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Research paper

Modelling the hot metal desulfurization process using artificial intelligence methods

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Abstract: The objective of conducted research on the hot metal desulfurization process was to determine the key process parameters that impact the ultimate outcome of desulfurization. As a result, the noticeable outcome of implementing these measures should be the improvement of quality control. In order to determine these parameters, used artificial intelligence methods like as neural networks (ANN). On the basis of the production data collected from the actual metallurgical aggregate for hot metal desulfurization, neural networks were built that used quantitative data (mass of hot metal, mass of used reagents, etc.) and qualitative data (chemical analysis of hot metal). The parameters of the desulfurization process were divided into state parameters and control parameters. From the point of view of the technology of conducting the desulfurization process and building an on-line model, only control parameters can be changed during desulfurization. To describe the problem of predicting change in the sulfur content during the hot metal desulfurization process is sufficient an MLP type neural network with a single hidden layer. Adopting a more complex network structure would probably lead to a loss of the ability to generalise the problem. The research was carried out in STATISTICA Automated Neural Networks SANN.

Keywords: desulfurization, hot metal, neural networks, steelmaking

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1. Introduction

Due to the developing market demand for steels with various mechanical and physico-chemical properties, the steel industry is facing increasing requirements concerning the chemistry of the steels manufactured. Meeting the stringent requirements is not easy and the solution to this problem should be addressed in a comprehensive manner. First, the problem should be precisely presented, and the most important stages of the production process, where the solution can be found, should be identified. The objective of this research is to meet the growing restrictions regarding the sulfur content in steel. Therefore, the hot metal desulfurization station was selected as a stage of the steel production process where the sulfur content is significantly reduced with the method of co-injection of reagents – lime and magnesium [1]. On the basis of the current process knowledge and observations of an actual hot metal desulfurization unit, it was found that the currently used models for determining the mass of reagents for the desulfurization process are insufficient.

The analysis of the desulfurization process leads us to a conclusion that both static and dynamic parameters may influence the final result. In this situation, it is very difficult to build a physico-chemical model, which would include both types of factors. Therefore, the application of artificial intelligence methods allowing all the relevant process parameters to be included seems very attractive [2]. The solution to the formulated problem was achieved by the application of artificial neural networks with various architectures. The dependence of the hot metal desulfurization process parameters on the final sulfur content after desulfurization was analyzed [3,4]. The available specialist literature contains a number of papers on the development of fundamental models of the desulfurization process. These models are very well reviewed in [5]. It appears from this summary that research based on the construction of ANN was devoted to the process in the torpedo ladle. Therefore, the presented findings concerning the hot metal charging ladle complement the research completed so far.

2. Desulfurization process analysis

Sulfur is an undesirable element in steel. It worsens weldability and formability as well as causes hot-shortness and lamellar cracking during rolling. Therefore, as new steel grades appear and a low sulfur content needs to be obtained in the final product, the hot metal desulfurization process is carried out. This process has already been established in the steel production technological line [6,7].

The main impurities in hot metal appearing in the blast furnace process are carbon, silicon, manganese, phosphorus and sulfur. During oxygen blowing in the basic oxygen process, such elements as Si, Mn and P are oxidized and pass into the slag. In the conditions of the basic oxygen process, at a temperature of between 1350°C and 1600°C, the thermodynamic probability of the reaction (2.1) between oxygen and sulfur to gaseous SO_2 is very low [8].

$$[S] + [0]_{ads} = \{SO_2\} \tag{2.1}$$

The equilibrium constant of the above reaction assumes extremely low values, which is also confirmed in industrial conditions, where we practically do not observe any reduction of the sulfur content with the participation of the gaseous phase [5].

In steelmaking processes, sulfur is removed from the melt by the reaction of an anion exchange which occurs as per the formula:

$$[S] + (O^{2-}) = (S^{2-}) + [O] \tag{2.2}$$

It follows from this formula that the desirable desulfurization process must be accompanied by an increase in the oxygen activity in the metal bath. The oxygen activity in the basic oxygen process is very high and it is the main barrier to the desulfurization process. Bear in mind that in the periodic system, sulfur and oxygen belong to the oxygen group, which means that oxygen competes with sulfur for the reaction with any other element that could be used for the formation of sulfides in order to remove sulfur from hot metal. Therefore, the best methods of sulfur removal do not rely on the oxidation reaction [8]. There is a conclusion that the sulfur removal requires a separate process upstream the basic oxygen process. There are many methods of hot metal desulfurization which are subject to the location of the process (either the torpedo or the hot metal ladle), and the type of reagents injected or the method of metal bath stirring [5]. The conducted industrial research concerns the method of hot metal desulfurization in the charging ladle by injecting a desulfurizing agent in a dedicated desulfurization station.

The described method of desulfurization with a lance determines the need to consider two mechanisms of the reaction course. The first one concerns the reaction occurring in the three-phase area including the desulfurizing agent, carrier gas and metal bath. The reaction rate in this area is very intensive and depends largely on kinetic factors. The other mechanism to be considered are the reactions occurring at the metal-slag interface, where thermodynamic factors play a more significant role. A number of models are presented in the available literature. They indicate a variable share of both mechanisms [9, 10]. It seems that it still constitutes a serious barrier to creating credible process control systems based on the fundamental model. Therefore, activities aiming at developing black box type models based on credible industrial database sets are very rational. Models of this type are limited by the possibility of the implementation only being carried out at the station that was verified. However, the model prediction quality is a great asset, as it allows it to be applied to the process control.

3. Description of the hot metal desulfurization unit

The study was conducted on the basis of data from an actual metallurgical unit for hot metal desulfurization, where the method of lime and magnesium co-injection is applied (Fig. 1).

In this method, reagents are fed through a single-nozzle refractory lance centric immersed directly in the 300 Mg hot metal ladle. Nitrogen is the carrier of reagents, and it transports the desulfurizing agent deep into the hot metal and agitates the melt. Each of the reagents is

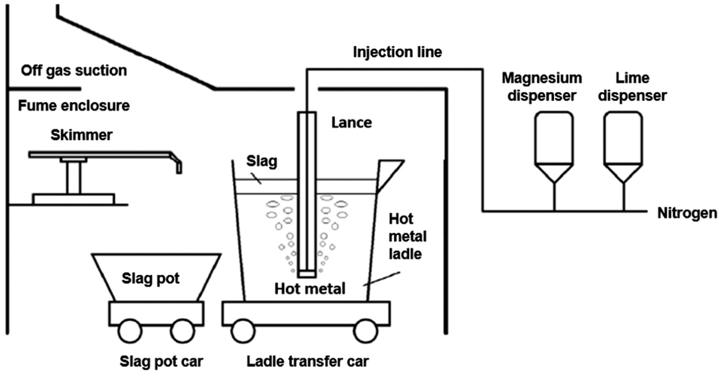

Fig. 1. Diagram of the desulfurization unit (co-injection of Ca-Mg)

stored in two tanks – the primary one, to which it is unloaded from the outside, and the intermediate one, from which the material is fed directly to the desulfurization process. Intermediate tanks are pressurized and the proper material flow depends on the tank pressure. Reagent flow rates assume the values given in Table 1. Reagent flow rates versus ladle capacity [11] depending on the hot metal ladle capacity.

Table 1. Reagent flow rates versus ladle capacity

Ladle capacity, Mg	Magnesium flow rate, kg/min	Lime flow rate, kg/min
80–150	6–15	20–45
150–300+	15–23	35–45

Reagents are mixed in an installation, which enables reagent mass proportions to be changed during the process. The Ca/Mg reagent ratio varies subject to the steel grade for which the process is carried out, and it may be 2:1, 4:1 or 6:1. During the desulfurization process, the reaction products – MgS and CaS – float to the slag layer. After the completed injection, those products are skimmed from the melt surface with a special skimmer. Thanks to the use of the described desulfurization method, it is possible to obtain a sulfur level below 10 ppm [11].

In the analysed case, the average mass of hot metal was 281 Mg, the average temperature after Blast Furnace (BF) was 1365°C, the average chemical composition of hot metal was: C 4.95%, Mn 0.112%, Si 0.594%, P 0.0886% and S 0.0308%.

4. Methodology of research on creating neural networks

For the research involving the creation of artificial neural networks as a solution to the problem presented, a database was used, which was created on the basis of the actual data from an operating metallurgical unit for hot metal desulfurization. The data set comprised

4,472 records (collected for the period from November 2020 to March 2022) - each record is one desulfurized heat at the desulfurization station; 29 various parameters were observed and they are presented in Table 2. The presented description shows that the number of parameters that can influence the desulfurization process is very large, and at this stage, it is difficult to assess their real impact on the process and the level of significance.

The technological assessment of the desulfurization operations conducted tells us to think about the strategy of searching for a model meeting the assumed prediction accuracy. In other words, the problem comes down to an answer to the question if we should look for a single versatile model or rather attempt to build a group of models, where each one is dedicated to strictly defined steel groups. Bearing this in mind, the available database of heats was assessed at the preliminary stage of the study.

Table 2. Control parameters and state parameters of the desulfurization process

State parameters	Control parameters
Chemical analysis of the hot metal before the desulfurization process (C, Si, Mn, P, S)	Consumption of reagents (magnesium, lime)
Chemical analysis of the hot metal after the desulfurization process (C, Si, Mn, P, S)	Average flow rate of reagents during the desulfurization process
Mass of hot metal	Pressure in reagent tanks
Hot metal temperature before and after the desulfurization process	Information from the operator about the initial and final sulfur content
Time of reagent feeding (magnesium, lime)	Initial mass of reagents in the tanks
Amount of slag skimmed after the process	Carrier gas pressure during the process

At this point, it's worth specifying the individual parameters, which are presented in Table 2. C_pouring, Mn_pouring, Si_pouring etc. it is the information about chemical analysis of the hot metal before the desulfurization process. T_pouring it's hot metal temperature before the desulfurization process, Mass_pouring is mass of the hot metal. Mg and Ca_used it's information about consumption of reagents (magnesium, lime). Mg and Ca_flow it's average flow rate of reagents during the desulfurization process. Mg and Ca_valve_OPEN it's information about time of reagent feeding. Mg and Ca_tank pressure is the pressure in reagent tanks. Mass_Ca_tank (and Mg) it's initial mass of reagents in the tanks. N_pressure – carrier gas pressure during the process. Time_between_pouring_deS – time between end pouring hot metal into the ladle and start desulfurization process. Ladle_age is information on how many heats the ladle has – i.e. how much it is used, because its volume changes with age.

Due to the steel grades produced, for which the desulfurization process was carried out, the database was divided into two groups (Table 3). The division criterion was the expected sulfur content after the desulfurization process. It is strictly related to the grades of the steels produced, which are widely applied, including rail, structural, electrotechnical or automotive steels.

Creating a correct database consisted in eliminating incomplete records, records diverging from the actual values arising from the hot metal characteristics, technical conditions of the desulfurization station operation or significantly differing from the other values of a specific parameter evaluated on the basis of historical data and professional experience.

Table 3. Database structure and set sizes

Group name	Characteristics (S content after process, ppm)	Group size
Data	10–280	4472
Group 1	≤ 100	3626
Group 2	> 100	846

STATISTICA Automated Neural Networks SANN was the tool used for the creation of artificial neural networks. In the first stage of creating models based on neural networks, an attempt to make a versatile model was made. The network was trained with a database containing all the gathered records. At the next stage, process models were searched for heat groups as defined in Table 3. During the search for a network meeting the requirements for the model, special attention was paid to:

1. obtaining network architecture which was a simple as possible and adequate for the complexity of the problem solved,
2. analysis of the significance of network input variables and comparison of sets of these variables for all the computation variants considered,
3. conducting an extended verification of the best networks on the basis of current production data.

5. Neural network learning programme

The first state is the selection of the analysis type. In the example concerned, it will be a regression problem because it corresponds to the specificity of the set analyzed, for which the considerations focus on an output variable with a quantitative nature. Next, the output variable and input variables should be defined. For obvious reasons, the sulfur content after the desulfurization process was defined as the output variable. The selection of the output parameter will not change in any of the subsequent calculations, regardless of the set of currently used data. As input parameters we mean any measurable quantities, which are attributed to a specific heat and constitute its individual characteristics, e.g. tonnage or temperature as well as parameters of the desulfurization process itself, which can be physically controlled in order to influence the final result of the process. The first computing performed for 1 output parameter – sulfur after the desulfurization process and 20 input parameters are presented in Fig. 2.

The other parameters shown in the list not included in the computing are used to identify individual records and to build and check the database.

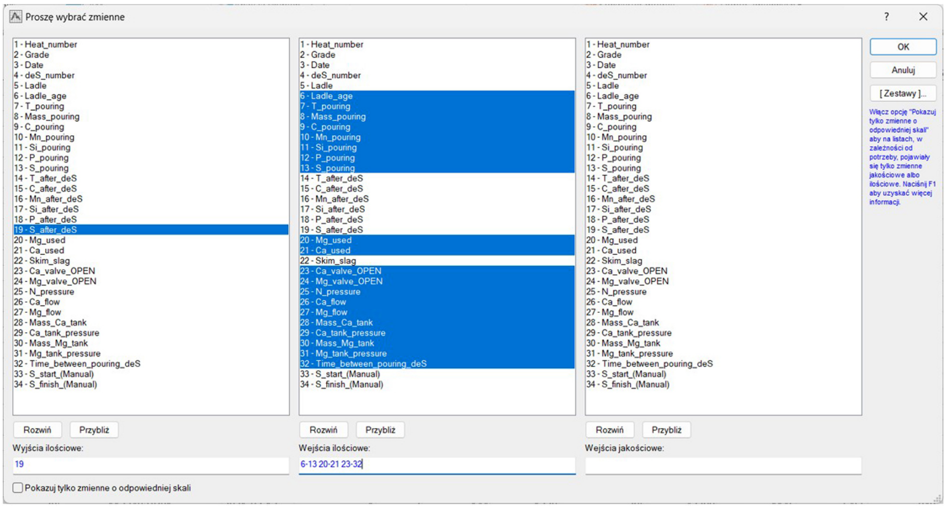

Fig. 2. Configuration of the input and output parameters for the first computing series

The next step is the selection of neural network creation mode. In the conducted study, we decided to use automatic network search mode. It allows many network architecture plans to be automatically tested and the best ones to be selected. In automatic mode, a space of various network types is searched, but ultimately an MLP (Multilayer Perceptrons) network is the most rational solution to the problem considered. On the basis of author's experiments, it was assumed that the minimum number of hidden neurons would be 4, and their maximum number would be 20. All networks created as a result of the search were saved for further verification.

6. Results of the first network learning and their assessment

To select the best network, the following activities were performed: on the generated sheet (Table 4), the column Quality (testing) was sorted in descending order, and networks with a low number of neurons in the hidden layers were selected ID MLP 20-5-1. After sorting, the first three networks with the lowest number of neurons in the hidden layer were selected.

The next action was computing the so-called network quotient. It is a quotient of the standard variation of prediction errors and the standard variation of the output variable. The results are presented in Table 5. The last step in determining the quality of the selected networks is computing the mean absolute error of prediction – it's means the difference between the real sulfur content in hot metal after desulfurization and obtained results from SANN. For the first learning cycle, the mean absolute error for the selected neural networks was 17 ppm.

Table 4. Summary of the found networks for the first computation series

Network ID	Quality (learning)	Quality (testing)	Quality (validation)	Activation (hidden)	Activation (output)
MLP 20-18-1	0.875248	0.874999	0.843381	Tanh	Linear
MLP 20-13-1	0.878585	0.877566	0.846219	Logistic	Tanh
MLP 20-9-1	0.873225	0.872194	0.840425	Exponential	Linear
MLP 20-20-1	0.876612	0.878794	0.846556	Tanh	Tanh
MLP 20-4-1	0.876133	0.873393	0.844912	Logistic	Logistic
MLP 20-16-1	0.884941	0.881240	0.841681	Tanh	Linear
MLP 20-21-1	0.881241	0.877286	0.843236	Logistic	Tanh
MLP 20-18-1	0.872436	0.876819	0.846373	Tanh	Logistic
MLP 20-5-1	0.886440	0.882045	0.845527	Tanh	Logistic
MLP 20-11-1	0.892352	0.874005	0.834171	Tanh	Exponential

Legend: Structure of MLP Network: MLP X-Y-Z, where X – number of neurons in the input layer; Y – number of neurons in the hidden layer; Z – number of neurons in the output layer.

The objective of the whole learning process is to build such neural networks where the prediction of the output parameter is as close to the actual parameter value as possible. In other words, it is to train the neural network regarding the correlation between the output parameter and the input parameters.

Table 5. Network quotient for the first computation series

Network ID	Standard deviation of the dependent variable	Standard deviation of the difference between the dependent variable and output value	Network quotient	Mean absolute error, ppm
6. MLP 20-5-1	51.612546	24.364551	0.4721	16.6
19. MLP 20-16-1	51.612546	24.397364	0.4727	16.8
16. MLP 20-20-1	51.612546	24.629556	0.4772	16.6
18. MLP 20-13-1	51.612546	24.768358	0.4799	17.1
20. MLP 20-18-1	51.612546	24.998564	0.4844	17.1

To improve the trained networks, in the next learning sequence these input parameters that do not influence the final results and that can sometimes worsen the quality of the created network should be discarded. The so-called Global sensitivity analysis should be used for the selection of parameters. It enables the parameters that are irrelevant for the neural network created to be indicated. During the subsequent learning sequence, thanks to limiting the number of input parameters, the structure of the neural network itself can be simplified and its quotient can be improved. According to the assumed definition, the sensitivity analysis isa quotient of the error obtained at starting the network for a data set without one variable and the error obtained with a whole set of variables. The higher the error is after discarding a variable in relation to the original error, the more sensitive the network will be to the shortage of this variable. If the error quotient is 1 or lower, the removal of a variable does not affect the network quality or it even improves it.

After completing a global sensitivity analysis for the selected neural networks, we sort the numeric values in descending order, and in the next learning sequence, during the selection of input parameters, we discard the ones for which the values from the global sensitivity analysis are lower or equal 1 (Fig. 3).

Sieci	1 6.MLP 20-5-1
Mg_used	4,35140094
S_pouring	3,26147429
Ca_valve_OPEN	1,27475578
Ca_tank_pressure	1,22546748
Mg_valve_OPEN	1,16160664
Ca_used	1,0931041
Mg_flow	1,07543231
C_pouring	1,05682753
Mn_pouring	1,05374254
Mass_Ca_tank	1,03558971
Mass_pouring	1,02826695
N_pressure	1,01583551
Si_pouring	1,01400091
Ladle_age	1,00767982
Time_between_pouring_deS	0,999414436
P_pouring	0,999238272
Mass_Mg_tank	0,996972908
Ca_flow	0,993962673
Mg_tank_pressure	0,993239143
T_pouring	0,991602615

Fig. 3. Global sensitivity analysis for the first learning cycle

In the case considered, the set of discarded parameters also contains values which intuitively should remain. We need to mention lime consumption or the mass of skimmed slag, for example. The adopted solution should be a compromise between the process knowledge and the objective statistical analysis. It happens that a network trained on the basis of the available database does not find dependencies on the mentioned process parameters and, at this stage, it is better to resign from statistically irrelevant parameters.

7. Results of neural network creation for defined steel groups

In accordance with the previously presented concept, in the next step in the study, neural networks were found to predict the final sulfur content after the desulfurization process for the groups defined in Table 3. In each case, the procedure was the same, identical to the methodology described above for the collective database.

The next step in the construction of models for the defined process groups is to select the best 5 networks featuring the lowest quotient and to perform the final selection on the basis of network architecture simplicity. Indeed, the last of the mentioned premises does not allow a precise selection to be made, but it is relevant for the possibilities of the network as regards its ability to generalize a problem. In fact, it is about applying a network, which is not too intelligent for the problem solved. The ultimate effect of the search for the networks that are the best at predicting the desulfurization process result for the defined heat groups is summarised in Table 6. For each of the selected networks in group 1, the mean absolute error is 16 ppm, while for group 2, this error for each of the neural networks is 25 ppm.

Table 6. Architecture and parameters of the selected neural networks verified for two groups of heats taking into account the level of hot metal desulfurization

Network ID	Standard deviation of the dependent variable	Standard deviation of the difference between the dependent variable and output value	Network quotient	Mean absolute error, ppm
Group 1				
1. MLP 20-7-1	39.732947	23.526111	0.5921	15.7
10. MLP 20-9-1	39.732947	23.545995	0.5926	15.4
17. MLP 20-13-1	39.732947	23.547910	0.5927	15.5
13. MLP 20-9-1	39.732947	23.645694	0.5951	15.7
18. MLP 20-13-1	39.732947	23.683885	0.5961	15.4
Group 2				
6. MLP 20-5-1	68.507238	33.502008	0.4890	25.5
19. MLP 20-16-1	68.507238	33.542977	0.4896	24.7
16. MLP 20-20-1	68.507238	34.183256	0.4990	25.2
18. MLP 20-13-1	68.507238	34.599170	0.5050	25.4
20. MLP 20-18-1	68.507238	35.291040	0.5151	26.4

To show differences between individual neural networks and their input parameters, Table 7 and Table 8 presents a collective summary of used vectors. Vector is a set of parameters involved in the learning process. The input parameters that exist in each neural network learning cycle deserve to be distinguished. These parameters include: sulfur content after the process of pouring hot metal into the charging ladle (S_pouring); consumption of magnesium for the hot metal desulfurization process (Mg_used); flow rate of magnesia during the process (Mg_flow), and the pressure in the lime tank (Ca_tank_pressure). The sulfur content after the pouring process and the amount of magnesium used for the process are the most logical and correct parameters occurring for each learning cycle, as these are parameters necessary for physical start of the hot metal desulfurization process (S_pouring) as well as the end of the process (Mg_used). A variable concerning the amount of used magnesium, also directly determines the level of hot metal desulfurization, or the dependent variable (S_after_deS), from the purely technological point of view – the more desulfurizing agent there is, the higher the desulfurization level will be. It is noteworthy that two subsequent parameters – the flow rate of magnesium during the process (Mg_flow) and the pressure in the lime tank – also influence the quality of the hot metal desulfurization process. The material flow is directly related to the time of its feeding, which can neither be too short (too short a process time prevents the whole reagent from reacting) nor too long (it causes the formation of too much slag thus extending the process time – extended slag skimming phase). This causes problems with the planning and logistics of steel production (danger of breaking the steel continuous casting process). Lime tank pressure is a purely technological parameter, related to the station structure and the desulfurization practice – it directly influences the rates of the fed reagents (magnesium and lime). Too high a lime tank pressure can cause problems with feeding the desulfurizing agent (magnesium).

Not only were the obtained networks assessed for the test set created earlier at the learning stage, but also on the basis of the most recent data obtained from the current industrial process. The obtained results had good compatibility with the results from Table 9. The already defined network quotient and the mean relative error of prediction variations were selected as a measure for the network quality evaluation. The last value is calculated according to the formula:

$$\Delta S = \frac{\sum_{i=1}^{N} \frac{|S_{\mathrm{real}} - S_{\mathrm{model}}|}{S_{\mathrm{real}}}}{N} * 100\,\% \tag{7.1}$$

where: ΔS – mean error of prediction variation, S_{real} – final real sulfur content after the desulfurization process in heat “i”, S_{model} – sulfur content in the process “i” computed from the model, N – number of heats.

The conducted analysis of sensitivity to input variables allowed us to define the final network architecture for each group of heats (Table 9). The mean absolute error for group 1 is 15 ppm, and for group 2 this error is 25 ppm.

Table 7. Summary of results of the conducted analysis of sensitivity of input variables for the three heat groups modelled (parameters 1–11)

Group	Learning cycle	Neural network	Network quantity	Absolute error	1	2	3	4	5	6	7	8	9	10	11
Data	1	MLP 20-5-1	0.4721	17 ppm	Depended variable	1	1	1	1	1	1	1	1	1	1
	2	MLP 13-8-1	0.4651	16 ppm		0	0	1	1	1	1	0	1	1	1
Group 1	1	MLP 20-7-1	0.5921	16 ppm		1	1	1	1	1	1	1	1	1	1
	2	MLP 10-5-1	0.5787	15 ppm		0	0	1	1	0	0	0	1	1	0
Group 2	1	MLP 20-9-1	0.4890	25 ppm		1	1	1	1	1	1	1	1	1	1
	2	MLP 8-10-1	0.4887	25 ppm		0	0	0	0	1	1	1	1	1	1

Legend: Names of parameters: 1 – S_after_deS (dependent variable); 2 – Ladle_age; 3 – T_pouring; 4 – Mass_pouring; 5 – C_pouring; 6 – Mn_pouring; 7 – Si_pouring; 8 – P_pouring; 9 – S_pouring; 10 – Mg_used; 11 – Ca_used; Values for individual parameters: 1 – used for training the network; 0 – not participating in the learning process.

Table 8. Summary of results of the conducted analysis of sensitivity of input variables for the three heat groups modelled (parameters 12–21)

Group	Learning cycle	Neural network	Network quantity	Absolute error	12	13	14	15	16	17	18	19	20	21
Data	1	MLP 20-5-1	0.4721	17 ppm	1	1	1	1	1	1	1	1	1	1
	2	MLP 13-8-1	0.4651	16 ppm	0	0	1	1	1	1	0	11	11	1
Group 1	1	MLP 20-7-1	0.5921	16 ppm	1	1	1	1	1	1	1	1	1	1
	2	MLP 10-5-1	0.5787	15 ppm	0	0	1	1	0	0	0	1	1	0
Group 2	1	MLP 20-9-1	0.4890	25 ppm	1	1	1	1	1	1	1	1	1	1
	2	MLP 8-10-1	0.4887	25 ppm	0	0	0	0	1	1	1	1	1	1

Legend: Names of parameters: 12 – Mg_valve_OPEN; 13 – Ca_valve_OPEN; 14 – N_pressure; 15 – Ca_flow; 16 – Mg_flow; 17 – Mass_Ca_tank; 18 – Ca_tank_pressure; 19 – Mass_Mg_tank; 20 – Mg_tank_pressure; 21 – Time_between_pouring_deS; Values for individual parameters: 1 – used for training the network; 0 – not participating in the learning process.

Table 9. Modified architecture and parameters of the selected neural networks verified for two groups of heats taking into account the level of hot metal desulfurization

Network ID	Standard deviation of the dependent variable	Standard deviation of the difference between the dependent variable and output value	Network quotient	Mean absolute error, ppm
Group 1				
2. MLP 10-5-1	39.732947	22.995274	0.5787	15.2
13. MLP 10-7-1	39.732947	23.184815	0.5835	15.0
5. MLP 10-11-1	39.732947	23.521487	0.5920	15.3
10. MLP 10-11-1	39.732947	23.698755	0.5965	15.6
12. MLP 10-12-1	39.732947	23.882739	0.6011	15.6
Group 2				
10. MLP 8-10-1	68.507238	33.478292	0.4887	25.5
18. MLP 8-9-1	68.507238	34.058714	0.4972	25.2
16. MLP 8-8-1	68.507238	34.182916	0.4990	25.8
15. MLP 8-6-1	68.507238	34.249814	0.4999	25.4
2. MLP 8-5-1	68.507238	34.533481	0.5041	25.8

8. Summary

The construction and verification of hot metal desulfurization process models based on artificial intelligence provides many interesting results, which can be used both in the area of control and for the theoretical analysis of the process. The conclusion concerning the theoretical analysis as regards models using artificial neural networks may seem overly optimistic because of a common belief that black box type models do not enrich our knowledge of the process. However, in the case in question, we deal with a situation where one of the key research questions is about the influence of static and dynamic factors on the process. With the problem formulated like this, the analysis of the input layer of a neural network combined with the analysis of significance of individual input parameters enables a qualitative assessment to be made.

In the conducted research, the accuracy of models dedicated to the three heat groups listed in Table 3 was very satisfying. It was better than the accuracy of the existing solutions and it could be the basis for the modernisation of the existing control system. The forecast error expressed by the absolute error value is about 15 ppm for heats with a sulfur content $<$ 100 ppm and 25 ppm for heats with the final sulfur content $>$ 100 ppm. These results should be treated as accurate due to the methodology of determining the chemical composition and its range of measurement error.

When training neural networks it was observed that some input parameters did not take part in the second and subsequent learning. This means that they did not bring relevant information for neural networks and finally did not influence the prediction of the output vector (Table 7, Table 8). There are also such parameters that exist in each learning cycle of neural networks, meaning that there is a correlation between these parameters and the output parameter and they influence the prediction. These parameters include the sulfur content before the desulfurization process, consumption of magnesium in the processes, its mean flow rate during the desulfurization process and the lime tank pressure. It is relevant information from the perspective of the desulfurization process practice because this information provides the basis for a change in process parameters, and consequently an improvement of the desulfurization process quality.

9. Conclusions

The conducted research and obtained results allow us to formulate a few relevant conclusions:

– an MLP type neural network with a single hidden layer is sufficient to describe the problem of predicting change in the sulfur content during the hot metal desulfurization process. Adopting a more complex network structure would probably lead to a loss of the ability to generalise the problem,
– the conducted analysis of the sensitivity of input variables indicated that the following were the most relevant parameters describing the hot metal desulfurization process: sulfur content before desulfurization process [ppm], consumption of magnesium in the process [kg], average flow rate of magnesium in the desulfurization process [kg/min] and lime tank pressure [kPa],
– taking into account the division of input parameters into state parameters and control parameters and taking into account the global sensitivity analysis, you can assume that, for the hot metal desulfurization station described, the control parameters were properly identified,
– in order to improve the quality of prediction of the constructed model, it is important to obtain new input variables to describe the process

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Modelowanie procesu odsiarczania surówki żelaza przy użyciu metod sztucznej inteligencji

Słowa kluczowe: odsiarczanie, sieci neuronowe, stalownictwo, surówka żelaza

Streszczenie:

Budowa i weryfikacja modeli procesu odsiarczania surówki żelaza opartych o sztuczną inteligencję dostarcza bardzo wiele interesujących wyników, które mogą być wykorzystane zarówno w obszarze związanym ze sterowaniem jak i do celów teoretycznej analizy procesu. Wniosek dotyczący analizy teoretycznej w odniesieniu do modeli wykorzystujących sztuczne sieci neuronowe może wydawać się zbyt optymistyczny, bowiem powszechnie uważa się, że modele typu black box nie wzbogacają naszej wiedzy o procesie. W omawianym przypadku mamy jednak do czynienia z sytuacją, w której jednym z kluczowych pytań badawczych jest odpowiedź jak duży wpływ na proces mają czynniki statyczne, a jaki dynamiczne. Przy tak sformułowanym problemie, analiza warstwy wejściowej sieci neuronowej połączona z analizą istotności poszczególnych wielkości wejściowych, umożliwia co najmniej ocenę jakościową. W przeprowadzonych badaniach, dokładność modeli dedykowanych

wymienionym w tablicy 3 grupom wytopów jest bardzo zadowalająca. Przewyższa ona dokładność dotychczasowych rozwiązań i może być podstawą do modernizacji istniejącego systemu sterowania. Średni błąd prognozy wyrażony za pomocą wartości błędu bezwzględnego to wynik rzędu 15 ppm dla wytopów o zawartości siarki < 100 ppm oraz 25 ppm dla wytopów o siarce końcowej > 100 ppm. Wyniki te należy traktować jako dokładne ze względu na metodę określania składu chemicznego (Optyczna spektroskopia emisyjna OES) oraz jej zakres błędu pomiarowego. Szczególnie interesujące jest porównanie wektorów wielkości wejściowych analizowanych grup wytopów. Ze względu na swój charakter wektory wejściowe zostały podzielone na dwie grupy – parametry stanu oraz parametry sterujące. Do grupy parametrów stanu należeć będą wszystkie te wielkości, które są stałe i nie ma możliwości ich zmiany bez udziału parametrów sterujących (skład chemiczny surówki wielkopiecowej, temperatura czy masa surówki). Parametry sterujące natomiast są to wszystkie wielkości, dla których istnieje realna możliwość ich regulacji – będą to parametry technologiczne stacji odsiarczania takie jak zużycie reagentów, ciśnienie azotu transportującego reagenty czy średni przepływ materiałów do procesu. W trakcie uczenia sieci neuronowych na podstawie globalnej analizy wrażliwości zauważono, iż pewne parametry wejściowe nie biorą udziału w drugim i kolejnym uczeniu. Oznacza to, że dla sieci neuronowych nie wnoszą one istotnych informacji i finalnie nie wpływają na predykcję wektora wyjściowego. Takimi parametrami są wiek kadzi zalewowej, temperatura surówki przed procesem odsiarczania, przepływ wapna, masa magnezu w zbiorniku przed rozpoczęciem procesu oraz czas pomiędzy nalaniem surówki do kadzi zalewowej a rozpoczęciem odsiarczania. Istnieją również takie parametry, które występują w każdym cyklu uczenia sieci neuronowych, co oznaczać będzie korelację pomiędzy tymi parametrami a parametrem wyjściowym i ich realny wpływ na predykcję. Do takich parametrów należą zawartość siarki przed procesem odsiarczania, zużycie magnezu w procesie, jego średni przepływ w trakcie procesu odsiarczania oraz ciśnienie zbiornika wapna. Jest to istotna informacja z punktu widzenia technologii prowadzenia procesu odsiarczania, ponieważ dzięki niej istnieje podstawa do zmiany parametrów procesu, a w konsekwencji polepszenie jakości procesu odsiarczania. Przeprowadzone badania i uzyskane wyniki pozwalają na sformułowanie kilku istotnych wniosków. Do opisu problemu predykcji zmiany zawartości siarki podczas procesu odsiarczania surówki wystarcza sieć neuronowa typu MLP z jedną warstwą ukrytą. Przyjęcie bardziej złożonej struktury sieci prowadziłoby prawdopodobnie do utraty zdolności generalizowania problemu. Przeprowadzona analiza wrażliwości zmiennych wejściowych wskazuje, że najistotniejszymi parametrami opisującymi proces odsiarczania surówki są: zawartość siarki przed procesem odsiarczania [ppm], zużycie magnezu w procesie [kg] średni przepływ magnezu w trakcie procesu odsiarczania [kg/min] oraz ciśnienie zbiornika wapna [kPa]. Uwzględniając podział parametrów wejściowych na parametry stanu i parametry sterujące oraz uwzględniając wykonaną globalną analizę wrażliwości, można przyjąć, że w przypadku opisywanego stanowiska do odsiarczania surówki żelaza parametry sterujące zostały właściwie zidentyfikowane. W celu poprawy jakości predykcji zbudowanego modelu ważnym kierunkiem będzie pozyskanie nowych zmiennych wejściowych opisujących proces.

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