NEURAL NETWORKS FOR DEFECTIVENESS MODELING AT ELECTRON BEAM WELDING

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Abstract: *This paper considers the process electron beam welding in vacuum of stainless steel 1H18NT. Neural network based models are developed and used for the description of the defectiveness, depending on the process parameters - 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. Neural network (NN) models, based on a multi-layered feedforward neural network, trained with Levenberg-Marquardt error backpropagation algorithm are compared with NN models, based on Pattern recording neural network, trained with Conjugate Gradient Algorithm. The neural networks are trained, verified and tested using a set of experimental data. The obtained models are implemented to predict areas of process parameters, where the appearance of defects is most probable and the location of welding regimes that should be avoided.*

Keywords: ELECTRON BEAM WELDING, NEURAL NETWORK MODELS, DEFECTS.

1. Introduction

The requirements for the quality of model design and automatic control in the process industries and at the same time the available computing power increased significantly in recent years. This leads to the opportunity of design systems with such intelligent functions as parallel data processing, learning and high-level decision making. Development of adequate models for real industrial processes is usually a complicated task due to the large uncertainties, caused by lack of direct measurements and necessity of inferential approach, high level of non-linearity and different types of disturbances. Building of models accurate enough in a broad range of operational conditions may be successful, if different intelligent modeling techniques are used [1, 2].

The electron beam has developed over the years into a flexible and economic manufacturing tool [3]. Due to the deep penetration in the work-piece, the electron beam is able to generate narrow weld with minimal thermal affected zone and without the usage of welding consumables. The high vacuum required by the method prevents the heated and melted material from oxidizing and affecting by atmosphere's pollutions. With the advanced development of computer control the number of electron beam applications has significantly increased. For the electron beam welding (EBW) technologies new applications the EBW plants has developed into a complex equipment containing highly stabilized power sources and electronic blocks, reliable and effective vacuum system, technology chamber with precision 3D manipulator, becoming truly software controlled programmed manufacturing tool with high efficiency and excellent reproducibility. Technological data gathered during the process enable quality monitoring and support to improve the testing process of the manufactured components as well as to be recorded for future analysis of the relations of adjusted process parameters and weld quality and stability.

The welding quality assurance contains the personnel, equipment and the welding process. For EBW process validation there are available norms and acceptation procedures [4, 5].

The quality of the welds has, so far, shown to be enough adequate in the most cases in spite of the fact that the optimization of the welding process and effects of non-controlled process parameters are still uncompleted. Nevertheless, there is not sufficient statistical data to make analysis of all kinds of weld defects, of root peaks (spikings) and of the flawlessness of the long term weld safety in critical applications.

In this study Neural network (NN) models, based on a multi-layered feedforward neural network, trained with Levenberg-Marquardt error backpropagation algorithm [6, 7] are compared with NN models, based on Pattern recording neural network, trained with Scaled Conjugate Gradient backpropagation algorithm [8, 9]. These models are developed and used for the description of the appearance of defects, depending on the process parameters - 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.

2. Experimental conditions

An experiment was performed with samples of stainless steel, type 1H18NT [10]. The accelerating voltage is 70 kV. 81 experimental weld cross-sections are investigated. The following operating process parameters are varied: power (P) - 4.2, 6.3 and 8.4 kW; welding velocity (v) - 80 cm/min, 40 cm/min and 20 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.

For the experimentally obtained weld cross-sections the number of defects is counted. For prediction and classification the experimental observations are separated into two groups (classes): 0 – with defects and 1 – without defects. The type of the defects is not taken into account.

3. Neural Networks

Neural networks are universal approximators with low sensitivity to errors, which determines the benefits of their use in different application areas [1, 2].

The modelled EBW process parameters define the input-output structure of the neural network-based model used, i.e. the neural network consists of 4 input neurons, hidden layer (with different number of neurons) and 1 output neuron.

Neural network (NN) models, based on a multi-layered feed forward neural network, trained with Levenberg-Marquardt error backpropagation algorithm are trained and compared with NN models, based on Pattern recording neural network, trained with Scaled Conjugate Gradient backpropagation algorithm.

The methodology, implemented for developing neural network models, consists of the following general steps: choosing the neural network model structure by training of the different neural networks, using the two back propagation methods and the experimentally obtained set of training data, to a satisfactory accuracy and recall of the trained neural network for prediction of the appearance of defects. For comparison of the neural network models the mean squared error (MSE), as well as the regression multiple correlation coefficient or the percent error values are calculated.

For training, validation and testing of the neural networks, the experimental data are randomly separated into 3 parts: 70% (57 datasets) for training, 15% (12 datasets) for validation and 15% (12 datasets) for testing.

3.1. Feedforward neural network

Feedforward neural network consist of a series of layers. The first layer has a connection from the network input. Each subsequent layer has a connection from the previous layer. The final layer produces the network's output.

Feedforward networks can be used for any kind of inputs to output mapping. A feedforward network with one hidden layer and enough neurons in the hidden layers can fit any finite input-output mapping problem. This is two-layer feed-forward network with sigmoid hidden neurons and linear output neurons (Fig. 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 backpropagation algorithm [6, 7].

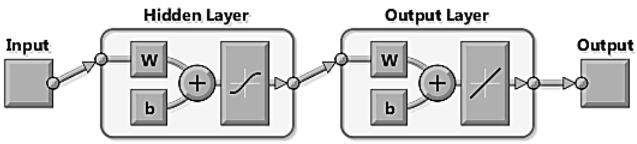


Fig. 1. Feedforward neural network structure

The described approach is implemented for training neural networks with different structures of the hidden layer – with 4 and 14 hidden units and different random sets for training (57 datasets), for validation (12 datasets) and for testing (12 datasets). The best two Neural network models, based on the experimental observations of the defectiveness (0 – with defects and 1 – without defects) are chosen.

The obtained results for the accuracy of the training of these two NN models are presented in Table 1.

Table 1. Feedforward neural network training results

	NN with 4 neurons	NN with 14 neurons
MSE	0.0558	0.0182
R	0.8075	0.9450

In the table are shown the values of the regression multiple correlation coefficient R and the Mean Square Error (MSE):

$$MSE = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}$$

where $\hat{y}$ and y is 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 ($\hat{y}$) and the experimental values y (target T) (Fig. 2). R value of 1 means full coincidence between predicted and the experimental target values and 0 - random relationship. If the value of the MSE is equal to zero, there is no prediction error.

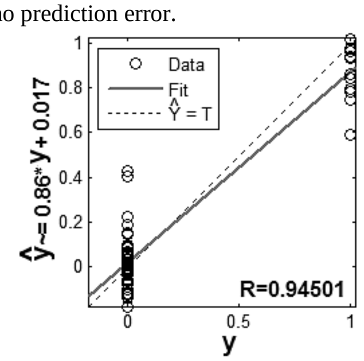


Fig. 2. Best feedforward neural network training results – 14 hidden neurons

The obtained results for the accuracy of the validation and of the testing of the considered two NN models are presented in Table 2 and Table 3 correspondingly.

Table 2. Feedforward neural network validation results

	NN with 4 neurons	NN with 14 neurons
MSE	0.0970	0.0633
R	0.7329	0.8483

Table 3. Feedforward neural network testing results

	NN with 4 neurons	NN with 14 neurons
MSE	0.1899	0.1720
R	0.5182	0.6853

From the tables it can be seen, that from these two structures better results will be obtained by using the neuron network models with a hidden layer, consisting from 14 hidden neurons, due to the smaller values of MSE and closer to 1 values of the coefficient R, obtained during training, validation and testing stages.

3.2. Pattern recording neural network

In pattern recording problems the neural network classify inputs into a set of target categories. A two-layer feed-forward network, with sigmoid hidden and output neurons (Fig. 3). The network is trained with Scaled Conjugate Gradient backpropagation algorithm [8, 9]. It belongs to the class of Conjugate Gradient Methods, which shows superlinear convergence on most problems and it is considerably faster than the standard backpropagation method [8, 9].

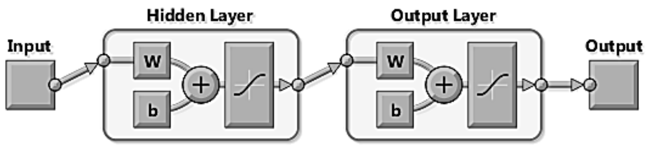


Fig. 3. Pattern recording neural network structure

Again two different structures of the hidden layers are considered - with 4 and 14 hidden units and different random sets for training, validation and testing.

The best two Pattern Recording Neural network models, based on the experimental observations of the defectiveness, are chosen for prediction and classification into two groups (classes): 0 – with defects and 1 – without defects.

For comparison of different neural models the values of the Percent Error (%E) and the Mean Square Error (MSE) are used during training, validation and testing stages. The obtained best results for the accuracy NN models with two structures of the hidden layers during training are presented in Table 4.

Table 4. Pattern recording neural network training results

	NN with 4 neurons	NN with 14 neurons
MSE	0.0109	0.00305
%E	19.29%	1.75%

Percent Error (%E) indicates the fraction of samples which are misclassified. A value of 0 means no misclassifications, 100 indicates maximum misclassifications.

$$\%E = \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{n} \times 100$$

where $\hat{y}$ and y is the predicted classified and the experimental classified values.

The results from the validation are shown in Table 5 and from the testing – in Table 6.

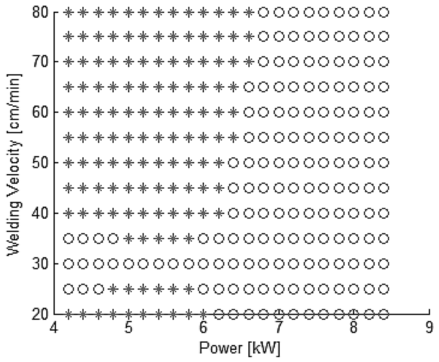
Table 5. Pattern recording neural network validation results

	NN with 4 neurons	NN with 14 neurons
MSE	0.0071	0.0277
%E	0	0

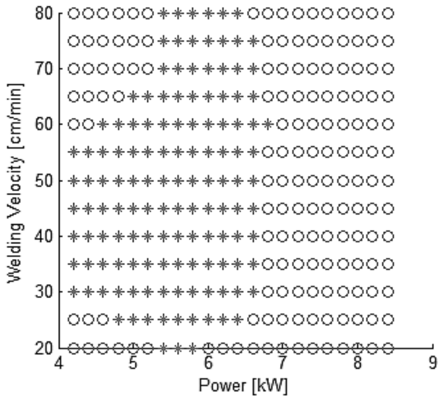
Table 6. Pattern recording neural network testing results

	NN with 4 neurons	NN with 14 neurons
MSE	0.0340	0.0136
%E	0	0

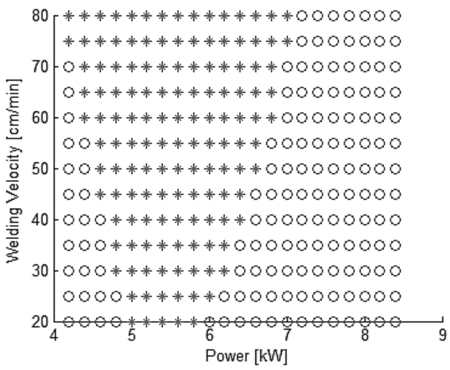
From the tables it can be seen that the trained two pattern recording neural networks have values of MSE close to zero, the first network misfits 19.29% of the observations and the second one misfits only 1.75%. During the validation and testing stages both neural networks have 100% accuracy of the prediction of the presence or the absence of defects at investigated experimental conditions.



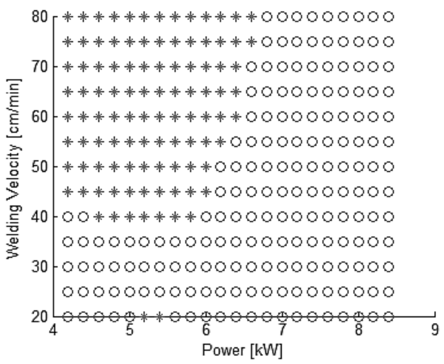
a) Feedforward neural network with 4 neurons



b) Feedforward neural network with 14 neurons



c) Pattern Recording neural network with 4 neurons



d) Pattern Recording neural network with 14 neurons

Fig. 4. Graphical presentation of the areas with (‘*’) or without (‘o’) defects at the EBW, depending on the variation of electron beam power and the welding velocity for constant distances z_o = 276 mm and z_p = 226 mm.

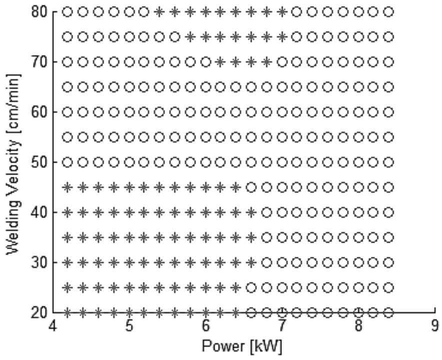
4. Results and discussion

The estimated neural networks are implemented for the prediction of the defectiveness, classified into two groups (classes): 0 – with defects and 1 – without defects, at changing the electron beam welding process parameters: electron beam power (P) and the welding velocity (v). The focus position is chosen to be at a distance z_o = 276 mm from the magnetic lens of the electron gun and the distance to the sample surface is z_p = 226 mm from the magnetic lens of the gun. The electron beam focus lies 50 cm below the sample surface. The type and actual number of the defects is not taken into account.

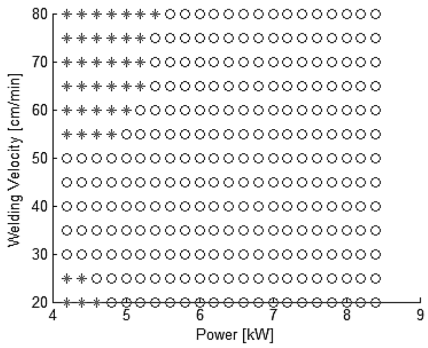
Fig. 4 presents the different areas for the considered process parameters, where the defects will appear (signed with ‘*’) and where there no defects are expected (signed with ‘o’)

It can be seen that the predicted areas a slightly different, but nevertheless, at the chosen position of the focus 50 mm below the sample surface, the chosen electron beam power should be larger than 7 kW in order to avoid the appearance of defects while the choice of the welding velocity value at these conditions will not affect the defect appearance.

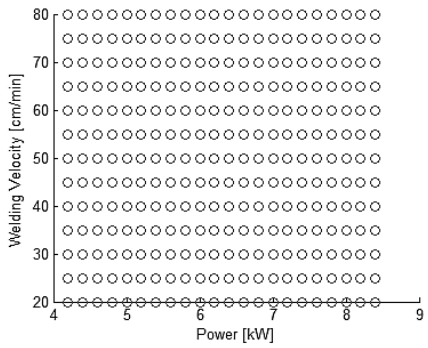
Since the best results for the accuracy from training, validation and testing are obtained from the Pattern recording neural network, trained with Scaled Conjugate Gradient backpropagation algorithm and having 14 neurons in the hidden layer, further predictions should be made by this NN model.



a)



b)



c)

Fig. 5. Graphical presentation of the areas with (‘*’) or without (‘o’) defects at EBW, depending on the variation of electron beam power and the welding velocity for constant distances a) z_o = 176 mm and z_p = 126 mm, b) z_o = 226 mm and z_p = 226 mm, c) z_o = 276 mm and z_p = 326 mm.

Fig. 5 shows the predictions of the areas with ('*') or without ('o') defects at EBW, depending on the variation of electron beam power and the welding velocity for different distances from the magnetic lens of the electron gun to the focus z_o and to the sample surface z_p, which correspond also to different positions and distances of the focus toward the sample surface.

Fig. 5a shows again a case of focus position 50 mm below the sample surface, but for different values of the distances z_o = 176 mm and z_p = 126 mm. The beam powers again should be chosen above 7 kW at all welding velocities, while the suggested welding velocities are in the region 50-65 cm/min, if choosing to work at beam powers less than 7 kW.

Fig. 5b presents the result from placing the focus position exactly at the sample surface - z_o = 226 mm and z_p = 226 mm. The choice of the beam power should exceed values of 5.4 kW for all welding velocities, or if working with smaller beam powers, defines working with welding velocities in the region 30-50 cm/min.

Fig. 5c visualizes the case, when the focus position is 50 mm above the sample surface for distances z_o = 276 mm and z_p = 326 mm. It can be seen that no defects are expected within the whole region of variation of the process parameters electron beam power and welding velocity.

During the investigation of other combinations of the distances to the focus and to the sample surface the following generalized conclusions are made in order to avoid defect appearance:

- in the case, when the focus position is again 50 mm above the sample surface for distances z_o = 176 mm and z_p = 226 mm, no defects are expected almost within the whole region of variation of the process parameters electron beam power and welding velocity with the exception of regimes with beam power 8.4 kW and welding velocities smaller than 30 cm/min.
- in the case, when the focus position is 150 mm above the sample surface for distances z_o = 176 mm and z_p = 326 mm, the working regimes that should be avoided is simultaneously working with beam powers larger than 6 kW and welding velocities smaller than 30 cm/min.
- in the case when distances z_o = 226 mm and z_p = 176 mm or position of the focus again 50 mm below the sample surface, the suggested welding velocities are in the region 40-50 cm/min for all beam powers. The area of the process parameter values leading to defects here is the largest.

5. Conclusions

In this study two neural network (NN) models, based on a multi-layered feedforward neural network, trained with Levenberg-Marquardt error backpropagation algorithm and two NN models, based on Pattern recording neural network, trained with Scaled Conjugate Gradient backpropagation algorithm are estimated for description of the defectiveness of stainless steel type 1H18NT welds obtained at electron beam welding. The variation of the following process parameters is investigated: 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.

From the comparison of the considered structures and different neural networks, it can be concluded that the best results for the accuracy from training, validation and testing are obtained from the Pattern recording neural network, trained with Scaled Conjugate Gradient backpropagation algorithm and having 14 neurons in the hidden layer. That is why, this NN model is suggested for further predictions and parameter optimization.

It was shown that only the position of the electron beam focus toward the treated sample surface is not sufficient enough for the prediction of the areas with defects. The distances from the magnetic lens of the electron gun to the focus of the beam and to the sample surface (z_o and z_p) should be taken into account.

For further optimization the formed weld geometry also should be considered in order to obtain welds with required dimensions simultaneously with the avoiding the defect appearance.

References

[1]. Koleva, E., N. Christova, K. Velev. Neural Network Based Approach for Quality Improvement of Orbital Arc Welding Joints – Proc. of Int. conf. IEEE Intelligent systems, London, UK, ISBN: 978-1-4244-5164-7, 2010, pp. 7-9.

[2]. Koleva, E., N. Christova, G. Mladenov, D. Trushnikov, V. Belenkiy. Neural Network Based Approach for Quality Improvement of Electron Beam Welding. Proceedings Conf. "Electonica 2014", 15 May 2014, Sofia, pp. 120-128.

[3]. Koleva E. G., G. M. Mladenov. Experience on electron beam welding. Practical Aspects and Applications of Electron Beam Irradiation Transworld Research Network, India, Editors: Monica R. Nemtanu and Mirela Brasoveanu, 94-134, ISBN: 978-81-7895-541-4, (2011)

[4]. Koleva E, Standards for the production practice of EBW (and related processes), Proc. Of the 1st Indo-Bulgarian Workshop on Electron Beam Technology and Application, ed. A K. Das, E. Kandaswamy, M. Mascarenwas, Mumbai, India, november 19-21 (2003), pp 334-347.

[5]. Koleva E. G., D.N.Trushnikov, V.Y.Belenkii, G.M.Mladenov. Robust Quality Optimization at Electron Beam Welding of Steels. Proceedings of international conference "ebeam 2012", 15-17 October 2012, Reno, NV, USA, pp. 124-144, 2013

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

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

[8]. Moller, M. A Scaled Conjugate Gradient Algorithm for Fast Supervised Learning, Neural Networks, 6 (4), 1993, pp. 525-533.

[9]. Moller, M. A Scaled Conjugate Gradient Algorithm for Fast Supervised Learning, DAIMI Report Series, No 339, ISSN 2245-9316, DOI: http://dx.doi.org/10.7146/dpb.v19i339.6570, 1990.

[10]. Koleva, E. EB weld parameters and thermal efficiency improvement, Vacuum 77, 2005, pp. 413-421.