Modelling of roller levelling of plates using machine learning algorithms

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1. Introduction

Precision metal plates characterized by good mechanical properties and surface qualities are important materials in aerospace, automotive and many other industries. Rolling, cold or hot, is the main processing method for metal plates. This process causes flatness imperfections due to internal stresses. One of the methods to increase the flatness of a plate is the multiroll leveller consisting of a set of rolls for bending the plates with different loads to achieve better levelling. The aim of this work is to build a model which will be able to predict a plate flatness after roller levelling process using machine learning algorithms [1–3]. Two models were developed. The linear regression model predicts the plate curvature factor after the levelling. The logistic regression model classifies whether the plate after levelling will be sufficiently flat. The developed models will be next used to determine the optimal control of the roller levelling machine.

2. Modelling

2.1. Data preparation

The collected data contains measurements of 34 plates before and after the levelling and the roller machine settings. he experimental data consists of 1225 flatness measurements. Due to the errors which often occur close to the edge of the plate, the values along all the edges were removed from the dataset. To normalize the measurement values, the mean value was subtracted from each of them. The roller machine settings included four parameters: inlet size (*in*), outlet size (*out*), roller conveyor velocity (v) and the angle (α) between the plate (y-axis) and the roller. Only three values of angle were examined: $\alpha = 0°$, $\alpha \approx 26.5°$, $\alpha = 90°$.Specification of the plate surface in the form of many flatness measurements are useless for model design purposes. Therefore, the plate curvature must be first described using just a few coefficients. Curvature factor (*cf*) was used to designate the quantity of flatness and it was defined as the difference between the highest and the lowest flatness value of the plate. The second used coefficient determines the curvature direction (*cd*). In order to calculate the curvature direction the plate was approximated by the two-dimension square function:

$$f(\mathbf{x}) = \mathbf{x}^T \mathbf{A}\mathbf{x} + \mathbf{b}^T \mathbf{x} + c \qquad (1)$$

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Next, the eigenvalues and eigenvectors of the matrix **A** were computed. The curvature direction was defined as the angle between the eigenvector of matrix **A** which corresponds to eigenvalue with the higher absolute value and the y-axis. The exemplary plate metal, its square approximation and the eigenvector of matrix **A** are presented in Figure 1.

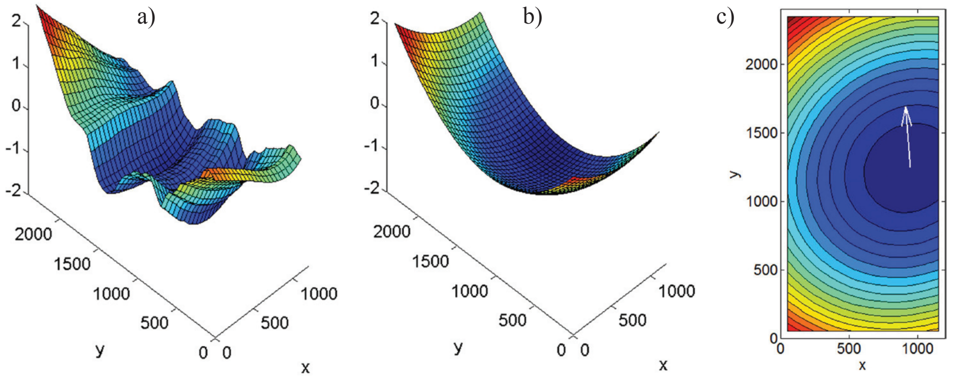

Figure 1. The exemplary plate metal (a), its square approximation (b) and the eigenvector which defines the curvature direction (c).

2.2. Features selection

Before the model can be developed, the vector of input values (features) must be defined. Based on the knowledge about the modelled process, the input vector for both models was set to five values: $\mathbf{x} = [cf, in, out, v, |cd - \alpha|]^T$. To validate the importance of selected features the linear correlation coefficient was calculated. The results are presented in Table 1.

Table 1. Values of linear correlation coefficient computed for initially selected features.

cf	*in*	*out*	*v*	$\|cd{-}\alpha\|$
0.68	0.53	-0.11	0.10	0.25

Based on the obtained results, inputs *out* and *v* were removed from the feature vector. Reducing the number of features decreases the risk of variance problem, especially when the number of available training records is low. However, using too few features many cause the bias problem. Therefore, in many cases new features, which are based on already used ones, are introduced. Due to the low number of available training records, new features were defined only as the second power of initial features and product of each two ones. The linear correlation coefficient computed for the new features are presented in Table 2.

Table 1. Values of linear correlation coefficient computed for initially selected features.

cf^2	$cf{\cdot}in$	$cf{\cdot}\|cd{-}\alpha\|$	in^2	$in{\cdot}\|cd{-}\alpha\|$	$\|cd{-}\alpha\|^2$
0.70	0.72	0.60	0.52	0.28	0.20

The final feature had the following form:

$$\mathbf{x} = \left[cf, in, |cd - \alpha|, cf^2, cf \cdot in, cf \cdot |cd - \alpha|, in^2, in \cdot |cd - \alpha|, |cd - \alpha|^2\right] \tag{2}$$

2.3. Modelling results

The dataset was divided into training and testing set in the ratio of 70/30 what results in 24 training and 10 testing records. Hypothesis used for linear and logistic regression are given by equations (3) and (4), respectively:

$$h_\theta(\mathbf{x}) = \boldsymbol{\theta}^T \mathbf{x} \tag{3}$$

$$h_\theta(\mathbf{x}) = (1 + e^{-\boldsymbol{\theta}^T \mathbf{x}})^{-1} \tag{4}$$

where: $\boldsymbol{\theta}$ – vector of model parameters, $\mathbf{x}$ – vector of features (2) with added element $x_0 = 1$.

The aim of the linear regression model was to predict the curvature factor of the plate after levelling process, while the aim of the logistic regression model was to classify whether the plate after the levelling process will be sufficiently flat, i.e. the curvature factor will be less than 2. The training was performed using gradient optimization procedure from the Matlab software. The evaluation of models was made using mean absolute error (5) and accuracy (6) in case of linear and logistic regression, respectively:

$$MAE = \frac{1}{m}\sum_{i=1}^{m} |\hat{y}_i - y_i| \tag{5}$$

where: m – number of testing records, $\hat{y}_i$ – model prediction, y_i – testing value.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

where: TP – true positive prediction, TN – true negative prediction, FP – false positive prediction, FN – false negative prediction.

Each run of the training procedure returns slightly different results due to random splitting of the data. Therefore, training of each model was performed 100 times and the results presented in Table 3 are mean values.

Table 3. The error of linear and logistic regression.

MAE	2.1612
ACC	0.827

3. Conclusion and future work

The analysis of the obtained preliminary results reveals that accuracy of the models is not entirely satisfactory but still promising. The mean absolute error is greater than the assumed threshold determining the sufficient flatness of the plate. The results for logistic regression model are better. However, the possibility of using it to determine the optimal control of the rolling leveller is more problematic.

The main way to improve the models accuracy is enlargement of the dataset. Moreover, different forms of feature vector can be tested and the regularization term should be included in the cost function.

References

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