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GENETIC PROGRAMMING AND SOFT-ANNEALING PRODUCTIVITY

GENETSKO PROGRAMIRANJE IN PRODUKTIVNOST MEHKEGA ŽARJENJA

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An optimal thermo-mechanical processing in the steel industry is difficult because of the multi-constituent and multiphase character of commercial steels, the variety of the possible processing paths and the plant-specific equipment characteristics. This paper shows a successful implementation of the genetic programming approach for increasing the furnace conveyor speed and consequently the higher productivity of the heat-treatment furnace in the soft-annealing process. The data (222 samples covering 24 different steel grades) on a furnace conveyor's speed, the chemical composition of the steel (weight percent of C, Cr, Mo, Ni and V) and the Brinell hardness before and after the soft annealing were collected during daily production. On the basis of the measured data a mathematical model for the hardness after the soft annealing was developed by genetic programming. According to the modelled influences on the hardness, a higher furnace conveyor speed was attempted in practice. The experimental results of the hardness after the soft annealing with the increased conveyor speed and the predictions of the mathematical model were compared with an agreement of 3.24 % (2.68 % at testing data set). The genetic model was also compared and verified with a linear regression model. As a consequence of the used computational intelligence approach, the productivity of the soft-annealing process increased (from the furnace conveyor speed 3.2 m/h to 7 m/h).

Keywords: steel, soft annealing, furnace productivity, hardness, modeling, genetic programming

Zaradi raznolikosti tehnoloških poti je v jeklarski industriji težko izbrati primerne parametre toplotne obdelave. V članku je predstavljen način, kako smo z metodo genetskega programiranja povečali produktivnost žarilne peči. Na podlagi podatkov o trdoti materiala pred mehkim žarjenjem in po njem (222 vzorcev, 24 različnih kvalitet jekla), o hitrosti žarjenja in kemični sestavi (C, Cr, Mo, Ni in V) smo z genetskim programiranjem dobili matematični model trdote materiala po mehkem žarjenju. Model smo preizkusili s testnimi podatki. Na podlagi modela, ki se odmika od eksperimentalnih podatkov za 3,24 % (2,68 % pri testnih podatkih), nam je uspelo hitrost žarjenja povečati s 3,2 m/h na 7 m/h.

Ključne besede: jeklo, mehko žarjenje, produktivnost peči, trdota, modeliranje, genetsko programiranje

1 INTRODUCTION

There is a strong demand in the steel industry for enhanced productivity, safety, and the environmental friendliness of the involved processes in parallel with the enhanced product variability and quality. In the past two decades, thermo-mechanical physical models have been increasingly developed for casting, rolling, and heat-treatment operations.[1] However, the current state of the art in physical modeling does not permit us to quantitatively model the whole range of steel behavior, neither from the microscopic materials science point of view, nor from the macroscopic process level. This is probably due to the multi-constituent and multi-phase character of the steel as well as due to the fact that the important physical processes took place over a huge range of length scales from the nanoscale up to 100 m. Physical modeling is thus increasingly connected with intelligent algorithms (such as, for example, artificial neural networks, evolutionary computation, swarm intelligence, artificial immune systems, and fuzzy systems)[2,3] which are to complement or replace the physical models in solving realistic industrial problems. An example of such symbiosis[4] is the continuous casting physical modeling with the evolutionary algorithm for searching the optimum casting conditions. The purpose of the heat treatment of steels is to obtain the desired changes in the metallurgical structure and thus material properties.[5] Soft annealing represents a heat treatment wherein a material is altered, causing changes in its ductility and hardness. Several attempts have been made to attain the control of the above-mentioned material properties during the soft-annealing treatment.[6–11] The aim of the present work is to determine the possibilities of increasing the furnace productivity (speed of the furnace conveyor) during the soft-annealing process. The genetic programming method is used in the present work to establish the relations between the chemical composition of the principal alloying elements (carbon, chromium, molybdenum, nickel and vanadium), the principal process parameters (such as the speed of the furnace conveyor), and the principal material property (hardness after soft annealing). Having the set of relations, more optimal conveyor speed could be easily determined with respect to the process-parameter constraints, i.e., the maximum possible speed of the conveyor, and product properties constraints, i.e., the maximum hardness.

Genetic programming is one of the methods of evolutionary computation.[12,13] In genetic programming, organisms which are more or less complicated computer programs, are subject to adaptation. In the present study the computer programs are in fact models for the prediction of hardness after soft annealing. 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 discussed in the paper.

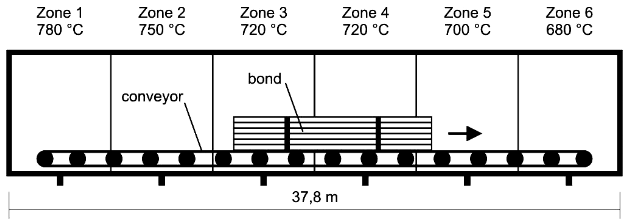

Figure 1: Heat-treatment furnace with its six equidistant soft-annealing temperature zones
Slika 1: Peč za toplotno obdelavo s šestimi ekvidistančnimi komorami z različnimi temperaturami

2 HEAT-TREATMENT FURNACE DESIGN AND EXPERIMENTAL DATA

All the experimental data used in the present paper were obtained from the pusher-type furnace of the Štore Steel steelworks, Slovenia, one of the major spring-steel producers in Europe. The scheme of the furnace is depicted in **Figure 1**. The hardness after the annealing process depends on the chemical composition of the steel and the furnace process parameters. The main difficulty with the research was that, according to the pace of production, the production lining parameters could only be monitored and not varied. The principal seven adjustable furnace process parameters are the six different temperatures of the heat-treatment zones and the time of the annealing (inversely proportional to the speed of the furnace conveyor). The principal two fixed construction parameters of the furnace are the maximum bond-specific weight of 2.5 t/m and the maximum conveyor speed of 7 m/h. The cross-sections of the round and flat bars in the bond varied from 43.28 mm^2 to 5676.40 mm^2. The temperature of the six heat-treatment zones was kept constant in all cases (see data in **Figure 1**). The only influential heat-treatment productivity process parameter was the speed of the furnace conveyor. The speed of the furnace conveyor was kept steady during the heat treatment of the individual bond. The required hardness of the annealed steel must be below 260 HB before the bond steel bars are subsequently saw-cut.

The number of each steel grade specimens and the average chemical composition (wt% of C, Cr, Mo, N and V) is shown in **Table 1**.

In the actual production technology only two furnace conveyor speeds of 2.5 m/h and 3.2 m/h were used for

Table 1: The number of steel grade specimens and the average chemical composition
Tabela 1: Število različnih kvalitet jekla in povprečna kemična sestava

			Composition				
#	Steel grade	Number of specimens	C [wt%]	Cr [wt%]	Mo [wt%]	Ni [wt%]	V [wt%]
1	15CrNi6	1	0.14	1.56	0.04	1.53	0
2	16MnCr5	1	0.19	1.03	0.02	0.09	0
3	17CrNiMo6	2	0.18	1.65	0.28	1.50	0
4	18 CrNi 8	1	0.19	1.95	0.02	2.01	0
5	18CrNiMo7-6	15	0.17	1.64	0.29	1.53	0.001
6	18CrNiMo7-6 HH	2	0.19	1.69	0.29	1.53	0
7	23MnNiCrMo5-2-A	12	0.22	0.49	0.21	0.47	0
8	25CrMo4	4	0.24	1.01	0.20	0.10	0
9	34CrNiMo6	28	0.36	1.61	0.22	1.60	0.003
10	41Cr4	7	0.42	1.08	0.03	0.11	0
11	42CrMo4	33	0.42	1.07	0.22	0.11	0
12	42CrMoS4	8	0.43	1.03	0.21	0.11	0
13	50CrMoS4	14	0.51	1.04	0.22	0.13	0
14	50CrV4	34	0.50	1.05	0.04	0.11	0.156
15	51CrMoV4	1	0.54	1.06	0.18	0.09	0.11
16	51CrV4	11	0.51	1.08	0.04	0.11	0.1555
17	51CrV4 HH	3	0.51	1.08	0.04	0.12	0.170
18	52CrMoV4	6	0.54	1.05	0.18	0.10	0.113
19	55Si7	16	0.57	0.29	0.04	0.12	0
20	70MnVS4	20	0.70	0.15	0.03	0.08	0.113
21	25CrMo4	1	0.24	1.05	0.21	0.14	0
22	42CrMo4	2	0.43	1.03	0.21	0.11	0
	SUM	222					

Table 2: Part of the monitored data set
Tabela 2: Del zbranih podatkov

#	Conveyor speed [m/h]	Hardness before the soft annealing [HB]	C [wt%]	Cr [wt%]	Mo [wt%]	Ni [wt%]	V [wt%]	Hardness after the soft annealing [HB]
1	3.2	298	0.51	1.09	0.22	0.19	0	219
2	3.2	248	0.43	1.08	0.02	0.1	0	191
13	3.2	313	0.69	0.14	0.02	0.08	0.11	229
4	3.2	309	0.70	0.13	0.02	0.08	0.12	215
5	3.2	290	0.55	0.28	0.04	0.12	0	229
6	3.2	290	0.59	0.36	0.05	0.12	0	229
…	…	…	…	…	…	…	…	…
220	3.2	298	0.17	1.64	0.29	1.53	0	198
221	3.2	290	0.40	1.04	0.22	0.08	0	207
222	3.2	333	0.52	1.14	0.05	0.11	0.15	229

soft annealing. The Brinell hardness for each data set before and after the soft annealing was measured at the bar centre at the three positions per bond: once from the bar taken from the bond surface and twice from the bar taken from the middle of the bond. Then the average hardness per bond was calculated and used for modeling. Only a part of the respective monitored data set is shown in **Table 2**.

3 GENETIC PROGRAMMING MODELING OF THE HARDNESS AFTER THE SOFT ANNEALING

Genetic programming is probably the most general evolutionary optimization method.[12,13] The organisms that undergo adaptation are in fact mathematical expressions (models) for the hardness after the soft annealing in the present work. The prediction consists of the available function genes (i.e., the basic arithmetical functions) and the terminal genes (i.e., the independent input parameters and the random floating-point constants). In the present case the models consist of the following function genes: addition (+), subtraction (–), multiplication (*) and division (/), and the following terminal genes: furnace conveyor speed (speed) in m/h, hardness before soft annealing (HB), in Brinell units, and the chemical composition of the principal alloying elements: carbon (C), chromium (Cr), molybdenum (Mo), nickel (Ni) and vanadium (V), in mass fractions (*w*/%). One of the randomly generated mathematical models (Mo/speed + V)·C/5.1 is schematically represented in **Figure 2** as a program tree with included function genes (*, + , /) and terminal genes (Mo, speed, V, C, and randomly generated real number constant 5.1).

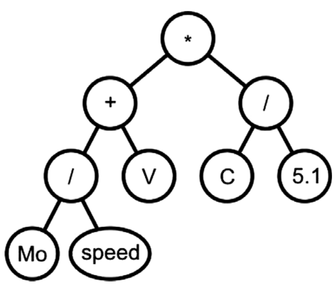

Figure 2: Randomly generated mathematical model for the hardness after the soft annealing, represented in the form of a program tree
Slika 2: Naključno ustvarjen matematični model za napovedovanje trdote po mehkem žarjenju, predstavljen kot programsko drevo

Random computer programs of 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 performed by means of genetic operations during several iterations, known as generations. After the completion of the variation of the computer programs, a new generation is obtained. Each generation is compared with the experimental data. The process of changing and evaluating the organisms is repeated until the termination criterion of the process is fulfilled. The maximum number of generations is chosen as a termination criterion in the present algorithm.

The following evolutionary parameters were selected for the process of simulated evolutions: 500 for the size of the population of organisms, 100 for the maximum number of generations, 0.4 for the reproduction probability, 0.6 for the crossover probability, 6 for the maximum permissible depth in the creation of the population, 10 for the maximum permissible depth after the operation of the crossover of two organisms, and 2 for the smallest permissible depth of organisms in generating new organisms. The genetic operations of reproduction and crossover were used. For the selection of the organisms the tournament method with a tournament size of 7 was used. A total of 100 independent civilizations of the mathematical models for the prediction of the hardness after the soft annealing have been developed. Each evolution of the 100 generations has been computed for an average of 1 h on a 2.39 GHz processor and 2 GB of RAM using an AutoLISP in-house coded program.

The model fitness has been expressed in the L_2 norm as:

$$f=\frac{\sum_{i=1}^{n}(E_i-G_i)^2}{n} \tag{1}$$

where n is the size of the monitored data (in the present case 222), E_i and G_i are the values of the actual measured hardness after soft annealing and the model-predicted hardness after soft annealing, respectively.

In order to make the presentation more clear, let us have a closer look at the development of one of the independent civilizations with the previously mentioned genes. The result of the blind random searching for mathematical models in the initial generation is not, as expected, accurate enough. The best mathematical model (out of 100) for the prediction of the hardness after the soft annealing in the initial generation is:

$$\mathrm{HB} - 9.44639\,(-\mathrm{Mo} + 4.24533\ \mathrm{speed}) \tag{2}$$

with a fitness of 4153.45 and an average percentage deviation of 21.36 %.

A better model develops (evolves) in generation 10:

$$2638.58 + \mathrm{HB} + \mathrm{Mo} - 0.105861\ \mathrm{HB}\,(4.24533 - \mathrm{Mo\ speed}) \tag{3}$$

with a fitness of 1082.28 and an average percentage deviation of 12.40 %. Increasingly better adopted and more complex mathematical models are created through further subsequent generations of the simulated evolution.

The best model of the civilization, also without the terminal gene Mo, occurred in the last, i.e., the 100th generation:

$$\begin{aligned}
&127.132 + 19.309\,\mathrm{Cr} + \frac{\mathrm{V}\left(3.436 + \mathrm{Mo} + 4.117\,\mathrm{Ni} - \frac{\mathrm{V}}{\mathrm{Mo}}\right)}{-2.234\,\mathrm{Mo} + 2\,\mathrm{Ni} + \frac{1}{\mathrm{speed}} + \mathrm{V}} + \frac{\left(\mathrm{C} + \frac{1+\mathrm{Cr}}{\mathrm{V}}\right)\mathrm{V}}{\mathrm{Ni}\left(-1.234\,\mathrm{Mo} - 1.234\,\mathrm{Ni} + 2.845\,\mathrm{speed} - \frac{\mathrm{V}}{\mathrm{Mo}}\right)} +\\
&\mathrm{C}\left(136.993 + 6.298\,\mathrm{Mo} + 38.664\,\mathrm{Ni} + 6.117\,\mathrm{V} - \frac{6\,\mathrm{V}}{\mathrm{Mo}} - \frac{\mathrm{V}}{\mathrm{Ni}} + \frac{-2.234\,\mathrm{Mo} + \mathrm{Ni} + \mathrm{V}}{\mathrm{Ni}} - \frac{-2.234\,\mathrm{Mo} + \mathrm{Ni} + 2\,\mathrm{V}}{\mathrm{Mo}}\right) +\\
&\mathrm{Mo}\left(-2.234 - 2.234\,\mathrm{Mo}\left(4.117 + \mathrm{C} + \frac{\mathrm{Cr}}{\mathrm{Mo}} - 2\,\mathrm{V}\right) + \mathrm{V} + \frac{\left(\mathrm{C} + \frac{1}{\mathrm{V}}\right)\mathrm{V}}{\mathrm{Ni\ speed}}\right)\left(\frac{\mathrm{Cr}}{\mathrm{Mo}} - \frac{(0.2429 + \mathrm{C})(-2.234\,\mathrm{Mo} + \mathrm{Ni} + 2\,\mathrm{V})}{\mathrm{speed}}\right) +\\
&0.021\left(\mathrm{HB} + \mathrm{Mo} + \frac{2 + 2\,\mathrm{Mo} + 5.117\,\mathrm{Ni} + \frac{\mathrm{speed}\left(2\,\mathrm{C} + \frac{1}{\mathrm{Cr\,V}}\right)}{\mathrm{Cr}} + \mathrm{V} - \frac{\mathrm{V}}{\mathrm{Ni}}}{-1 + 19.075\,\mathrm{Mo} + 6.117\,\mathrm{Ni} - \frac{4.117\mathrm{V}}{\mathrm{Mo}} - \frac{\left(\mathrm{C} + \frac{\mathrm{Cr}}{\mathrm{Mo}}\right)\mathrm{V}}{\mathrm{speed}} - \frac{\mathrm{V}}{\mathrm{Ni+V}}}\right) +\\
&2.845\left(\mathrm{speed} + \mathrm{V}\left(19.309\,\mathrm{Cr} - 1.234\,\mathrm{Mo} + \frac{\frac{\mathrm{C} + \frac{\mathrm{Cr}}{\mathrm{Ni}}}{\mathrm{speed}} + \frac{\mathrm{C} + \frac{\mathrm{Cr}}{\mathrm{V}}}{\mathrm{speed}}}{19.309\,\mathrm{Mo} + 5.117\,\mathrm{Ni} + 4.117\,\mathrm{V} - \frac{\mathrm{V}}{\mathrm{Mo}}} - \frac{4.117\,\mathrm{Ni} + \frac{\frac{\mathrm{Cr}}{\mathrm{V}} + \mathrm{C}\,(4.117 + 4.117\mathrm{V})}{\mathrm{speed}}}{-2.234 + 20.309\,\mathrm{Mo} + 2\,\mathrm{Ni} + \mathrm{V} - \frac{2\,\mathrm{V}}{\mathrm{Mo}}}\right)\right)
\end{aligned} \tag{4}$$

with a fitness of 90.79 and an average percentage deviation of 3.24 %.

The development of the best organism – the best mathematical model for hardness after soft annealing can be easily represented with the fitness curve in **Figure 3**.

The randomly driven process builds the fittest and complex models from generation to generation and uses

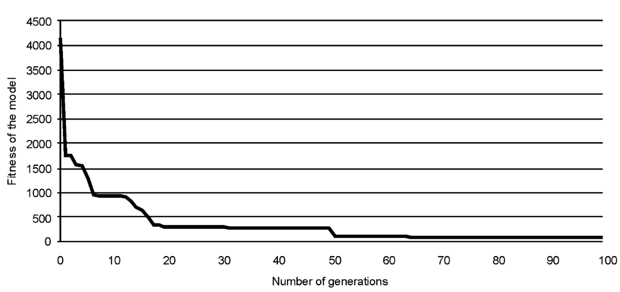

Figure 3: Fitness curve from generation 0 to 100
Slika 3: Uspešnost generacij od 0 do 100

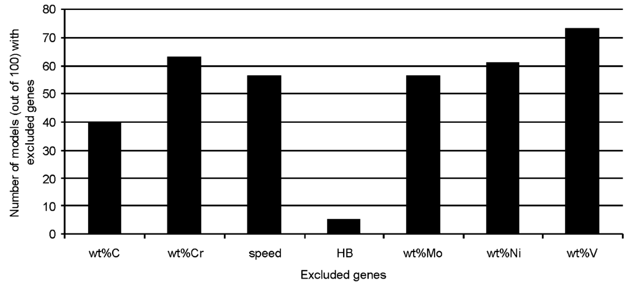

Figure 4: Frequency of the excluded genes from the best 100 mathematical models for hardness after soft annealing
Slika 4: Število genov, ki so bili izločeni v najboljših 100 matematičnih modelih za napovedovanje trdote po mehkem žarjenju

ingredients that are most suitable for the experimental environment adaptation. The analysis of the excluded genes (parameters) from the model is presented in **Figure 4**.

According to the number of excluded genes in 100 obtained mathematical models, we may assume the influence of the parameters on the hardness after soft annealing. It is clear from **Figure 4** that out of 100 genetically obtained mathematical models only 5 models exclude the parameter hardness before soft annealing. So we can speculate that this parameter is probably one of the most important parameters influencing the hardness after soft annealing. It also seems that the conveyer speed does not influence the material hardness after soft annealing.

4 MODEL COMPARISON AND VERIFICATION

For a comparison and verification of the usefulness of the genetic programming approach the linear-regression method for modeling the hardness after soft annealing was also used. The same monitored data set (**Table 2**) give us the results collected in **Table 3** and the idea how the classical modeling approach can deal with temperature-treating furnace-productivity problems.

The linear-regression model according to results is:

$$\begin{aligned}
&-0.624 \cdot \mathrm{speed} + 0.018 \cdot \mathrm{HB} + 128.076 \cdot \mathrm{C} + 17.942 \cdot\\
&\cdot \mathrm{Cr} - 14.613 \cdot \mathrm{Mo} + 5.717 \cdot \mathrm{Ni} - 12.123 \cdot \mathrm{V} +\\
&+ 141.409
\end{aligned} \tag{6}$$

with a selected genetic programming fitness (the average squares of deviation from the monitored data) of 173.79 and an average percentage deviation 4.50 %. The linear regression results show that the conveyor speed, the hardness before soft annealing, and the $w(\mathrm{Mo})/\%$ and $w(\mathrm{V})/\%$ (significance is above 0.05) do not significantly influence the hardness after soft annealing.

The genetic programming results of the fitness of 90.79 and the average percentage deviation of 3.24 % are favorable, compared to the results obtained by the classical statistical analysis.

Table 3: Linear regression results
Tabela 3: Rezultati linearne regresije

Coefficients					
Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.
	B	Std. Error	Beta		
(Constant)	141.409	12.017		11.767	0.000
Conveyor speed [m/h]	-0.624	3.028	-0.010	-0.206	0.837
Hardness before soft annealing	0.018	0.023	0.057	0.781	0.436
wt%C	128.076	12.501	0.955	10.245	0.000
wt%Cr	17.942	3.634	0.420	4.937	0.000
wt%Mo	-14.613	17.045	-0.073	-0.857	0.392
wt%Ni	5.717	2.484	0.183	2.302	0.022
wt%V	-12.123	21.483	-0.044	-0.564	0.573

5 PRACTICAL IMPLEMENTATION

The maximum furnace conveyor speed, declared by the furnace producer, is 7 m/h. As previously mentioned, the required hardness of the cutting material should be below 260 HB in order to satisfy the product's quality requirement.

Both approaches – genetic programming and linear regression – show that the conveyer speed is not one of the influencing parameters.

The previously mentioned results and behavior regarding the sensitivity of the furnace conveyor speed in the soft-annealing process allow us to carefully (in several steps) increase the conveyor speed up to 5 m/h and finally for 7 m/h in industrial practice. The experimental results of the hardness for 13 specimens are shown in **Table 4**, compared with the calculated values from the computational intelligence model and the linear regression model.

The hardness of all 13 measured specimens was below the required 260 HB. The average percentage deviation was as low as 2.68 % and 4.44 % for the genetic programming model and the linear regression model, respectively.

6 CONCLUSIONS

The possibility of a productivity enhancement for the heat-treatment furnace with the soft annealing of round and flat steel bars in the Štore Steel company was studied. The Brinell hardness after the process was measured for 24 different steel grades as a function of the furnace process parameters and steel composition. This established an experimental database for the deve-

Table 4: Measured and calculated hardness after soft annealing
Tabela 4: Izmerjene in izračunane trdote po mehkem žarjenju

#	Conveyor Speed [m/h]	Hardness before soft-annealing	C [wt%]	Cr [wt%]	Mo [wt%]	Ni [wt%]	V [wt%]	Hardness after the soft annealing (monitored) [HB]	Hardness after the soft annealing (genetic programming model) [HB]	Hardness after the soft annealing (linear regression model) [HB]	Percentage deviation (genetic programming)	Percentage deviation (linear regression)
	5.0	298.0	0.59	0.28	0.05	0.13	0.00	229	237.089	227.062	3.53%	0.85%
	5.0	464.0	0.34	1.51	0.20	1.50	0.01	229	235.528	225.618	2.85%	1.48%
3	5.0	335.0	0.53	1.13	0.05	0.19	0.14	229	236.332	233.940	3.20%	2.16%
4	5.0	438.0	0.36	1.64	0.23	1.64	0.01	229	241.571	230.406	5.49%	0.61%
5	5.0	438.0	0.34	1.51	0.20	1.50	0.01	229	234.982	225.150	2.61%	1.68%
6	5.0	339.0	0.43	1.18	0.22	0.15	0.00	215	224.551	221.085	4.44%	2.83%
7	5.0	339.0	0.43	1.18	0.22	0.15	0.00	215	224.551	221.0859	4.44%	2.83%
8	5.0	309.0	0.7	0.12	0.02	0.07	0.11	215	216.467	237.2396	0.68%	10.34%
9	5.0	309.0	0.7	0.12	0.02	0.07	0.11	215	216.467	237.2396	0.68%	10.34%
10	5.0	309.0	0.7	0.13	0.02	0.08	0.12	215	214.519	237.355	0.22%	10.40%
11	7.0	335.0	0.55	1.14	0.03	0.12	0.15	249	237.717	236.3271	4.53%	5.09%
12	7.0	313.0	0.53	1.13	0.03	0.10	0.15	239	235.34	233.0758	1.53%	2.48%
13	7.0	361.0	0.54	1.08	0.17	0.09	0.12	249	250.438	232.5842	0.58%	6.59%
									Average percentage deviation	2.68%	4.44%	

lopment of 100 models deduced through genetic programming methodology. Genetic programming predicts the hardness after the soft annealing with an average percentage deviation of only 3.24 %. Also, the linear regression method was used for modeling and gave us similar results of an average percentage deviation of 4.50 %. The best models (genetic programming and linear regression) were closely analyzed and it was established that the furnace conveyer speed is not a sensitive parameter for influencing the hardness after the soft annealing. A statistically significant influence, according to linear regression, comes from the *w*(C)/%, *w*(Cr)/% and *w*(Ni)/%.

These findings lead to changes of the maximum furnace conveyor speed from 3.2 m/h up to 7 m/h in production practice. The substantially higher conveyor speed did not influence the hardness of the steel after soft annealing, as expected from the model prediction. The hardness after the soft annealing was below the required hardness of 260 HB also in the case of the enhanced conveyor speed in all 13 tested cases. The agreement between the tested and the calculated data is 2.68 % and 4.44 % for the genetic programming model and the linear regression model, respectively. Our future research, coming straight from the present paper, is aimed to continue towards the possibility of optimizing other material properties, for instance tensile strength. In this case also the variation of the annealing temperature in the six control zones of the heat-treatment furnace probably has to be taken into account. There are many important topics connected with the relations of the steel composition and the material properties of the steel (including the hardness) that require the additional attention of the computational intelligence and materials science community. The present paper shows the relevance and success of using the genetic programming for straightforward analyses and the optimization of an industrial problem.

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