MODELING OF INPUT-OUTPUT RELATIONSHIPS FOR ELECTRON BEAM BUTT WELDING OF DISSIMILAR MATERIALS USING NEURAL NETWORKS

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Electron beam butt welding of stainless steel (SS 304) and electrolytically tough pitched (ETP) copper plates was carried out according to central composite design of experiments. Three input parameters, namely accelerating voltage, beam current and weld speed were considered in the butt welding experiments of dissimilar metals. The weld-bead parameters, such as bead width and depth of penetration, and weld strength in terms of yield strength and ultimate tensile

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strength were measured as the responses of the process. Input-output relationships were
established in the forward direction using regression analysis, back-propagation neural network
(BPNN), genetic algorithm-tuned neural network (GANN) and particle swarm optimization
algorithm-tuned neural network (PSONN). Reverse mapping of this process was also conducted
using the BPNN, GANN and PSONN approaches, although the same could not be done from
the obtained regression equations. Neural networks were found to tackle the problems of both
forward and reverse mappings efficiently. However, neural networks tuned by the genetic al-
gorithm and particle swarm optimization algorithm were seen to perform better than the BPNN
in most of the cases but not all.

Keywords: Electron beam butt welding; dissimilar metals; BPNN; GANN; PSONN; forward
mapping; reverse mapping.

1. Introduction

Welded joints of dissimilar metals, such as copper to stainless steel are commonly
used in the fabrication of heat transfer devices subjected to high heat fluxes. They
also play significant roles in the fields of cryogenics, electrical and electronic indus-
tries. Joining of dissimilar metals and alloys with widely differing melting point and
thermal conductivity and limited solid solubility in one another is complicated.1 The
formation of hard and brittle intermetallics and micro-cracks in the heat affected
zone (HAZ) of stainless steel plate induced by the diffusion of copper into the grain
boundaries of the unmelted steel needs to be eliminated or minimized for obtaining
good quality weld.2 Electron Beam Welding (EBW) is a suitable process for joining
dissimilar metals due to the high cooling and solidification rates. The proper selection
of process parameters reduces the formation of micro-cracks in the electron beam
butt welding of dissimilar metals.3

EBW is a welding process, where energy required for melting and fusion is
achieved by impingement of high speed electrons on the work surface. The kinetic
energy of the beam electrons is transformed to the work material, which produces
intense heating and thereby, causing melting and fusion. The physical dimensions of
the weld pool or fusion zone, such as weld bead width and depth of penetration are
important parameters, which are required to be optimized to obtain a good quality
weld. The quality of the electron beam welds depends on the input process para-

ters, namely accelerating voltage, beam current, welding speed, focus positions,
ambient pressure, amount of dissolved and adsorbed gases present in the material to
be welded, and others. Tensile strength and yield strength of the butt welded samples
are evaluated as a part of the weld procedure qualification. Therefore, modeling of
the EBW process is required to decide on the process parameters to be set to obtain
desired weld quality and hence, to automate the process.

2. Literature Review

Several analytical models for the analysis of the EBW process had been developed by
various researchers.4–10 The exact solutions of the developed differential equations
correlating the input parameters and physical phenomena of EBW process with the
outputs, such as weld-bead profile and mechanical properties are very difficult and time consuming to obtain. The analytical model requires exact dimension of the focal spot diameter and hence, power density, which is very difficult and time consuming to measure with a given accuracy. The models are also developed from the input-output data obtained through real experiments performed according to some statistical designs and then analyzed by regression methods to predict the required output. Several conventional welding phenomena were modeled using regression analysis by various researchers. Modern welding processes, such as laser beam welding (LBW) and EBW were also modeled using regression analysis. Benyounis et al. used response surface methodology (RSM) successfully to predict weld profile in laser welding. The regression analysis was used by Elena Koleva and Dey et al. to develop the input-output correlations for electron beam welding of austenitic stainless steel.

Neural network-based models had been used extensively for the modeling of various conventional and modern welding processes. Neural network-based models are well established in the control and monitoring of the welds and the most useful neural network models are those whose inputs are easily measured. Vitek et al. used neural network to predict the weld pool shape parameters in pulsed Nd:YAG laser welds of Al-alloy. Cook et al. developed an artificial neural network (ANN) for monitoring and control of the plasma arc welding process and suggested that the ANNs could yield real-time results, which might be required for the automation of the process. Olabi et al. used back-propagation neural network (BPNN) for optimizing the butt welding of medium carbon steel using CO$_2$ laser. Okuyucu et al. developed an ANN model for the analysis and simulation of friction stir welding (FSW) of aluminum plates. Dey et al. used BPNN, Genetic Algorithm-tuned Neural Network (GANN) and Radial Basis Function Neural Network (RBFNN) for the modeling of electron beam bead-on-plate welding process. Jha et al. studied the electron beam butt welding of SS 304 and used BPNN and GANN for the input-output modeling of the process.

Sun and Karppi presented an overview of the applications of EBW for the joining of dissimilar metals and demonstrated the advantages of EBW over conventional fusion-welding processes. Magnabosco et al. carried out microstructure characterization of the EBW process of three different dissimilar welded joints of ETP copper-stainless steel (304, 304L and 316L). All the samples showed a microstructure characterized by a mixture of two nonequilibrium phases, one was rich in Cu and the other one was austenite with Fe, Cr and Ni. Intergranular micro-cracks were observed at the interface between the fusion zone and stainless steel. Mai and Spowage investigated the laser welding of dissimilar metals without filler materials using a 350 W pulsed Nd:YAG laser. The laser beam was positioned 0.2 mm towards the steel plate and any melting of the copper and aluminum was through contact heat transfer rather than direct heating from the laser beam. They found that the number of pores and melting depth decreased with an increase in welding speed. The mixing behavior of the materials in the fusion zone, microstructure, presence of
defects, hardness and residual stress of the joints were also investigated. It was shown that controlling the melting ratio of metals is an important factor for defect-free welding of dissimilar metals. Ahmed et al.\textsuperscript{38} carried the hardness and microstructural studies of electron beam welded joints of 1 mm thick Zircaloy-4 and stainless steel plates and predicted that the formation of harmful inter-metallic compound could be reduced considerably in electron beam welding. Liu et al.\textsuperscript{39} studied the laser welding of dissimilar metals, namely Ni-based cast superalloy K418 and alloy steel 42CrMo. The authors found that weld depth increases with laser power, and both the depth and width of weld-bead decrease with the increase in velocity. Beretta et al.\textsuperscript{40} investigated the laser welding of AISI304 to AISI420 stainless steels and found that the maximum welding efficiency could be obtained, when the beam is aligned to the joint. Anawa and Olabi\textsuperscript{41} presented the optimization of tensile strength of ferritic/austenitic steel laser welded components using Taguchi method. The authors found that tensile strength increases with laser power but decreases with welding speed. Torkamany et al.\textsuperscript{42} studied the effect of process parameters, viz., peak power, pulse duration and overlapping factor on the laser beam welding of carbon steel to 5754 aluminum alloy by Nd:YAG pulsed laser and presented an optimized set of parameters for the welded joint with low percent of intermetallic components (PIC), high tensile strength and penetration depth, small weld width and good quality of weld surface.

Although a considerable amount of work had been carried out on input-output modeling of various welding processes using statistical regression analysis, the input-output modeling of butt welding of dissimilar metals using EBW has not yet been carried out. This modeling may be required in both forward and reverse directions to automate the process. The forward mapping of the process could be carried out easily using the conventional regression analysis, it might not be always possible to conduct the reverse mapping using the obtained regression equations as the transformation matrix related to the input-output modeling could be singular. Moreover, regression analysis is carried out response-wise. Thus, it might not be able to capture the complete dynamics of the process. These problems could be solved using neural network-based approaches. Although some qualitative studies (microstructure characterization) of dissimilar metal welding using EBW had been carried out, the study of input-output modeling of butt welding of dissimilar metals using EBW has not yet been conducted.

The primary objective of the present study is to develop input-output relationships of the butt welding of dissimilar metals using electron beam in both forward and reverse directions, which might be required for its automation. Input parameters considered for the butt welding of dissimilar metals were accelerating voltage, beam current and welding speed, whereas width and depth of fusion zone, ultimate tensile strength and yield strength properties were taken as the output parameters.

The remaining part of this paper is organized as follows: Section 3 describes the experimental details and data collection methods adopted in the present study.
Section 4 explains the method of analysis. Results are stated and discussed in Sec. 5 and some concluding remarks are made in Sec. 6.

3. Data Collection

Butt welding experiments for dissimilar metals were carried out using 60 kV, 8 kW Techmeta, France make EBW machine located at Atomic Fuels Division (AFD), Bhabha Atomic Research Centre, Trombay, Mumbai, India. Figure 1 shows the EBW machine used for the experiments. It consists of a work chamber with job handling table, electron beam gun column with indirectly heated tungsten filament as emitter, high frequency power supply, control panel and vacuum system. The vacuum chamber is equipped with 20° diffusion pump assembly backed by the roots-rotary combination of vacuum pumping system. The work chamber of EBW machine with an inner working space of 600 mm × 600 mm × 600 mm was evacuated to a base vacuum in the range of $8 \times 10^{-5}$ mbar to $5 \times 10^{-5}$ mbar during the experiments. The electron beam gun chamber was evacuated to a vacuum level of $5 \times 10^{-6}$ mbar by an independent vacuum system consisting of turbo-molecular pump backed by a double stage, direct drive rotary vane vacuum pump.

3.1. Sample preparation

Butt welding was carried out on 6.4 mm thick SS 304 and ETP Copper plates. The SS 304 and ETP Copper plates of required dimensions, i.e., 85 mm (length) × 65 mm (width) were cut from the large sheets using Doall cutting band saw machine. The square edge of the plate samples for carrying out the EBW was prepared using a milling machine. The chemical compositions of the ETP copper and SS 304 plates used for the experiments are given in Table 1.
3.2. Cleaning and degassing

The ETP copper and SS304 plates were cleaned using isopropyl alcohol and allowed to dry. The bead-on-plate runs were taken on SS304 and ETP copper plates initially, as a part of trial runs to fix the ranges of various input parameters for the actual butt welding experiments. The weld quality appeared to be good for the SS304 plates, whereas the weld bead on ETP copper plates showed a lot of spatter. The dissolved and adsorbed gases might be the reasons for the spatter, and weld bead quality seemed to be unacceptable. In the subsequent trial run, the ETP copper plate was scanned with a low power defocused beam for at least 10 times prior to the EB weld pass at desired power. The weld quality was improved and no spatters were observed, but pre-heating resulted in a wider weld bead. In the third set of trial runs, the plates were pre-heated and allowed to cool for one hour before taking the final EBW pass. Thus, the quality of weld-bead was found to be very good and no spatter was observed. Hence, it was decided to preheat all the weld samples and then cool it in the controlled environment before the welding. All the cleaned and dried samples of ETP copper and SS 304 plates were heated in an oven up to 100°C for about 20 min to outgas the moisture adsorbed due to atmospheric humidity. The dried and baked plates were allowed to cool to the room temperature and stored in a humidity controlled room. The plates were then taken for electron beam butt welding. The weld quality turned out to be very good and none of the 74 butt welds showed any spatter. The electron beam was provided with an oscillation of 0.3 mm at the target surface, while carrying out the butt welding.

3.3. Design of experiments

The process parameters that may have significant influence on the quality of electron beam butt welding of dissimilar metals are accelerating voltage ($V$), beam current ($I$), weld speed ($S$), ambient pressure, and offset of the incident electron beam from the weld seam location. The ambient pressure was maintained in the range of $8 \times 10^{-5}$ mbar to $5 \times 10^{-5}$ mbar during the complete set of experiments in order to avoid contamination, which may result into the depression of tensile strength. The offset of the incident electron beam from the weld seam location is an important parameter to be set for conducting butt welding of dissimilar metals with widely differing thermal conductivity and melting point. The trial runs were carried out to find out optimum offset of the incident beam required for obtaining the maximum tensile strength in case of butt welding of 6.4 mm thick copper and SS 304 plates.
using the electron beam. Figure 2 shows the variations of tensile strengths as a function of the offset of the incident beam from the weld seam location.

This figure indicates that the maximum tensile strength and yield strength of the electron beam butt welded samples were obtained, when the incident beam was located directly on the weld seam. Therefore, it was decided to carry out the complete set of experiments by locating the incident electron beam directly on the weld seam location. Three factors, namely $V$, $I$, and $S$ were considered for the electron beam butt welding of ETP copper plates and SS304 plates with a window of fixed size. The ranges for $V$, $I$ and $S$ were decided according to the previous experience and a few trial runs. The experiments were performed according to central composite design (CCD) methodology, in which $2^3 + 2 \times 3 + 3 = 17$ combinations of input process parameters were considered. The process parameters set at their three levels are given in Table 2.

The CCD matrix for the electron beam butt welding of ETP copper and SS304 plates using three factors, each set at its three levels (i.e., two end points and a centre point) is given in Table 3. As three replicates were considered for each combination of input parameters, a total of $3 \times 17 = 51$ experiments were conducted.
3.4. Training and test data

Experiments were carried out on ETP copper and SS304 plates according to the combinations of process parameters given in Table 3. For the verification of the developed input-output models, experiments were conducted for an additional set of eight test cases (selected at random) after keeping the same ranges of process parameters. Table 4 displays the combinations of process parameters used for the test cases.

The dimensions of the ETP copper and SS 304 plates for carrying out the electron beam butt welding were 85 mm × 65 mm × 6.4 mm. Figure 3 shows some of the EB butt welded ETP Copper and SS304 plates.

The EB butt welded specimens were cut at a minimum distance of 10 mm from the edge for preparing the specimens for tensile testing and cylindrical mounts.
to carry out bead profile measurement. The cylindrical mounts of diameter \( \phi 25 \text{ mm} \times 25 \text{ mm} \) (height) were made using cold setting resin. The grinding and polishing of all the mounts were carried out using France make Mecatech 334 polishing machine. The polished samples were first electrochemically etched using a saturated solution of oxalic acid followed by chemical etching using a chemical solution of 2 g potassium dichromate along with 4 cc HCl, 8 cc H\(_2\)SO\(_4\) and 100 cc water to reveal the microstructure.

The images of all the etched samples were taken on Leica make optical microscope to measure the bead profile in terms of bead width (BW), and bead penetration (BP). The bead profiles for all the experimental runs and test cases were measured and recorded. Figure 4 shows the photograph of the parent metal and fusion zone for one of the butt welded samples.

The specimens were cut from the Butt welded samples for tensile testing. The tensile specimens were prepared according to the dimensional details given in

Fig. 3. ETP copper to SS304 electron beam butt welded samples.

Fig. 4. Photograph of the parent metal and fusion zone of butt welded ETP Copper to SS304 plate using electron beam.
Fig. 5(a) by milling process. The tensile specimens were machined such that the final thickness of the specimen became equal to the depth of penetration obtained from the bead profile measurement. Figure 5(b) shows some of the tensile test specimen of ETP Copper to SS 304 butt welded samples. The tensile test for all the specimens was carried out on INSTRON universal testing machine. Thus, the output parameters for butt welding experiment of dissimilar metals using electron beam, viz., Bead Width (BW), Bead Penetration (BP), Yield Strength (YS) and Ultimate Tensile Strength (UTS) for all the cases were determined and recorded.

4. Methods of Analysis

Modeling of input-output relationships for the butt welding of dissimilar metals using electron beam was carried out using non-linear statistical regression analysis and neural networks as discussed below.

4.1. Forward mapping

The purpose of forward mapping is to predict the response or output of a process as a function of the input parameters. Nonlinear statistical regression analysis and three NN-based algorithms were used for developing the models to predict the weld profile in terms of bead width and bead penetration, and weld strength in terms of yield strength and ultimate tensile strength for the electron beam butt welding of SS 304 plates and ETP Copper plates for a given set of input parameters. There were three input parameters to be controlled, namely accelerating voltage, beam current and welding speed.

Approach 1: Statistical regression analysis

The input-output relationships were established by carrying out a nonlinear regression analysis of the data obtained from the experimental runs using Minitab 14 software. Nonlinear relationship of the response with the input process parameters
can be represented as given below.\(^{43}\)

\[
Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i=1}^{k} \sum_{i<j}^{k} \beta_{ii} X_i X_j + \varepsilon,
\]

where \(\varepsilon\) represents the error in fitting. The above equation contains linear terms, such as \(X_1, X_2, \ldots, X_k\); squared terms, like \(X_1^2, X_2^2, \ldots, X_k^2\); interaction terms, such as \(X_1 X_2, X_1 X_3, \ldots, X_{k-1} X_k\). The coefficients, that is, \(\beta\) values can be determined using the principle of a least square error.

**Approach 2: Back-propagation neural network (BPNN)**

A BPNN model was developed consisting of three layers, namely input layer with three neurons, a hidden layer with sixteen neurons and output layer with four neurons. The three neurons in the input layer correspond to three input parameters, namely accelerating voltage, beam current and welding speed. Similarly, the four output neurons represent the outputs or responses of the process in terms of bead width, bead penetration, yield strength and ultimate tensile strength. The connecting weights between the input and hidden layers \([V]\) and those between the hidden and output layers \([W]\) were allowed to lie in the range of 0.0 to 1.0, whose initial values were generated at random. Figure 6 shows the schematic view of the NN. A mean squared deviation (MSD) in predictions of the outputs is used to...
optimize the parameters of the neural network, whose expression is given below.

$$MSD = \frac{1}{L} \sum_{l=1}^{L} \frac{1}{M} \sum_{m=1}^{M} \frac{1}{2} (T_{om}^l - O_{om}^l)^2,$$

(2)

where $L$ denotes the number of training cases, $M$ represents the number of outputs, $T_{om}^l$ and $O_{om}^l$ indicate the target and predicted outputs, respectively, of $m$th neuron lying on the output layer corresponding to $l$th training case.

The connecting weights were updated to reduce the MSD during the training of the network. A batch mode of training was adopted to train the network using one thousand training cases. The $17 \times 3 = 51$ training cases were generated through experiments and 949 training cases were artificially generated using the regression equations.

**Approach 3: Genetic algorithm-tuned neural network model (GANN)**

The GANN model used Genetic Algorithm (GA) as an optimization tool to tune the connecting weights, bias values and other parameters of the NN. Each variable was represented by five bits and the total number of real variables was decided by the number of neurons in the hidden layer. The GA-string carried information of the network architecture and the parameters, namely bias value, connecting weights of the input-hidden and hidden-output layers and constants of the log-sigmoid transfer functions for the hidden and output layers. Figure 7 shows a schematic view of the GANN system. Thus, the GA-string looks as follows (for 3 input, 24 hidden and 4 output neurons):

$$\begin{align*}
10011 & \quad \cdots \quad 10010 & \quad 01010 & \quad \cdots \quad 10001 & \quad 101000 & \quad 11001 & \quad 1011 \\
v_{11} & \quad \cdots \quad v_{24} & \quad w_{11} & \quad \cdots \quad w_{24} & \quad a_h & \quad a_o & \quad b
\end{align*}$$

In the above string, $v$ represents connecting weights between the input and hidden layers, $w$ denotes connecting weights between the hidden and output layers, $a_h$ is the coefficient of log-sigmoid transfer function for the hidden layer, $a_o$ represents coefficient of transfer function for output layer and $b$ denotes the bias value. The fitness of the GA-string was calculated as the average MSD obtained according to Eq. (2) by using one thousand training data.

**Approach 4: Particle swarm optimization algorithm-tuned neural network (PSONN)**

In this approach, the parameters of the neural network like connecting weights, bias values and transfer functions were tuned using Particle Swarm Optimization (PSO). The PSO is a population-based stochastic approach proposed by Kennedy and Eberhart for solving optimization problems. The variables, which are required to be optimized, form the population of solutions and are denoted by the particles. Each particle has its own position and velocity to move around the search space. The position of a particle represents a possible solution to the optimization problem and the velocity is directed towards the new and better position. Thus, each particle in
the swarm is composed of three D-dimensional vectors, where D is the dimensionality of the search space. These are the current position, previously found best position and velocity of a particle in the direction towards the new position. The velocity and position of \( i \)th particle and its \( d \)th dimension are changed according to the following equations:

\[
v_{id}(t + 1) = w v_{id}(t) + c_1 R_1 (P_{\text{best}} - x_{id}(t)) + c_2 R_2 (G_{\text{best}} - x_{id}(t)),
\]

\[
x_{id}(t + 1) = x_{id}(t) + v_{id}(t + 1),
\]

Fig. 7. A schematic view of GA-NN system (reproduced from the second author’s textbook Soft Computing © 2008 Narosa Publishing House, New Delhi).
where \( v_{id}(t) \) represents velocity of the particle at iteration \( t \), \( x_{id}(t) \) indicates its position at iteration \( t \), \( P_{\text{best}} \) is the best previous position of the particle, \( G_{\text{best}} \) denotes the global best previous position of the particle, \( w \) is called inertia weight, \( c_1 \) and \( c_2 \) represent the cognitive and confidence coefficients, respectively, \( R_1 \) and \( R_2 \) are the two random numbers lying in the range from 0 to 1. The schematic view of a PSONN system is shown in Fig. 8. A batch mode of training had been adopted with the help of one thousand training data, in which the fitness of a PSO particle was calculated as the average MSD obtained using Eq. (2).
4.2. Reverse mapping

Reverse mapping of a process aims to predict the input parameters required to obtain a desired set of outputs or responses, which may be required for its automation. The neural network-based models were developed for the reverse mapping of input-output parameters. However, it could not be done using the obtained nonlinear regression equations. The models using BPNN, GANN and PSONN-based approaches were utilized to predict the input parameters (namely accelerating voltage, beam current, and welding speed) required to be set to obtain the desired outputs or responses (such as BW, BP, YS and UTS). Thus, the reverse model had four inputs and three outputs.

5. Experiments and Results

Results related to input-output mappings of the electron beam butt welding of dissimilar metals in both forward and reverse directions have been stated and discussed below.

5.1. Results of forward mapping

Four approaches were used to carry out forward mapping of this process, whose results are explained in this sub-section.

5.1.1. Results of approach 1

During the statistical regression analysis carried out using MINITAB15 software, significance test was conducted to investigate the contributions of process parameters on each of the responses. The adequacy of the developed model was tested through an analysis of variance (ANOVA). The ANOVA was carried out at a confidence level of 95%. The performance of the developed model was checked by comparing the predicted values of the responses with their corresponding experimentally obtained target values for some test cases. The bead-geometric parameters, yield strength and tensile strength were represented as the functions of input process parameters as given below.

5.1.1.1. Weld bead width (BW)

Weld bead width (BW) was obtained as a second-order polynomial function of input variables in the coded form. The input variables, namely accelerating voltage (V), beam current (I) and welding speed (S) were represented by the symbols $X_1$, $X_2$, and $X_3$, respectively, on a coded scale (from $-1$ to $+1$). The interactions between the variables were represented by $X_1X_2$ (V and I), $X_1X_3$ (V and S) and $X_2X_3$ (I and S). The obtained regression equation for the BW in coded form is given below.

$$
\text{BW}_{\text{coded}} = 1.22969 + 0.02227X_1 + 0.03547X_2 - 0.04327X_3
+ 0.05063X_1^2 - 0.01537X_2^2 + 0.00697X_3^2
+ 0.07158X_1X_2 - 0.04008X_1X_3 + 0.00033X_2X_3.
$$

(5)
Table 5 displays the results of significance test for BW. The regression analysis was carried out at a confidence level of 95%. From the p (probability) values of Table 5, $X_1$, $X_2$, $X_3$, $X_1^2$, $X_1X_2$, and $X_1X_3$ were found to be significant. The relationship between $X_1$ (acceleration voltage) and bead width was found to be nonlinear. The bead width was seen to be linear with beam current ($X_2$) and welding speed ($X_3$). The combined effects of $X_1X_2$ (accelerating voltage and beam current) and $X_1X_3$ (accelerating voltage and welding speed) were also found to be significant. The coefficient of correlation was found to be equal to 0.773, which is less than the ideal value of 1.0. The model was built based on the experimental data. Although several precautions were taken, some experimental and measurement errors could not be totally avoided. The adequacy of the model was also checked through ANOVA test (refer to Table 6). ANOVA test had been used to analyze the variances present in the experiment with the help of Fisher’s test (F-test). The ‘F’ value for regression, which is defined as the ratio of adjusted mean squared value to the residual error, is generally used to test the hypothesis. If the ‘F’ value calculated based on the experimental data is found to be more than its theoretical value available in the standard table, then the statistical means are considered to be significant and the model will be statistically adequate for making predictions. The F values shown in Table 6 were found to be greater than the theoretical values obtained from F-distributions table. Hence, the model was statistically adequate for making predictions. The lack of fit was seen to be insignificant. Thus, insignificant terms can be removed from the model.

The un-coded form of BW was found to be as follows:

$$\text{BW}_{\text{un-coded}} = 4.57953 - 0.11708V - 0.0216365I + 0.000726352S$$
$$+ 0.000791153V^2 - 1.53662E - 04I^2 + 1.74178E$$
$$- 0.75^2 0.000894792VI - 2.50521E - 05VS$$
$$+ 1.66667E - 07IS. \tag{6}$$
The surface plots of BW with accelerating voltage, beam current and welding speed are shown in Fig. 9. The bead width was found to be increasing with the increasing beam current. It decreased with welding speed at the higher accelerating voltage and remained more or less unchanged at the lower accelerating voltage. Moreover, it was seen to decrease with accelerating voltage at the lower beam current and increase at the higher beam current. The minimum achievable focal spot diameter of the electron beam decreases with increasing accelerating voltage at low beam current and hence, bead width was found to decrease with the accelerating voltage. The minimum achievable focal spot diameter increases with the increasing beam current due to space charge effect. Therefore, at the higher beam current, bead width increases with the increasing V due to the increase in beam power or energy

Table 6. Results of ANOVA test for BW.

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Seq SS</th>
<th>Adj. SS</th>
<th>Adj. MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
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<td>0.298737</td>
<td>0.298737</td>
<td>0.033193</td>
<td>15.51</td>
<td>0.000</td>
</tr>
<tr>
<td>Linear</td>
<td>3</td>
<td>0.108771</td>
<td>0.108771</td>
<td>0.036257</td>
<td>16.94</td>
<td>0.000</td>
</tr>
<tr>
<td>Square</td>
<td>3</td>
<td>0.028423</td>
<td>0.028423</td>
<td>0.009474</td>
<td>4.43</td>
<td>0.009</td>
</tr>
<tr>
<td>Interaction</td>
<td>3</td>
<td>0.161543</td>
<td>0.161543</td>
<td>0.053848</td>
<td>25.16</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual error</td>
<td>41</td>
<td>0.087744</td>
<td>0.087744</td>
<td>0.002140</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lack-of-fit</td>
<td>5</td>
<td>0.004076</td>
<td>0.004076</td>
<td>0.000815</td>
<td>0.35</td>
<td>0.878</td>
</tr>
<tr>
<td>Pure error</td>
<td>36</td>
<td>0.083668</td>
<td>0.083668</td>
<td>0.002324</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>50</td>
<td>0.386481</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

![Fig. 9. Surface plots of BW with V, I and S.](a)(b)(c)
deposition rate. Therefore, welding should be carried out at low beam current and high accelerating voltage and high welding speed to obtain small bead width. Liu et al.\cite{lu} investigated the laser welding of dissimilar metals and found that the weld width decreased with the increase in welding velocity. Thus, the observation of the present study matches with that of Liu et al.\cite{lu}

The performance of the developed model was tested on eight test cases. The percent deviations in predictions of bead width are shown in Fig. 10. The maximum value of percent deviation in predictions of BW was found to be equal to $-10.44\%$. The average absolute percent deviation in predictions of BW was seen to be equal to 4.46.

5.1.1.2. Weld bead penetration (BP)

It was found from the significance test conducted during regression analysis for BP that $X_1$, $X_3$, and $X_2X_3$ were significant. Thus, accelerating voltage, welding speed and the combined effect of beam current and welding speed were found to be significant. The coefficient of correlation was turned out to be 0.6561 for BP. The lower value of coefficient of correlation might be attributed to some errors during the experiment and measurement of the response. The model was also found to be adequate for making further predictions through the ANOVA. The lack of fit was seen to be significant. Thus, in-significant terms could not be removed from the model.

The un-coded form of BP was found to be as follows:

\[
BP_{\text{un-coded}} = 9.23519 - 0.0875508V - 0.00538011I - 0.00148132S \\
+ 0.000931558V^2 - 1.92136E - 04I^2 - 1.76174E - 07S^2 \]
\[
+ 0.000148958VI - 1.27083E - 05VS + 2.70833E - 05IS. \tag{7}
\]

The surface plots of BP with accelerating voltage, beam current and welding speed were also studied. The bead penetration was found to increase with the increasing accelerating voltage and beam current due to an increase in the energy deposition rate. The BP was found to decrease with the increase of welding speed. It can be concluded that the welding should be done at high accelerating voltage and beam current, but at low welding speed to obtain the large depth of penetration. These observations perfectly matched with that of Liu et al.,\cite{lu} who predicted that the weld
depth increased with laser power and decreased with welding speed for laser welding of dissimilar metals.

The performance of the developed model was checked on eight test cases collected through real experiments. Figure 11 displays the values of percent deviations in predictions of BP for the eight test cases. The maximum value of percent deviation in predictions of BP was found to be equal to $-3.92\%$. The average absolute percent deviation in predictions of BP was seen to be equal to 1.36.

5.1.1.3. Yield strength (YS) of the welds

The regression analysis for YS carried out in coded form indicated that $X_3$, $X_1^2$ and $X_2X_3$ were significant. The YS was found to increase with welding speed and decrease with accelerating voltage and beam current. The combined effect of $X_2X_3$ (i.e., IS) was also significant. The coefficient of correlation for the yield strength was found to be equal to 0.771. The adequacy of the model was also checked through ANOVA test. The lack of fit was seen to be in-significant. Thus, in-significant terms could be removed from the model.

The un-coded form of YS was found to be as follows:

$$
YS_{\text{un-coded}} = -466.983 + 12.3065V + 7.47933I + 0.130277S
- 0.125959V^2 - 0.0218803I^2 + 7.10077E - 0.45S^2
- 0.00963906VI + 0.00119862VS - 0.00385819IS.
$$

The surface plots of Yield Strength (YS) with accelerating voltage, beam current and welding speed were plotted. The yield strength was found to increase with the increase in welding speed. The cooling rate increases with the increase in welding speed. The higher cooling rate results in fine grain structure, which might be the reason for an increase in yield strength. The higher yield strength might also be due to the decrease in porosity with the increase in welding speed. The YS was seen to be decreasing with an increase in beam current. The YS initially increased with accelerating voltage, but a further increase in accelerating voltage showed a decreasing trend in the YS. The increase in welding power (due to increase in accelerating voltage and beam current) results in high percent of intermetallic components, which
might be the reason for a decrease in YS. Therefore, the welding should be carried out at high welding speed, medium accelerating voltage and low beam current for obtaining high yield strength.

Figure 12 displays the values of % deviations in predictions of YS for the eight test cases. The maximum value of percent deviation in predictions of YS was found to be equal to $-10.87\%$. The average absolute percent deviation in predictions of YS had turned out to be equal to 3.90.

5.1.1.4. Ultimate tensile strength (UTS) of the welds

The terms: $X_2$, $X_3$, $X_1X_2$ and $X_1X_3$ were found to be significant during the regression analysis conducted for UTS of the welds. The combined effects of $X_1X_2$ ($V$ and $I$) and $X_1X_3$ ($V$ and $S$) were found significant. The coefficient of correlation was found to be equal to 0.7959. The adequacy of the model was checked through the ANOVA test. The lack of fit was found to be insignificant. Thus, insignificant terms could also be removed from the model.

The un-coded form of the response equation related to UTS was obtained as follows:

$$
UTS_{\text{un-coded}} = 27.7540 + 9.64350V + 7.70353I - 0.641379S \\
- 0.0745727V^2 - 0.00217653I^2 + 0.000133309S^2 \\
- 0.144646VI + 0.00835781VS - 2.475E - 04IS.
$$

(9)

The surface plots of UTS with accelerating voltage, beam current and welding speed were also studied. The UTS of the weld was found to generally decrease with the increasing accelerating voltage and beam current. However, it was found to increase with $V$ at low beam current and high welding speed. The UTS was found to increase with the increase in welding speed. The increase in welding speed results in lowering of the interaction time between copper and stainless steel, which results in the decrease of percent of intermetallics and in turn, increases the UTS of the weld. Welding carried out at high power (i.e., high $V$ and $I$) results in the high percent of intermetallics, due to which UTS decreases. At low beam current and high welding speed, the increase in accelerating voltage results in the decrease of the focal spot.
diameter and hence increase in power density. This causes the lowering of molten pool width, which results in the decrease of the percent of intermetallic components. Therefore, the UTS increases with the increase in $V$ at low beam current and high welding speed. So, electron beam welding of dissimilar metal should be carried out at high welding speed and high accelerating voltage, but at a low beam current for obtaining high ultimate tensile strength.

The performance of the developed model was tested on eight test cases. The values of percent deviation in predictions of UTS are shown in Fig. 13. The maximum value of percent deviation in predictions of UTS was found to be equal to 5.94%. The average absolute percent deviation in predictions of UTS was seen to be equal to 3.78.

5.1.2. Results of approach 2

As the performance of an NN depends on its parameters, a parametric study was conducted by varying one parameter at a time and keeping the others fixed. The set of optimal parameters, namely number of hidden neurons, coefficients of transfer functions for the hidden and output layers, momentum constant, learning rates, and others were obtained for the developed NN. The value of bias was kept fixed to 0.000001. Figure 14 shows the results of parametric study and Table 7 displays the optimized parameters of the BPNN model.

The test cases were passed through the optimized BPNN to check the performance of the model. The values of percent deviation in prediction of the output parameters were recorded (refer to Fig. 15). The values of average absolute percent deviation in predictions of different responses, as obtained by this approach, are displayed in Table 8.

5.1.3. Results of approach 3

The developed GANN model was tuned to minimize the fitness function. The appropriate number of hidden neurons, and GA-parameters like population size,
Fig. 14. Results of the parametric study carried out for the BPNN (a–g).
probability of mutation ($p_m$) and maximum number of generations ($Gen_{\text{max}}$), as shown in Fig. 16, were obtained thorough a parametric study.

The optimized number of hidden neurons was found to be equal to 24 through the above study. The best fitness was obtained for a population size of 60 and maximum generations of 1100. The optimized value of probability of mutation was obtained as 0.00019. The performance of the developed model was tested on eight test cases. The values of percent deviation in predictions of the responses are shown in Fig. 15. Moreover, Table 8 shows the values of average absolute percent deviation in predicting different responses by using this approach.

5.1.4. Results of approach 4

The detailed parametric study was carried out to determine the optimal parameters for PSONN-based model. The maximum number of runs had been kept fixed to 50. The optimum number of neurons in the hidden layer came out to be equal to 26 and the optimum number of executions or iterations in each run turned out
Fig. 15. Comparisons of different approaches in terms of percent deviation in predictions of various responses using regression analysis, BPNN GANN and PSONN-based forward models (a–d).
to be equal to 15000. The inertia weight $w$ was taken as $w = 1/(\ln 2)$ and the cognitive and confidence coefficients were fixed as $c_1 = c_2 = (0.5 + \ln 2)$. Figure 17 shows the details of the parametric study carried out for the determination of optimal PSO parameters.

The performance of the developed model was checked on eight test cases. Figure 15 displays the values of percent deviation in predicting different responses, as yielded by this approach. Moreover, the values of average absolute percent deviation in predictions of different responses are shown in Table 8. In forward mapping, the performances of NN-based approaches were found to be comparable with that of the regression analysis. Moreover, the GANN approach could perform a slightly better than the other two NN-based approaches for some of the responses.

### 5.2. Results of reverse mapping

The reverse mapping of the electron beam butt welding of dissimilar metals was carried out using NN-based approaches only, as it could not be done using the

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**Table 8.** Average absolute % deviation in predictions of different responses using regression analysis, BPNN, GANN and PSONN-based forward models.

<table>
<thead>
<tr>
<th>Sr. No.</th>
<th>Output or Response</th>
<th>Average Absolute % Deviation Using Regression Analysis</th>
<th>Average Absolute % Deviation Using BPNN Model</th>
<th>Average Absolute % Deviation Using GANN Model</th>
<th>Average Absolute % Deviation Using PSONN Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Bead width</td>
<td>4.46</td>
<td>5.20</td>
<td>4.87</td>
<td>6.84</td>
</tr>
<tr>
<td>2</td>
<td>Bead penetration</td>
<td>1.36</td>
<td>1.76</td>
<td>2.23</td>
<td>1.58</td>
</tr>
<tr>
<td>3</td>
<td>Yield strength</td>
<td>3.90</td>
<td>3.05</td>
<td>2.92</td>
<td>3.12</td>
</tr>
<tr>
<td>4</td>
<td>Ultimate tensile strength</td>
<td>3.78</td>
<td>3.65</td>
<td>3.73</td>
<td>3.72</td>
</tr>
</tbody>
</table>
Fig. 16. Results of the parametric study of the GANN approach (a–d).

Fig. 17. Results of the parametric study of PSO-NN (a–b).
obtained regression equations. The models for reverse mapping were developed with four input and three output neurons. The results of the reverse mapping are discussed below.

5.2.1. Results of approach 1 (BPNN approach)

The optimal parameters for the NN were determined through a detailed parametric study. Table 9 displays the optimized parameters of the BPNN model used for the reverse mapping.

The performance of the optimized BPNN model was checked by passing the test cases through it and recording the values of percent deviation in predictions of the process parameters. The values of percent deviation in predictions of the process parameters are shown in Fig. 18.

5.2.2. Results of approach 2 (GANN approach)

A systematic study was carried out to decide the appropriate number of hidden neurons, and GA-parameters, namely population size, probability of mutation ($p_m$) and maximum number of generations ($Gen_{max}$). The optimized number of hidden neurons was seen to be equal to 23. The best fitness was obtained for a population size of 50 and maximum number of generations of 500. The optimized value of probability of mutation was found to be equal to 0.0001. The performance of the developed model was verified on eight test cases. Figure 18 shows the values of percent deviation in predictions of the process parameters as obtained by this approach.

5.2.3. Results of approach 3 (PSONN approach)

The network was tuned to obtain the optimum number of neurons in the hidden layer and that of executions or iterations in each run. The optimum number of hidden neurons turned out to be equal to 28 and that of executions or iterations in each run came out to be equal to 15000 through a detailed parametric study.

<table>
<thead>
<tr>
<th>Sr. No.</th>
<th>Parameters</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Number of neurons of the hidden layer</td>
<td>$H_n$</td>
<td>26</td>
</tr>
<tr>
<td>2</td>
<td>Coefficient of transfer function</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>for hidden layer,</td>
<td>$a_h$</td>
<td>7.4</td>
</tr>
<tr>
<td></td>
<td>for output layer</td>
<td>$a_o$</td>
<td>6.0</td>
</tr>
<tr>
<td>3</td>
<td>Learning rate between</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>input and hidden layers,</td>
<td>$\lambda_i$</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>hidden and output layers</td>
<td>$\lambda_o$</td>
<td>0.60</td>
</tr>
<tr>
<td>4</td>
<td>Momentum constant</td>
<td>$\alpha$</td>
<td>0.35</td>
</tr>
<tr>
<td>5</td>
<td>Bias</td>
<td>$b$</td>
<td>0.000029</td>
</tr>
<tr>
<td>6</td>
<td>Maximum No. of Iterations</td>
<td>$z$</td>
<td>10000</td>
</tr>
</tbody>
</table>
Fig. 18. Comparisons of different approaches in terms of percent deviation in predictions of various process parameters using BPNN, GANN and PSONN-based reverse models (a–c).
Figure 18 displays the values of the percent deviations in predictions of the process parameters for a desired set of outputs or responses.

Table 10 shows the values of average absolute percent deviation in predictions of different input parameters using the BPNN, GANN and PSONN-based reverse models. All the three NN-based approaches were able to perform the reverse mappings efficiently. Although GANN could perform a slightly better than the other two NN-based approaches for some of the cases but not all, their performances were found to be data dependent.

6. Concluding Remarks

Butt welding of dissimilar metals, namely SS 304 and ETP copper plates were carried out using electron beam welding set-up, according to a central composite design of experiments. The input-output relationships of the process were developed using regression analysis, BPNN, GANN and PSONN models in the forward direction. The weld-bead profile (in terms of weld width and depth of penetration) and weld strength (in terms of yield strength and ultimate tensile strength) had been predicted using these models. Reverse mapping of the welding process was also conducted, and the set of input parameters required to get the desired output had also been determined using BPNN, GANN and PSONN models. The following conclusions were drawn through this study:

- The offset of the incident electron beam with respect to the weld seam is not required for the electron beam butt welding of dissimilar metals with widely differing thermal conductivity and melting point, when the oscillation of 0.3 mm at target location is provided in the beam.
- The cleaning and degassing of the copper plates are necessary before taking up for electron beam welding to obtain sound and spatter-free weld with a narrow bead.
- Electron beam welding should be carried out at high accelerating voltage, low beam current and high welding speed to obtain small bead width.
- Electron beam welding should be carried out at high accelerating voltage and beam current and low welding speed to obtain large depth of penetration.
- Electron beam welding of the dissimilar metals should be carried out at medium accelerating voltage, low beam current and high welding speed to obtain high yield strength.

<table>
<thead>
<tr>
<th>Sr. No.</th>
<th>Process Parameters</th>
<th>Average Absolute % Deviation Using BPNN Model</th>
<th>Average Absolute % Deviation Using GANN Model</th>
<th>Average Absolute % Deviation Using PSONN Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Accelerating voltage</td>
<td>8.29</td>
<td>7.28</td>
<td>7.77</td>
</tr>
<tr>
<td>2</td>
<td>Beam current</td>
<td>8.02</td>
<td>7.51</td>
<td>7.07</td>
</tr>
<tr>
<td>3</td>
<td>Weld speed</td>
<td>9.45</td>
<td>10.71</td>
<td>15.61</td>
</tr>
</tbody>
</table>

Table 10. Average absolute % deviation in predictions of different process parameters using BPNN, GANN and PSONN approaches for reverse mapping.
Electron beam welding of the dissimilar metals should be carried out at high accelerating voltage and welding speed and low beam current to obtain high ultimate tensile strength.

Neural networks were found to tackle the problem of both forward and reverse mapping efficiently. However, neural networks trained by the genetic algorithm and particle swarm optimization algorithm were seen to perform a slightly better than the BPNN in most of the cases but not all.

The present study could be considered as an important step towards automating the process and hence, to develop a smart EBW machine.

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References


