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EMPIRICAL MODELING OF BEAD GEOMETRY AND OPTIMIZATION IN LASER BEAM WELDING

G. HARINATH GOWD AND A. GOPALA KRISHNA

Abstract

Laser beam welding (LBW) is a field of growing importance in industry with respect to traditional welding methodologies due to lower dimension and shape distortion of components and greater processing velocity. Because of its high weld strength to weld size ratio, reliability and minimal heat affected zone, laser welding has become important for varied industrial applications. In this work Butt welds were carried out on INCONEL 600 plates using pulsed ND:YAG Laser beam welding machine. The overall goal of this research is to model and optimize Laser beam welding process. The primary requisite to automate a process is to develop the governing relationships between process parameters and weld bead geometry. Accurate prediction mathematical models to estimate Bead width, Depth of Penetration & Bead Volume were developed from experimental data using Response Surface Methodology (RSM). These predicted mathematical models are used for optimization of the process. Total volume of the weld bead, an important bead parameter, was optimized (minimized), keeping the dimensions of the other important bead parameters as constraints, to obtain sound and superior quality welds. Further the optimization of weld bead volume was carried out using the optimization module available in the MATLAB 2010a version software package.

Keywords: ND-YAG Laser Beam welding, Weld bead geometry, Response surface methodology, Constraints, Genetic algorithm, Optimization.

1. INTRODUCTION

Lasers are now widely used in Automotive, Aerospace, Electronic and Heavy manufacturing industries to join and machine a variety of metals and alloys. Laser Beam welding is a high-energy-density welding process and well known for its deep penetration, high speed, small heat-affected zone, fine welding seam quality, low heat input per unit volume, and fiber optic beam delivery.

Laser beam welding (**LBW**) processes is a welding technique used to join multiple pieces of metal through the heating effect of a concentrated beam of coherent monochromatic light. Light amplification by stimulated emission of radiation (LASER) is a mechanism which emits electromagnetic radiation, through the process of simulated emission. Lasers generate light energy that can be absorbed into materials and converted into heat energy. Laser Beam welding is a high-energy-density welding process and well known for its deep penetration, high speed, small heat-affected zone, fine welding seam quality, low heat input per unit volume, and fiber optic beam delivery [1]. The energy input in laser welding is controlled by the combination of focused spot size, focused position, shielding gas, laser beam power and welding speed. For the laser beam welding of butt joint, the parameters of joint fit-up and the laser beam to joint alignment [2] becomes important. An inert gas, such as helium or argon, is used to protect the weld bead from contamination, and to reduce the formation of absorbing plasma. Depending upon the type of weld required a continuous or pulsed laser beam may be used.

The principle of operation is that the laser beam is pointed on to a joint and the beam is moved along the joint. The process will melt the metals in to a liquid, fuse them together and then make them solid again thereby joining the two pieces. The beam provides a concentrated heat source, allowing for narrow, deep welds and high welding rates. The process is frequently used in high volume applications, such as in the automotive industry.

In this research Butt welding of ICONEL 600 is carried out at by varying the input parameters. INCONEL 600 is a precipitation-hardenable nickel-iron base super alloy widely used in gas turbines, rocket motors, space craft, nuclear reactors pumps and tooling due to its excellent combination of corrosion resistance, oxidation resistance, and good tensile and creep properties

In any welding process, bead geometrical parameters play an important role in determining the mechanical properties of the weld and hence quality of the weld [3]. In Laser Beam welding, bead geometrical variables are greatly influenced by the process parameters such as Pulse frequency, Welding speed, Input energy, Shielding gas, [4] -[5]. Therefore to accomplish good quality it is imperative to setup the right welding process parameters. Quality can be assured with embracing automated techniques for welding process. Welding automation not only results in high quality but also results in reduced wastage, high production rates with reduce cost to make the product.

To automate an arc welding, it is essential to develop the governing relationships between the process parameters and the bead geometrical variables. These relationships are important to optimize weld quality and total process cost. The traditional practice of selecting the process parameters is based on a trial-and-error methods and/or experience and judgment of the particular welder. Although it is a costlier and time-intensive process, yet it does optimize neither the quality nor the cost.

Some of the significant works in literature regard to the modeling and optimization studies of welding are as follows: Yang performed regression analysis to model submerged arc welding process [6]. Dey Vidyut optimized the bead geometry of electron beam welding after constructing quantitative models using regression analysis [7]. Kim used regression analysis together with Genetic Algorithm in order to find a set of welding process variables that could produce the desired weld-bead geometry in GMAW [8]. Gunaraj and Murugan minimized weld volume for the submerged arc welding process using an optimization tool in Matlab [9]. Bead height, bead width and bead penetration were taken as the constraints. The above optimization problem was solved using *Quasi-Newton* method. Bead parameters were predicted using regression analysis. The Taguchi method was utilized by Tarng and Yang to analyze the affect of welding process parameter on the weld-bead geometry [10]. Casalino has studied the effect of welding parameters on the weld bead geometry in laser welding using statistical and taguchi approaches [11]. Nagesh and Datta developed a backpropagation neural network, to establish the relationships between the process parameters and weld bead geometric parameters, in a shielded metal arc welding process [12]. Jantre applied artificial neural networks to predict the pulsed current Gas Metal Arc Welding (GMAW) process [13]. Balasubramanian applied neural networks to modeling [14] and Buvanasekaran studied the Analysis of Laser welding parameters using artificial neural network [15]. However, neural networks do not establish the quantitative relationships between the input variables and the output variables. In another study on Laser welding, Hsuan Liang Lin has applied Taguchi and a Neural network based methods to modeling and optimization of ND:YAG laser micro weld process [16]. Young whan park has applied Genetic algorithms and Neural network for process modeling and parameter optimization of aluminium laser welding automation [17]. Mishra and Debroy showed that multiple sets of welding variables capable of producing the target weld geometry could be determined in a realistic time frame by coupling a real-coded GA with and neural network model for Gas Metal Arc Fillet Welding [18]. Vasudevan used a Genetic Algorithm (GA) to achieve the target bead geometry in Tungsten Inert Gas welding by optimizing the process parameters [19]. Gunaraj have determined the main and the interaction effects of process parameters on the bead geometry using response surface methodology (RSM) [20]. Saurav data has applied RSM to modeling and optimization of the features of bead geometry including percentage dilution in submerged arc welding using mixture of fresh flux and fused slag [21]. Benyounis applied response surface methodology to predict weld profile in laser welded medium carbon steel [22].

The literature shows that the most dominant modeling tools used till date are Taguchi based regression analysis and artificial neural networks. However, the accuracy and possibility of determining the global optimum solution depends on the type of modeling technique used to express the objective function and constraints as functions of the decision variables. Therefore effective, efficient and economic utilization of laser welding necessitates an accurate modeling and optimization procedure.

Like the said approaches, although, artificial neural networks (ANN) have also been used extensively in the literature for modeling, but they have the drawback of not able to quantify the relationships between inputs and outputs.

In the present work, RSM is used for developing the relationships between the weld bead geometry and the input variables. The models derived by RSM are utilized for optimizing the process by using the Genetic Algorithm based optimization module available in the MATLAB software package.

2. EXPERIMENTAL WORK

The experiments are conducted on High peak power pulsed ND:YAG Laser welding system with six degrees of freedom robot delivered through 300 um Luminator fiber., Model Number JK 300D, made by GSI group laser division, United Kingdom which is available with M/s. Optilase Techniks (I) PVT. LTD. Chennai, Tamilnadu. The maximum average power produced at laser is 300W. The ND-YAG Robotic Laser Beam welding equipment used for the study is shown in Figure 1 and the conditions at which the experiments were carried out is detailed in Table 1.

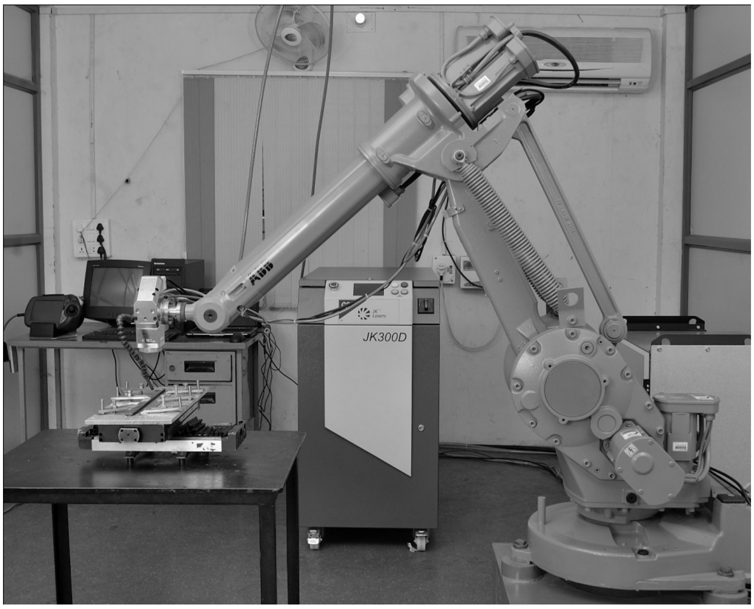

Figure1. ND-YAG Robotic Laser Beam welding equipment

Table 1. Welding conditions

S.No	Parameters	
1	Type of Laser	Pulsed ND:YAG laser welding
2	Maximum Average power at Laser	300 W
3	Type of gas used as medium	Argon
3	Work piece material	INCONEL 600
4	Chemical composition	Ni-72%,Cr-14-17%, Fe-6-10%, Mn-1%, Cu-0.5%, Si-0.5%, C-0.15%, Su-0.015%
4	Work piece dimensions	30 mm L×30 mm B×2.5 mm H
5	Type of Joint	Butt Joint with No filler material
6	Location of work piece	At the center of table using specially designed fixture

In this research Butt welding of ICONEL 600 is carried out at by varying the input parameters. INCONEL 600 is a precipitation-hardenable nickel-iron base super alloy widely used in gas turbines, rocket motors, space craft, nuclear reactors pumps and tooling due to its excellent combination of corrosion resistance, oxidation resistance, and good tensile and creep properties is used as the work material.

The size of each plate was 30mm long x 30mm width with thickness of 2.5 mm. The laser beam is focused at the interface of the joints. No filler material is used for the laser welding of the samples. An inert gas such as helium or argon is used to protect the weld bead from contamination, and to reduce the formation of absorbing plasma.

Based on the literature survey and the trail experiments, it was found that the process parameters such as pulse duration (x_1), pulse frequency(x_2), speed (x_3), and energy (x_4) have significant affect on weld bead geometrical features such as penetration (P), bead width (W), and bead volume (V).

In the present work, they were considered as the decision variables and trial samples of butt joints were performed by varying one of the process variables to determine the working range of each process variable. Absent of visible welding defects and at least half depth penetrations were the criteria of choosing the working ranges. The upper limit of a factor was coded as +2 and the lower limit as -2. The coded values for intermediate values were calculated from the following relationship;

$$X_i = \frac{2\left[2X - (X_{\max} + X_{\min})\right]}{(X_{\max} - X_{\min})} \quad (1)$$

where X_i is the required coded value of a variable X. X is any value of the variable from X_{min} to X_{max}. X_{min} is the lower level of the variable and X_{max} is the upper level of the variable. The process variable levels with their units and notations are given in Table 2.

Table 2: Range of Process Parameters Used

Process parameters	Units	Notation	Levels				
			-2	-1	0	1	2
Pulse Duration	μs	x_1	1	2	3	4	5
Pulse Frequency	Hz	x_2	6	10	14	18	22
Welding Speed	mm/min	x_4	100	300	500	700	900
Pulse Energy	J	x_3	9	12	15	18	21

The selected design matrix is a five-level, four-factor, central composite rotatable factorial design consisting of 31 sets of coded conditions. It comprises a full replication of 2^4(=16) factorial design plus seven center points and eight star points. All welding variables at their intermediate level (0) constitute the center points, and the combinations of each of the welding variables at either its lowest (-2) or highest (+2) with the other three variables at their intermediate level constitute the star points. Thus, the 31 experimental runs allowed the estimation of the linear, quadratic and two-way interactive effects of the welding variables on the bead geometry.

After conducting the experiments as per the design matrix, For measuring the output responses i.e bead geometry features such as Bead penetration & Bead width, Each welded joint was sectioned perpendicular to the weld direction. The specimens were then prepared by the usual metallurgical polishing methods and then etched. The profiles were then traced using a precision optical profile projector and the bead dimensions were measured accurately.

The study was focused to investigate the effects of process variables on the structures of the welds. An average of three measurements taken at three different places and the output responses were recorded for each set. The output responses recorded were shown in the Table 3.

Table 3. Experimental dataset

S.No	x1	x2	x3	x4	Penetration	Bead width	Bead Volume
1	2	10	300	12	1.8	1.200	0.469
2	4	10	300	12	2.23	1.020	0.46
3	2	18	300	12	1.9	1.150	0.5
4	4	18	300	12	2.28	1.210	0.5
5	2	10	700	12	1.7	0.819	0.33
6	4	10	700	12	2.07	0.910	0.34
7	2	18	700	12	1.8	0.805	0.495
8	4	18	700	12	2.01	0.856	0.5
9	2	10	300	18	1.84	1.010	0.444
10	4	10	300	18	2.24	0.990	0.486
11	2	18	300	18	1.95	1.015	0.531
12	4	18	300	18	2.18	1.015	0.58
13	2	10	700	18	1.77	0.768	0.318
14	4	10	700	18	2.18	0.950	0.352
15	2	18	700	18	2.01	0.756	0.5
16	4	18	700	18	2.155	0.978	0.52

S.No	x1	x2	x3	x4	Penetration	Bead width	Bead Volume
17	1	14	500	15	1.5	0.900	0.4
18	5	14	500	15	2.26	1.060	0.42
19	3	6	500	15	1.912	0.940	0.15
20	3	22	500	15	2.17	1.015	0.54
21	3	14	100	15	2.25	1.269	0.555
22	3	14	900	15	1.94	0.701	0.4
23	3	14	500	9	1.8	1.015	0.39
24	3	14	500	21	2.25	0.984	0.5
25	3	14	500	15	2.05	0.980	0.512
26	3	14	500	15	2.07	0.958	0.5
27	3	14	500	15	2.08	0.950	0.52
28	3	14	500	15	2.105	0.936	0.491
29	3	14	500	15	2.098	0.928	0.487
30	3	14	500	15	2.05	0.916	0.49
31	3	14	500	15	1.961	0.900	0.49

3. PROPOSED METHODOLOGY

The overall schematic of the proposed methodology is shown in Figure 2 and the following section discusses the various steps involved in it in brief: Among the several process variables involved in LBW, the significant variables found out based on the pilot experiments and the literature survey are considered in the proposed work as the inclusion of insignificant variables excessively increases the computational complexity of the models. In view of the costly process and the material, Design of Experiments (DOE) are used to reduce the number of experiments needed to carry out the analysis with the same accuracy and the precision.

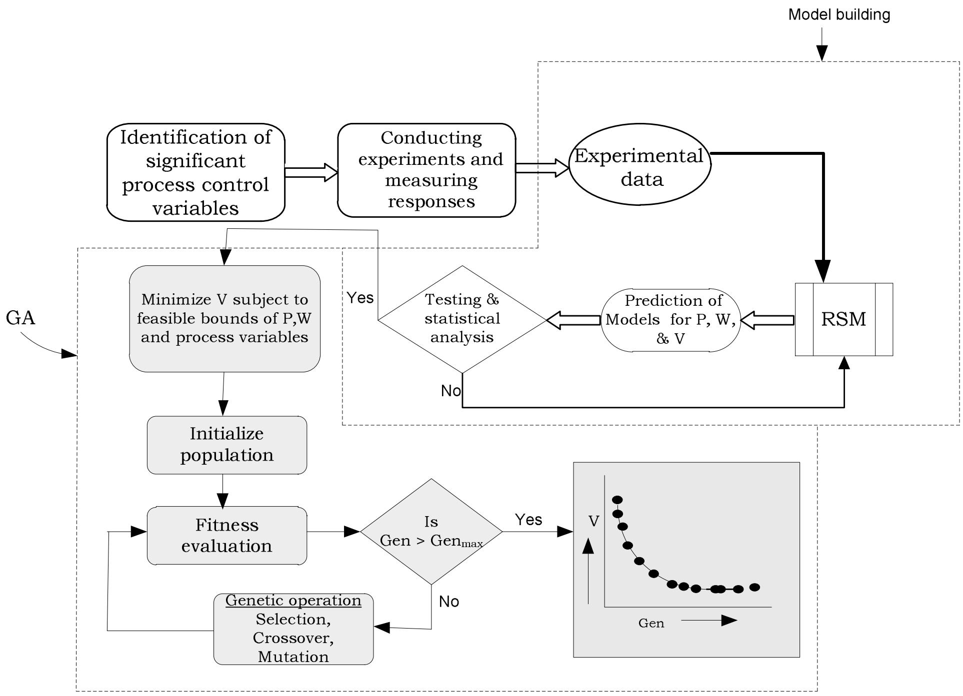

Figure 2. Overall schematic of the proposed methodology

4. RESPONSE SURFACE METHODOLOGY

Response surface methodology (RSM) was introduced by Box and Wilson [23] to develop empirical models of complex processes. Response Surface Methodology (RSM) is a collection of statistical and mathematical techniques useful for the modeling and analysis of problems in which a response of interest is influenced by several independent variables (input variables) and the objective is to optimize the response (output variable) [24].

It is a sequential experimentation strategy for empirical model building and optimization. By conducting the experiments and applying regression analysis, a model of the response to some independent input variables can be obtained.

In RSM, it is possible to represent independent process parameters in quantitative form as

$Y = f(x_1, x_2, \ldots x_n) + \varepsilon$ is called *Response Surface Methodology*. (2)

Where Y is then response, f is the response function, ε is the experimental error, and x_1, $x_2, \ldots x_n$ are independent parameters.

By plotting the expected response of Y, a surface known as the response surface is obtained. The form of *f* is unknown and may be very complicated. Thus, RSM aims at approximating *f* by a suitable lower ordered polynomial in some region of the independent process variables, the function can be written as:

$$Y = C_0 + C_1X_1 + C_2X_2 + \ldots + C_n X_n \pm \varepsilon \quad (3)$$

However, if a curvature appears in the system, then a higher order polynomial such as the Quadratic model may be used:

$$Y = C_o + \sum_{i=1}^{n} C_i X_n + \sum_{i=1}^{n} d_i X_i^2 \pm \varepsilon$$

(4)

The objective of RSM is not only to investigate the response over the entire factor space, but also to locate the region of interest where the response reaches its optimum or near optimum value, By studying carefully the response surface model, the combination of factors, which gives the best response, can be established.

The procedure of response surface methodology comprises the following steps

1. Design a series of experiments for adequate and reliable measurement of the response of interest.
2. Develop an empirical or mathematical model of the second order response surface with the best fittings.
3. Find the optimal set of experimental parameters that produce a maximum or minimum value of response.
4. Represent the direct and the interactive effects of process parameters through two and three dimensional plots.

5. OPTIMIZATION USING GENETIC ALGORITHMS

Genetic algorithms were first developed by John Holland [25] & Goldberg [26] are one of the most well-known evolutionary computing methods for optimization. A genetic algorithm is a random search technique that mimics some mechanisms of natural evolution. Genetic algorithms belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover.

The algorithm works on a population of designs. In this algorithm, a population of strings (called chromosomes), which encode candidate solutions (called individuals) to an optimization problem, evolves toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. Genetic algorithms find application in bioinformatics, phylogenetics, computational science, engineering, economics, chemistry, manufacturing, mathematics, physics and other fields.

The basic flow chart of the Genetic Algorithm is shown in Figure 3 and it involves the following steps.

1. Initial population: Generate random population of chromosomes.
2. Fitness: Evaluate the fitness of each chromosome in the population.
3. Test: If the end condition is satisfied, stop, and return the best solution in current population.
4. New population: Create a new population by repeating following steps until the new population is complete.
5. Reproduction: Select two parent chromosomes from the population according to their fitness.
6. Crossover: With a crossover probability, crossover the parents to form a new offspring (children). If no crossover was performed, offspring is an exact copy of parents.
7. Mutation: With a mutation probability, mutate new offspring at each locus (position in chromosome).

8. Replace: Use new generated population for a further run of algorithm.
9. Loop: Go to step 2.

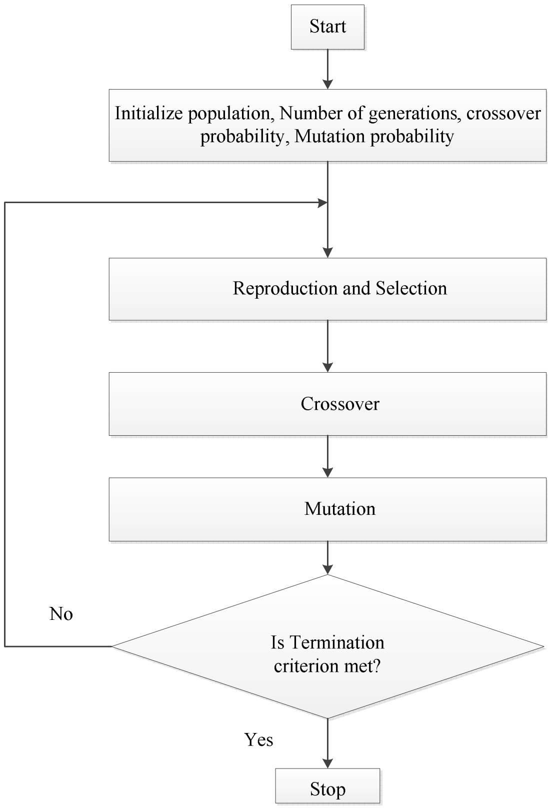

Figure 3. Flow chart of Genetic Algorithm

5.1. Individual representation

In most GAs, finite length binary coded strings of ones and zeros are used to describe the parameters for each solution. In a multi parameter optimization problem, individual parameter coding is usually concatenated into a complete string which is shown in Figure 4.

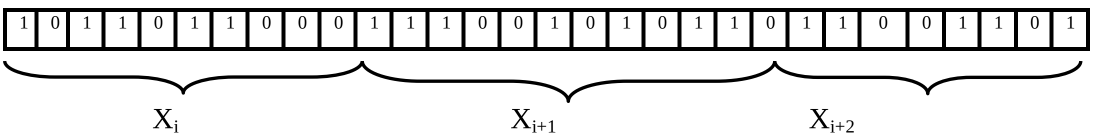

Figure 4 : Binary representation in GA.

The length of the string depends on the required precision. The mapping from a binary string to a real number is completed in two steps:

Step 1: Find code length for x_i (i = 1, . . ., n):

$$c = (x_i^{max} - x_i^{min}) * r \tag{5}$$

$$\text{Where, } 2^n < c < 2^{n+1}$$

Where r is the required precision (10^1, 10^2, 10^3, . . .).

Code length for x_i is as follows: $lx_i = n + 1$ (6)

Total string length is given by $l = \sum_{1}^{n} lx_i$ (7)

Step 2: Mapping from a binary string to a real number is

$$x_i = x_i^{\min} + \frac{\left(x_i^{\max} - x_i^{\min}\right)}{2^n - 1} \sum_{i=1}^{n} q_{ij} 2^{j-1} \tag{8}$$

where q_{ij} € [0,1]

In order to generate the chromosomes, the length of the chromosome is calculated first. Then random numbers in the range of {0, 1} are generated to form the chromosome.

5.2. Genetic operators

The genetic algorithms contains several operators e.g. reproduction, crossover, mutation, etc that are used to generate new solutions form the existing ones.

5.2.1. Reproduction

Reproduction involves selection of chromosomes for the next generation. In the most general case, the fitness of an individual determines the probability of its survival for the next generation. After assessing the fitness value for each string in the initial population, only a few strings with high fitness value are considered in the reproduction. There are many different types of reproduction operators which are proportional selection, tournament selection, ranking selection, etc. In this study, tournament selection is selected, since it has better convergence and computational time compared to any other reproduction operator [27]. In tournament selection, two individuals are chosen from the population at random. Then the string which has best fitness value is selected. This procedure is continued until the size of the reproduction population is equal to the size of the population.

5.2.2. Crossover

The crossover operator is the most important operator of GA. This operation partially exchanges information between any two selected individuals. In crossover, generally two chromosomes, called parents, are combined together to form new chromosomes, called offsprings. The parents are selected among existing chromosomes in the population with preference towards fitness so that offspring is expected to inherit good genes which make the parents fitter. By iteratively applying the crossover operator, genes of good chromosomes are expected to appear more frequently in the population, eventually leading to convergence to an overall good solution. The crossover operation is illustrated in Figure 5.

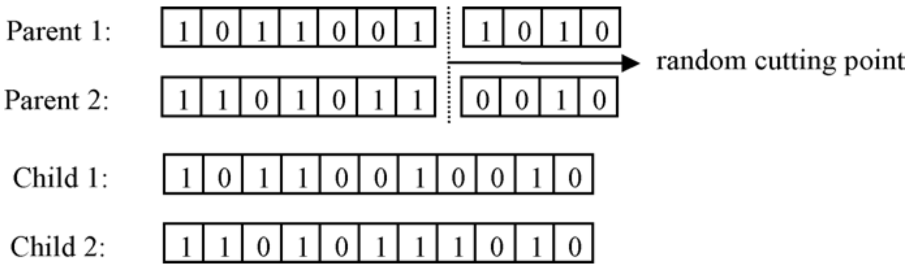

Figure 5 : Illustration of crossover operator.

In order to carry out the crossover operation, two individuals are selected from the population at random. Then a random number in the range of {0, 1} is generated. If this random number is less than the probability of crossover then these individuals are subjected to crossover, otherwise they are copied to new population as they are. Also the crossover point is selected at random. Probability of crossover (Pc) is selected generally between 0.6 and 0.9.

5.2.3. Mutation

The mutation operator introduces random changes into characteristics of chromosomes. This is the process of randomly modifying the string with small probability. Mutation is generally applied at the gene level. In typical GA implementations, the mutation rate (probability of changing the properties of a gene) is very small and depends on the length of the chromosome. Mutation operator changes 1–0 and vice versa. Therefore, the new chromosome produced by mutation will not be very different from the original one. Mutation plays a critical role in GA. Mutation reintroduces genetic diversity back into the population and assists the search escape from local optima. The need for mutation is to keep diversity in the population [28]. This is to prevent falling all solutions in population into a local optimum of solved problem. Figure 6 illustrates the mutation operation at seventh bit position.

1	0	1	1	0	1	1	1	0	1	1

→

1	0	1	1	0	1	1	1	0	1	1

Mutation

Figure 6 : Illustration of Mutation operator.

In order to determine whether a chromosome is to be subjected to mutation, a random number in the range of {0, 1} is generated. If this random number is less than the probability of mutation, selected chromosome will be mutated. Probability of mutation should be selected very low as a high mutation will destroy fit chromosomes and degenerate the GA into a random walk. Pm should be selected between 0.02 and 0.06 [28].

6. DEVELOPMENT OF EMPIRICAL MODELS

The initial effort in this work is to develop mathematical relationships between the control variables and the output responses for Bead width, Depth of Penetration and Bead Volume using RSM. Design expert, 7.1 v, statistical analysis software [29], is used to compute the regression coefficients of the proposed models. Because of the lower predictability of the first-order model for the present problem, the second-order models are postulated. The developed empirical models are tested for their adequacy using the following tests; Analysis of variance (ANOVA) is carried out for the Quadratic response surface models. The statistics of ANOVA for Bead Penetration, Bead width & Bead volume are given in Tables 4, 5 and 6 respectively. In case of Bead penetration, it can be observed from Table 4 that the value of "Prob. > F" for the model is less than 0.05, which indicates that the model is significant [30]. Similarly for Bead width and Bead volume, the value of "Prob.>F" is less than 0.05 which indicates that the model is significant.

Table 4. ANOVA [Partial sum of squares] for Penetration

Source	Sum of Squares	d. f.	Mean Square	F-Value	Prob > F
Model	1.0167	14	0.0726	15.22	0.0001*
X1	0.6987	1	0.6987	146.42	0.0001*
X2	0.0393	1	0.0393	8.23	0.0111
X3	0.0754	1	0.0754	15.80	0.0011
X4	0.0858	1	0.0858	17.98	0.0006
X1X2	0.0260	1	0.0260	5.45	0.0329
X1X3	0.0058	1	0.0058	1.22	0.2860
X1X4	0.0026	1	0.0026	0.55	0.4689
X2X3	0.0002	1	0.0002	0.04	0.8447
X2X4	0.0004	1	0.0004	0.07	0.7895
X3X4	0.0179	1	0.0179	3.75	0.0707
X1^2	0.0587	1	0.0587	12.29	0.0029
X2^2	0.0007	1	0.0007	0.15	0.7012
X3^2	0.0020	1	0.0020	0.43	0.5221
X4^2	0.0023	1	0.0023	0.49	0.4938
Residual	0.0764	16	0.0048		
Pure Error	0.0140	6	0.0023		
Cor Total	1.0931	30			
Std. Dev.	0.069			R^2	0.9301
Mean	2.02			Adj. R^2	0.8690
* - Refers to Significant terms					

Table 5. ANOVA [Partial sum of squares] for Bead Width

Source	Sum of Squares	d. f.	Mean Square	F-Value	Prob > F
Model	0.4573	10	0.0457	23.92	0.0001*

Source	Sum of Squares	d. f.	Mean Square	F-Value	Prob > F
X1	0.0220	1	0.0220	11.49	0.0029
X2	0.0030	1	0.0030	1.57	0.2253
X3	0.3514	1	0.3514	183.81	0.0001*
X4	0.0126	1	0.0126	6.59	0.0184
X1X2	0.0042	1	0.0042	2.21	0.1527
X1X3	0.0294	1	0.0294	15.39	0.0008
X1X4	0.0082	1	0.0082	4.28	0.0516
X2X3	0.0031	1	0.0031	1.61	0.2189
X2X4	0.0000	1	0.0000	0.02	0.8833
X3X4	0.0234	1	0.0234	12.25	0.0023
Residual	0.0382	20	0.0019		
Pure Error	0.0043	6	0.0007		
Cor Total	0.4955	30			
Std. Dev.	0.044			R^2	0.9228
Mean	0.96			Adj. R^2	0.8843
* - Refers to Significant terms					

Table 6. ANOVA [Partial sum of squares] for Bead Volume

Source	Sum of Squares	d. f.	Mean Square	F-Value	Prob > F
Model	0.2128	14	0.0152	12.16	0.0001*
X1	0.0015	1	0.0015	1.22	0.2864
X2	0.1214	1	0.1214	97.14	0.0001*
X3	0.0357	1	0.0357	28.53	0.0001*
X4	0.0053	1	0.0053	4.25	0.0559
X1X2	0.0000	1	0.0000	0.00	0.9833
X1X3	0.0000	1	0.0000	0.01	0.9279

Source	Sum of Squares	d. f.	Mean Square	F-Value	Prob > F
X1X4	0.0012	1	0.0012	0.97	0.3403
X2X3	0.0112	1	0.0112	8.95	0.0086
X2X4	0.0011	1	0.0011	0.91	0.3539
X3X4	0.0005	1	0.0005	0.38	0.5471
X1^2	0.0071	1	0.0071	5.67	0.0301
X2^2	0.0293	1	0.0293	23.41	0.0002
X3^2	0.0000	1	0.0000	0.03	0.8654
X4^2	0.0013	1	0.00139	1.1168	0.3063
Residual	0.0199	16	0.00124		
Pure Error	0.0009	6	0.00016		
Cor Total	0.2327	30			
Std. Dev.	0.035			R^2	0.9141
Mean	0.46			Adj. R^2	0.8389
* - Refers to Significant terms					

The normal probability plots of the residuals for the output responses are shown in Figures 7, 8 and 9.

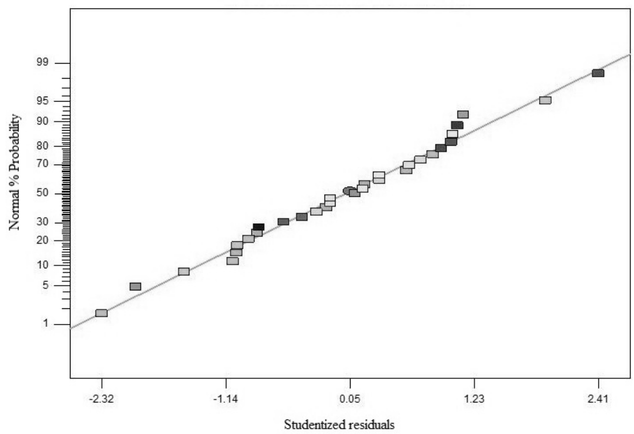

Figure 7. Normal probability plot of residuals for penetration.

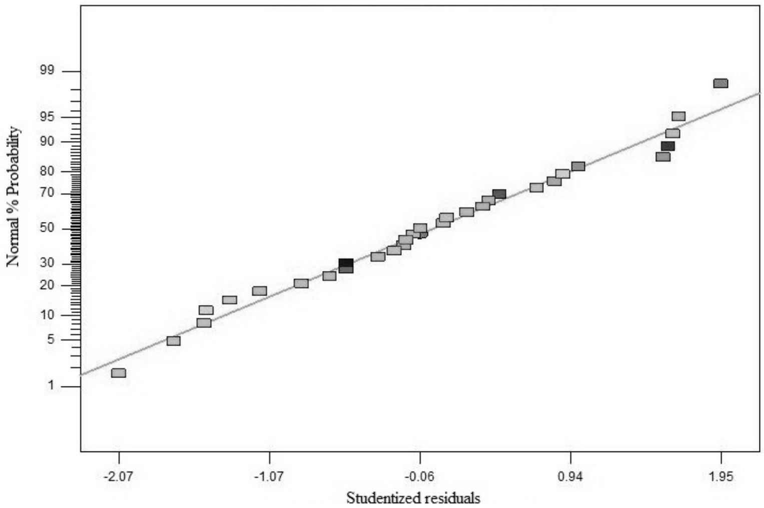

Figure 8. Normal probability plot of residuals for Bead width.

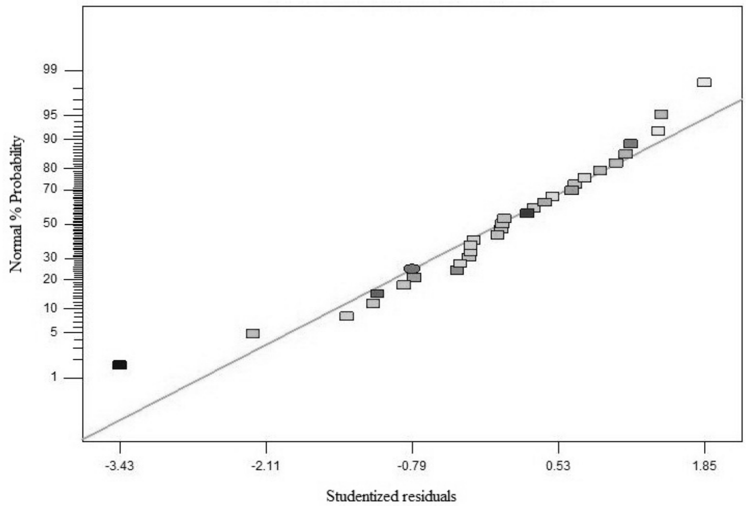

Figure 9. Normal probability plot of residuals for Bead volume.

A check on the plots reveals that the residuals are located on a straight line which means that the errors are distributed normally and the regression models are fairly well fitted with the observed values. To check whether the fitted models actually describe the experimental data, the multiple regression coefficients (R^2) were computed. The multiple regression coefficients

(R^2) for Penetration, Bead width and Bead volume are found to be 0.93, 0.922 and 0.914, respectively. This shows that the second-order model can explain the variation in the Penetration, Bead width and Bead volume up to the extent of 93%, 92.2% and 91.4%. On the basis of the high values of the multiple regression coefficients, it can be said that the second-order models are adequate in representing the process. The following equations were obtained for Penetration, Bead width and Bead volume in terms of coded factors:

penetration = 2.06 + 0.34 * x1 + 0.081* x2 - 0.11 * x3 + 0.12 * x4 - 0.16 * x1 * x2 - 0.076 * x1 * x3 - 0.051 * x1 * x4 + 0.014 * x2 * x3 + 0.019 * x2 * x4 +0.13 * x3 *x4 - 0.18 * x1*x1 - 0.020 * x2*x2 + 0.034* x3*x3 - 0.036* x4*x4 (9)

Bead width = 0.96 + 0.060 * x1 + 0.022 * x2- 0.24 *x3 - 0.046 * x4 + 0.065* x1* x2 + 0.17 * x1 * x3 + 0.091 * x1 * x4 - 0.055 * x2 * x3 - 0.0065 * x2 * x4 + 0.15*x3 *x4 (10)

Bead Volume = 0.50 + 0.016* x1 + 0.14 * x2 - 0.077 * x3 + 0.030 * x4 - 0.00075* x1 *x2 - 0.00325* x1 * x3 + 0.035* x1 * x4 + 0.11 * x2 * x3 + 0.034* x2 * x4- 0.022* x3 * x4 - 0.063 * x1*x1 - 0.13 * x2*x2 + 0.00455 * x3*x3 - 0.028 * 4*x4 (11)

7. ANALYSIS OF EFFECTS OF PROCESS PARAMETERS BASED ON DEVELOPED MODELS

After checking the model adequacy, the individual significant parameters have been found by computing the p-values. Tables 4, 5 and 6 summarize them for Bead penetration, Bead width & Bead volume respectively.

If P-value for a factor is less than 0.05, then the factor is considered as statistically significant at 95% confidence level. From Table 4, it is observed that the control factor Pulse duration (x_1) found to be significant on Bead penetration as the value of "Prob.>F" is less than 0.05. The plots for the significant terms on Bead penetration are drawn and analyzed and is shown in Figure 10.

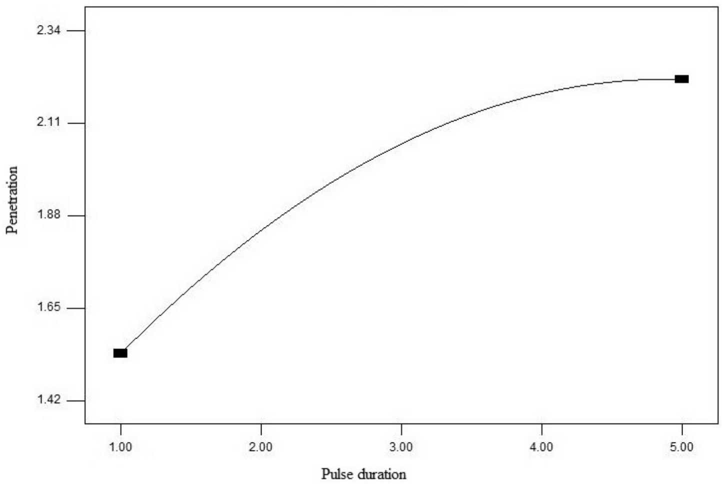

Figure 10. Effect of Pulse duration on penetration.

From the Figure 10, it is observed that the depth of penetration increases with increase in pulse duration. This is due to increase of the overlapping of the pulses. Overlapping of pulses increases the density of pulse and in turn increases the weld depth. Hence inorder to obtain more depth of penetration, the Pulse duration should be increased.

Similar analysis is carried out for both Bead width and Bead volume. From Table 5, it is observed that the control factor welding speed (x_3) found to be significant on Bead width, as the value of "Prob.>F" is less than 0.05. The plots for the significant terms on Bead width are drawn and analyzed and is shown in Figure 11.

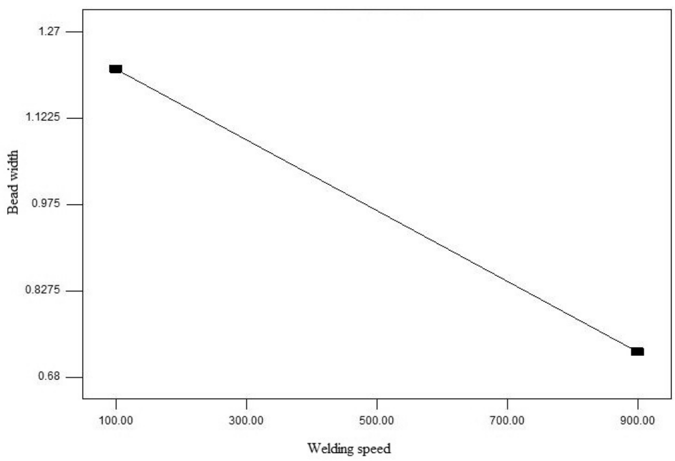

Figure 11. Effect of Welding speed on bead width.

The effect of Welding speed on Bead with as seen in figure 11, It is observed that as the welding speed increases, the welding torch travels at great speed over the base metal, resulting in a lower metal deposition rate on the joint. Also the heat input decreases appreciably when welding speed increases. Hence because of less heat input and a lower metal deposition rate, bead volume decreases.

From Table 6, it is observed that the control factors Pulse frequency (x_2) and Welding speed (x_3) found to be significant on Bead volume, as the value of “Prob.>F” is less than 0.05. The plots for the significant terms on Bead volume are drawn and analyzed and are shown in Figure 12 and Figure 13.

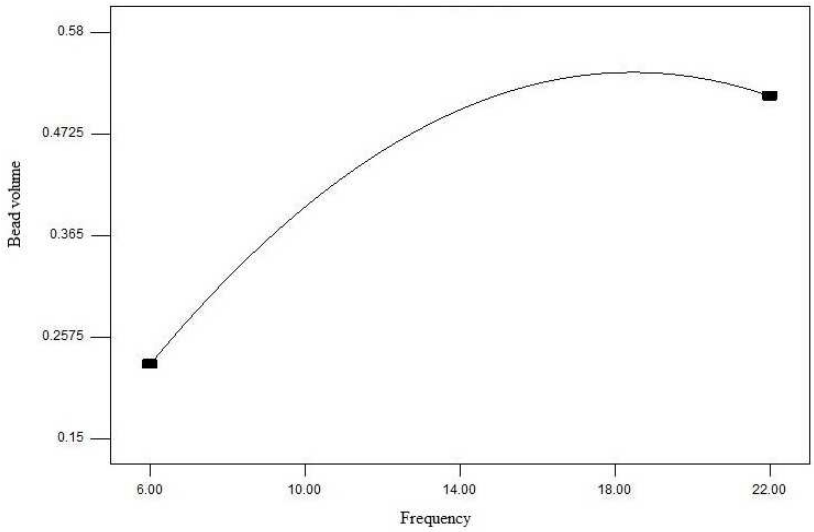

Figure 12. Effect of Frequency on bead volume.

The individual effect of Frequency on bead volume can be observed from figure 12.The bead volume increases with increase in laser frequency. This matter is attributed to increasing the number of pulses with frequency, which in turn increases the heat induced in the material.

The effect of Welding speed on bead volume as seen in figure 13, It is observed that as the welding speed increases, the welding torch travels at great speed over the base metal, resulting in a lower metal deposition rate on the joint. Also the heat input decreases appreciably when welding speed increases. Hence because of less heat input and a lower metal deposition rate, bead volume decreases.

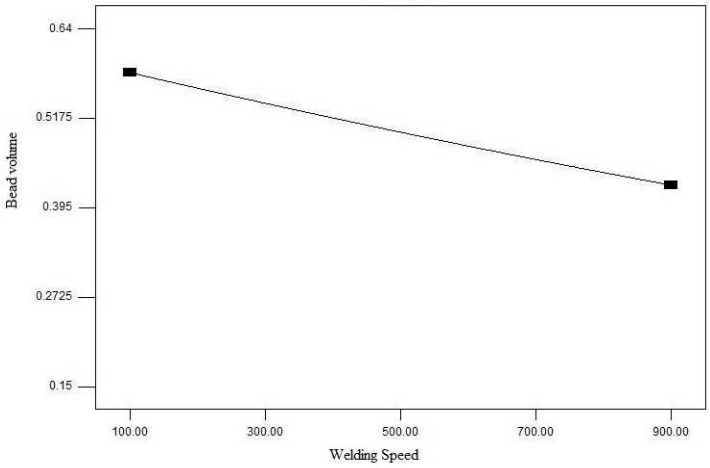

Figure 13. Effect of Welding speed on bead volume.

It is observed from the above analysis that the Pulse duration is significant on Bead penetration, Welding speed is significant on Bead width and Pulse frequency and Welding speed is significant on Bead volume.

8. FORMULATION OF OPTIMIZATION PROBLEM

In the present work, the bead geometrical parameters were chosen to be the constraints and the minimization of volume of the weld bead was considered to be the objective function. Minimizing the volume of the weld bead reduces the welding cost through reduced heat input and energy consumption and increased welding production through a high welding speed [31].

The present problem is formulated an optimization model as shown below:

Minimize bead volume V

Subject to: $P \geq 2.25$, $W \leq 0.7$

$1 \leq x_1 \leq 5$, $6 \leq x_2 \leq 22$, $100 \leq x_3 \leq 900$, $9 \leq x_4 \leq 21$

In the above model, P, W and V represent the equations (9), (10) and (11) respectively. The bead parameters and the feasible ranges of the input variables were established with a view to have defect-free welded joint. Feasible bounds of the control variables are listed in the Table 7.

Table 7. Feasible bounds of the control variables

Variable	Lower limit	Upper limit
Pulse duration (x1)	1	5
Pulse frequency (x2)	6	22
Welding speed (x3)	100	900
Pulse energy (x4)	9	21

The optimal values shown in Table 8 are found out by using the GA Optimization module available in MATLAB 6.1 is used in the present work.

Table 8. Optimal values

Variable	x_1 *(Pulse Duration)* (µs)	x_2 *(Pulse frequency) (Hz)*	x_3 *(Welding Speed) (J)*	x_4 *(Pulse Energy) (mm/min)*	Penetration	Bead Width	Bead Volume
Value	3.929	6.31	761.444	15.932	2.24	0.7	0.2688

CONCLUSIONS

Weld quality in a Laser Beam welding process is strongly characterized by bead geometry. This is because bead geometry plays a vital role in determining the mechanical properties of the weld. However, the selection of right combination of input parameters in LBM is difficult as the process involves a large number of control variables. The present work proposed a methodology to determine the optimal process parameters in LBM. First RSM was used to develop the second-order polynomial models for the Bead penetration, Bead width and Bead volume by using the Experimental data. Later, the problem was formulated as an optimization model minimizing the Bead volume subjected to the constraints of Bead penetration and bead width. The Volume is optimized by using the Genetic algorithm module available in the MATLAB6.1. The proposed approach is a full-fledged approach to find the optimal values of the process variables in LBW process and hence enable the industries to have automation of the process.

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G. Harinath Gowd
Associate Professor
Department of Mechanical Engineering,
Sri Krishnadevaraya Engineering College,
Gooty, PIN- 515 401, Andhra Pradesh, India.
Email: hari.skd@gmail.com

A. Gopala Krishna
Associate Professor,
Department of Mechanical Engineering,
College of Engineering, Jawaharlal Nehru Technological University,
Kakinada, PIN - 533 003, Andhra Pradesh, India.
Email: dr.a.gopalakrishna@gmail.com,