6th Australasian Congress on Applied Mechanics

	model fixed at both ends for flow-induced instability analysis	Investigations of Friction and Wear Phenomena in Water-Lubricated Bearings	Fiber Reinforced Composites during Stamp Forming	Condition Monitoring
14:05 to 14:25	Jarrad S. Kapor [1041] Fluid-Structure Interaction Using Mesh-Free Modelling	Ronghao Bao [1115] From Stokes roughness to Reynolds roughness: a perturbation characterisation	Phuc Nguyen [1121] Investigation of Thermo-Mechanical Properties of Thermal Barrier Coatings Fabricated using the Slurry Spray Technique	Mohsen Askari [1201] Multi Objective Optimal Placement of Structural Control Actuators
TOPIC		**Machine Dynamics**		**Computational Mechanics**
14:25 to 14:45	Ben Hoea Tan [1130] Hydroelastic Stability of an Inhomogeneous Flexible Panel in a Uniform Mean Flow	Ray Malpress [1180] Assessment of an eccentric link in the connecting rod of a spark ignition engine intended for variable compression ratio operation	Garry Leadbeater [1226] Processing and properties of porous Ti-Nb-Ta-Zr alloy for biomedical applications using the powder metallurgy route	F. Kolahan [1254] Modeling and optimization of the electron beam welding process using statistical approaches
14:45 to 15:05	Mohammad Reza Mobinipouya [1138] A promising avenue for the intensification of turbulent free convection in square cavities using an adequate selection of binary gas mixtures	F. Ding [1189] Modelling and Dynamic Analysis of a Heavy Duty Truck with Rear Tandem Axle Bogie Suspension System	Y C Lam [1005] Surface roughness, hardness and strength of an aluminum mold fabricated by hot embossing	Mohammad Reza Mobinipouya [1139] Deviation of the calculated vapor and liquid density of refrigerant fluids at different temperatures and pressures using aforementioned equations of state from literature data
15:05 to 15:30	Afternoon Tea Break			
SESSIONS	NINE			
ROOM NO	5	6	7	8
TOPIC	**Fluid Structural Interaction** **Session Chair: Dr. Mark Pitman**	**Machine Dynamics** **Session Chair: Dr Brian Boswell**	**Structural Mechanics** **Session Chair: Prof Tongxi Yu**	**Computational Mechanics** **Session Chair: Dr James Jewkes**
15:30 to 15:50	Novak S. J. Elliott [1268] Wave propagation in an elastic waveguide: fluid-structure interactions in a spinal disease	Vladis Kosse [1090] Advanced mathematical modelling and experimental investigation of new torque arms for shaft-mounted drives	Dong (Tracy) Ruan [1188] Experimental investigation of the lateral crushing behaviour of short sandwich tubes	M. H. Abolbashari [1045] Topology optimization of continuum structures with elasto-plastic behaviour using evolutionary structural optimization based on stress and stiffness criteria
TOPIC	**ACOUSTICS**			
15:50 to 16:10	Daniel R. Wilkes [1018] Application of the Fast Multipole Boundary Element Method to Underwater Acoustic Scattering	Kazem Abhary [1233] A new analytical method for kinematic analysis of planar mechanisms	Bijan Samali [1195] Adaptive Neuro-Fuzzy Modelling of a high-rise structure equipped with an Active Tuned Mass Damper	F. Kolahan [1252] Optimization Of Process Parameters In Laser Welding By Simulated Annealing Algorithm
16:10 to 16:30	Jie Pan [1223] Near field sound radiation from a finite-sized loudspeaker in a room	Zhongwei Wang [1262] The Development of Lumped Mass Dynamic Modeling Methods of Planetary Gearbox for Fault Detection and Diagnosis	M.H. Abolbashari [1071] Analytical solution of functionally graded plates with any combination of clamped and simply supported boundary conditions under transverse mechanical loading	F. Kolahan [1251] Optimizing of fair curves based on the strain energy criterion using Tabu Search algorithm
16:30 to 16:50		Ding Fei [1184] Study on bifurcation characteristics of front wheel self-excited shimmy	M.H. Abolbashari [1003] Overall Deflection Minimization of Structures Using Morphing Evolutionary Structural Optimization Method	
16:50 to			M.H. Abolbashari [1046]	

6th Australasian Congress on Applied Mechanics, ACAM 6
12-15 December 2010, Perth, Australia

Optimization process parameters in laser welding by Simulated Annealing Algorithm

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Abstract: In this paper, two issues in laser welding have been addressed. First, using mathematical modelling, the effects of process parameters values on the tensile strength have been investigated. In this regard, using regression modelling, the effects of three input parameters; namely laser power, welding speed, and wire feed, on the tensile strength are evaluated. Various regression functions have been fitted on the experimental data to establish the relations between laser welding process variables and its output characteristic. Then, Analysis of Variance (ANOVA) approach is performed to find the most fitted model. The influence of each process parameter is also determined. Next, a Simulated Annealing (SA) algorithm has been employed to optimally determine the values of laser welding process parameters for any desired tensile strength. Computational results show that the proposed models and solution procedure perform very well in modeling and optimizing of laser welding process variables.

Keywords: Laser welding, ANOVA, Mathematical modeling, Optimization, Simulated Annealing.

1 Introduction

Among various novel welding techniques, Laser Beam Welding (LBW) is one of the most successful methods used to join a variety of metals and alloys. The Nd:YAG laser beam has a reputation for rapid, precise and easy operation in welding. The nature of the LBW enables it to focus on a small spot, allowing high-power density, deep penetration, narrow heat affected zones, and reduced tendency to spiking, under bead spatter, incomplete fusion, and root bead porosity [1, 2]. As a result, this technique produces good metallurgical properties with high-production rate and increases automation possibilities [3]. Another important advantage of LBW is its ability to work on non-ferrous and hard to weld alloys including aluminium alloys [4, 5].

However, it is well known that whatever the welding method, fusion welding generally involves heating the two joined parts together which can cause loss of material characteristics. In other words, the properties of the area around the Heat Affected Zone (HAZ) would be affected with variations in hardness, reduction of tensile strength and toughness, etc [6]. When AA5182 aluminium alloy is welded only by a laser, the strength may be reduced after welding. Pastor *et al.* [7] asserted that the strength reduction was caused by porosity, underfill, and magnesium loss. To overcome these problems, aluminium alloy welding using filler wire was proposed [8]. Generally, in laser welding of aluminium alloys, quality of the weld is influenced by such process parameters variables as welding speed, laser power, and wire feed rate [9]. The use of inappropriate settings can reduce the quality of the joints [10]. Therefore, the main thrust of this research is to develop accurate mathematical models to establish the relations between process parameter settings and the resultant tensile strength in LBW. In the next phase of this research, an optimization procedure is proposed to determine the best set of parameters settings for any desired process output levels.

In the following sections, we first develop mathematical model to estimate the tensile strength for AA5182 aluminium alloy with AA5356 filler wire. That can adequately model the relationships between process variables and tensile strength in aluminium alloy laser welding. Next, a SA approach is proposed to determine the optimal values for process parameters. The proposed solution procedure is developed in such way that it can accurately determine the best process variables through minimization of an error function with respect to any desired tensile strength. Finally, an numerical example is presented, based on the experimental data, to illustrate the application of the proposed approach and to evaluate the performance of the SA technique in predicting proper process variables.

2 Model development

The objective of the section is to establish relationships between the process parameters and process response characteristic, using the statistical regression analysis carried out on the data collected as per full factorial design of experiments (DOE). The most important process parameters in laser welding are the laser power (*P*), welding speed (*V*), and wire feed (*S*). The process response characteristic considered here is tensile strength (*T*). The experimental results were obtained using design of experiment (DOE) technique. For illustrative purposes, the data presented by Park and Rhee [11] are used in this research. In the experimental tests, each input parameters had 3 levels, resulting in a total of 27 (3^3) tests based on full factorial DOE matrix. Table 1 shows the experiment settings (first three columns) and the results (last column) obtained for AA5182 aluminium alloy.

Table 1: Experimental results based on DOE matrix for aluminium laser welding

Exp. No.	S (m/min)	P (KW)	V (m/min)	T (N/mm^2)
1	2	4	6	282
2	2	4	7.5	280
3	2	4	9	275
4	2	3.5	6	277
5	2	3.5	7.5	273
6	2	3.5	9	227
7	2	3	6	283
8	2	3	7.5	211
9	2	3	9	166
10	3	4	6	285
11	3	4	7.5	271
12	3	4	9	258
13	3	3.5	6	271
14	3	3.5	7.5	256
15	3	3.5	9	242
16	3	3	6	267
17	3	3	7.5	206
18	3	3	9	177
19	4	4	6	282
20	4	4	7.5	278
21	4	4	9	252
22	4	3.5	6	261
23	4	3.5	7.5	204
24	4	3.5	9	187
25	4	3	6	192
26	4	3	7.5	159
27	4	3	9	111

Different regression functions (linear, curvilinear, and logarithmic) have been fitted to the above data and the coefficients values are calculated using regression analysis. The Stepwise elimination process removes the insignificant terms to adjust the fitted quadratic model. The final proposed curvilinear models are presented below:

Linear Model

$$T = 168 - 19.4\ V + 76.7\ P - 18.6\ S \quad (1)$$

Curvilinear Model

$$T = 619 - 107\ S - 18.5V^{2} - 27.1\ P^{2} + 26.2\ V.P + 25.2\ P.S \quad (2)$$

Logarithmic Model

$$T = e^{5.44}\ V^{-0.260}\ P^{1.27}\ S^{-0.645} \quad (3)$$

The best model is the most fitted function to the experimental data. Such a model can accurately represent the actual laser welding process with minimum error [12]. In this research, the adequacies of various functions have been evaluated using analysis of variance (ANOVA) technique with 95% confidence level. The model adequacy checking includes test for significance of the regression model and test for significance on model coefficients. The ANOVA results recommend that the curvilinear model is the best fit in this case. The associated *P*-value for this model is lower than 0.05; i.e. more than 95% confidence level. This illustrates that the model is statistically significant. Table 2 shows the values of correlation factor (R^2) for each term of the three models. As shown in Table 2, the value of R^2 in curvilinear model is almost 95% for the tensile strength. This means that this model provides an excellent representation of the actual process in terms of joint's tensile strength.

Table 2: ANOVA results for tensile strength models

Model	Variable	R-Square	F value	P_r>F
Linear	*T*	80.2%	30.97	<0.0001
Curvilinear	***T***	**94.3%**	**68.98**	**<0.0001**
Logarithmic	*T*	77.6%	22.38	<0.0001

For illustrative purposes, the distribution of real data around regression lines for curvilinear model is illustrated in Figure 1. This figure demonstrates a good conformability of the developed model to the real process.

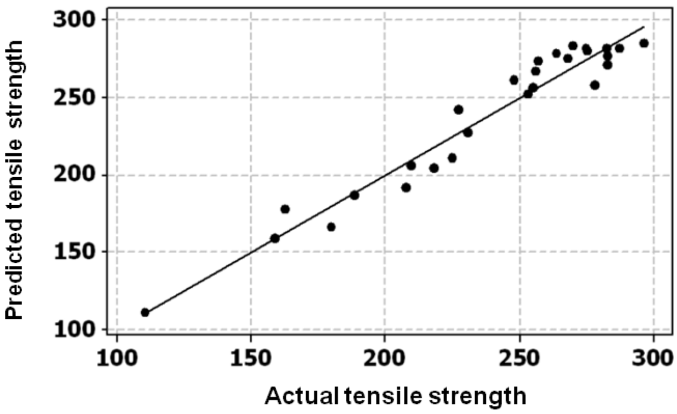

Figure 1: Predicted tensile strength vs. actual values

4 The optimization procedure

In many practical situations, one needs to set the process parameters in such a way that a desired output is obtained (in this case tensile strength). The mathematical models provided above can be used to determine a set of process parameters values for a desired *T* specification within feasible range. To find the optimal values of input parameters for a given *T*, requires inverse solving of the mathematical model of the process. This is a problem of combination explosion and hence evolutionary algorithms can be employed as the optimizing procedure. These techniques would make the combination converge to solutions that are globally optimal or nearly so.

Evolutionary algorithms are powerful optimization techniques widely used for solving combinatorial problems. As a promising approach, one of these algorithms called Simulated Annealing (SA) is implemented in this research.

SA is a technique that simulates the thermodynamic process of annealing (cooling a molten metal slowly to the solid state). It is an optimization technique that can theoretically converge to the global optimum solution, if the initial temperature is high enough and the cooling rate is infinitely slow. In this algorithm, an improving solution to the current objective function value is always accepted. However, to escape from local optima, a non-improving solution is also selected with a certain probability; which is given by Boltzmann function as follow:

$$e^{-\Delta c/T_0} \geq ran(0,1) \tag{4}$$

Where T_0 is initial temperature and Δc is acceptance probability function. For optimization process, we define the objective function in the form of an error function as follow:

$$E = \frac{\text{Target } (T_d) - \text{Predicted } (T_p)}{\text{Predicted } (T_p)} \times 100 \tag{5}$$

This function is used as the fitness criterion in the optimization process [12]. In the above function, T_d is desired tensile strength, and T_p is the predicted value given by the curvilinear model. The objective is to set the process parameters at such levels that the desired tensile strength is achieved. In other words, we want to minimize the difference between the desired output and the output given by the SA algorithm. This is done by minimizing the error function given by Equation (5).

5 An illustrative example

In this section a numerical example is presented to illustrate the performance of the proposed model and the solution procedure. The error function given in (5), along with curvilinear model of the laser welding is embedded into the SA algorithm. The objective is to determine the values of control parameters (*V*, *P*, *S*) in such a way that the process output response (*T*) converges towards its target value.

The algorithm was coded in MATLAB software and executed on a Pentium 4 computer. The best set of search parameters, found through several trial runs, is as follow: initial temperature (T_0) = 250; cooling rate (α) =0.98; and termination criteria = 500 iterations or error less than 0.01.

The code was run for 5 example problems with various values of desired (target) tensile strength. The comparison between predicted and desired values of process responses is shown in Table 3. As shown, the errors for all the test problems are negligible. These results illustrate that the proposed procedure can be efficiently used to determine optimal process parameters in laser welding process.

Table 3: Comparison of target and calculated values

No.	Predicted parameters			Target	Predicted	Error (%)
	P	*S*	*F*	T_d	T_p	*T*
1	3.50	8.39	2.37	242	242.71	0.292
2	3.79	7.57	2.33	273	273.67	0.245
3	3.78	6.58	3.37	278	278.16	0.057
4	3.56	6.42	2.51	282	282.12	0.042
5	3.72	6.50	2.90	285	284.87	0.046

3 Conclusions and recommendations

In this research, a procedure was proposed to model and optimize laser welding process for aluminium alloy. Since the relationships between tensile strength characteristic and laser welding output variables are complicated, a regression based method was employed to model the process. Along this line, different mathematical models were developed to establish the relationships between welding input parameters and tensile strength output. The ANOVA results performed on different regression functions denote that the curvilinear model is the best representative for the actual laser welding process. In this research, this model was employed as a part of optimization procedure to determine process parameter levels for any desired tensile strength. A Simulated Annealing technique was developed to minimize the error function consisting of desired and calculated tensile strength. By minimizing such a function, the process parameters can be determined so as the resultant tensile strength has the least deviation from its desired value. Computational results indicate that the proposed SA method can efficiently and accurately predict laser welding parameters. As the extensions to this research modelling and optimization of other welding techniques may be considered.

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