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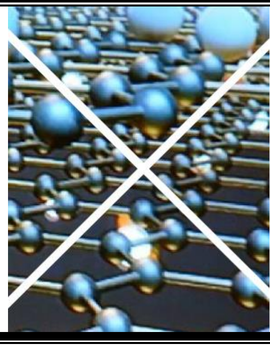

MODELING AND OPTIMUM PARAMETERS OF CO_2 LASER MIG HYBRID WELDING PROCESS

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Abstract

In engineering applications, the welding process is vitally important for many industrial areas. Generally, Hybrid Laser-MIG Welding (HLAW) is a preferred process in shipbuilding, road transport, rail transport, oil and gas. Principally, the quality of Hybrid Laser-MIG welding is dominantly determined by some welding criteria and also plays an essential role in the characterization of their mechanical properties. In this study, the effect of HLAW process parameters (power, torch angle, the distance between laser and welding torch, focal distance from workpiece surface) on weld quality and weld penetration depth responses were investigated. Mathematical models were developed for optimization and prediction of weld penetration depth. Also, a multiple non-linear regression analysis was applied to construct relationships between welding process parameters and weld penetration in HLAW. Firstly, a mathematical model was developed to predict section weld penetration. The mathematical model for estimating the HLAW phenomenon was found to be able to accurately predict the process as a result of multiple regression analysis. In the optimization step, "Random Search" methods were used. As a result of the work done, the optimum weld penetration depth was gained. The results showed that welding penetration increased with decreasing the torch angle.

Keywords: Hybrid Laser-MIG Welding (HLAW), Stochastic Optimization Method, Neuro-Regression Approach, Torch Angle.

1. Introduction

Recently, Hybrid Laser–MIG Welding becomes frequently used production operations with a wide range of applications requiring high precision in railway, maritime, bridges, construction sector, automotive, aviation, etc. The MIG welding process is an extremely complex phenomenon that has high temperatures and causes severe distortions and permanent stresses. Laser welding is a non-contact high energy beam. A laser-supported welding process can be

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used for situations where other welding methods are not used because the laser can stabilize the arc. HLAW, which allows the combination of a laser beam and an electric arc, can produce welds with many technical advantages compared to those made using only one laser. The main advantages of this process are i) higher speeds, ii) deeper welding penetration, iii) better weld lead surface, iv)low distortion and greater tolerance to fit-up, and v) a clear improvement of joining process reliability [1-3]. As the two approaches are combined in a single process, a good welding quality can be obtained only by finding suitable process parameters and controlling them. The parameters of each welding can be adjusted according to the wanted conditions of the process. There are many individual and combined welding process parameters such as laser power, arc power, focal point position, focal length, torch angle and direction, electrode position, the distance between two processes, wire feed rate, welding position, and welding speed. The selection of proper welding parameters is essential to obtain optimum welding penetration [4]. In most of the applications and research discussed the effect of different welding parameters on welding penetration, weld shape, and welding efficiency in laser hybrid arc welding. Qin et al. (2007) investigated the effect of hybrid laser welding parameters on welding shape defined by weld penetration depth, and weld width. The results showed that laser energy is the main factor affecting weld penetration and increases weld speed. The weld width is also mainly dependent on the welding arc at a specific welding speed. Besides, this study revealed that an optimum laser-arc distance and laser focus location are required for deeper penetration [5]. While the laser arc distance is too short, it reduces the penetration of the laser beam due to the melted drops blocking the laser [6], on the other hand, the thermal efficiency of the welding process decreased at a higher laser-arc distance [7]. The increase in laser power leads to an improvement in the overall power of the heat sources and the coupling effect between the laser and the arc, which means increased weld penetration [5, 8, 9]. On the other hand, the downward flow of high-temperature melt is accelerated [10, 11]. Generally, the desired penetration of welding parameters is determined by experience or based on a handbook. However, it is not possible to ensure that weld processing parameters are used for the desired optimum weld penetration in a given welding process and environment. Optimization of parameters plays a very important role in providing output characteristics such as weld strength, weld penetration depth, and weld part geometry in the design of all complex systems and engineering structures. Several statistical studies have been conducted using analysis of variance (ANOVA) in the experimental data set to find the effect of different welding parameters on the welding quality in hybrid CO_2 Laser-MIG welding [12, 13]. Casalino [14] utilized the regression analysis to determine the dominated contributions and relations among the operation parameters of CO_2 laser-MIG welding. According to results, an increasing in laser power cause deeper weld penetration. Ghosal and Chaki [15] introduced an ANN–Quasi-Newton optimization hybrid model for CO_2 laser–MIG welding of 5005 Al-Mg alloy. The objective function is penetration depth, the design variables are i) power, ii) focal distance from the workpiece surface, iii) torch angle and iv) the distance between the laser and the welding torch. They found that ANN–GA approach has produced optimum results compared to ANN–SA and ANN–Quasi-Newton models [16]. All of these studies use only one or two regression models on welding quality modeling and optimization and generally coefficient of determination (R^2) value of the model was only calculated. However, the high R^2 value is not sufficient to define all the process.

In this study, two types (conventional linear, and rational-linear) of multiple regression models were used and adjusted, training and testing coefficient of determinations also calculated besides R^2 value for each model. The mathematical model of HLAW including input parameters and welded geometry were given. A stochastic optimization algorithm "Random Search" (RS) was used to investigate the effects of laser–MIG hybrid welding input parameters on weld penetration depth. This study aims to determine the optimum welding torch angle (A) providing maximum penetration.

2. Materials and Methods

2.1. Experimental Details

In Figure 1, a schematic representation of the experimental setup is given. Basically, laser – MIG hybrid welding quality is strongly characterized by welding penetration with various quality characteristics. There are four significant parameters of a Hybrid laser-MIG welding setup.

These are the focal distance from the workpiece surface (F in mm), torch angle (A in deg.), the distance between the laser and the welding torch (S in mm), weld penetration depth (D in mm) and power (P in W) [14]. The measured weld penetration depth for different input parameters are given in Table 1.

Various quality characteristics of welding were calculated under the maximum welding penetration condition. In order to solve these problems, an objective function belonging to the penetration of welding has been created. In the solution process of the optimization problems, a stochastic algorithm the RS was used.

2.2. Regression Analysis

In this study, two regression models were preferred because of the complexity of the problem. Model validation or comparison is an important implementation of regression analysis. To reach a curve that fits well between the model and experimental data of a system, it is one of the best indicators of the success of a mathematical model. However, a good fit is not always proof that the model is correct. It is important to be careful at this stage to make sense of the work done. The estimation of parameters is a direct result of regression. Mathematica's "*FindFit*" solver is selected to reach appropriate regression models [17].

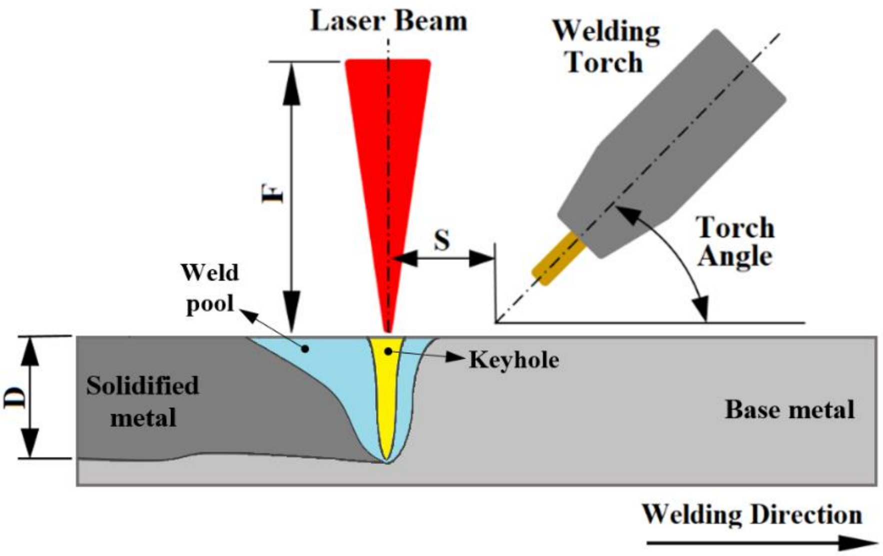

Figure 1. Schematic representation of the experimental welding setup [14].

Table 1. Experimental data [14, 15].

Experiment Number	Inputs data				Output data
	S (mm)	P(W)	F(mm)	A(deg)	Weld penetration depth, D (mm)
1	5	1200	0	60	2.63
2	20	1050	3.5	60	1.66
3	10	1200	0	45	2.78
4	5	900	0	60	2.06
5	20	900	2.5	60	1.46
6	5	900	2.5	60	2.52
7	20	1050	0	60	1.59
8	5	1050	3.5	60	3.21
9	5	1200	2.5	60	3.17
10	20	1050	2.5	60	1.63
11	10	1050	0	45	2.35
12	5	900	3.5	60	2.8
13	20	900	3.5	60	1.32
14	20	900	0	60	1.61
15	20	1200	2.5	60	1.71
16	20	1200	0	60	1.65
17	5	1200	3.5	60	3.26
18	5	1050	2.5	60	3.07
19	20	1200	3.5	60	1.85
20	5	1050	0	60	2.52

After the modeling step, the coefficient of determination "R^2" is calculated to see the accuracy of the model results. R^2 can be calculated as in the following equation [18].

$$R^2 = 1 - \frac{SSE}{SST} \quad (1)$$

Eq.(1) contains the sum of square errors (SSE) and the total sum of squares (SST) which are determined before the calculation of R^2. Eqs. (2) and (3) represent the formulation of them.

$$SSE = \sum_{i=1}^{n} (f_i - f_i')^2 \quad (2)$$

$$SST = \sum_{i=1}^{n} (f_i - \bar{f})^2 \quad (3)$$

Where f_i is the i^{th} experimental value, f_i' is i^{th} result obtained from the regression model, and $\bar{f}$ is the mean value of f_i [18].

By examing the literature studies in modeling and optimization of the cutting process, it is seen that the researchers usually take one or two different regression models and their goal is just to determine R^2 for the experimental data even though, determination of high R^2 value is not enough for identified physical phenomena. In other words, high R^2 values are not always good and low R^2 values are not always bad for the real systems [19]. For this reason, adjusted R^2 must be calculated in order to make a meaningful test to the fitted model. Equation 4 represents $R^2_{adjusted}$ [18].

$$R^2_{adjusted} = 1 - (1 - R^2)\frac{(n-1)}{(n-k-1)} \quad (4)$$

Where n defines the number of experiments and the number of design variables is denoted by k. It is understood from Equation 4, $R^2_{adjusted}$ will be smaller or equal to R^2 . The difference between them, depends on the number of experiments for the same independent design variables. If the number of data is increased, the difference between them will decrease, so it is important to get accurate results.

2.3. Neuro Regression Approach

Based on the neuro-regression approach, 80% and 20% of the experimental data given in Table 1 were randomly separated as training and testing parts, respectively. First, the training process was performed by using conventional regression analysis based on the ordinary least square method. The second step was to check the prediction capability of the training model on the test data [20]. It was seen that the training model's prediction was in good agreement with the actual output response (depth of weld penetration).

2.4. Optimization

There are many optimization algorithms to solve engineering design problems. These can be classified as traditional and non-traditional methods [21]. Nontraditional methods use stochastic processes and intuitively based search techniques to achieve the results and generate approximate solutions. No need for derivative knowledge, and because of its advantages such as the ease of adaptation to the full number of programming, the ability to go to conclusions from both sets of discrete and continuous solutions, they are preferred in engineering optimization problem-solving. In this study, Random Search (RS) method was used to solve the optimization problem.

2.4.1. Single objective optimization

Single objective optimization is the case where there is one objective function that is wanted to minimize or maximize. This optimization approach includes design variables and constraints. Problems solved with a one-objective optimization approach are described in the following way.

Minimize or Maximize $f\,(\theta_1, \theta_2 \ldots.. \theta_n)$

Subjected to

$h_1(\theta_1, \theta_2 \ldots.. \theta_n) \geq 0\ ; i = 1,2,\ldots,r$

$g_1(\theta_1, \theta_2 \ldots.. \theta_n) = 0\ ; j = 1,2,\ldots,m$

$\theta_L \leq (\theta_1, \theta_2 \ldots.. \theta_n) \leq \theta_U$

Here, f is the objective function, $\theta_1, \theta_2 \ldots.. \theta_n$ are the design variables, h_1 and g_1 are inequality and equality constraints. Lower and upper bounds of the problem are denoted by θ_L and θ_U, respectively.

2.4.2. Multi-objective optimization

A multi-objective optimization problem can be expressed as follows.

Minimize or Maximize $\{f_1\ (\theta_1, \theta_2 \ldots.. \theta_n),\ f_2\ (\theta_1, \theta_2 \ldots.. \theta_n),\ f_3\ (\theta_1, \theta_2 \ldots.. \theta_n), \ldots\ f_t\ (\theta_1, \theta_2 \ldots.. \theta_n)\}$

Subjected to

$h_1(\theta_1, \theta_2 \ldots.. \theta_n) \geq 0\ ; i = 1,2,\ldots,r$

$g_1(\theta_1, \theta_2 \ldots.. \theta_n) = 0\ ; j = 1,2,\ldots,m$

$\theta_L \leq (\theta_1, \theta_2 \ldots.. \theta_n) \leq \theta_U$

2.4.3 Random Search Algorithm

One of the efficient stochastic based optimization algorithms is Random Search (RS). In this algorithm, two sequential steps (scale, transform) are applied to the resulting values in the first step. They are vital to produce good proximity to the distribution. The main advantage of the RS algorithm is the ability to achieve general optimality for non-convex, differentiable functions, including continuous and discrete domains. The implementation of the RS method to complicated design problems is relatively simple. In general, RS algorithms are known to be "powerful" and perform well because they quickly result in poorly structured global optimization problems. Figure 2 shows a flow chart containing the basic working principles of the method.

Table 2. Forms of different multiple regression models [19].

Model Name	Nomenclature	Formula
Multiple Linear	L	$Y = a_0 + a_1 * d + a_2 * s$
Multiple Linear Rational	LR	$Y = (a_0 + a_1 * d + a_2 * s)/(b_0 + b_1 * d + b_2 * s)$

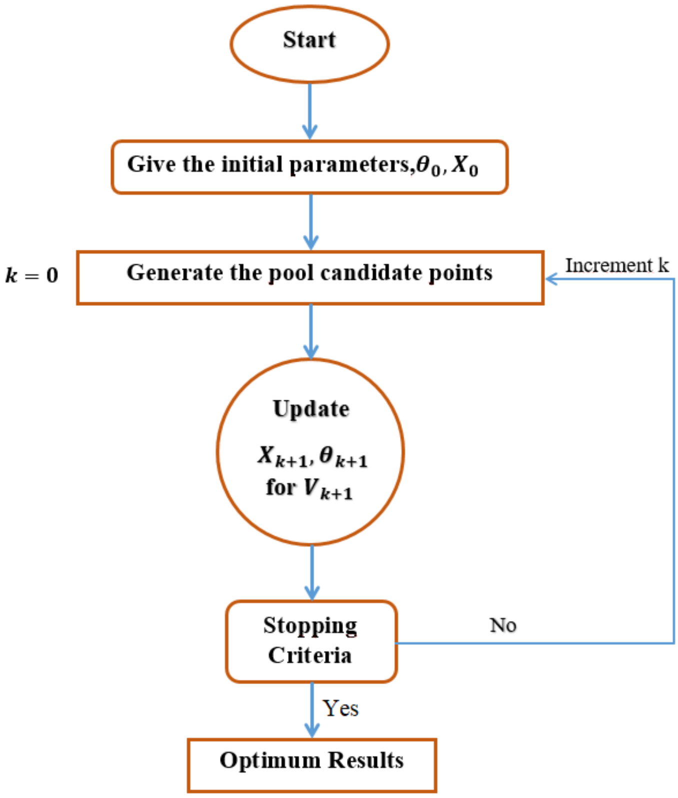

Figure 2. Flowchart of RS algorithm [22]

2.5. Mathematical Optimization Problem Definition

The data and parameters were defined by selecting from the reference study [15]. The weld penetration, mechanical properties depend on geometrical parameters and processing parameters. Independently controlled process parameters that affect weld penetration and quality of weld penetration, are (a) focal distance (F in mm) from workpiece surface, (b) torch angle (A in deg.),(c) distance between laser and welding torch (S in mm), (d) power (P in W). The definition of the optimization problem is presented in Table 3.

Table 3. Definition of the optimization problem.

Objective Function	Design Variables	Constraints
Maximization of weld penetration depth (D)	Focal Distance (F) Torch Angle (A) Laser-arc distance (S) Power (P)	$0\ mm \leq F \leq 3.5\ mm$ $45° \leq A \leq 60°$ $5\ mm \leq S \leq 20mm$ $900\ W \leq P \leq 1200\ W$

Table 4. Evaluated R^2 and $R^2_{adjusted}$ values of the different regression model

Model	R^2	$R^2_{adjusted}$	$R^2_{training}$	$R^2_{testing}$
FOL	0.92	0.82	-	-
FOLR	0.98	0.94	0.99	0.85

3. Results and Discussion

Various regression models for weld penetration have been tested with the calculation of the coefficient of determinations. According to Table 4, First-order multiple linear regression(FOL) model was not found to be appropriate due to low $R^2_{adjusted}$ value for experimental data at the end of all calculations by Mathematica. The first multiple linear rational regression(FOLR) was to be appropriate due to the minimum differences between R^2 and $R^2_{adjusted}$ values. For this model, $R^2_{training}$ and $R^2_{testing}$ values were calculated. The training process was performed to determine the error between the experimental and predicted values of the model. The testing process gives insight into the predictive ability of the model. It is found that the FOLR regression model is to be a realistic objective function.

Torch angle is a direct factor in all dimensional changes that occur in penetration as shown in Table 5. It was observed that the weld penetration depth increased by approximately 10-25% by reducing the torch angle at three different levels of power, focal distance and laser arc distance. This increase is particularly high in conditions where power, laser arc distance, focal length are maximum, i.e. 1200W, 20mm and 3.5mm respectively, with an increase of approximately 25 percent. On the other hand, the lowest penetration depth was observed at the maximum available conditions [14]. This may be related to the increase in the distance between the laser and the arc. Studies have shown that increased power and focal distance has a positive effect on weld penetration depth. Also, the laser distance is too long or short to reduce the weld penetration depth because of insufficient thermal efficiency or blocking the laser by the melted drops, respectively [6, 7]. In cases where the focal length is 0, the power, the arc, and laser arc distance are the lowest, the penetration values are close to the penetration obtained at higher power and focal length.

Table 5. Effect of different torch angle and input parameters on weld penetration depth [14].

Weld Penetration Depth (mm)	Laser-arc distance (mm)	Power (W)	Focal Distance (mm)	Torch Angle (°)
2.478	5	900	0	45
2.060	5	900	0	60
2.691	10	1050	2.5	45
2.448	10	1050	2.5	60
2.339	20	1200	3.5	45
1.85	20	1200	3.5	60

It was reported that i) weld penetration increases with the variation of torch angle up to 50 degrees, ii) The gas flow along the welding direction, which can be controlled by the arc torch, deflects the plasma caused by the laser. Moreover, when CO_2 lasers are applied, the absorption of the laser beam diminishes. Hereby, the torch angle is frequently selected about 40-50 degrees [23]. Results of the Random Search optimization operations are represented in Table 6. The optimum weld depth has been found to be D=5.76 mm at F = 3,5 mm A = 45° P=1200W and S = 5 mm welding conditions. On the other hand, the highest experimental value for the penetration depth of the weld was found to be 3.26 under the conditions F=3.5 mm, A = 60°, S = 5 mm P = 1200W in the experimental studies [14, 15]. This means that changing the torch angle from 60° to 45°, increase penetration depth of the weld from 3.26 mm to 5.76 mm.

Table 6. Optimization results based on RS method for the weld penetration depth (D).

Optimization Method	Weld penetration depth (mm)	Focal Distance (mm)	Torch Angle (°)	Laser–arc distance (mm)	Power (W)
Random Search	5.76	3.5	45	5	1200

4. Conclusions

In this study, the effect of the torch angle of the HLAW process on weld quality and depth of weld penetration responses were investigated. Mathematical models were developed for optimization and prediction of weld penetration depth. It was succeeded in associating with the presented model, experiments of premade test conditions, weld penetration, and torch angle. This study proposed that different regression models can identify engineering problems, besides stochastic optimization method can also be utilized to obtain the maximum depth of weld penetration. Different regression models with measured values and closed-up of results optimized by the Random Search optimization method. This includes finding the coefficients of the regression model and checking(predicting) the availability of the regression model with R^2, $R^2_{adjusted}$, $R^2_{training}$, $R^2_{testing}$. After these operations, one optimization algorithm (Random Search Method) has been applied systematically to the maximum weld penetration depth parameter design problem for different torch angles. As a result it can be said that welding penetration is increased by approximately 10-25% with decreasing the torch angle in all dimensional change. Moreover, the value of weld penetration was one of the most important output (weld penetration depth) factors determining the mechanical properties of the welding seam. For this reason, it is necessary to optimize the welding input parameters (back width, back height, front width, the front height of weld pool geometry) to obtain the most ideal weld penetration. This study is a purely numerical study that aims to use the modeling-optimization pair more effectively by using the data of a previous study in the literature, no experimental verification has been made.

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