Control Parameters Optimization of Laser Beam Machining Using Genetic Algorithm

Ruben Phipon[1], B.B.Pradhan[2]
[1] Mechanical Engineering Department, SMIT, Sikkim, India.
[2] Mechanical Engineering Departments, SMIT, Sikkim, India.

Abstract
To improve and optimize the responses of a Laser Beam machining process, the various input machining control parameters are to be set at an optimal value. As such one has to adopt experimental methods, which are cumbersome, time consuming, costly and at times not feasible. During such situations, optimization techniques like Genetic Algorithm (GA) can be used as it provides a cost effective method for solution of such complex problems. Unlike traditional optimization techniques, GA is a robust and performs well in multimodal optimization problems. Considering these advantages of GA, optimization of Nd:Yag Laser beam machining process is done using this technique. In this research work, the desired responses are minimum kerf taper and surface roughness. The process control parameters considered are Oxygen pressure, pulse width, pulse frequency and cutting speed. Experiments are designed and the mathematical models correlating the desired responses and the control parameters are established using Response Surface Methodology (RSM). Finally, GA is applied to search the optimal parametric values for the optimal responses. Using Genetic Algorithm, minimum Kerf taper obtained is 0.14695° which is 0.313° less in magnitude than experimentally measured value. Also, minimum surface roughness predicted using GA is 1.2625µm which is 0.3375µm better in value compared to the experimental measured value. The average percentage prediction error of GA is found to be 3.35% for kerf taper and 4.02% for surface roughness. Thus, the results prove GA to be a novel optimization technique which can be used to optimize Laser beam machining processes.

Keywords: Laser Beam Machining (LBM), Response surface methodology (RSM), Genetic Algorithm (GA), Optimization.

1. Introduction

Laser beam machining (LBM) is a novel thermal energy based advanced machining process which can be used for machining a wide range of materials. In this process, a laser beam is focused for melting and vaporizing to remove material from the workpiece as per the desired shape [1]. Hence, the characteristic of non-contact between the tool and the workpiece makes this machining process desirable as it removes chances of workpiece deterioration due to cutting tool force. It is suitable for cutting complex geometric profiles, for drilling miniature holes in sheet metal and precision machining of micro-parts. However, improvement in LBM process performance can be made by studying the different factors that affect the quality characteristics. Thus, process performance can be improved by proper selection of process control parameters.

Kuar et al.[2] performed experiments to investigate into CNC pulsed Nd:YAG laser micro-drilling of zirconium oxide (ZrO_2). The optimal setting of process parameters such as pulse frequency and pulse width, lamp current, assist air pressure for achieving minimum HAZ thickness and taper of the micro-hole was determined. Dubey and Yadav [3] while cutting thin sheet of aluminium alloy using pulsed laser performed multi-objective optimization of kerf quality such as kerf deviation and kerf width. They observed assist gas pressure and pulse frequency make significant affect on the kerf quality in the operating range of process parameters. Sharma et al. [4] conducted experiments based on the Taguchi quality design concept for parameter optimization of the kerf quality characteristics during pulsed Nd:YAG laser cutting of nickel based superalloy thin sheet. The results indicate that the optimum input parameter levels suggested for curved cut profiles are entirely different from straight cut profiles.

Optimization of the machining process first requires a mathematical model to be established to correlate the desired response and the process control parameters. Thereafter an optimization technique is applied to find optimal setting of the control parameters to derive the desired responses. Mukherjee and Ray [5] presented a generic framework for parameter optimization in metal cutting processes for selection of an appropriate approach. Response Surface Methodology (RSM) is generally employed to design experiments with a reduced number of experimental runs to achieve optimum responses. Lalwani et al. [6] applied RSM to investigate the effect of cutting parameters on surface roughness in finish hard turning of MDN250 steel using coated ceramic tool. Soveja et al. [7] studied the influence of the operating factors on the laser texturing process using two experimental approaches: Taguchi methodology and RSM. Dubey and Yadav [8] present a hybrid Taguchi method and response surface method (TMRSM) for the multi-response optimization of a laser beam cutting process.

Yildiz [9] demonstrated the superiority of the hybrid optimization approach over the other techniques in terms of convergence speed and efficiency. Yusup et al. [10] discussed evolutionary techniques in optimizing machining process parameters for both traditional and modern machining. They observed evolutionary techniques while optimizing machining process parameters positively gives good results. Samanta and Chakraborty [11] proved the applicability and suitability of evolutionary algorithm in enhancing the performance measures of non traditional machining processes. Jain et al. [12] used GA for optimization of process parameters of mechanical type advanced machining processes Traditional optimization methods are not suitable to solve problems where the formulated objective functions and constraints are very complicated and implicit functions of the decision variables. Unlike conventional optimization techniques, GA is a robust and can be effectively applied for multi modal problems. Hence, considering these advantages of GA, an attempt has been made to optimize the LBM process in this research paper using this technique.

2. Mathematical Modeling Using Rsm

RSM is a statistical technique employed to design experiments with a reduced number of experimental runs to achieve optimum responses. It is used to establish mathematical models which correlate the responses and the independent control parameters. Sharma and Yadav [13] performed experiments in a 200W pulsed Nd: YAG laser beam machine system with CNC work table. Surface quality i.e. kerf taper and surface roughness are the required measures of response. Process parameters considered that affect these responses are assist gas pressure (x_1), pulse width (x_2), pulse frequency (x_3), and cutting speed (x_4).The relationship of process parameters and output responses is represented mathematically in the form of a polynomial. The 1st order polynomial does not provide higher order interaction and the 3rd order are not desirable as they are difficult to solve. As such 2nd order polynomial is suitable for higher order interaction and gives better result. CCRD technique is applied to provide good predictions throughout the permissible region of interest. CCRD requires a minimum of five levels of all control parameters for the calculation of regression coefficients. The process control parameters and their values at different levels are shown in Table 1. A total of 31 experimental runs are designed which consist of 2p factorial runs, 2p axial runs and 7 centre point runs where p is the number of control parameters. The designed experiments and the recorded response values are listed in Table 2.

Thus, the 2nd order polynomial correlating independent process control parameters and responses are given in equations 1 and 2.

Table 1 Process control parameter values at different levels.

Input parameters	Symbol	Units	Coded Levels				
			-2	-1	0	1	2
Oxygen pressure	x_1	Kg/cm^2	4	5	6	7	8
Pulse width	x_2	ms	1.6	1.7	1.8	1.9	2
Pulse frequency	x_3	Hz	8	9	10	11	12
Cutting speed	x_4	mm/min	6	7	8	9	10

Table 2 Experimental design and measured responses

Expt. run	Parameter levels				Ta(deg)	Ra(μm)
	x_1	x_2	x_3	x_4		
1	0	0	0	0	0.16370	2.54
2	-1	-1	-1	-1	0.22100	2.00
3	1	-1	-1	-1	0.19372	1.60
4	-1	1	-1	-1	0.19646	2.42
5	1	1	-1	-1	0.17740	1.90
6	0	0	0	0	0.16650	2.42
7	-1	-1	1	-1	0.22650	2.78
8	1	-1	1	-1	0.16920	2.53
9	-1	1	1	-1	0.19100	2.96
10	1	1	1	-1	0.18282	2.90
11	0	0	0	0	0.15558	2.58
12	-1	-1	-1	1	0.26740	3.03
13	1	-1	-1	1	0.22100	2.46
14	-1	1	-1	1	0.33830	2.96
15	1	1	-1	1	0.15553	2.44
16	0	0	0	0	0.17189	2.64
17	-1	-1	1	1	0.30834	2.94

18	1	-1	1	1	0.18010	2.68
19	-1	1	1	1	0.31921	2.54
20	1	1	1	1	0.19920	2.05
21	0	0	0	0	0.18554	2.39
22	-2	0	0	0	0.29195	3.01
23	2	0	0	0	0.16095	2.67
24	0	-2	0	0	0.20463	2.60
25	0	2	0	0	0.16100	2.42
26	0	0	0	0	0.17740	2.48
27	0	0	-2	0	0.19650	2.81
28	0	0	2	0	0.18010	3.06
29	0	0	0	-2	0.16659	2.51
30	0	0	0	2	0.22922	3.12
31	0	0	0	0	0.15280	2.60

The models are developed using Minitab software. Mathematical model developed for minimum Kerf Taper is as follows:

$$Ta = 0.167621-0.035356\,x_1-0.004663\,x_2-0.001023\,x_3+0.023064\,x_4+0.018484\,x_1^2+0.007575x_2^2+0.008947x_3^2+0.011348\,x_4^2-0.004594\,x_1x_2-0.002558\,x_1x_3-0.022681x_1x_4+0.002551\,x_2x_3+0.006302\,x_2x_4+0.002899\,x_3x_4 \qquad (1)$$

Similarly, the mathematical models developed for surface roughness is,

$$Ra = 2.52143-0.15625\,x_1-0.00875\,x_2+0.12792\,x_3+0.13458\,x_4+0.03579\,x_1^2-0.04671\,x_2^2+0.05954\,x_3^2+0.02954\,x_4^2-0.00688\,x_1x_2+0.05937\,x_1x_3-.03812\,x_1x_4-0.06937\,x_2x_3-0.14938\,x_2x_4-0.24563x_3x_4 \qquad (2)$$

where, Ta and Ra are the desired responses for kerf taper and surface roughness respectively.
x_1,x_2, x_3, x_4 are the process control parameters of oxygen pressure, pulse width, pulse frequency and cutting speed respectively.

3. Optimization Using Ga

3.1 Genetic Algorrrithm

Genetic algorithm replicates the idea of survival of the fittest using an interbreeding population to create a robust search strategy. A population of solutions to a specified problem is maintained. It then iteratively creates new populations from the old by ranking the solutions according to their fitness values through the process of selection . Selection in GA is based on biological evolution where only the fittest survive and their gene pool contributes to the creation of the next generation. Hence, the likelihood of a chromosome (solution point) being selected as a good one is proportional to its fitness value. This is followed by interbreeding the fittest to create new offsprings which are optimistically closer to the optimum solution to the problem at hand. This process of crossover may be regarded as artificial mating of two fit chromosomes to create the chromosome for the next generation. The idea is some genes with good characteristics from one chromosome may combine with some good genes in the other chromosome to create a better solution represented by the new chromosome. Lastly, mutation makes random adjustment in the genetic composition. The mutation operator changes the current value of a gene to a different one. It is useful for introducing new traits in the solution pool

3.2 Optimization of LBM process using GA

The present research work optimizes the desired responses and control parameters by writing .M-files and then solved by GA using the MATLAB software. Figure 1 shows the GA output of best measured response of minimum kerf taper as 0.14695°. GA was run for 50 generations as the result remained stagnant even after increasing the number of generations further.
Three different initial population sizes were considered while running the GA. A test of 20 runs were conducted for each population size and the best five results have been shown. Table 3 lists the values of control parameters and the response predicted using GA for minimum kerf taper.

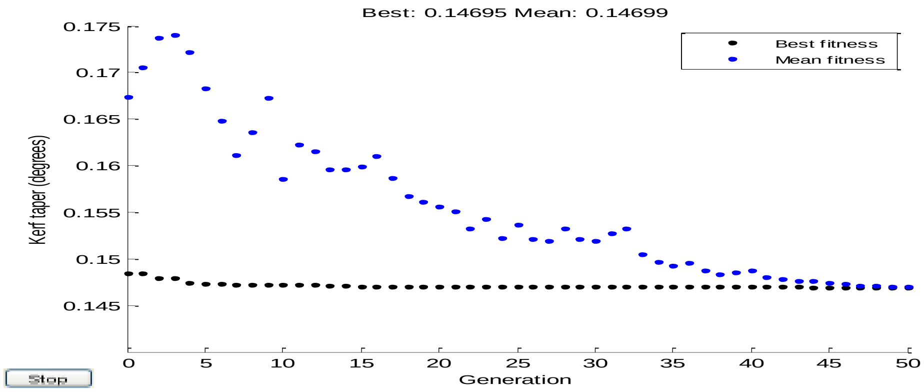

Fig.1 Plot of GA predicted result for minimum Kerf taper

Table 3 GA predicted test results for Kerf taper

Expt. No.	Process variables				Response
	Oxygen pressure. (Kg/cm^2)	Pulse width. (ms)	Pulse frequency. (Hz)	Cutting speed. (mm/min)	Kerf taper, T_a
Population size 30					
1	5	1.9	9	9	0.34724
2	5	1.7	11	9	0.33891
3	5	1.9	11	9	0.33971
4	4	1.8	10	8	0.32975
5	7	1.7	9	9	0.31837
Population size 60					
6	5	1.7	11	7	0.20013
7	5	1.7	9	7	0.20413
8	7	1.9	11	9	0.19853
9	6	1.8	10	8	0.19413
10	7	1.9	9	9	0.18765
Population size 90					
11	7	1.9	11	7	0.17452
12	6	1.8	10	8	0.16352
13	5	1.9	9	7	0.15445
14	7	1.7	9	7	0.14895
15	7	1.8	10	9	0.14695

Similarly, Figure 2 shows the GA output of best measured response of minimum surface roughness as 1.2625 µm. Also, Table 4 lists the values of control parameters and the response predicted using GA for minimum surface roughness.

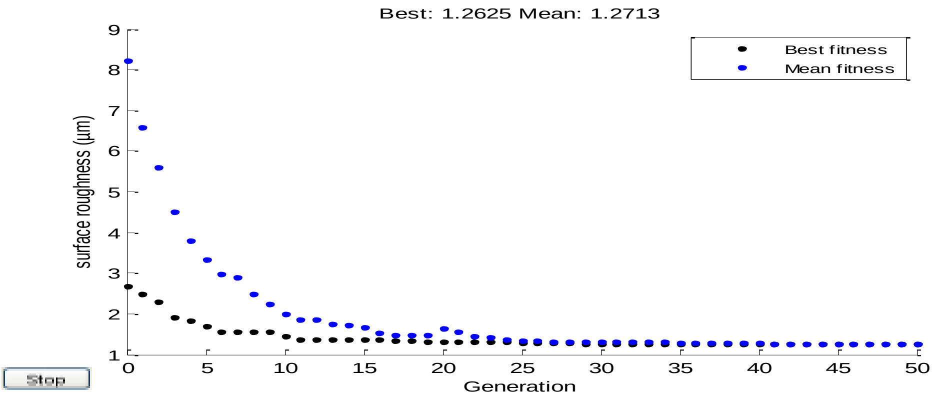

Fig. 2 Plot of GA predicted result for minimum Surface roughness

Table 4 GA predicted test results for surface roughness

Expt. No.	Process variables				Response
	Oxygen pressure. (Kg/cm^2)	Pulse width. (ms)	Pulse frequency. (Hz)	Cutting speed. (mm/min)	Surface roughness, Ra
Population size 30					
1	5	1.7	9	9	3.9567
2	4	1.8	10	8	3.7532
3	6	1.8	10	8	3.7256
4	6	1.8	10	9	3.5245
5	6	1.9	10	8	3.4245
Population size 60					
6	6	1.8	10	8	2.9785
7	5	1.7	11	7	2.8684
8	5	1.9	11	7	2.8622
9	5	1.9	9	9	2.6231
10	6	1.8	10	8	2.4146
Population size 90					
11	6	1.8	10	8	2.3856
12	5	1.7	9	7	2.2345
13	8	1.8	10	7	1.7562
14	7	1.9	9	7	1.8553
15	7	1.7	9	7	1.2625

3.3 Validation

Validation of the GA predicted results with the experimental results is done in order to conform the GA predicted results to be acceptable for practical use. Percentage of prediction error shows the amount of variation with the actual experimental results. The percentage of prediction error is calculated as

Prediction error%

$$= \frac{\text{Experimental result - GA predicted result}}{\text{Experimental result}} \times 100$$

In order to validate the test results predicted by GA, six random experimental results are compared with the GA predicted results as shown in Table 5.

Table 5 Comparison of experimental and GA predicted results.

Sl.no.	Experimental result		GA predicted result		Prediction error %	
	Kerf taper	Surface roughness	Kerf taper	Surface roughness	Kerf taper	Surface roughness
1	0.15552	1.9	0.14695	1.83	5.51	3.68
2	0.221	2.53	0.23	2.6	3.91	3.84
3	0.19372	3.01	0.189	2.95	2.43	1.99
4	0.30834	3.12	0.3112	3.25	0.919	4
5	0.29195	2.78	0.2845	2.65	2.543	4.67
6	0.3383	2.05	0.3554	2.18	4.811	5.96
Average percentage of error					3.35	4.02

Figures 3 and 4 show the plot for comparison of experimental results with the GA predicted results for minimum kerf taper and surface roughness respectively.

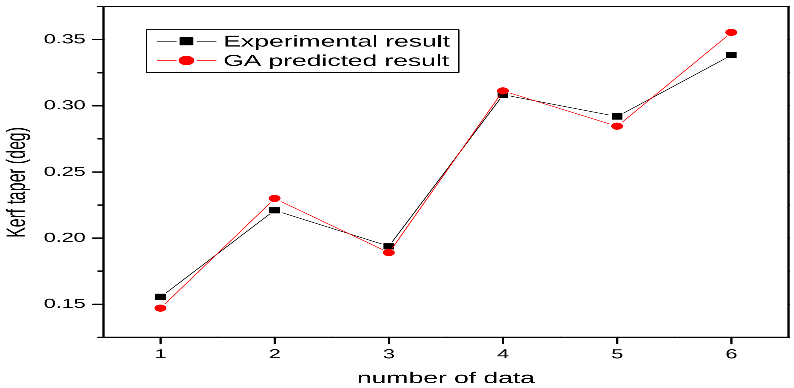

Fig. 3 Plot for comparison of experimental and GA predicted results for minimum kerf taper

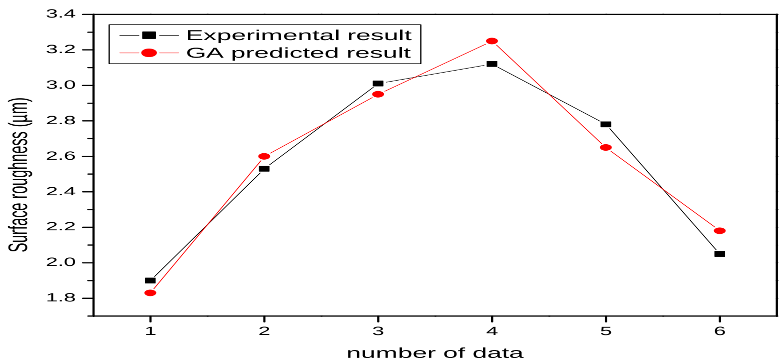

Fig. 3 Plot for comparison of experimental and GA predicted results for minimum surface roughness.

4. Result and Analysis

Heuristic analyses using GA 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. Tables 3 and 4 list the values of process control parameters and the GA predicted responses of kerf taper and surface roughness respectively. It is observed from these tables that as the population size (possible solutions) in GA increases, the responses decrease showing improvement of the desired response quality. This can be attributed to the fact that more number of possible solutions provide opportunities of reproducing better offsprings or solutions.

However, the result remains stagnant when population size of more than 50 is used. Thus, global optima is achieved at population size 50 and no further improvement in the response values are attained by further increase in the population size.

This research shows the comparison of results between GA and past researches. Tables 5 highlight the comparison of outcome for optimality analyses. On comparison of the test results for the desired responses, GA based optimality analysis achieve better fitness function values as compared to those derived by the past researchers. Through GA, minimum kerf taper obtained is 0.14695° which is 0.313° less in magnitude than experimentally measured value. The result suggests that average to low values of oxygen pressure and pulse width combined with average to high values of pulse frequency and cutting speed gives optimal results for minimum kerf taper. Similarly, using GA the minimum surface roughness predicted at optimal parameter setting is 1.2625µm which is 0.3375µm better in value compared to the experimental measured value. The result suggests that a medium high value of oxygen pressure and medium low values of pulse width, pulse frequency and cutting speed are to be set for obtaining better or minimum surface roughness.
The tabulated values while comparing experimental and GA predicted results at RSM predicted combination of optimal parametric setting are listed in Table 6.

Table 6 Comparison of experimental and GA predicted results at RSM predicted combination of Optimal parametric setting

Results	Expt.	GA
Kerf taper	0.15553	0.14695
Surface roughness	1.6	1.53159
Percentage error (%) for kerf taper		5.5
Percentage error (%) for surface roughness taper		4.27

From this table, it is observed that GA based predicted results at optimal parametric setting is closer to the values as measured by actual experiments. This is shown by percentage prediction error which is 5.5 % and 4.27 % for kerf taper and surface roughness respectively. Thus, it is observed for GA to be a cost effective, robust yet simple and fast method for optimizing the process control parameters of a Nd:Yag LBM for desired responses of minimum kerf taper and minimum surface roughness.

5. Conclusion

The following conclusions are drawn from this research work.

(i) GA provides a cost effective soft computing technique for optimizing machining operations.

(ii) Based on the test results predicted using GA, this technique can be accommodated within an intelligent manufacturing system for automated process planning.

(iii) future work can be done taking into consideration more independent control parameters.

(iv) Multiobjective optimization can be taken as further work.

References

[1] Avanish Kumar Dubey and Vinod Yadava, "Laser beam machining—A review,"International Journal of Machine Tools & Manufacture, vol. 48, 2008, pp.609– 628.

[2] A.S. Kuar, B. Doloi, B. Bhattacharyya, " Modelling and analysis of pulsed Nd:YAG laser machining characteristics during micro-drilling of zirconia (ZrO2)," International Journal of Machine Tools & Manufacture, vol. 46,2006, pp. 1301–1310.

[3] Avanish Kumar Dubey and Vinod Yadava, "Optimization of kerf quality during pulsed laser cutting of aluminium alloy sheet," Journal of materials processing technology, vol. 204, 2008, pp.412–418.

[4] Amit Sharma,VinodYadava, Raghavendra Rao, "Optimization of kerf quality characteristics during Nd: YAG laser cutting of nickel based superalloy sheet for straight and curved cut profiles," Optics and Lasers in Engineering, vol. 48,2010, pp. 915–925.

[5] Mukherjee, I and Ray, P.K, "A review of optimization techniques in metal cutting processes", Computers& Industrial Engineering, Vol. 50, 2006, pp. 15-34.

[6] D.I. Lalwani, N.K. Mehta, P.K. Jain, "Experimental investigations of cutting parameters influence on cutting forces and surface roughness in finish hard turning of MDN250 steel," Journal of materials processing technology, vol.206, 2008, pp.167–179.

[7] A. Soveja, E. Cicala, D. Grevey, J.M. Jouvard, " Optimization of TA6V alloy surface laser texturing using an experimental design approach," Optics and Lasers in Engineering, vol. 46, 2008, pp. 671– 678.

[8] Avanish Kumar Dubey and Vinod Yadava, " Multi-objective optimization of laser beam cutting process," Optics & Laser Technology, vol. 40, 2008, pp. 562–570.

[9] Ali R. Yildiz, "A comparative study of population-based optimization algorithms for turning Operations," Information Sciences, vol. 210, 2012, pp. 81–88.

[10] Norfadzlan Yusup, Azlan Mohd Zain, Siti Zaiton Mohd Hashim, "Evolutionary techniques in optimizing machining parameters: Review and recent applications (2007–2011)," Expert Systems with Applications, vol. 39, 2012, pp. 9909–9927.

[11] Suman Samanta and Shankar Chakraborty, "Parametric optimization of some non- traditional machining processes using artificial bee colony algorithm," Engineering Applications of Artificial Intelligence, vol. 24, 2011, pp. 946–957.

[12] Neelesh K. Jain, V.K. Jain, Kalyanmoy Deb, " Optimization of process parameters of mechanical type advanced machining processes using genetic algorithms," International Journal of Machine Tools & Manufacture, vol. 47, 2007, pp. 900–919.

[13] Sharma, A. and Yadava,V. (2012) "Modelling and optimization of cut quality during pulsed Nd:YAG laser cutting of thin Al-alloy sheet for straight profile", *Optics & Laser Technology*, Vol. 44, 2012, pp. 159–168.