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Theoretical and experimental analysis of thermo-mechanical phenomena during electron beam welding process

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ABSTRACT

The goal of the work is the analysis of electron beam welding process parameter impact on the geometry of fusion zone and on the distribution of residual stresses in the specimen.

Electron beam welding technology is used in the aircraft industry to join structural and load bearing elements made of titanium and aluminum alloys, and landing gears made of high strength steel.

In the series of experiments 49 welds were created for chrome-nickel steel plates using different values of welding control parameters. The analyzed parameters included welding speed, beam current, accelerating voltage, beam focus, beam deflection and frequency. Partial Least Square method was used to build the models predicting the geometry of fusion zone cross-section based on the values of the control parameters. Three models were created predicting fusion zone cross-section depth and width, area and shape.

The information about fusion zone geometry was subsequently used to define heat source. The numerical model based on Finite Element Method utilized heat source model to describe the evolution of temperature and stress field during and after welding process. The calculated temperature field was compared against the shape of the actual fusion zone. The PLS-FEM model predicted the shape of fusion zone with satisfying accuracy. The values of calculated residual stresses were compared with X-ray diffraction measurements.

1. Introduction

1.1. EBW technology

Electron beam welding, EBW, is described in [1,2]. EBW technology is based on the fact that electrons have negative charge and electric field can be used to accelerate them. Kinetic energy of accelerated electrons is converted into heat upon collision with external surface of welded object. EBW must be performed in vacuum or in partial vacuum in order to avoid collisions of electrons with gas particles which would lead to beam defocus and loss of welding power.

Precise control of electron beam allows for achieving power densities up to 10^7 W/cm^2 and beam powers ranging from 0.5 to 300 kW. Welds from 0.2 to 300 mm can be produced. At high power densities EBW unit can operate in deep penetration mode. In this mode heat is produced at such high rate that material is unable to transfer it using conduction and metal starts to vaporize. Vapor creates cavity trough which electron beam can access deeper layers of material. As a result it is possible to produce welds that are characterized by high depth to width ratio. The size of produced fusion zone, FZ, and heat affected zone, HAZ, is smaller compared to arc welding technologies.

Modern EBW units can be equipped with diagnostics systems that allow for analysis and assurance of beam quality during welding. Dilthey [3] describes the system that has capability to determine the minimal size of electron beam cross-section, measure beam power distribution, identify beam parameter deterioration due to cathode adjustment, cathode distortion, variation of the vacuum level or variation of electrical system parameters. The supplied information can be used to modify beam parameters during welding. The diagnostics system facilitates the three-dimensional contour welding, thick plate welding and slope welding.

Zhao [4] suggests that recent developments in beam deflection technology coupled with diagnostics system could be used to produce welds with multiple beams. In the presented setup three beams were created. The first beam was used for pre-heating in order to reduce the impact of high energy input which might cause cracking. The second beam was used for welding and the third beam was used for smoothing the weld seam.

EBW has numerous applications [2]. In aircraft industry it is used for manufacturing turbines, welding of structural and load bearing elements made of titanium and aluminum alloys and welding of landing gears made of high strength steel.

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1.2. Weld geometry models

The majority of welding simulations ignores physics of heat generation and instead prescribes distribution of heat input [5]. The goal of heat source definition is to achieve temperature distribution that is consistent with experimental results. Usually heat source model is calibrated using inverse method based on the results obtained from welding process. If it is necessary to run welding simulation without performing experiments predictive model of FZ geometry is usually applied. The predicted FZ geometry is basis for further heat source calibration. The most common predictive models include: local multiphysics model that predicts temperature distribution as a function of welding control parameters and material properties, neural networks and regression techniques that predict FZ geometry based on data set containing information about dependence of FZ geometry on welding control parameters.

Sudnik [6,7] developed multiphysics model predicting geometry of weld pool for laser beam welding, LBW, process. The model takes into account laser-induced channel formation, multiple reflection of the laser beam in the channel, plasma generation, flow driven by capillary movement, recirculating flow driven by temperature dependent surface tension and by vapor friction at the capillary wall, and convexity of the weld pool surface resulting from thermal expansion of molten pool. The model takes as input only process parameters and material properties.

Rai [8] suggested first phenomenological model considering three-dimensional heat transfer and fluid flow for EBW process. It was noted that EBW, unlike LBW, is performed in vacuum and different physical processes occur. In case of EBW there is significant variation of cavity wall temperatures with depth and Marangoni convection currents affect convective heat transfer within weld pool. It was shown that convection was dominant mechanism of heat transfer in weld pool and that gradient of surface tension has significant impact on fluid flow. The predicted geometry of FZ is in good agreement with experimental measurements.

Sloma [9] developed model describing transport of molten material from arc to weld for gas metal arc, GMA, welding process. The model takes into account melting and solidification, multiphase flow, heat transfer with radiation and energy occurring in electric arc. Numerical results were compared with pictures recorded by high speed camera. The shape of welding pool and the face of the crystallizing weld were depicted in proper way.

Bollig [10] presented application of neural network as a model predictive controller, MPC, of LBW process along three-dimensional path. Depending on the path curvature welding speed changes and as a result also the depth of fusion changes. The goal of MPC is to detect changes in weld depth and to determine the sequence of steps that will restore welding process to the correct state. MPC takes into account future modifications of welding speed due to movement along welding trajectory and suggest appropriate sequence of changes in beam power that will compensate for the changes in speed. After the first step of the sequence is executed the system response is analyzed and the new sequence of steps is calculated. Depth of weld is estimated based on the intensity of plasma emission. Neural model requires definition of regression vector and calibration of weights and hidden neuron count. Regression vector comprises past values of power, speed and plasma emission. Additionally known future values of speed and predicted future values of emission are included in regression vector.

Yang [11] suggested application on Partial Least Squares, PLS, method to prediction of FZ cross-section geometry for gas metal arc welding process. The model takes as input welding control parameters: wire feed rate, wire extension, welding speed, gas flow, welding voltage and welding current. The goal of the model is prediction of weld depth, width and reinforcement. The amount of variation in dependent data explained by latent variables is 79% for depth, 67% for width and 70% for reinforcement.

Ganjigati [12] described new approach to modeling relationship between welding process parameters and bead geometry. It was suggested that instead of building global regression model cluster-wise regression analyses should be performed. Global model gives accurate results at data points used in building the model but there is high probability of error if model is applied to intermediate data. The solution is application of entropy-based fuzzy clustering method in order to identify distinct regions in input data. For every cluster the separate local regression model is built. Clusterwise regression gives slightly better results but they are comparable to results produced by global model.

Once the geometry of FZ zone is known heat source model can be calibrated to produce appropriate temperature distribution. Different heat source models used in welding simulations were described in [13].

2. Fusion zone cross-section model

2.1. Model description

The goal of the model is prediction of the geometry of FZ cross-section as a function of welding process control parameters. The results provided by the model will be further used to calibrate a heat source model used during FEM simulation. For the purpose of the modeling FZ cross-section is described by its depth and width, area, and shape of FZ contour.

The model uses PLS method to predict the FZ cross-section geometry. The advantages of PLS include capability of dealing with multiple input variables, data noise and variables collinearity.

PLS unlike ordinary least squares, OLS, ignores noise in the input data that is not predictive of changes in the output data. As a results it gives lower accuracy of prediction for the training data and higher accuracy for the test data that were not used to build a model. The comparison of PLS and OLS models built based on steel welds showed that PLS model gives better accuracy than OLS for Inconel welds [14].

PLS model can analyze collinear data i.e. input variables that are correlated with each other. This feature can be useful when the model is extended to take into account material properties given as a function of temperature. For instance, temperature dependent thermal conductivity values are correlated in such a way that if thermal conductivity is high at ambient temperature it tends to not change significantly after increasing temperature to 100 °C. The model will be extended in future to include input data for several alloys.

Additional advantage is that PLS does not require configuration which is necessary in case of neural networks where the number of hidden neurons and optimal weights must be defined.

2.2. Partial Least Squares regression

Partial Least Squares regression is multivariate linear model that predicts values of dependent variables Y based on values of independent variables X [15]. The distinct feature of PLS method is that it expresses Y variables in terms of latent variables, unlike OLS method which expresses Y variables directly in terms of X variables. The latent variables are linear combination of X variables. They are constructed in such a way that they predict maximum variance in Y variables and ignore noise in the relationship between X and Y variables. The main concept is that physical process is a function of several latent variables that manifest themselves in observable X and Y variables. The focus on latent