measured (a) check data, and (b) training data set of upper width

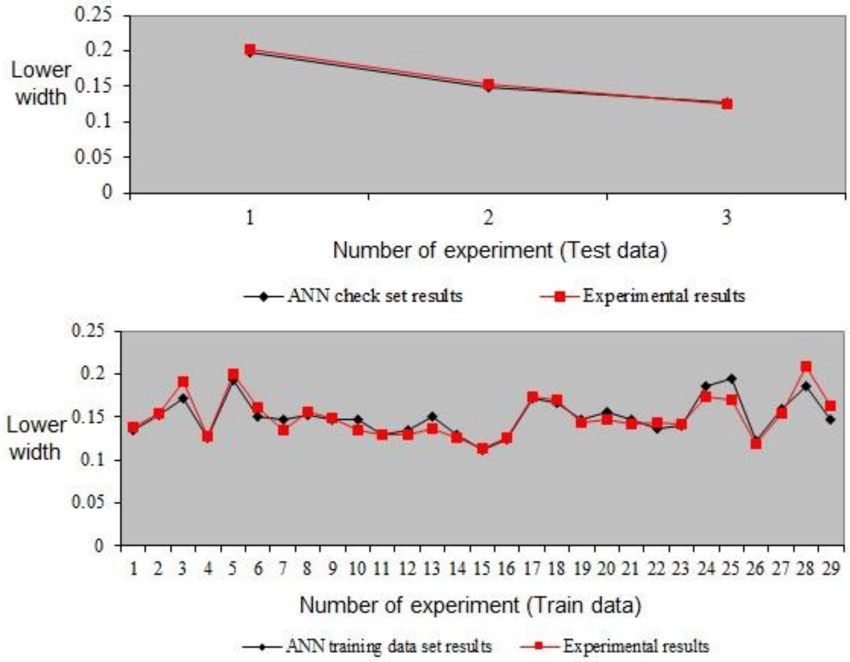

Fig. 7 Graphical comparison of predicted ANN with measured (a) check data, and (b) training data set of lower width

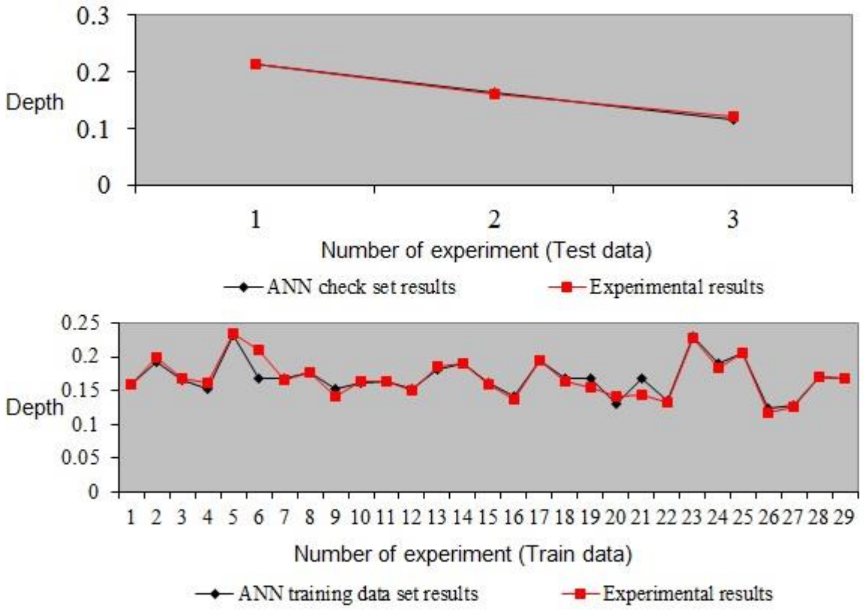

Fig. 8 Graphical comparison of predicted ANN with measured (a) check data, and (b) training data set of depth

3.3 Optimization using genetic algorithm

Genetic algorithm is a population-based search methodology for solving optimization problems stochastically that is based on the mechanism of natural selection that simulates the biological progression process developed from Darwin's theory of survival of the fittest [28]. In this systematic method, originally a set of possible solutions or chromosomes (normally as a string of genes) are randomly chosen, which serves as the generation (initial population). In GA, new generations are created by five major operations such as encoding (ranks and signifies the chromosomes by means of a string of bits); selection (choosing better fitness function value for minimization or maximization problems); reproduction (pairing the chromosomes by probabilistically to reproduce new generation); crossover (interchanging the information and genes between chromosomes); and mutation (flipping a particular bit of a chromosome to obtain smart convergence). This process continues in a repetitive manner until the chromosomes have the best fitness or potential (optimum) solution for a specific problem is obtained. Immediately after the new generation is created, it is further assessed and checked through experimentation for the conformability and agreement [29].

In this work Matlab toolbox was utilized for optimization purpose by implementing GA technique with the aim to minimize the dimensional deviation. In laser microgrooving, multi-objective optimization problem can be formally defined in following manner:

Find: input parameter (X_1, X_2, X_3, X_4, and X_5), (8)
Minimize: f (Y_{UWD}, Y_{LWD}, and Y_{DD}), (9)
Allowable range of parameters are: 0.4kgf/cm^2 ≤ air pressure (X_1) ≤ 2.0kgf/cm^2, 14.5A ≤ lamp current (X_2) ≤ 24.5A, 1kHz ≤ pulse frequency (X_3) ≤ 5kHz, 0% ≤ pulse width (X_4) ≤ 8%, and 12mm/s ≤ cutting speed (X_5) ≤ 28mm/s (10)

Here for mathematical descriptions, the objective function f(Y_{UWD}), f(Y_{LWD}) and f(Y_{DD}) are developed by RSM model Eqs. (2)-(4) for deviation of upper width, lower width and depth, respectively. Figure 9 presents the optimization history, which aims to minimize the various dimensional deviations ($Y_{UPD,}$ Y_{LWD}, Y_{DD}) of microgroove in the presence of algorithm-specific parameters of GA. In the present study, the critical (algorithm-specific) parameters are taken concerning population size of 250, mutation rate of 0.10, crossover rate of 1.0, number of genes in each population member equal to 20, and maximum number of iterations equal to 500. By solving the optimization problem with GA, the optimized process parameters for minimizing microgrooving variables in laser machining of aluminum oxide (Al_2O_3) ceramic material are pressure 1.2 kgf/cm^2, lamp current 19.5 A, pulse frequency 4 kHz, pulse width 6%, cutting speed 24 mm/s, with estimated deviations of upper width (UWD) of -0.0278 mm, lower width (LWD) of 0.0102 mm and depth (DD) of -0.0308 mm. Same has presented in Table 6.

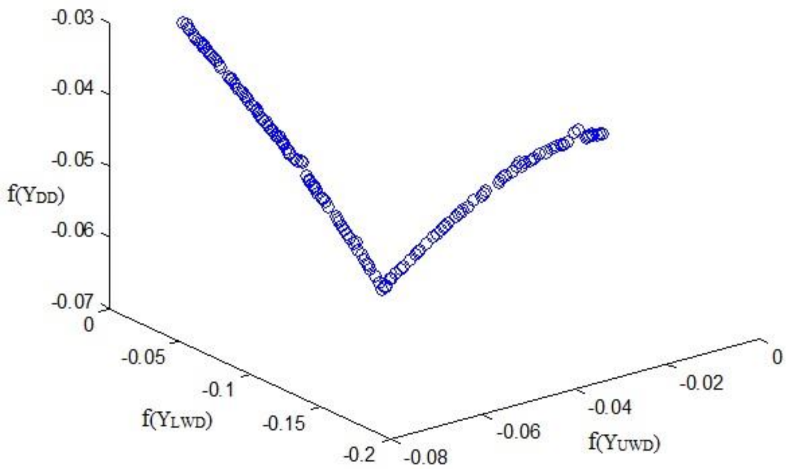

Fig. 9 GA based multi-objective optimization results for upper width, lower width and depth

Table 6

Dimensional deviations of microgroove under GA-based optimum parametric conditions

Optimum process parameters					Targeted output in mm			Dimensional deviations in mm		
Lamp current (A)	Pulse frequency (kHz)	Pulse width (%)	Air pressure (kgf/cm^2)	Cutting speed (mm/s)	Upper width	Lower width	Depth	Upper width deviation	Lower width deviation	Depth deviation
19.5	4 kHz	6	1.2	24	0.2	0.2	0.2	-0.0278	0.0102	-0.0308

Table 7

Comparison results of ANN prediction, GA-based optimization and actual experimentally observed dimensional deviations of microgroove on Al_2O_3

Responses	ANN prediction in accordance with GA process parameters	Optimization result based on GA	Experimental result in accordance with GA process parameters
Upper width deviation	-0.025	-0.0278	-0.0261
Lower width deviation	0.0098	0.0102	0.0110
Depth deviation	-0.0276	-0.0308	-0.0301

Finally, an additional experiment is performed with the optimal configuration (suggested by GA) in order to compare this result with the ANN prediction model using same pre-cited optimum conditions, are listed in Table 7. As can be seen, the experimental result obtained by confirmation test, matches the predicted results obtained by ANN and GA fairly well with a realistic degree of approximation. Therefore, the proposed approach (RSM-ANN-GA) can be effectively used to predict the various responses in laser microgrooving operation. The comparison results of ANN-GA-Experimental are presented in Fig. 10, which predicts upper width and depth are continuously negative while lower width is constantly positive.

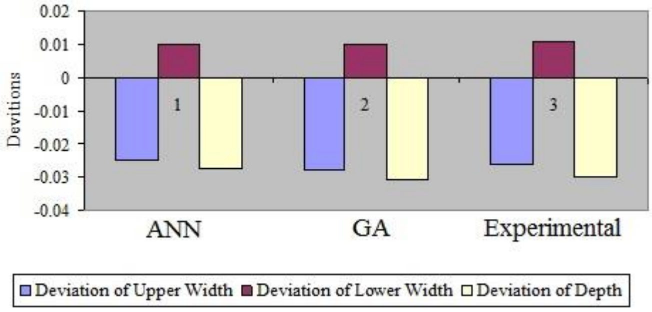

Fig. 10 Comparison of ANN, GA and experimental results

4. Conclusions

In the present study, design of experiments (DOEs), response surface methodology (RSM), artificial neural network (ANN), and genetic algorithm (GA) have been applied for experimentation, mathematical modeling and multi response optimization of laser microgrooving operation on aluminum oxide ceramic workpiece. Based on the series of experiment and analysis of results, the following conclusions are drawn.

- The quadratic (second order) mathematical model proposed for various dimensional deviations of microgroove using RSM not only capable of achieving precise required dimension of microgrooves on aluminum oxide but also useful for predicting new experiments.
- The performance of predictive ANN model based on 5-8-8-3 architecture, gave the minimum error (MSE = 0.000099) and presented highly promising to

confidence with percentage of error less than 3% while compared it with experimental result data sets.

- Optimization employing GA technique shows the optimal setting of process parameters in microgrooving operation of aluminum oxide by Nd:YAG laser treatment at lamp current of 19.5 A, pulse frequency of 4 kHz, pulse width 6%, cutting speed of 24 mm/s and air pressure of 1.2 kgf/cm^2 with estimated minimal deviation of upper width -0.0278 mm, lower width 0.0102 mm and depth -0.0308 mm.
- The present research based on GA, ANN, and statistically multi-regression analysis (RSM) have demonstrated the ability to optimize and to accurately model the dimensional deviations of microgroove through advances in computer technology.
- The proposed multiple approaches (experimental, evolutional, statistic, and stochastic) present reliable methodologies to improve laser microgrooving process and they can be employed in real-time process monitoring, model predictive control and optimization in several machining processes.

REFERENCES

[1] *B. Doloi, D. Dhupal and B. Bhattacharyya*, "Investigations into Nd:YAG Laser Micro-Grooving on Alumina", Proceedings of International Conference on Advanced Manufacturing Technologies, Durgapur, India, 2007, pp. 125-135.

[2] *G. Chryssolouris*, Laser Machining: Theory and Practice, Springer, New York, 1991.

[3] *F.O. Olsen and L. Alting*, "Pulsed Laser Materials Processing, ND-YAG versus CO_2 Lasers", CIRP Annals - Manufacturing Technology, **vol. 44**, no. 1, 1995, pp. 141-145.

[4] *S.M.H. Darwish, M.H. Saied, N. Ahmed and A.M. Al-Ahmari*, Laser Beam Micro-milling of Micro-channels in Aerospace Alloys, Springer, Singapore, 2017.

[5] *K. Farooq and A. Kar*, "Removal of laser-melted material with an assist gas", Journal of Applied Physics, **vol. 83**, 1998, pp. 7467-7473.

[6] *J.P. Davim*, "A note on the determination of optimal cutting conditions for surface finish obtained in turning using design of experiments", Journal of Materials Processing Technology, **vol. 116**, nos. 2-3, 2001, pp. 305–308.

[7] *S. Khamel, N. Ouelaa and K. Bouacha*, "Analysis and prediction of tool wear, surface roughness and cutting forces in hard turning with CBN tool", Journal of Mechanical Science and Technology, **vol. 26**, no. 11, 2012, pp. 3605-3616.

[8] *S.R. Das, D. Dhupal and A. Kumar*, "Study of surface roughness and flank wear in hard turning of AISI 4140 steel with coated ceramic inserts", Journal of Mechanical Science and Technology, **vol. 29**, no. 10, 2015, pp. 4329-4340.

[9] *A.S. Kuar, B. Doloi and B. Bhattacharyya*, "Modelling and analysis of pulsed Nd:YAG laser machining characteristics during micro-drilling of zirconia (ZrO_2)", International Journal of Machine Tools and Manufacture, **vol. 46**, nos. 12-13, 2006, pp. 1301–1310.

[10] *D. Dhupal, B. Doloi and B. Bhattacharyya*, "Pulsed Nd:YAG laser turning of micro-groove on aluminum oxide ceramic (Al_2O_3)", International Journal of Machine Tools and Manufacture, **vol. 48**, no. 2, 2008, pp. 236–248.

[11] *D. Dhupal, B. Doloi and B. Bhattacharyya*, "Parametric analysis and optimization of Nd:YAG laser micro-grooving of aluminum titanate (Al_2TiO_5) ceramics", International Journal of Advanced Manufacturing Technology, **vol. 36**, nos. 9-10, 2008, pp. 883–893.

[12] *R. Biswas, A.S. Kuar, S.K. Biswas and S. Mitra*, "Characterization of hole circularity in pulsed Nd:YAG laser micro-drilling of TiN–Al_2O_3 composites", International Journal of Advanced Manufacturing Technology, **vol. 51**, nos. 9-12, 2010, pp. 983–994.
[13] *S. Prakash, B. Acherjee, A.S. Kuar and S. Mitra*, "An experimental investigation on Nd:YAG laser microchanneling on polymethyl methacrylate submerged in water", Journal of Engineering Manufacture, **vol. 227**, no. 4, 2013, pp. 508–519.
[14] *G. Kibria, B. Doloi and B. Bhattacharyya*, "Predictive model and process parameters optimization of Nd:YAG laser micro-turning of ceramics", International Journal of Advanced Manufacturing Technology, **vol. 65**, nos. 1-4, 2013, pp. 213–229.
[15] *R. Biswas, A.S. Kuar and S. Mitra*, "Process optimization in Nd:YAG laser microdrilling of alumina–aluminium interpenetrating phase composite", Journal of Materials Research and Technology, **vol. 4**, no. 3, 2015, pp. 323–332.
[16] *D. Dhupal, B. Doloi and B. Bhattacharyya*, "Optimization of process parameters of Nd:YAG laser microgrooving of Al_2TiO_5 ceramic material by response surface methodology and artificial neural network algorithm", Journal of Engineering Manufacture, **vol. 221**, no. 8, 2007, pp. 1341–1351.
[17] *S.K. Dhar, A.S. Kuar and S. Mitra*, "An artificial neural network approach on parametric optimization of laser micro-machining of die-steel", International Journal of Advanced Manufacturing Technology, **vol. 39**, nos. 1-2, 2008, pp. 39–46.
[18] *R. Biswas, A.S. Kuar, S.K. Biswas and S. Mitra*, "Artificial neural network modelling of Nd:YAG laser microdrilling on titanium nitride—alumina composite", Journal of Engineering Manufacture, **vol. 224**, no. 3, 2010, pp. 473–482.
[19] *C.F.J. Kuo, Q.V. Huy, G. Dewantoro and L.W. Luen*, "Multi-objective optimization of laser-scribed micro grooves on AZO conductive thin film using Data Envelopment Analysis", Optics and Laser Technology, **vol. 44**, no. 6, 2012, pp. 1959-1970.
[20] *S.L. Campanelli, G. Casalino, A.D. Ludovico and C. Bonserio*, "An artificial neural network approach for the control of the laser milling process", International Journal of Advanced Manufacturing Technology, **vol. 66**, nos. 9-12, 2013, pp. 1777–1784.
[21] *S. Mishra and V. Yadava*, "Modeling and optimization of laser beam percussion drilling of thin aluminum sheet", Optics & Laser Technology, **vol. 48**, 2013, pp. 461-474.
[22] *D. Dhupal, B. Doloi and B. Bhattacharyya*, "Modeling and optimization on Nd:YAG laser turned micro-grooving of cylindrical ceramic material", Optics and Lasers in Engineering, **vol. 47**, no. 9, 2009, pp. 917-925.
[23] *T.V. Sibalija, S.Z. Petronic, V.D. Majstorovic, R.P. Cvetkovic and A. Milosavljevic*, "Multi-response design of Nd:YAG laser drilling of Ni-based superalloy sheets using Taguchi's quality loss function, multivariate statistical methods and artificial intelligence", International Journal of Advanced Manufacturing Technology, **vol. 54**, nos. 5-8, 2011, pp. 537-552.
[24] *M.K. Mohammed, U. Umer and A. Al-Ahmari*, "Optimization of laser micro milling of alumina ceramic using radial basis functions and MOGA-II", International Journal of Advanced Manufacturing Technology, **vol. 91**, nos. 5-8, 2017, pp. 2017–2029.
[25] *D.C. Montgomery*, Design and analysis of experiments, John Wiley & Sons Inc, New York, 2004.
[26] *S.O. Haykin*, Neural Networks: A Comprehensive Foundation, Pearson, Singapore, 2002.
[27] *M.H. Hassoun*, Fundamentals of artificial neural network, MIT Press, London, 1998.
[28] *G.C. Vosniakos and A. Krimpenis*, "Optimisation of Multiple Tool CNC Rough Machining of a Hemisphere as a Genetic Algorithm Paradigm Application", International Journal of Advanced Manufacturing Technology, **vol. 20**, no. 10, 2002, pp. 727-734.
[29] *J.H. Shaik and J. Srinivas*, "Optimal selection of operating parameters in end milling of Al-6061 work materials using multi-objective approach", Mechanics of Advanced Materials and Modern Processes, **vol. 3**, no. 5, 2017, pp. 1-11.