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Prediction of Cutting Interruptions for Laser Cutting Using Logistic Regression

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Abstract

Cutting interruptions in 2D laser cutting are undesired for several reasons: They lead to an unnecessarily high material consumption and decrease the productivity of the laser cutting machine. Furthermore, they can contaminate the laser cutting head and thus influence subsequent processes negatively or cause long set-up times. Therefore, we developed a model to predict cutting interruptions, exemplarily for 3 mm stainless steel. We have set 1050 different combinations of the cutting parameters nozzle-sheet distance, gas pressure, nozzle-focus distance and speed on a state-of-the-art laser cutting machine. It was then determined whether separating the sheet was possible or not. The experimentally generated database was used to train a simple, interpretable machine learning model to predict cutting interruptions reliably. An averaged accuracy and recall larger than 95 % could be obtained with a polynomial logistic regression approach. In addition to that, it could be shown that speed and focal position are the most crucial parameters.

Keywords: laser macro processing; laser cutting; cutting interruptions; logistic regression

1. Introduction

Today, laser cutting is the most common application of the laser with a share of 35 % of all industrial applications according to Kincade et al., 2018. In conventional laser cutting machines the laser beam is guided through the focusing optics of the cutting head, it then passes through a nozzle from which a coaxial gas jet flows. The high energy density of the focused beam enables it to melt or evaporate the underlying material. The gas jet is used to both remove the melt from the kerf and to protect the optics (Steen and Mazumder, 2010).

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Laser cutting has many advantages compared to competing processes. Of particular interest in industrial applications are the simultaneous maximization of quality and productivity (Poprawe et al., 2010). To achieve these two goals, operators often need to adjust the process parameters to the current conditions, e.g. material properties. As laser cutting is a very complex process, changing the parameters through an inexperienced operator might, in the worst case, result in a cutting interruption. Cutting interruptions waste material and they can contaminate both optics and nozzle and thus influence subsequent processes negatively or cause machine downtimes. Therefore, they are very cost and time consuming and should be avoided. Adelmann et al., 2015 presented a possible solution, an optical sensor that can be attached to the laser cutting machine to detect cutting interruptions by measuring the process radiation. Nevertheless, it would be advantageous to avoid cutting interruptions a priori. For this purpose, a reliable model to predict cutting interruptions for all possible combinations of the process parameters is required.

The objective of this paper is to model the risk of a cutting interruption based on 4 dominant cutting parameters with a simple, interpretable machine learning model and to increase the understanding of the complex effects and interdependencies of the cutting parameters. First, the experimental setup and the logistic regression model are introduced. Then the risk of a cutting interruption is analyzed separately for every considered process parameter and finally the performance of the model is evaluated.

2. Methods

2.1. Experimental setup

In order to generate the data base for the machine learning model, we tried to cut 1103 parts on a modern laser cutting machine with a disk laser (TruLaser 5030 fiber with TruDisk 12001). In the experiment considered here only 3 mm thick stainless steel of one batch was cut with the standard cutting process.

The laser cutting process depends on numerous cutting parameters, 4 of which were modified for this experiment: nozzle-sheet distance, gas pressure, nozzle-focus distance and cutting speed. The nozzle-sheet distance is the distance between the tip of the nozzle and the top side of the sheet. The gas pressure is the pressure of the assist gas (here nitrogen) that is blown within the kerf to drive out the molten material. The nozzle-focus distance is the distance between the tip of the nozzle and the focus of the laser beam. A focus position below the tip of the nozzle results in a negative value, whereas the nozzle-focus distance is positive when the focus of the beam is located within the cutting head. As the machine is equipped with flying optics, the laser cutting head moves above the sheet with the cutting speed. All other parameters (e.g. laser power of 8 kW, focus diameter of 150 µm) were held constant.

The ranges and steps of the parameter variation are shown in Table 1. In the last column of the table the optimum of each parameter is shown respectively, as specified in the manual of the laser cutting machine.

Table 1. Ranges, step widths and optima of modified cutting parameters

Parameter	Unit	Minimum	Maximum	Step width	Number of steps	Optimum
Nozzle-sheet distance	mm	0.5	3	0.5	6	1.5
Gas pressure	bar	9	21	3	5	15
Nozzle-focus distance	mm	-3.5	-0.5	0.5	7	-2
Cutting speed	m/min	13	29	4	5	21

These 4 cutting parameters were combined fully factorially, which results in 1050 different parameter combinations, 5 % of which were repeated randomly. This leads to 1103 parameter combinations in total. We cut squares with a side length of 10 cm. For every part it was documented whether cutting was successful (with the cut quality not being considered here) or not. The corners were rounded off and the power was not reduced there, because only straight cuts were investigated.

When performing cutting experiments that go beyond the stability limit of the cutting process, it is very important to monitor the status of the machine. To make sure that the nozzle and the optics were clean, the nozzle and the protection glass (which is positioned in the laser cutting head between nozzle and optics) were checked every 25 parts. In addition to that, beam caustic measurements were performed at the same interval to make sure that there was no abnormal thermal behavior, caused for example by back-reflections of the laser beam. The nozzle-sheet distance is controlled capacitively, so that it is constant although the sheet is not perfectly flat. This control system performs poorly if a plasma is formed between nozzle and sheet. For this reason, the quality of the control system was monitored constantly.

2.2. Logistic regression model

Logistic regression is one of various tools for understanding and working with data using statistical learning. The linear, multivariate logistic regression model for binary classification (output Y ϵ {0,1}) is defined by

$$p(X) = \frac{e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\dots+\beta_n X_n}}{1+\ e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\dots+\beta_n X_n}} \tag{1}$$

with p(X) = Pr(Y = 1|X), n input features X = (X_1, X_2, …, X_n) and n + 1 coefficients β_0, β_1, …, β_n (James et al., 2017).

In this paper p(X) is the probability of a cutting interruption for a specific combination of the input features. Here the input features are based on the cutting parameters (nozzle-sheet distance, gas pressure, nozzle-focus distance and cutting speed), supplemented by the focus position, which is a combination of nozzle-sheet distance and nozzle-focus distance. The focus position is the position of the focus relative to the top side of the sheet, which is calculated by simply adding nozzle-sheet and nozzle-focus distance. If the focus is located within or below the sheet, the focus position is negative. If it is located above the sheet, the focus position is positive. To model the nonlinearity these 5 features were extended by all polynomial combinations of degree 3 or smaller, which results in a total number of n=55 features.

After selecting the model, the coefficients β_0, β_1, …, β_n have to be estimated such that p(X) is close to 1 for all feature combinations that result in a cutting interruption and close to 0 for all feature combinations that result in a successful separation of the sheet (the threshold is 0.5). There are many approaches to the fitting of the model. We have used the LogisticRegression model of the Python library sci-kit learn (Pedregosa et al., 2011), with the following settings: penalty = 'l2', solver = 'liblinear', class_weight = 'balanced'. The model was trained on 75 % of the data and tested on randomly selected, previously unseen 25 % of the data.

To visualize the performance of the algorithm, we use the confusion matrix (James et al., 2017). The two rows represent the instances of the predicted class, while the two columns represent the instances of the true class. The matrix contains the numbers of true positives TP (prediction: cutting interruption, true class: cutting interruption), true negatives TN (prediction: cutting successful, true class: cutting successful), false positives FP (prediction: cutting interruption, true class: cutting successful) and false negatives FN (prediction: cutting successful, true class: cutting interruption). From these numbers the following evaluation metrics can be deduced (Kubat, 2015):

$$accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (2)$$

$$recall = TP/(TP + FN) \quad (3)$$

$$precision = TP/(TP + FP) \quad (4)$$

3. Results

3.1. Analysis of the data base

Of the 1103 parameter combinations, 6 samples had to be deleted because the quality of the nozzle-sheet distance control was insufficient. 223 or 20.3 % of the remaining 1097 parameter combinations resulted in cutting interruptions, 874 or 79.7 % in successful cuts. There are 996 unique combinations of the 4 cutting parameters, 48 are at least double. 4 of these 48 parameter combinations resulted once in a cutting interruption and once (or more) in a successful cut. They are listed in Table 2.

Table 2. Parameter combinations that resulted in both cutting interruptions and successful cuts

Nozzle-sheet distance in mm	Gas pressure in bar	Nozzle-focus distance in mm	Cutting speed in m/min	Number of cutting interruptions	Number of successful cuts
0.5	9	-3.5	17	1	1
2.0	21	-0.5	25	1	1
2.5	15	-1.5	29	1	1
3.0	15	-1.0	21	1	3

The dependency of the risk of a cutting interruption on each of the 4 varied cutting parameters is shown in Figure 1.

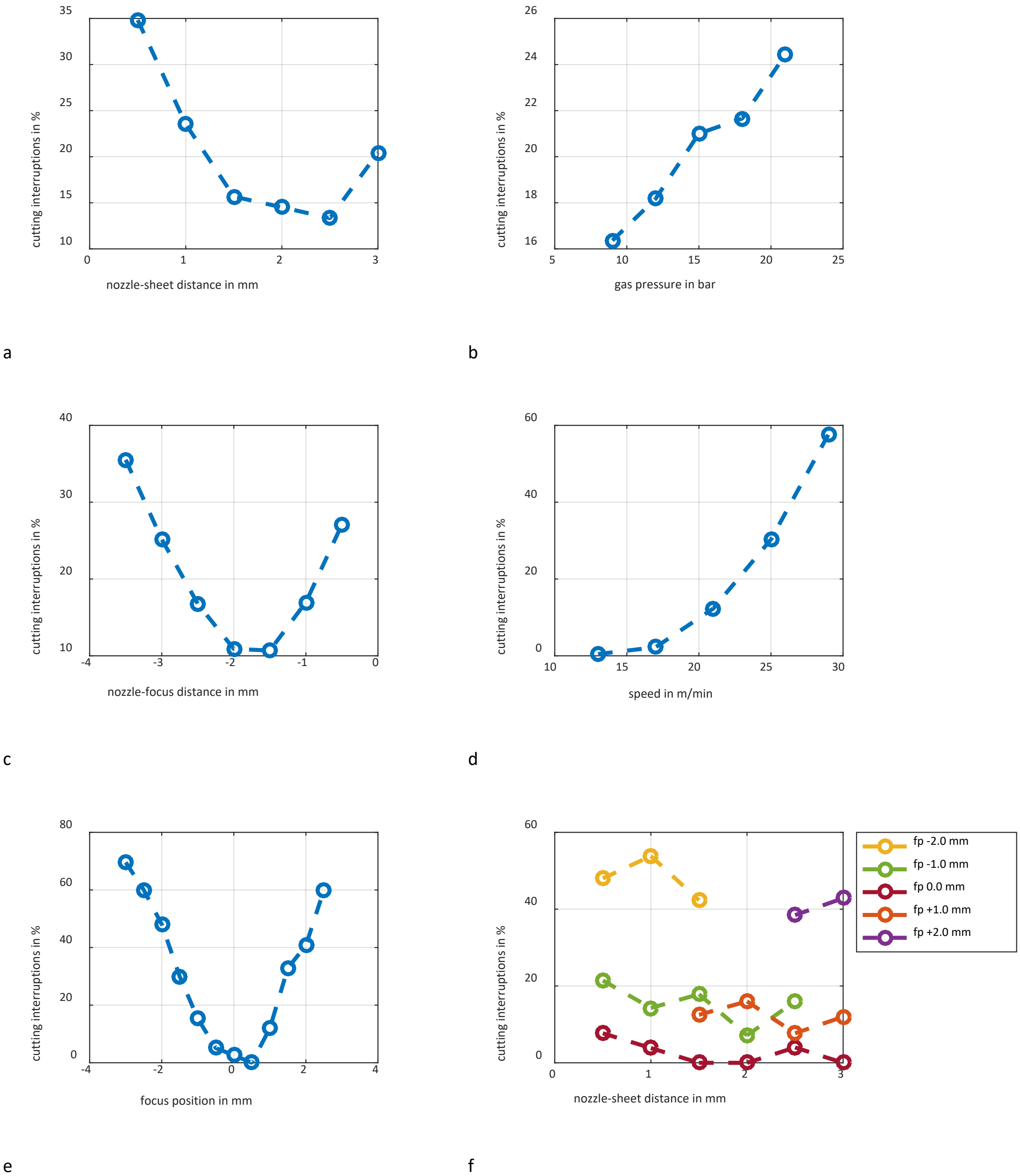

Fig. 1. Risk of a cutting interruption dependent on nozzle-sheet distance (a), gas pressure (b), nozzle-focus distance (c), cutting speed (d), focus position (e) and nozzle-sheet distance for constant focus positions (fp) (f)

The nozzle-sheet distance (Figure 1 a) shows a U-shaped curve with a minimum at 2.5 mm which is not consistent with the recommended value of 1.5 mm. In the case of the nozzle-focus distance (Figure 1 c) there is a U-shaped curve as well with a minimum at the optimum value of -2 mm. The stable range is even smaller than for the nozzle-sheet distance. The relation between gas pressure (Figure 1 b) and number of cutting interruptions corresponds to a polynomial of first order. The higher the gas pressure the larger is the risk of unsuccessful cutting, but it should be mentioned that the cutting interruptions increase by less than 10 % over the whole pressure range. The relation between cutting interruptions and speed seems to be at least cubic (Figure 1 d). It increases from close to 0 % for 13 m/min to 58 % for 29 m/min.

It must be considered that changing the nozzle-sheet distance does not only change the gas dynamics, but it also has an impact on the position of the focus (when the nozzle-focus distance is kept constant). Therefore, it makes sense to look at the focus position, which is the combination of these 2 parameters. At the margins, at focus positions lower than -2 and higher than +2 mm, the risk of cutting interruptions is even larger than for a cutting speed of 29 m/min (see Figure 1 e).

The impact of the gas dynamics when altering the nozzle-sheet distance is relatively low compared to the influence of the focus position. In Figure 1 f the number of cutting interruptions is plotted over the nozzle-sheet distance for constant focus positions. The effect of only changing the distance between nozzle and sheet and thus changing the gas dynamics is in the order of magnitude of the gas pressures' impact.

It can be concluded that the most important cutting parameters for predicting the success or failure of a parameter combination are focus position and speed.

3.2. Performance of the model

The performance of the model is visualized in the confusion matrix in Figure 2 a. To test how well the model generalizes, it was tested on 280 previously unseen samples.

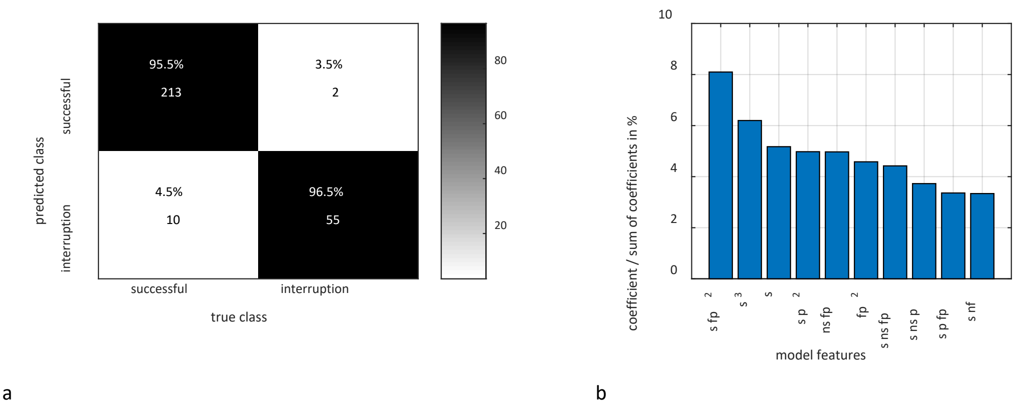

Fig. 2. Confusion matrix of multivariate, polynomial logistic regression model (a), 10 features with the largest coefficients (b)

The performance of the model on the test set is satisfactory: Only 10 of 223 parameter combinations that result in successful cuts are misclassified as cutting interruptions. A successful cut is assumed wrong for only 2 of 57 parameter combinations. The accuracy is 96 %, the precision is 85 % and the recall is 96 %. The low precision value (compared to the recall) is acceptable, because a wrong classified cutting interruption is much more disadvantageous than the other way around. To demonstrate that the performance is reproducible the results of a cross validation (with 4 folds) are shown in Table 3.

Table 3. Evaluation of model performance

	Misclassified cutting interruptions (fn)	Misclassified successful cuts (fp)	Accuracy	Precision	Recall
Test set 1	4 of 56	11 of 214	0.9466	0.8254	0.9286
Test set 2	3 of 56	7 of 217	0.9643	0.8833	0.9464
Test set 3	3 of 56	8 of 216	0.9607	0.8689	0.9464
Test set 4	0 of 55	14 of 210	0.9498	0.7971	1.0
Mean			**0.9554**	**0.8437**	**0.9554**
Std			0.0073	0.0343	0.0268

One big advantage of this model is its interpretability. In Figure 2 b the features with the 10 largest coefficient values are shown in descending order. Each coefficient was divided by the sum of all 56 coefficients, thus their proportional influence on the prediction of the model can be visualized. These 10 features represent 49 % of the total influence, the remaining 51 % are shared among the other 46 features.

Unsurprisingly, the feature with the largest coefficient consists of the combination of speed (s) and focus position (fp) as already assumed in section 3.1. The cutting parameter speed is part of 8, the focus position is part of 5 of the shown 10 features. The nozzle-sheet distance (ns) is found 3 times, the pressure (p) twice and the nozzle-focus distance (nf) only once. However, it should be emphasized, that the nozzle-focus distance only changes the position of the focus, which is represented by the focus position feature as well.

4. Conclusion

In this paper, a polynomial logistic regression model was developed to predict cutting interruptions dependent on the cutting parameters nozzle-sheet distance, gas pressure, nozzle-focus distance and speed reliably. The performance of the model is repeatable, and it generalizes well. An averaged accuracy of more than 95 % and an averaged recall better than 95 % could be achieved. We showed that speed and focus position (which is influenced by nozzle-sheet and nozzle-focus distance) are the most crucial influence variables.

The presented model could be improved by including further influence variables like for example laser power, focal width, complex contours and different material qualities.

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