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Modelling the shape of electron beam welding joints by neural networks

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Abstract. This article discusses the experimental results from multi-pool electron beam welding, with dynamic positioning of the electron beam (beam splitting) [1], resulting in the formation of two consecutive welding pools. The 12Cr18Ni10Ti stainless steel samples are welded with a change in the process parameters: the distance between the two electron beams (electron beam positions) and the ratio between the two mean electron beam powers, the frequency of the deflection signal, the beam current and the welding velocity. The focusing current is kept at a constant value. The weld cross-sections, experimentally obtained at different process parameters, are used to train, validate and test neural models. The accuracy of prediction of the shapes of the welds (the form of the molten pool) is discussed and compared with that of an estimated regression model.

1. Introduction

Electron beam multi-pool welding with dynamic positioning of the electron beam [1] is applied for welding of heterogeneous materials [2], materials that are difficult to weld, reactive metals and alloys [3], etc. The implementation of this method results in the possibility to weld simultaneously different welds or distribute the beam power at different places along the axis of the movement of the electron beam, post-heating or pre-heating of the welds. Its main advantages are connected with the weld seam quality. The multi-pool electron beam welding (EBW) produces more homogenous weld seams, with minimum deformations, less cracks and other defects, uniformly distributed stress in the welded samples [2, 3], porosity and considerably reduced root spiking.

Development of adequate models for real industrial processes is usually a complicated task due to the large uncertainties, caused by the lack of direct measurements, the necessity of an inferential approach, the high level of non-linearity and different types of disturbances. Building models accurate enough in a broad range of operational conditions may be successful, if different intelligent modelling techniques are used [4-10].

The development of neural network-based models for the EBW performance characteristics consists of the following general steps:

- Construction of the neural network model structure.



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- Training of the created neural network by using the back propagation method [5, 8, 9] experimentally obtained (and/or numerically simulated) set of training data to a satisfactory accuracy.
- Recall of the trained neural network for prediction and parameter optimization.

Feedforward networks can be used for any kind of inputs to output mapping. The two-layer feed-forward network with sigmoid hidden neurons and linear output neurons is shown on figure 1. It can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer. The network is trained with Levenberg-Marquardt back propagation algorithm [5, 8, 9].

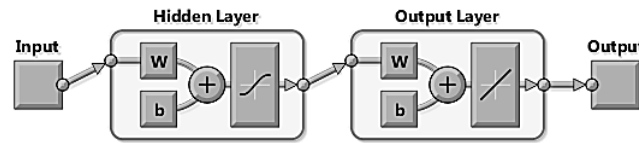


Figure 1. Feedforward neural network structure.

The linear activation function, produces output results equal to the activation potential $\{u\}$, having its mathematical expression given by:

$$g(u) = u \quad (1)$$

The sigmoid function is defined by:

$$g(u) = \frac{1}{1 + e^{-\beta u}} \quad (2)$$

where β is a real constant associated with the function slope in its inflection point.

This article presents the implementation of an empirical modeling approach for prediction of the shapes of the welds (the form of the molten pool) $H(x)$ in the cross-section (along the x-axis) perpendicular to the electron beam movement direction (y-axis). The weld cross-sections, experimentally obtained at different process parameters, are used to train, validate and test neural models. The accuracy of prediction of the shapes of the welds (the form of the molten pool) is discussed and compared with that of an estimated regression model.

2. Experimental conditions

The experimental results from the multi-pool electron beam welding (EBW), with dynamic positioning of the electron beam (beam splitting) [1] are studied. The process was held with the beam deflection into two beam positions (two beams) thus performing dual-pool welding. The deflection was performed by transmitting rectangular signal to the deflection coils. 12Cr18Ni10Ti stainless steel samples were welded at changing the EBW process parameters: the distance between the two electron beams (electron beam positions or pools) L [mm], the ratio between the two mean electron beam powers γ (gamma), the frequency of the deflection signal F [kHz], the beam current I_b [mA] and the welding velocity v [mm/s]. The focusing current was kept constant $I_f = 835$ mA. The obtained weld cross-section shapes $H(x)$ of 19 process experimental sets were considered.

The energy distribution between the two resulting beams (Z3) is determined by the parameter γ (gamma):

$$\gamma = \frac{(P_2 - P_1)}{(P_1 + P_2)} \quad (3)$$

where P_1 and P_2 are the corresponding beam powers – on the front and on the back beams. If γ has a positive value then the back electron beam has more power than the front one.

The EBW process parameter variation regions for this experiment are presented in table 1. Figure 2 and figure 3 present two weld cross-sections, obtained for different sets of the process parameters, after cutting and polishing.

Table 1. EBW process parameter variation regions.

Factor (Z_i)	Dimension	Coded	Lower level ($Z_{\min,i}$)	Upper level ($Z_{\max,i}$)
L - Z_1	mm	x_1	2	6
F - Z_2	kHz	x_2	3	20
γ - Z_3	-	x_3	-0.3	0.3
v - Z_4	mm/s	x_4	5	15
I_b - Z_5	mA	x_5	40	64.5



Figure 2. Weld cross-section: weld depth $H = 7.63$ mm and weld width $B = 4.6$ mm at: $L = 6$ mm, $F = 10$ kHz, $\gamma = 0$, $v = 5$ mm/s, $I_b = 55$ mA.



Figure 3. Weld cross-section: weld depth $H = 8.29$ mm and weld width $B = 5.26$ mm at: $L = 6$ mm, $F = 10$ kHz, $\gamma = 0$, $v = 5$ mm/s, $I_b = 64.5$ mA.

3. Regression and neural models for the welds shapes

A regression model for the obtained weld cross-section shapes $\hat{h}(x)$ [11] as a function of the coordinate x along the x-axis, perpendicular to the electron beam movement direction (y-axis) is estimated:

$$\begin{aligned} \hat{h}(x) = & 4.7281073 - 0.20834179x_3 - 0.97473541x_4 + 0.60515907(1.9075x+0.012465) \\ & + 0.37969849x_4^2 - 23.456768(1.9075x+0.012465)^2 + 19.405712(1.9075x+0.012465)^4 \\ & + 0.36239221x_1x_3 + 0.34001364x_2x_4(1.9075x+0.012465) + 0.32241341x_3(1.9075x+0.012465) \\ & - 0.81914549x_4x_5 + 0.55651984x_5(1.9075x+0.012465) + 0.80811398x_1x_4(1.9075x+0.012465) + \\ & 0.2792938x_1^2(1.9075x+0.012465)^3 - 0.64377674x_1x_3^2(1.9075x+0.012465) \end{aligned} \quad (4)$$

The data processing is carried out in a coded scale, in order to avoid problems related to possible multicollinearity, other numerical problems at the evaluation of the regression coefficients and small

prediction values of the quality indicator. The process parameters, shown in table 1, are coded in the range from -1 to 1, depending on their experimental ranges. The conversion from natural (Z_i) to dimensionless coded (x_i) values and vice versa can be done by the formula [12]:

$$x_i = \frac{2Z_i - (Z_{max,i} + Z_{min,i})}{Z_{max,i} - Z_{min,i}} \quad (5)$$

The coordinate x in the equation is given in mm, with zero value in the center of the weld (where the maximal weld depth $\hat{h}_{max}(x) = H$ is measured). The positive and negative values give the deviation from this central coordinate ($x = 0$ mm).

The determination coefficient $R^2 = 76.001\%$ (the square of the multiple correlation coefficient) and the adjusted determination coefficient $R^2_{adj} = 74.606\%$ are measures for the model accuracy (the model is better, if the coefficient is closer to 100%). The regression model gives the possibility to simulate the weld shape $\hat{h}(x)$ for a given set of technological parameters (Z_1 - Z_5).

Neural network (NN) models, based on a multi-layered feed forward neural network, trained with Levenberg-Marquardt error backpropagation algorithm were obtained. The accuracy of the neural models is compared by juxtaposing the calculated mean squared error (MSE) and the regression multiple correlation coefficient (R) at the cross-validation of the models by the predicted and experimentally observed parameter values.

The EBW process parameters define the input-output structure of the estimated neural network-based model. The inputs are defined by the process parameters in table 1 and the coordinate x . The accuracy of training, validation and testing of neural networks with different hidden layer structures are compared – with 7, 11 and 12 neurons.

For training, validation and testing of the neural networks, the experimental data were randomly separated into 3 parts: 80% (209 datasets) for training, 10% (26 datasets) for validation and 10% (26 datasets) for testing. The obtained results for the accuracy of the training of the best obtained NN models with the considered different NN model structures are presented in table 2 and figure 4.

The obtained results for the accuracy from the validation and testing of these NN models are presented correspondingly in table 3, figure 5 and in table 4, figure 6.

Table 2. Feedforward neural network training results.

	NN with 7 neurons	NN with 11 neurons	NN with 12 neurons
MSE	0.420906	0.287991	0.169591
R	0.961473	0.975402	0.984424

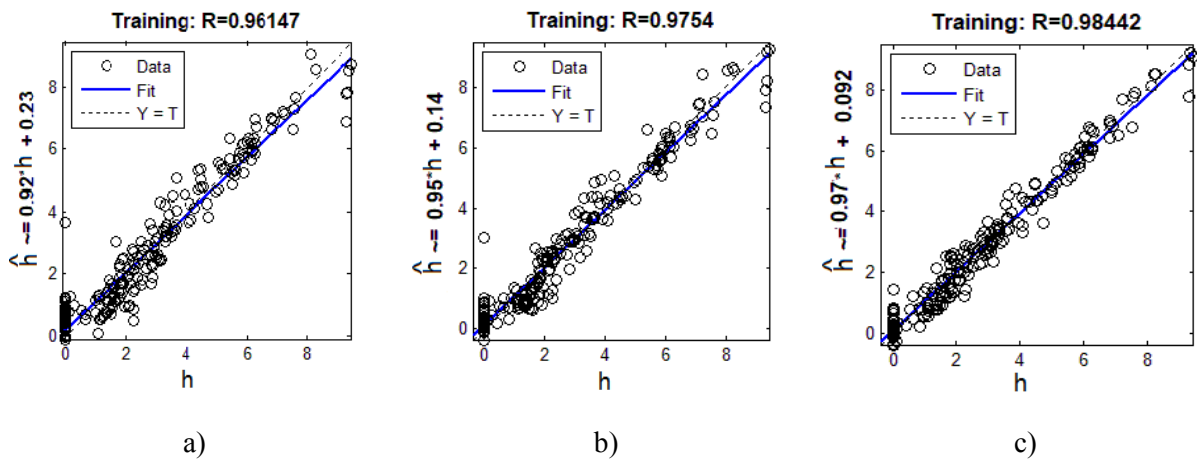


Figure 4. Feedforward neural network training results: a) 7, b) 11 and c) 12 hidden neurons.

In the tables, the values of the regression multiple correlation coefficients R and the Mean Square Error (MSE) are shown:

$$MSE = \frac{\sum_{i=1}^n (\hat{h}_i - h_i)^2}{n} \quad (6)$$

where $\hat{h}$ and h are the predicted and the experimental values, n is the number of data.

The values of the regression coefficient R measure the correlation between the calculated outputs ($\hat{h}(x)$) and the experimental values $h(x)$. R value of 1 means full coincidence between predicted ($\hat{h}$) and the experimental (h) values and 0 - random relationship. If the value of the MSE is equal to zero, there is no prediction error.

Table 3. Feedforward neural network validation results.

	NN with 7 neurons	NN with 11 neurons	NN with 12 neurons
MSE	0.306778	0.695732	0.348747
R	0.970232	0.916773	0.967627

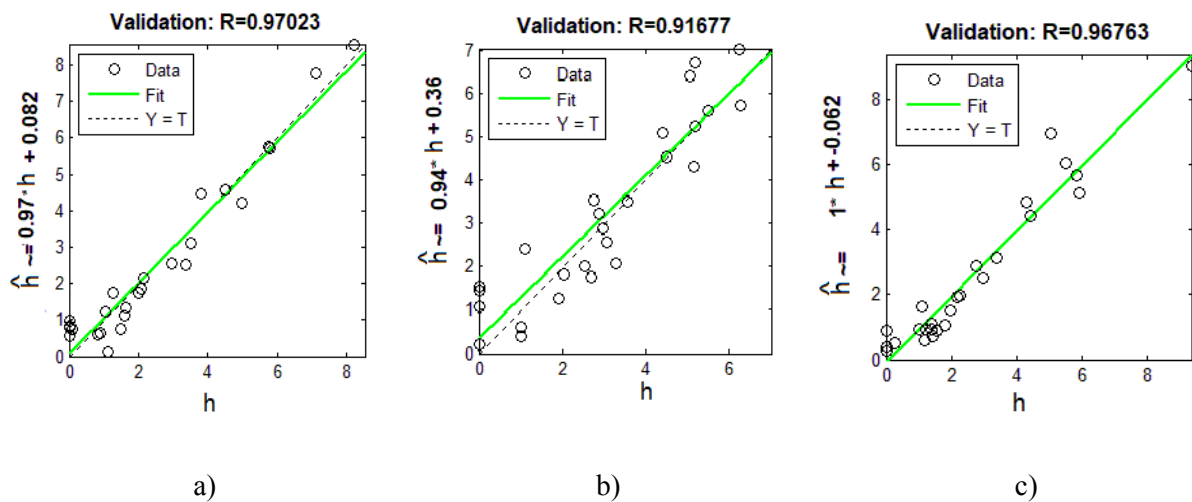


Figure 5. Feedforward neural network validation results: a) 7, b) 11 and c) 12 hidden neurons.

Table 4. Feedforward neural network testing results.

	NN with 7 neurons	NN with 11 neurons	NN with 12 neurons
MSE	0.564184	0.376664	0.388378
R	0.950565	0.951579	0.969721

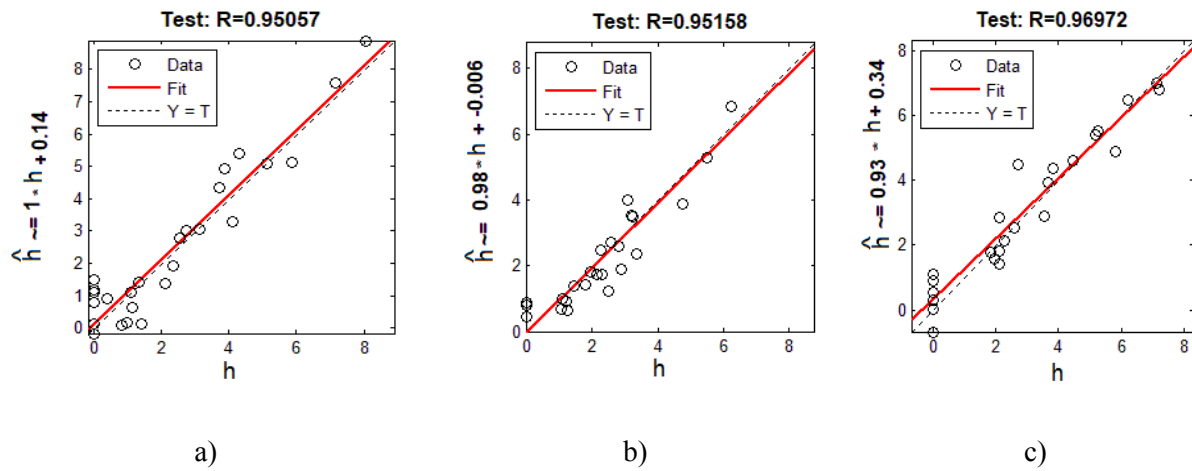


Figure 6. Feedforward neural network test results: a) 7, b) 11 and c) 12 hidden neurons.

From the tables (2-4) and figures (4-6) it can be seen, that from the considered three NN model structures better results are obtained by using a hidden layer consisting from 12 hidden neurons, due to the smaller values of MSE and the closer to 1 values of the coefficient R, obtained during training, validation and testing stages.

In figure 7 and figure 8, weld cross-section plots are presented for verification of the experimental data, estimated regression function and the neural model with 12 neurons for two experimental cases:

case 1 (figure 7): the process parameters are: $L = 6$ mm, $F = 10$ kHz, $\gamma = 0$, $\nu = 5$ mm/s, $I_b = 55$ mA; the obtained geometry parameters are: weld depth $H = 7.63$ mm and weld width $B = 4.6$ mm.

case 2 (figure 8): the process parameters are: $L = 6$ mm, $F = 10$ kHz, $\gamma = 0$, $\nu = 5$ mm/s, $I_b = 64.5$ mA; the obtained geometry parameters are: weld depth $H = 8.29$ mm and weld width $B = 5.26$ mm.

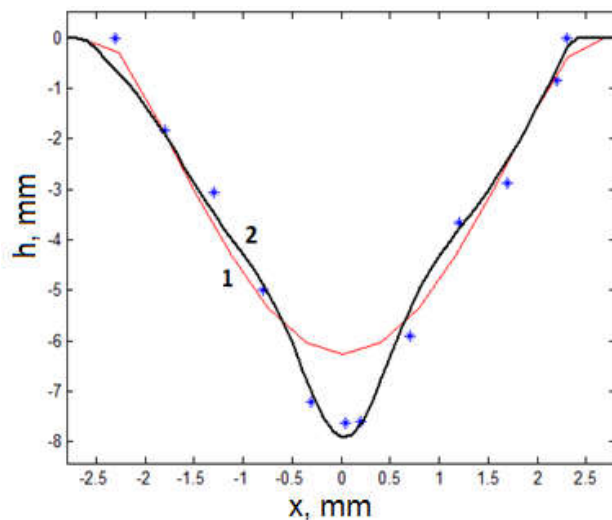


Figure 7. Weld cross-section: weld depth $H = 7.63$ mm and weld width $B = 4.6$ mm at process parameters: $L = 6$ mm, $F = 10$ kHz, $\gamma = 0$, $\nu = 5$ mm/s, $I_b = 55$ mA (* – experimental data, 1 – regression function, 2 – NN model).

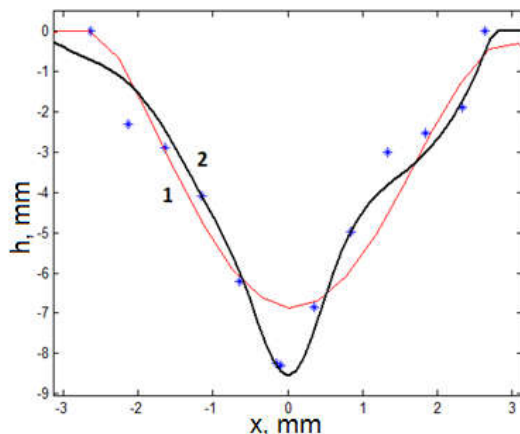


Figure 8. Weld cross-section: weld depth $H = 8.29$ mm and weld width $B = 5.26$ mm at process parameters: $L = 6$ mm, $F = 10$ kHz, $\gamma = 0$, $v = 5$ mm/s, $I_b = 64.5$ mA (* – experimental data, 1 – regression function, 2 – NN model).

4. Conclusion

In this article it is demonstrated, that on base of experimental data, empirical models can be estimated implementing regression analysis and neural network training. In the considered cases, the neural network models give better approximation results and accuracy of prediction. By trained neural network models, it is possible to predict the technological results as well as to select the processing parameters for obtaining desirable shapes and dimensions at joining of metal parts by electron beam welding. Estimated models can be used further for optimization of the weld shapes by appropriate process parameter settings.

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