Neural network based approach for quality improvement of electron beam welding

Elena Koleva, Nikolinka Christova, Georgi Mladenov, Dmitrii Trushnikov, Vladimir Belenkiy

Neural network models for the dependence of the geometry characteristics of welds from 38Cr2Ni2Mo high-strength steel, obtained at electron beam welding in presence of longitudinal beam deflection oscillations, are estimated. This methodology is implemented together with the response surface methodology (statistical approach). The results obtained by neural networks and regression models are analyzed and compared for the investigation of the influence of electron beam welding process parameters – focusing current, frequency and amplitude of beam deflection oscillations – on the obtained weld depth, width of the fusion and the heat affected zones.

Подход базиран на невронни мрежи за повишаване на качеството на електроннолъчево заваряване (Е. Колева, Н. Христова, Г. Младенов, Д. Трушников, В. Бененкий). *Оценени са невронни модели за зависимостите на геометричните характеристики на заваръчни шевове от високоякостна стомана 38Cr2Ni2Mo, получени чрез електронно лъчево заваряване при наличие на осцилации на лъча по посока на движението му. Тази методология е приложена заедно с методологията на откликовата повърхност (статистически подход). Анализирани и сравнени са резултатите, получени чрез невронни мрежи и регресионни модели, като е изследвано влиянието на параметрите на електроннолъчевото заваряване – ток на фокусировка, честота и амплитуда на осцилациите на лъча – върху дълбочината на шевовете, ширината на стопената и на термично повлияните зони.*

Introduction

Artificial neural networks [4], [9] have revolutionized the way researchers solve many complex and real-world problems in engineering, science, economics, and finance. In this study Neural network (NN) models, based on a multi-layered feed forward neural network, trained with Error Back Propagation (EBP) algorithm [2], [6] are created and investigated. The NN models present the EBW performance characteristics and are further applied for quality improvement of electron beam welding.

The model-based statistical approach for improving the quality of the process [3], [8] can be successfully applied to different industrial processes. Such modeling, based on experimental data and the Response surface methodology, avoids the difficulties and the uncertainties at the description of the complex physical processes taking place during electron beam welding by analytical models.

Electron beam welding, which implements oscillations of the beam, is flexible toward tuning the process with respect to the weld quality. There are various possibilities for the oscillations of the beam, but generally they can be along and across the zone of interaction.

In this paper the influence of the process parameters – focusing current, frequency and amplitude of the deflection oscillations (linear along the interaction zone) of the electron beam on the obtained weld and heat affected zone geometries is investigated.

Experimental conditions

Artificial neural networks [4], [9] have revolutionized the way researchers solve many complex and real-world problems in engineering, science, economics, and finance. In this study Neural network (NN) models, based on a multi-layered feed forward neural network, trained with Error Back Propagation (EBP) algorithm [2], [6] are created and investigated. The NN models present the EBW performance characteristics and are further applied for quality improvement of electron beam welding.

The model-based statistical approach for improving the quality of the process [3], [8] can be successfully applied to different industrial processes. Such modeling, based on experimental data and the Response surface methodology, avoids the difficulties and the uncertainties at the description of the complex physical processes taking place during electron beam welding by analytical models.

Electron beam welding, which implements oscillations of the beam, is flexible toward tuning the process with respect to the weld quality. There are various possibilities for the oscillations of the beam, but generally they can be along and across the zone of interaction.

In this paper the influence of the process parameters – focusing current, frequency and amplitude of the deflection oscillations (linear along the interaction zone) of the electron beam on the obtained weld and heat affected zone geometries is investigated.

Table 1

Process parameters – experimental regions

Param.	Dim.	Coded	Min.	Max.
I_f	mA	x_1	820	850
F	Hz	x_2	90	1400
A	mm	x_3	0.27	3.4

Neural network models

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques [4], [9]. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze.

Feed-forward neural network (FNN), also referred to as multilayer perceptrons (MLPs), has drawn great interests over the last two decades for its distinction as a universal function approximator [2]. As an important intelligent computation method, FNN has been applied to a wide range of applications, including curve fitting, pattern classification and nonlinear system identification and so on [5], [6].

A multi-layered neural network has one or more hidden layers along with the input and output layer (Fig. 1). Each layer has a certain number of nodes and all the nodes in one layer are connected with all the other nodes in the succeeding layer. Associated with each connection, a numerical value is assigned, which is termed as weight, where the actual associative knowledge between the inputs and outputs is stored.

Input patterns are submitted during the EBP training sequentially. If a pattern is submitted, and its classification or association is determined to be erroneous, the weights are adjusted so that current least square classification error is reduced. Usually, mapping error is cumulative and computed over the full training set.

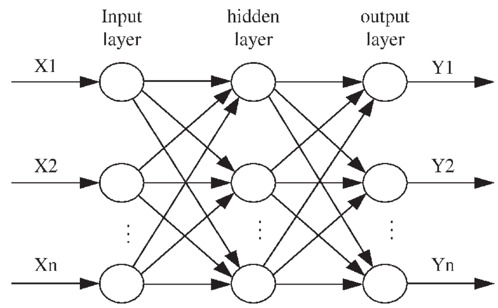


Fig. 1. Feed-forward neural network structure

A neural network model is a structure that can be adjusted to produce a mapping from a given set of data to features of or relationships among the data. The model is adjusted, or trained, using a collection of data from a given source as input, typically referred to as the training set. After successful training, the neural network will be able to perform classification, estimation, prediction, or simulation on new data from the same or similar sources.

The proposed methodology for developing NN based models for EBW performance characteristics consists of the following general steps:

- Construction of the neural network model structure.
- Training of the created neural network by using the back propagation method and 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.

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 3 input neurons and 1 output neuron. NN models for each output (weld depth, weld width and the width of the heat affected zone) are considered (see Fig. 2).

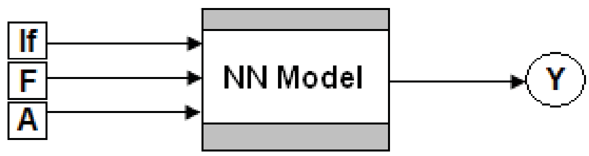


Fig. 2. Neural networks input-output parameters

Table 2

RMSE and NDEI Measures for weld depth H, weld width B_{sw} and the width of the heat affected zone B_{haz}

(36 obs., 6 units)	**Training *H***	**Training Bs_w**	**Training B_{haz}**
RMSE	0.349002	0.27086	0.268902
NDEI	0.165209	0.352831	0.313965

For comparison of the neural network 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:

$$(1) \qquad RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}};$$

$$(2) \qquad NDEI = \frac{RMSE}{\sigma},$$

where $\hat{y}_i$ and y_i 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.

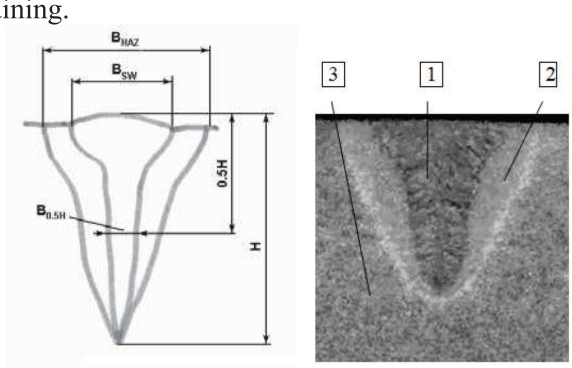


Fig. 3. Weld geometry characteristics

At electron beam welding of high-strength steel of 38Cr2Ni2Mo type the obtained welds have three clearly defined zones – molten zone during welding (inner zone 1 on Fig. 3), the heat affected zone 2 (lying outside the molten zone) and the zone 3 that is not influenced by the electron beam treatment. The investigated geometry characteristics are: weld depth *H*, weld width B_{sw} and the width of the heat affected zone B_{haz} at the welded sample surface.

The neural network model structure was estimated for the weld depths *H*, weld width B_{sw} and the width of the heat affected zone B_{haz} at the welded sample surface. The best results for neural network models (defined by minimum of the root mean squared error (*RMSE*) and the non-dimensional error index (*NDEI*) and for different number of hidden units), obtained with 6 hidden units, are presented in Table 2. In all the considered cases, the implementation of neural network models with 6 hidden units give better prediction results than with less hidden units. The experimental results (marked with points) and the predicted results (connected with the straight lines), using the training dataset (36 observations) for the weld depth *H* and neural network model with 6 hidden units are presented in Fig. 4.

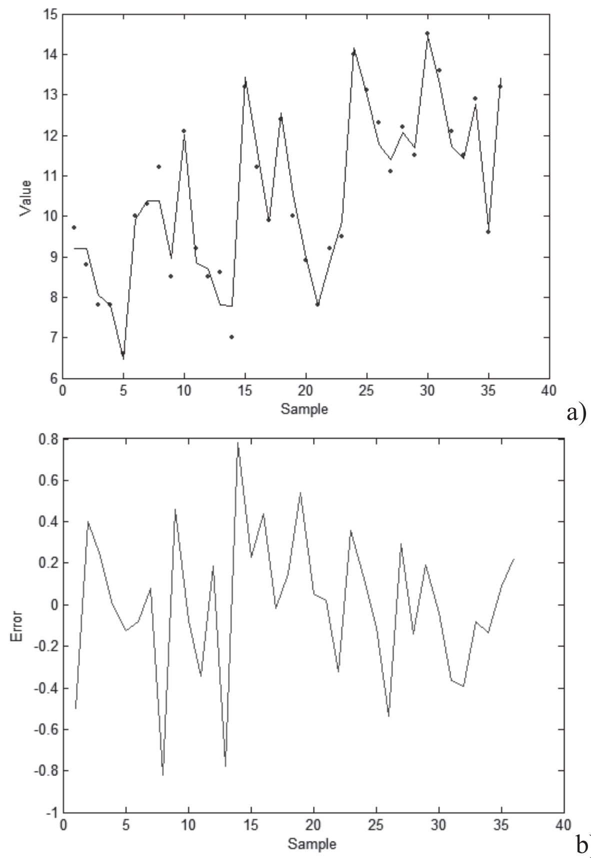
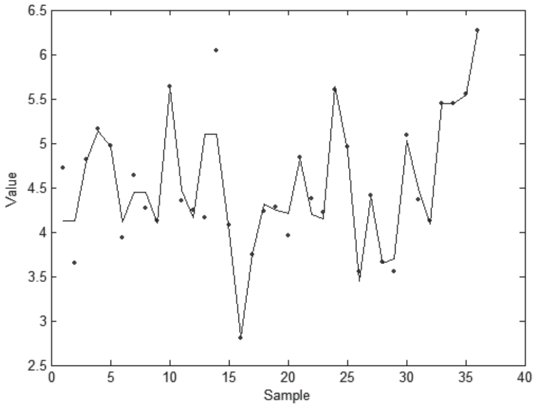
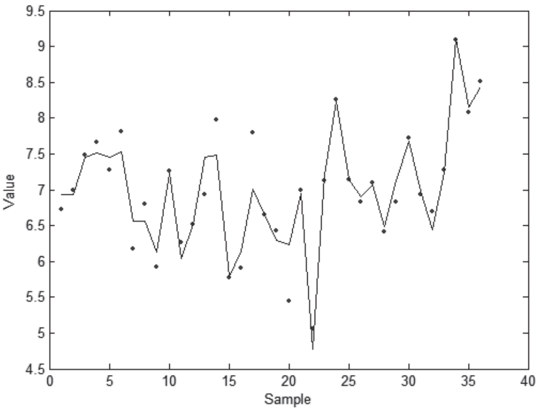


Fig. 4. Values for the weld depth H – training: a) predicted (line) and experimental (dots) b) absolute error values (the differences between the experimental and the predicted weld depths H)

The absolute value of the errors, presented as the difference between the predicted and the measured values of the weld depths H, are calculated and graphically presented in Fig. 5, connected with lines. Generally the error values are situated in the region (-0.5÷0.5 mm) with the exception of only 3 errors.



a)



b)

Fig. 5. Predicted (line) and experimental (dots) values a) for the weld width B_{sw} – training; b) for the heat affected zone width B_{haz} – training

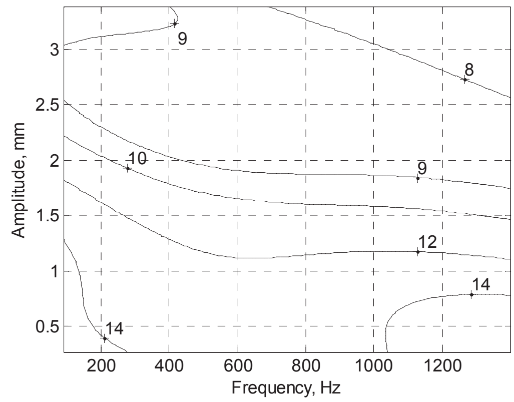
In Fig. 5 the experimental results (marked with points) and the predicted results (connected with the straight lines) for the weld width B_{sw} and the width of the heat affected zone B_{haz} utilizing neural network models with 6 hidden units are presented.

It could be seen the good coincidence between the measured and the estimated values for all investigated geometry characteristics, in spite of the comparatively small number of experimental observations.

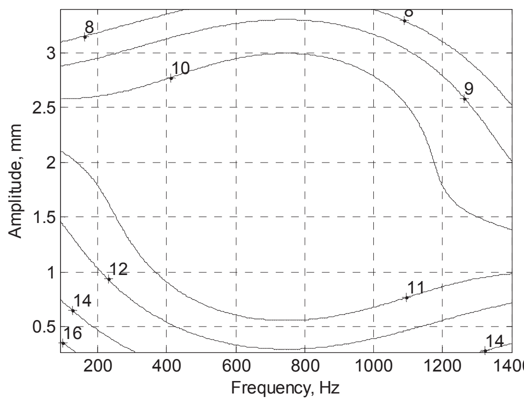
In Fig. 6 a contour plot of the weld depth H, depending on the frequency and the amplitude of the beam deflection oscillations, applying neural network model with 6 hidden units, for beam focusing current I_f = 835 mA is presented.

Statistical modeling and analysis

Experimental results of welded samples of high strength steel of 38Cr2Ni2Mo type are used for the estimation of regression models, based on the principles of the Response Surface Methodology. During the performed experiments the EBW parameters that were varied [7] are: the focusing current z_1, z_2 and z_3 – the frequency and the amplitude of deflection oscillations.



a)



b)

Fig. 6. Weld Depth H for beam focusing current I_f = 835 mA estimated by:
a) neural network model; b) regression model

The natural levels of the parameters (z_i) are coded in the region [-1÷1] and the relation between the coded (x_i) and the natural values (z_i) is given by:

$$x_i = (2z_i - z_{i,max} - z_{i,min})/(z_{i,max} - z_{i,min}),$$

where $z_{i,min}/z_{i,max}$ are the corresponding values of the minimum and the maximum of the process parameters during the experiment (Table 1). The obtained regression models, together with the square of the multiple correlation coefficients R^2, are presented in Table 3.

The estimated regression models have good characteristics and it can be concluded that they can be used for prediction and optimization.

In Fig. 6b a contour plot of the weld depth H, depending on the frequency and the amplitude of the beam deflection oscillations, applying the estimated regression model (Table 3), for beam focusing current

Table 3

Regression models for the weld geometry characteristics

Param.	Regression models	R^2, %
H	$10.3 + 1.67\, x_1 + 1.16\, x_3 + 1.63\, x_1x_2 - 1.05\, x_1^2 + 3.79\, x_1x_2^2 - 3.47\, x_2^2x_3 - 1.07\, x_2^3 - 2.95\, x_3^3$	88.2
B_{sw}	$3.83 - 0.879\, x_1 + 0.501\, x_2 - 2.00\, x_1x_3 + 1.91\, x_1^2 + 0.978\, x_3^2 + 1.36\, x_1^2x_3 + 0.591\, x_1x_2^2 - 1.40\, x_1x_3^2 - 0.909\, x_2x_3^2 + 0.632\, x_1^3$	83.5
B_{haz}	$5.70 - 0.924\, x_2 - 1.14\, x_1x_3 + 2.41\, x_1^2 + 0.859\, x_2^2 + 0.954\, x_3^2 + 0.627\, x_1^2x_2 - 1.07\, x_1x_2^2 + 1.02\, x_1x_3^2 + 1.16\, x_2^2x_3 + 1.48\, x_2^3$	78.8

Table 4

RMSE and NDEI measures for the geometry characteristics of the welds based on regression models

(36 obs.)	$\boldsymbol{H}$	$\boldsymbol{Bs_w}$	$\boldsymbol{B_{haz}}$
RMSE	0.746406	0.318362	0.445457
NDEI	0.353412	0.414534	0.520394

Table 5

Experimental results, neural network and regression model predictions

	Process parameters			Experimental			NN models - prediction			Regression models - prediction		
№	I_f	F	A	H	B_{sw}	B_{haz}	H	B_{sw}	B_{haz}	H	B_{sw}	B_{haz}
1	830	90	1.00	10.90	6.00	8.390	12.48	4.29	4.10	11.71	3.85	5.91
2	840	130	1.00	12.80	4.73	7.380	12.93	4.36	6.16	13.74	4.14	6.01
3	840	660	1.00	12.10	4.86	6.730	11.81	4.22	5.78	10.60	4.17	6.64

Table 6

Comparison of RMSE and NDEI measures for neural network and regression models

	NN models			Regression models		
	H	B_{sw}	B_{haz}	H	B_{sw}	B_{haz}
RMSE	0.9305	1.0756	2.6328	1.1239	1.34743	1.63660
NDEI	0.9683	1.5393	3.1475	1.1697	1.92765	1.95766

I_f = 835 mA is presented. The obtained contour plot differs from the one obtained in Fig. 8 from the neural network model. The regression model averages the values of the weld depth (which filters the random error of the experimental observations), while the neural network more precisely describes the available experimental results (together with the random error).

In order to compare the models with the corresponding neural network models the root mean squared error (*RMSE*) and the non-dimensional error index (*NDEI*) are calculated for the regression models too. They are presented in Table 4. It can be seen that the obtained results for the estimated regression models are worse than that in the cases with neural network models with 6 hidden units.

According the results connected with RSME and the NDEI the preferable approach is neural network based modeling.

Model verification based on additional experiments

Three additional experiments inside the investigated experimental regions for the process parameters are obtained in order to compare the prediction capabilities of the estimated neural network based models and regression models. The experimental process conditions and the results for the weld geometry are presented in Table 5, together with the neural network and regression model predictions.

In Table 6 a comparison of *RMSE* and *NDEI* measures for neural network and regression models is presented. It gives a quantitative estimation of the precision of the predicted values by implementation of different approaches. As it can be seen that regression models predict better the values of the weld depth H and the weld width of the heat affected zone B_{haz}, while the neural network models predict better for the weld width B_{sw}.

Conclusions

Neural networks are versatile in that they are capable of being incorporated in various modeling and control methods and strategies. In this paper, a new systematic methodology based on neural networks for the construction of nonlinear models, being able to predict the geometry characteristics of the obtained through electron beam welding high-strength steel (38Cr2Ni2Mo type) joints at presence of electron beam deflection oscillations, has been proposed.

The obtained results 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.

It was shown that the regression models predict future experiments better than the estimated neural network models in the case of modeling the heat affected zone B_{haz}, in spite of the better *RMSE* and *NDEI* measures for the neural network models. The reason for this can be the small number of experiments for the training of the neural networks. Another reason can be that the regression models average the values of the mentioned weld geometry characteristics (which filters the random error of the experimental observations), while the neural network more precisely describes the available experimental results (together with the random error), and consequently in the cases of larger random error of the performance characteristic, the regression models predict better future observations.

Generally, the neural network models give better results for prediction of the geometry of the welded samples, in spite of the comparatively small number of available observations.

Acknowledgements

The authors would like to thank for the financial support by RFBR 13-08-00397, 14-08-96008_a_ural and by Ministry of Perm district Education.

REFERENCES

[1] Christova N., E. Koleva. Neural Network–Based Modeling and Optimization of EBW of Stainless Steel. Electronics and Electrical Engineering, 5-6, 2009, 104-111.

[2] Hornik, K., M. Stinchcombe, and H. White.. Multilayer feedforward networks are universal approximators. Neural Networks, vol. 2, no. 5, 1989, pp. 359–366.

[3] Koleva E., I. Vuchkov. Model-based approach for quality improvement of EBW applications in mass production, Vacuum 77, 2005, 423-428.

[4] Rumelhart, D., and J. McClelland (Eds.). Paralel Distributed Processing: Explorations in the Microstructure of Cognition, MIT Press, Cambridge, Mass.

[5] Smith M. 1993. Neural Networks for Statistical Modelling, Van Nostrand Reinhold, New York, 1986.

[6] Tang, H., K. C. Tan, Z. Yi.. Neural Networks: Computational Models and Applications. Springer, 2007.

[7] Trushnikov D., E. Koleva, V. Belenkiy, G. Mladenov. Experimental investigations of the weld cross section at electron beam welding of high-strength steel, Electronics and Electrical Engineering 5-6, 2012, Sofia, Publ. CEEC, 5-6, 2012, 108-114.

[8] Vuchkov I., L. Boyadjieva. Quality Improvement with Design of Experiment. In. A. Keller, editor, Kluwer Academic Publishers: The Netherlands, 2001.

[9] Zurada, J.M. Introduction to Artificial Neural Systems, Jaico Publishing House, Bombay, 1995.

Assoc Prof. Dr. Eng. Elena G. Koleva *- Institute of Electronics, laboratory "Physical problems of electron beam technologies" – Bulgarian Academy of Sciences, Bulgaria, Director of Technological Center on Electron Beam and Plasma Technologies and Techniques – TC EPTT Ltd., Bulgaria, Lecturer at University of Chemical Technology and Metallurgy – Sofia, Bulgaria. Main fields of scientific research are: information technologies, physical electronics and radio-physics, electron and ion technologies, nano-technologies and materials, powerful electron beam characterization, information and control technologies, automation, statistics, mathematical modelling, simulation, optimization, quality control.*

tel.: +359 895537899 e-mail: eligeorg@abv.bg

Assoc. Prof. Dr. Nikolinka G. Christova - *Department of Automation of Industry, University of Chemical Technology and Metallurgy – Sofia, Bulgaria. Her main research interests are in the field of Computerized Integrated Industrial Control and Environmental Management, Fuzzy Logic and Neural Network Applications to Simulation, Control and Fault Diagnosis in Industrial Systems, Decision Support Systems for Business Management. E-mail: nchrst@uctm.edu*

Corr. Memb. of BAS, Prof. DSc. Georgi M. Mladenov *- Institute of Electronics – Bulgarian Academy of Sciences, Bulgaria and Technological Center on Electron Beam and Plasma Technologies and Techniques, Bulgaria He is the author of 10 books, 26 inventions and more than 200 articles. His research interests include electron beam microscope accelerators, electron beam technologies, electron devices physics, electron beam welding, melting and refining metals in vacuum, electron spectroscopy simulation, electron lithography, vacuum technology.*

tel. +359 899902510 e-mail: gmmladenov@abv.bg

Dr. Dmitriy N. Trushnikov *- Department of Applied physics, Department of Welding production and technology of construction materials, Perm National Research Polytechnic University, Perm, Russian Federation; Education - 1999 Department of Aerospace, Perm National Research Polytechnic University; Research Areas – control, monitoring and simulation of electron beam welding;*

tel.: +79194785031 e-mail: trdimitr@yandex.ru

Prof. Dsc. Vladimir Ya. Belenkiy *- State National Research Polytechnic University of Perm, Department of Welding production and technology of construction materials, Perm, Russia;*

tel.: +7(342) 2403796 e-mail: mtf@pstu.ru

Received on: 21.06.2014