Crack presence modeling after rolling by genetic programming

Modeliranje prisotnosti razpok z genetskim programiranjem

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Abstract: The optimal material processing in steel industry is difficult because of the multi-constituent and multiphase character of the commercial steels, variety of the possible processing paths, and plant specific equipment characteristics. This paper shows implementation of the genetic programming approach for crack presence modeling after rolling. The data (110 samples covering 7 different steel grades) on diffusive annealing, last pass rolling temperature, chemical composition of steel (weight percent of Mn, Cr, Mo and V), steel bar dimensions (width and thickness), heating time of the first and the last batch billet were collected during daily production. The manual ultrasound method was used for crack detection. On the basis of the monitored data a mathematical model for crack presence was developed by genetic programming. For the modeling it was adopt that after the rolling the material was treated equally. According the modeling results it is possible to assume that the material processing after rolling is probably very influential on crack occurrence.

Izvleček: Optimalna obdelava materiala v jeklarstvu je v splošnem otežena zaradi raznolikosti komercialnih jekel, možnih obdelovalnih procesov in specifične obdelovalne in procesne opreme. V članku je opisana uporaba metode genetskega programiranja za modeliranje prisotnosti razpok v jeklu po valjanju. Podatki (110 primerov, 7 različnih kvalitet) so zbrani med dnevno proizvodnjo: kemijska sestava (masni procenti Mn, Cr, Mo in V), širina in debelina palice ter čas ogrevanja prve in zadnje gredice. Prisotnost napak smo ugotavljali z ročnim ultrazvokom. Na podlagi monitoringa podatkov je bil razvit matematični model za ugotavljanje prisotnosti razpok v jeklu. Pri modeliranju smo predpostavili, da je bil postopek po valjanju (ohlajevanje) za ves material enak. Rezultati modeliranja kažejo na to, da je rokovanje po valjanju izredno pomembno za pojav razpok.

Key words: steel, cracks, modeling, genetic programming
Ključne besede: jeklo, razpoke, modeliranje, genetsko programiranje

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Introduction

The processes in steel industry are often specific and hardly defined according to different production linings and used technologies. There is a strong trend in steel industry for enhanced productivity, safety, and environmental friendliness of the involved processes, in parallel with the enhanced product variety and quality. In the last two decades, the thermo-mechanical physical models are increasingly developed for casting, rolling, and heat treatment operations[1].

The aim of the research was to find out possibilities to control cracks after rolling which occur between cooling process on the cooling bed. Several attempts for cracks control after rolling have been made[2] with also included artificial intelligence approach[4, 5].

According to obscure data on crack presence after rolling and lack of teorethical background in the paper the genetic modeling method for crack presence is proposed. Genetic programming has been successfully implemented into several manufacturing processes[6, 7].

Genetic programming is one of the methods of the evolutionary computation[7]. In the genetic programming, organisms which are more or less complicated computer programs, are subject to adaptation. The computer programs are in fact models for prediction of the hardness after the soft annealing in the present study. Many different prediction models, differing in the quality of prediction and the complexity of the structure, were obtained during the simulated evolution. Only one model out of many is presented in the paper.

Experimental setup

The experiment was performed in the factory Štore Steel Ltd. In the research rolling process was monitored. Rolling process consists of heating, rolling and cooling. The Figure 1 shows rolling mill layout. The number of each steel grade specimens and the average chemical composition (content of Mn, Cr, Mo, and V) is presented in Table 1.

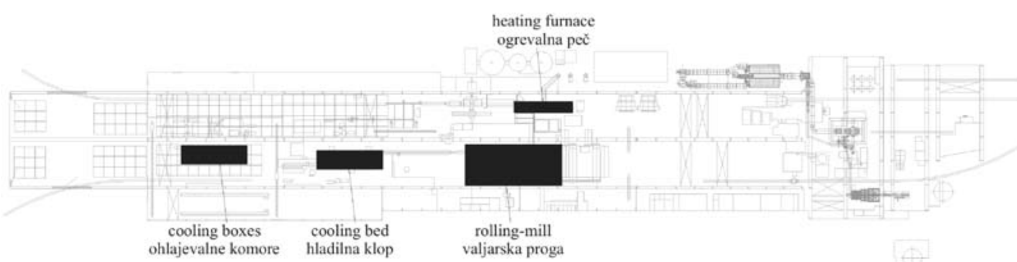

Figure 1. Štore Steel Ltd. rolling mill layout
Slika 1. Tloris Štore Steel d.o.o.

Table 1. The number of each steel grade specimens and average chemical composition and standard deviation
Tabela 1. Število kvalitet vzorcev in povprečna kemijska sestava s standardno deviacijo

		Composition	w(Mn)/%	w(Cr)/%	w(Mo)/%	w(V)/%
#	Steel grade	Number of specimens				
1	16MnCrS5	1	1,17	0,96	0,01	0
2	20MnCr5	1	1,21	1,16	0,03	0
3	50CrV4	38	1,045 (±0,058)	1,139 (± 0,031)	0,046 (± 0,014)	0,130 (± 0,020)
4	51CrMoV4	66	0,942 (±0,037)	1,071 (± 0,022)	0,177 (± 0,019)	0,118 (± 0,010)
5	51CrV4	2	1,045 (±0,007)	1,130 (± 0,0141)	0,050 (± 0,014)	0,165 (± 0,021)
6	55Si7	1	0,71	0,24	0,04	0
7	ČSN 15230.3	1	0,54	2,27	0,04	0,12
SUM		110				

Before rolling some of the batches were diffusive annealed. Monitored heating parameters were time of the first and the last batch billet heating. The temperature regime in the heating furnace was the same in all cases. The only rolling parameter was the last rolling pass temperature.

The cooling was carried out on the cooling bad and at last in cooling boxes. In the cooling boxes the bars were in general isolative covered. The exact data on covering the bars could not be obtained. The cooling is also dimension dependent, so the bar width and thickness were also recorded.

After the cooling the manual ultrasound method (Krautkrämer USM-22 ultrasound device) for each bar was used for crack detection. That bar was taken from the bond

Table 2. Experimental data
Tabela 2. Eksperimentalni podatki

#	Diffusive annealing	Last rolling pass temperature, T/°C	w(Mn) /%	w(Cr) /%	w(Mo) /%	w(V) /%	Width, a/mm	Thickness, d/mm	First batch billet heating time t_{fb}/min	Last batch billet heating time t_{lb}/min	Crack presence
1	1	960.0	0.920	1.060	0.200	0.130	11.0	44.0	134.0	134.0	1
2	0	817.0	0.940	1.080	0.170	0.120	100.0	77.0	172.0	184.0	1
3	0	862.0	1.040	1.140	0.040	0.180	100.0	35.0	258.0	258.0	1
4	0	887.0	0.970	1.110	0.040	0.150	100.0	40.0	163.0	164.0	1
5	0	869.0	0.920	1.080	0.020	0.180	100.0	42.0	106.0	152.0	1
	…	…	…	…	…	…	…	…	…	…	…
106	1	942.0	0.910	1.040	0.170	0.120	100.8	56.0	118.0	120.0	0
107	0	850.0	1.060	1.150	0.040	0.120	99.6	50.0	127.0	127.0	0
108	0	833.0	1.040	1.120	0.050	0.140	100.1	51.0	129.0	126.0	0
109	1	935.0	0.990	1.080	0.180	0.110	100.0	60.0	124.0	124.0	0
110	0	897.0	0.880	1.010	0.190	0.110	75.0	32.0	98.0	95.0	0

from the cooling box. Whole bond was inspected. The Table 2 shows collected experimental data. Each bond was identified by its identification number from 1 to 110. If the crack in any bar from the bond was found the crack presence in the Table 2 was marked with value 1 and absence with 0, respectively. Also the diffusive annealing treated material before heating process is marked with value 1.

Crack presence modeling

Genetic programming is probably the most general evolutionary optimization method[[7]]. The organisms that undergo adaptation are in fact mathematical expressions (models) for hardness after soft annealing prediction consisting of the available function genes (i.e., basic arithmetical functions) and terminal genes (i.e., independent input parameters, and random floating-point constants). In our case the models consist of: function genes of addition (+), subtraction (-), multiplication (*) and division (/), terminal genes of diffusive annealing (*DA*), last pass rolling temperature (*T*), chemical composition of steel (Mn, Cr, Mo and V), steel bar dimensions width (*width*) and thickness (*thick*), heating time of the first (t_{fb}) and the last batch billet (t_{lb}).

Random computer programs of various forms and lengths are generated by means of selected genes at the beginning of simulated evolution. Afterwards, the varying of computer programs during several iterations, known as generations, by means of genetic operations is performed. After completion of varying of computer programs a new generation is obtained that is evaluated and compared with the experimental data, too.

The result of models for crack presence prediction more than zero predicted crack presence (value 1), otherwise crack absence (value 0). Evaluation of models were determined by Bayesian analysis (true positive *TP*, true negative *TN*, false positive *FP*, false negative *FN*) applying sensitivity $SENS = TP/(TP+FN)$, specificity $SPEC = TN/(FP+TN)$, positive predictive value $PPV = TP/(TP+FP)$ and negative predictive value $NPV = TN/(FN+TN)$. Models with higher *SPEC*, *SENS*, *PPV*, *NPV* have higher probability to contribute in operations of reproduction and crossover.

The process of changing and evaluating of organisms is repeated until the termination criterion of the process is fulfilled. This was the prescribed maximum number of generations.

For the process of simulated evolutions the following evolutionary parameters were selected: size of population of organisms 500, the greatest number of generation 200, reproduction probability 0.4, crossover probability 0.6, the greatest permissible depth in creation of population 6, the greatest permissible depth after the operation of crossover of two organisms 10 and the smallest permissible depth of organisms in generating new organisms 2. Genetic operations of reproduction and crossover were used. For selection of organisms the tournament method with tournament size 7 was used.

We have developed 100 independent civilizations of mathematical models for prediction of the crack presence. Only the best one out of 100 is presented here:

$$\frac{\left(DA + \frac{-tfb+tlb}{Cr} + Cr\left(Cr + DA - DA^2 + \frac{tfb-tlb}{-MoT+DA\cdot tfb+thick}\right) + \frac{-tfb+tlb}{DA^2 - MoT + thick + Mo\left(DA^2+\frac{-tfb+tlb}{DA\cdot T - Mo\cdot T+thick}\right)+width}\right)}{\left(\left(Cr + Cr\cdot Mn\left(DA+\frac{-tlb+(DA+Mn)tlb}{T}\right)\right)\cdot \left(T + Cr^2(7.6572+D+Mn-DA\cdot Mo\cdot T+Mo\cdot tfb+thick-Mo\cdot tlb)\cdot \left(DA^2+\frac{-tfb+Cr\cdot tlb}{T}\right)\cdot\left(-Mo\cdot T+thick+width\left(DA^3+\frac{-tfb+tlb}{DA\cdot T-Mo\cdot T+thick}\right)+width\right)\right)\right)}$$

with sensibility of 0.8545, specificity 0.8182, positive predictive value 0.8246, negative predictive value 0.8491 and test efficiency 0.8363.

The results about the best models in 100 civilizations are collected in Table 3.

Table 3. The best models in civilizations results
Tabela 3. Rezultati najboljših modelov civilizacij

	Test efficiency	Sensibility	Specificity	Positive predictive value	Negative predictive value
AVERAGE	0,746	0,703	0,789	0,776	0,732
STDEV	0,0398	0,093	0,0824	0,0547	0,0523
MAX	0,836	0,891	0,909	0,878	0,867
MIN	0,663	0,491	0,564	0,636	0,632

CONCLUSIONS

In this study genetic programming approach was applied for crack presence prediction. In genetic programming mathematical expressions (models for crack presence prediction) undergo adaptation. During simulated evolution models gradually improve. Experimental data set (110 samples) was used to obtain the model for crack presence prediction. Evaluation of models was determined by Bayesian analysis. Average values of all 100 models were: sensibility 0.7033, specificity 0.7898, positive predictive value 0.7764, negative predictive value 0.7321 and test efficiency 0.7466. The best model values are: sensibility of 0.8545, specificity 0.8182, positive predictive value 0.8246, negative predictive value 0.8491 and test efficiency 0.8363.

According to the results of the modeling it is possible to conclude that there are some more influential parameters, witch were not monitored during research, or that the experimental data, especially on cooling process, is obscure. So further researches will be based on cooling parameters precise analysis and their mutual dependence. In addition, parameters optimization could be possible.

Povzetek

V tej študiji smo uporabili genetsko programiranje za napovedovanje prisotnosti razpok. Pri genetskem programiranju so matematični izrazi (modeli za napovedovanje prisotnosti razpok) izpostavljeni prilagajnju. Med simulirano evolucijo modeli postopoma napredujejo. Modeliranje je bilo izvedeno na podlagi 110 primerov. Modele smo ovrednotili z Bayesovo analizo. Povprečne vrednosti vseh 100 modelov so: občutljivost 0.7033, specifičnost 0.7898, pozitivna sposobnost napovedovanja 0.7764, negativna sposobnost napovedovanja 0.7321 in učinkovitost modela 0.7466. Vrednosti najboljšega modela pa so: občutljivost 0.8545, specifičnost 0.8182, pozitivna sposobnost napovedovanja 0.8246, negativna sposobnost napovedovanja 0.8491 in učinkovitost modela 0.8363.

Glede na rezultate modeliranja je možno zaključiti, da obstajajao vplivni parametri, ki jih med raziskavo nismo spremljali ali pa da so obstoječi podatki, vsaj pri ohlajevanju na hladilni klopi in hladilnih komorah, pomanjkljivi. Zato bi bilo potrebno podrobneje analizirati parametre ohlajevanja in njihovo soodvisnost. Dodatno bi lahko izvedli tudi optimizacijo le-teh.

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