

# REDUCTION OF SURFACE DEFECTS AND OPTIMIZATION OF CONTINUOUS CASTING OF 70MnVS4 STEEL

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## Abstract

High-strength steel 70MnVS4 is often used for forging connecting rods in the automotive industry. Connecting rod performance depends also on surface quality. Several defects, including surface defects, originate from the continuous casting process. The paper presents the monitoring of the most influential parameters (casting temperature, type of mould steel jacket, casting speed, water flux in the mould and the difference between input and output water temperature in the mould) during continuous casting of 70MnVS4 steel. Also the results of surface control of the rolled material (automatic control line) were collected. Using the gathered data, the model for predicting the ratio between material with surface defects and the examined material was developed using linear regression and genetic programming. Based on modelling results, only one type of mould steel jacket was used, while casting speed and mould water flow were increased from 1.13 m/min to 1.18 m/min and from 1300 l/min to 1500 l/min, respectively. In the period from January 2015 to October 2018 the scrap rate of 70MnVS4 and overall scrap rate was reduced by 22.29 % and 18.04 %, respectively.

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**Key Words:** Steel, Continuous Casting, Surface Defects, Casting Parameters, Modelling and Optimization, Genetic Programming

## 1. INTRODUCTION

In the steelmaking industry, continuous casting is the most used process for solidifying steel melt of defined chemical composition into cast semi-products (e.g. billets, blooms, slabs) [1].

The typical continuous casting process is presented in Fig. 1. After discharging the melted steel into the ladle, the slag is formed, the melting bath is deoxidized, desulfurized and, finally, alloying and homogenization (i.e. argon stirring) are carried out. The melt pours into the tundish after the sliding gate is opened, with continuous casting being established throughout a casting system with impact pod, stoppers, submerged entry nozzles and water-cooled copper moulds. After exiting the mould, the strands are cooled by a water spray system. Solidified cast semi-products (e.g. billets) are cut and cooled down to room temperature or directly and slightly reheated before hot deforming (i.e. rolling) [1-3].

During solidification, several types of defects can be attributed to extreme thermo-mechanical conditions in the mould [2-5] (Fig. 2). Due to the diversity of serial production equipment, which includes a wide spectrum of influencing parameters, it is difficult to predict the cast semi-product properties and quality [2-6].

A literature review reveals that several experimental studies (e.g. [7-9]) that include a few actual implementations in practice have been conducted (e.g. [6, 10-12]).

In [7] several casting parameters were monitored – those which can be controlled (casting speed, melt level, cooling water flow) and those without a possibility of being controlled (casting temperature and casting powder quantity). Using the collected data, the statistical analysis of influencing parameters and prediction of cracks, inclusions, bleedings, oscillation marks and depressions were predicted. The authors concluded that only temperature measurements are a statistically significant parameter.

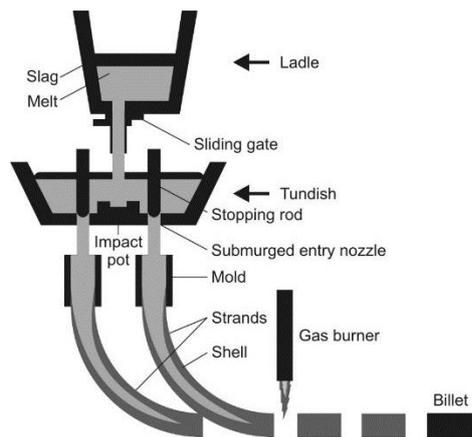


Figure 1: Typical continuous casting process.

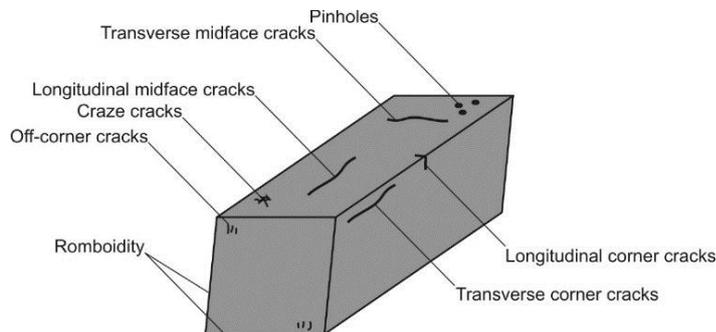


Figure 2: Continuously cast product and defects originating from the mould.

Similarly, the same authors [8] designed a control system for detecting surface defects during continuous casting. The same system could be used for preplanning of cast semi-products which can be used directly after casting or, on the other hand, after reheating. The authors emphasized again that the continuous casting control system should only be based on thermocouples temperature measurements in the mould, which are highly correlated with surface defects.

Santos et al. [9] introduced a 2-dimensional solidification model with input casting parameters (primary cooling in the mould and secondary cooling) that can be controlled. The selection of proper settings is conducted using a genetic algorithm. Surface quality is very much determined by uniformity of cooling conditions. This made it possible to obtain the optimal strand temperature and casting length. It can be seen that the model and optimization results have been validated throughout the literature and in experiments in production.

Meng et al. [13] analysed the thermo-mechanical behaviour of thin solidified shell during mould oscillation. On the basis of steel flow and bending of the solidified shell due to oscillation, the initial crack formation was modelled using mathematical modelling. Also taken into account in terms of crack propagation were formed primary dendrites. It was discerned that the most important factor is mould oscillation.

In [14], the friction of solidified steel passing through the mould was analysed. The surface quality of the cast product is influenced by the friction of the solidified shell during strand withdrawal from the mould. On the basis of steel grade, casting powder and oscillation parameters, the prediction of power needed for strand withdrawal was conducted using a neural network model.

Similarly, Thomas et al. [15] discussed the influences oscillation and melt level in the mould have on surface defect occurrences. It was discovered that the deeper oscillation marks correlated with deep depressions that cause defects during solidification of the melt. The depth of the oscillation marks and depressions strongly influence heat removal, which can be

detected using thermocouples that were already installed in the mould. On the basis of real data, improved melt level control was implemented. The defects were eliminated.

In [16], crack formation during continuous casting of slabs were analysed. A model pertaining to crack occurrence was obtained on the basis of casting speed, casting powder chemical composition, mould parameters (cooling and geometry) and secondary cooling.

Konishi et al. [17] developed a model for longitudinal midface crack occurrence during continuous casting of peritectic steel based on a 1-dimensional delta-to-gamma transformation model, 2-dimensional temperature and stress field. The stress field was obtained using ABAQUS software. It was established that for a crack-free shell a uniform temperature and, consequently, uniform stress field is needed.

Heat removal was analysed also in [4]. It was established that lower casting powder viscosity, and its melting point, increased heat flux in the mould; on the other hand, increased casting speed reduced heat flux in the mould. The heat removal was higher during casting of steel with higher carbon content. The same was true of reducing submerged entry nozzle depth. Among the several observed parameters, the most influential was copper mould thickness. Cracks could be avoided through controlling the heat removal from the mould in the off-corner depressions.

In [10] primary cooling and secondary cooling system parameters were used to develop a finite difference heat transfer model. The input parameters were optimized using genetic algorithms. Based on casting equipment and parameters constraints, productivity was increased, smaller temperature gradients were achieved and water consumption was reduced.

Through making changes to the steelmaking process (i.e. deoxidation of steel), the authors of this paper succeeded also in reducing surface defects of C45 [6] in the casting process. Several parameters during ladle treatment (i.e. treating the steel melt) and continuous casting were taken into account. The model obtained with genetic programming was used for optimization of influential parameters. The scrap rate was reduced by more than 35-times.

There are also several other interesting papers that study the manufacturing of steel, and that implement optimizations and/or numerical analyses of continuous casting of steel, iron and alloys as well as optimization of surface integrity, e.g. [18-23].

For the purpose of this article the most influential parameters during three-strand continuous casting of 70MnVS4 steel were monitored. The ratio between material with surface defects and the examined material during automatic control line examination was predicted on the basis of the collected data. Consequently, the optimization of the continuous casting process was conducted. This paper begins with an explanation of the methods; then the modelling and implementation of results into practice is presented, before, finally, conclusions are drawn.

## **2. MATERIALS AND METHODS**

In Štore Steel Ltd., which is one of Europe's major flat spring steel producers, 70MnVS4 steel is produced from scrap that is melted using an electric arc furnace. After reaching tapping temperature, the melt is discharged into the ladle, the slag is formed, the melting bath is deoxidized, desulfurized and, finally, alloying and homogenization (i.e. argon stirring) are carried out. The average batch weighs 50 t. The melt pours into the tundish after the sliding gate is opened, with continuous casting being established throughout a casting system with impact pod, stoppers, submerged entry nozzles and water-cooled copper moulds. For casting of the 180 × 180 mm billets, a three-strand continuous caster with 6 m radius is used.

The billets are reheated up to rolling temperature and rolled into round bars with a diameter of up to 50 mm. The same rolled bar surface is also examined using the automatic control line. The surface control is based on the flux leakage method, meaning that the surface

of the material is locally magnetized and that deviations of magnetic flux (i.e. flux leakage) at the opened cracks (Fig. 3) are detected.

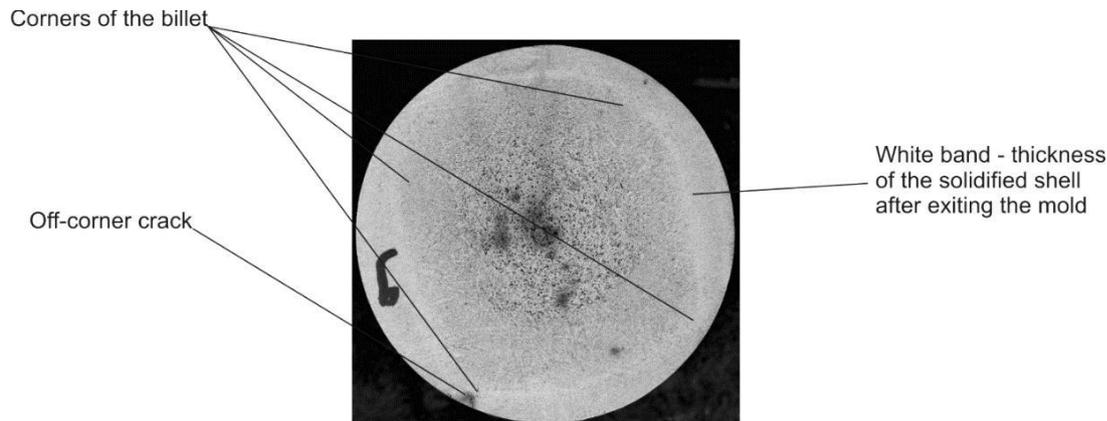


Figure 3: Surface crack (off-corner crack) at macro-etched  $\phi 40$  70MnVS4 rolled bar cross-section.

In 2014, 175 consecutively batches of 70MnVS4 were cast. The following parameters were gathered:

- Average casting temperature [ $^{\circ}\text{C}$ ] influences thermo-mechanical processes during melt solidification.
- The number of constructional steel jackets used in the mould housing. Additionally, stainless steel jackets can be used. Steel jackets assure uniform water distributions all over the copper mould at a water flow rate of 1400 l/min. Note that in Štore Steel Ltd. the gap between the steel jacket and the mould is only 4 mm and that the surface roughness of the corroded steel drastically influences the water flow regime and, consequently, heat removal. Typical mould housing is schematically presented in Fig. 4.
- Average casting speed of an individual strand [m/min]. Casting speed is influenced by casting temperature and it is automatically regulated during casting.
- Average mould water flow [l/min] for each mould. Water provides intensive mould cooling. During cooling, the input and output water temperature changes.
- The average difference between input and output water temperature for each mould [ $^{\circ}\text{C}$ ].
- The ratio between material with surface defects and the examined material after surface examination using automatic control line (i.e. flux leakage method). Note that not all material with surface defects is nonconform (i.e. scrap) – it depends on permissible defect depth. Accordingly, we should distinguish between material with surface defects and scrap.

The average values and standard deviations of gathered parameters for 70MnVS4 are presented in Table I.

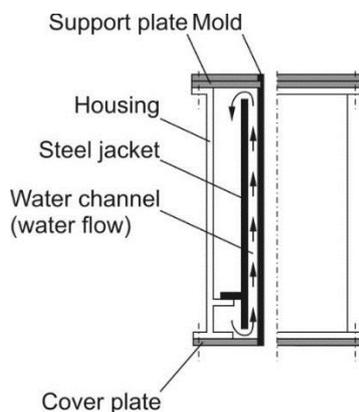


Figure 4: The mould and its housing.

Table I: The average values and standard deviations of gathered parameters for 70MnVS4.

Parameter	Label	Average	St. dev.
Average casting temperature [°C]	<i>CT</i>	1517.4	5.12
Number of constructional steel jackets	<i>J</i>	0.70	0.61
Average casting speed 1 [m/min]	<i>CS1</i>	1.111	0.0191
Average casting speed 2 [m/min]	<i>CS2</i>	1.111	0.0185
Average casting speed 3 [m/min]	<i>CS3</i>	1.113	0.0190
Average mould water flow 1 [l/min]	<i>W1</i>	1416.8	22.70
Average mould water flow 2 [l/min]	<i>W2</i>	1416.1	23.08
Average mould water flow 3 [l/min]	<i>W3</i>	1413.8	21.72
Average difference between input and output mould water temperature 1 [°C]	<i>DT1</i>	7.54	0.307
Average difference between input and output mould water temperature 2 [°C]	<i>DT2</i>	7.53	0.278
Average difference between input and output mould water temperature 3 [°C]	<i>DT3</i>	7.65	0.294
The ratio between material with surface defects ( $Q_d$ ) and examined material ( $Q$ ) [%]	$\frac{Q_d}{Q}$	41.59	19.87

### **3. MODELLING OF THE RATIO BETWEEN MATERIAL WITH SURFACE DEFECTS AND THE EXAMINED MATERIAL**

On the basis of the collected data (Table I), the prediction of the ratio between material with surface defects and the examined material was conducted using linear regression and genetic programming.

For the fitness function, the average deviation between predicted and experimental data was selected. It is defined as:

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

where  $n$  is the size of the monitored data and  $Q_i$  and  $Q'_i$  are the actual and the predicted ratios between material with surface defects and the examined material, respectively.

#### **3.1 Linear regression modelling**

On the basis of the linear regression results, it is possible to conclude that the model significantly predicts the ratio between material with surface defects and the examined material ( $p < 0.05$ , ANOVA) and that only 12.60 % of total variances can be explained by independent variables variances ( $R$ -square). There are no significantly influential parameters ( $p > 0.05$ ). The linear regression model is:

$$\begin{aligned} \frac{Q_d}{Q} = & 0.0006 \cdot CT - 0.0036 \cdot J - 0.557 \cdot CS1 - 1.831 \cdot CS2 + \\ & + 1.593 \cdot CS3 + 0.0007 \cdot W1 + +0.0017 \cdot W2 - 0.0005 \cdot W3 - \\ & - 0.055 \cdot DT1 + 0.118 \cdot DT2 + 0.088 \cdot DT3 + 2.767 \end{aligned} \quad (2)$$

Its average deviation from experimental data is 15.16 %. The calculated influences of individual parameters (individual variables) on the ratio between material with surface defects and the examined material are presented in Fig. 5. If the parameters were statistically significant and thus influential, we could conclude that average casting speeds 1 and 2 and average mould water flow 2 are the most influential parameters.

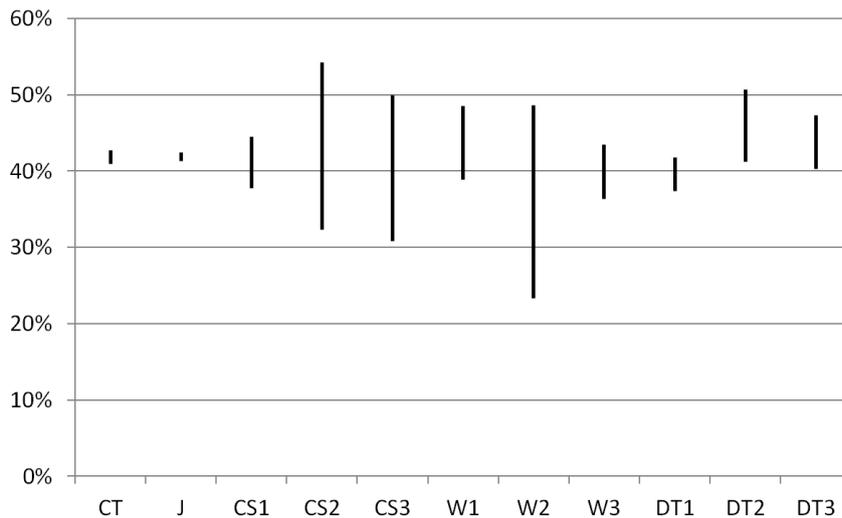


Figure 5: The influences of individual parameters on the ratio between material with surface defects and examined material using linear regression model.

### 3.2 Genetic programming modelling

Genetic programming is probably the most general evolutionary optimization method [24, 25]. A large amount of different problems in the field of steel casting, forming, and batch planning in steel industry were studied so far by the use of evolutionary computation methods including genetic programming, e.g. [26-30].

In GP, the organisms that undergo adaptation are in fact mathematical expressions (models) for predicting the ratio between material with surface defects and the examined material. The models – that is, computer programs – consist of the selected functions (i.e. basic arithmetical functions) and terminal genes (i.e. independent input parameters, and random floating-point constants). Typical function genes are: addition (+), subtraction (-), multiplication (\*) and division (/), and terminal genes (e.g.  $x$ ,  $y$ ,  $z$ ).

Random computer programs for calculating various forms and lengths are generated by means of the selected genes at the beginning of the simulated evolution. The varying of the computer programs is carried out by means of genetic operations (e.g. crossover, mutation) during several iterations, called generations.

After the completion of the variation of the computer programs, a new generation is obtained. Each result obtained from an individual program from a generation is compared with the experimental data. The process of changing and evaluating organisms is repeated until the termination criterion of the process is fulfilled.

In-house genetic programming system, programmed using AutoLISP, which is integrated into AutoCAD (i.e. commercial computer-aided design software), was used [31-33]. Genetic operations of reproduction and crossover were used. The evolutionary parameters settings were: size of the population of organisms 1000, maximum number of generations 100, reproduction probability 0.4, crossover probability 0.6, maximum permissible depth during the creation of the population 6, maximum permissible depth after the operation of crossover of two organisms 10, and smallest permissible depth of organisms in generating new organisms 2. For selection of organisms the tournament method with tournament size 7 was used.

The AutoLISP based in-house genetic programming system was run 100 times in order to develop 100 independent civilizations. Each run lasted approximately 14 minutes and 40 seconds on an i7 Intel processor and 8 GB of RAM.

The best mathematical model obtained from 100 runs of genetic programming system is:

$$\begin{aligned}
 & \left( DT2 + \frac{CS2 + DT2}{CS2} + \frac{CS2 + DT2}{J} + 0.325 \cdot J(CS2 - W2) - \right. \\
 & \quad \left. - \frac{1}{DT3 - W2} + 2 \frac{-3.079 + W2}{CS2 \cdot J} \right) \\
 & + \frac{CT + CS2(J - 2) + W2}{J^2} + \frac{-3.079 + 5.503 \cdot W2}{DT2 + \frac{CS2(DT2 + W1 - W2)}{-3.079 - DT2}} + \\
 & \quad + \frac{3.079 + 2 \cdot DT2}{CS3 + \left( \frac{3.079 + DT2}{CS2(W2 - W1)} \right)} \\
 & \frac{CS1(3.079 \cdot J + CS2(-3.079 + W2) + CS2^2(-3.079 + W2)(W2 - W1))}{CS2 \cdot J(16.94 + CS1 \cdot CS2 \cdot J(W2 - W1))} + \\
 & + \left( \frac{-3.079 + CT - W2 + \frac{3.079 + DT2}{CS2 \cdot W1 - CS2 \cdot W2} + \right. \\
 & \quad \left. + \frac{1 + \frac{5.502 \cdot CS2}{CS1 \cdot J} + \frac{2 \cdot DT2}{CS2}}{DT2 + J + W1 - W2 - \frac{CS2 + DT2}{DT2 + W2}} \right) + \tag{3} \\
 & + \frac{3.079(0.182 + DT2)}{CS1 \left( DT2 + \frac{3.079 + DT2}{CS2 \left( DT2 + \frac{3.079 + DT2}{CS2(W2 - W1)} \right)} \right)} + \frac{16.942}{CS1 \left( DT3 + \frac{3.079 + 2 \cdot DT3}{CS2(W2 - W1)} \right)} \\
 & \frac{CS2 \left( 4.915 + \frac{1.787(DT2 + 0.325(CS2 + DT2))}{CS1(CT - W1) \left( CS2 + \frac{3.079 + DT2}{CS2 + \frac{3.079 + DT2}{CS2(W2 - W1)}} \right)} \right)}{+S3 + DT2 + DT3}
 \end{aligned}$$

The average deviation from experimental data is 12.96 %, which is 1.169-times better than with the linear regression model. The calculated influences of individual parameters (individual variables) on the ratio between material with surface defects and the examined material are presented in Fig. 6. Based on the same figure, it is possible to conclude that the number of constructional steel jackets, average casting speed 2, average mould water flow 1 and the average difference between input and output water temperature 2 are the most influential parameters.

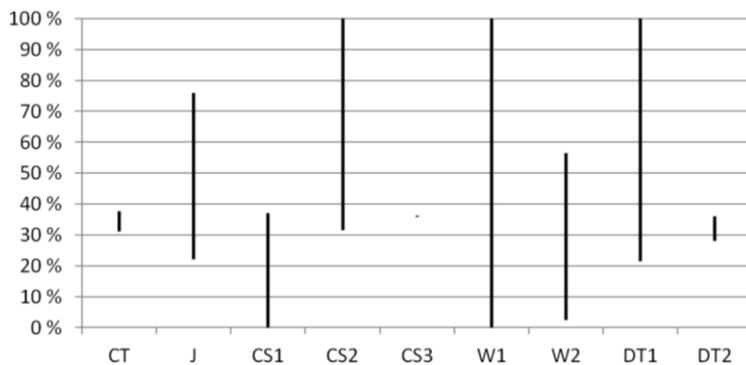


Figure 6: The influences of individual parameters on the ratio between material with surface defects and the examined material using genetic programming.

#### 4. OPTIMIZATION OF CASTING PARAMETERS

On the basis of the modelling results, the following changes were made in January 2015:

- Removal of constructional steel jackets and usage only of stainless steel jackets.
- Increasing of casting speed from 1.13 m/min to 1.18 m/min.
- Increasing of mould water flow from 1300 l/min to 1500 l/min.

From January to October 2015, 62 70MnVS4 batches were consecutively cast. The same parameters were collected and used for predicting the ratio between material with surface

defects and the examined material. The already-developed linear regression model and the genetic programming model were used. The deviations between experimental data and linear regression model and genetic programming model are 15.51 % and 11.31 %, respectively.

While using the linear regression model, the calculated average ratio between material with surface defects and the examined material decreased from 41.59 % (in 2014) to 28.37 % (from January to October 2015). Similarly, the calculation with the genetic programming model revealed the decreasing from 38.59 % (in 2014) to 23.84 % (from January to October 2015). The actual reduction of the ratio between material with surface defects and the examined material was from 41.59 % (in 2014) to 25.57 % (from January to October 2015).

It must be emphasized that, consequently, the scrap rate in the period from January 2015 to October 2018 for 70MnVS4 and in general reduced by 22.29 % and 18.04 %, respectively.

## **5. CONCLUSIONS**

The article presents decreasing surface defects on rolled bars made from 70MnVS4 steel grade. Several defects, including surface defects, originate from the continuous casting process. Accordingly, the most influential parameters during three-strand continuous casting (casting temperature, type of mould steel jacket, casting speed, water flow in the mould and the difference between input and output water temperature in the mould) of 70MnVS4 steel were monitored in 2014, when 175 consecutive batches of 70MnVS4 were cast.

Using the gathered data, the model for predicting the ratio between material with surface defects and the examined material was developed using linear regression and genetic programming. For the fitness function, average deviation between predicted and experimental data was selected.

The linear regression results show that there are no significantly influential parameters ( $p > 0.05$ ). The linear regression model's average deviation from the experimental data is 15.16 %.

In-house genetic programming system was also used for modelling of the ratio between material with surface defects and the examined material. The developed model's average deviation from experimental data is 12.96 %, which is 1.169-times better than with the linear regression model. On the basis of the calculated influences of individual parameters on the ratio between materials with surface defects, it is possible to conclude that the number of constructional steel jackets, average casting speed 2, average mould water flow 1, and the average difference between input and output water temperature 2 are the most influential parameters.

On the basis of the obtained results, we made some changes to the system for continuous casting of steel. First, we substituted the steel construction jackets with the stainless steel jackets. Then, we increased the casting speed and mould water flow. After the implementation of the above mentioned changes which are explained in more detail in section 4, we reduced the scrap rate for 70MnVS4 by 22.29 %, and the overall scrap rate by 18.04 %.

In 2016, a new two-strand continuous caster with 9 m radius replaced the old one with three strands and 6 m radius. The same findings were implemented in practice also during the operation of the new continuous caster.

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