GRAPHICAL USER INTERFACE FOR OPTIMIZATION OF ELECTRON BEAM WELDING BY NEURAL AND REGRESSION MODELS FOR OBTAINING DEFECT-FREE WELDS

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Abstract: *This paper considers the process electron beam welding of stainless steel type 1H18NT in vacuum. Based on experimental data, the influence of the variations of the following process parameters: electron beam power, welding velocity, the distances from the magnetic lens of the electron gun to the beam focus and to the surface of the treated sample is investigated.*

Neural and regression models for the geometry characteristics of the welded joints: surface of the weld cross-sections, weld depths and mean weld widths of the samples are estimated, as well as models for defining the areas of the process parameters, where the appearance of defects is or is not expected. The obtained models are used for developing the graphical user interface aiming investigation and prediction of the electron beam welding characteristics and process parameter optimization. This software can be implemented for supporting the operator's choice of appropriate work regimes, obtaining the required welds quality standards, for education and investigations.

Keywords: STAINLESS STEEL; ELECTRON BEAM WELDING; GRAPHICAL USER INTERFACE; NEURAL NETWORK MODELS; DEFECTS; OPTIMIZATION

1. Introduction

The complexity of the processes occurring at intensive electron beam interaction with the material in the welding pool and the vaporized treated material hinders the development of physical or heat model for enough accurate prediction of the geometry of the weld cross-section and adequate electron beam welding process parameter selection. Concrete reason for the lack of adequate prognostication is the casual choice of the heat source intensity distribution, not taking into account the focus position toward the sample surface and the space and angle distribution of the electron beam power density, the distance to the sample surface at constant beam formation conditions, etc.

In this paper various empirical modelling approaches for the estimation of adequate models for the dependencies of the electron beam weld characteristics on the process parameters as well as process optimization on that base are considered. An expert system for supporting the operator's choice of appropriate work regimes, obtaining the required welds quality standards, for education and investigation is developed and its functional elements are presented.

2. Methodologies

2.1. Response surface methodology

Response surface methodology (RSM) is a collection of mathematical and statistical techniques for empirical model building. Regression models (polynomial models of some order), giving an adequate functional relationship between a response of interest y (performance characteristic) and a number of associated control (or input) variables (process parameters) x_1, x_2, … x_m, are estimated:

$$\hat{y}(\vec{x}) = \sum_{i=1}^{k} \hat{\theta}_i f_i(\vec{x}) + \varepsilon$$

ε is a random experimental error, assumed to have a zero mean, $\hat{\theta}_i$ are the estimates of the model coefficients.

2.2. Robust engineering design

During the industrial processes despite of the control there always occur variations in the process parameters and uncontrolled noises that cause variations in the product quality parameters. These errors cause additional variations in the performance characteristics of the obtained welds, which are not due to the intentional changes of the process parameters. The idea of the robust engineering approach to model the variation (variance) of the performance characteristics depending on these measurement and control errors and by the minimization of this variance optimal solutions that are robust (less sensible) towards the errors in the process parameters to be found [1, 2].

The robust engineering design involves the estimation of two models describing the mean value and the variance of the performance characteristics at production conditions [3]. The mean value model of the response is:

$$\tilde{y}(\mathbf{x}) = \mathrm{E}[y(\mathbf{z})] = \eta(\mathbf{x}) + \boldsymbol{\theta}^{\mathbf{T}}\mathrm{E}(\mathbf{g}),$$

where $\mathbf{z} = \mathbf{x} + \mathbf{e}$ is a vector of the real parameters values in production conditions (with errors $\mathbf{e}$). The first term $\eta(\mathbf{x}) = \mathbf{f}^{\mathbf{T}}\hat{\boldsymbol{\theta}}$ is a response model, obtained in laboratory conditions without errors in process parameter levels. The second term takes into account the variations of the process quality characteristics caused by these errors. $\hat{\boldsymbol{\theta}}$ is a vector of estimates of the model coefficients; $E(\mathbf{g})$ is the mathematical expectation of vector $\mathbf{g}$ ($\mathbf{g} = \mathbf{h} - \mathbf{f}$, where $\mathbf{f}$ is a vector of the regressors $\mathbf{x}$ – known functions of process parameters x_i, and $\mathbf{h}$ is a vector of the regressors $\mathbf{z}$).

The variance model of the response is:

$$\sigma^2 = \sigma^2[y(\mathbf{z})] = \mathrm{E}\left(\hat{\boldsymbol{\theta}}^{\mathbf{T}}\boldsymbol{\psi}\boldsymbol{\psi}^{\mathbf{T}}\hat{\boldsymbol{\theta}}\right) + s_\varepsilon^2 = \hat{\boldsymbol{\theta}}^{\mathbf{T}}\boldsymbol{\Psi}\hat{\boldsymbol{\theta}} + s_\varepsilon^2,$$

where:

$\boldsymbol{\psi} = \mathbf{g} - \mathrm{E}(\mathbf{g})$; the matrix $\boldsymbol{\Psi} = \mathrm{E}(\boldsymbol{\psi}\boldsymbol{\psi}^{\mathbf{T}})$ depends on the structure of the resulting model; s_ε^2 is an estimate of the random error of the response.

2.3. Neural networks

Neural networks are universal approximators with low sensitivity to errors, which determines the benefits of their use in different application areas [4, 5].

For developing the expert system two type of neural networks are used: feedforward neural and pattern recording problems the neural network.

The neural network consists 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 neural network

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 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 [5, 6].

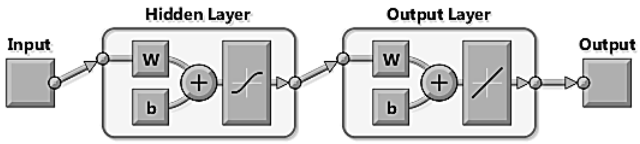

Fig. 1. *Feedforward neural network structure*

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

$$g(u) = u$$

The sigmoid function is defined by:

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

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

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. 2). The network is trained with Scaled Conjugate Gradient backpropagation algorithm. 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 [6, 7].

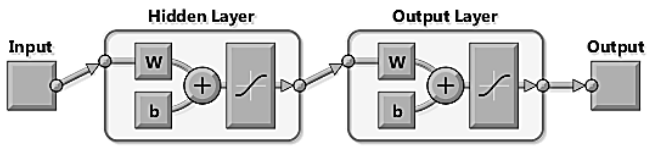

Fig. 2. *Pattern recording neural network structure*

2.4. Multi-criteria graphical optimization

The implemented here approach for multi-criteria optimization is the graphical optimization approach. It applies the estimated models (regression, robust or neural models) for building contour plots of the investigated performance characteristics, depending on the process parameters. By superimposing of these diagrams compromise zones for the process parameters can be found. For each response, the acceptable tolerance limits must be defined and the low and upper limits are represented by contours on the contour diagrams. After superimposing of the low and upper limit contours, the regions for the process parameters can be determined, where all required tolerance limits are fulfilled

3. Experimental investigation and modelling

An experiment was performed with samples of stainless steel, type 1H18NT [8]. 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.

The following quality characteristics are considered: transverse toward the movement of the electron beam weld cross-section area – S, weld depth H, mean weld width B, and the number of defects is counted. For prediction and classification the experimental observations are separated into three groups (classes): 0 – without defects, 1 – with one defect and 2 – with two defects. The type of the defects is not taken into account.

The collected data are used to obtain and estimate the regression models for the geometry characteristics of the welded joints: cross-section area – S, weld depth – H and mean weld width – B, as well as the appearance of defects is or is not expected [4, 9].

For each of the considered performance characteristics two models, describing their mean value and variance at production conditions, are estimated. They take into consideration the errors of the process parameters (Table 1) and their transmission as variation of the output characteristics [4].

Table 1. *Tolerance limits for EBW parameters*

Process parameter	Coded	Tolerance limits	Coded variances σ_i^2
P [kW]	x_1	$x_1 \pm 3\%\ x_1$	$\sigma_1^2 = 0.0009 +$ $+0.0002\, x_1$ $+\,0.0001\, x_1^2$
v [cm/min]	x_2	$x_2 \pm 3$	$\sigma_2^2 = 0.011$
z_o [mm]	x_3	$x_3 \pm 5$	$\sigma_3^2 = 0.011$
z_p [mm]	x_4	$x_4 \pm 5$	$\sigma_4^2 = 0.000278$

Another implemented approach is to predict appearance of defects and the weld characteristics by neural models. For development purposes, two types of neural networks are trained: Feedforward and Pattern recording neural network that contains different count of hidden neurons in there hidden layer. [4, 10, 11]

For training, validation and testing of the each neural network, 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.

The estimated set of empirical models is used for developing the graphical user interface.

4. Expert system

The graphical user interface, representing an expert system, consists from three functional parts (Fig. 3)

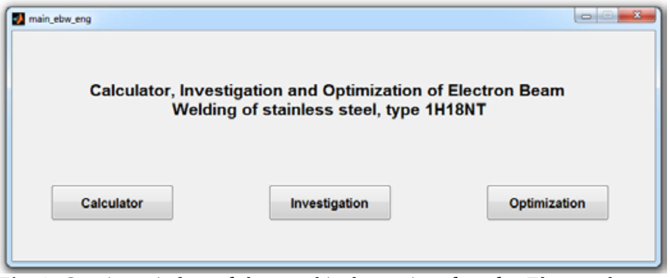

Fig. 3. *Starting window of the graphical user interface for Electron beam welding of stainless steel type 1H18NT*

- *Calculator* – for calculation of the geometric characteristics of the welds as well as for prediction of the appearance of defects.
- *Investigation* – gives the user the opportunity to investigate the welds at different working regimes.
- *Optimization* – multi-criteria graphical optimization is performed to find the regions of the process parameters where the requirements (given by acceptable tolerance limits) are met and the welds are defect-free.

From the starting window shown on Fig. 3 the operator has to choose between these three options. The first is the Calculator (Fig. 4). This window is used to calculate the geometric characteristics of the welds: weld cross-section area – S, depth – H and mean weld width – B, as well as the defects.

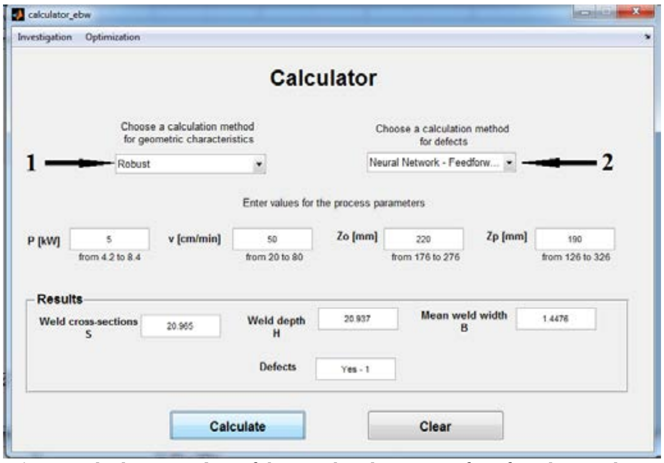

Fig. 4. *Calculator window of the graphical user interface for Electron beam welding of stainless steel type 1H18NT.*

The Calculator has two pop-up menus:

- Pop-up menu 1 – gives the user the opportunity to choose between three options for the way to calculate the geometric characteristics:
  1. Regression models,
  2. Robust regression models,
  3. Neural Networks.

- Pop-up menu 2 has 8 different options to calculate and predict the defects:
  1. Regression (Yes/No defects)
  2. Neural Network – Feedforward - with 4 hidden neurons (Yes/No defects)
  3. Neural Network - Feedforward - with 14 hidden neurons (Yes/No defects)
  4. Neural Network - Pattern recording - with 4 hidden neurons (Yes/No defects)
  5. Neural Network - Pattern recording - with 14 hidden neurons (Yes/No defects)
  6. Neural Network – Feedforward - with 4 hidden neurons (2, 1 or 0 defects)
  7. Neural Network – Feedforward - with 8 hidden neurons (2, 1 or 0 defects)
  8. Neural Network – Feedforward - with 14 hidden neurons (2, 1 or 0 defects)

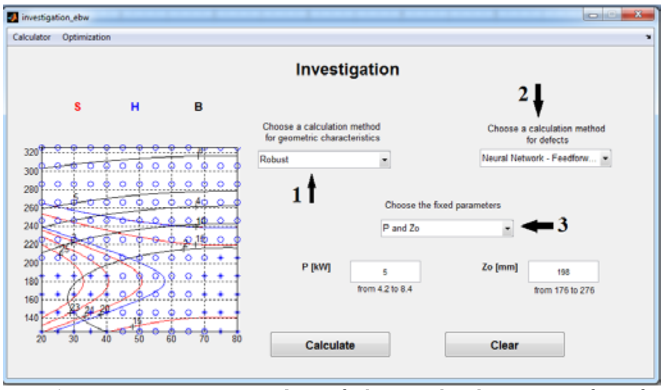

Fig. 5. *Investigation window of the graphical user interface for Electron beam welding of stainless steel type 1H18N, where S – red, H – blue, B – black, "o" – defects free zone, "*" – have defects/have 1 defect and "+"- zone with 2 defects.*

The Investigation (Fig. 5) feature has the same two pop-up menus that give the user chance to choose between different ways to predict the geometric characteristics and defects. Since the investigated process parameters are four, for the graphical investigation two of them should be chosen to vary and two of them should be fixed at constant values. That is why there is a third pop-up menu from where it is possible to choose which two of the process parameters will be varied and which two will be fixed. The calculation results are shown as contour plot where the contours of the weld cross section area are given with red color, the weld depth – blue color, the mean weld width B – black color and the defects - sign "o" indicates that it is a defect free zone, star "*" is a symbol for predicted presence of defects in this area, (in the cases of prediction of 0, 1 or 2 defects "*" means 1 defect and plus "+" indicates two critical defects).

Fig. 6 represents the Graphical optimization interface. This view again gives the opportunity to choose through the pop-up menus the estimated empirical models for the prediction of the geometric characteristics and the defects, as well as the two parameters that will be fixed on specified constant values.

Here the operator has to set the requirements for the minimum and maximum acceptable limits for the weld geometric shapes. After that the program will return a diagram that will help to choice the working regime where all criteria are fulfilled.

The optimization window has two clear buttons too.

- Clear figure – clears only the graphical representation of the calculation and saves all other choices and criteria's. In such way the user can change only some of them and don't lose the others.
- Clear all – returns the window in a "start" position for new optimization.

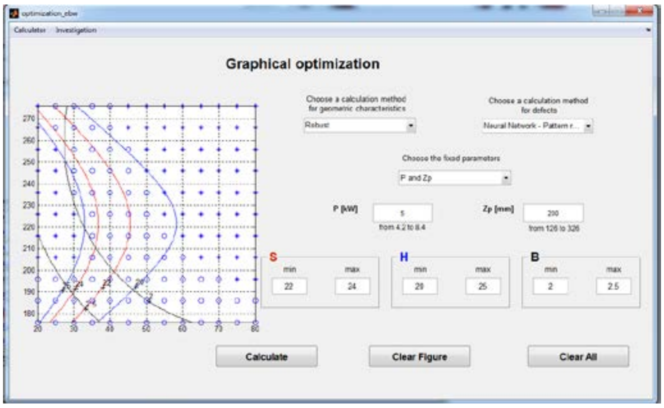

Fig. 6. *Optimization window of the graphical user interface for Electron beam welding of stainless steel type 1H18N, where S – red, B – blue, B – black, "o" – defects free zone, "*" – have defects/have 1 defect and "+"- zone with 2 defects.*

On Fig. 6 is shown an example, where the electron beam power is P = 5 kW and the distance between the main surface of the magnetic lens of the electron gun and the beam focusing plane is z_p = 200 mm. The acceptable tolerance limits for the performance characteristics are set as follows: weld cross-section area between 22 and 24 mm^2, weld depth from 20 to 25 mm and width: 2-2.5 mm. The graphic optimization shows that if the welding velocity is between 30 and 40 cm/min and the distance z_o is from 185 to 210 mm the obtained welds will meet all set requirements and will be defect-free.

5. Conclusions

The developed graphical user interface system aims investigation of the electron beam welding process of stainless steel type 1H18NT and process parameter optimization. It can be used for obtaining the weld joints with specific characteristics and lack of defects. The program can be used to support the operator's choice of appropriate work regimes, obtaining the required quality standards, education and investigation.

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