Model-based optimization of electron beam welding for obtaining defect-free welds

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The optimization of welds obtained by electron beam welding is a multi-criterial task, involving the requirements for the geometrical characteristics of the welds, together with the fulfilment of the requirements for lack of defects. This complex task can be solved through estimation of adequate models for the dependencies of the quality characteristics on the process parameters and finding optimal solutions that fulfil simultaneously all criteria.

In this paper, only the appearance of critical defects at certain regime conditions is considered, without taking into account of the type or the number of the defects. The modelling is done by implementation of two approaches – statistical approach based on regression analysis and discriminant analysis for defining the areas of the process parameters, where the appearance of defects is or is not expected. Different modelling approaches are compared and their applicability is discussed. Experimental data are used for the investigation of the influence of the variation of different electron beam welding regime conditions - electron beam power, welding velocity, the distances from the main surface of the magnetic lens of the electron gun to the beam focusing plane and to the sample surface on the considered performance characteristics.

Моделно базирана оптимизация на процеса електроннолъчево заваряване за получаване на бездефектни заваръчни шевове. (Елена Г. Колева, Лиляна С. Колева, Георги М. Младенов). *Оптимизацията на заваръчните шевове, получени чрез заваряване с електронен лъч, е многокритериална задача, включваща изисквания за геометричните характеристики на заваръчните шевове, както и изпълнението на изискването за липса на дефекти. Тази сложна задача може да бъде решена чрез оценка на адекватни модели за зависимостта на качествените характеристики от параметрите на процеса и намиране на оптимални решения, които изпълняват едновременно всички критерии. В тази статия се разглежда само появата на критични дефекти при определени режимни условия, без да се взема предвид вида или броя на дефектите. Моделирането се осъществява чрез прилагане на два подхода - статистически подход, базиран на регресионен анализ и дискриминационен анализ за определяне на областите на параметрите на процеса, при които се наблюдава или не се наблюдава появата на дефекти. Различните подходи за моделиране са сравнени и се обсъжда тяхната приложимост. Експериментални данни се използват за изследване на влиянието на вариацията на различните режимни условия при електроннолъчево заваряване - мощност на електронния лъч, скорост на заваряване, разстоянията от главната повърхност на магнитната леща на електронната пушка до фокуса на лъча и до повърхността на заварявания образец върху изследваните изходни характеристики.*

Introduction

The electron beam has developed over the years into a flexible and economic manufacturing tool. 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. 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. 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. The quality control in electron beam welding is similar to that in other welding processes, where the primary goal is to consistently produce defect-free and structurally sound welds. Existing process controls in EB welding typically are directed at controlling the essential machine settings, which include the accelerating voltage, beam current, focus coil current, vacuum level, travel speed, and work distance. Additional quality-control checks are performed after the completion of the weld, with non-destructive evaluation techniques to detect any potential defects in the components. In the case of critical applications preliminary destructive tests of welded samples to adjust welding regime to consumer requirements at real time equipment conditions are typical.

Prognoses and optimization of the weld parameters in an integrated intelligent process support system for operator assistance and automatic control of electron beam welding (EBW) with deep penetrating beam in vacuum can be done by implementation of different modelling approaches that take into account the values of different process parameters. Despite of the strong effort in developing complex and sophisticated physical and thermal models of the electron beam welding [1], 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. The weld depth, mean half width, thermal efficiency and number of defects for various beam powers, welding speeds and various positions of beam focus towards the sample surface plane for the investigated electron beam welding machine are investigated and analyzed [2-7] by implementation of statistical approaches – response surface methodology and neural networks. The estimation of regression and neural models based on experimental observations gives good and accurate engineering solutions for any process optimization.

The discriminant analysis [8] is conducted for predictive and classification purposes. When it is conducted for predictive purposes, it formulates a linear discriminant function describing the importance of the independent variables in differentiating observations of known group membership. Discriminant analysis conducted for classification purposes validates the predictive discriminant function as means of classifying fresh observations of unknown group membership sampled from the same populations. The first stage, discriminant predictive analysis, is used to optimize the predictive functions. The second stage, discriminant classification analysis, uses the predictive functions derived in the first stage to either classify new sets of data of known group membership, thereby validating the predictive function; or if the function has previously been validated, to classify new sets of observations of unknown group membership.

Discriminant analysis is based on the linear model:

$$D_t = \lambda_{t0}+\lambda_{t1}x_1+\lambda_{t2}x_2+\lambda_{t3}x_3+\ldots+\lambda_{tp}x_p,$$

where D_t is the predicted discriminant score, t – the number of differentiated by t discriminant functions, x_i the measured values of p independent variables.

The derived discriminant coefficients may be interpreted as indicative of the importance of the respective p independent variables entered into the discriminant analysis. Although these coefficients indicate importance, they are not appropriate for assessing the relative importance or discriminatory power of the variables, i.e., the proportion of total discriminating power attributable to a specific variable. The importance of the m independent variables that entered in the predictive function is defined in part by:

$$I_p=\left|\lambda_p\left(\bar{x}_{p1}-\bar{x}_{p2}\right)\right|,$$

where I_p is the importance of the p-th variable, λ_p is the unstandardized discriminant coefficient for the p-th variable and $\bar{x}_{pt}$ is the mean of the p-th variable for the t-th group. The relative importance of the variables can be calculated by:

$$R_p = \frac{I_p}{\sum_{p=1}^{m} I_p}.$$

In this paper, only the appearance of critical defects at certain regime conditions is considered, without taking into account of the type or the number of the defects. The modelling is done by implementation of two approaches – statistical approach based on regression analysis and discriminant analysis (binary logistic regression) for defining the areas of the process parameters, where the appearance of defects is or is not expected. Different modelling approaches are compared and their applicability is discussed. Experimental data are used for the investigation of the influence of the variation of different electron beam welding regime conditions - electron beam power, welding velocity, the distances from the main surface of the magnetic lens of the electron gun to the beam focusing plane and to the sample surface on the considered performance characteristics.

Weld geometry characteristics

The experiment, considered in this paper, is the electron beam welding of samples of austenitic stainless steel, type 1H18NT. The following operating parameters are varied: electron beam 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. In Table 1 are presented the regions of variation of the process parameters (z_i) during the performed experiments.

Table 1

EBW process parameters variation region

Parameter	Signature, coded	z_0	z_{min}	z_{max}
P [kW]	x_1	6.3	4.2	8.4
v [cm/min]	x_2	50	20	80
z_0 [mm]	x_3	226	176	276
z_p [mm]	x_4	226	126	326

The following quality characteristics describing the geometry of the obtained welded joints are considered here: weld depth H and mean weld width B.

The data are separated into two groups: 69 experiments are used for regression model estimation and 12 experiments are used for model validation by the root mean square error RSME:

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

where $\hat{y}_i$ and y_i are the predicted and the experimental values and n is the number of data.

The estimated regression models, together with the square of the multiple correlation coefficient R^2 and the square of the adjusted multiple correlation coefficient R^2_{adj} are presented in Table 2. The values of both coefficients are high and the estimated models for the weld depth and mean width can be considered as good enough for prediction and parameter optimization.

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 model verification results (RSME values) are shown in Table 2.

Defectiveness

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

In order to apply the discriminant analysis 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):

$$D_1 = -27.9791+2.7578\,P+0.0951v+0.0888\,z_o+ +0.0585\,z_p;$$

- for group 2 (with defects):

$$D_2 = -23.2625+2.2976\,P+0.0867\,v+0.1023\,z_o+ +0.0366\,z_p.$$

The percentage of the correctly predicted observations is 79.7% (76.5% - group 1, 88.9% - group 2).

The relative importance of the process parameters for the classification is estimated and presented in Table 3 for groups 1 (without defects) and 2 (with defects).

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.

Table 2

Regression models of the geometrical characteristics of the welds.

Parameter	Regression model	R^2	R^2_{adj}	RSME
H	$22.543402+3.0600233x_1-6.1054893x_2+6.4516174x_3-14.991258x_4-1.8782424x_1^2+3.0634013x_2^2-2.5851823x_3^2-19.000408x_4^2-2.644216x_1x_2+16.014092x_3x_4-3.5085771x_1^2x_3+6.3731112x_1^2x_4+3.6245613x_1x_3^2-10.980193x_1x_3x_4+12.332458x_1x_4^2-1.5648706x_1x_4-1.4669825x_1^2x_2$	0.95153	0.93537	2.9848
B	$1.9481327-0.58997133x_2-0.93012607x_3+2.6799217x_4+0.4981557x_2^2+0.29162612x_3^2+2.4010783x_4^2+0.21615508x_1x_3-2.3838706x_3x_4-0.88752918x_1^2x_4+0.2790095x_1x_2^2-0.80178036x_3x_4^2+0.26854894x_1^2x_3$	0.81156	0.77118	0.2953

Table 3

Relative importance of process parameters

Parameter	Means		Group 1 (p_1)		Group 2 (p_2)	
	Group 1 (p_1)	Group 2 (p_2)	I_p	R_p, %	I_p	R_p, %
P [kW]	6.5059	5.4833	2.82015	53.40	2.34957	56.58
v [cm/min]	47.059	45.556	0.14289	2.70	0.13034	3.14
z_0 [mm]	227.96	223.22	0.42082	7.97	0.48493	11.68
z_p [mm]	227.57	195.11	1.89766	35.93	1.18761	28.60

In order to apply the regression analysis a regression model for the defects D, considered as continuous variable, is estimated:

$$\begin{aligned}D = {} & 0.2109-0.1215x_1+0.2799x_2+0.4249x_3-1.0284x_4 \\ & -0.1413x_1^2+0.1682\,x_2^2-0.1411x_1x_3+0.7325x_2x_3x_4 \\ & +0.3750x_1x_4-0.3208x_1^2x_2-0.5553x_1^2x_3 \\ & +0.8828x_1^2x_4-0.3042x_1x_2x_4-1.0112x_1x_3x_4 \\ & +1.0028x_1\,x_4^2-1.1492889x_2x_4^2.\end{aligned}$$

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].

The values of the multiple correlation coefficient R^2 and the square of the adjusted multiple correlation coefficient R^2_{adj} are: R^2 =0.76318 and R^2_{adj} =0.67706. Both coefficients are comparatively high and the estimated models for the defects can be considered as good enough for prediction and parameter optimization.

The value of D_l=0.5 is accepted as a conditional limit between the regions with (D>0.5) and without (D<0.5) defects.

Some better results are obtained by applying the regression analysis – 88.41% of the observations are predicted correctly (92.16% - group 1, 77.78% - group 2).

If the aim is to make more correct predictions for classification for the group 2 - less mistakes 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 a smaller value of the limit D_l (for example, if D_l=0.3, then the overall percentage of the correctly predicted observations will be 85.5%, but for group 1 – 84.31% and for group 2 – 89.89%).

For validation of the regression model 12 experiments are used. The predicted correctly observations are 75% and all misclassified observations are with true observation with no defects and estimated appearance of defects.

Electron beam welding product optimization

The optimization of welds obtained by electron beam welding is a multi-criterial task, involving the requirements for the geometrical characteristics of the welds, together with the fulfilment of the requirements for lack of defects.

The estimated and validated models can be implemented for parameter optimization of the quality characteristics of the steel welding joints obtained by electron beam process. The requirements are set to obtaining welds with depth H between 20 and 22 mm, mean width below 2 mm and without defects.

There are many multi-criterial optimization methods, the implementation of which depends on the optimization task formulation. Here it is applied the graphical optimization method, which applies the superimposing of the estimated quality characteristic values, depending on the process parameter variation.

On Fig. 1 - Fig. 4 are presented the results from the graphical optimization and the implementation of discriminant functions and regression models.

Fig. 1 and Fig. 2 represent the contour lines of the constrains for the weld depth and width (H = 20 mm, H = 22 mm and B = 2 mm). The limit value $D_l = 0.5$, separating the regions with defect and defect-free welds, is calculated by the corresponding regression model and is also presented. Fig. 1 shows the dependence of these characteristics as a function of the variation of electron beam power P and the welding velocity v at constant values of the distances to the beam focus and to the sample surface $z_0 = z_p =$ 226 mm. On Fig. 2 are presented the dependencies of the quality characteristics on the distances to the beam focus z_0 and to the sample surface z_p at constant values of the beam power P and the welding velocity v (P = 6.3 kW, v = 50 cm/min).

The colored areas present the zones where all the set requirements are fulfilled.

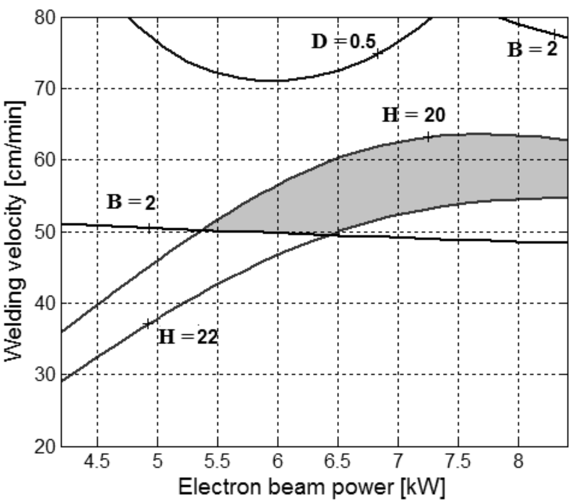

Fig. 1. Graphical optimisation – regression model for defects D and distances $z_0 = z_p = 226$ mm.

Fig. 3 and fig. 4 represent the contour lines of the constrains for the weld depth and width, together with the classified by estimated discriminant functions defect and defect-free regions ('□' for region without defects and '*' for the region with defects).

It can be seen that both approaches give estimation for the process parameters in areas without defects. The areas with and without defects are identical for both cases (Fig. 2 and Fig. 4) of the dependencies of the quality characteristics on the distances to the beam focus z_0 and to the sample surface z_p at constant values of the beam power P and the welding velocity v (P = 6.3 kW, v = 50 cm/min).

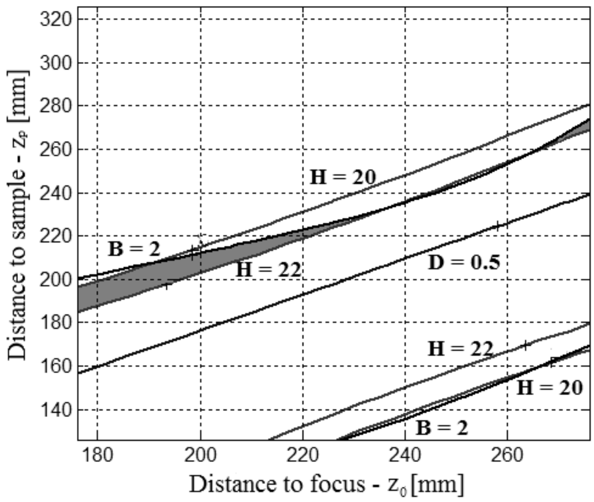

Fig. 2. Graphical optimisation – regression model for defects D and P = 6.3 kW, v = 50 cm/min.

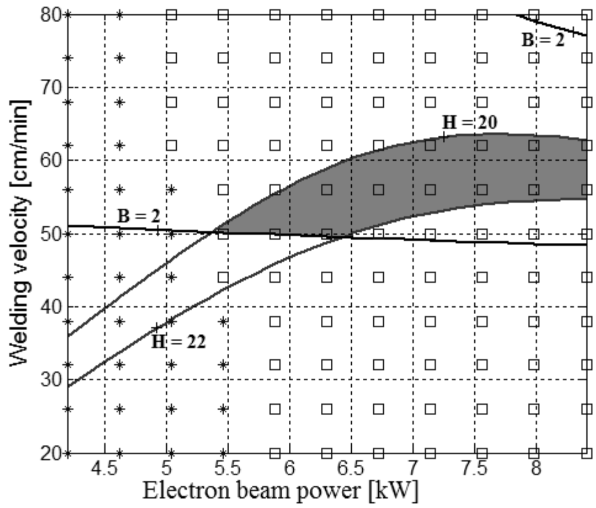

Fig. 3. Graphical optimisation – discriminant functions for defects D and distances $z_0 = z_p = 226$ mm ('□' for region without defects and '' for the region with defects).*

There is a difference in the estimation of the zones with and without defects in the cases for the dependence of the quality characteristics as a function of the variation of electron beam power P and the welding velocity v at constant values of the distances to the beam focus and to the sample surface $z_0 = z_p =$ 226 mm. The reason for this difference is the accuracy of the estimated regression model for D and the discriminant functions.

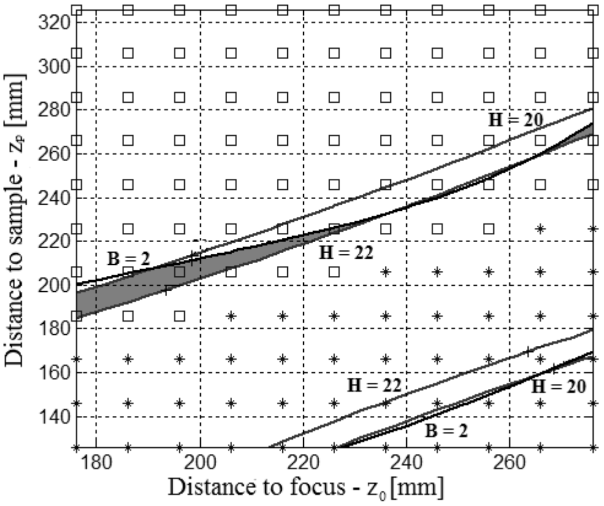

Fig. 4. Graphical optimisation – discriminant functions for defects D and P = 6.3 kW, v = 50 cm/min ('□' for region without defects and '' for the region with defects).*

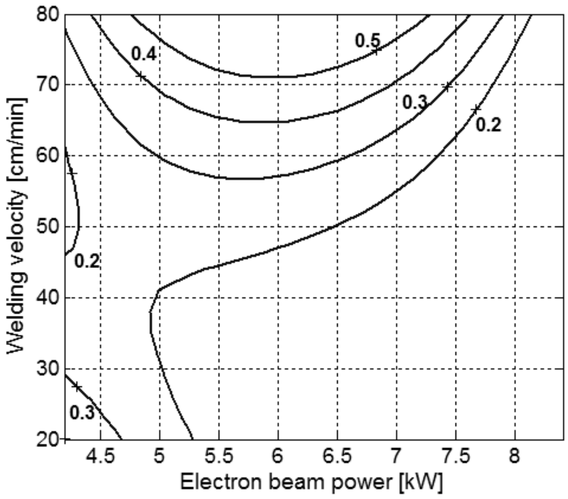

Fig. 5. Contour plot of the defects (regression model) as a function of electron beam power P and the welding velocity v at distances $z_0 = z_p = 226$ mm.

Fig. 5 shows the contour plot of the defects, estimated by the regression model, as a function of electron beam power P and the welding velocity v at distances $z_0 = z_p = 226$ mm. It can be seen that lowering the limit value between the defect and defect-free zones to $D_l = 0.2$ will combine the two estimations in favor of the guarantee for the increase of the accuracy of the correct predictions for classification for the group 2 - less mistakes of the type that the process parameters will produce welds without defects, while the truth is that there are defects.

Conclusion

In this paper, a new systematic methodology based on models, being able to predict the geometry characteristics of the obtained through EBW joints, as well as the defectiveness, has been proposed.

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

The beneficial implementation of statistical models 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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