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NEURAL NETWORK BASED APPROACH FOR PROCESS OPTIMIZATION OF ELECTRON BEAM WELDING

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Abstract: In this paper neural networks are implemented for the investigation of the defined as quality characteristics of electron beam welding: mean weld widths, weld depths, thermal efficiency and defectiveness. Different modelling approaches are compared and their applicability is discussed. Neural networks are trained using a set of experimental data containing different welding regime conditions (electron beam power; welding velocity, the distance between the main surface of the magnetic lens of the electron gun and the beam focusing plane and the distance between the main surface of the magnetic lens of the electron gun and the sample surface). The implementation of considered approaches and their applicability for process parameter choice, optimization and automatic control aiming improving of the quality of the obtained welds is compared.

Key words: Neural network-based models, electron beam welding, weld geometry characteristics, optimization.

INTRODUCTION

Neural networks have been attached the growing interest of researchers in various scientific and engineering areas [1, 2]. The number and variety of applications of neural networks have been increasing, ranging from consumer products and industrial process control to medical instrumentation, information systems, and decision analysis. Neural networks were developed to provide computational power, fault tolerance, and learning capability to the systems. Neural networks have been shown to have the capability of modeling complex nonlinear processes to arbitrary degrees of accuracy [3, 4]. Neural networks are complementary technologies in the design of intelligent systems [5].

Electron beams are finding numerous applications in research and industry as a concentrated energy thermal source. Electron beam deep penetration welding of materials in vacuum is the most widely used method of non-conventional technologies for joining machine parts.

Nevertheless, the high effort in developing complex and sophisticated physical and thermal models of the electron beam welding (EBW) [6], the acceptance of computer simulations for practical applications in this field is still limited to approximated evaluation of order of the expected weld geometry parameters. Integration of the created models in expert or control computer systems is still desirable and under development [7].

Prognoses of the weld parameters in an expert system for the operator assistance and the automatic control of the electron beam welding with deep penetrating beam could be done by neural network models that take into account the values of the distances between the electron gun focusing lens and both the sample surface and the beam focusing plane position. The weld depth, mean half width, thermal efficiency and number of defects for various beam powers, welding speeds and two geometry peculiarities, for the investigated electron beam welding machine and various positions of beam focus towards the sample plane are investigated and analyzed. The sample material investigated was stainless steel type 1H18NT. In this paper, different modelling approaches for process optimization of EBW are compared and their applicability is discussed.

NEURAL NETWORK IMPLEMENTATION

One of the most promising fields of the Artificial Intelligence is related to the Neural Networks (NN) [3] that has the ability to learn and approximate any functional relationship. The proposed methodology for developing NN-based models for EBW performance characteristics consists of the following general steps:

1. Construction of the neural network model structure (Fig. 1 and Fig. 2).
2. Training of the created neural network by using the back propagation method [3] and experimentally obtained (and/or numerically simulated) set of training data to a satisfactory accuracy.
3. Recall of the trained neural network for prediction and parameter optimization.

The experiment, considered in this paper, [6] is the electron beam welding of samples of austenitic stainless steel, type 1H18NT. The following operating parameters are varied: power (P) - 4.2, 6.3 and 8.4 kW; welding velocity (v) - v=80 cm/min, 20 cm/min and 40 cm/min; distance between the main surface of the magnetic lens of the electron gun and the beam focusing plane (z_o) - 176 mm, 226 mm and 276 mm; and different distances between the main surface of the magnetic lens of the electron gun and the sample surface (z_p) in the region 126 mm and 326 mm. The accelerating voltage is 70 kV. 81 experimental weld cross-sections are investigated. The following quality characteristics are considered: weld depth H, mean weld width B, thermal efficiency η_T.

The modelled EBW process parameters define the input-output structure of the neural network-based model used, i.e. the neural network should consist of *4* input neurons and *1* output neuron, as it is presented in Fig. 2. NN models for each output (weld depth H, mean weld width B and the process thermal efficiency η_T [6]) are considered. In [7] neural networks were trained for the thermal efficiency, considering different input-output structures, and the obtained models are validated using an independent test experimental data excerpt.

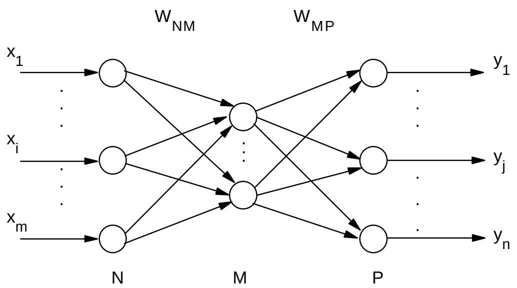

Fig. 1. Neural network structure

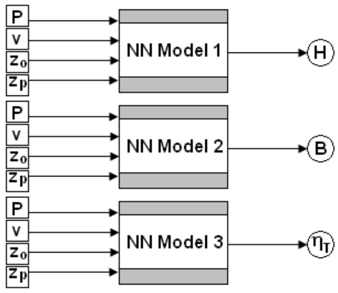

Fig. 2. Neural networks input-output parameters

The best results for Neural network models for the weld depth H, mean width B and the thermal efficiency η_T were obtained with 5 hidden units and different number of iterations for training (above 10000 iterations). For the purpose of validation the data were split into two parts: training datasets containing 73 observations and the testing datasets limited to 8 observations each (for H and for B). For each performance characteristic randomly were chosen 10 datasets (73 training and 8 test observations) and for each dataset the best network model was obtained and verified. For comparison of the models the absolute value of the error calculated as the difference between the predicted and the measured values of the weld geometry characteristics, as well as root mean squared error (*RMSE*) and the non-dimensional error index (*NDEI*) are used. The last two are calculated by:

$$RMSE = \sqrt{\frac{(\hat{y}-y)^2}{n}}\,; \qquad NDEI = \frac{RMSE}{\sigma},$$

where $\hat{y}$ and y is the predicted and the experimental values, n is the number of data and σ is the standard deviation of the data points. These error measures are defined on the basis of the training error (average loss over the training sample) and the generalization error (expected prediction error on an independent sample). Their values are minimized during the neural network training.

The experimental results (marked with points) and the predicted results (connected with the straight lines) using the estimated best model for the weld depth H using the training dataset (73 observations) are presented in Fig. 3 to illustrate the results of this approach.

The absolute value of the errors, presented as the difference between the predicted and the measured values of the weld depths, are calculated and graphically presented in Fig. 4, connected with lines. Generally the error values are situated in the region (-2÷2 mm) with the exception of only 5 errors.
The model precision is estimated quantitatively by RMSE and NDEI and the results are presented in Table 1 for the welds depth, width and the thermal efficiency from the best NN model training and validation results.

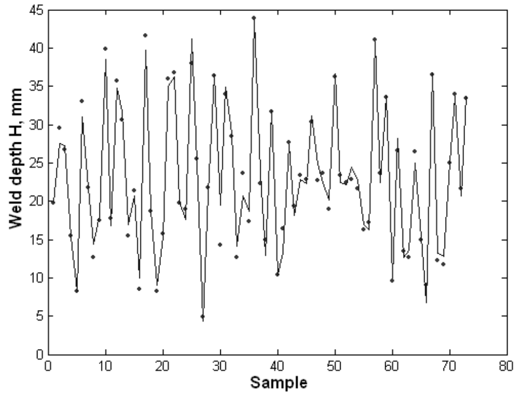

Fig. 3. Predicted end experimental values for the weld depth-training

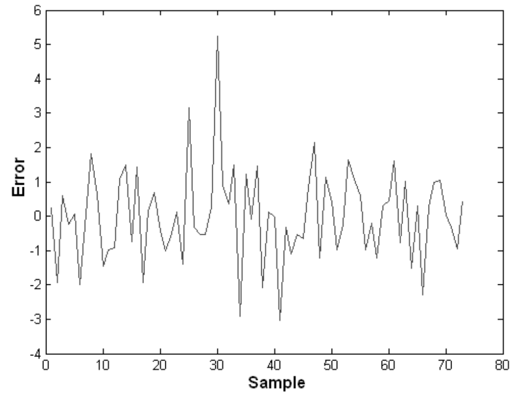

Fig. 4. Absolute error values (the differences between the experimental and the predicted weld depths) – training

Table 1. RMSE and NDEI error measures

	Training (73 obs.)	Testing (8 obs.)	
RMSE	1.33382	1.52107	H
NDEI	0.141456	0.162708	
RMSE	0.226097	0.131611	B
NDEI	0.231885	0.116459	
RMSE	0.0290363	0.0273294	η_T
NDEI	0.47571	0.3782120	

The trained neural networks are implemented for prediction of the considered performance characteristics over the experimental region and their individual optimization (for the H and η_T – maximum and for B - minimum). In Table 2 and Table 3 are presented the optimal results, the corresponding optimal process parameter values and the values of the rest two performance characteristics predicted at the same EBW process conditions. It can be seen that the most deep welds do not coincide with the regimes with maximum thermal efficiency, the minimum width of the welds is obtained for weld depths about 25 mm, the maximum thermal efficiency is reached at regime conditions at which the focus position is 150 mm above the sample surface and the welds are comparatively wide and shallow.

In Fig. 5. is presented a contour plot of the thermal efficiency, depending on the distances to the beam focus and to the sample surface (z_0 and z_p), at optimal values of the beam power P = 7.14 kW and the welding velocity v = 20 cm/min, at which the maximum thermal efficiency is reached (Table 3). It can be seen that values above 0.5 (50%) are reached at focus positions considerably below the sample surface. Fig. 6 shows the corresponding (the same process parameters P and v) contour plots of the weld depth and mean width. At these conditions the most deep and narrow welds are obtained for small distances to the sample surface and focus positions a below its surface. Since the optimal solutions for each performance characteristic are different, a compromise solution must be found, fulfilling the requirements for all the characteristics at the same time.

Table 2. Optimal regimes

	P, kW	v, cm/min	z_o, mm	z_p, mm
H_{max}	8.4	20	196	126
B_{min}	8.4	74	266	126
$\eta_{T,\,max}$	7.14	20	176	326

Table 3. Optimal weld quality performance characteristics

	H, mm	B, mm	η_T
H_{max}	**45.69**	2.60	0.356
B_{min}	24.69	**0.01**	0.266
$\eta_{T,\,max}$	12.38	5.27	**0.687**

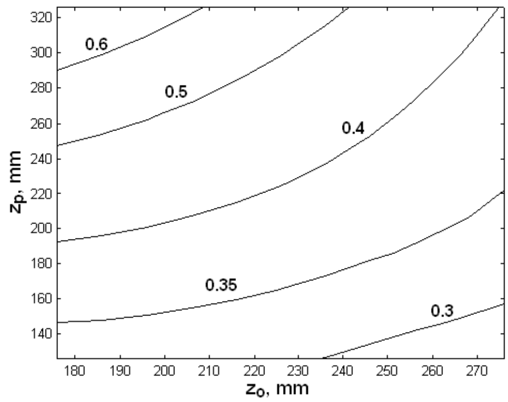

Fig. 5. Contour plot of the thermal efficiency, depending on the distances z_0 and z_p, at values of P = 7.14 kW and v = 20 cm/min

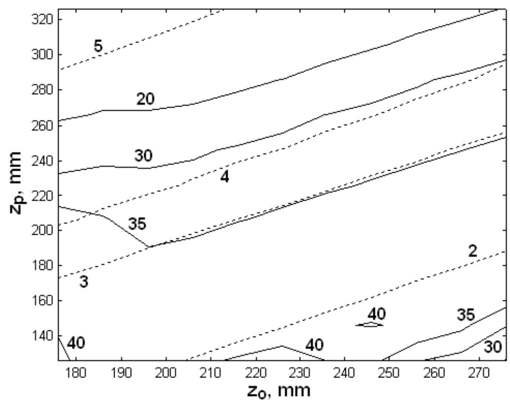

Fig. 6. Contour plot of the weld depth (solid lines) and the weld mean width (dashed lines), depending on the distances z_0 and z_p, at P = 7.14 kW and v = 20 cm/min

COMPERANCE OF DIFFEREN APPROACHES FOR DEFECT-FREE WELDS

For the experimentally obtained weld cross-sections the number of defects (experimentally obtained data are 0, 1 or 2) is counted. Several approaches are applied for the prediction of the process parameter regions, where the probability for appearance of defects is smaller: discriminant analysis, binary logistic regression and regression analysis.

In order to apply the discriminant analysis (and binary logistic regression) for prediction and classification the experimental observations are separated into two groups (classes): 1 – with defects and 2 – without defects. The type of the defects is not taken into account. The discriminant functions for the two groups are estimated and on the base of the obtained values for the squared distance functions and the corresponding posterior probabilities the observations are classified and new results can be predicted. The squared distance value is that value from observation to the group centroid, or the mean vector. Observations are assigned to the group with the highest posterior probability. For a given observation (process parameter values), the group with the smallest squared distance has the largest value of the linear discriminant function:

- for group 1 (without defects):
  D_1=-27.550+2.665*P+0.083*v+0.096*z_o+0.053*z_p;
- for group 2 (with defects):
  D_2 =-22.414+2.162*P+0.075*v+0.108*z_o+0.031*z_p.

The percentage of the correctly predicted observations is 81.5% (79% - group 1, 89.5% - group 2). The relative importance of the process parameters for the classification is estimated:

- for group 1 (without defects):
  P – 53.4%, v – 4.6%, z_o -11.4%, z_p – 30.6%;
- for group 2 (with defects):
  P – 55.3%, v – 5.3%, z_o – 16.4%; z_p – 23.0%.

The most influential process parameters, which should be considered, in order to avoid the defect appearance, are electron beam power and the distance to the surface of the sample.

The best results are obtained by applying the regression analysis – 94% of the observations are predicted correctly (95% - group 1, 89.5% - group 2). In order to apply the regression analysis a regression model for the defects is estimated:

$$\begin{aligned}D = {} & -0.177-0.341x_1-0.113x_2+0.562x_3-\\ & -1.188x_4+0.495x_1^2+0.260x_2^2+0.314x_3^2+1.097x_1x_4-\\ & -0.368x_2^2x_3-0.383x_1^2x_3+0.553x_1^2x_4-0.271x_1^2x_2x_4\\ & +0.379x_1x_3^2-1.867x_1x_3x_4+ +1.803x_1x_4^2+0.677x_2^2x_4\\ & +0.320x_1^2x_2x_3-0.586x_1^2x_3^2+2.037x_1^2x_3x_4-2.083x_1^2x_4^2\\ & -0.232x_1x_2^2x_3-0.742x_1x_3x_4^2-1.890x_2^2x_3x_4\\ & +1.886x_2^2x_4^2-0.310x_2x_3x_4^2\end{aligned}$$

In these model the process parameters (x_1 – beam power, x_2 – welding velocity, x_3 – distance to the beam focus and x_4 – distance to the sample surface) are coded in the region [-1÷1] and can be obtained from the factors natural values by: x_1=0.476*P–3, x_2=0.0333*v–1.6667, x_3=0.02*z_o–4.52, x_4=0.01*z_p–2.26.

The value of D=0.5 is accepted as a conditional limit between the regions with (D>0.5) and without (D<0.5) defects. If there is need to make the correct predictions for classification for the group 2 - 100% (no mistake of the type that the process parameters will produce welds without defects, while the truth is that there are defects), the limit between the 2 regions should be set to D=0.4 (then the overall percentage of the correctly predicted observations will be 87.7%, but for group 1 – 83.9%).

The best results for neural network models for number of defects were obtained with 6 hidden units and different number of iterations for training (above 10000 iterations). The model precision is estimated quantitatively by RMSE and NDEI and the results are presented in Table 4.

Table 4. RMSE and NDEI error measures for defects

	Training (73 obs.)	Testing (8 obs.)
RMSE	0.112353	1.80553
NDEI	0.180964	3.90039

The trained neural network model, at assuming a conditional limit between the regions with (D>0.5) and without (D<0.5) defects, give precision of 98.77%: for group 1 – 98.39%, for group 2 - 100%. Therefore there is no mistake of the type that the process parameters will produce welds with unwanted presence of defects.

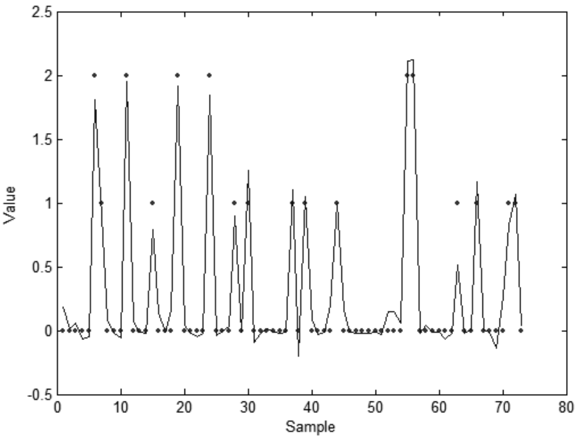

Fig. 7. Predicted end experimental values for the number of defects - training

The experimental results (marked with points) and the predicted results (connected with the straight lines) using the estimated best model for the defect number using the training dataset (73 observations) are presented in Fig. 7.

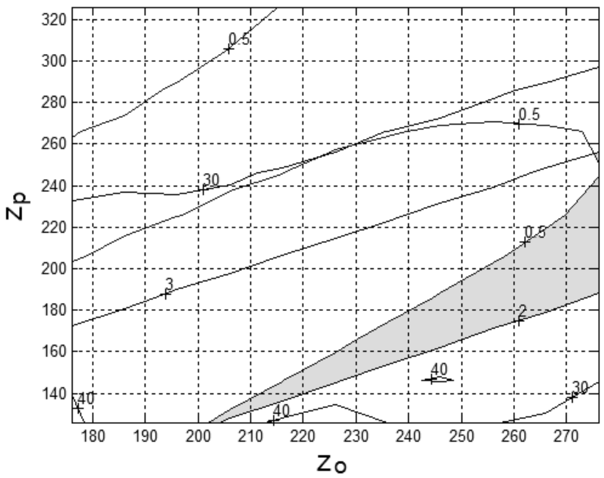

Fig. 8. Optimal process parameter area at beam power P= 4.2 kW and welding velocity v=80 cm/min

Parameter optimization, based on the trained and tested neural network models, can be performed. Fig. 8 presents the area for the distance to the focusing plane (z_o) and the distance to the sample surface (z_p) (colored zone) for obtaining welding joints with mean half width between 2 mm and 3 mm, depth larger than 30 mm and no defects at beam power P= 4.2 kW and welding velocity v=80 cm/min.

CONCLUSION

Neural networks are versatile in that they are capable of being incorporated in various modelling and control methods and strategies. In this paper, a systematic methodology based on neural networks for the construction of nonlinear models, being able to predict the geometry characteristics of the obtained through EBW joints, as well as the thermal efficiency and the defectiveness, has been proposed.

The results obtained have shown that the proposed Intelligent Neural-Network-based approach can be implemented for parameter optimization at specific requirements for the geometry of the welds and is applicable to industrial EBW processes.

The implementation of considered approaches and their applicability for process parameter choice, optimization and automatic control aiming improving of the quality of the obtained welds has been compared. The beneficial implementation of NN in the computer operator-aided or process control systems will compensate the lack of precise knowledge about the physics of the involved complex processes, the uncertainties of the thermo-physical properties of the processing material etc. In such way the quality of the product and the process could be improved and, at the same time, the cost of destructive trial runs and the losses due to non-optimum operation of the process will decrease.

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