Journal of
Ceramic Science
and Technology

J. Ceram. Sci. Technol., **11** [2] 81-90 (2020)
DOI: 10.4416/JCST2020-00009
available online at: http://www.ceramic-science.com

Modelling the Wear of MC 98/15 Refractory Material in the Slag Spout Zone of an Oxygen Converter with the Use of Artificial Neural Networks

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received February 17, 2020; received in revised form August 4, 2020; accepted August 9, 2020

Abstract

In oxygen converters, the high temperature and aggressive alloys affect the refractory lining, which is most frequently made of MgO-C materials. The refractory lining of a converter is worn zonally along with the progress of the campaign. This paper describes a trial conducted to forecast the wear of the refractory material depending on the selected parameters of the metallurgical process. Based on the results of industrial measurements, a wear model of the magnesia-carbon refractory material for the converter slag spout zone was developed. For the construction of the model, multilayer artificial neural networks were used. The accuracy of the forecast of the refractory material wear in the wear classes achieved in the experiment equals 63.9 % with the network architecture consisting of the following numbers of the neurons 17: h(20,10,5) :10, where the parameter h(20,10,5) contains the number of neurons in individual hidden layers. The calculations were made i.a. in the R language and environment.

Keywords: Refractories, MgO-C, BOF converter, artificial neural network, statistical analysis

I. Introduction

The oxygen converter is one of the two principal steel aggregates used in the preparation of steel for secondary treatment. The volume of steel manufactured in the converter process currently reaches over 50 % of smelted steel [1].

In the converter, carbon, silicon, phosphorus and manganese are oxidized, and the liquid is heated to the temperature necessary for further metallurgical operations. Slag formation is the consequence of the oxidation reaction of the applied non-metallic additives and dissolution of the converter's refractory lining. The chemical composition of the liquid metal, slag and the bath temperature vary during the process lasting not more than 70 minutes. It is shown in Fig. 1. The wear of the refractory lining of the converter decides on its lifespan.

The multiple variations in the wear of the refractory materials mean simplifications are necessary for its description, which is demonstrated by the Noyes-Nernst formula [3] for dissolution of the components of a refractory material:

$$\frac{dC(t)}{d(t)} = \frac{D \cdot A}{\delta \cdot V} \cdot (Cs - C(t)) \qquad (1)$$

where: *C(t)* means the concentration of a component of the refractory material in the slag in the moment *t*, *Cs* – the saturation concentration of a component of the refractory material in the slag, *D* – diffusion coefficient, *A* – contact surface between the refractory material and the slag, δ – thickness of the liquid diffusion layer, *V* – volume of the liquid that infiltrates the porous refractory material.

The solution of the Noyes-Nernst formula (NN) is a dependence of the dissolved component concentration of the refractory material on time *t*. The solubility expressed by the NN formula implicitly takes into consideration the temperature and selected properties of the microstructure of the refractory material. A practical application of that formula as an instrument for forecasting the wear is impossible, as the user expects a connection of the parameters of the metallurgical process, collected throughout the entire campaign, with the observed wear of the refractory lining. One method to find such a connection is dimensional analysis, which makes it possible to determine criterial equations. Such an approach was applied by Potschke [4], as well as Vollmann and collaborators [5–7]. A dimensional analysis in a forecast of the wear of refractory materials with consideration of process and material factors was also employed by Lech and Zelik [8,9]. Determination of coefficients for criterial equations requires the utilization of regression methods. A solution is an equation that combines selected variables with the forecast value.

The ability to forecast the wear degree of the lining with the employment of numerical models is necessary both for the consumers as well as the manufacturers of refractory materials. Safety of the operation of campaigns, under-

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standing of the cause-and-effect relationship between the process parameters and the wear of the refractory materials and lastly the logistics of supplies of ceramic linings are the paramount advantages arising from the application of that model.

Hence the purpose of this article is an attempt to apply an artificial, multi-layer neural network, which is a strong predictive method [10], for forecasting the wear of refractory materials in an oxygen converter, and thereby for forecasting its lifespan. There is a lack of known investigations dedicated to the applications of artificial neuron networks in the subject of prediction of oxygen converter refractory lining lifespan at the present time, especially those that simultaneously take the process and operational parameters into account.

II. Construction and Operation of a TBM Oxygen Converter

The best known and oldest type of oxygen converter (BOF) is that with a top blow (LD). The newer version of the device, i.e. the TBM oxygen converter, originated as a result of the implementation of the inert gas blow system into the liquid metal through the converter bottom. There are also other types of converters [1,2]. So far, all modifications of the design of an oxygen converter have served the improvement of the quality of the manufactured steel. A TBM oxygen converter is a chemical reactor with a capacity from 50 to 400 tonnes in the form of a steel vessel lined inside with refractory materials. A diagram of the zones in a TBM oxygen converter lined with various refractory materials is presented in Fig. 2.

The zone of the refractory lining of an oxygen converter with the highest wear, which is the subject of research and modelling, is the so-called slag spout zone. In that zone thermal and chemical stresses are concentrated that result from the dynamically varying chemical composition of the slag during a heat. The slag spout zone consists of two converter areas (left and right spout) with constricted access for maintenance, hence, heat after heat, they are subject to severe wear. The converter trunnions also make for an area of severe wear of the refractory material. In those areas, the highest grades of MgO-C refractories are used with graphite contents over 12 % and a share of fused magnesias with large crystals and purities over 97.5 % of MgO by weight.

In the oxygen converter with a nominal capacity of 350 t, for which the attempt was made to develop a model for the refractory material wear, 2 063 heats had been completed. The converter had been shut down because of the wear of the refractory materials in the slag spout zone. The converter had been in operation for about five months. In the slag spout zone a high-quality pitch-bonded MC 95/10 refractory was used according to *PN-EN ISO 10081 – 3:2006 (Classification of dense shaped refractory products - Part 3: Basic products containing from 7 percent to 50 percent residual carbon)*. The properties of the MC 95/10 refractory are given in Table 1.

Table 1: Properties of the MC 95/10 refractory used in the slag spout zone of the TBM oxygen converter

Property	Typical value	Standard
MgO in the magnesia part	97.7 %	XRF – X'Unique II
CaO in the magnesia part	1.5 %	XRF – X'Unique II
SiO_2 in the magnesia part	0.4 %	XRF – X'Unique II
Fe_2O_3 in the magnesia part	0.3 %	XRF – X'Unique II
Al_2O_3 in the magnesia part	0.1 %	XRF – X'Unique II
Open porosity	1.5 %	PN-EN 993 – 1
Apparent density	$3.05\ g \cdot cm^{-3}$	PN-EN 993 – 1
Crushing strength	35 MPa	PN-ISO 10059 – 1
Total carbon	14 %	HFF-IR Leco CS300

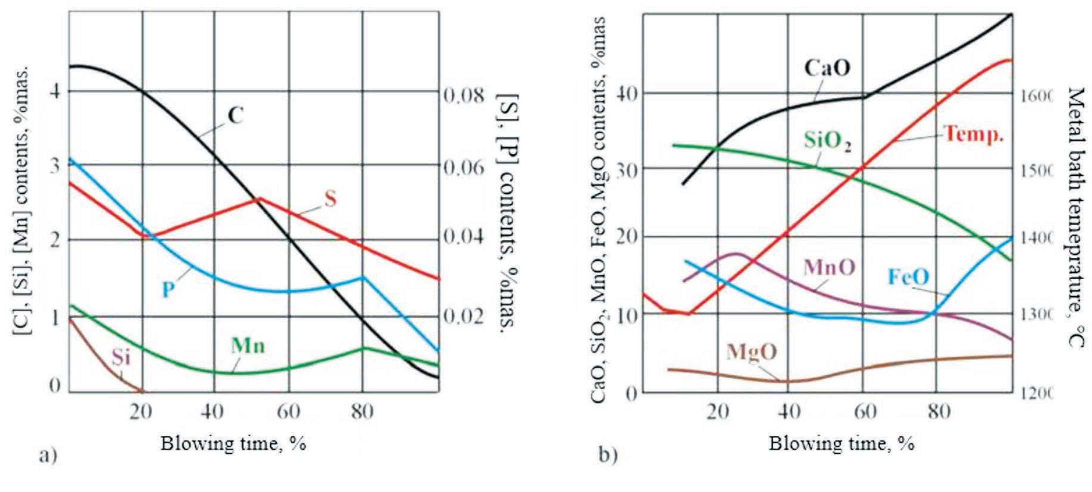

Fig. 1: Metal composition (a) and slag composition (b) during a heat conducted in an oxygen converter [2].

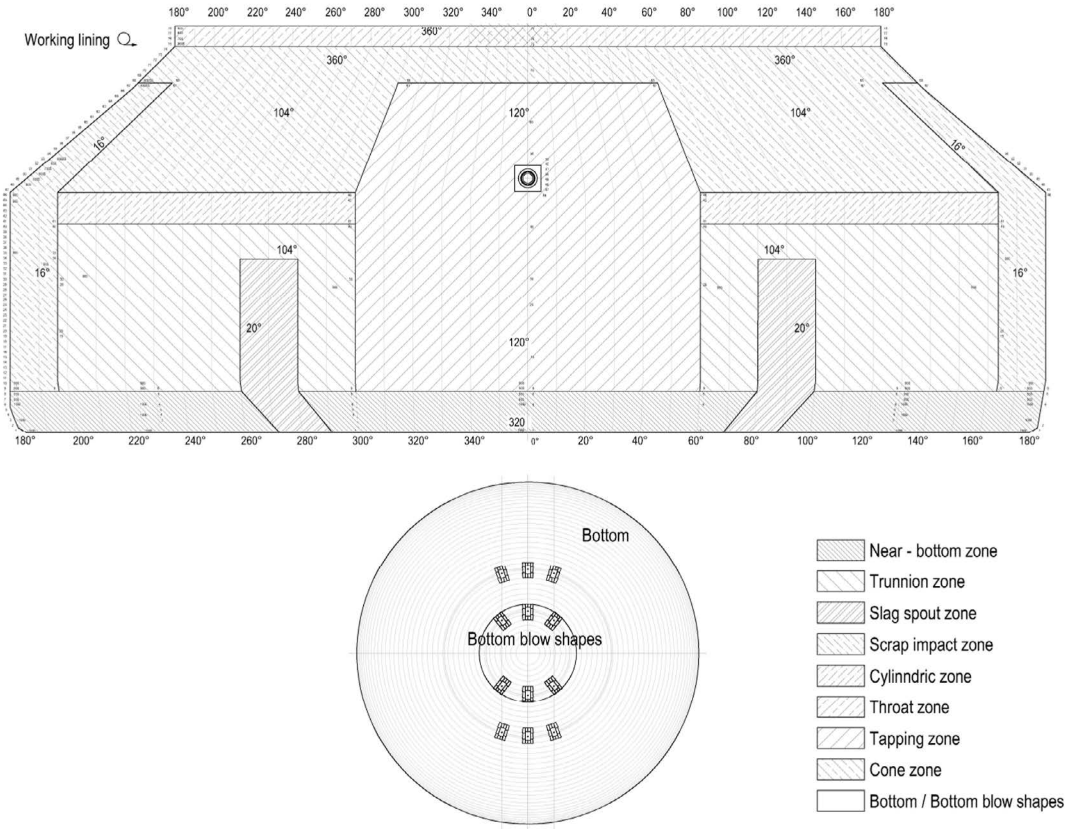

Fig. 2: Schematic development of the refractory working lining of a TBM oxygen converter with its zones marked, including its highest wear zone, i.e. the slag spout zone. Below the development, a projection of the converter bottom is shown.

The initial thickness of the working lining in the slag spout zone was 900 mm. The zone was lined with a combination of flat wedges 90/80 and 90/20 with the dimensions of 900 x 100 x 190/110 and 900 x 100 x 160/140 mm, respectively. The converter was not equipped with a slag splashing installation. During its campaigns, the converter was maintained by gunning and slagging. Average chemical compositions of final slags resulting from the composition of the hot metal, applied non-metallic additives and dissolved refractory lining are presented in Table 2.

Table 2: Average concentrations and standard deviations of the principal brick components

Oxide	Average, wt%	Standard dev, wt%	Number of measurements, n
MgO	97.7	1.30	1 459
CaO	1.5	3.75	1 459
SiO_2	0.4	2.21	1 459
Al_2O_3	0.1	0.46	1 459
Fe_{tot}	1.5	3.29	1 459

The converter charge consists of scrap wetted with desulphurized hot metal. Next, lime and other metallic and non-metallic additives are added to the charge. Gaseous oxygen with a set flow rate is blown into the converter from the top through a water-cooled lance. The inert gas is supplied from the bottom through ceramic shapes made using MgO-C refractories. The source of heat for the liquid metal are exothermic reactions occurring with various rates, the principal ones being:

$$[C] + \frac{1}{2}O_2 \rightarrow CO + \Delta H_1 \tag{2}$$

$$[C] + [O] \rightarrow CO + \Delta H_2 \tag{3}$$

$$[Si] + O_2 \rightarrow SiO_2 + \Delta H_3 \tag{4}$$

$$2[P] + \frac{2}{5}O_2 \rightarrow P_2O_5 + \Delta H_4 \tag{5}$$

$$[Mn] + \frac{1}{2}O_2 \rightarrow MnO + \Delta H_5 \tag{6}$$

After the blowing has been stopped and the quality of the obtained melt has been confirmed, the metal is poured from the converter into a ladle. The set of the melts executed from the moment of the start of the converter operation until its termination is called a campaign.

III. Factors Influencing the Wear of the Refractory Lining of an Oxygen Converter

The rate of wear of refractory linings is expressed through the index of wear of their refractory materials calculated per one heat. That index depends on many parameters. That dependence is connected with the parameters of the conducted process and properties of the refractory material used in a given zone. A high operating temperature, aggressive and liquid slags as well as variable oxygen partial pressure cause the loss of the refractory materials in the converter. The factors that cause the wear of the converter refractory lining are among others: (1) hot metal weight, kg; (2) hot metal temperature, °C; (3) C in the hot metal, wt%; (4) Si in the hot metal, wt%; (5) S in the hot metal, wt%; (6) lime, kg; (7) total weight of the applied MgO-introducing additives, kg; (8) total volume of O_2 blown in through the lances, Nm^{-3}per heat; (9) additional blowing, YES/NO; (10) steel temperature, °C; (11) active oxygen, ppm; (12) MgO dissolved in the slag, wt%; (13) slag basicity CaO/SiO_2, wt%/wt% (dimensionless value); (14) total Fe in the slag, wt%; (15) SiO_2 in the slag, wt%. Additionally, for each heat, the information on gunning, Mg/day and slagging, number of slaggings/ day, was registered in the database. The above variables were used in the developed model of the refractory lining wear in the examined oxygen converter.

A measurement of the wear of the refractory lining in a converter is conducted with a laser device with a frequency resulting from the load and availability of the device, but not less frequently than a dozen or so per a campaign. The measured residual thickness of the lining is a basis to take decisions connected with the converter maintenance, consisting of gunning, slagging or utilization of the slag splashing technology. The state of the refractory lining and analysis of the costs incurred for shaped and unshaped refractory materials used in the campaign, as well as for auxiliary materials, is a basis to take a decision to terminate a converter campaign.

IV. The Database Used to Build the Model for the Wear of the Converter Refractory Lining

Values of all input variables obtained from industrial measurements were normalized to the range from 0 to 1. The following function was used for the normalization:

$$N(x) = (x - \min(x))/(\max(x) - \min(x)) \qquad (7)$$

where: x is measured value of the investigated variable, N(x) is normalized value of the variable. A sample diagram for the dispersion of normalized results from the measurement of Si content in the hot metal is shown in Fig. 3.

The values of the above-mentioned factors influencing the wear of the refractory lining of the examined oxygen converter were measured during the campaigns of the examined converter. In the collected measurement results, there were missing data and erroneous values of readings. In the modelling, the erroneous readings were taken as missing data. Missing data (NA – Not Available) were filled with the employment of the R language and environment and the kNN algorithm (k nearest neighbours, in the calculation k = 5 was adopted). In the individual variables the following missing data occurred: hot metal weight - 32 NA (which accounted for 1.55 % of the number of measurements) and then the hot metal temperature - 52 NA (2.52 %), C in the hot metal - 218 NA, (10.57 %), Si in the hot metal - 218 NA (10.57 %), S in the hot metal - 218 NA (10.57 %), lime - 106 NA (5.14 %), MgO carriers - 166 NA, (8.05 %), volume of oxygen in the top blow - 66 NA, (3.2 %), additional blow - 0 NA (0 %), steel temperature - 145 NA (7.03 %), active oxygen - 502 NA (24.33 %), MgO in the slag - 604 NA (29.28 %), slag basicity - 604 NA (29.28 %), total Fe in the slag - 604 NA (29.28 %), SiO_2 in the slag – 604 NA (29.28 %).

Calculations conducted in order to complete the missing data were made using the VIM (Visualization and Imputation of Missing Value) library. The result of the completion of the missing data for e.g. the contents of silicon in the hot metal is shown in Fig. 4.

A precise measurement of the residual thicknesses of the refractory material in the slag spout zone during the campaign is the basic condition to construct a correct model of the refractory lining wear. 25 laser measurements of residual thicknesses of the slag spout zone refractory lining of the oxygen converter were made during the campaign consisting of 2 063 heats. The measurements were always taken in the same places on the lining. The residual thicknesses of the left and right spout of the oxygen converter were measured. The sum of the residual thickness was divided by two and the mean was taken as the measured thickness of the lining. The results of these measurements and calculations are shown in Fig. 5 by the dot points.

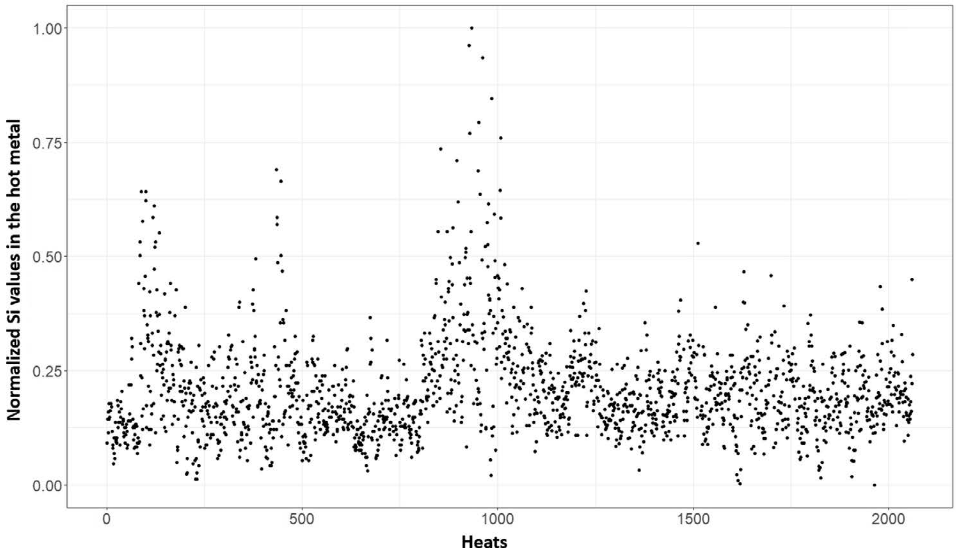

Fig. 3: Diagram showing the dispersion of normalized contents of Si in the hot metal.

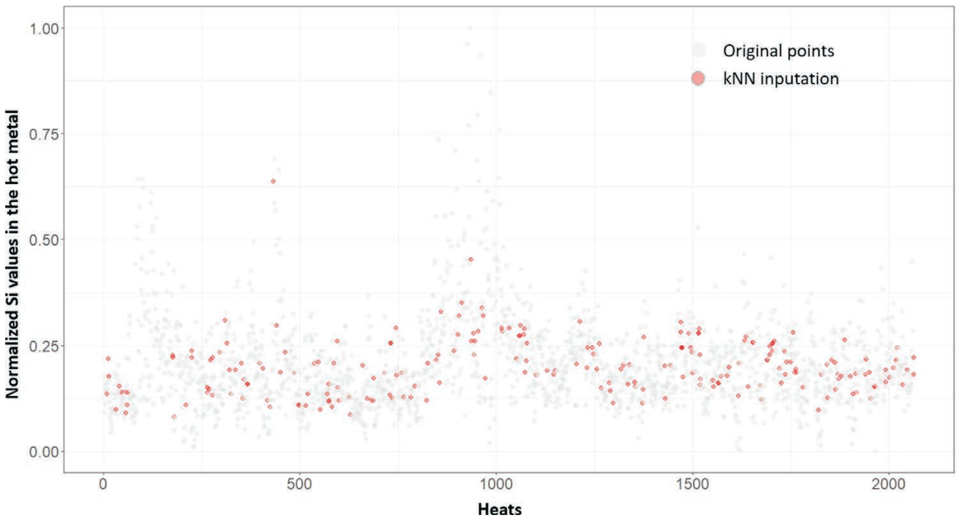

Fig. 4: Diagram showing the dispersion of normalized contents of Si in the hot metal together with missing data (NA) completed by means of the kNN algorithm.

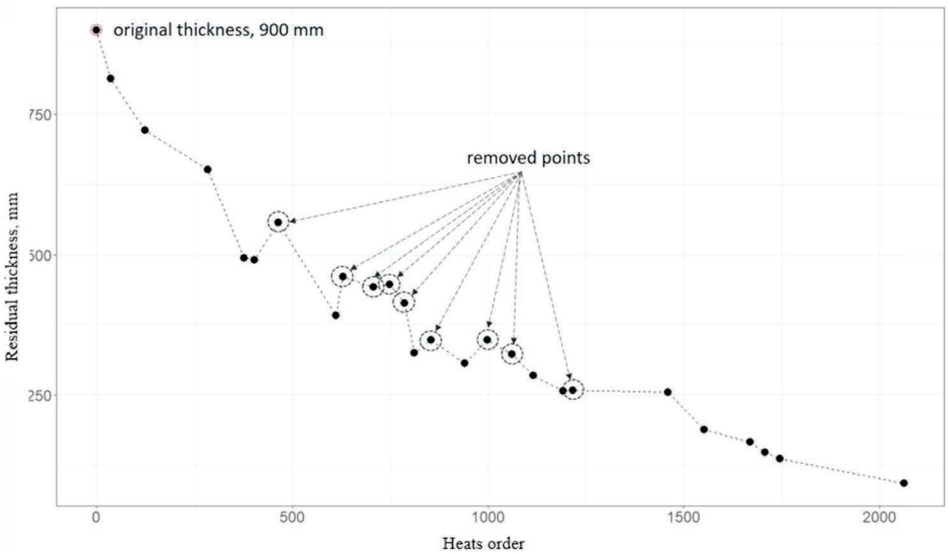

Fig. 5: Calculated residual thicknesses of the slag spout zone refractory lining of the oxygen converter as a function of consecutive heats (the first point: the initial shape thickness of 900 mm).

The ordinate of the first point with the abscissa of 0 in the chart shown in Fig. 5 is the thickness of the converter lining before the start of operation. Furthermore, a few increments of the refractory lining thickness are observed in Fig. 5. The increments are caused by the extraordinary treatments (gunning and/or slagging) performed in places of damage to the lining coinciding with the measurement positions. Therefore the increments are treated as the random deviations, because reduction of the thickness of refractory lining during the operation of the oxygen converter is a normal phenomenon in operation. Hence, the 9 points out of 25 points shown in Fig. 6 were removed from model calculations. The remaining residual thicknesses of the lining taken for model calculations are shown in Fig. 6. These results meet the condition of reduction of refractory lining during the campaign.

Linear interpolation was used for calculation of the residual thickness of the lining for (2063 – 16 = 2047) remaining heats performed between heats with the simultaneous measurements of thickness. The results of the interpolation calculations are shown in Fig. 6 by 16 sections marked by the dotted lines and they make it possible to calculate the specific wear of the slag spout zone refractory lining for each heat. And the data set of residual thickness of the refractory lining graphically shown in Fig. 6 is used for calculations of the wear class (dependent variable) in the model developed using the artificial neural network.

A quick loss of the refractory material is observed in the beginning of the converter campaign shown in Fig. 6. The reasons for the wear of the converter refractory lining at that stage of the campaign should rather be sought on the side of thermo-mechanical factors than thermo-chemical factors. An initial attempt to explain a quicker wear of thermal vessels in the initial stages of their operation was undertaken by König and co-workers in their work [11].

The obtained specific wear index, expressed in mm/heat, was divided into 10 equal classes, the 0 class containing very small wear indexes close to zero, whilst the 9th class

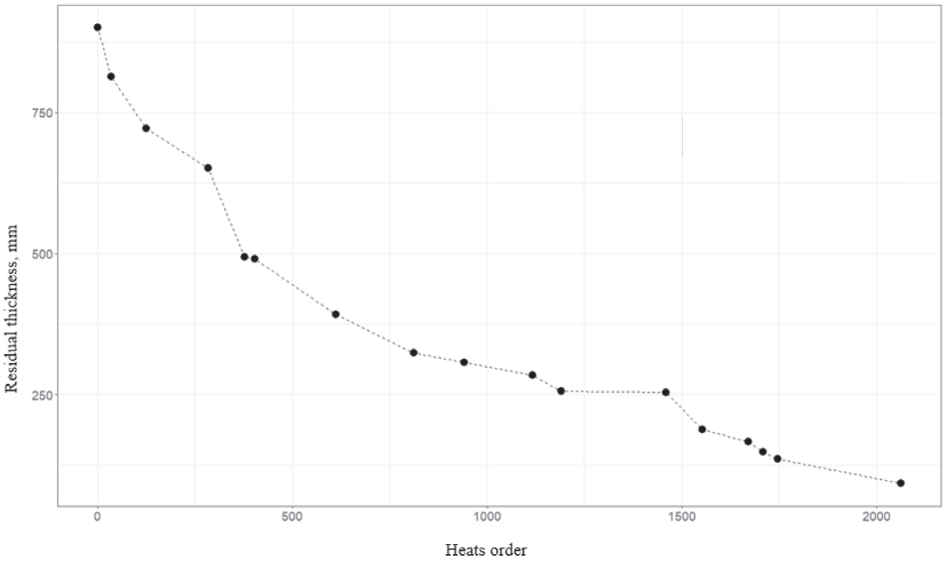

Fig. 6: The chosen residual thickness of the refractory lining as a function of consecutive heats.

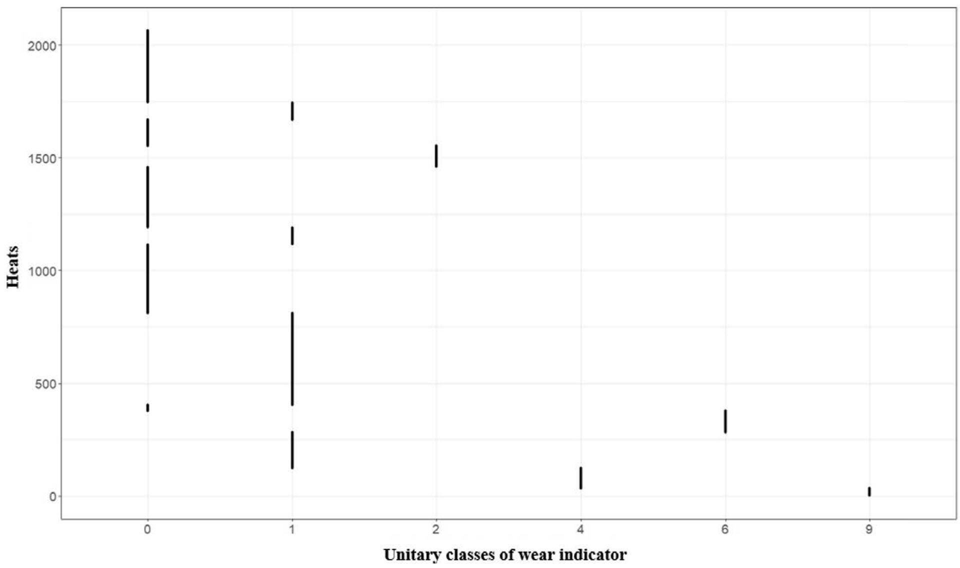

Fig. 7: The wear classes of the MgO-C refractory material in the slag spout zone of the TBM converter.

contains wear indexes with very high values. The results of division of the wear indexes of the training set into classes in step with the progress of campaign are graphically shown in Fig. 7.

The upper boundary of the class interval (*up*) is calculated according to the formula:

$$up = t \cdot w/10 \tag{8}$$

where: the class number $t = 1 \ldots 10$, whereas w is the maximum value of the wear index of the refractory material (e.g. when $w = 1$ mm/heat, then the width of the interval is 0.1 mm/heat, and the upper boundary of each interval are respectively 0.1, 0.2. ... to 1.0 mm). It is shown in Fig. 7 that the wear of the refractory material in the oxygen converter in the slag spout zone calculated per a heat is very low and is mainly located in the classes 0 and 1, except for short campaign parts. Only a small part of the results are located in the classes with medium and high wear indexes, i.e. in the classes 4 and 6.

V. Construction of the Wear Model of the Converter Refractory Lining with the Use of Artificial Neural Networks

The model was fully developed in the R language and computing environment with the employment of the Keras library [12] that contains an ensemble of rules that make it possible to employ multilayer artificial neural networks for deep learning. In the model the 17 input variables, normalized to values from the interval of 0 to 1, and 10 outputs, corresponding with the wear classes of the refractory material marked by numbers from 0 to 9, were used. The issue was treated as a problem of multilayer classification.

A random division of experimental data set into a learning set and a test set was made in the following proportion: about 70 % of the number of the records for the learning set and remaining about 30 % of the records for the test set. A neural network with three hidden layers was built. The number of neurons in every layer was determined experimentally by adopting the value of the prediction error as the criterion.

The designed architecture of the neural network was: 17:h(20,10,5):10, where: the number of the predictors equals 17 as it was mentioned above, h(20,10,5) contains the number of neurons in individual hidden layers, and 10 is the number of the wear classes of the refractory lining. In the course of the calculations it was found that an increase in the number of hidden layers and an increase in the number of neurons in those layers over the detected value favours over-learning. That means that the model adjusts itself very well to the learning data. A chunk of code of the model is shown below:

```
> model = keras_model_sequential()
> model %>%
+    layer_dense(units = 20,
+                input_shape = 17 ,
+                activation = "relu") %>%
+    layer_dense(units = 10, activation = "relu") %>%
+    layer_dense(units = 5, activation = "relu") %>%
+    layer_dense(units = 10, activation = "softmax")
```

The model was compiled with the use of the loss function called *categorical crossentropy* function [10, 12]. The quality of the solution was controlled by means of the *adam* algorithm.

The results of the application of the designed artificial neural network to the test data were measured by the accuracy of predictions calculated as the ratio of correct classifications into classes of the wear of refractory materials against all results received for the test set. The course of the network learning process is shown in Fig. 8 and it was stopped after the execution of 200 iterations. The prediction quality for the learning set was 64.56 %, and for the test set it was slightly higher and amounted to 66.21 %, which is visible in Fig. 8.

VI. Calculation Results and their Discussion

As an example of the wear class calculation result of the refractory material in the oxygen converter is shown below. The normalized data used in the calculation was as follows:

a/numeric variables:
V1 (hot metal weight) = 0.05836576
V2 (hot metal temperature) = 0.292887
V3 (C in the hot metal) = 0.7435897
V4 (Si in the hot metal) = 0.671822
V5 (S in the hot metal) = 0.4018692
V6 (lime) = 0.4505495
V7 (MgO carriers) = 0.2613636
V8 (oxygen in the top blow) = 0.4751157
V10 (steel temperature) = 0.7533333
V11 (active oxygen) = 0.6158771
V12 (MgO in the slag) = 0.1198668
V13 (basicity) = 0.007643312
V14 (total Fe in the slag) = 0.3949323
V15 (SiO_2 in the slag) = 0.4226254
b/logical values:
V9 (additional blow) = 1 (YES)
V16 (gunning) = 0 (NO)
V17 (slagging) = 0 (NO)

Model calculations based on the above data classified the refractory material wear in the 4th class.

The results of the classification of the wear of the refractory material in the slag spout zone on the basis of the created database in the proposed model are shown in Table 3. The correctly qualified cases, situated on the diagonal of the distribution table, are shown in Table 3. The artificial neural network correctly assigned 226 cases of near-zero wear (class 0), seven cases of very high wear (class number 9). However, it has to be pointed out that in the test data there were only 15 real cases with wear indexes inside class 9. The neural network in turn recognized even 25 such cases, wherein it erroneously qualified 18 cases, which can be seen in Table 3.

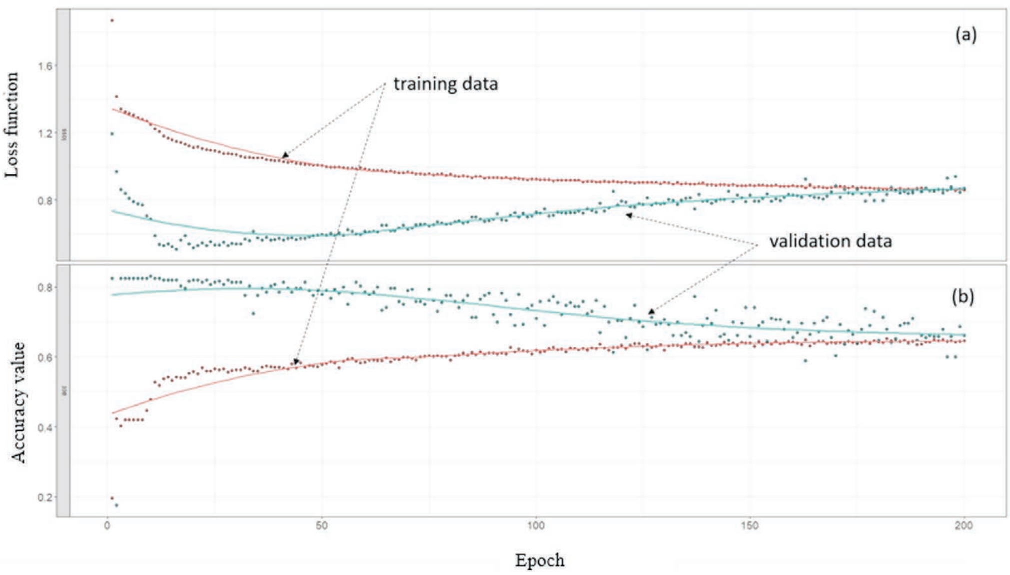

Fig. 8: The upper chart (a): error function calculated for the learning and test sets. The lower chart (b): classification accuracy for the learning and test sets.

Results of calculations conducted with the employment of the artificial neural network indicate a high share of the wear index of the refractory material from the slag spout zone in low classes: about 84.32 % of 625 results from the test set in classes 0 and 1. Percentage-wise, most mistakes also occur there. Qualitatively the most severe error of the model is the imputation of the ten records belonging to the first real wear class to the highest forecast wear class number 9.

Results of calculations according to the model executed in the R environment were verified with the employment of the other software Orange 3.21. The result of the verification is shown in Fig. 9. The results are convergent, as the quality of the prediction expressed by the CA parameter (classification accuracy) reached 63.9 %. The surface area under the ROC curve (AUC) reached 0.802.

The importance of variables was calculated using the machine learning method based on The Boosted Trees [10].

Table 3: Distribution table of the results of classification of the refractory material wear from the slag spout zone.

Forecast wear classes	Real wear classes										
	0	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*Σ*
0	**226**	60	19	0	4	0	1	0	0	0	310
1	63	**128**	2	0	4	0	12	0	0	0	209
2	9	1	**6**	0	0	0	0	0	0	0	16
3	0	0	0	0	0	0	0	0	0	0	0
4	12	12	10	0	0	0	7	0	0	8	49
5	0	0	0	0	0	0	0	0	0	0	0
6	0	6	0	0	5	0	**5**	0	0	0	16
7	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0
9	0	**10**	0	0	6	0	2	0	0	**7**	25
Σ	310	217	37	0	19	0	27	0	0	15	625

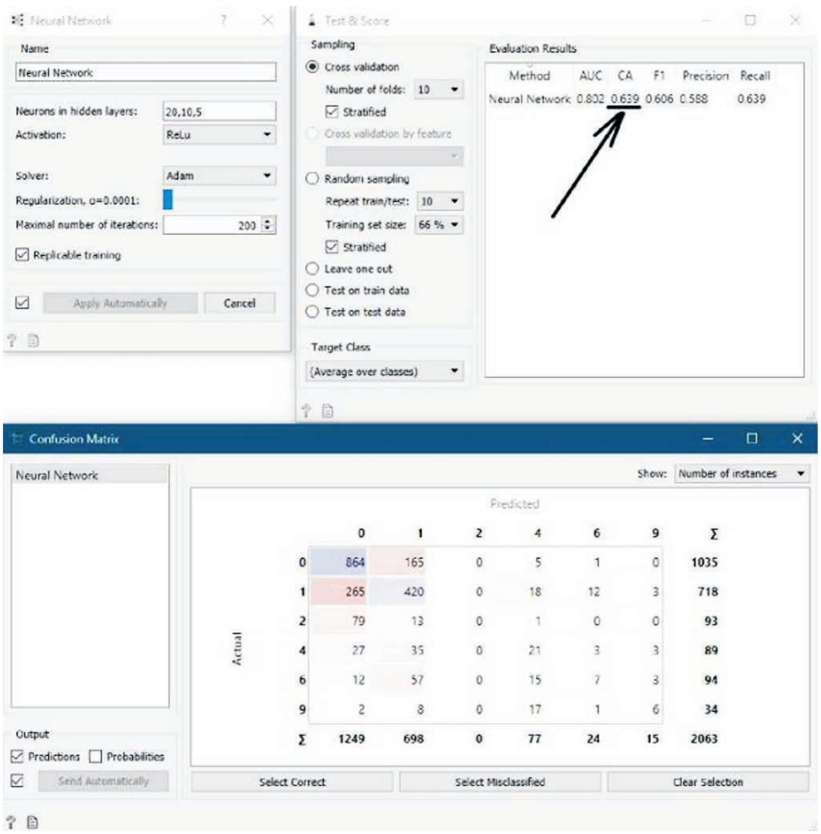

Fig. 9: Verification of the solution by means of the Orange programme. The black arrow indicates the result of the classification accuracy.

The result of the variable importance analysis is shown in Fig. 10. Calculations were made using Statistica 13.5 software package intended i.a. for data analysis, predictive modelling, classification.

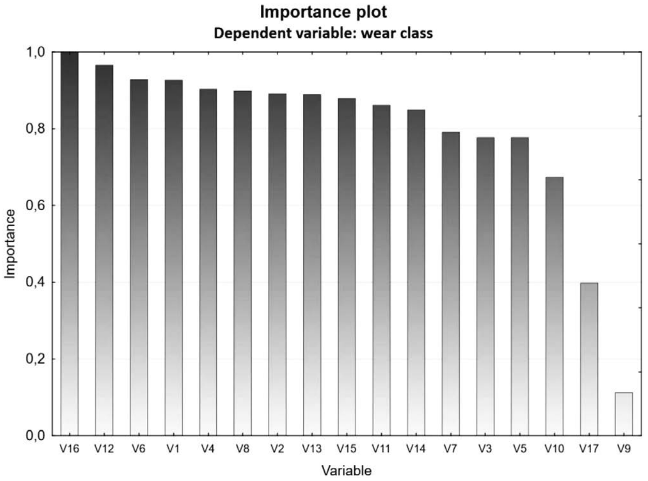

Fig. 10: Variable importance plot based on the experimental data set.

The importance values reflect on the strength of the relationship between the predictors and the dependent variable. The three variables V10, V17 and V9 reveal of the weakest relationship with the dependent variable. They stand out as the most important predictors. But at the current stage of the research they are not rejected from the designs of the experiments and the model.

VII. Conclusions

With the application of artificial neural networks, a possibility was demonstrated to develop a prognostic model for the wear of refractory materials in the slag spout zone of an oxygen converter lined with a well-known MgO-C material, where maximal wear of refractory materials takes place. Data originating from industrial trials executed during campaigns were used. Furthermore, suitability of the models for evaluation of the lifetime of those refractory lining elements of the device that condition the span of its operation. The results of the model calculations lead to the following further conclusions:

1. The accuracy of the forecast of the refractory material wear in the wear classes achieved in the experiment equals 66.21 % using the designed network architecture 17: h(20,10,5): ... 10 and R calculation environment. Verification of this result carried out using Orange 3.21 software shows a similar result 63.9 %.
2. The reasons for which the expected level of the quality of the forecast higher than 90 % was not reached should be sought in the database of the input data, including the scarce available number of measurements of the wear of refractory materials in the slag spout zone, in the lack of data and accuracy of the measurements of residual thickness of the refractory lining.
3. In the case of the input data, it would first of all be purposeful to increase the number of the measurements of the wear of refractory materials in the converter, as well as such execution of the measurements that would make it possible to measure the wear thickness before the planned converter maintenance at the given stage of the campaign. Furthermore, an improvement in the prediction quality will take place as a result of an increase in the number of the analysed converter campaigns.
4. In the learning data set, data losses were supplemented by application of the simplest linear interpolation and kNN method. The procedure employed for definition of the wear index of materials from laser measurements by means of a linear interpolation seems to be an appropriate approach.
5. Properties of the material and factors influencing the thermo-mechanical wear of the refractory lining in the initial stage of the campaigns were not variables of the forecast presented in this article. That is why in further research work an attempt should be considered to prepare a model with consideration of factors influencing the wear of the converter refractory lining in the initial period of a campaign.

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