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Optimization of Reactive Gas Laser Cutting Parameters based on a combination of Semi-Analytical modelling and Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract

We demonstrate an optimization procedure to determine optimal process parameters in reactive gas laser cutting of metals. The optimization procedure is based on a combination of a semi-analytical model for reactive gas laser cutting and an adaptive neuro-fuzzy inference system (ANFIS). The semi-analytical model was employed to generate training and testing data for ANFIS. Exemplarily, we show results for 10 mm thick DD11 steel plates. The system parameters consisted of two inputs: the cutting speed and the focal position of the laser with respect to the workpiece. The optimization was done with respect to the striation amplitude. For each output a corresponding ANFIS-network was built. The optimal process parameters were extracted via a 3D surface or control plot of the generated fuzzy output for the striation amplitudes as a function of the two input parameters.

Keywords: Macro-Processing; Cutting; Fundamentals and Process

Introduction

Laser cutting is one of the most widely used Laser Beam Machining processes. Among the materials, that exhibit favourable thermal and optical material properties for laser cutting, we can find, for example, metals. Therefore, laser cutting is ideal for metal plates. However, there are several side effects that limit the quality of metal cutting. One of the main features is the formation of a typical roughness pattern at the edges that has the form of periodic striations. In different publications these striations are also called grooves, strokes or patterns [1], [2], [3]. A second relevant quality parameter is dross formation at the bottom side of the

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workpiece, which results from solidification of expelled liquid metal. Both adverse effects can be reduced via damping the striation and dross formation, i.e. by a judicious choice of laser cutting parameters. Thus, it is important to have a procedure to identify the optimal laser cutting parameters. In recent years, several publications on intelligent modelling of laser cutting and on optimization of laser cutting parameters with the help of ANFIS Networks trained with experimental data sets were published, e.g. references [4], [5].

In this contribution we apply optimization schemes based on a combination of semi-analytical model and ANFIS to reactive gas laser cutting. Specifically, the semi-analytical model is used to generate training and testing data for ANFIS.

1.1. The reactive gas laser cutting process

In the process of reactive gas laser cutting a high power continuous wave laser beam is focused to a spot on the workpiece where it melts the metal. Additionally, a high pressure reactive assist gas is supplied with a nozzle in order to 1) remove the molten material from the melting pool and 2) add energy via chemical reaction between gas and molten material. In practice oxygen is widely used as assist gas. The heterogeneous chemical reaction of iron oxidation with the accompanied release of heat in the laser pool will take place primarily at the cutting front. The added process energy allows for an almost threefold increase in cutting speed as compared with cutting in an inert gas environment (argon, helium or nitrogen) [3] [6].

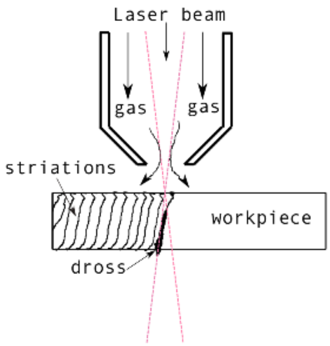

Fig. 1. Schematic of laser cutting.

Oxidation of iron in an oxygen atmosphere results in a complex interplay and in periodic cycles of ignition, combustion and decay. The reaction rates themselves are controlled by heat- and mass-transfer between the gaseous, liquid and solid phases of the metal. As consequence, the cut surface develops roughness and deep striations. As mentioned before the striation formation process can be dampened by choosing the optimal laser cutting parameters.

2. Laser cutting experiments

In order to generate training and testing data for ANFIS, we performed accurate laser cutting experiments. The laser cutting parameters used in the experiments are summarized in table 1.

Table 1. Laser cutting parameters

Parameter	Value
Source	CW fiber laser
Laser power	5000 W
Workpiece	DD11 steel plate
Workpiece thickness	10 mm
Focal position*	[-9.5,-4.5] mm
Cutting speed	[1.4, 2.3] m/min

*Note that in our reference system a negative value for the focal position corresponds to the focus of the laser being above the workpiece. If the focus is at the top surface of the workpiece, the corresponding focal position is zero and positive if lower.

3. The semi-analytical model for reactive gas laser cutting

In article [7] we present a theoretical model for the process of reactive gas laser cutting of metals. This semi-analytical model is based on the driven damped oscillator equation. It is able to estimate the striation amplitudes on the cutting edges and therefore the corresponding roughness profile. In order to generate training and testing data for ANFIS, we calculated with the help of this model the striation amplitudes and the corresponding roughness for the laser cutting parameters as given in table 1.

4. Neuro-Fuzzy System (ANFIS)

ANFIS is a type of Artificial Intelligence (AI) that combines the advantages of fuzzy systems and Artificial Neural Networks (ANNs) [8]. It can be used to model both linear and nonlinear relationships between input and output parameters. Since ANFIS combines the properties of fuzzy logic and Artificial Neural Networks it can process imprecise and vague data and at the same time it has the capability to train the network and adapt to the system. ANFIS learns from the input training data by clustering them to the same class using the neural network. Fuzzy rules that can be represented through linguistic variables or terms will be generated from the trained network. The training of ANFIS can be performed by the hybrid learning procedure as described in Ref. [8]. Here, we use the ANFIS version implemented as a MATLAB tool.

5. Methodology

5.*1. Generation of training and testing data sets*

In this article we present two neuro-fuzzy models: one that was trained and tested with a data set from the semi-analytical model and one that was trained and tested with a data set resulting from accurate laser cutting experiments. The second neuro-fuzzy model is used for validation purposes. Training and testing data sets were generated for different cutting speeds as well as focal positions. Since the generation of data by means of experiments and measurements is a time consuming and resource intensive task, we were limited to work with a small set of experimental training and testing data. Therefore, we worked only with small ANFIS-networks of four membership functions.

5.2. Modelling of Laser Cutting for striation formation

In our article [7] we present a theoretical model for the process of reactive gas laser cutting of metals. This model is able to calculate the striation amplitudes on the cutting edges and therefore the corresponding roughness profile on the cutting edges. With the help of this theoretical model we generate the training and testing data for an ANFIS network. In the striation model we consider two input process parameters, namely the cutting speed and the focal position. As output parameter we choose the resulting striation amplitude, i.e. the values of the roughness on the cutting edge. Figure 2 shows the block diagram of the ANFIS-Model (Sugeno type) corresponding to the model for striation formation. The right hand side of the diagram shows the output striation amplitude, i.e. the roughness. The middle part shows the Sugeno type ANFIS model engine, where, as membership function, we have chosen the Gaussian function. The membership functions for each input variable are shown in figures 3a and 4b. The Gaussian membership function led to the best results.

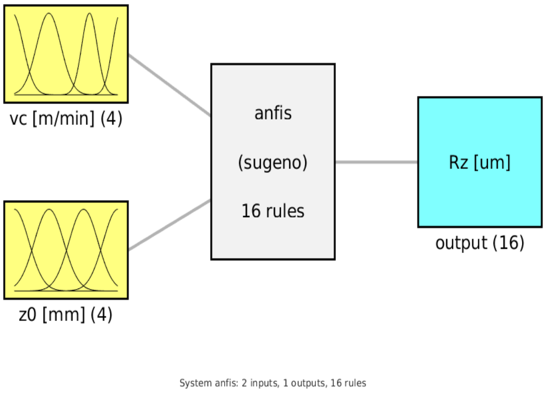

Fig. 2. Block diagram of ANFIS-Mode for roughness.

As there are two inputs each having four membership functions, the total number of fuzzy rules formed will be 16 (4x4). The first neuro-fuzzy model was trained by using the data set generated by our theoretical model for the reactive gas laser cutting. The second neuro-fuzzy model was trained by using experimentally measured data set. This neuro-fuzzy model was used for validation purposes. The ANFIS-Networks were trained for 40 epochs. The training error as function of the number of epochs is depicted in figure 4.

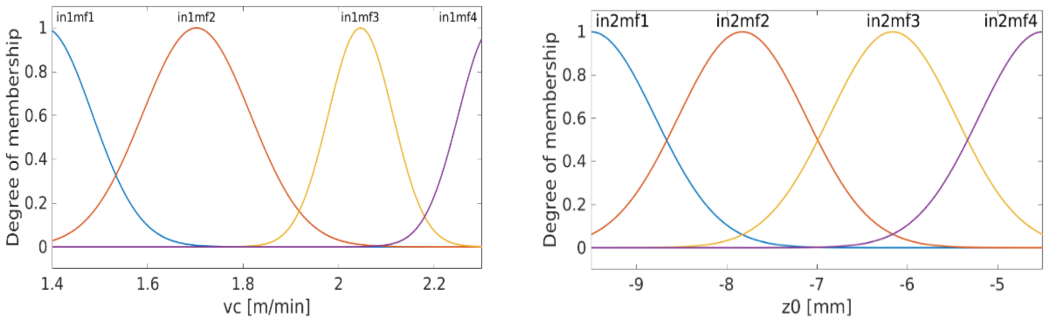

Fig. 3. (a) Membership functions for the different cutting speeds; (b) Membership functions for the different focal positions.

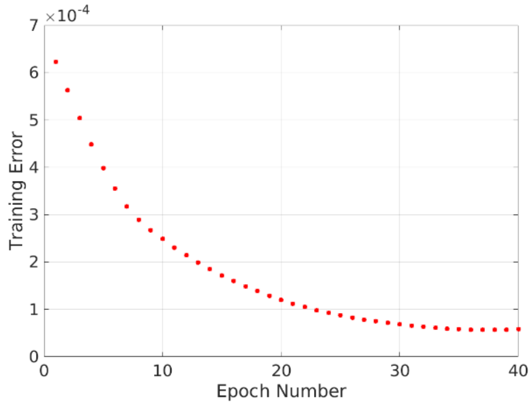

Fig. 4. Training error vs. epoch number.

6. Results and Discussion

In figure 5 the resulting control plots are depicted. In figure 5a the control plot corresponding to the neuro-fuzzy model trained and tested with data sets resulting from the theoretical calculations is depicted. In figure 5b the control plot corresponding to the neuro-fuzzy model trained and tested with data sets obtained from the laser cutting experiments is shown.

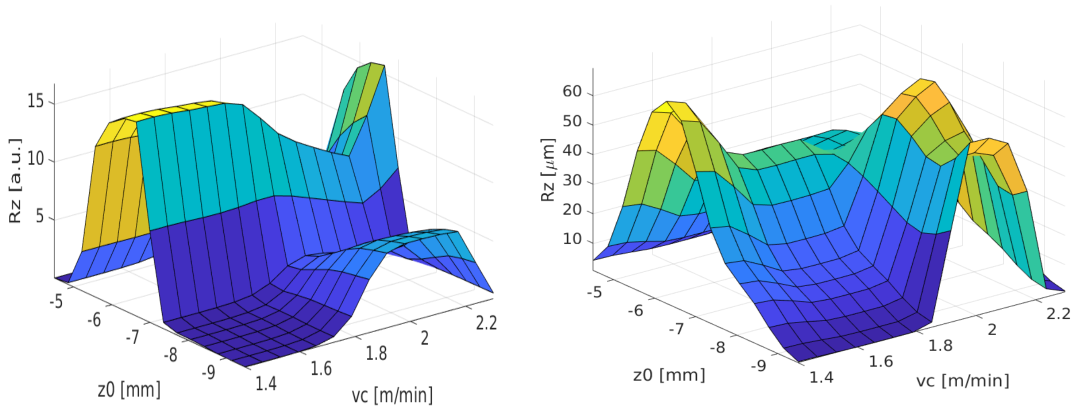

Fig. 5. (a) Control plot for theoretical values; (b) Control plot for measured values.

The z-axis in figure 5 indicates the roughness value R_z. While for experimental values (Fig.5b) R_z is given in absolute values, the theoretical R_z values (Fig. 5a) are in arbitrary units. The reason is that the theoretical model does not produce absolute values for the roughness. It is only able to estimate relative roughness values. For an optimization of laser cutting parameters this information is sufficient since we are only interested in identifying regions of the input parameter space that correspond to the lowest possible roughness. A comparison of figures 5a and 5b indicates good agreement between experimental and theoretical results. Figures 6 shows the results of Fig. 5 projected onto a plane. We can see that regions of low roughness values (dark blue) are found if the focus is more than 7 mm above the metal surface and if the cutting velocity does not exceed 1.8 m/min.

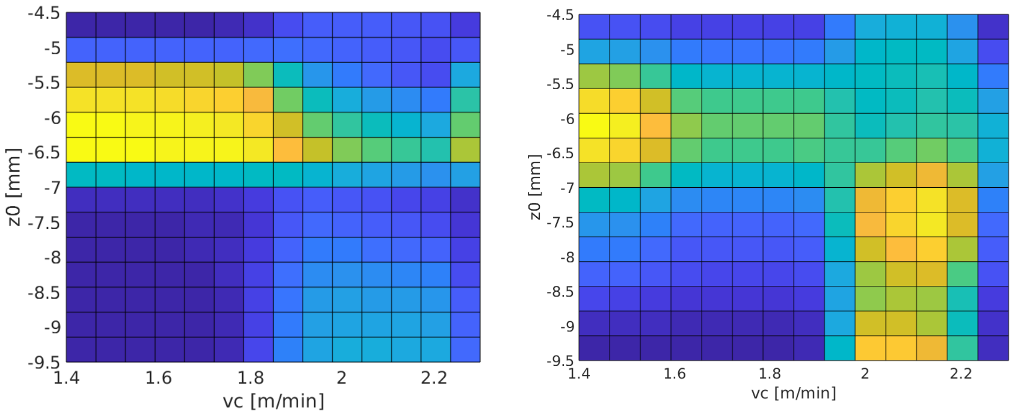

Fig. 6. (a) Projection onto plane (theoretical values); (b) Projection onto plane (measured values).

In summary, we demonstrated a neuro-fuzzy model trained and tested with data sets obtained from a semi-analytical model as well as from experimental data. In both cases we were able to identify regions in the input parameter space which correspond to the lowest roughness values. Results from theoretical modelling agree well with those obtained via experiments.

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