ENGINEERS AUSTRALIA

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]	

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Modeling and optimization of the electron beam welding process using statistical approaches

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Abstract: In this research, an attempt is made to determine input-output relationships of the Electron Beam Welding (EBW) process using regression analysis based on the data collected as per central composite design of experiments. The directly measured process characteristics include bead width (BW), depth of penetration (BP) and bead reinforcement (BH). Other relevant bead geometry parameters may be calculated using these outputs. To model EBW process, several regression functions have been fitted to the experimental data in order to establish the relationships between EBW process variables and its response characteristics. The best set of models is then selected based on the statistical analysis. In the final stage of this research, Simulated Annealing (SA) algorithm has been employed to find the best set of process parameter levels in order to obtain desired weld bead geometry. Computational results demonstrate that the proposed SA method is quite effective and efficient in optimizing process parameter values for any desired weld bead geometry in EBW.

Keywords: Electron Beam Welding (EBW), Modelling, optimization, Simulated Annealing (SA).

1 Introduction

Created in the 1950s, electron beam welding (EBW) has been improved many times during the last several decades. In this technique, an extremely high energy density irradiates the workpiece material which makes it melt and partly vaporise. This results in a deep and narrow keyhole formation which in turn creates deep, narrow and defect-free joints [1]. EBW has become one of the best welding technologies to date, displaying superior performance. This technique has little sensitivity to the power fluctuations and operational environment and can produce high welding precision. The greatest advantage of this technique is its ability to produce welds with very high joining rates. Electron beam welding is applicable to weld steel plates as thin as 0.2mm and as thick as 300mm in a single run.

The fusion zone is generally characterized by weld bead geometry, namely bead width (BW), height (BH) and penetration (BP). The shape of the fusion zone depends upon a number of parameters such as thermal properties of materials welding speed, accelerating voltage, beam current, etc. Like any other welding technique, the quality of joint in EBW is, to the large extends, affected by the process parameters settings. Thus, the proper determination of parameter settings is important for the successful application of EBW processes.

Numerous research works exist on the modelling and optimization of process parameters in various types of welding processes. Ganjigatti et al. [2] determined input-output relationships of the MIG welding process using regression analysis based on the data collected as per full-factorial design of experiments.Park and Rhee [3] used neural network and genetic algorithm for Process modeling and parameter optimization on the laser welding AA5182 of aluminum alloy with AA5356 filler wire. Datta and Kumar [4] used quadratic response surface methodology and Taguchi to modeling and optimization of features of bead geometry in submerged arc welding using mixture of fresh flux and fused slag. Nagesh and Datta [5] and Dey et al. [6] used regression and Genetic Algorithm for modeling and optimization of fillet welded joints for GMAW and EBW processes, respectively. Comprehensive surveys in this field can be found in literature [7].

Nevertheless, most of the proposed models are complicated and highly non linear. In addition, most studies have attempted to model the directed measured BH, BW and BP only, regardless of the important shape relations of the weld bead. Some important shape relations such as weld reinforcement form factor (WRFF) and weld penetration shape factor (WPSF), have significant impact on the quality of weld.

In the present work, an attempt has been made to model and optimize EBW using the data collected by Dey et al. [6] as per central composite design of experiments. In the following section we first derive the required formulas to calculated important shape relations based on weld bead geometry. Next, to model EBW process based on the experimental data, regression analysis is carried out using various mathematical functions. Analysis of variance (ANOVA) is the performed on the developed models to identify the best model representing the actual process. Finally a Simulate Annealing procedure is proposed and implemented to optimize the process parameters of EBW.

2 Shape relations calculations

Figure 1 shows the simplified weld bead geometry, with its direct and indirect shape characteristics.

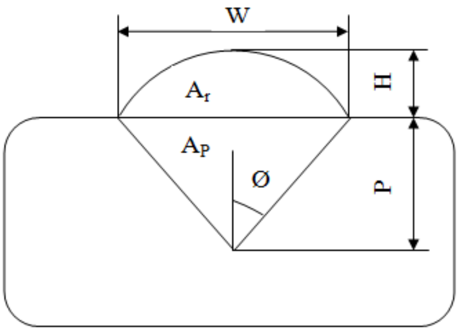

Figure 1: Simplified weld bead geometry

The calculation of shape relations, in terms of direct weld bead characteristics, may be carried out as follows. With respect to the Figure 1 and assuming the shape of bead cross-section to be a circular sector, total bead cross sectional area can be determined using Equations 1-4.

$$\tan\phi = \frac{W}{2p}, \qquad (\phi \text{ in degree}) \tag{1}$$

$$A_t = (P+H)^2\phi, \quad (\phi \text{ in radian}) \tag{2}$$

$$A_p = \frac{WP}{2} \tag{3}$$

$$A_t = A_p + A_r \tag{4}$$

In the above formulas A_r is Area of reinforcement, A_p is area of penetration and A_t is the total bead cross sectional area. The shape relations, including weld penetration shape factor (WPSF), weld reinforcement form factor (WRFF) and percentage of dilution (%D), are then calculated as follows:

$$\mathrm{W}PSF = \frac{W}{P} \tag{5}$$

$$WRFF = \frac{W}{H} \tag{6}$$

$$\%D = \frac{A_p}{A_t} \times 100 \tag{7}$$

In order to achieve optimum welding performance, it is important to properly set the welding parameters. The chosen inputs or process parameters, in this study, are as follows: welding speed (S), Accelerating voltage (V), Beam current (C). The input factors and their levels of the EBW process are shown in Table 1.

Table 1: Input factors and their levels of the EBW process

Parameter	Units	Notation	Level 1	Level 2	Level 2
welding speed	cm/min	(S)	60	80	100
Accelerating voltage	kV	(V)	60	75	90
Beam current	mA	(C)	7	8	9

The responses considered are like the following: Weld penetration shape factor (WPSF), Weld reinforcement form factor (WRFF), Area of penetration (Ap), Area of reinforcement (Ar), Bead cross sectional area (At) and %Dilution (%D). The calculated weld bead geometry is shown in Table 2. The aim of the present investigation is to establish relations between the process parameters (inputs) and responses (outputs) for Electron Beam Welding process, using regression analysis, where each response would have a single regression equation relating it to the process parameters for the whole domain of the investigation. And finally, finding the optimum input parameters using SA algorithm.

Table 2: Calculated weld bead geometry

SI. No.	WPSF	WRFF	Ar	Ap	At	%D
1	0.837687	7.02368	0.43681	2.34389	2.7807	84.2915
2	0.475894	4.29711	0.87093	4.12302	4.99395	82.5603
3	0.534106	4.82851	0.92023	4.48156	5.4018	82.9643
4	0.475165	4.32228	1.27173	6.06949	7.34122	82.6768
5	0.903326	8.06525	0.2795	1.73107	2.01057	86.0985
6	0.493893	4.78245	0.51509	2.66427	3.17936	83.7989
. . .	. . .	. . .	. . .	. . .	. . .	. . .
47	0.604299	6.556	0.67054	4.23286	4.9034	86.325
48	0.554934	7.0777	0.35897	2.6705	3.02948	88.1506
49	0.53367	5.06762	0.60032	3.09616	3.69649	83.7596
50	0.432749	4.82071	0.4592	2.70809	3.16729	85.5018
51	0.520797	5.33719	0.52105	2.91894	3.43999	84.8531

3 The solution procedure – SA algorithm

For real and large size optimization problems, the traditional optimization methods are often inefficient and time consuming. With the advent of computer technology and computational capabilities in the last few decades, the applications of heuristic algorithms are widespread. These techniques are usually based on the physical or natural phenomena. In 1953, Metropolis proposed a procedure used to simulate the cooling of a solid for reaching a new energy state. The annealing process, used in metal working, involves heating the metal to a high temperature and then letting it gradually cools down to reach a minimum stable energy state. If the metal is cooled too fast, it won't reach the minimum energy state. Later Kirkpatrick and his colleagues [8] used this concept to develop a search algorithm called Simulated Annealing (SA). Among different heuristic algorithms, SA is one of the most powerful optimization methods that simulates the cooling process of a molten metal. The general stages of the SA algorithm for the job scheduling on parallel machines are as follows:

1. BEGIN: Initialize the temperature parameter T 0 and the cooling schedule; r $(0 < r < 1)$ and the termination criterion (e.g. number of iterations $k = 1\ldots K$). Generate and evaluate an initial candidate solution (perhaps at random); call this the current solution, c.

2. Generate a new neighbouring solution, m, by making a small change in the current permutation of jobs and evaluate this new solution.

3. Accept this new solution as the current solution if:

3-a) The objective value of new solution, f (m), is better than of the current solution, f (c).

3-b) The value of acceptance probability function given by (exp (f (m) – f (c)) / T k) is greater than a uniformly generated random number “rand”; where 0 < rand < 1.

4. Check the termination criterion and update the temperature parameter (i.e., T k = r * T k-1) and return to Step 2.

The main advantages of SA are its flexibility, its fewer tuning parameters, and its ability to escape local optima and to approach global optimality.

The algorithm is quite versatile since it does not rely on any restrictive properties of the mathematical formulation of the problem and hence can be adapted to a wide range of problems. In addition, for any heuristic optimization procedure, the algorithm parameters should be tuned to enhance its performance. Therefore, the ease of tuning a given algorithm is an important feature in selecting a proper solution technique. In SA there are only two major tuning parameters - the initial temperature and cooling schedule. As a result, SA can easily be "tuned" with minimum trial runs.
Simulated annealing can avoid local optima by occasionally taking downward steps. That is, a non-improving neighbor may be accepted as the new current solution. To do so, the initial temperature, T, starts out large and is gradually reduced as search progresses (see Step 4). The result is that early in the search, the current solution "bounces around" the search landscape with little inhibition against moving to the solutions of lower fitness. As the number of iterations increases, the bounces become lower in amplitude and worse neighbors are accepted with lower probabilities and only when they are not much worse than the current solution. Thus, at the start of SA most worsening moves are accepted, but at the end only improving ones are likely to be accepted. This, to a large extend, helps the algorithm jump out of local optima. The details of this technique and its various applications are well documented in relate literature.

4 Model Development

To develop the mathematical models, various linear and curvilinear regression functions have been fitted to the experimental data. The best set of models is then chosen based on two criteria, namely; correlation coefficient and Analysis of Variance (ANOVA) results, with 95% confidence level. The calculated correlation factor for regression functions are shown in Table 3.

Table 3: The calculated correlation factor for regression functions

objective function	WPSF	WRFF	Ar	Ap	At	%D
First order	80.44	78.61	88.49	90.17	90.72	56.66
Second order	92.57	87.58	96.18	96.07	96.95	61.81
Third order	93.22	88.88	97.47	96.33	97.21	69.93

Since third degree of freedom for WPSF, WFRR, Ar, At, Ap and %D has the most correlation factor, they will be used for optimization. But first insignificant factors should be removed from equations using step backward elimination with 95 percent confidence level. Therefore, the modified regressions are as follows:

$$WPSF = 7.67 - 1.38\ C - 0.0233\ S - 0.000303\ V^2 + 0.0585\ C^2 + 0.000141\ S^2 + 0.00474\ VC \qquad (8)$$

$$WRFF = 110 - 33.9\ C - 0.0138\ V^2 + 2.44\ C^2 + 0.000600\ S^2 + 0.271\ VC - 0.0101\ CS - 0.0276\ VC^2 + 0.00135\ CV^2 \qquad (9)$$

$$Ar = - 26.4 + 0.359\ V + 6.85\ C - 0.0175\ S - 0.401\ C^2 + 0.000157\ S^2 - 0.0933\ VC - 0.000028\ VCS + 0.00548\ VC^2 + 0.000049\ CV^2 \qquad (10)$$

$$Ap = - 10.5 + 0.0927\ V + 3.28\ C + 0.000375\ S2 - 0.0457\ VC - 0.00986\ CS + 0.000284\ CV^2 - 0.000003\ SV^2 \qquad (11)$$

$$At = - 12.2 + 0.119\ V + 3.72\ C + 0.000590\ S^2 - 0.0491\ VC - 0.000555\ VS - 0.0120\ CS + 0.000303\ CV^2 \qquad (12)$$

%D = 36.6 + 1.41 S + 0.787 C^2 + 0.140 VC - 0.0174 VS - 0.176 CS + 0.0023 VCS - 0.0189 VC^2 (13)

Where S, V and C are as follows: welding speed (S), Accelerating voltage (V), Beam current (C) and SV, SC... VC^2 and VCS are interaction effects of the mentioned parameters.

5 Optimization

SA Algorithm is used to optimally determine input parameters levels in order to obtain any desired set of outputs. Usually, for high quality joint in EBW the Ar, WRFF and WPSF should be as low as possible while Ap and %D should be at their highest possible values. To achieve this, a multi-objective fitness function, based on mean square error, is defined as follows:

$$Fitness = \frac{(WPSF_d - WPSF)^2}{WPSF^2} + \frac{(WFRR_d - WFRR)^2}{WFRR^2} + \frac{(Ar_d - Ar)^2}{Ar^2} + \frac{(Ap_d - Ap)^2}{Ap^2} + \frac{(\%D_d - \%D)^2}{\%D^2} \quad (14)$$

In turn, $WPSF_d$, $WFRR_d$, Ar_d, Ap_d and $\%D_d$ are the desired values of the process output characteristics set by the operator. The algorithm along with its objective function has been coded in Matlab® software. In our computations, the relative importance (weights) of the output parameters are set to unity. In practices, these weights may be set at any relative values as required. SA parameters are as follows: initial temperature: 1000, cooling rate: 0.99, termination criterion: 1000 iterations. The convergence curve of the SA is shown in Figure 2.

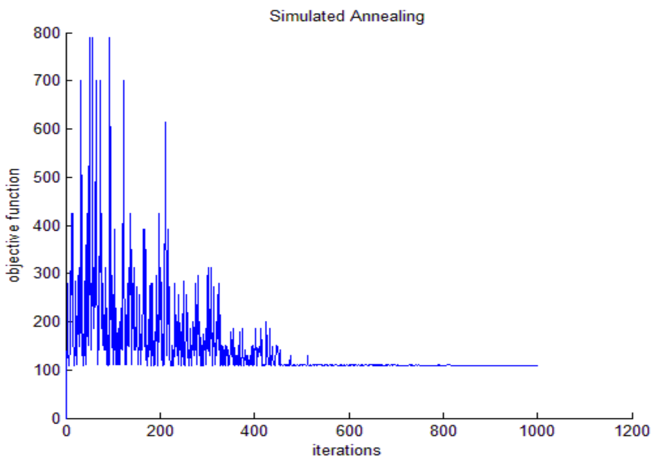

Figure 2: The convergence curve of the SA algorithm

The best input parameters to gain optimum results are as follows: S: 60, V: 90, C: 9. Since in all runs, which were started from random point, lead to one specific above mentioned answer, the answer is the global answer of the process**.**

6 Conclusions

Weld bead geometry is the most important quality measure in all types of welding techniques. To achieve a high quality weld, welding parameters should be set in such way that the desired bead geometry is obtained. The relationships between bead geometry and welding parameters are quite complicated involving many interactions. The main trust of this research was to establish the mathematical relationships between input and output parameters and to explore the possibility of using SA algorithm in predicting input parameters values in Electron Beam Welding for austenitic stainless steel plates. Along this line, using DOE approach and regression analysis, different mathematical models were developed to establish the relationships between welding input parameters and weld bead geometry. The ANOVA results denote that the curvilinear models are the best representative for the actual EBW process. The direct use of these models is to calculate weld bead geometry for any given set of process parameters. In this research, these models were put to use as a part of prediction procedure for determining process parameters for any desired weld bead geometry. To achieve this, a SA technique was developed to minimize an error function consisting of desired and calculated weld bead geometry. By minimizing such a function, the process parameters can be determined so as the resultant bead geometry has the least deviation from its desired value. Computational results indicate that the proposed SA method can efficiently and accurately determine welding parameters for a desired bead geometry specification.

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