Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

Estimation of Quality Parameters of Trimmed Steel Plates using Laser Sensors

A. Zeiler * **A. Steinboeck** * **W. Kemmetmüller** * **M. Jochum** ***
A. Kugi *,**

* *Automation and Control Institute (ACIN), TU Wien, Vienna, Austria (e-mail: {zeiler,steinboeck,kugi}@acin.tuwien.ac.at).*
** *Center for Vision, Automation and Control, AIT Austrian Institute of Technology, Vienna, Austria.*
*** *AG der Dillinger Hüttenwerke, 66763 Dillingen/Saar, Germany.*

Abstract: This paper deals with the estimation of the contour of hot-rolled steel plates and of quality parameters characterizing the trimmed edge. Suboptimal process parameters can cause camber or a saw-tooth shaped contour and imperfections on the trimmed edges. Quantitative measures of these imperfections enable a seamless quality control and can be used as input quantities for data-based or control engineering applications. The presented method utilizes measurements from 2D-laser sensors installed at the side of the production line after a trimming shear. A model-based optimization algorithm estimates the contour and a possible rotation of the plate. Signal processing and sensor fusion are employed to estimate additional quality parameters. Validation with measurement data from a rolling mill demonstrates the high accuracy of the proposed method. The camber is estimated with an accuracy lower than $\pm 0.04\,\mathrm{mm/m}$, which reveals that the proposed method is more accurate than existing solutions for camber estimation.

Keywords: steel rolling mill, contour estimation, trimmed edge, quality control, model-based estimation, edge quality.

1. INTRODUCTION

Among the last process steps in the finishing part of rolling mills are side trimming and occasionally longitudinal slitting of the plates. These process steps determine the contour geometry of the plate and the shape of the trimmed edges. The objective is to achieve rectangular plates and trimmed edges.

Common trimming techniques like rolling-cut shearing tend to entail quality imperfections on the contour and the trimmed edges of the plate (Zeiler et al., 2019a). A well known imperfection is camber with the amplitude Δ_c as shown in Fig. 1. In addition, there may occur

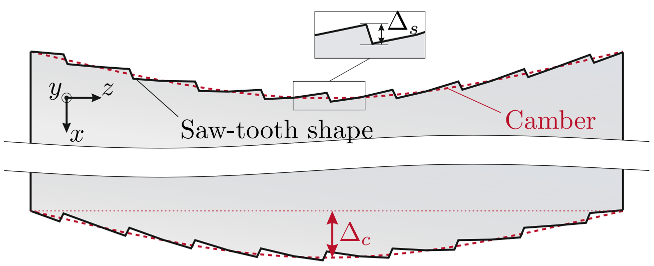

Fig. 1. Top view of a trimmed plate exhibiting camber and saw-tooth shaped contour imperfections.

local imperfections along the trimmed contour. A saw-tooth shape with the local amplitude Δ_s superimposed to the camber as shown in Fig. 1 is characteristic for non-continuous trimming techniques like rolling-cut shearing, due to a variation of lateral forces within a single cut, see (Zeiler et al., 2019a). Furthermore, mechanically trimmed edges may entail shape imperfections like rollover and a non-zero crack depth as shown in Fig. 2. Such quality

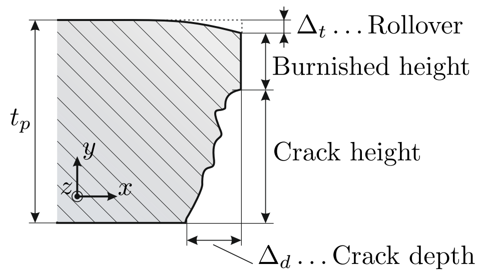

Fig. 2. Typical cross-sectional view of a trimmed edge entailing quality imperfections.

imperfections entail a high post-processing effort and a loss of material, if the trimmed edges have to be regrinded. This becomes more relevant, since the quality demands of the contour and trimmed edges clearly have increased over the past decade.

An important prerequisite to avoid these quality imperfections is their accurate and complete measurement. These measurement data can be utilized for process optimization and for setting up a seamless quality control, which is essential in modern production processes.

1.1 Existing Works

Existing solutions in the literature generally measure either the camber or the quality of the trimmed edges, but not both together. Several solutions exist for the measurement or estimation of the camber. Most of them are based on 2D CCD cameras installed above the production line to record top view images of the plate. A vision-based approach for camber measurement in hot strip rolling was presented by Montague et al. (2005). They record the whole strip within a single image and apply a geometric transformation of the image to eliminate perspective distortion. Subsequently, they perform edge detection based on a machine vision algorithm. The achieved accuracy is ± 0.9 mm/m. Abdelgawad et al. (2016) presented a similar solution for camber estimation in hot rolling. They use a fuzzy logic-based algorithm for precise edge detection. They succeed to enhance the accuracy to ± 0.09 mm/m. However, this approach limits the maximal measurable strip length by the field of view of the CCD camera. Another interesting approach for online camber estimation during hot rolling was presented by Schausberger et al. (2015). In a receding horizon manner, several subimages of the plate are captured while it is conveyed on the roller table. Based on a machine vision algorithm combined with a mathematical model of the plate movement and an optimization algorithm, the contour as well as the translational and rotational motion of the plate are estimated in real-time manner. Two approaches in an endless hot rolling mill using image stitching were presented by Kim et al. (2015) and Kong et al. (2011). However, they did not consider a possible rotation of the strip.

For the inspection and measurement of the quality of trimmed edges, there exist several works using CCD cameras which record images of the trimmed edges. Zeiler et al. (2019b) introduced an algorithm which segments the recorded surfaces of the trimmed edges into areas of high quality and areas with quality imperfections like fractured area or burr. Moreover, the algorithm calculates aggregate values to classify the quality of the trimmed edge. Another vision-based inspection system was presented by Hlobil et al. (2016). This system detects burr and other specific quality imperfections on the surface of the trimmed edge. There exist several further investigations dealing with vision-based inspection of trimmed edges, however, none of these enables an estimation of the profile shape of the trimmed edge.

1.2 Motivation and Objectives

In fact, all published solutions to measure or estimate the camber are based on CCD cameras. Typically, infrared cameras are used and they are tailored to hot rolling, where the thermal contrast between the plate and the background is relatively high. In sections of the plant where the plates have room temperature, like after a rolling-cut shear, it may be more challenging to ensure a robust and precise edge detection by machine vision. Furthermore, these cameras require a precise camera calibration and a suitable mounting location that is protected against vibrations, dust, and steam. Apart from this, practically all published measurement methods for the trimmed edge quality concentrate on the visual appearance or the ratio of fractured surface areas of the trimmed edge. These methods fail in measuring the geometric profile shape of the cross section of the trimmed edge as shown in Fig. 2.

Based on this state of the art, the current work aims at developing a unified estimation method for the camber, for imperfections along the contour, i.e. saw-tooth shape, and for the profile shape of the trimmed edge. Laser sensors are an appropriate technology to measure all these quantities in the finishing part of a rolling mill, where the plates usually exhibit room temperature. In contrast to the solutions known from the literature, this work measures the final contour of the plate after trimming. Hence, the measures directly reflect the quality delivered to the customer. An additional objective of the present work is to achieve a higher accuracy of the camber estimation compared to the solutions known from the literature where the highest accuracy found is 0.09 mm/m. In particular for plates longer than 15 m this is important to meet the strict requirements of the customers. This goal can only be reached if a possible rotation of the plate during the measurement is systematically taken into account.

The developed estimation method exhibits the following features and advantages:

- Quality measures are obtained for each plate after the trimming shear.
- This enables a seamless quality control and documentation for all plates.
- This allows to set up a predictive maintenance system for dedicated machine parts of the trimming shear.
- Valuable data are generated which can be used in machine-learning applications for process optimization.
- No CCD cameras are required.

1.3 Description of Measurement Setup

The developed measurement method is based on three 2D-laser sensors (A,B,C), which are installed directly after the trimming shear at the side of the production line. The sensors record the cross-sectional profile shape of the trimmed edge, see Fig. 3, while the plate is conveyed by pinch rolls with the velocity $v_z(t)$ along the direction z. Hence, each sensor provides 2D coordinates of the edge

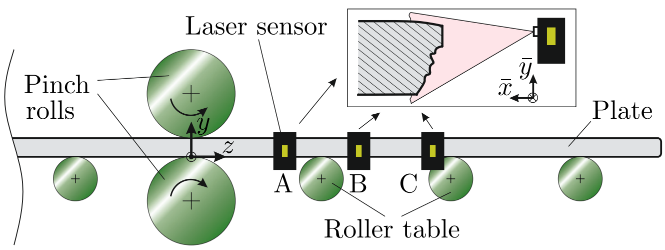

Fig. 3. Side view of the measurement setup.

profile in the xy-plane. In this work, 2D-laser sensors of the type *scanControl LLT2700-100* from the company *Micro-Epsilon* are used. These sensors provide up to 320 measured coordinate points per profile with a spatial resolution of 15 µm along the direction x and a sampling time $T_s = 10$ ms. Figures 3 and 4 illustrate the measurement setup implemented at the rolling mill of AG der Dillinger

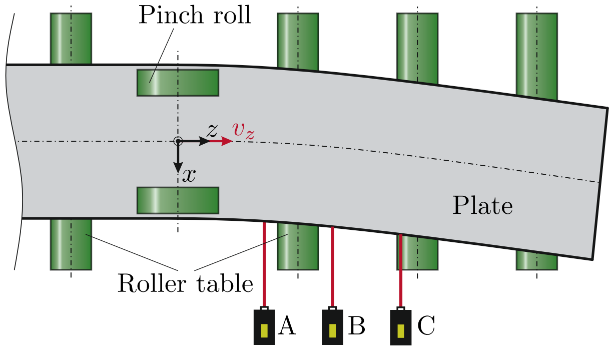

Fig. 4. Top view of the measurement setup.

Hüttenwerke, Germany. All three laser sensors (A,B,C) are used on one side, as the camber is assumed to be equal on both sides. A further sensor on the opposite side could also capture asymmetric edge profiles. As will be discussed in Section 2.2, two laser sensors and the assumption of zero slip between the plate and the pinch rolls (plate is clamped at the origin of the global coordinate frame (x,y,z)) suffice to estimate the plate contour and the rotation of the plate. The third redundant sensor used in this work improves the robustness of the proposed identification method against measurement inaccuracies and noise. The advantage of the third sensor in view of the estimation accuracy will be discussed in Section 3.

2. ESTIMATION METHOD

This section presents the proposed estimation method. In a first step, the measured profiles are processed and quality measures characterizing the cross-sectional profile shape of the trimmed edges, like rollover Δ_t or crack depth Δ_d according to Fig. 2, are obtained. A sensor fusion approach is applied to incorporate the redundant information from the three laser sensors. In the second step, the contour and the rotation of the plate are estimated. This estimation is performed based on a kinematic model of the plate in combination with an optimization algorithm. In the last step, aggregate quality measures of the camber and the saw-tooth shape are calculated based on the estimated contour.

2.1 Estimation of Quality Measures Characterizing the Shape of the Trimmed Edge

As discussed in Section 1.3, each laser sensor provides a set of measured profile coordinates $(\bar{\boldsymbol{y}}_m, \bar{\boldsymbol{x}}_m)$ of the trimmed edge at the sampling instance t_k. Based on the plate velocity $v_z(t)$, the times t_k can be attributed to cross-sections of the edge of the plate passing the location of the respective sensor. At first, specific quality measures are obtained for each individual edge profile. The second step is devoted to the fusion of this redundant information obtained by the three sensors.

Figure 5 shows such a set of measured profile coordinates $(\bar{\boldsymbol{y}}_m, \bar{\boldsymbol{x}}_m)$ as blue crosses for a heavy plate with a nominal thickness of $t_p = 18\,\text{mm}$. Due to the rough and reflective surface of the trimmed edge, the measurement is superimposed by distinctive noise and some outliers. Smoothing of the profile eliminates these outliers and the noise and thus

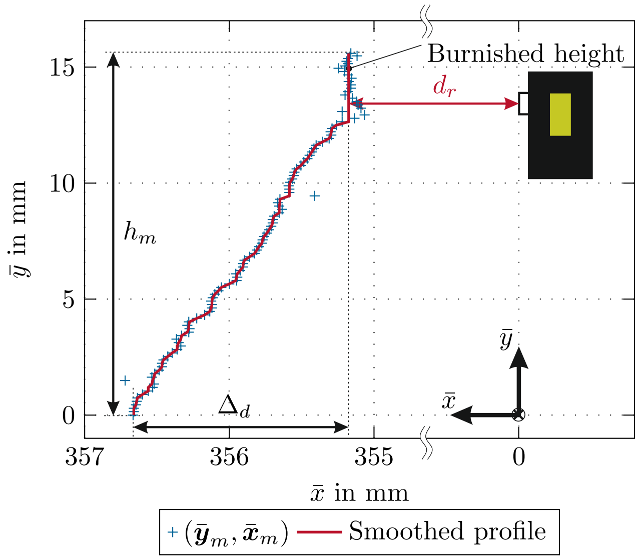

Fig. 5. Measured profile coordinates $(\bar{\boldsymbol{y}}_m, \bar{\boldsymbol{x}}_m)$, smoothed profile and illustration of the scalar distance measure d_r.

allows a robust calculation of the quality measures crack depth Δ_d and rollover Δ_t. Furthermore, the subsequent contour estimation requires a scalar distance measure d_r between the laser sensor and the edge of the plate. The distance d_r has to be identified in the same way for each measured 2D profile. It is known from the shearing process that the burnished height is approximately an even surface in the $\bar{y}\bar{z}$-plane. This surface determines the contour of the plate in top view. Hence, d_r is measured with respect to exactly this surface. Assume that $\bar{\boldsymbol{x}}_b$ contains the measured coordinates $\bar{x}$ of points belonging to the burnished height, whereas this height is generally known for the specific materials. The distance d_r is computed in the form

$$d_r = \text{median}\left(\bar{\boldsymbol{x}}_b\right). \tag{1}$$

Evaluating (1) for each measured profile and each sensor $i \in \{A, B, C\}$ yields the values

$$d^i_{r,k} = \text{median}\left(\bar{\boldsymbol{x}}^i_b(t_k)\right), \tag{2}$$

which will be utilized in Section 2.2 for contour estimation.

To ensure a robust calculation of the crack depth, outliers in the measured profiles have to be removed first. Applying a sliding window median filter $\Psi(\cdot)$ yields the smoothed profile

$$\bar{\boldsymbol{x}}_{d,f} = \Psi\left(\bar{\boldsymbol{x}}_d\right), \tag{3}$$

where $\bar{\boldsymbol{x}}_d$ contains the coordinates $\bar{x}$ corresponding to the crack height. The crack depth of a single profile can be computed in the form

$$\Delta_d = \max\left(\bar{\boldsymbol{x}}_{d,f}\right) - d_r. \tag{4}$$

The rollover follows in the form

$$\Delta_t = t_p - h_m, \tag{5}$$

see Fig. 2, with the known nominal plate thickness t_p and the measured height

$$h_m = \max\left(\bar{\boldsymbol{y}}_m\right) \tag{6}$$

at the trimmed edge.

Calculating the crack depth Δ_d and the rollover Δ_t for each measured edge profile yields numerous samples of the quality measures $\Delta^i_{d,k}$ and $\Delta^i_{t,k}$ along the plate obtained by the three sensors $i \in \{A, B, C\}$. The harsh environment in the rolling mill and the reflective surface of the trimmed edge cause measurement noise, inaccuracies and outliers in the measured profiles. In order to exploit the redundant and uncertain information, a sensor fusion approach is applied. Various sensor fusion techniques exist in the literature, see, e.g., (Durrant-Whyte and Henderson, 2008). In the current work, a probabilistic approach is used. The rollover Δ_t is known to be constant along the plate. Hence, for each sensor and each plate, a Gaussian probability distribution of rollover measurements is estimated. The sample mean of the rollover for each sensor follows in the form

$$\mu_t^i = \frac{1}{N}\sum_{k=1}^{N} \Delta_{t,k}^i \quad \text{for} \quad i \in \{A, B, C\}, \tag{7}$$

where N denotes the number of measured profiles. The corresponding sample variance reads as

$$\sigma_t^i = \frac{1}{N}\sum_{k=1}^{N} \left(\Delta_{t,k}^i - \mu_t^i\right)^2 \quad \text{for} \quad i \in \{A, B, C\}. \tag{8}$$

In order to estimate a scalar quantity for the rollover value, the maximum a posteriori estimate

$$\widehat{\Delta}_t = \frac{\left(\sigma_t^A\right)^{-2}\mu_t^A + \left(\sigma_t^B\right)^{-2}\mu_t^B + \left(\sigma_t^C\right)^{-2}\mu_t^C}{\left(\sigma_t^A\right)^{-2} + \left(\sigma_t^B\right)^{-2} + \left(\sigma_t^C\right)^{-2}}, \tag{9}$$

is computed, see Abdulhafiz and Khamis (2013).

In contrast to the rollover, the crack depth Δ_d may vary along the length of the plate due to the saw-tooth shape in case of non-continuous trimming techniques (Zeiler et al., 2019a). Thus it is not reasonable to describe the crack depth by a single value. Therefore, all measured profiles, i.e. the crack depths, are divided into three sets depending on their position relatively to the saw-tooth shape. Then the presented sensor fusion approach is applied to each measurement set, which yields the scalar quantities $\widehat{\Delta}_{d1}$, $\widehat{\Delta}_{d2}$, and $\widehat{\Delta}_{d3}$ characterizing the crack depth depending on their position relatively to the saw-tooth steps.

2.2 Optimization-Based Contour Estimation

If the plate solely moves in the longitudinal direction z with the known velocity v_z, a single laser sensor suffices to measure the contour. However, the plate can experience rotations with respect to the vertical axis y.

These rotations may result from laterally asymmetric circumferential speeds of the pinch rolls or from laterally asymmetric trimming forces. Because of these rotations, the measurement readings d_r^i of the laser sensors are superpositions of the actual plate contour and its rotation. To separate these two effects at least two sensors are required and it must be assumed that the plate is clamped at the origin of the fixed global coordinate system (x,y,z) (zero-slip assumption at the pinch rolls), see (Schausberger et al., 2015). In this work, three laser sensors are used to improve the robustness with respect to inaccuracies and noise.

In the following, a model-based optimization algorithm is presented, which allows the separate estimation of both, the contour and the rotation of the plate based on the three distance signals $d_{r,k}^A$, $d_{r,k}^B$, and $d_{r,k}^C$. The algorithm utilizes the nonlinear kinematic model

$$\frac{\mathrm{d}}{\mathrm{d}t}\begin{bmatrix}\Delta z\\ \Delta x\\ \varphi\end{bmatrix} = \begin{bmatrix}v_z - \omega\Delta x\\ \omega\Delta z\\ \omega\end{bmatrix} \tag{10}$$

of the plate motion. As indicated in Fig. 6, this model describes the 2D motion of the plate-fixed coordinate frame $(\tilde{x},\tilde{y},\tilde{z})$ with the lateral displacement Δx, the longitudinal displacement Δz, and the rotation φ. The unknown angular velocity ω of the plate with respect to the y-axis and the known longitudinal velocity v_z constitute model inputs. Integration of (10) using the explicit Euler method

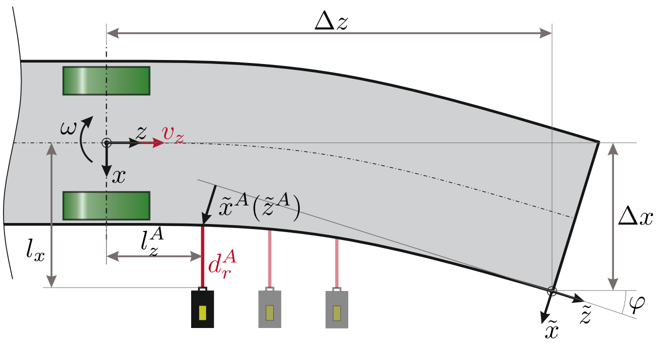

Fig. 6. Plate motion and geometric parametrization of the camber.

on a discrete-time grid $\tilde{t}_m$ with $m = 0, 1, \ldots, (N_{opt} - 2)$ yields the discrete-time system

$$\begin{bmatrix}\Delta z_{m+1}\\ \Delta x_{m+1}\\ \varphi_{m+1}\end{bmatrix} = \begin{bmatrix}\Delta z_m + \Delta\tilde{t}_m\left(v_z(\tilde{t}_m) - \omega_m\Delta x_m\right)\\ \Delta x_m + \Delta\tilde{t}_m\omega_m\Delta z_m\\ \varphi_m + \Delta\tilde{t}_m\omega_m\end{bmatrix}, \tag{11}$$

with $\Delta\tilde{t}_m = \tilde{t}_{m+1} - \tilde{t}_m$ and the initial state

$$\Delta z_0 = l_z^A \tag{12a}$$

$$\Delta x_0 = l_x - d_{r,0}^A. \tag{12b}$$

In the following ω_m and φ_0 will be estimated in an optimization problem. The number of integration points $(N_{opt}-2)$ determines the dimension of this static optimization problem. The velocity $v_z(t)$ is not constant because the plate is either moved by the pinch rolls or clamped and trimmed. Figure 7 shows the typical time evolution of

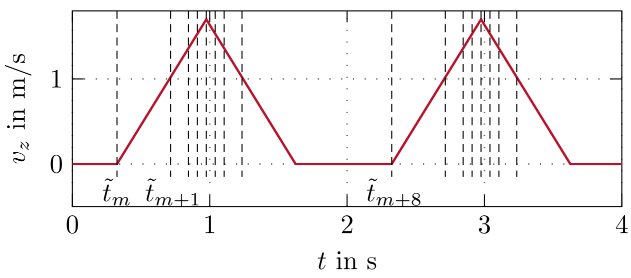

Fig. 7. Longitudinal velocity v_z and illustration of the time grid $\tilde{t}_m$.

$v_z(t)$. Instead of an equidistant time grid, it makes sense to choose the sampling periods $\Delta\tilde{t}_m$ so that the plate moves by the same spatial increment in each sampling period, i.e., $\Delta\tilde{t}_m v_z(\tilde{t}_m) = \text{const.}$. Such a time grid is indicated in Fig. 7 for N_{opt} chosen in order to attain 8 integration points per meter plate length.

For the time being, assuming the values d_r^A, ω_m, φ_0 and thus φ_m are known, the coordinate transformation

$$\begin{bmatrix} \tilde{z}_m^A \\ \tilde{x}_m^A \end{bmatrix} = \begin{bmatrix} \cos(\varphi_m) & -\sin(\varphi_m) \\ \sin(\varphi_m) & \cos(\varphi_m) \end{bmatrix} \begin{bmatrix} l_z^A - \Delta z_m \\ l_x - d_r^A(\tilde{t}_m) - \Delta x_m \end{bmatrix} \tag{13}$$

yields the discrete points $\left(\tilde{z}_m^A, \tilde{x}_m^A\right)$ on the plate contour which are measured by sensor A. By analogy to (13), the contour points $\left(\tilde{z}_m^B, \tilde{x}_m^B\right)$ and $\left(\tilde{z}_m^C, \tilde{x}_m^C\right)$ can be computed based on the readings of sensors B and C, respectively. Because of a time shift between the measurements of the three sensors A, B, and C, (13) has to be evaluated on shifted time grids defined by

$$\tilde{\boldsymbol{t}}^A = \left[\tilde{t}_0, \tilde{t}_1, \ldots, \tilde{t}_{kAe}\right]^{\mathrm{T}} \tag{14a}$$

$$\tilde{\boldsymbol{t}}^B = \left[\tilde{t}_{kBs}, \tilde{t}_{kBs+1}, \ldots, \tilde{t}_{kBe}\right]^{\mathrm{T}} \tag{14b}$$

$$\tilde{\boldsymbol{t}}^C = \left[\tilde{t}_{kCs}, \tilde{t}_{kCs+1}, \ldots, \tilde{t}_{kN_{opt}}\right]^{\mathrm{T}}, \tag{14c}$$

where t_{kBs} and t_{kCs} represent the starting times and t_{kAe} and t_{kBe} the end times of the measurements for the corresponding sensor readings. Interpolation of the contour points $\left(\tilde{z}_m^i, \tilde{x}_m^i\right)$ on a common plate-fixed spatial grid $\tilde{z}_j$ with $j = 1, 2, \ldots, N_J$, with the number of points N_J, should ideally give the correspondence

$$\tilde{x}^A(\tilde{z}_j) \approx \tilde{x}^B(\tilde{z}_j) \approx \tilde{x}^C(\tilde{z}_j). \tag{15}$$

In reality however, there will be a discrepancy between the shapes $\tilde{x}^i(\tilde{z}_j)$ because of the plate rotation. The unknown values φ_0 and ω_m can now be estimated by minimizing this deviation. For this purpose, the static optimization problem

$$\begin{aligned} \min_{\hat{\boldsymbol{u}} \in \mathbb{R}^{N_{opt}}} J(\hat{\boldsymbol{u}}) = \sum_{j=1}^{N_J} \Big[& \Psi\left(\tilde{x}^A(\tilde{z}_j; \hat{\boldsymbol{u}}) - \tilde{x}^B(\tilde{z}_j; \hat{\boldsymbol{u}})\right)^2 \\ & + \Psi\left(\tilde{x}^A(\tilde{z}_j; \hat{\boldsymbol{u}}) - \tilde{x}^C(\tilde{z}_j; \hat{\boldsymbol{u}})\right)^2 \\ & + \Psi\left(\tilde{x}^B(\tilde{z}_j; \hat{\boldsymbol{u}}) - \tilde{x}^C(\tilde{z}_j; \hat{\boldsymbol{u}})\right)^2 \Big] \end{aligned} \tag{16a}$$

$$\text{s.t.} \quad (11)\text{–}(13) \tag{16b}$$

is solved, with the optimization variables

$$\hat{\boldsymbol{u}} = [\hat{\omega}_0 \; \hat{\omega}_1 \; \ldots \; \hat{\omega}_{N_{opt}-2} \; \hat{\varphi}_0]^{\mathrm{T}} \tag{17}$$

and the contours $\tilde{x}^i(\tilde{z}_j; \hat{\boldsymbol{u}})$ calculated based on $\hat{\boldsymbol{u}}$. This optimization problem minimizes the quadratic deviation between the estimated contour. $\Psi(\cdot)$ constitutes a sliding window median filter equivalent to (3). This filter suppresses errors which might occur due to a small asynchronism of the three laser measurements.

Solving the static optimization problem (16) yields the optimal estimates $\hat{\boldsymbol{u}}^*$. Substituting $\hat{\boldsymbol{u}}^*$ into (11)–(13) results in three nearly identical estimations of the contour. Finally, pointwise arithmetic averaging gives the estimated plate contour.

2.3 Quality Measures Characterizing Camber and Saw -Tooth Shape

The quality measures Δ_c and Δ_s, which characterize the camber and the local saw-tooth shapes, can be easily obtained from the estimated contour, see Fig. 1. A Savitzky-Golay filter of order 2 eliminates the saw-tooth shape from the contour line, see red dashed line in Fig. 1. Then Δ_c can be easily calculated as the maximum deviation from a straight line. Subtracting the filtered contour line from the original one yields the saw-tooth shape, and Δ_s is calculated by extracting and averaging the amplitudes of the saw-tooth shaped contour.

3. MEASUREMENT RESULTS

In this section, estimation results are compared to measurement data for typical steel plates rolled at the mill of AG der Dillinger Hüttenwerke in Germany. Moreover, further validation measurements were conducted to evaluate the accuracy of the estimation.

Table 1 lists the material and geometric parameters of the test plates. They were selected to cover a broad spectrum of plate types.

Table 1. Material and geometric parameters of the test plates.

No.	Thickness	Width	Length	Yield strength
1	20.3 mm	1.5 m	9.5 m	397 MPa
2	39.6 mm	1.7 m	18.7 m	550 MPa
3	29.8 mm	3.3 m	9.7 m	409 MPa
4	19.7 mm	3.2 m	18.0 m	519 MPa
5	25.0 mm	4.0 m	12.0 m	425 MPa

3.1 Validation of Contour and Camber Estimation

For the validation, a contour measurement device (CMD) was used to obtain a reference measurement. For this purpose, the test plates had to be transported to this device. In contrast, the proposed measurement setup is located directly in the production line and does not delay the production process. For the contour estimation, the initial guess $\hat{\boldsymbol{u}} = \boldsymbol{0}$ was chosen. The parameters N_{opt} and N_J were selected to get 50 points per meter plate length.

Measurements from the CMD are available for plates 1, 2, and 3. Figure 8 compares the measurements obtained by the CMD with the estimated contour using the three laser sensors according to Fig. 4. Although the CMD measurements are deteriorated by noise, the comparison shows a very good agreement. It was found that considering a rotational plate motion in the considered kinematic model is essential for this high degree of accuracy for the proposed estimation method.

Table 2 summarizes the results for the camber value Δ_c measured by the CMD and the estimated values $\widehat{\Delta}_c$. It

Table 2. Results of camber estimation.

	Δ_c	$\widehat{\Delta}_c$		**Accuracy**	
	CMD	2 LS	3 LS	2 LS	**3 LS**
1	2.5 mm	2.9 mm	2.6 mm	0.04 mm/m	0.01 mm/m
2	13.4 mm	16.5 mm	14.2 mm	0.18 mm/m	0.04 mm/m
3	0.6 mm	0.4 mm	0.5 mm	0.02 mm/m	0.01 mm/m

can be seen that the maximum deviation for a measurement setup with three laser sensors (3 LS in Table 2) is 0.04 mm/m, which is significantly lower than the benchmark values reported in the literature. For comparison reasons, also the estimation results obtained for a setup with only two laser sensors are listed in Table 2. As it was expected, the third laser sensor clearly improves the accuracy of the proposed estimation approach.

3.2 Validation of Edge Profile Estimation

For validation of the estimated rollover and local saw-tooth amplitude, manual measurements with a vernier caliper and measuring wedges were conducted for the plates [1] 4 and 5 of Table 1. Table 3 gives the corresponding measurement and estimation results. It can be seen that the deviations between measurement and estimation are quite small and within the measurement tolerance.

Table 3. Experimental results of rollover and saw-tooth estimation.

	Rollover		Saw-tooth	
No.	Δ_t	$\widehat{\Delta}_t$	Δ_s	$\widehat{\Delta}_s$
4	1.0 mm	1.1 mm	0.6 mm	0.6 mm
5	1.8 mm	2.0 mm	1.1 mm	1.0 mm

4. CONCLUSIONS

This work presents an estimation method for the contour of hot-rolled steel plates and for quality parameters characterizing their trimmed edges. The method uses 2D-laser sensors installed at the side of the production line. The estimation strategy of the contour is based on an optimization problem that also captures a possible rotation of the plate. A sensor fusion approach is utilized to estimate the quality parameters of the trimmed edges.

[1] Unfortunately, measurements are not available for plates 1, 2, 3.

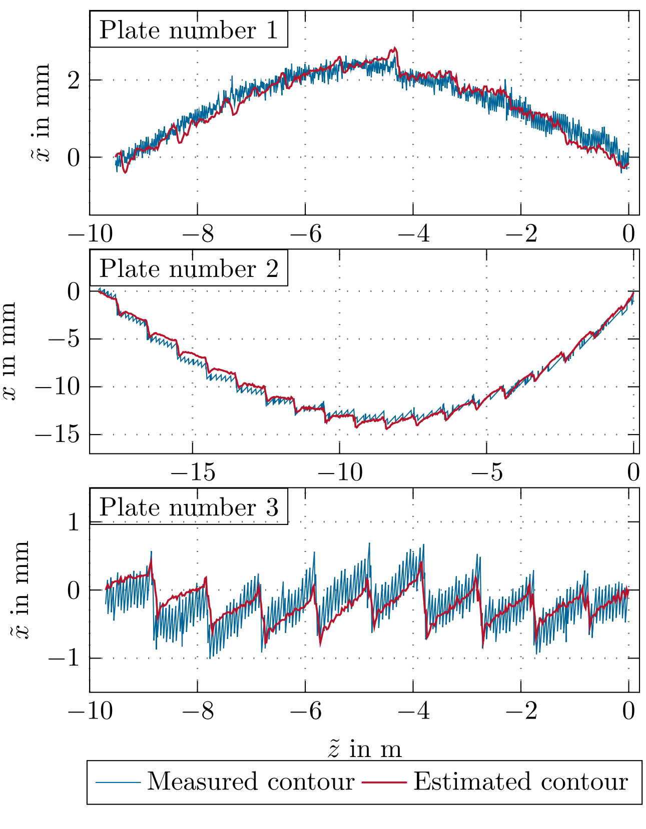

Fig. 8. Contour measurement and estimation results for three representative test plates.

The results of the proposed method are compared with measurements obtained from the rolling mill of AG der Dillinger Hüttenwerke, Germany. This comparison demonstrates the high accuracy of all estimated quantities. The camber is estimated with an accuracy lower than 0.04 mm/m. This is more accurate than the camber estimation methods reported in the literature. The estimation of the edge profile also proved to be accurate. Moreover, the developed estimation method is robust against measurement noise, outliers, and further inaccuracies, like small asynchronism of the laser measurements. Based on the encouraging results, it has been decided to use the developed system for permanent quality inspection at the heavy-plate rolling mill of AG der Dillinger Hüttenwerke. This enables a seamless quality control and the implementation of a predictive maintenance system for certain wearing parts, as e.g. the blade, of the trimming shear. Moreover, these data can be utilized to optimize the process by employing tailored machine learning.

REFERENCES

Abdelgawad, M.S., Abdelkader, S.F., and Bastawrous, H.A. (2016). A robust fuzzy logic-based real-time automatic camber detection and measurement in hot rolling mill. In *Proc. of IEEE 5th Global Conference on Consumer Electronics, Japan*, volume 5, 2p.

Abdulhafiz, W.A. and Khamis, A. (2013). Handling data uncertainty and inconsistency using multisensor data fusion. *Advances in Artificial Intelligence*, 11p.

Durrant-Whyte, H. and Henderson, T. (2008). *Sensor Fusion*. Springer, New York.

Hlobil, H., Doulfis, N., Nassarian, A., Vallee, T., and Smith, B. (2016). Improvement of sidetrimming quality based on use of optical inspection device. In *Proc. of the Iron & Steal Technology Conference, USA*, volume 3, 2895–2901.

Kim, M., Lee, W., l, J.Y., and Park, P. (2015). Image stitching algorithm for camber measurement in hot rolling process: Cross-correlation approach. In *Proc. of the 15th International Conference on Control, Automation and Systems (ICCAS 2015)*, volume 15, 4p.

Kong, N., Yoo, J., Lee, J., and Yun, S. (2011). Vision-based camber measurement system in the endless hot rolling process. *Optical Engineering*, 50(10), 1–11.

Montague, R., Watton, J., and Brown, K. (2005). A machine vision measurement of slab camber in hot strip rolling. *Journal of Materials Processing Technology*, 168, 172–180.

Schausberger, F., Steinboeck, A., and Kugi, A. (2015). Optimization-based estimator for the contour and movement of heavy plates in hot rolling. *Journal of Process Control*, 29, 23–32.

Zeiler, A., Steinboeck, A., Kugi, A., and Jochum, M. (2019a). Lateral forces in rolling-cut shearing and their consequences on common edge defects. *Journal of Manufacturing Science and Engineering*, 141(4), 041001 1–9.

Zeiler, A., Steinboeck, A., Vincze, M., Jochum, M., and Kugi, A. (2019b). Vision-based inspection and segmentation of trimmed steel edges. In *IFAC-PapersOnLine*, volume 52(14), 165–170.