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Predicting of Roll Surface Re-Machining Using Artificial Neural Network

Miha Kovačič*, Andrej Mihevc, Milan Terčelj, Uroš Župerl

Abstract: The paper presents a model for predicting the roll wear in the hot rolling process. It includes all indicators from the entire continuous rolling line that best predict the roll wear in the hot rolling process. Data for model development were obtained from annual production on the first rolling stand of the continuous roll mill. The main goal of the research was to determine significant parameters that affect the wear of the roll in the process of hot rolling. It has been found that the amount of rolled material before the re-machining of the roll surface has the greatest impact on the life of the roll contour. Therefore, the amount of material rolled before re-machining of the roll was used to estimate the wear of the roll. An artificial neural network was used to predict this amount of rolled material and was validated using data from one-year production.

Keywords: artificial neural network; hot rolling; linear regression; prediction; roll wear

1 INTRODUCTION

In hot rolling, the dimensions of the long bars vary according to the groves of the rolls. The surface of the cooled roll wears out due to the constant contact with the hot-rolled bars. Surface cracks also occur on the surface of the roll due to temperature gradients. The reason for the formation of temperature gradients is the constantly changing thermo-mechanical tribological rolling conditions, which depend on the rolled material and the roll, the temperature of the coolant and the rolling speed.

In addition to the above, it is necessary to know the effects that rollers have on the surface defects of rolled bars. There is a lot of research in this field [1-5].

Understanding roll wear and the ability to accurately predict the wear is essential for the steelmaking industry. Practical guidelines for reducing roll wear during hot rolling are given in the literature. Practical instructions can be divided into 5 sets.

The first set combines guidelines for extending the life of rolls by modifying existing roll material [6].

The second set includes approaches to reduce roll wear by applying additional surface coatings to the rolls [1, 3].

The third set combines instructions for the use of lubricants [2, 7, 8, 4].

The fourth set contains instructions for changing the geometry of the groves of rolls [9-12] and the last set provides instructions for reducing roll wear by changing the rolling conditions (e.g. rolling load, rolling temperature) [2, 13-16].

Some excellent mathematical models for predicting roll wear have been published in the literature. The best-known researchers who have studied this topic are Archard, Yasada, Lim and Ashby, Sibakin, Oike, Somers, Tong and Chakko [1, 3]. However, none of these models can be practically applied in industrial environments, where the specifics of different types of steels appear, where different rolling regimes are used and where delivery deadlines need to be met.

In a one-year period, the 7 influencing parameters on the wear of the roll of the first rolling stand of the continuous roll mill for long round bars were investigated. In our very flexible environment, the diameter of the roll, geometry of groves, its surface, contact time, carbon equivalent of rolled material, rolling temperature and amount of the rolled material were analysed. It should be noted that the survey included data for more than 220 serial-produced steels. The bars were rolled to a diameter range of ∅20 mm to ∅58 mm.

In this study, the effects of the entire hot rolling process of round bars on the wear of the rolls were identified and analysed. The first part of the paper presents the experimental setup, including the industrial environment and description of collected parameters. The following chapter presents a model for predicting roll wear based on artificial neural networks and linear regression. In developed models, roll wear is defined as the amount of rolled material before re-machining the rolls. The developed models were validated using the data from one-year production. The last chapter provides conclusions and plans for future work.

2 STEEL ROLLING PROCESS, MATERIALS AND METHODOLOGY

The small and flexible steelworks Štore steel Ltd. produces over 200 types of steel with various chemical compositions. Steel production begins with the melting of scrap steel in an electric arc furnace. After melting, tapping and ladle treatment is performed, after which the melt is continuously cast into billets of dimensions 180 × 180 mm. A two-strand continuous caster performs this procedure.

To further roll the billets in the rolling mill, the billets are heated to 1250 °C. The heated material is led to a descaling device and through a duo reversible rolling stand. The billets are made in 7 passages over a stand with rollers of 800 mm diameter. The billets are rolled into bars with a circular cross-section to a final diameter of between 90 mm and 110 mm.

The bars are then transported on a duo reversible rolling stand with 650 mm diameter rolls. After four passes and the last cooling by-pass, the material cools down to the rolling temperature and exits the rolling stand.

An infrared pyrometer is used to control the rolling temperature.

Table 1 The chemical composition of the outer working layer of the roll

C (%)	Si (%)	Mn (%)	P (%)	S (%)	Cr (%)	Ni (%)	Mo (%)
3.1-3.9	1.1-1.9	0.4-0.9	<0.059	<0.019	0.6-1.3	0.9-2.9	0.2-0.6

The material is then transported to the final continuous rolling line with rollers of 460 mm diameter and length of 700 mm (Fig. 1).

The following number of passes on a continuous rolling line is required to make the desired cross-sections of the bars:

- 9 passes for making a bar with a diameter between 20 mm and 38 mm.
- 7 passes for making a bar with a diameter between 38 mm and 49 mm.
- 5 passes for making a bar with a diameter between 50 mm and 59 mm.

The continuous rolling line is made of 14 devices. The first device is a descaling device, followed by six horizontal and four vertical rolling mills. For hot cutting both ends of the rolled bar, two shears are integrated on the line and additional ones for cutting the bar to the final dimension before it enters the cooling bed.

The rollers of the continuous rolling mill consist of two layers (according to Inspection certificate provided by the roll producer). The outer working layer is made of steel and the core is made of nodular cast iron. The working layer of the roll consists of perlite and bainite. The ratio depends on the required hardness. The thickness of the working layer of the roll is determined by adding approx. 35 mm to the geometry of the groove. The core of the roll is made of perlite, which contains free cementite and spherical pearlite.

After the appearance of roll wear and fatigue cracks, the rollers are re-machined with the turning process. The re-machining process is carried out at the Štore steel Ltd. steel plant. The re-machining process is repeated until all the working layer of the roller is removed and the core layer of cast iron is displayed. Then the rollers must be discarded.

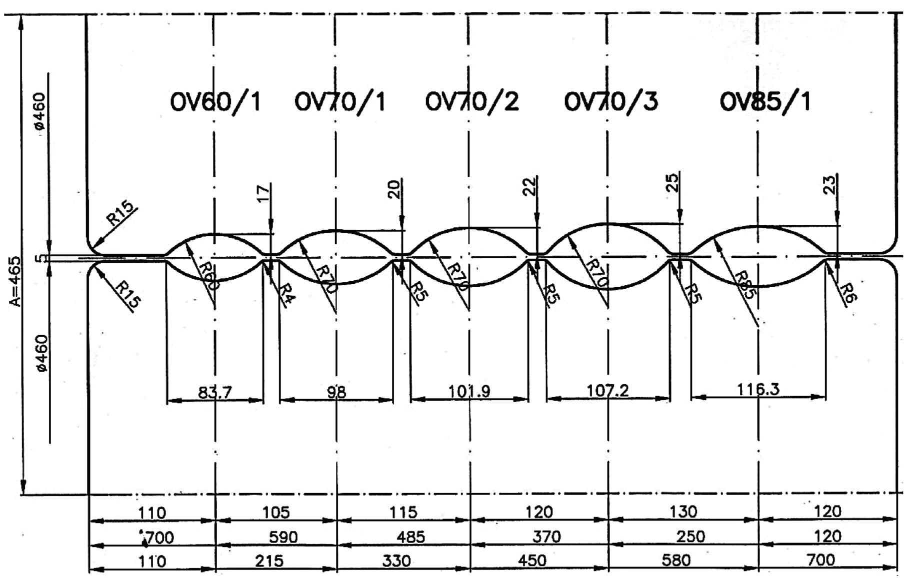

Figure 1 Roller groves on the first rolling mill place of the continuous rolling line

In the test year, the lifespan of rolls was analysed on the first roll stand of the continuous roll mill, where long round bars with diameters from ∅20 mm to ∅58 mm are rolled.

In a one-year experiment, the groove surface after machining *GS* (mm^2), the rolls diameter after re-machining *RD* (mm), the contact time *CT* (s), the average carbon equivalent *CE* (%), the average rolling temperature before entering first rolling mill place *RT* (°C) and amount of rolled material before machine operation *Q′* (kg) were monitored.

In the case of worn rollers, a cutting process must remove the affected part of the surface.

Based on available data from the steel plant, it is possible to conclude that there is no information on the primary cause of the re-machining of the rolls.

The reduction of the roll diameter *RD* and the groves surface *GS* on the first rolling mill place of the continuous rolling line throughout the roll life cycle is shown in Tab. 2.

The time between entry and exit of the rolled piece from the deformation zone is defined as contact time *CT*. It is calculated by the Eq. (1).

$$CT = \frac{l}{v}, \tag{1}$$

l is the contact length (mm) and is determined by the Eq. (2):

$$l = \sqrt{\frac{RD}{2} \cdot \Delta h}, \tag{2}$$

$$\Delta h = h_0 - h_1, \tag{3}$$

where h_0 and h_1 are the effective heights of the input and output workpiece,

$$v = \frac{v_r}{\prod_i^n R\_f_i}, \tag{4}$$

where v is roll circumferential speed. v_r is rolling speed and R_f_i are reduction factors for calculation of rolling speed at i–1 stand.

Table 2 Change in cylinder diameter and surface area of individual groves during the entire life cycle of the roll

Roll diameter *RD* (mm)	OV60/1 (mm²)	OV70/1 (mm²)	OV70/2 (mm²)	OV70/3 (mm²)	OV85/1 (mm²)
420	122848	142254	148634	157547	166361
419	111317	128774	134461	142381	150445
417.2	111036	128445	134115	142011	150057
415	110474	127788	133424	141271	149282
413.5	109855	127065	132663	140457	148428
411.2	109433	126572	132144	139903	147846
408	108786	125816	131349	139052	146953
406.4	108027	124928	130416	138054	145905
404.2	107436	124238	129690	137277	145089
401	106817	123514	128929	136463	144235
420.3	106114	122692	128065	135538	143265

Tab. 3 shows the reduction factors for rolling round bars with a diameter of 21 mm on the continuous rolling line in the Štore steel plant.

Table 3 Reduction factors for rolling round bars with a diameter of 21 mm on the continuous rolling line in the Štore steel plant

Roll mill place	Reduction factor
1H	1.188
2H	1.143
3V	1.285
4H	1.190
5V	1.147
6H	1.000
7V	1.000
8H	1.000
9V	1.000

A one-digit number representing the influential alloying chemical elements represents carbon equivalent *CE*. In the research, it was determined by the Eq. (5).

$$CE = \mathrm{C}(\%) + \frac{\mathrm{Mn}(\%)}{6} + \frac{\mathrm{Si}(\%)}{6} + \frac{\mathrm{Cr}(\%)}{5} + \frac{\mathrm{Mo}(\%)}{5} + \\ + \frac{\mathrm{V}(\%)}{5} + \frac{\mathrm{Cu}(\%)}{15} + \frac{\mathrm{Ni}(\%)}{15}. \tag{5}$$

Tab. 3 shows some of the most important parameters selected from year-round production (2014).

3 MODELS FOR PREDICTING ROLL WEAR

This research aims to design and test the methodology for predicting the roll wear in the Štore steel plant.

With linear regression and artificial neural networks, two models were developed to predict the amount of rolled material before re-machining the rolls.

The data from Tab. 4 are used for modelling.

The average deviation between the predicted and experimental data is selected for the Fitness function, which is calculated according to the equation:

$$\Delta = \frac{\sum_{i=1}^{n} \frac{(Q_i - Q'_i)}{Q'_i}}{n}, \tag{6}$$

where n is the size of the acquisition data and Q'_i and Q_i are the actual and the predicted amount of rolled material before re-machining of the roll.

3.1 Linear Regression Model

The results of the linear regression obtained by ANOVA show that the model does not predict in a significant way the amount of rolled material before the re-machining of rolls ($p > 0.05$).

The results also show that only 18.34 % of total variances can be explained by independent variables variances (*R*-square).

The results also show that the surface of the individual grove is the only significant parameter ($p < 0.05$).

A linear regression model for predicting the amount of rolled material before re-machining the rolls is given by:

$$Q = 30 \cdot (-1.045 \cdot GS + 912.6 \cdot RD + 629703.9 \cdot CT + \\ +38012.9 \cdot CE - 107.7 \cdot TR + 169073.9). \tag{7}$$

The relative deviation of the regression model from the experimental data is 70.9 %.

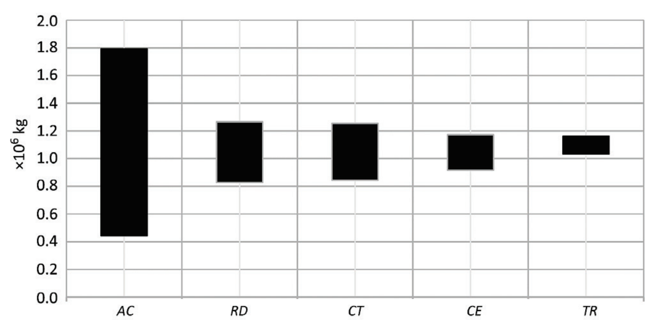

Figure 2 Calculated effects of parameters on the amount of rolled material before re-machining of rolls

Fig. 2 shows the effects of individual parameters (individual variables) on the amount of rolled material before re-machining the rolls.

The results in Fig. 2 show that the surface area of an individual groove is the most significant parameter in predicting the amount of rolled material before the re-machining of rolls.

Table 4 Parameters from year-round production included in the survey

Roll diameter after re-machining *RD* (mm)	Groove surface after re-machining *GS* (mm^2)	Amount of rolled material before re-machining *Q'* (kg)	The temperature of rolled material in front of the first rolling mill place *TR* (°C)	Contact time *CT* (s)	Carbon equivalent *CE* (%)
420	111317	776655	925	0.0503	0.6976
420	134461	1199692	925	0.0593	0.7375
420	128774	2325086	925	0.0588	0.8234
420	142381	738174	925	0.0696	0.7615
420	134461	356011	925	0.0558	0.7874
420	150445	535935	925	0.0623	0.7136
419	111036	1153021	925	0.0480	0.6796
419	134115	2145107	925	0.0597	0.6966
419	128445	1514654	925	0.0574	0.8283
419	142011	678049	925	0.0661	0.8513
419	150057	456329	925	0.0602	0.7036
415	109855	1369647	925	0.0502	0.6647
415	132663	2210526	925	0.0585	0.7505
415	148428	143922	925	0.0561	0.7076
415	139976	745241	925	0.0696	0.8114
413.5	126638	2496935	925	0.0579	0.8164
413.5	139976	232599	925	0.0576	0.6707
413.5	132213	744329	925	0.0587	0.8234
413.5	147923	619444	925	0.0640	0.7605
413.5	109489	1208941	925	0.0495	0.6727
413.5	132213	1217757	925	0.0599	0.7365
411.2	108786	1366408	925	0.0577	0.7764
411.2	139052	716366	925	0.0668	0.7954
411.2	131349	645335	925	0.0605	0.8363
411.2	146953	159756	925	0.0554	0.6307
411.2	108786	1136483	925	0.0490	0.6816
411.2	131349	3848595	925	0.0594	0.7335
408.5	124928	1134203	925	0.0577	0.7794
408.5	138054	594424	925	0.0694	0.8204
408.5	130416	363868	925	0.0607	0.7695
408.5	145905	103325	925	0.0682	0.6367
408.5	108027	1419997	925	0.0492	0.6327
408.5	130416	2005371	925	0.0584	0.7226
406.4	124238	1333465	885	0.0565	0.7964
406.4	137277	804124	885	0.0672	0.8413
406.4	129690	544296	885	0.0579	0.7635
406.4	145089	603241	885	0.0613	0.6916
406.4	107436	1127698	885	0.0508	0.6527
406.4	129690	1956519	885	0.0588	0.7265
404.2	123514	1637308	925	0.0572	0.8563
404.2	136463	370057	925	0.0637	0.8543
404.2	128929	253466	925	0.0543	0.7964
404.2	144235	179304	925	0.0594	0.7395

3.2 Artificial Neural Network Model

In this chapter, the adaptation of the artificial neural network (ANN) architecture to the problem of predicting the amount of rolled material before re-machining of rolls is presented in detail.

To perform modelling of the amount of rolled material before re-machining of rolls, the popular three-layer neural network architecture was used. A standard backpropagation learning algorithm was selected. The network architecture with 5 input neurons is selected. The optimal number of hidden layers, the number of neurons in each hidden layer, the training parameters, and the optimal type of activation function were determined by systematically changing the parameters in the simulations. The optimal ANN architecture containing 4, 6 and 3 neurons in each level is determined by simulations [17-19]. The only output of ANN is the amount of rolled material before re-machining of rolls; therefore, only one output neuron is needed.

Signals are transmitted at synapses between neurons, where they are processed by Dot product input and output Sigmoid-bi activation function [20, 21]. Fig. 3 shows the detailed architecture of the developed neural model for predicting the amount of rolled material before re-machining of rolls.

Four steps are required to construct a neural prediction model of the amount of rolled material before re-machining of rolls [22, 23].

In step 1, experimentally obtained training and testing data were delivered to the neural network [24].

1200 data points were dedicated to train 120 ANN. Additional 600 data points were used to test and validate the developed ANN. The generalization capability of ANN and the accuracy of the predicted results was determined by the testing process.

The optimal ANN architecture and learning parameters were determined in Step 2. In this step, the optimal number of hidden layers, the number of hidden neurons in each level, the momentum rate (β), the learning speed (α), the total network error, and the maximum number of iterations were searched with simulation.

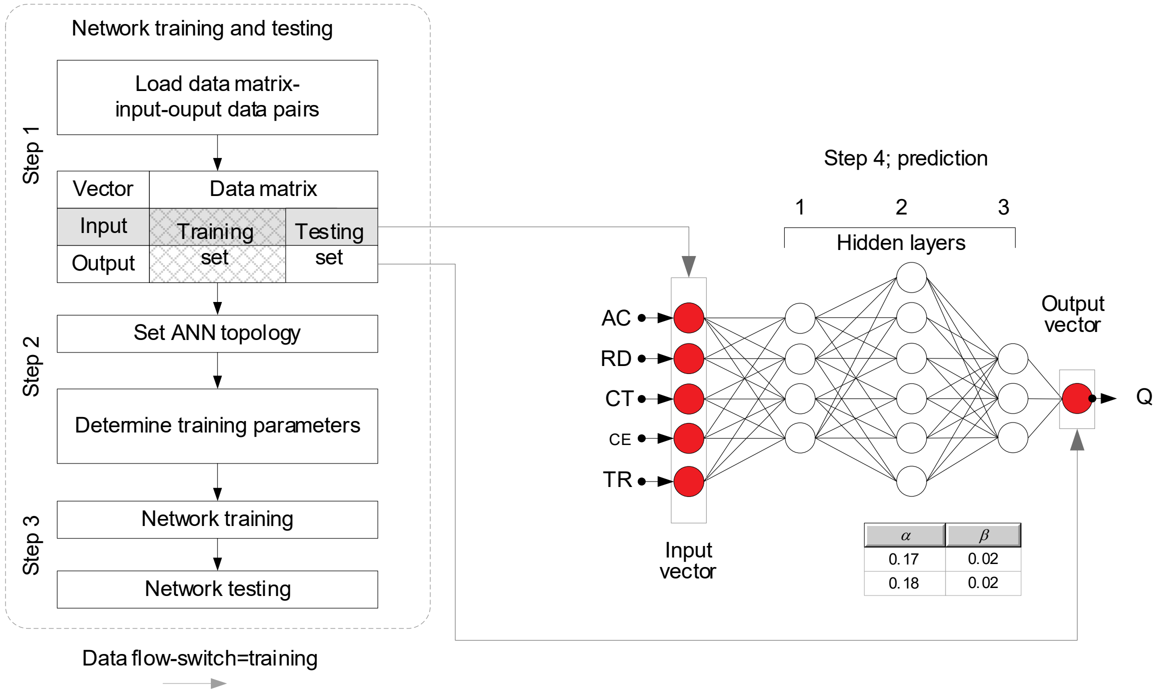

Figure 3 Block diagram of training and using the ANN model for predicting the amount of rolled material before re-machining of rolls with its detailed structure

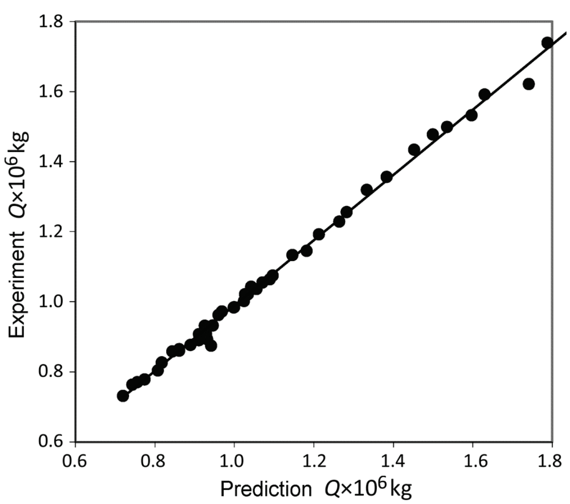

Figure 4 Scatter diagram of predicted and experimentally obtained Q for testing data set

Performances of 49 neural networks were evaluated with fitness function and the number of training repetitions.

The simulations results of 49 different neural networks showed that the most suitable for predicting the amount of rolled material before re-machining of rolls was a neural network with 13 neurons in three hidden layers, where the learning rate α must be less than 0.2 and the momentum rate β must be between 0.005 and 0.02.

The process of training and testing the artificial neural network is performed in step 3.

During training, ANN adjusts the weights on the synapses, thus adjusting its internal structure to correctly predict the te amount of rolled material before re-machining of rolls according to the input parameters.

1200 sets of experimental data were used for the training process.

The training process ended after 910 iterations of training when the prediction model error fell below a predefined lower error limit. The test error for 600 data points was found to be close to 4%. Fig. 4 shows a scatter diagram of the predicted values and experimentally obtained values of the amount of rolled material before re-machining of rolls for the test data set. After 910 iterations of training, the model is built and ready for use.

The model is then tested with additional pairs of input-output data that were not included in the training process.

The predicted values were compared with the actual amount of rolled material before re-machining of rolls after which the prediction errors were calculated.

Finally, in the last step, a trained ANN is used to predict the amount of rolled material before re-machining of rolls.

Fig. 3 shows a block diagram of ANN fabrication and testing for predicting the amount of rolled material before re-The relative deviation of the artificial neural network model from the experimental data is 41% which is 1.72-times better than the linear regression model.

Fig. 5 shows the effects of individual parameters on the amount of rolled material before re-machining the rolls. The results in Fig. 5 show that the roll diameter is the most significant parameter in predicting the amount of rolled material before the re-machining of rolls.

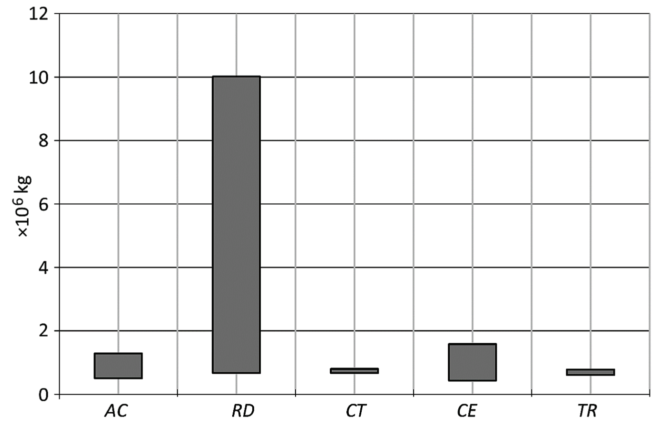

Figure 5 By ANN obtained effects of parameters on the amount of rolled material before re-machining of rolls

4 MODELS VALIDATION

Based on the analysis of the results of the neural network model and the linear regression model, it was determined:

- Both models have relatively low performance.
- Surface of each groove after re-machining and roller diameter after re-machining are the most significant parameters.

However, these two parameters are highly dependent on the machining of the rollers, so it is necessary to include accurate additional data and information on the main reason for the decision to re-machining.

For this purpose, an experiment was carried out throughout 2015. The additional data obtained are presented in Tab. 5. The decision to re-machining was made in all cases only based on detected rollers wear. Throughout the year of the experiment, no fatigue cracks were detected on the rollers, so this was never a reason for re-machining.

The relative deviation of the artificial neural network model from the experimental data is 32.8 %. The relative deviation of the linear regression model from the experimental data is 57.2 %.

The improved performance of both models in terms of the amount of rolled material before rolls re-machining can be attributed to the fact that fatigue cracks as the main reason for re-machining were excluded from the data obtained in 2015.

Only tool wear is considered as the only reason for re-machining.

Table 5 Parameters included in the survey collected during 2015 annual production

Roll diameter after re-machining *RD* (mm)	Groove surface after re-machining *GS* (mm^2)	Amount of rolled material before re-machining *Q'* (kg)	The temperature of rolled material in front of the first rolling mill place *TR* (°C)	Contact time *CT* (s)	Carbon equivalent *CE* (%)
460.0	142255	945915	925	0.0609	0.8079
460.0	122848	1196252	925	0.0535	0.6836
460.0	148634	2146607	925	0.0629	0.7373
458.6	141334	33192382	925	0.0614	0.8487
458.6	165275	6042556	925	0.0610	0.6477
458.6	147666	23033377	925	0.0630	0.7413
456.0	121330	14101331	925	0.0513	0.6786
456.0	146768	17867192	925	0.0625	0.7214
456.0	140479	30322521	925	0.0618	0.7632
456.0	146768	9038047	925	0.0616	0.7512
456.0	164265	6610225	925	0.0674	0.6249
453.4	139624	16724445	925	0.0610	0.8079
453.4	120598	12175954	925	0.0514	0.6269
453.4	145869	29559639	925	0.0620	0.7632
450.6	138737	11690848	925	0.0606	0.8348
450.6	144935	20958064	925	0.0621	0.7831

5 CONCLUSIONS

In the one-year experiment, the groove surface after machining (mm^2), the diameter of the roll after re-machining [mm], the contact time (s), the average carbon equivalent (%), the average rolling temperature before entering the first rolling mill place (°C) and amount of rolled material before machine operation *Q'* (kg) were monitored.

With linear regression and artificial neural networks, two models were developed to predict the amount of rolled material before re-machining the rolls.

The average relative deviation between predicted and experimental data was chosen for the fitness function.

The relative deviation of the artificial neural network model from the experimental data is 41.0%. The relative deviation of the linear regression model from the experimental data is 70.9%. The results of the neural network model were 1.72 times better than the results of the linear regression model.

Both models have relatively low performance.

To validate and improve both models, additional data were collected in an experiment conducted throughout 2015. Fatigue cracks as a main reason for re-machining were excluded from the entire database obtained. Both models have developed once again, accordingly.

The relative deviation of the newly developed artificial neural network model from the experimental data is 32.8%.

The relative deviation of the new linear regression model from the experimental data is 57.2%.

Distinctive improved performance of both models in terms of the amount of rolled material before rolls re-machining can be attributed to the fact that fatigue cracks as the main reason for re-machining were excluded from the data obtained in 2015. Only tool wear is considered as the only reason for re-machining. Future research will focus more on collecting data related to rolls wear. As a result, it will be possible to predict the wear of the rolls and the maintenance of the rolls relatively accurately according to the rolling quantities in the timetable. It should also be noted that a customized methodology could be used in different rolling mill environments (e.g. rolling stands, different pass designs, and different rolls).

Notice

The paper will be presented at MOTSP 2022 – 13th International Conference Management of Technology – Step to Sustainable Production, which will take place in Primošten/Dalmatia (Croatia) on June 8–10, 2022. The paper will not be published anywhere else.

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Authors' contacts:

Miha Kovačič, Assoc. Prof.
(Corresponding author)
ŠTORE STEEL d.o.o., Štore
Železarska cesta 3, 3220 Štore, Slovenia
University of Ljubljana, Faculty of mechanical engineering, Ljubljana
Aškerčeva cesta 6, 1000 Ljubljana
College of Industrial Engineering Celje, Celje
Mariborska cesta 2, 3000 Celje, Slovenia
+386 (0)3 7805 262, miha.kovacic@store-steel.si

Andrej Mihevc
ŠTORE STEEL d.o.o., Štore
Železarska cesta 3, 3220 Štore, Slovenia

Milan Terčelj, Prof.
Faculty of Natural Sciences and Engineering, Department of Materials and
Metallurgy, Aškerčeva cesta 12, 1000 Ljubljana, Slovenia
+386 1 4704 506, milan.tercelj@ntf.uni-lj.si

Uroš Župerl, Assoc. Prof.
University of Maribor, Faculty of mechanical engineering, Maribor
Smetanova ulica 17, 2000 Maribor, Slovenia
+38622207621, uros.zuperl@um.si