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# Neural Network Model of the Process Nickel-Smelting of Copper Raw Materials in Furnaces

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***Abstract: -*** oven is the unit of continuous action, the task of which is reduced to the enrichment of copper matte and slag NIJ depletion resulting from the smelting process, called process [1-5]. Components processed mixture (rich in content of copper ore, copper concentrate is filtered, poor turnover, sandstone and other materials) are loaded onto the surface of the melt rapidly bubbled where oxidized by oxygen-air mixture

(Fig. 1). Products are copper matte smelting, slag and flue gases. Matte enrichment at the expense of higher dissociation sulfides [1-5]:

$$2CuFeS2 \rightarrow Cu2S + 2\ Fees + 1/2\ S2 \qquad (1)$$

Enriching the quality mattes and depletion of copper slag is characterized in the final products: Cush - in matte, Cush - in the slag. For managing the need to heat the chemical composition of matte in real time, which can not be carried exists at present. task of forecasting qualitative melting can be solved using a mathematical model of the process

In [1-5, 11, 12], describes the relationship between the concentration of magnetite ($Fe_3O_4$) and contains the zanies copper slag. Also experimentally confirmed loss curve with copper slag, depending on the composition of the matte. Proposed depending applicable for deep theoretical analysis of the process, but use of the them to automatic process control is not possible, since it does not include the effect of random factors that have both a direct and indirect impact on the results of melting. In [10] analyzed the factors affecting the process and the algorithm proposed by the introduction of generalized factors that simplify the process of computing. The output parameter of the model adopted in the matte copper Cush. Input the parameters are proposed and justified by the following factors:

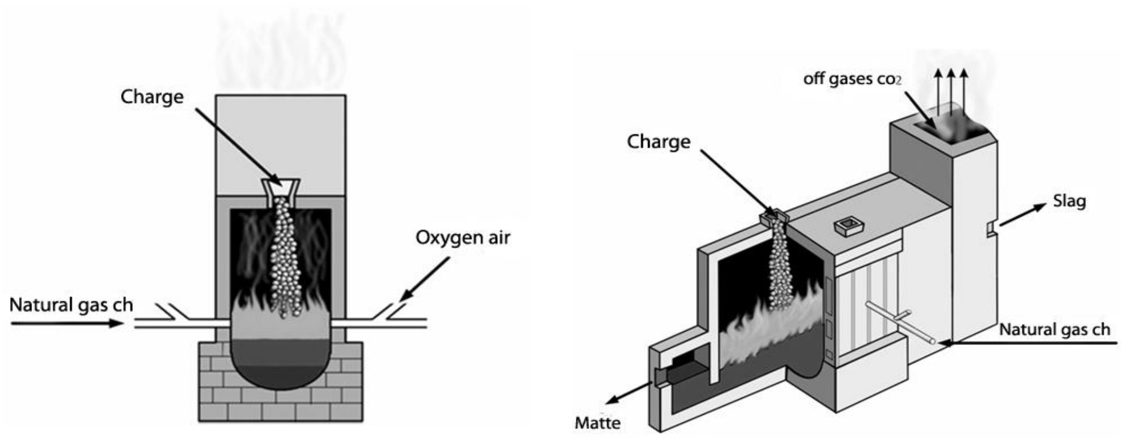



Fig. 1. Oven Vanyukov sectional

false algorithm introducing generalized factors that simplify the process of computing. The output parameter of the model adopted in the matte copper Cush. Input the parameters are proposed and justified by the following factors:

K - rate the depth of oxidation sulfides, which is determined by the expression:

$K$ = qO2 /, м3/т, ( 2 )
$F_{шх}$

where QO2 - process flow oxygen for the oxidation of sulfide Fish - the total load of the charge in the furnace; Cush - copper content in the starting material; Sash - sulfur content in the starting material; Cush (t - τ) - copper in matte with delayed-vainer τ , Fn - consumption sandstone melting.
However, the frequency of measurement of parameters such as copper and sulfur in the mixture is from 1 to 10 days, which is not possible to synthesize a model for the operational management process. Therefore, it is proposed to use the quality of the input parameter flow FME. loaded metal-containing materials, which is calculated by the expression:

$F$Me = $F$шх – $F$п. ( 3 )

The delay τ is equal to discrete measurements of the output parameter, and is 2 hours So at the moment the analysis of the chemical composition of the matte, the model must be developed to calculate the composition of those matte-Kusch time. Thus, the model will predict children, matte on the chemical composition of 2 hours ahead.
For the synthesis of such a model is proposed we used a mathematical apparatus of artificial neural networks (ANN). As a single-layer structure of the network topology chosen energy of a radial basis function activation (Radial basis function network - RBF) [6, 8]. Its by feature is the absence of iterations when setting weight coefficient-ΦP × P = patients.
To describe the principle of the RBF network, we introduce the following concepts:
• The column vector X j input and output parameters Yj at a fixed time instant j:

X j = { X 1,j , ….. , X I , j , ….. X m;j } T
= {K j , K me j , F nj , CU t j-ʈ } T ( 4 )

Y j = { y 1 . ʲ , …… , Y 1.j , ……, Y n .j } ( 5 )

where xi, j, yi, j - respectively, the values of i-th of the input and output parameters in the time instant j; M = 4, N = 1 -, respectively, the number of input and output parameters.
• Number of time samples, the result will be the vectors of input and output parameters, as well L. All time readings combine vectors of input parameters and obtain a matrix input XM × L. Similarly, we define the matrix output YN × L.
Column vector centers radial basis function, which describes the output neuron p «hidden" layer:

$Cp$ ={$c$1,$p$, ..., $ci$,$p$, ..., $cM$,$p$}T , ( 6 )

where ci, p - value of the center of the basis function for the i-th input parameter p-th neuron (p = 1 ÷ P); P - the number of neurons in the layer of RBF network. • Weights - connections between p-th neuron "hidden" layer and the i-th output of neural network - wi, p.

**A matrix of weights:**

( $w$1,1 ... $wi$,$p$ ... $w$1,$P$ )

$WN$×$P$ = ( 7 )
( wn,1 ... $wn$,$p$ ... wn,$P$ )

radial basis function - describes the form of the activation function of neurons RBF network:

∑($Xij$−$cip$)−

$f$ ($X$ $j$,$Cp$) = $e$ ——— ( 8 )

σ$p$2

where σp - the width of radial basis function. • The interpolation
matrix - describes the interpolation points of the space of output parameters:

$\Phi P \times P =$

$$\left\{ \begin{matrix} f(X1, X1) \ldots f(X1, Xi) \ldots f(X1, XP) \\ f(Xp, X1) \ldots f(Xp, Xi) \ldots f(Xp, Xp) \end{matrix} \right\}$$

For the calculation of the matrix of weights, we use the procedure described in the works in accordance with the structure of RBF network, you can write an expression for the calculation of the content of the copper in the matte at time j:

$$\text{CU}\; jj(X j) = \sum_{p=1}^{p} wi,p \cdot f(X j, Cp) \,. \quad (10)$$

With this notation we can write the expression (10) in the form of a matrix equation:

$$YN \times P = \Phi P \times P \times WN \times P \quad (11)$$

The solution of equation (11) gives the values of the weights. Approximation error depends on how adequate are selected centers and the width of the activation functions in the construction of the interpolation matrix. In the literature [6, 7], as centers of activation votive functions is proposed to use the values of input parameters (CP = Xj), and The number of neurons equal to the number of training examples (P = L). Application of the method of the first taco has a significant drawback. The calculation of the matrix of weights requires considerable computing power and the time, because the number of samples L, as a rule, amounts to more than 103. When building a model of the object is requested to follow the procedure described in [10], and further classify statistics by Coonan maps [9]. This approach allows us to select the most informative groups of data, eliminate repetition and reduce the number of time samples. Testing algorithm performed on statistical data derived from the furnace of work Copper Plant (MOH) "MMC" Norilsk Nickel "in 2009, the number of time-ton of the original sampling statistics was L = 8350. After classification number L is significantly reduced, in this case - almost 58 times (up to 144). Such an amount of experimental data allows the synthesis of the RBF network with the size of the layer P = 144.

However, the problem of choosing the width of the radial basis function σp remains. For this reason, not all are encouraged to use the Coonan neural network, and only two neurons - "Win-Tel" and prior to it, then the size of the layer RBF network is P = 2. Denote the weights of the neuron "winner":

$$wvK = \{w1,v, \ldots, wi,v, \ldots, wM,v\}, \quad (12)$$

and the weights of the neuron, "preceded yes chemo winner":

$$wvK-1 = \{w1,v-1, \ldots, wi,v-1, \ldots, wm,v-1\}. \quad (13)$$

Superscript K indicates accessory weights Coonan layer and the subscript v - they belong to her, Ron "winner." Will take center radial basis functions equal to the coefficient of neurons "winners":

$$C1 = wvK, C2 = wvK-1. \quad (14)$$

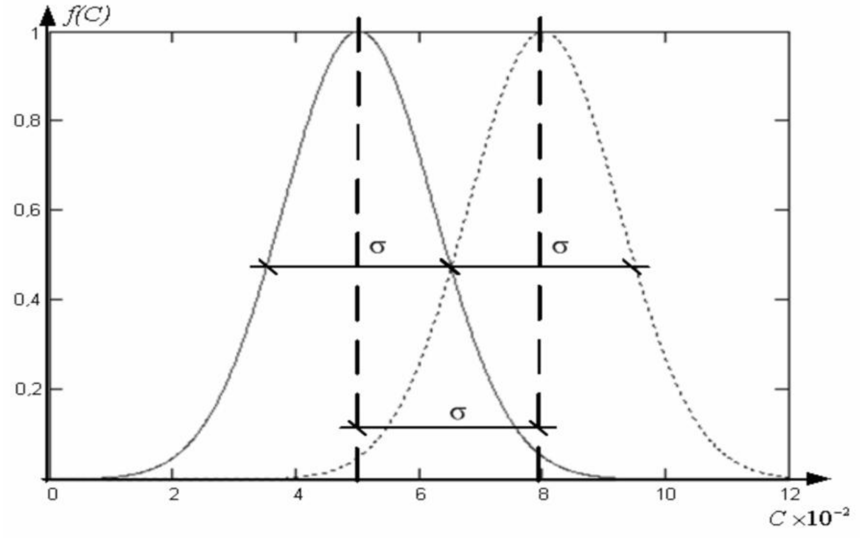



Fig. 2. Determination of the width of the radial basis function

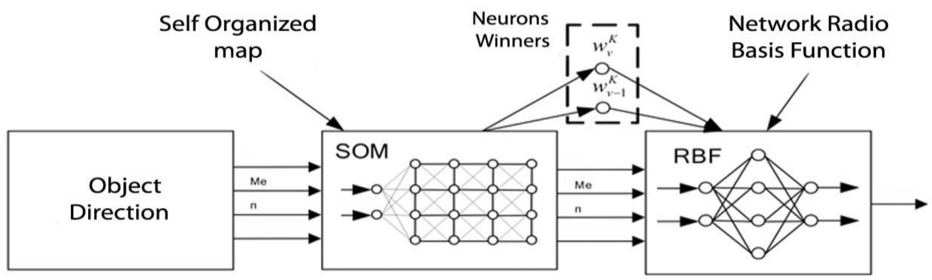



Fig. 3. Functional diagram of neural network model

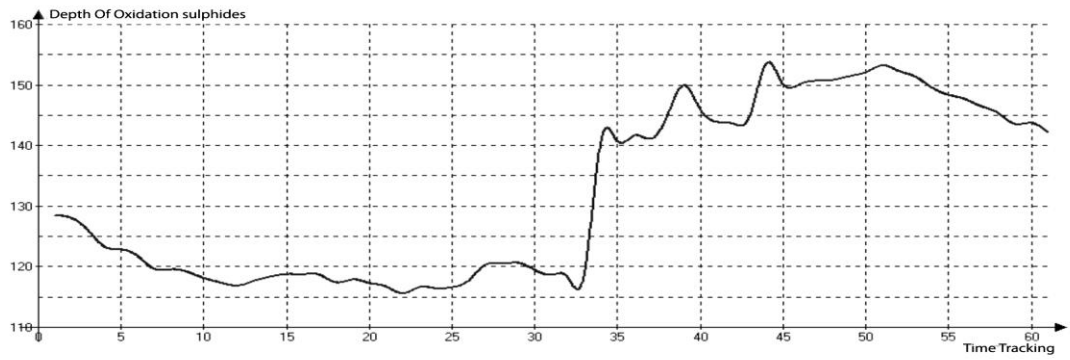
With only two centers, one can calculate the distance between them (Fig. 2), which is equal to the width of the radial basis function

$$\acute{O}\,p = C1 - C2 = \sum_{i=1}^{m} (w_{i,p})2 - \sum_{i=1}^{m} (w_{i,p})2 \qquad (15)$$

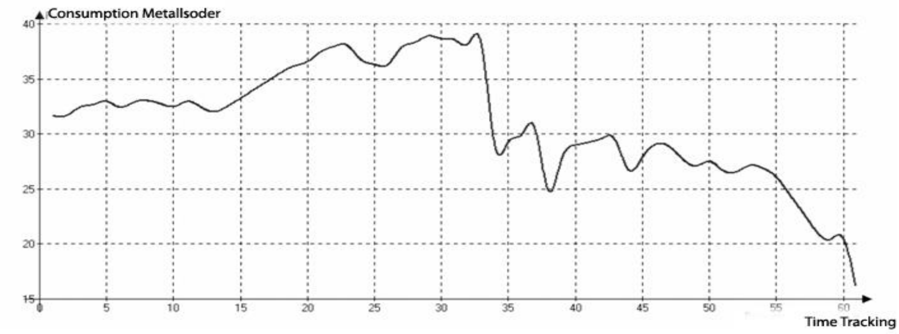
Thus, classifying the statistics and determine the parameters of RBF network, we obtain a functional diagram of a model that predicts copper in matte (Fig. 3) Operating mode of the proposed model is as follows E t and n 1.

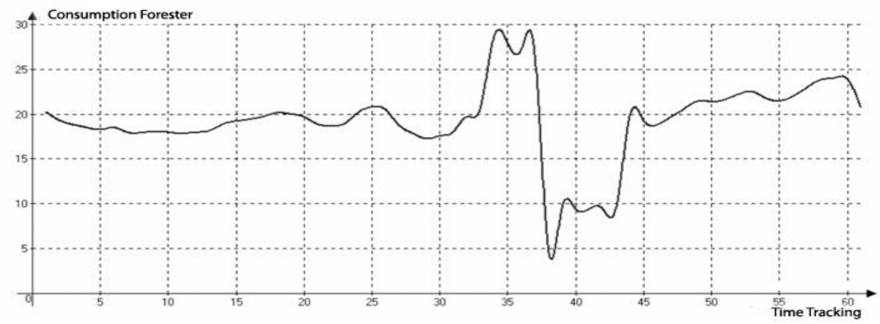
The measured values of the input parameters of the process are calculated network parameters: the depth of sulfide oxidation by the expressions (3), (6) and (7) [10], and metal

a)




b)

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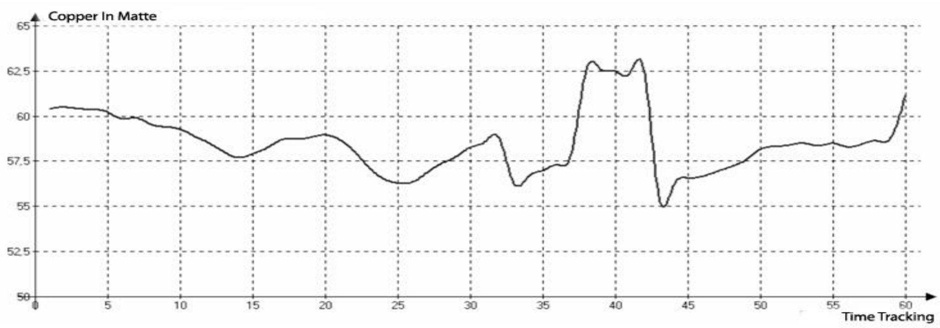


E )

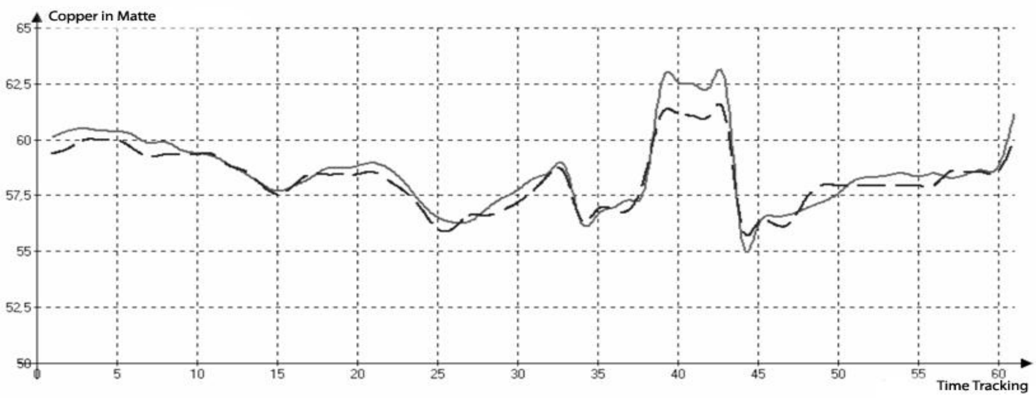


Fig. 4. Graph of copper (a) and sulfur (b) in the charge, the depth of oxidation of sulfides ()
copper in matte in the previous (r) and the current step (e)
(-------) - Experimental, (-----) - calculated curve

containing components of the charge by the expression (3). Calculated input parameters to the input of the classifier is trained Coonan. With the proximity of input parameters are selected neuron "winner" and the preceding neuron

E t and n 2. According to expressions (14) and (15) are calculated to be the center and the width of the radial basis functions of RBF network. Then construct the interpolation matrix (9) and the calculated values of weights layer RBF network based on the equation (11) E m and n 3. The inputs of the newly synthesized RBF network is fed a set of input parameters, and finally calculates the output parameters from the expression (10) Testing of the model is on the statistical data obtained in the course of work furnace MOH in 2010 Figure 4 shows the results of the proposed mathematical model. Graphs (Fig. 4a-d) show the change in the input parameters. According to the schedule of the output parameter (Figure 4 d) that the model qualitatively repeats the content of copper in matte Estimation accuracy of the model was carried out by F-Fisher test. The empirical value of the Fisher criterion was F

= 1.535. At a significance level of P = 0,05 and degrees freedom compared variances n = 61, the critical Fisher criterion was F = 1.528 cr EMF. Comparing empirical and critical criterion value (1.535> 1.528), it was decided on the validity of the hypothesis of equal variances .

## RESULTS

Thus, the developed neural network model with sufficient accuracy for practical reflects a real change in copper matte smelting in furnaces synthesized neural network modeling quality indicator in the smelting process furnaces e - copper in matte. Feature of the proposed network is pre-classification statistics Coonan self-organizing map and use two neurons "winners" for the synthesis of RBF network The experimental verification of the proposed neural network model. To implement the model does not require additional hardware to implement enough of the existing level of automation of the MV

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