Process Optimization for Laser Cladding Operation of Alloy Steel using Genetic Algorithm and Artificial Neural Network

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Abstract:
This paper presents an investigation on single objective optimization for CO_2 laser cladding process considering clad height (H) and clad width (W) as performance characteristics. This optimization of multiple quality characteristics has been done using Genetic Algorithm (GA) approach. The aim of this work is to predict the performance characteristics (H and W) at optimized condition by applying back propagation method of artificial neural network (ANN). The essential input process parameters are identified as laser power, scan speed of work table and powder feed rate. In order to validate the predicted result, an experiment as confirmatory test is carried out at the optimized cladding condition. It is observed that the confirmatory experimental result is showing a good agreement with the predicted one. It has also been found that the optimum condition of the cladding parameters for multi performance characteristics varies with the different combinations of weighting factors.

Keywords: Laser cladding, Taguchi method, Optimization, GA, ANN

1. Introduction:

Laser surface cladding is a popular non-traditional coating technology in recent days. This is because of the superior surface uniqueness of the coat in which the surface with resistance to wear, corrosion and hardness can be resulted. In fact, from the application point of view, the coating on any component produced by laser is highly comparable to other coating processes such as plasma coating and spray coating. Laser cladding is one of the thermal type techniques in which laser is used as heat source to deposit a thin layer of a desired metal (by melting) on the substrate surface. Laser cladding using powder can be performed in two distinct ways. In the first process, powder is pasted on the surface by some adhesive and then the clad is formed by laser beam. In the second process, powder is pneumatically fed into the melt pool on a substrate surface so that powder jet and laser beam are focused on the same area and the clad is formed on the surface; the second process is called 'blown powder method'[1]. Some of the important process parameters are- laser power, scan speed of work table, stand-off distance and powder mass flow rate. Generally, the effect of laser cladding process performance is evaluated on the basis of clad bead dimension such as clad height, clad width and depth of penetration [2, 3]. The powder injection method has been applied in the present study. The present work is performed to study laser cladding process on 20MnCr5 substrate as they are potentially used in automobile and mechanical industries.

A lot of experimental investigations have been done to analyze the effect of process parameters on clad bead geometry and clad quality by varying one factor at a time [4-6]. But a large number of experiments need more time and money. To overcome this drawback, many researchers [7-9] were applied design of experiments (DOE) technique to analyze their experimental data and optimize the process parameters for desired response(s). In recent years, Taguchi method has become a powerful tool for improving the productivity during research and development state so that quality of product can be obtained in the economical way. It is found that the traditional Taguchi method was applied to optimize a single quality characteristic in the literature. However, single-objective optimization method is easier than multi-objective optimization technique.

In the present investigation, single-objective optimization has been applied for two quality characteristics such as clad width (W) and clad height (H) during CO_2 laser cladding for manganese steel surface using Genetic Algorithm. Nature of one objective is larger-the-better for clad width and smaller the better for other one (clad height). After finding the optimum condition the optimum results are predicted by developing ANN model and compared with confirmation test.

2. Experimental Approach

The equipment used for laser cladding is a 3.5 kW continuous wave CO_2 Laser Rapid Manufacturing (LRM) system. The LRM set-up consists of a high power laser system integrated with the beam delivery system, powder feeding system and job/beam manipulation system [13]. Fig. 1 depicts the schematic arrangement of the LRM machine. Ni-Cr-Mo powder has been fed into the molten pool using a volumetric-controlled powder feeder through a co-axial powder feeding nozzle. Argon gas is used as a shielding gas and powder carrier. The key process parameters are selected from the literature survey and those are laser power, scan speed and powder feed rate. First, a number of single tracks are deposited at various machining conditions to obtain continuous and uniform tracks which lead to facilitate to determine the range of process parameters for control levels in Taguchi method (Table.3). Then the actual experiments are performed as per the L_9 Taguchi orthogonal array. Focal length (f=2 mm) and stand-off-distance (SOD=16 mm) have been kept constant throughout the experimentation. Experiments are performed by expecting to obtain the aspect ratio (W/H) of clad bead nearby 15.

The experiments are performed on Φ 3 inch x 0.5 inch thick specimens of 20MnCr5 steel. The surfaces of the substrate are sand blasted prior to laser cladding. The powder (feeding material) used in laser cladding is Inconel-625 powder. The powder particles are of globe-shaped with size of 45-106 µm. Chemical composition of the powder is shown in Table 1. In order to improve the surface characteristics of this substrate an anticorrosive powder material is used as the clad material. It is a non-magnetic, corrosion and oxidation resistant. Nickel and chromium provide resistance to oxidizing environment, while nickel and molybdenum to non-oxidizing environment. Pitting and crevice corrosion are prevented by molybdenum [10].

Table1: composition of Inconel-625

Elements	Chromium	Molybdenum	Nickel
Percentage in weight	20%	5%	Balance

The design of experiment is a statistical tool which helps to minimize the number of experiments so that appropriate data will be collected [11]; the minimum number of experiments will be performed to acquire the necessary technical information and suitable statistical methods will be used to analyze the collected data. Taguchi's method for experimental design is straightforward and easy to apply to many engineering situations, making it a powerful yet simple tool [12, 13]. The initial task of this stage is to find out the key process control parameters with their ranges and performance evaluation parameter (output) that is to be measured. The levels of each variable represent the range for which the effect of that variable is desired to be known.

In order to minimize the number of experiments, the experiments are planned against a three level Taguchi's Orthogonal Array that required 9 runs in total to be carried out. The process parameters of laser power, scan speed of the table and powder feed rate have been varied to investigate the process responses of clad quality. The selected L_9 orthogonal array in the present analysis is presented in Table 2.

Table 2: L_9 Taguchi orthogonal array

Experiment No.	Laser Power- (kW)	Scan speed-V (mm/min)	Powder eed rate-C (mm^3/m
1	1.0	0.3	5
2	1.0	0.5	8
3	1.0	0.8	11
4	1.25	0.3	8
5	1.25	0.5	11
6	1.25	0.8	5
7	1.5	0.3	11
8	1.5	0.5	5
9	1.5	0.8	8

2.1 Collecting the experimental data

The quality characteristics of clad bead are determined by measuring clad width (W) and clad depth (D) [Fig.1]. For each of the clad beads three measurements at different location have been taken and averages of them are considered. The measured values of two responses H and W using L_9 orthogonal array are shown in Table 3.

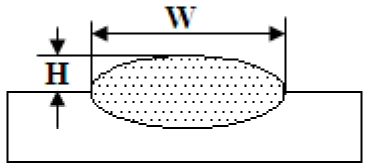

Fig.1 Geometry of cross-section of a single layer and single bead clad

Table 3: Experimental Observations using L_9 OA

Trials Run	Clad Height (H)-mm	Clad Width (W)-mm
1	0.39	0.94
2	0.34	0.88
3	0.47	0.99
4	0.81	1.33
5	0.41	0.97
6	0.16	0.75
7	1.22	1.97
8	0.24	1.3
9	0.25	0.92

3. Application of Genetic Algorithm to the Laser Cladding Process

The genetic algorithm (GA) is a stochastic searching method which searches throughout the solution space to find the best solution for a given optimization criteria, mimicking the process of natural evolution, the principle of survival of the fittest. The evolution usually starts from a population of randomly generated chromosomes and happens in generations. In each generation, the fitness of every individual chromosome in the population is evaluated. This fitness function is always problem dependent. Depending on the problem in hand, one has to select or design a suitable fitness function. The chromosome having the best fitness value is included in a new population for the next generation directly without any modification. Such chromosomes are called elite chromosomes. Thereafter, from the rest of the parent chromosomes for that generation, multiple ones are stochastically selected based on their fitness (selection) and recombined (crossover) and randomly mutated (mutation) to be included in the new population. The new population is then used in the next iteration of the algorithm. Generally, the algorithm terminates when a pre-defined number of generations have been produced, or a satisfactory fitness level has been reached by the population. However, if the algorithm has terminated due to a pre-defined number of generations, a satisfactory solution may or may not have been reached. Also, a satisfactory fitness level may require a huge number of generations to be executed. Hence, a trade-off between the maximum of number of generations and the desired fitness level is often called for. A pseudo-code for a Simple Genetic Algorithm (SGA) is presented in Fig.2.

```
Begin
Initialize population;
Evaluate population;
    repeat
        Reproduction;
        Crossover;
        Mutation;
        Evaluate population;
until (termination criteria);
end.
```

Fig. 2 A pseudo-code for a Simple Genetic Algorithm (SGA)

Here, we have used single objective real coded genetic algorithm for obtaining the combination of laser power, scan speed and powder feed rate at optimized condition. The optimization is done twice: once for minimizing the clad height and once for maximizing the clad width. The initial population in both cases was a set of randomly generated real numbers in the given range. The maximum number of chromosomes in the population was fixed to be 100. Each chromosome size is three numbers long, one number for each of the laser power, scan speed and powder feed rate.

The following equations of clad height and clad width, obtained for given values of laser power, scan speed and powder feed rate by multiple regression analysis, were used as the objective functions respectively for minimizing clad height and maximizing clad width.

$$Clad\ Height(mm) = 2.5141 - 4.4317*A - 4.9585*B + 0.4663*C - 0.6222*A*B - 0.1962*A*C - 0.2862*B*C + 2.5143*A^2 + 6.0714*B^2 \ldots\ldots(i)$$

$$Clad\ Width(mm) = 4.3322 - 6.5057*A + 0.8294*B + 0.0156*C - 3.2*A*B + 0.061*A*C - 0.1095*B*C + 3.3486*A^2 + 2.8651*B^2 \ldots\ldots(ii)$$

The maximum number of generations was fixed to 500. The parametric values of crossover probability and mutation probability were chosen to be 0.8 and 0.001 respectively. The number of elite chromosomes to be preserved was fixed to 2.

Since GA is a heuristic search process sometimes it may get stuck at local minima or maxima during optimization. So, optimization for minimizing clad height and maximizing clad width is executed 10 times each. Table 4 presents the optimized process parameters for the minimum value of clad height and maximum value of clad width along with the respective standard deviations.

Table 4: Optimized Process Parameters using GA

Responses	Optimized Control Factors			Optimized Value	Standard Deviatio (%)
	Laser Power	Scan Speed	Powder Feed Rate		
Clad Height	1.2252	0.6205	5.3475	0.0951	1.06
Clad Width	1.4970	0.3024	10.9668	1.9710	1.92

4. Process Prediction through ANN during Optimization

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems [14]. As in nature, the network function is determined largely by the connections between elements. One can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network [15].

There are various algorithms in the artificial neural network (ANN). In the present study the back propagation training algorithm is used. The aim of the ANN modeling is to establish a correlation of input process variables such as laser power, scan speed and powder feed rate with output parameters namely clad width and clad depth. The back propagation neural networks are usually referred to as feed forwarded and multi layered perceptron (MLP) with number of hidden layers. The error back-propagation process consists of two passes through the different layer of the network: a forward pass and a backward pass. In the forward pass an activity pattern (input vector) is applied to the sensory nodes of the network and its effect propagates through the network layer by layer. Finally, a set of output is produced as the actual response of the network. During the backward pass, all synaptic weights are adjusted in accordance with the error correction rule with the following formula.

$$\Delta\Omega(t) = \beta\delta_i O_i + \alpha\Delta w_{ij}(t-1) \qquad \text{.........................(iii)}$$

Where, β = learning rate, α = momentum coefficient and δ= local error gradient, O_i= output of the ith unit, w_{ij}= weighting factor connecting the ith neuron of the input vector to the jth neuron of the output vector.

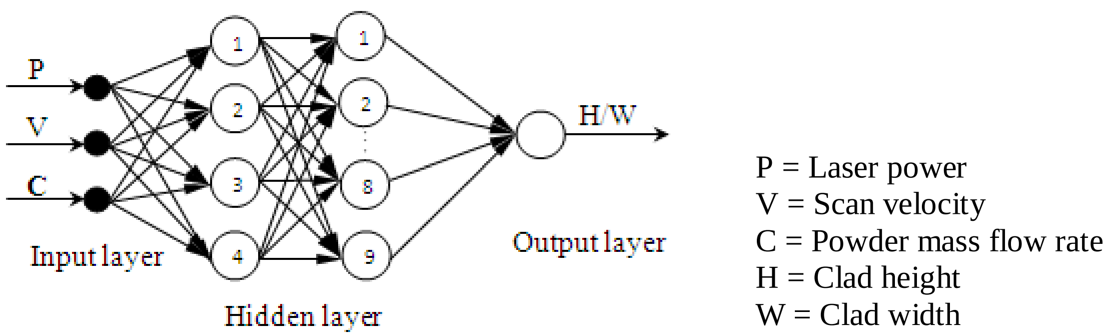

Fig.3: Structure of 4 layered ANN model for clad width

4.1 Training phase of neural network

To increase the accuracy and speed of the network the normalized data set obtained from Equation (iv) is used in the training and testing phase. Out of total available data set, 70% data set was used for training the network and remaining used for testing the network. There are two responses considered in the present process, one model for clad width (W) and another model for clad depth (D) formed separately. Therefore the number of neurons in the input and output layer has been set to three and one respectively in the present neural network architecture. Several network structures are formed by keep on changing the number of neurons in the hidden layers and finally 3-4-9-1 configuration is selected for clad width and 3-8-11-1 is selected for clad depth. The error plot for clad width is shown in Fig.4 and same kind of trend is also obtained in case of clad depth. The selected values of model parameters for clad width are shown in Table 5.

$$\eta_i = \frac{D_{ij}}{D_i^*} \qquad \text{.............................(iv)}$$

Where D_{ij} = Experimental valu at i-th number of experiment for j-th response, D_i^* = Maximum value for j-th response.

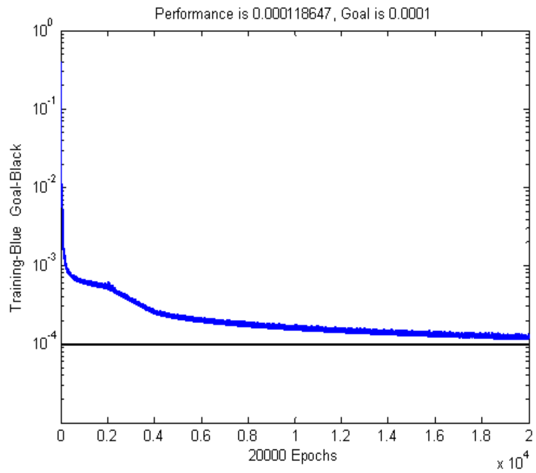

Fig.4: Variation of total error with number of Epochs in 3-4-9-1 network for clad width

Table 5: Selected Training Parameters of ANN for Clad Width

No. of epochs	20000
Goal	0.0001
Learning rate	0.05
Max_fail	5
Mu_max	10^{10}
Transfer function	Log sigmoid

5. Confirmatory test

For validation of the predicted results at optimum condition, experiments are conducted as per the optimum condition and observed that the average results are fairly close to the predicted results.

The estimated clad height or clad width $\bar{\eta}$ at the optimal level can be calculated as follows.

$$\bar{\eta} = \eta_m + \sum_{i=1}^{o} (\eta_i - \eta_m) \qquad \text{................ (v)}$$

Where, η_m is the total mean clad height, η_i is the mean clad height at the optimal level and o is the number of main design parameters that affect the quality characteristics. Table 6 shows the comparison of the estimated responses (calculated using equation (v)) with the actual responses obtained from the experiment using the optimal process parameter combination. The absolute prediction error (APE) in percentage has been calculated using the following formulae.

$$\text{APE} = \left| \frac{\text{Experimental - Predicted}}{\text{Experimental}} \right| \text{X100\%} \qquad \text{................ ..(vi)}$$

Table 6: Validation of the ANN Predicted Results

Responses	Experimental Valu (mm)	Predicted Value (mm)	APE (%)
Clad Height	0.121	0.0872	27.94
Clad Width	2.124	2.3211	9.28

6. Conclusion

In the context of CO_2 laser cladding process performance for 20MnCr5 substrate using Inconel-625 powder as cladding material, an attempt is made to determine the optimum combination of laser power, scan speed and powder feed rate to maximize clad width as well as to minimize clad height at a time using Genetic Algorithm approach. From optimization method using GA, the optimum values obtained for H and W are 0.0951 mm and 1.9710 mm respectively which are showing great improvement in performance characteristics.

The artificial neural network model using BP-MLP technique has been developed specially for predicting the clad bead characteristics at optimum cladding condition. This model also helps to find the responses at other combinations of process variables. It is observed that developed ANN model shows a good agreement with the experimental results.

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