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Reduction of surface defects by optimization of casting speed using genetic programming: An industrial case study

Kovacic, M.[a,b,c,*], **Zuperl, U.**[d], **Gusel, L.**[d], **Brezocnik, M.**[d]

[a]ŠTORE STEEL, d.o.o., Research and Development, Štore, Slovenia
[b]University of Ljubljana, Faculty of Mechanical Engineering, Laboratory for Fluid Dynamics and Thermodynamics, Ljubljana, Slovenia
[c]College of Industrial Engineering, Celje, Slovenia
[d]University of Maribor, Faculty of mechanical engineering, Maribor, Slovenia

A B S T R A C T

Štore Steel Ltd. produces more than 200 different types of steel with a continuous caster installed in 2016. Several defects, mostly related to thermomechanical behaviour in the mould, originate from the continuous casting process. The same casting speed of 1.6 m/min was used for all steel grades. In May 2023, a project was launched to adjust the casting speed according to the casting temperature. This adjustment included the steel grades with the highest number of surface defects and different carbon content: 16MnCrS5, C22, 30MnVS5, and 46MnVS5. For every 10 °C deviation from the prescribed casting temperature, the speed was changed by 0.02 m/min. During the 2-month period, the ratio of rolled bars with detected surface defects (inspected by an automatic control line) decreased for the mentioned steel grades. The decreases were from 11.27 % to 7.93 %, from 12.73 % to 4.11 %, from 16.28 % to 13.40 %, and from 25.52 % to 16.99 % for 16MnCrS5, C22, 30MnVS5, and 46MnVS5, respectively. Based on the collected chemical composition and casting parameters from these two months, models were obtained using linear regression and genetic programming. These models predict the ratio of rolled bars with detected surface defects and the length of detected surface defects. According to the modelling results, the ratio of rolled bars with detected surface defects and the length of detected surface defects could be minimally reduced by 14 % and 189 %, respectively, using casting speed adjustments. A similar result was achieved from July to November 2023 by adjusting the casting speed for the other 27 types of steel. The same was predicted with the already obtained models. Genetic programming outperformed linear regression.

A R T I C L E   I N F O

Keywords:
Continuous casting of steel;
Surface defects;
Automatic control;
Machine learning;
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Prediction;
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**Corresponding author:*
miha.kovacic@store-steel.si
(Kovacic, M.)

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1. Introduction

Modern steel production is hard to imagine without continuous casting. However, due to the thermomechanical behaviour during continuous casting, especially in the mould, several types of defects can occur on the cast material. These defects can also manifest on the rolled material. They can be reduced or eliminated with several approaches:

- Optimization of casting equipment (e.g., tundish, submerged entry nozzles, mould or water sprays geometry, casting powder, tundish powder),
- Optimization of secondary metallurgy (e.g., deoxidation, refinement, homogenization, stirring), and

- Optimization of casting parameters (e.g., casting temperature, speed, cooling water flow and pressure).

In the literature, adjustments to the casting speed have been discussed in relation to casting defects (e.g., surface defects [1-13], breakouts [9, 14, 15]) and productivity [1, 3, 14-16]. These discussions have involved individual steel grades [1, 9] or have been more general [3-5, 10-12, 15-17]. Additional factors such as the melt level in the mould [17, 18], melt level fluctuations [12, 17, 18], and melt flow [3] have also been examined. Artificial intelligence approaches have been utilized as well [4, 7, 10, 16, 17]. Unfortunately, these attempts have only been practically implemented in an industrial environment a few times [11, 15, 17].

This article investigates the reduction of surface defects, detected during the examination (via an automatic control line) of the rolled material, using casting speed adjustments based on the casting temperature. The average casting speed adjustments were calculated for several different grades using an in-house developed solidification model [19, 20]. The primary objective during simulations was to maintain the same metallurgical length (i.e., the distance from the mould to the location where the entire melt solidifies) by adjusting the casting speed when the casting temperature changed. Based on several simulations, for every 10 °C deviation from the prescribed casting temperature, the speed was adjusted by 0.02 m/min. The casting temperature was determined based on the content of carbon, sulphur, and aluminium, the liquidus temperature (calculated using the Wensel equation [21]), and the number of cast sequences (several batches – individual melts are continuously cast without interruption).

The materials and methods section discusses the significance of data collection. Subsequently, this data is utilized to predict the ratio of rolled bars with detected surface defects and their lengths using linear regression and genetic programming methods. The results are then analysed and implemented in practice. Finally, the general results are analysed and conclusions are drawn.

2. Materials and methods

Production at the Štore Steel plant begins with scrap melting in an electric arc furnace, followed by tapping, ladle treatment (i.e., secondary metallurgy), and continuous casting of billets measuring 180 mm × 180 mm. The billets can undergo additional heat treatment or be cooled under hoods. Before rolling, they are reheated. The rolled bars can then be straightened, examined for inner soundness and surface quality, cut, sawn, chamfered, drilled, and peeled.

Since March 2016, a new two-strand continuous casting machine with a radius of 9 m has been in operation. The solidification process involves a water-cooled copper mould for primary cooling, water sprays for secondary cooling, and air cooling for tertiary cooling.

During primary cooling, the solidified shell is subjected to thermomechanical stresses, which can lead to numerous casting defects. In the case of square billets, non-uniform shell solidification (i.e., non-uniform heat removal in the mould) can result in rhombic distortion (i.e., rhomboidity). This distortion can cause off-corner cracks, which manifest as longitudinally opened surface defects on the rolled material. These defects are typically detected during an automatic control line examination.

The origin of open surface defects on rolled material can be confirmed based on metallurgical reports, which include analyses of billets and both flat and round bars, dating back to the initiation of the continuous caster in 2016. Fig. 1 displays a macro-etched sample of the billet's cross-section. A typical bright macrostructure is observable due to the operation of the mould's electromagnetic stirrers (indicated by arrows). Subsurface cracks outside the corner are also visible in the upper left and lower right corners. The same billet macrostructure and open cracks outside the corners can be seen in the cross-section of the macro-etched round rolled bar, as shown in Fig. 2.

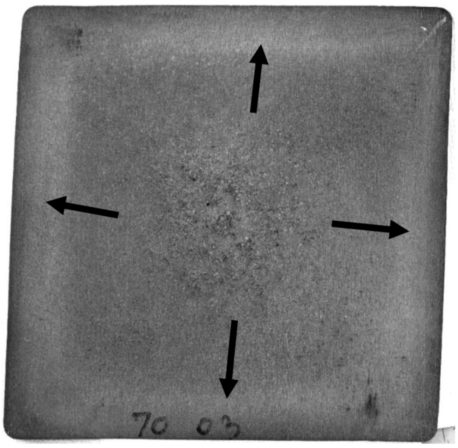

Fig. 1 A macro-etched sample of the billet's cross-section reveals a typical bright macrostructure, which can be observed due to the operation of the mould's electromagnetic stirrers (indicated by arrows). Subsurface cracks outside the corner are also visible in the upper left and lower right corners.

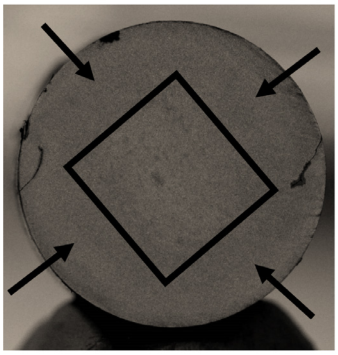

Fig. 2 The black square signifies the orientation of the billet. Both defects (on the left and right) are located at the corner of the billet, indicating the presence of off-corner cracks in the billet, which is a cast semi-product. The operation of the mould's electromagnetic stirrers results in a typically bright macro-structure, as indicated by the arrows.

In May 2023, a project was started where the casting speed was adjusted according to the casting temperature. This adjustment involved steel grades with the highest number of surface defect occurrences (i.e., the average ratio of rolled bars with detected surface defects and their lengths) and varying carbon contents: 16MnCrS5, C22, 30MnVS5, and 46MnVS5. For every 10 °C deviation from the prescribed casting temperature, the speed was altered by 0.02 m/min. The number of cast batches, the average ratio of rolled bars with detected surface defects, and their lengths for the one-year period from May 2022 to May 2023 are presented in Table 1.

In an effort to reduce casting defects on the rolled material, the following parameters were collected for the batches cast from May 2023 to June 2023. This two-month period involved adjustments to the casting speed based on the casting temperature. The adjustments were specifically applied to steel grades with the highest occurrences of surface defects, namely 16MnCrS5, C22, 30MnVS5, and 46MnVS5:

- Chemical composition: Content of carbon, silicon, manganese, sulphur, chromium, nickel, aluminium and vanadium. Chemical composition influence on material properties also during solidification (e.g., shrinkage, ductility, mechanical properties).
- Casting parameters:
  - Average casting temperature (in °C). Casting temperature influences the thermal field in the mould, which influences the heat removal and solidification.
  - Changes of the casting speed based on deviation from the prescribed casting temperature (m/min). For every 10 °C deviation from the prescribed casting temperature, the speed was changed by 0.02 m/min. Casting speed influences the heat removal and solidification.

- – The average mould water flow (in l/min). The highest heat removal occurs in the mould, where thermomechanical behaviour influences on shell solidification.
- – The average cooling water pressure (in bar) and flow (in l/min) are observed in the first zone of secondary cooling, which is directly below the mould. The melt primarily solidifies in the mould. After exiting the mould, the strand is cooled by water sprays. The water flux can be automatically adjusted, varying the water pressure and flow. Secondary cooling also influences the thermomechanical behaviour during solidification.
- Average ratio of rolled bars with detected surface defects (in %).
- Average length of detected surface defects (in mm/mm).

Rolled bars are examined using an automatic control line equipped with a flux leakage inspection system, which has a surface defect depth detection limit of 0.15 mm. Data on defect depths and lengths for each examined bar are available. It's important to note that scrap is considered when the maximum permissible depth of surface defects is exceeded. The maximum permissible depth is defined by the customer or international standards (e.g., ISO 9443, EN 10221, EN 10277-1) and can be significantly (i.e., several times) larger than the detection limit. Accordingly, this study uses data on detectable defects that are deeper than the detection limit of 0.15 mm.

Table 1 The number of cast batches, average ratio of rolled bars with detected surface defects and their lengths for individual steel grade for the one-year period from May 2022 and May 2023

Steel grade	Number of cast batches	Average ratio of rolled bars with the detected surface defects, %	The length of the detected surface defects, mm/m
C45S	255	12.92	10.57
46MNVS5	67	25.52	18.08
16MNCRS5	70	11.27	1.41
30MNVS6	29	16.28	12.29
42CRMOS4	26	13.90	3.73
28MNCRNIB	43	6.97	4.88
20MNCRS5	43	5.65	0.30
C45	36	6.36	3.07
20MNV6	83	2.62	0.57
C22	17	12.73	1.425
S355J2	28	7.59	1.46
42CRMO4	23	8.79	1.55
51CRV4	22	8.52	3.48
20NICRMOS2-2	16	8.26	0.63
16MNCR5	28	3.81	0.47
23MNNICRMO5-2	15	7.04	8.80
18CRNIMO7-6	18	5.84	0.07
C35S	7	11.38	32.62
25CRMOS4	6	10.91	9.88
28MNCRB7	6	9.15	1.80
25CRMO4	8	6.30	0.06
100CR6	9	5.02	2.13
C60	19	2.25	0.26
20MNCR5	6	6.04	0.27
31CRMOV9	4	6.67	2.71
38MNVS6	7	3.34	0.50
16NICRS4	7	3.06	6.62
17NICRMOS6-4	4	2.09	0.08
30CRNIMO8	3	2.11	2.67
15CRNI6	3	2.06	0.40
P460NH	3	1.38	0.09

Before implementing changes to the casting speed based on deviations from the prescribed casting temperature into the continuous casting process, models were developed using linear regression and genetic programming. These models predict the ratio of rolled bars with detected surface defects and the length of these defects. By comparing the calculated ratios of rolled bars with detected surface defects and their lengths, with or without changes in casting speed, further measures were taken.

Table 2 Data from May 2023 to June 2023 where the casting temperature has been adjusted, including steel grades with the highest number of surface defect occurrences – 16MnCrS5, C22, 30MnVS5 and 46MnVS5

Batch number	Steel grade	C *C*, %	Si *Si*, %	Mn *Mn*, %	S *S*, %	Cr *Cr*, %	Ni *Ni*, %	Al *Al*, %	V *V*, %	Changes of the casting speed *SPEED*, m/min	The average cooling water flow in the mould *FLUXM*, l/min	The average cooling water flow in the first zone of secondary cooling *FLUXZ1*, l/min	The average cooling water pressure in the first zone of secondary cooling *PRESS*, bar	The average casting temperature *TEMP*, °C	Average ratio of rolled bars with the detected surface defects, %	The length of the detected surface defects, mm/m
1	16MNCR5	0.16	0.24	1.11	0.009	1.00	0.19	0.021	0.01	0.00	1780.03	35.21	2.42	1553.0	0.58	0.12
2	16MNCR5	0.16	0.24	1.12	0.008	1.02	0.17	0.022	0.01	0.00	1780.01	35.19	2.42	1552.0	1.80	0.11
3	16MNCR5	0.16	0.25	1.12	0.008	1.00	0.13	0.022	0.01	0.02	1780.04	34.99	2.55	1564.0	0.59	0.12
4	16MNCR5	0.17	0.25	1.12	0.007	0.99	0.16	0.022	0.01	0.00	1780.05	34.84	2.43	1551.0	2.27	0.17
5	30MNVS6	0.29	0.58	1.43	0.027	0.12	0.09	0.013	0.09	0.02	1780.01	35.09	2.41	1542.0	2.91	0.67
6	30MNVS6	0.30	0.60	1.40	0.033	0.12	0.07	0.016	0.08	0.00	1780.03	35.01	2.44	1539.0	2.44	1.03
7	30MNVS6	0.29	0.56	1.41	0.033	0.20	0.12	0.013	0.09	0.02	1779.99	35.14	2.49	1542.0	5.56	0.21
8	30MNVS6	0.30	0.60	1.37	0.026	0.19	0.10	0.013	0.10	0.00	1780.03	34.97	2.47	1538.0	0.97	0.09
9	46MNVS5	0.47	0.65	1.15	0.062	0.26	0.15	0.006	0.11	0.00	1780.03	32.26	2.30	1517.0	3.45	1.22
10	46MNVS5	0.47	0.63	1.17	0.063	0.26	0.16	0.006	0.11	0.02	1780.02	32.11	2.28	1524.0	3.52	1.32
11	46MNVS5	0.47	0.64	1.15	0.068	0.24	0.16	0.005	0.11	0.02	1779.97	31.94	2.00	1513.0	2.45	0.31
12	46MNVS5	0.47	0.65	1.15	0.063	0.24	0.16	0.005	0.11	0.02	1780.03	32.53	2.08	1525.0	11.16	1.41
13	46MNVS5	0.47	0.64	1.15	0.063	0.24	0.16	0.005	0.11	0.00	1780.01	32.10	2.03	1514.0	21.10	2.16
14	46MNVS5	0.47	0.66	1.15	0.066	0.25	0.16	0.005	0.11	0.02	1780.01	31.81	1.99	1516.0	18.07	2.36
15	46MNVS5	0.47	0.66	1.15	0.060	0.25	0.17	0.005	0.11	0.02	1780.02	32.25	2.04	1534.0	12.48	4.85
16	46MNVS5	0.47	0.64	1.15	0.067	0.24	0.17	0.005	0.11	0.00	1780.00	31.72	1.98	1526.0	17.58	9.21
17	46MNVS5	0.47	0.64	1.15	0.064	0.24	0.16	0.005	0.11	0.00	1780.00	31.96	2.01	1513.0	16.28	19.68
18	46MNVS5	0.47	0.66	1.14	0.063	0.24	0.16	0.005	0.11	0.00	1780.00	31.90	2.11	1516.0	2.22	2.07
19	C22	0.22	0.21	0.43	0.006	0.20	0.11	0.020	0.00	0.00	1780.03	42.22	3.50	1554.0	2.43	0.14
20	C22	0.22	0.24	0.41	0.007	0.14	0.10	0.019	0.00	0.02	1779.98	42.16	3.49	1558.0	1.45	0.04
21	C22	0.22	0.23	0.44	0.006	0.10	0.07	0.018	0.00	0.02	1779.95	42.15	3.48	1555.0	1.39	0.12
22	C22	0.22	0.25	0.43	0.003	0.08	0.08	0.024	0.00	0.02	1779.99	42.20	3.49	1552.0	1.82	0.64
23	C22	0.23	0.24	0.43	0.004	0.11	0.08	0.020	0.00	0.02	1780.02	42.18	3.48	1553.0	1.55	0.18
24	C22	0.22	0.25	0.46	0.008	0.14	0.09	0.020	0.00	0.00	1780.00	42.17	3.48	1555.0	2.18	0.12

3. Results and discussion

Based on the collected data (Table 2), the prediction of the average ratio of rolled bars with detected surface defects, as well as the average length of detected surface defects, was conducted using linear regression and genetic programming. The fitness function was defined as the average deviation between the predicted and experimental data. It is defined as follows:

$$\Delta = \frac{\sum_{i=1}^{n} |X_i - X'_i|}{n} \tag{1}$$

where n is the size of the monitored data and X'_i and X_i are the actual and the predicted (i.e. calculated) values, respectively.

3.1 Modelling of the ratio of rolled bars with detected surface defects and their lengths using linear regression

Linear regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables. It provides a way to predict the dependent variable's value based on the values of the independent variables, making it a valuable tool in fields such as machine learning, economics, engineering, and biology.

Based on the linear regression results, it can be concluded that the model significantly predicts the average ratio of rolled bars with detected surface defects ($p < 0.05$, ANOVA). It is found that 72.78 % of total variances can be explained by the variances of independent variables (R-square). The only significantly influential parameter is the average cooling water pressure in the first zone of secondary cooling (*PRESS*) ($p < 0.05$).

The linear regression model for predicting the average ratio of rolled bars with detected surface defects is as follows:

$$-0.789 \cdot C - 0.450 \cdot Si - 1.357 \cdot Mn + -0.235 \cdot S + 3.577 \cdot Cr - 0.302 \cdot Ni - 0.576 \cdot Al + 2.822 \cdot \mathrm{V} + 3.772 \cdot SPEED + 0.711 \cdot FLUXM + 0.015 \cdot FLUXZ1 - 0.455 \cdot PRESS + 0.002 \cdot TEMP - 1268.557. \quad (2)$$

The average deviation from experimental data is 2.32 %.

Similarly, the second model significantly predicts the average length of detected surface defects (p < 0.05, ANOVA). However, in this case, only 50.17 % of total variances can be explained by the variances of independent variables (R-square). Interestingly, in this context, there are no significantly influential parameters (p < 0.05).

The linear regression model for predicting the average length of detected surface defects is as follows:

$$-179.589 \cdot C + 44.737 \cdot Si - 116.991 \cdot Mn - 7.780 \cdot S - 99.020 \cdot Cr - 32.913 \cdot Ni - 39.153 \cdot Al + 409.933 \cdot V + 188.939 \cdot SPEED - 22.826 \cdot FLUXM - 2.781 \cdot FLUXZ1 - 17.145 \cdot PRESS + 0.228 \cdot TEMP + 40476.188. \quad (3)$$

The average deviation from the experimental data is 5.44 mm/m.

Based on the data gathered in Table 2 and the developed linear regression models, the average ratio of rolled bars with detected surface defects and the average length of detected surface defects were also calculated in the scenario where changes to the casting speed were not made.

According to calculations from both linear regression models, changes in casting speed contributed to a decrease in the average ratio of rolled bars with detected surface defects and the average length of detected surface defects, from 6.47 % to 5.68 % and from 3.81 mm/m to 2.01 mm/m, respectively.

3.2 Modelling of the ratio of rolled bars with detected surface defects and their lengths using genetic programming

Genetic programming is an evolutionary algorithm, similar to genetic algorithms, used for automatic generation of computer programs to solve problems. It involves evolving a population of computer programs over several generations, using genetic operators like crossover and mutation to produce new candidate solutions. The programs are represented as tree structures, allowing for the evolution of complex solutions. In genetic programming, the representation of solutions as tree structures enables the evolution of diverse and complex programs, allowing for the exploration of a broad solution space. Unlike genetic algorithms which typically evolve fixed-length strings, which are intended to solve a very broad spectrum of problems [22-28], genetic programming evolves variable-sized structures, allowing for more flexibility in representing solutions of varying complexity [29-31]. Genetic programming can automatically discover both the structure and parameters of a solution, making it suitable for problems where the optimal solution's form is not known a priori. The genetic programming operates on variable-length structures, making it more suitable for evolving complex solutions, especially in symbolic regression and automatic code generation.

The genetic programming method was used several times in Štore Steel Ltd. [32-36]. For the purposes of this study, organisms that underwent adaptation were indeed represented as mathematical expressions, i.e., models for predicting the average ratio of rolled bars with detected surface defects, and models for predicting the average length of detected surface defects. These models consist of the selected functions, i.e., basic arithmetical functions of addition, subtraction, multiplication and division, and terminal genes, i.e., independent input parameters, and random floating-point constants.

The LISP based in-house genetic programming system was run 200 times to develop independent civilizations. In each run we obtain either the model for prediction of the average ratio of rolled bars with detected surface defects or the average length of detected surface defects. After the modelling phase, we analysed the results and selected the two best prediction models.

The best genetically developed mathematical model for predicting the average ratio of rolled bars with detected surface defects obtained from 100 runs of genetic programming system is:

$$\frac{S}{Si}+\frac{Si}{PRESSZ1}+2SPEED+V\left(\frac{S}{Al}+\frac{Si}{PRESSZ1}+\frac{Si}{MnPRESSZ1(-5.45733+Si)(-S+SPEED+(Si+C(6.32902+C)Si)SPEED)}+(6.32902+PRESSZ1+6.32902Si)V\left(S\Big/\left(C(-S+SPEED+(Si+C(6.32902+C)Si)SPEED)\left(-5.45733+1\Big/\left((-S+SPEED+(Si+C(6.32902+Mn)Si)SPEED)\left(-5.45733+1\Big/\left(Mn(-S+SPEED+(Si+Si^2)SPEED)(-5.45733+(-5.45733+Si)Si(-S+SPEED+(Si+C(6.32902+C)Si)SPEED))\right)\right)\right)\right)\right)\right)-\left(0.1832\left(Si+C(6.32902+Si)\right)\right)\Big/\left(MnPRESSZ1Si\left(-S+Si^2+SPEED+\left(\frac{S}{C}+Si\Big/\left(MnPRESSZ1(-5.45733+Si)(-S+SPEED+(Si+C(6.32902+C)Si)SPEED)\right)\right)V\right)\right)\right). \tag{4}$$

The average deviation from experimental data is 1.59 %. The model obtained by genetic programming is 1.47-times better than the one obtained using linear regression.

The best mathematical model for predicting the average length of detected surface defects obtained from 100 runs of genetic programming system is:

$$\left(\frac{S+\dfrac{S}{-Mn+PRESSZ1+\dfrac{(-Mn+C(PRESSZ1+S))SPEED}{\dfrac{S}{Mn}+\dfrac{S+\dfrac{S}{-Mn+PRESSZ1+\dfrac{PRESSZ1+2CS-\frac{S}{SPEED}}{Mn}}+\dfrac{SPEED\left(-Mn+PRESSZ1+\frac{SPEED}{Mn}\right)}{Mn+S}}{(-1+PRESSZ1+2CS)(PRESSZ1-S+CMn(C+S))}}}}{(-1+PRESSZ1+2CS)\left(-Mn+PRESSZ1+\frac{SPEED}{Mn+S}\right)\left(PRESSZ1+CS-\dfrac{S+\dfrac{S}{-Mn+PRESSZ1+\frac{SPEED}{Mn}}+\dfrac{SPEED\left(-Mn+PRESSZ1+\frac{SPEED}{Mn}\right)}{Mn+S}}{(-1+PRESSZ1)S\left(PRESSZ1-S+\frac{SPEED}{C^2Mn}\right)}\right)}\right). \tag{5}$$

The average deviation from experimental data is 0.97 mm/m. The model obtained by genetic programming is 5.63-times better than the one obtained using linear regression.

Based on calculations using the two obtained genetic programming models, changes in casting speed contributed to a decrease in the average ratio of rolled bars with detected surface defects and the average length of detected surface defects, from 6.1 % to 6.0 % and 8.87 mm/m to 1.57 mm/m.

3.3 Discussion and validation of modelling results

Based on modelling results the average ratio of rolled bars with detected surface defects and the average length of detected surface defects could be decreased in the best case scenario from 6.47 % to 5.68 % (for 1.14-times) and from 8.87 mm/m to 1.57 mm/m (for 5.65-times), if the casting speed would be adjusted based on deviations from the prescribed casting temperature, respectively.

Accordingly, the casting speed was adjusted based on the casting temperature for all casting batches from July 2023 to November 2023. The data obtained was compared to a one-year period (May 2022 to May 2023) where no casting speed adjustments were made. These results are collected in the Table 3.

Based on actual data the average ratio of rolled bars with detected surface defects and the average length of detected surface defects decreased statistically significantly (t-test, $p < 0.05$) from 10.63 % to 8.82 % and from 6.20 mm/m to 3.40 mm/m in the period without (from May 2022 to May 2023) and with casting speed adjustments (from July 2023 to November 2023), respectively.

Out of 31 different steel grades the average ratio of rolled bars with detected surface defects and the average length of detected surface defects statistically significantly decreased in 11 and 15 steel grades, respectively, while the rest remained statistically significantly the same (t-test, $p < 0.05$).

Table 3 Data from May 2023 to June 2023 where the casting temperature has been adjusted, including steel grades with the highest number of surface defect occurrences - 16MnCrS5, C22, 30MnVS5 and 46MnVS5

Steel grade	Number of batches from May 2022 to May 2023 (period without casting speed adjustments)	Number of batches from July to November 2023 (period with casting speed adjustments)	Number of batches from July to November 2023 (period with casting speed adjustments), where the casting speed was actually adjusted	The average ratio of rolled bars with detected surface defects from May 2022 to May 2023 (period without casting speed adjustments), %	The average ratio of rolled bars with detected surface defects from July to November 2023 (period with casting speed adjustments), %	The average length of detected surface defects from May 2022 to May 2023 (period without casting speed adjustments), mm/m	The average length of detected surface defects from July to November 2023 (period with casting speed adjustments), mm/m	The average ratio of rolled bars with detected surface defects – significance (t.test, $p<0.05$)	The average length of detected surface defects – significance (t.test, $p < 0.05$)
17NICRMOS6-4	4	3	3	2.09	4.62	0.18	0.08	NO	NO
30CRNIMO8	3	2	2	2.11	0.56	2.67	0.02	NO	NO
C60	19	9	6	2.25	3.47	0.26	0.83	NO	NO
20MNV6	83	39	23	2.62	1.29	0.57	0.19	YES	YES
16NICRS4	7	4	3	3.06	2.79	6.62	0.21	NO	YES
38MNVS6	7	6	2	3.34	6.88	0.50	1.03	NO	NO
16MNCR5	28	12	5	3.81	4.01	1.31	0.47	NO	YES
100CR6	9	2	0	5.02	10.43	2.13	1.98	NO	NO
18CRNIMO7-6	18	7	4	5.84	5.89	0.07	0.05	NO	NO
20MNCR5	6	2	1	6.04	3.19	0.27	0.35	NO	NO
25CRMO4	8	8	5	6.30	4.84	0.06	0.09	NO	NO
C45	36	18	16	6.36	1.95	3.07	0.32	YES	YES
31CRMOV9	4	4	3	6.67	7.46	2.71	2.82	NO	NO
28MNCRNIB	43	8	4	6.97	5.40	4.87	1.27	YES	YES
15CRNI6	3	2	1	6.98	2.06	1.48	0.40	YES	YES
23MNNICRMO5-2	15	9	3	7.04	6.50	8.80	0.51	NO	YES
S355J2	28	10	4	7.59	3.78	1.46	0.76	YES	NO
51CRV4	22	4	4	8.52	12.18	3.48	0.62	NO	YES
42CRMO4	23	5	2	8.79	10.54	1.55	0.96	NO	NO
28MNCRB7	6	4	2	9.15	16.04	1.80	1.55	NO	NO
P460NH	3	4	2	9.23	1.38	0.75	0.09	YES	YES
20MNCRS5	43	15	1	10.59	5.65	1.12	0.30	YES	NO
25CRMOS4	6	3	2	10.91	6.00	9.88	0.57	NO	YES
16MNCRS5	70	39	9	11.27	7.93	1.41	1.29	YES	NO
C35S	7	4	2	11.38	5.61	32.62	6.00	YES	NO
C22	17	18	9	12.73	4.11	1.43	0.15	YES	YES
C45S	255	141	65	12.92	13.00	10.57	6.46	NO	YES
20NICRMOS2-2	16	9	3	13.45	8.26	1.83	0.63	NO	NO
42CRMOS4	26	10	5	13.90	9.71	3.73	3.28	NO	NO
30MNVS6	29	12	5	16.28	13.40	12.29	4.57	NO	NO
46MNVS5	67	35	4	25.52	16.99	18.08	9.98	YES	YES

4. Conclusion

In the article the reduction of surface defects, detected during examination (automatic control line) of the rolled material, with casting speed adjustments based on the casting temperature, is presented. For all produced steel grades, the same casting speed of 1.6 m/min was used before. The average casting speed adjustments were calculated for several different grades based on in-house developed solidification model. For every 10 °C deviation from the prescribed casting temperature, the speed was changed by 0.02 m/min.

The reduction of surface defects was designed as follows:

- Period with casting speed adjustments based on the casting temperature involving steel grades with highest occurrences of surface defects and with various carbon content: 16MnCrS5, C22, 30MnVS5 and 46MnVS5.
- Modelling of the average ratio of rolled bars with detected surface defects and the average length of detected surface defects using linear regression and genetic programming.
- Implementing of modelling results based on four most problematic steel grades (16MnCrS5, C22, 30MnVS5 and 46MnVS5) into practice – the casting speed adjustments were used for all steel grades from July 2023 to November 2023.

- Analysis of the average ratio of rolled bars with detected surface defects and the average length of detected surface defects for batches cast from July 2023 to November 2023.
- Comparison of the batches produced prior (from May 2022 to May 2023) and after (from July 2023 to November 2023) the implementation of casting speed adjustments.

Chemical composition (content of carbon, silicon, manganese, sulphur, chromium, nickel, aluminium and vanadium) and casting parameters (casting speed adjustments, the average mould cooling water flow, the average cooling water flow and pressure in the first zone of the secondary cooling, casting temperature) were gathered for the batches cast from May 2023 to June 2023.

Based on gathered data modelling was performed using linear regression and genetic programming. For the fitness function, the average deviation between predicted and experimental data was selected.

The average deviation of the linear regression model for predicting the average ratio of bars with detected surface defects from experimental data is 2.32 %. The average deviation of the linear regression model for predicting the average length of detected surface defects from experimental data is 5.44 mm/m. Based on calculations from both linear regression models, the changes in casting speed contributed to a decrease in the average ratio of rolled bars with detected surface defects and the average length of detected surface defects, from 6.47 % to 5.68 % and 3.81 mm/m to 2.01 mm/m, respectively.

The average deviation of the genetic programming model for predicting the average ratio of bars with detected surface defects from experimental data is 1.59 %. The model obtained by genetic programming is 1.47 times better than the one obtained using linear regression. The average deviation of the linear regression model for predicting the average length of detected surface defects from experimental data is 0.97 mm/m. The model obtained by genetic programming is 5.63 times better than the one obtained using linear regression. Based on calculations using both obtained genetic programming models, the changes of casting speed contributed to decreasing the average ratio of rolled bars with detected surface defects and the average length of detected surface defects, from 6.1 % to 6.0 % and 8.87 mm/m to 1.57 mm/m, respectively.

Accordingly, the casting speed has been adjusted based on the casting temperature for all cast batches from July 2023 to November 2023. The obtained data were compared with a one-year period (from May 2022 to May 2023) where adjustments to the casting speed were not made. Based on actual data, the average ratio of rolled bars with detected surface defects and the average length of detected surface defects decreased statistically significantly (t-test, $p < 0.05$) from 10.63 % to 8.82 % and from 6.20 mm/m to 3.40 mm/m in the period without (from May 2022 to May 2023) and with casting speed adjustments (from July 2023 to November 2023), respectively. Out of 31 different steel grades, the average ratio of rolled bars with detected surface defects and the average length of detected surface defects statistically significantly decreased in 11 and 15 steel grades, respectively, while the rest remained statistically insignificantly the same (t-test, $p < 0.05$).

Until June 2024, detailed analyses of the possible casting speed adjustments for individual steel grades will be conducted with the in-house developed solidification model. The geometry of the mould and the geometry, pumps, and nozzles of the secondary cooling will be changed.

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