

Research Article

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Intelligent methods for root cause analysis behind the center line deviation of the steel strip

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Abstract: This article presents a statistical prediction model-based intelligent decision support tool for center line deviation monitoring. Data mining methods enable the data driven manufacturing. They also help to understand the manufacturing process and to test different hypotheses. In this study, the original assumption was that the shape of the strip during the hot rolling has a strong effect on the behaviour of the steel strip in Rolling, Annealing and Pickling line (RAP). Our goal is to provide information that enables to react well in advance to strips with challenging shape. In this article, we show that the most critical shape errors arising in hot rolling process will be transferred to critical errors in RAP-line process as well. In addition, our results reveal that the most critical feature characterizes the deviation better than the currently used criterion for rework. The developed model enables the user to understand better the quality of the products, how the process works, and how the quality model predicts and performs.

Keywords: smart decision support, data driven manufacturing, machine learning, steel strip rolling, GBM

1 Introduction

Constantly emerging demands for the product properties increase the need to manage the manufacturing processes more effectively and in a more automated way in steel making. With a good process control, the production of defec-

tive products, fault situations, waste and external failure costs, which arise when the product does not meet the design quality standards, can be prevented and the competitiveness of the company increases.

The use of data mining methods in manufacturing processes has gradually become more common along with industry 4.0. Therefore, the area of machine learning (ML), including the fields of artificial intelligence (AI), data mining (DM) and knowledge discovery (KD), have become one of the key interests in manufacturing process development [1]. Especially data mining is widely used for quality diagnostics and improvement in complex steel manufacturing processes. Current manufacturing process development is heading towards data driven smart manufacturing. The topic is elaborated with examples in [2].

Data based statistical methods enable the discovery of the knowledge that cover the whole product selection in manufacturing and the whole process with a single model [3–5]. With that knowledge, the process outcomes can be predicted and relationships between process parameters can be found. Moreover, data mining approaches have enabled the development of intelligent tools for extracting useful information and knowledge automatically from the industrial data [6]. With this kind of automated support for decision-making, the workload and the cognitive load of the workers can be decreased and they can concentrate on improving the process when an alarm for increased risk of failure occurs, for example. Statistical prediction models are especially suitable for the decision-making; with their ability to predict the future outcome, the reaction time after an alarm is longer [7]. The performance of the prediction models can be improved by personalizing the base models dynamically by using incremental methods [8]. In the steel making domain the personalizing can be done based on the products groups, for example.

In Tornio, the stainless steel is cold rolled with an integrated rolling, annealing and pickling line, which is called a RAP-line. The center line deviation of the steel strip in the RAP-line is a major quality factor that can produce serious problems if the strip did not stay in place during RAP processing. In the worst case, a diverged strip position can stop the whole production and brake the devices.

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Hot rolling strip center line deviation at the previous process step is a commonly used and easily available measurement of the strip shape. In Tornio, the center line measurement is followed in white collar level and it's also used as a rework criterion. The center line measurement is a good way to rate strip shape, but it does not tell the whole story of the asymmetrical flatness. Center line is relative to the mass of the strip that's already on the roller table. The longer/heavier the strip is on the roller table, the less sensitive it becomes for the center line deviation.

It could be possible to simulate the behaviour of the strip with a certain shape in the RAP-line during different individual phases. Ilmola et al. present a very exact picture of simulating the rolling and water cooling processes of the steel strip in two parts, the hot rolling and heat transfer and microstructure formation during water cooling [9]. However, in this case, the incoming strips at the RAP-line include a large amount of different shapes, and to get the big picture of the whole production, all of them require simulating. In addition, there are hundreds of products behaving differently because of their chemical composition or the mechanical properties, and thus that the simulation work would be huge if not practically impossible. With data mining methods, the big picture of the process can be achieved quickly. These methods can process a large set of different process settings and products data simultaneously and take into account the variation caused by the measurement error or actual realization related to the features of the products and the process parameters [10–12]. Powerful machine learning methods are capable of modeling highly nonlinear process parameter dependencies and enable the effective use of the process data.

In the beginning of this study, the hypothesis was that the behavior of the strip in the RAP-line is highly dependent on the shape measurements of the strip in an earlier stage of the process, during hot rolling. In that case, it would be easy to react well in advance to strips with challenging shapes. In this article, we propose a method for finding root causes behind the center line deviation of the steel strips. Our results support the original hypothesis, and furthermore, we have been able to determine the most defective values for the critical process parameters.

The article is organized as follows: Section 2 introduces the used data and data pre-processing process, statistical methods and feature extraction are explained in Section 3. Modelling results and implementation are then presented in Section 4. Finally, the conclusion is in Section 5.

2 Data description

The data consists of over 5,400 steel strips and over 50 variables from the hot rolling process to the RAP-line. The dataset includes samples from all the main product groups, and it was collected from Outokumpu Stainless Oy, Tornio, Finland steel strip mill process during 2017 with two different measurement devices which produced hundreds of data points for each strip and variable. The data collection involved a considerable amount of manual work, which limited the number of observations.

During hot rolling process, each strip is measured with a device equipped with pyrometer and X-ray. The measured variables relate to asymmetrical flatness, position deviation, crown and wedge shape of the strip. From these measurements, descriptive features used in the modeling process are extracted. For example, the asymmetrical flatness is calculated by fitting a slope between the edges of the strip. Figure 1 illustrates the transversal slope, which is calculated from the normalized 3D flatness data. The variable `slope_max` is the absolute maximum of the calculated slope values.

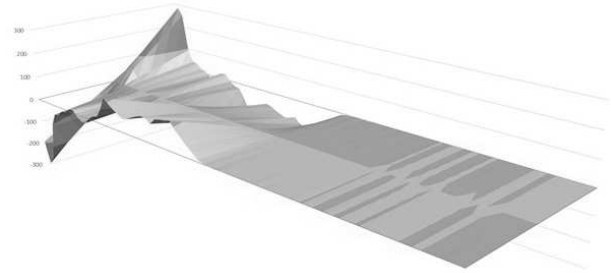


Figure 1: The transversal slope, which is calculated from the normalized flatness data of the strip.

The second device measures at the RAP-line, and the data set includes the center line deviation measurements. Again, hundreds of data points are gathered from each strip and each variable. The response variable is calculated from these measurements.

A lot of attention has been paid to the combination of the hot rolling and RAP-line data sets and the extraction of the features. Careful pre-processing was done in order to remove redundant variables and clearly defective observations. More than half of the data had to be removed because of the exceptional rolling process, such as another preceding process step after hot rolling line, too short a measurement sequence, a roll change during the rolling process, over 30 minutes pause during the process, or ex-

ceptionally low processing speed. Proper pre-processing ensures that the data is more reliable and the statistical analysis is more accurate. The final data set includes 2,071 steel strips.

3 Methods for quality prediction

3.1 Machine learning methods for process data utilization

In this application, the center line deviation is predicted by using gradient boosting methods (GBM) [13]. The idea of this machine learning algorithm is to form a strong learner by combining together the set of iteratively estimated weak learners. The model is able to treat efficiently the complex and nonlinear relationships within the data set, which is mandatory with industrial applications. Other advantages are that the method is capable of processing observations with missing information, and contrary to neural networks, it works also with smaller data sets.

The availability of the variable importance and the possibility to visualize the relationships between the variables and the predictions of the model help to understand the modelled process better. Partial dependence plots (PDP) can be drawn independently for each variable in the model and also the interaction between variables based on H-statistic can be visualized [14, 15].

Especially, when a high center line deviation has been predicted for a product, it is important to find out the reasons behind the high risk for this particular product. Game theory based SHAP (SHapley Additive exPlanation) values relate to the change in the expected model prediction based on each input variable [16]. The method enables the finding of the high-risk variables for each product based on its individual background compared to similar products in general.

3.2 Feature extraction

GBM-model is trained using features extracted from the data measured from the hot rolling process. The original raw data included about 50 variables, but the number was reduced with the feature extraction and the knowledge of domain experts. One example of extracted variable was the slope of asymmetrical flatness of the strip during hot rolling. Additional 14 new features were constructed from the original variables. These features were different minimums and absolute maximum values of slope, crown

and wedge shapes of the strip. Additionally, thickness of the strip was classified in two classes and width in three classes. Steel type was divided into five indicator vectors, with 1 or 0, depending on if the strip was that type or not. Variables about the chemical composition (Cr, Ti, Nb and N) were included as well. Furthermore, three variables were left out due to strong correlation with other variables. The final number of variables used for model training was 18.

Due to the complexity of the center line deviation assessment, a lot of attention has been paid to the selection of the response variable that describes the position deviation best. We ended up considering the 90 m of the inner circle of the strip coil and calculated the mean of the process variable, ST6 super position for describing the center line position of the strip. The RAP process is continuous, that is, the consecutive strips are seamed together. This seam area was left out in order to concentrate on the stable area, where the preceding strip has no influence anymore, and the measurement from hot rolling can be assumed to be stable.

Next, we applied an average filtering ($n=10$) for ST6 super position values of the selected length and calculated the difference between the mean of the ST6 super position and the filtered curve. Figure 2 illustrates the calculation of the response variable. The solid line shows ST6 super position values and the dotted line indicates the average filtered curve of the ST6 super position. The formed response variable was predicted with GBM model that was implemented with R-program.

4 Practical use case

4.1 Results of the center line deviation modeling

The data set was divided into five parts in chronological order. The first 70% from every part was selected in the training set and the last 30% to the test set. The procedure reduced the dependence of the training and the test sets and increased the temporal coverage of the test set. Thus all the steel types were represented both in training and test sets.

Features described in Section 3 were used to train the GBM model. The performance and generalization based on the test set results of the GBM-model are presented in Table 1. According to the results, the overall correlation (R) between the measured and predicted values of the test set was 0.74, the root mean square error (RMSE) was 7.2 and the mean absolute error (MAE) was 4.6. The scatter plot be-

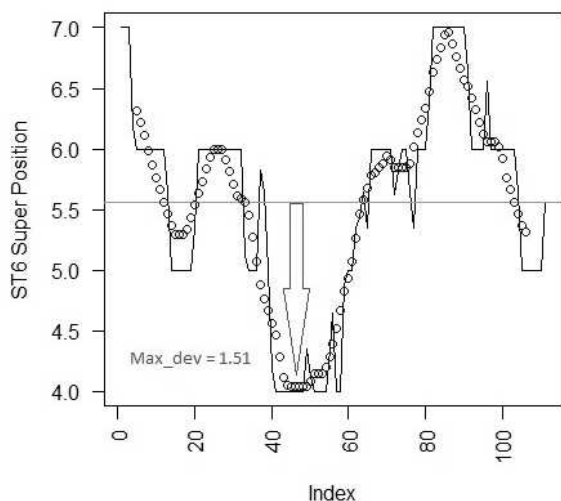


Figure 2: The ST6 super position values (solid) and an average filtered curve ($n=10$) (dotted). The straight line indicates the mean of the ST6 super position. Max_dev (arrow) is the calculated maximum difference of the mean of the ST6 super position and the filtered curve.

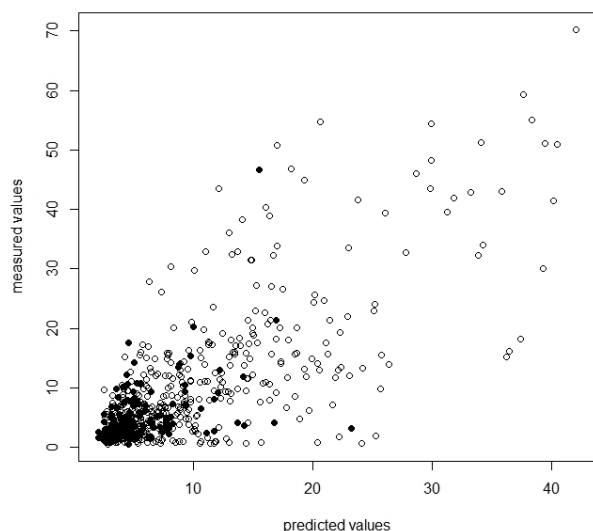


Figure 3: Predicted ST6 super position (x-axis) vs. measured values (y-axis) in the test set. A product group with inferior performance is highlighted (black).

tween the predicted response variable and the measured values in the test set are shown in Figure 3. The majority of the observations have been predicted quite accurately, but there is some deviation due to the complexity of the process and variability of the products. Especially, one product group (highlighted in black) is quite different on its

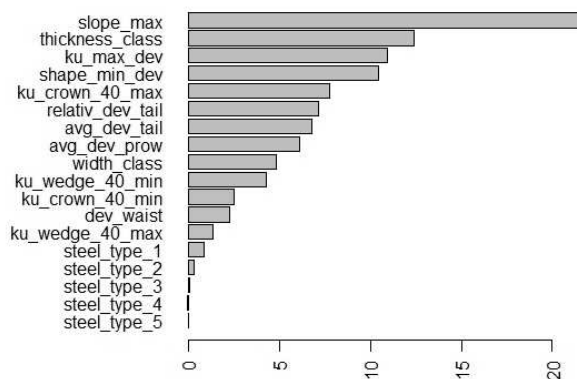


Figure 4: The importance of each variable in the model.

mechanical properties, and thus, behaves differently from others during RAP process. Generally, as can be seen in Figure 3, this type of products behaves well at the production line, but the sparse deviations are difficult to predict, and thus, the observations belonging to this group reduce the overall performance of the model.

Table 1: Root mean squared errors (RMSE), mean absolute error (MAE) and correlations (R) of the models in test and training set

	train	test
RMSE	6.5	7.2
MAE	4.2	4.6
R	0.81	0.74

In GBM, the relative importance of the input variables is determined by their occurrence on the splits during the tree building process and how much each variable then improves the MSE (mean squared error) of the whole prediction model. The importance in the model for each variable affecting the center line position is shown in Figure 4. The overall sum of variable importance values is 100. The most important one is the hot rolling parameter slope_max, which describes the maximum slope of the strip asymmetrical flatness during the hot rolling process. With Partial Dependence Plots (PDP), the effect of each variable on the response variable can be visualized. From PDP in Figure 5, it can be clearly seen that the higher the slope_max is during hot rolling, the higher the center line deviation is in RAP process correspondingly. The increase in deviation is especially large after 40 units. This result proved the hypothesis that the shape errors in hot rolling forecast problems also in RAP-line. The next important feature is the thickness of the strip. As we can see

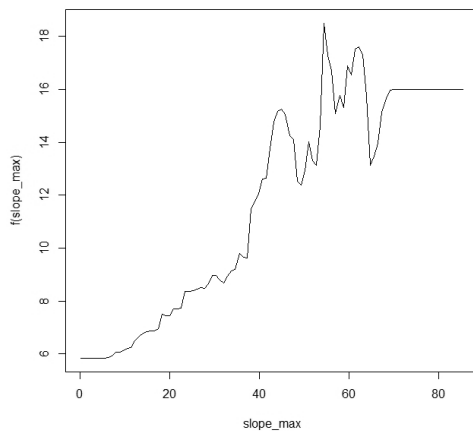


Figure 5: The PDP for *slope_max* reveals the feature's increasing impact on the response. Especially, after 40 units, the feature has a hazardous effect on the center line position.

in Figure 6, the center line deviation risk is larger with the thinner strips class, for which the thickness was below 3.5 mm. Thin strips are more vulnerable under the force of the roller than the thicker ones because of the lower mass of the strip, and thus, the risk of the shape errors increases. Like variable *slope_max*, the absolute maximum deviation (*ku_max_dev*) calculated from first 50 m of the strip head lengthwise, and the absolute minimum deviation (*shape_min_dev*) from the same area have influence on the response variable as well. Figure 7 shows the relation between *ku_max_dev* and the response variable. Up to the present, the *ku_max_dev* is used as a rework criterion in hot rolling process and this analysis proves that the *slope_max* is a much better criterion. Therefore, it is interesting to analyze if the asymmetrical flatness measurement could give a better indicator of strip behavior during the next process step, compared to the hot rolling center line deviation measurement. Additionally, absolute maximum of crown measured 40 mm from the side (*ku_crown_40_max*) and both relative and average deviation of the last 5 m of the inner circle of the strip coil (*relativ_dev_tail*, *avg_dev_tail*) have some influence on the response variable. These variables describe the shape errors of the strip during hot rolling process. Modeling results showed that it is possible to find the strips, which have an increased risk for center line deviation later in RAP process, and to inform the operators immediately after hot rolling step. Thus, the risk for breaking devices and stopping the RAP line production can be decreased.

Less critical shape errors were the minimum and absolute maximum wedge shape measured 40 mm from the

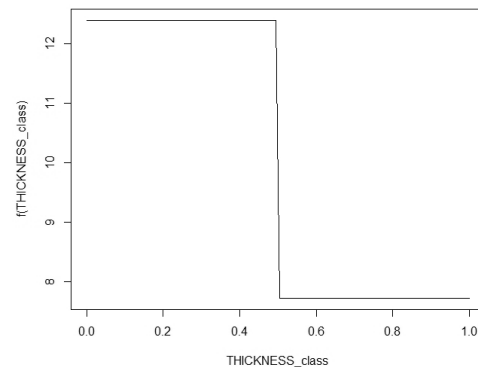


Figure 6: The PDP for classified thickness shows that the thicker strips are less vulnerable for the defect.

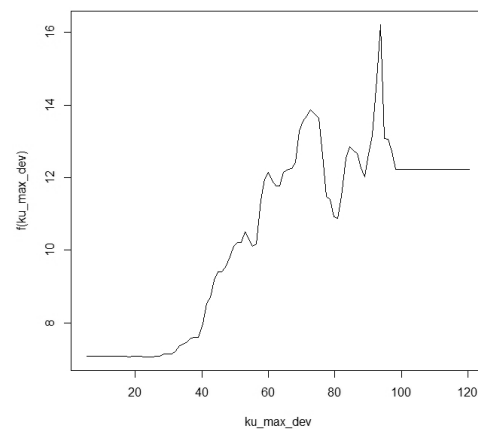


Figure 7: The PDP of maximum deviation of the strip in hot rolling shows the feature's increasing risk on the response.

side (*ku_wedge_40_max*, *ku_wedge_40_min*) and the deviation in the middle part of the strip (*dev_waist*) measured during hot rolling. Clearly, the shape errors in heads of the strip are riskier for center line deviation than the errors in the middle part of the strip. Additionally, it seems that the crown is worse than wedge shape of the strip for the center line deviation. Even though the steel type is the least important factor in the model, it is known that the variance between the steel types is large, because of the different chemical compositions and the mechanical properties. For example, one strip can be more elastic and softer than other one, which adds complexity to the manufacturing.

In manufacturing, the result is not only dependent on the features independently, but also the interactions of the variables have their impact. In GBM, the interactions of the variables can be included in the model and in this

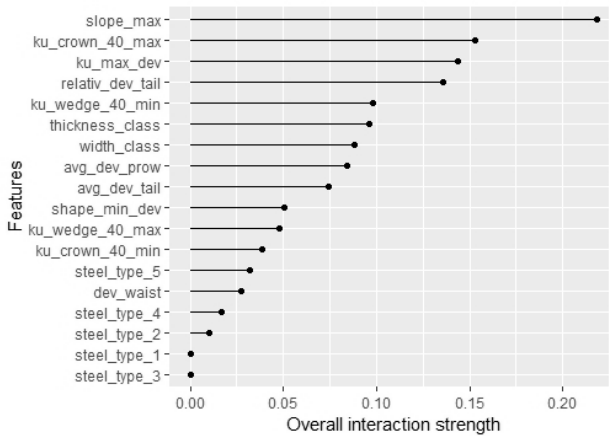


Figure 8: The overall interaction strength (H-statistic) for each feature independently.

application, the interaction depth (the highest level of interactions between variables allowed during training the model) was three. Figure 8 shows how strongly the hot rolling features interact with each other. The interaction strength value corresponds to the proportion of explained variance of $f(x)$ for each feature. The value is between 0 when there is no interaction and 1 if all variation depends on a given feature's interactions. Some of the variables may have quite strong impact on interactions, but most of them do not interact actively with the other variables. In practice, the impact of the most important individual variables always outperforms that of interactions. For each feature, it is possible to inspect visually the strongest interaction partners as well. In Figure 9, the interaction between the most important feature `slope_max` and other features are shown. The strongest interaction is between the `slope_max` and the absolute maximum crown measured 40 mm from the side of the strip (`ku_crown_40_max`). Overall, most of the interactions between other features and `slope_max` is quite weak.

It is important to reveal the reasons behind the predictions, especially, when a product has a higher predicted risk for the failure. SHAP visualizations enable to inspect the reasoning behind the estimation for each observation individually. The selection of the reference group has to be done carefully, because the visualization should be able to reveal the difference between the prediction of the current observation and the average prediction result of the other similar products. In this application, SHAP values for each product were calculated based on the product group. Thus, the products were compared to the average performance within the group of similar products. We selected two examples from the same steel type (`steel_type_3`) to demonstrate the usage of the method; the product with

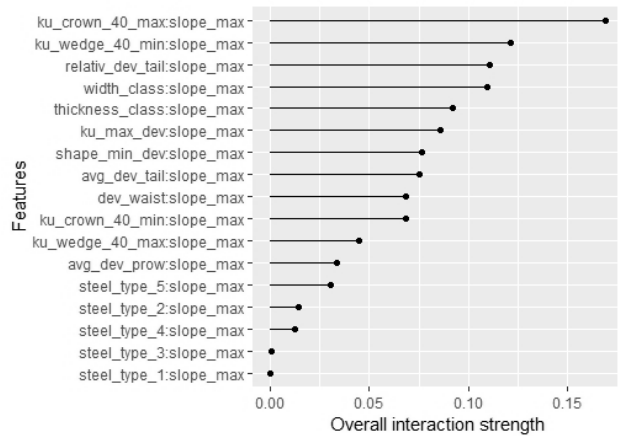


Figure 9: The 2-way interaction strengths (H-statistic) between the most important feature `slope_max` and the other features.

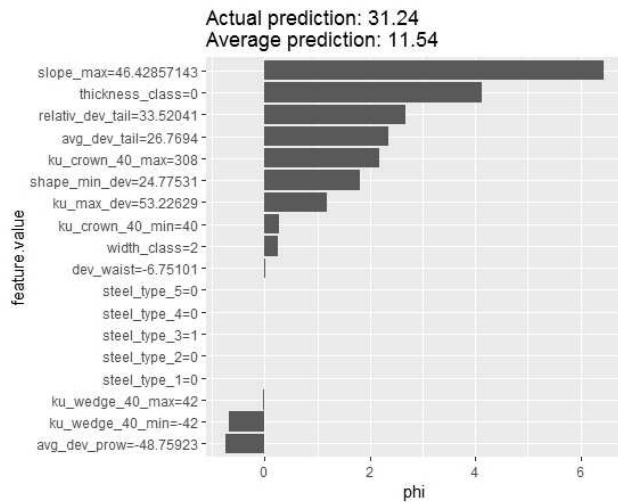


Figure 10: SHAP values for a bad product with a prediction of 31.24, while the average prediction is 11.54 inside the group of `steel_type_3`.

bad prediction is shown in Figure 10 and the good one in Figure 11. As can be seen, the prediction for center line deviation is 31.24 with the bad one, when the average prediction is 11.54 for this steel type in general. The phi value describes the strength of the feature value contribution in the prediction. The strongest candidate behind a poor prediction is `slope_max`. Also, the membership in the thinner strips class increases the risk. The strip with a good prediction result in Figure 11 has properties that have decreasing impact on the deviation; thicker and wider strips can be controlled better. In this case, the harmful `crown_40_max` value cannot outweigh the positive values.

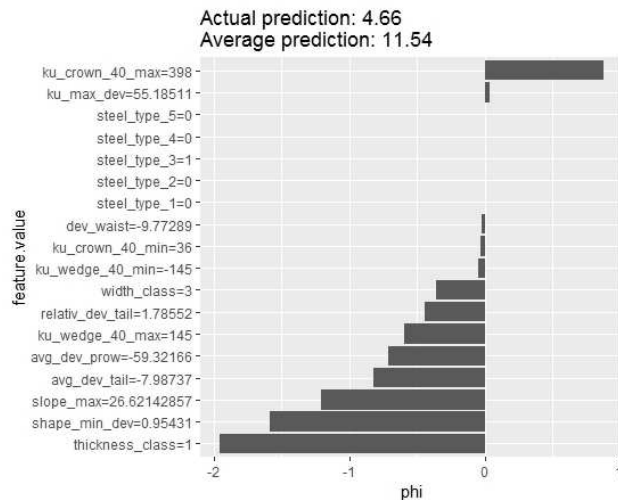


Figure 11: SHAP values for a good product with a prediction of 4.66, while the average prediction is 11.54 inside the group of `steel_type_3`.

4.2 Smart decision support

The model can be implemented for the online monitoring of the process. Thus, the operator can get an alarm for the risk of divergent position effectively. We have built in co-operation with VTT (Oulu, Finland) an online quality monitoring tool that presents the product quality information during manufacturing with easy-to-understand colouring for a selected period [7]. The tool is web based, and it has an online access to the process and product information database. The visualized quality information is based on the prediction results, and in this case, the colour-coding will be selected based on the center line deviation risk.

As a result of this research, we found the best response variable that describes the center line deviation. Our root cause analysis behind the center line deviation gives essential knowledge to the process development workers at the Tornio mill. Based on the Partial dependence plot, in Figure 5, we were able to define a clear critical limit value 40 for `slope_max`. In the first step, this information can be used for redirecting the strips which exceed the limit to repair treatment before RAP-line. It is also possible to implement the model for online use and to predict more efficiently the products that need to be repaired. The individual information behind the prediction for each product provides useful guidance for the rework.

Next, the driving parameters of the RAP line can be used for finding out what is the best way of dealing with the high-risk strips. By comparing the current high-risk product to its counterparts, the best process settings can be found. Especially, when the analysis reveals a less suc-

cessful production plan, the operator can be provided with a recommendation for better settings. With the proposed method, it is possible to build smart decision support tools that enable faster actions to prevent malfunctioning. Furthermore, it is possible to test in advance different process settings and find out which ones produce the best results.

5 Conclusion

In this article, we presented a machine learning based method for steel strip center line deviation analysis. In addition to the quality prediction, our ensemble model provides information about the variable behavior during prediction. This information is valuable for the result interpretation and process understanding. Our research showed that the most critical shape errors arising during hot rolling process will be transferred to critical errors in RAP-line process as well. The modeling results indicate that the currently used criterion for rework is not the best candidate to characterize the strip behavior. Instead, the most important parameter is the `slope_max`, which describes the asymmetrical shape of the strip during hot rolling. The thickness of the strip has an impact on the response variable as well. Our results reveal also the less critical shape errors, which are the wedge shape and the longitudinal deviation measured from the middle of the strip.

The developed model enables the user to understand better the quality of the products, how the process works, and how the quality model predicts and performs. The results can be developed further to a smart decision support tool that helps to find out the best way of dealing with the critical products. The tool enables the identification of the quality problems of the steel strips at the earliest possible moment, which leads to the reduction of the rejection risk and to increased profits for the producer. Because of the laborious and manual data collection, the current model covers the main product groups. The performance of the model can be improved by collecting more data from the product groups with a smaller number of representatives, but online learning methods could provide a more serviceable solution in the long run.

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