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OPTIMIZATION OF SURFACE ROUGHNESS AND MATERIAL REMOVAL RATE IN LASER BEAM MACHINING OF AL_2O_3 / CNT COMPOSITES USING PARTICLE SWAM OPTIMIZATION

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Abstract:-
Alumia (Al_2O_3) based composites materials are widely used in variety of engineering applications due to its superior properties over the engineering materials. Optimization of surface roughness and material removal rate in machining is helpful to evaluate the process better responses. This paper aims to make use of particle swarm optimization method to optimize the surface roughness and material removal rate in laser beam machining of alumina (Al_2O_3) / Carbon nano tube (CNT) material composites. The control parameters considered are oxygen pressure, Pulse frequency, Cutting speed and wt.% of CNT. Experiments are planned and executed according to Taguchi's L25 orthogonal array in design of experiments on an laser beam machining. A quadratic model was developed for surface roughness and material removal rate prediction using RSM. An attempt has been made to optimize the control parameters for the minimization of surface roughness and material removal rate using particle swarm optimization (PSO). The results indicates that the potential offered by PSO for finding the optimum control parameters for the minimization of surface roughness and maximum material removal rate.

1. LITERATURE

Alumina (Al_2O_3) is one of the most commonly used engineering ceramics in various industrial applications owing to its good mechanical strength, good heat and fire resistance, high corrosion and wear resistance, and high electric insulation. It is generally used in making machine tools, heat-resistant packings, electrical and electronic components, attachments to melting ducts, and refractory linings [1]. Alumina substrates further possess several unique features, such as excellent

dielectric strength, thermal stability and conductivity, good surface with high smoothness/flatness and less porosity, high thermal shock resistance, low warpage and camber, high temperature and chemical stability, and very stable breaking strength as well as shape/dimension variance. Therefore, they are widely applied in the electronics industry as chip resistor substrates, hybrid integrated circuit (IC) substrates, electrical isolations, etc [2]. Considering the wide use of the ceramic, alumina (Al_2O_3) was selected as the major experimental sample in this programme.
There are several crystalline forms of alumina, namely α, β, γ, δ-Al_2O_3, etc. The most thermodynamically stable form is α-Al_2O_3 known as corundum or sapphire in its crystalline form. It has an internal crystal structure where the oxygen ions are packed in a close-packed hexagonal arrangement with aluminium ions in two-thirds of the octahedral sites, as shown in Figure 1.

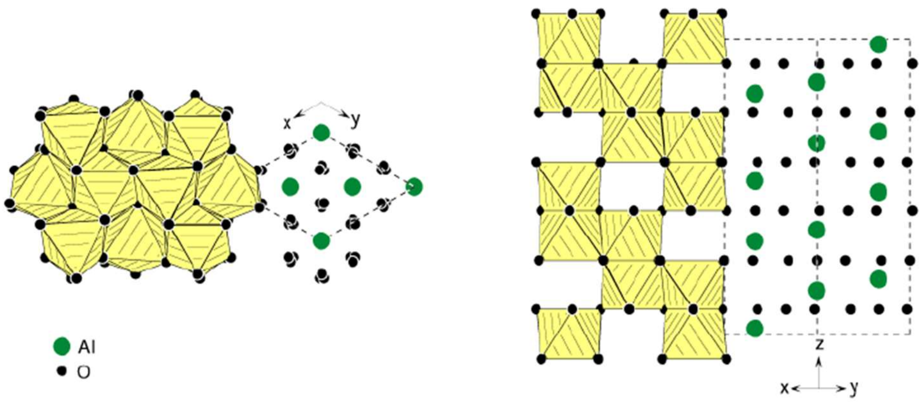

Figure 1. The rhombohedral crystal structure of α-Al_2O_3 (space group R3,-c). At right-hand side such a layer is projected along [3] direction [4].

Cutting parameters composed of Laser Power, Cutting Speed, Gas Pressure, Material Thickness, Pulse Energy, Pulse Frequency, Pulse Duration (for Laser beam machining operation), have essential effects on the machining productivity and cost. The selection of cutting parameters has long depended on the skills and experience of machine tool operators or handbooks, and conservative cutting parameters are usually selected. This situation would cause significant productivity loses and lead to a costly machining operation.

The determination of optimum cutting parameters is a combinatorial optimization problem and is usually realized by applying optimization algorithms. These algorithms include neural network [5], geometric programming [6], simulated annealing [7], genetic algorithm (GA) [8], particle swarm optimization (PSO) [9], etc. GA was considered as a suitable algorithm for solving any type of machining process optimization problem [10]. However, encoding and decoding operations for each individual are involved and the complexity of genetic operations will be increased when variables to be optimized are more than two. It will decrease the process efficiency greatly.

PSO is discovered through simulation of the social behavior of bird flocking for food. It was used for optimization of continuous nonlinear functions. In PSO, the variables to be optimized need not to be encoded. Therefore, PSO will be more efficient when the number of variables to be optimized is more than two. Because of the convenience of realization and promising optimization ability in various problems, it has been paid more and more attention [11]. Opposite to the well-developed optimization algorithms, “PSO is still in its infancy and there are many associated problems that need further study” [12].

M Madic et. al. has been worked on an experimental analysis and optimization of CO2 laser cutting process on stainless steel plates. In this paper, multi-objective optimization of the cut quality characteristics such as surface roughness, width of HAZ and kerf width in CO2 laser cutting of stainless steel was presented [13]. The applied methodology integrates modelling of the relationships between the laser cutting factors (laser power, cutting speed, assist gas pressure and focus position) and cut quality characteristics using ANNs, formulation of the multi-objective optimization problem using weighting sum method and solving it by CSA (Comparative Sequence Analysis).Cuckoo search method is used for optimization purpose.

K Venkatesan & R Ramanujam have been worked on an experimental Analysis of Cutting Forces and Temperature in Laser Assisted Machining of Inconel 718 using Taguchi Method [14]. This paper discussed about L9 orthogonal array, S/N ratio and ANOVA were adopted for finding the optimal process parameter for the performance measures of feed force (Fx), thrust force (Fy) and cutting force (Fz).

M Lakshmi Chaitanya & A Gopal Krishna have been worked on Multi-objective Optimization of Laser Beam Cutting Process [15]. The material used for experiments was silicon carbide (SiCp) reinforced aluminum metal matrix composite which are the most advantageous engineering materials due to their properties such as low weight, heat-resistant, wear-resistant and low cost. Their work was about machining conditions involving the minimization of HAZ and Ra. The mathematical models for the HAZ and Ra are developed through the response surface methodology (RSM).A very popular evolutionary algorithm, non-dominated sorting genetic algorithm II (NSGA-II), was used to retrieve the multiple optimal sets of input variables [15].

Ruben Phipon & B.B.Pradhan [16] have been worked on Control Parameters Optimization of Laser Beam Machining Using Genetic Algorithm. Their work was on Heuristic analyses using GA (genetic algorithm) for optimizing the cut quality namely kerf taper and surface roughness during pulsed Nd:YAG laser cutting of thin Al-alloy sheet for straight profile is performed.

Koji Hirano and Remy Fabbro have investigated striation generation mechanism in inert gas laser cutting of steel by observation of hydrodynamics of melt layer on the kerf front [17]. Melt flows in the regions of kerf side and kerf front exhibit instability in different velocity ranges. They used

8 KW disk laser beam which was focused on to 3 mm thick low carbon steel with beam diameter 1.7 mm. the gas pressure of nitrogen was set to 2.5 bar and cutting speed was varied from 1 to 6 m/min. They observed melt dynamics exhibited instability depends upon the cutting velocity. In lowest velocity ranges ($v < 2$ m/min) the melt flow in the both the central and side region of the kerf front are instable. In intermediate velocity range (2 m/min $< v <$ 6 m/min) the central flow becomes stable, while the side region remains unstable. The unstable region becomes more restricted to the side with increase of v, until whole region becomes stable at $v = 6$ m/min. The observed instability can be explained by a combination of thermal instability of melting process and hydro dynamical instabilities due to surface tension[17].

Avanish Dubey In laser beam cutting (LBC) process, It has been found that the kerf width during LBC is not uniform along the length of cut and the unevenness is more in case of pulsed mode of LBC[18,19]. In this paper, two kerf qualities such as kerf deviation and kerf width have been optimized simultaneously using Taguchi quality loss function during pulsed Nd: YAG laser beam cutting of aluminium alloy sheet (0.9 mm-thick) which is very difficult to cut material by LBC process. A considerable improvement in kerf quality has been achieved. [18,19]. In the present study, modelling and optimisation has been done for two quality characteristics, i.e., average surface roughness (Ra) and material removal rate during laser machining process laser circular cutting of Al_2O_3/CNT. Particle swarm optimization and RSM approach been used. The selected material is Al_2O_3/CNT. Initially, experiments have been designed using taguchi method only to determine the optimum process parameters for Ra and MRR. The optimum level of input parameters so obtained is further used as central value in RSM. Then particle swarm optimisation results have been found using the MATLAB software. Finally, these results have been compared with the results of gray relational method only.

2. MATERIALS & METHODS

The work material used for the present study is alumina (Al_2O_3) and carbon nano tubes (CNT) composites of different weight percentages of 1% - 9%, The Al_2O_3/CNT used in this investigation are manufactured by so-gel process. The carbon nano tubes with 1%, 3%, 5%, 7% and 9% used is alumina material.

3. EXPERIMENTAL DETAILS

In this study, the influence of laser beam machining parameters on the machined surface morphology was experimentally studied applying the nanosecond pulse ytterbium fibre laser and Al_2O_3/CNT as working material. The influence of Oxygen Pressure, Pulse frequency /Repetition Rate, Cutting speed, Wt.% of CNT on surface finish and material removal rate and the quality of machined surface was examined via

Taguchi method (L27 orthogonal matrix was used) in the preliminary experiment [23].The aim of preliminary experiment was to define the laser beam machining parameters which affect the machined surface quality in significant way. These chosen parameters and its levels are summarized in Table 1, but a number of experiments required by a 3k full factorial design having four factors is 81. Therefore the Taguchi orthogonal matrix L25 was chosen for the experiment realization, 25 runs have been carried out.3

Table 1. Process parameters and levels used for the experimentation

Symbol/ Variable	Process Parameters	Units	Levels				
			1	2	3	4	5
P_1	Oxygen Pressure	Kg/cm^2	2	3	4	5	6
P_2	Pulse frequency / Repetition Rate	Hz	5	10	15	20	25
P_3	Cutting speed	mm/min	10	20	30	40	50
P_4	Wt.% of CNT	%	1	3	5	7	9

The experiment has been performed using a high precision laser machining centre Mogad Laser Machining Pvt. Ltd., Bangaloure, 80 Shape equipped by solid-state pulsed fiber ytterbium laser with an average output power of 100 W, pulse duration of 120 ns and wavelength of 1064 nm as shown in Figure 2.

Al2O3/CNT with various percentages of (1%, 3%, 5%, 7% and 9%) was chosen as the working material (manufacturer Glynwed, GmbH). It is an easily producible and relatively cheap type of ceramic with the following properties: apparent density of 3.7 – 3.95 g.cm-3, mean grain size of 10 μm, hardness (Knopp, 100 g) of 23000 MPa, specific heat of 850 J.kg-1.K-1 and thermal conductivity of 30 W.m-1.K-1. Testing samples were a cylindrical and square in shape with the diameter of 10 mm and the thickness of 3 mm. Testing cavities (squared in shape with a side length of 2.5 mm) have been manufactured on the planar surfaces of testing sample (average surface roughness Ra of 3.56 μm) at a given combination of laser beam parameters.

Experimental results revealed that the laser pulse energy (defined by the Oxygen Pressure, Pulse frequency /Repetition Rate,) and Wt.% of CNT affect the studied surface roughnness and material removal rate and quality of machined surface significantly. Material ablation has taken part in laser micro-machining process only if the pulse frequency values are higher than 25Hz. Machined surface quality is affected by the Oxygen Pressure, Pulse frequency /Repetition Rate, Cutting speed, Wt.% of CNT significantly. This preliminary experiment confirmed difficult machinability of Al_2O_3/CNT of various percentages of CNT i.e., 1%, 3%, 5%, 7% and 9% and defined main process parameters: Oxygen Pressure, Pulse frequency /Repetition Rate, which will be analyzed subsequently in more detailed way described in the next part of the paper.

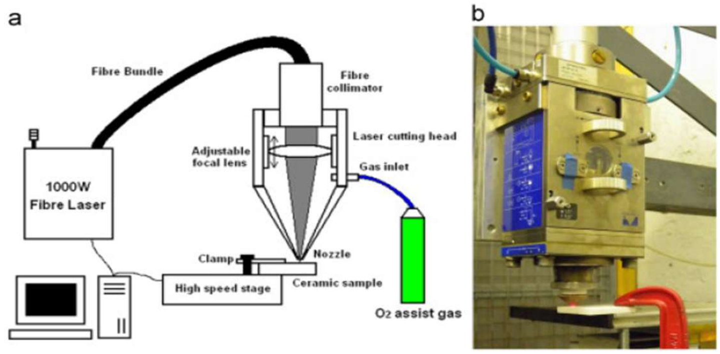

Figure 2. Experimental setup incorporating a fibre laser, focusing optics, gas and a high speed linear motor stage. (a) Schematic diagram of the experimental setup. (b) A photograph of the Precitec laser cutting head for the experiments.

Table 2. Design Matrix with coded & uncoded values

Exp. No.	Coded Values				Original Values			
	Oxygen Pressure (Kg/cm^2)	Pulse frequency (Hz)	Cutting speed (mm/min)	Wt. % of CNT (%)	Oxygen Pressure (Kg/cm^2)	Pulse frequency (Hz)	Cutting speed (mm/min)	Wt.% of CNT (%)
1	1	1	1	1	2	5	10	1
2	1	2	2	2	2	10	20	3
3	1	3	3	3	2	15	30	5
4	1	4	4	4	2	20	40	7
5	1	5	5	5	2	25	50	9
6	2	1	2	3	3	5	20	5
7	2	2	3	4	3	10	30	7
8	2	3	4	5	3	15	40	9
9	2	4	5	1	3	20	50	1
10	2	5	1	2	3	25	10	3
11	3	1	3	5	4	5	30	9
12	3	2	4	1	4	10	40	1
13	3	3	5	2	4	15	50	3
14	3	4	1	3	4	20	10	5
15	3	5	2	4	4	25	10	7
16	4	1	4	2	5	5	40	3
17	4	2	5	3	5	10	50	5
18	4	3	1	4	5	15	10	7
19	4	4	2	5	5	20	20	9

20	4	5	3	1	5	25	30	1
21	5	1	5	4	6	5	50	7
22	5	2	1	5	6	10	10	9
23	5	3	2	1	6	15	20	1
24	5	4	3	2	6	20	30	3
25	5	5	4	3	6	25	40	5

In machining process identifying the low surface finish and maximum material removal rate in Al_2O_3/CNT composites. Table 2 shows the experimental conditions used machining process. Figure 2 demonstrates the experimental setup used for machining of Al_2O_3/CNT.

3.1 Response Surface Methodology (RSM)

The surface roughness (R_a) and material removal rate (MRR) in laser beam machining process of Al_2O_3/CNT composite is important in manufacturing engineering applications from the economical point of view. The quality of the part depends on proper election of cutting conditions. In order the surface roughness (R_a) and material removal rate (MRR) in advance, it is necessary to employ theoretical models making it feasible to do prediction in function of control parameters [20,21]. RSM is a statistical techniques and is useful for modeling and analysis of problems in which a response is influenced by several variables and the objective is to optimize this response. In many engineering problems, there is a relationship between an output variable 'y' and a set of control variables [x_1,x_2……x_n], in some problems, the relationship between y and x values might be known. Then, a model can be written in the form.

$$Y = f(x_1, x_2 \cdots\cdots\cdots x_n + \varepsilon \qquad (1)$$

Where ε represents noise or error observed in the response 'y'
If we denote the expected response be
$E(Y) = f(x_1, x_2, \text{-----} x_n) = \hat{Y}$ is called response surface.

The first step is to find suitable approximation for the true functional relationship between y and set of independent variables employed usually a quadratic model is used in RSM.

$$\hat{Y} = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_i \sum_j \beta_{ij} X_j + \varepsilon \qquad (2)$$

MINITAB-18 software was used to determine the regression coefficients of the model for the specific energy consumption.

3.2 Taguchi's S/N Ratios

Taguchi S/N ratio is a statistical measure of performance or quality for data analysis and prediction of optimal parameters setting [22, 23]. The S/N ratio is the ratio of the mean signal to the standard deviation (Noise). It depends on the quality characteristics of the process to be optimized. The standard S/N ratios generally used include: Nominal-is-Best (NB), Lower-the-better (LB) and Higher-the-Better (HB). In this investigation, MINITAB-18 was used to solve the optimization problem. Surface roughness (R_a) and material removal rate (MRR) was taken as LB characteristic, aimed at minimizing the response. The LB-S/N ratio was computed using equation (4)

$$S/N = -10\log\frac{1}{n}\sum_{i=1}^{n} y_i^2 \qquad (3)$$

4. PARTICLE SWARM OPTIMIZATION (PSO)

PSO is a global optimization technique that has been developed by Kennedy and Eberhardt [24]. PSO is swarm intelligence meta-heuristic inspired by the group behavior of animals, i.e., bird flocks or fish school. Similar to genetic algorithm (GAs), it is population based method. It represents the state of algorithm by a population, which is iteratively modified until a termination criterion is satisfied. In PSO algorithms, the population P=[p_1…. p_n] of the feasible solution is often called swarm. The feasible solution P,.......P_n are called particles. For solving practical problems the number of particles is usually chosen between 10 and 50. Thus, a PSO algorithm can be employed to solve an optimization problem.

Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. The fitness value is called ‘pbest. Another ‘best’ value is tracked by the global version of the PSO.

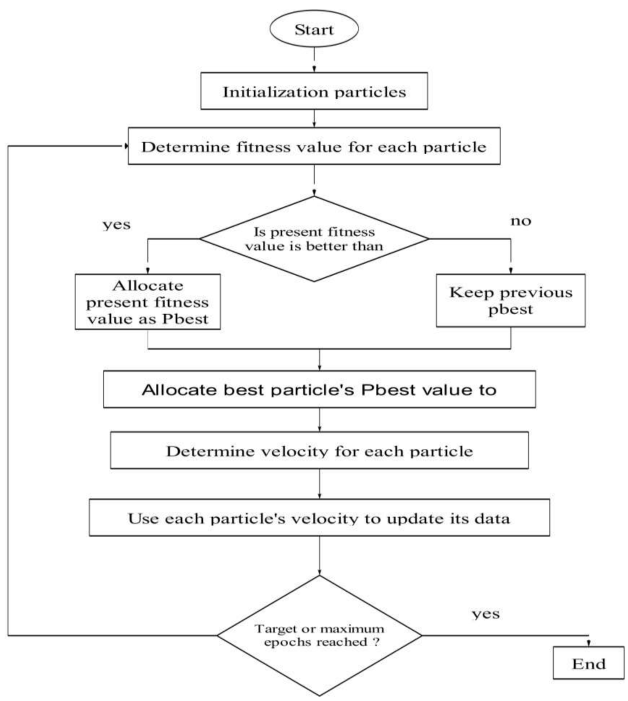

Figure 3. Flow chart of PSO

The PSO considers a swarm S containing n particles (S = 1, 2…...n) in a d-dimensional continuous solution space. The position and velocity of individual s_i are represented as the vectors xi = (x^{i1}………x^{id}) and vi = (v^{il}………..v^{id}), respectively. A bird adjusts its position in order to find a best position, according to its own experience and the experience of its companions. Using the information, the updated velocity of individual i is modified using equation (4).

$$V_{td}^{t+1} = W V_{id}^{T} + C_1 r_1 * (P_{td}^{t} - x_{td}^{t}) + C_2 r_2 * (P_{gd}^{t} - x_{td}^{t}) \quad (4)$$

V_{td}^{t+1} : a component in dimension d of the i[th] particle velocity in iteration t

X_{td}^{t} : a component in dimension d of the i[th] particle position in iteration t

C_1, C_2: weighing factors

P_i: best position achieved so far by particle i

P_g: best position achieved so far by neighbors of particle i

r_1, r_2: random factors in range [0, 1]

W: inertia weight

Control parameters of PSO

Number of generations = 75

Number of particles (N) =4

$c_1 = 1.6$

$c_2 = 2$

w = 1.0

Coding of particle = binary

Number of bits per parameter is taken as 4.

Number of significant parameters = 4

Total length of particle = 12

Fitness parameter: minimization of Specific energy consumption

4.1 Coding

Generate each particle using binary coding. Here the binary format particle is decoded by using equation (6).

$$X_1 = X_I^L + \frac{x_i^u - x_i^L}{2^n - 1} S_i \quad (5)$$

Where x_i^u and x_i^L are the decoded upper and lower limit of the control parameters, and n is the substring length (=4) and S_i is the decoded value of the i[th] chromosome. Accuracy is given by equation (7). Figure 3. shows the flow chart of PSO

$$Accuracy = \frac{x^u - x^l}{x^n - 1} \quad (6)$$

5. RESULTS AND DISCUSSION

Experiments are planned executed on an laser beam machining according to L_{25} orthogonal array in DOE and the results obtained are shown in Table 3.

Table 3. Experimental conditions and results.

S.No.	Oxygen Pressure (Kg/cm^2)	Pulse frequency (Hz)	Cutting speed (mm/min)	Wt.% of CNT (%)	Surface Roughness (Ra)	S/N ratio	Material Removal Rate (MRR)	S/N ratio
1.	4	5	10	1	3.56	-11.0290	1.28	-4.7609
2.	4	10	20	3	4.32	-12.7097	1.51	-5.8893
3.	4	15	30	5	5.46	-14.7439	1.52	-3.4637
4.	4	20	40	7	5.58	-14.9327	1.65	-6.8088
5.	4	25	50	9	6.15	-15.7775	1.86	-6.5021
6.	6	5	20	5	4.56	-13.1793	1.35	-4.5885
7.	6	10	30	7	4.35	-12.7698	1.62	-5.6931
8.	6	15	40	9	5.53	-14.8545	1.56	-5.6297
9.	6	20	50	1	3.86	-11.7317	1.98	-3.4637
10.	6	25	10	3	6.32	-16.0143	1.42	-5.3434
11.	8	5	30	9	4.96	-13.9096	1.65	-6.4112
12.	8	10	40	1	3.67	-11.2933	1.93	-7.5861
13.	8	15	50	3	3.98	-11.9977	1.90	-7.0975
14.	8	20	10	5	5.12	-14.1854	1.56	-6.2941
15.	8	25	10	7	5.24	-14.3866	1.56	-4.7307
16.	9	5	40	3	3.97	-11.9758	1.96	-7.1815
17.	9	10	50	5	4.07	-12.1919	1.72	-5.8981

18.	9	15	10	7	4.47	-13.0062	1.46	-5.9245
19.	9	20	20	9	5.45	-14.7279	1.56	-7.1281
20.	9	25	30	1	4.19	-12.4443	2.21	-7.7192
21.	10	5	50	7	4.23	-12.5268	1.86	-6.4526
22.	10	10	10	9	4.32	-12.7097	1.35	-7.7049
23.	10	15	20	1	4.34	-12.7498	2.50	-9.1636
24.	10	20	30	3	4.36	-12.7897	2.23	-7.7833
25.	10	25	40	5	4.52	-13.1028	2.12	-8.7929

5.1 Regression Analysis

The MINITAB-18 Software was used to develop the surface roughness (R_a) and material removal rate (MRR) model in terms of control viz., Oxygen Pressure, Pulse frequency, Cutting speed, Wt.% of CNT

Ra $=-0.55 + 1.031 P_1 + 0.374 P_2 - 0.023 P_3 - 0.178 P_4 - 0.0597 P_1^2 - 0.00218 P_2^2 - 0.001909 P_3^2 - 0.0127 P_4^2 0.0391 P_1*P_2 + 0.0082 P_1*P_3 + 0.0237 P_1*P_4 + 0.00158 P_2*P_3 + 0.00342 P_1*P_4 + 0.00630 P_3*P_4$ (7)

MRR $= 0.572 + 0.056 P_1 - 0.0678 P_2 + 0.1184 P_3 - 0.271 P_4 + 0.0110 P_1^2 + 0.001208 P_2^2 - 0.000369 P_3^2 - 0.00333 P_4^2 + 0.00899 P_1* P_2 - 0.01123 P_1* P_3 + 0.0139 P_1* P_4 - 0.001196 P_2* P_3 - 0.00029 P_2* P_4 + 0.00426 P_3* P_4$ (8)

5.2 Analysis of variance for the SEC Model

The experimental results are analyzed with ANOVA to identify the factors that significantly affect the performance measure on the total variance of the results. The ANOVA is carried out at $\alpha=0.05$ significance level (95%) confidence level) gave results are surface roughness (R_a) and material removal rate (MRR) shown in Table 4 and 5. The sources with P-value < 0.05 are considered as highly statistically significant.

Table 4. ANOVA table for Surface Roughness (R_a)

Source	DF	Adj SS	Adj MS	F-Value	P-Value

Oxygen Pressure	4	0.6632	0.16580	6.79	0.011
Pulse frequency	4	0.2877	0.07192	2.94	0.091
Cutting speed	4	0.7729	0.19323	7.91	0.007
Wt.% of CNT	4	0.4543	0.11358	4.65	0.031
Error	8	0.1955	0.02444		
Total	24	2.3367			

Table 5. ANOVA table for Material Removal Rate (MRR)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Oxygen Pressure	4	1.7127	0.42818	1.44	0.305
Pulse frequency	4	4.3267	1.08167	3.65	0.056
Cutting speed	4	0.3582	0.08955	0.30	0.869
Wt.% of CNT	4	4.7926	1.19816	4.04	0.044
Error	8	2.3734	0.29668		
Total	24	13.5887			

The coefficient of determination R^2 =95.96 for surface roughness (R_a) and R^2 = 96.02 material removal rate (MRR). Hence, the developed model is statistically significant. From the Table 3, it was observed that wt. of CNT is the most significant parameter followed by Oxygen Pressure, Pulse frequency, Cutting speed and Oxygen Pressure most significant parameter followed by Pulse frequency, Cutting speed, wt.% of CNT for material removal rate.

5.3 S/N Ratio Analysis for Optimum Settings

In Taguchi method the term “Signal” represents the desirable value an “noise” represents the undesirable value. The objective of using S/N ratio is the measure of performance to develop products and processes insensitive to noise factors [25]. The process parameters setting with highest S/N ratio always yield the optimum quality with minimum variance. The MINITAB-18 Software was used to analyze the main effect of S/N ratio on the optimization analysis for surface roughness (R_a) and material removal rate (MRR). Figure 3 shows the main effect plot and the corresponding S/N response for surface roughness (R_a) and material removal rate (MRR). The overall mean response is represented by the horizontal line at the centre of the curve.

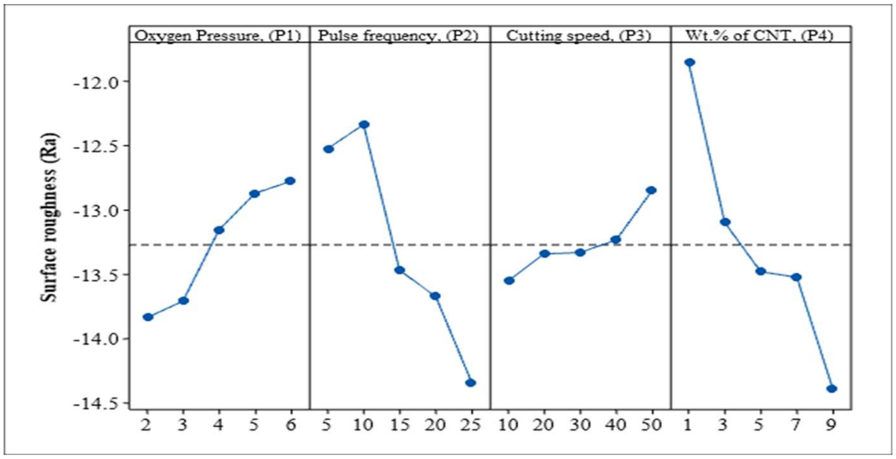

Figure 4. Main effect plot (surface roughness) for S/N ratios

Table 6. Response Table for Signal to Noise Ratios of surface roughness

Level	Oxygen Pressure	Pulse frequency	Cutting speed	Wt.% of CNT
1	-13.84	-12.52	-13.56	-11.85
2	-13.71	-12.33	-13.34	-13.10
3	-13.15	-13.47	-13.33	-13.48
4	-12.87	-13.67	-13.23	-13.52
5	-12.78	-14.35	-12.85	-14.40
Delta	1.06	2.01	0.71	2.55
Rank	3	2	4	1

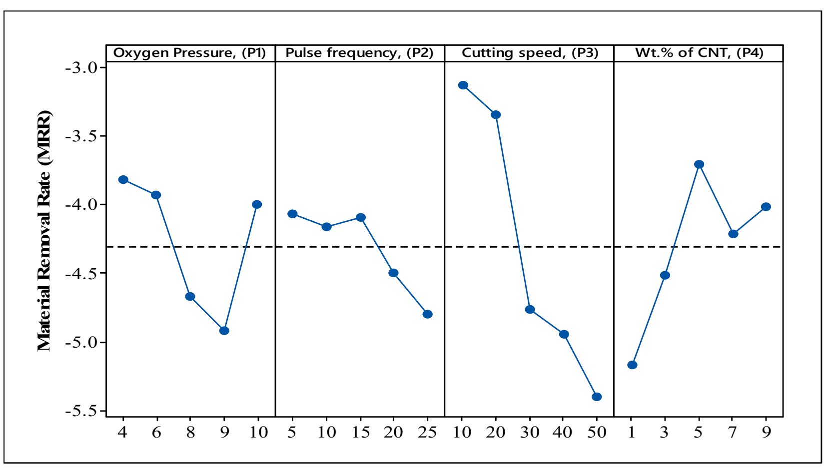

Figure 5. Main effect plot (material removal rate) for S/N ratios

Table 7. Response Table for Signal to Noise Ratios of material removal rate

Level	Oxygen Pressure	Plus frequency	Cutting speed	Wt. % ofCNT
1	-3.820	-4.067	-3.135	-5.727

2	-3.928	-4.160	-4.502	-5.002
3	-4.672	-4.864	-5.206	-4.269
4	-4.919	-4.995	-5.259	-4.216
5	-5.890	-5.143	-5.400	-4.014
Delta	2.070	1.075	2.265	1.713
Rank	2	4	1	3

From the S/N ratio analysis in Figure 4 & 5, the level of the factors with the highest S/N ratio was taken as the optimum level for the response, therefore the optimal process parameters are Oxygen pressure 4Kg/cm^2, plus frequency 5 Hz, cutting 40 mm/min, wt.% of CNT 3% to minimize the surface roughness (R_a) and oxygen pressure 10 Kg/cm^2, plus frequency 15 Hz, cutting 20 mm/min, wt.% of CNT 7% The response table for S/N ratio is shown in Table 6 and & 7. From the table it is inferred that wt.% of CNT is the most predominant parameter followed by plus frequency, oxygen pressure and cutting speed does not have any influence on surface roughness (R_a) similarly cutting speed is the most predominant parameter followed by oxygen pressure, wt. % of CNT, plus frequency.

6. OPTIMUM PARAMETER SETTING BY PSO

MATLAB is used to generate the PSO code. The input control parameters and their levels are fed to the PSO program. It is possible to determine the conditions at which the machining operation has to be carried out in order to get the optimum surface roughness and material removal rate. Figure 5 shows the Ra & MRR versus no. of iterations.

Table 8. Optimum Process Parameters for laser beam machining process.

C1	C2	Population Size	Iterations	Oxygen Pressure (Kg/cm^2)	Pulse frequency (Hz)	Cutting speed (mm/min)	Wt.% of CNT (%)	Surface roughness (R_a), µm	Material removal rate (MRR), mm^3/sec
0.5	1	100	80	2.65	5.25	22.11	3.26	3.96	1.56
0.6	1.5	50	100	3.81	15.25	16.54	1.25	3.45	1.36
0.1	2.5	40	60	2.20	5.22	32.35	1.45	4.25	2.15
0.1	2.5	30	60	2.66	20.56	42.72	1.78	5.36	1.67
1.6	2	100	120	3.51	7.56	12.59	1.69	3.75	1.64

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1.4	1.9	100	80	5.15	11.12	32.35	4.94	3.49	2.12
0.4	1.5	90	80	4.52	20.56	18.54	3.15	3.64	1.25
0.5	1.5	100	80	5.52	25.51	42.72	4.25	3.79	1.97
0.1	2	70	90	6.42	5.63	48.20	3.45	3.91	1.58
1.4	**2.6**	**70**	**95**	**3.56**	**20.52**	**43.74**	**3.72**	**3.12**	**3.38**
0.4	1.5	80	80	2.24	14.36	42.88	3.25	4.58	1.35
0.1	1.5	50	65	2.65	12.25	49.59	3.68	5.15	1.94
0.1	1.1	40	65	6.45	5.45	38.83	3.76	4.56	1.68
0.2	1.9	110	75	2.15	22.12	15.08	4.22	3.45	1.95
0.4	2.1	80	120	2.75	23.54	**20.29**	1.65	2.56	1.78
0.9	1.8	90	110	3.58	26.67	12.62	3.54	3.48	2.06

Table 8 shows the performance of the optimum combination of control parameters to minimize the surface roughness & maximum material removal rate. It has been found that the minimum value of surface roughness **is 3.12µm** which at a oxygen pressure (3.56 Kg/cm^2), Pulse frequency (20.52Hz), Cutting speed (43.74 mm/min) and Wt.% of CNT (3.72%) and maximum material removal rate is **is** 3.38 mm^3/sec Hence, it is concluded that optimal combination of control parameters could be obtained using PSO to minimize the machining responses. The application of PSO approach is very much helpful to set the optimal machining conditions in computer aided machining process for the production of quality goods with acceptable tolerances.

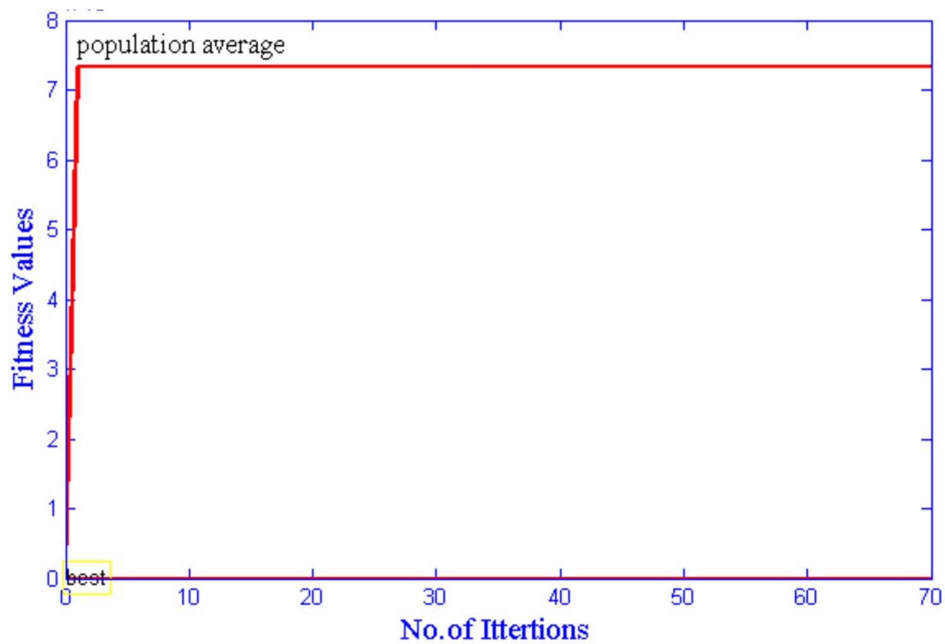

Figure 5. Performance of PSO

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