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SENSITIVITY ANALYSIS OF LASER WELDING PROCESS BY ANFIS METHODOLOGY

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Abstract: *In this study was analyzed the influence of laser welding parameters on output parameters prediction. Adaptive neuro-fuzzy inference system (ANFIS) was applied for the variable selection process to determine the parameters influence on the lap-shear strength and weld-seam width prediction. The used inputs were: laser power, welding speed, stand-off distance and clamping pressure. Experimental test were used to acquire the training data for the ANFIS network. The ANFIS network was used to predict the lap-shear strength and weld-seam width according to the input variables separately. Root mean square error (RMSE) was used as statistical indicators for comparison. The results from this study could be used as benchmark results in order to improve the laser welding process.*

Key words: *ANFIS; laser welding; prediction; sensitivity*

Određivanje uticaja parametara na proces zavarivanja laserom primenom ANFIS metodologije. *U ovom radu je analiziran uticaj parametara na proces zavaravanja laserom. Adaptivna neuro fazi metodologija ANFIS je korišćena za proces selekcije najuticajnijih parametara. Ulazni parametri su snaga laserskog zraka, brzina zavarivanja, rastojanja pri zavarivanju i pritisak pri zavarivanju. Eksperimentalni testovi su urađeni kako bi bili sakupljeni podaci za primenu u ANFIS metdologiji. ANFIS je korišćen za predikciju parametara laserkog zavarivanja za pojedine ulazne parametre. Greška najmanjih kvadrada RMSE je korišćena za rangiranja uticaja parametara na lasersko zavarivanje.*

Ključne reči: *ANFIS; lasersko zavarivanje; predikcija; osetljivost parametara*

1. INTRODUCTION

Chip based machining is still important engineering Laser welding process is a technology in numerous industries for advanced manufacturing because of laser versatility. Laser welding technique is non-contact, not-contaminating, very precise and adaptable process for easy automation. By this process laser beam penetrates to the upper part and the penetration is converted in heat by the connecting the lower part. The melting area is formed only in the controlled sections or only in the joining section of the both parts. The mechanical performances of the weld are in relation to the absorption of laser energy. The most important parameters for the laser welding process are laser power, welding speed, laser beam size on the work piece and pressure of clamping. There were many investigations which studied the parameters effects on the quality of laser weld.

In article [1] the finite element method (FEM) and neural network were applied for predicting the bead shape in laser spot welding of type 304 thin stainless steel sheets and it was shown that the combined model of finite element analysis and neural network could be effectively applied for the prediction of bead shapes of laser spot welds, because the numerical analysis of laser spot welding for the work piece with gap between two sheets is highly limited. Control of a laser keyhole welding process was presented in article [2] where the objective was to maintain the penetration depth of the laser welding process at a desired value under system uncertainties and the results were demonstrated that the fuzzy models provided an accurate estimation of both the welding geometry and its variations due to uncertainties. The optimal parameters of the pulsed laser micro-weld process were determined in article [3] by simulating parameters using a well-trained back-propagation neural network model. In study [4] was aimed to develop a control module to obtain good quality joints of laser welding by using Artificial Neural Network (ANN) model consisting of two stages, fault detections and parameter adjustments. The welded joints of different materials have been widely used in automotive, ship and space industries. The joint quality is often evaluated by weld seam geometry, microstructures and mechanical properties. To obtain the desired weld seam geometry and improve the quality of welded joints, in paper [5] was proposed a process modeling and parameter optimization method to obtain the weld seam with minimum width and desired depth of penetration for laser butt welding of dissimilar materials. Morphology of molten pool was significantly associated with welding quality [6]. The need for the control of the depth of laser weld penetration was remain of a long term interest in the automated welding process. In study [7], the relationship between the depth of weld penetration and the acoustic signal acquired during the laser welding process of high strength steels is investigated. In paper [8] was presented the inverse determination of the laser power in welding process with a given width penetration using the modified Newton–Raphson method (MRN) and the results were shown that the proposed method was an accurate and robust method to inversely estimate the laser power for a given width penetration. The present work establishes S correlation between the laser transmission welding parameters and output variables though a nonlinear model was developed in paper [9] by ANN and the simulation data obtained from the neural network confirms the feasibility of this model in terms of applicability and shows better agreement with the experimental data, compared to those from the regression models. The results in research [10] showed a comprehensive and usable prediction of the laser welding parameters for butt joints using neural network.

The quality can be presented in relation to the bead geometry, mechanical properties and distortion. Proper definition of the processing parameters is required in order to get defined laser weld quality. The selection of the input parameters of the laser welding process is very time consuming task. Therefore in this study was applied an empirical methodology in order to select the most influential parameters for the laser welding process. The main goal in this study was to avoid high nonlinearity of the mathematical approaches by using soft computing methodology. Soft computing methods do not require knowledge of internal system and these methods can provide compact solution for muilti-variable problems.

In this investigation adaptive neuro-fuzzy inference system (ANFIS) [11] was used to determine the most dominant factors for the laser welding quality prediction. ANFIS is a hybrid soft computing methodology which merges the ability of neural networks and fuzzy systems [12-15].

2. METHODOLOGY

2.1 Experimental measurement

Coherent FAP-diode laser was used in this investigation. The system has maximal optimal power of 40 W and wavelength output of 810 nm. The optical irradiation was delivered by SMA905 connector. Two lenses were imagining module of the system at the end of the connector. To maintain the area of lapping constant a fixture was used. To ensure good contact between two welding parts a hydraulic clamp pressure was applied. The strength of the lap-shear was calculated for the maximum load to failure. The width of weld-stem was measured using Mitutoyo Tool microscope. The used inputs and outputs are presented in Table 1.

Inputs and outputs	Parameters description
input 1	Power (W)
input 2	Laser welding speed (mm/min)
input 3	Distance of stand-off (mm)
input 4	Clamp pressure (MPa)
output 1	Strength of lap-shear (N/mm)
output 2	Width of weld-seam (mm)

Table 1. Input and output parameters

2.2 ANFIS methodology

The structure of ANFIS network with two inputs is shown in Figure 1.

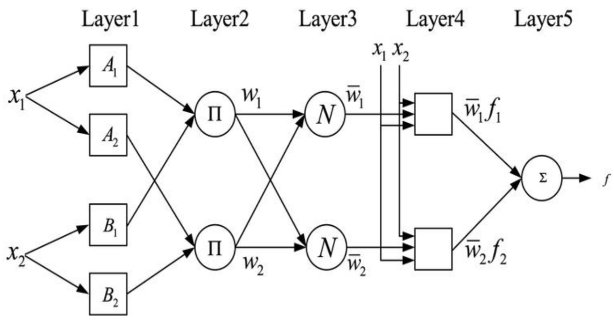

Fig. 1. ANFIS structure with two inputs

The first ANFIS layer presents inputs of membership function (MF). Each node here is considered an adaptive node having a function which is dependable on MF. The second layer is the membership layer where firing strength of rules are determined. In the third layer the fuzzy inference is made based on the training data. The fourth layer provides inference of fuzzy rules. The fifth layer gives the final output which is crisp number.

The ANFIS network is trained by hybrid methodology in order to ensure the best regression of the data. One part of the methodology optimize the ANFIS parameters in forward direction. The second part of the methodology optimize the ANFIS parameters in backward direction from the last up to the first ANFIS layer.

3. RESULTS

ANFIS network was trained for every input separately in order to determine the RMSEs for every inputs. The input with the smallest training RMSE has the highest influence or relevance on the output. Testing RMSE was used to track overfitting between training and testing data. If testing RMSE becomes too high it means the regression of the data is not good.

Results for the strength of lap-shear prediction based on the all inputs separately are presented below:

- in1 --> trn=12.0310, chk=11.1459
- in2 --> trn=10.6775, chk=9.9164
- **in3 --> trn=10.2826, chk=10.2687**
- in4 --> trn=11.8319, chk=12.1698

One can note the smallest training RMSE for input 3. In other words the input 3 has the highest influence on the output. Further one can combine two inputs in order to find the most influential combinations of inputs on the output. The RMSEs for the combinations of the two inputs are presented bellow for the strength of lap-shear prediction

- in1 and in2 --> trn=10.2812, chk=14.9691
- in1 and in3 --> trn=10.0194, chk=35.3298
- in1 and in4 --> trn=10.6217, chk=19.0495

- **in2 and in3 --> trn=1.6319, chk=34.4350**
- in2 and in4 --> trn=10.0678, chk=11.5213
- in3 and in4 --> trn=9.8302, chk=12.9440

According the training RMSE the combination of inputs 2 and 3 forms the optimal combination which has the highest influence on the output parameter. The same inputs were selected for the width of weld-seam prediction as can be seen bellow:

- in1 --> trn=0.3848, chk=0.3724
- in2 --> trn=0.2935, chk=0.4344
- **in3 --> trn=0.2421, chk=0.3905**
- in4 --> trn=0.3915, chk=0.4259

- in1 and in2 --> trn=0.2922, chk=0.7139
- in1 and in3 --> trn=0.1980, chk=0.6987
- in1 and in4 --> trn=0.3843, chk=1.0257
- **in2 and in3 --> trn=0.0891, chk=0.5481**
- in2 and in4 --> trn=0.2779, chk=0.4109
- in3 and in4 --> trn=0.2414, chk=0.4059

The inputs 2 and 3 were extracted in order to make the ANFIS prediction surface. Figure 2 shows the prediction surface for the strength of lap-shear prediction based on the inputs 2 and 3 and Figure 3 shows the prediction surface for the weld-seam prediction based on the inputs 2 and 3.

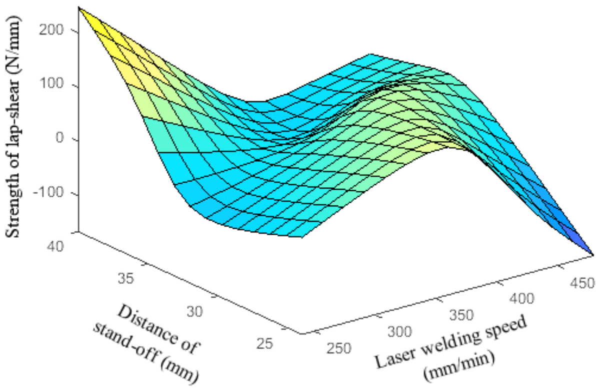

Fig. 2. Strength of lap-shear prediction surface

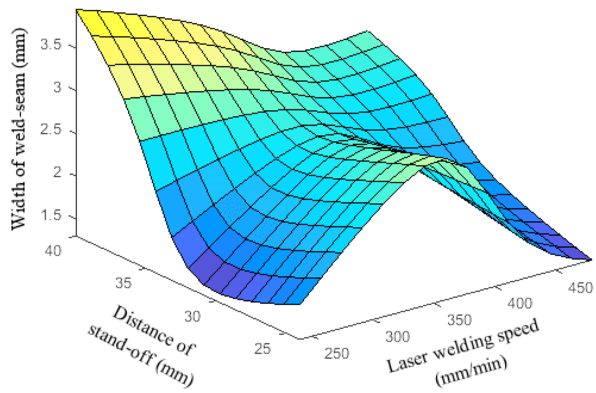

Fig. 3. Width of weld-seam prediction surface

4. CONCLUSION

The main goal of the paper to apply ANFIS methodology in order to determine the most influential factors for the laser welding process. Weld strength and weld dimensions were the main output factors for the weld quality estimation.

Laser weld quality prediction is complex task due to the many factors. Therefore in this study was applied a soft computing methodology to overcome the prediction by removing some unnecessary input parameters. ANFIS methodology was used to select the most dominant factors for laser welding process. Results were shown that the laser welding speed and stand-off distance are very important parameters for the laser welding quality.

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