Optimization of chemical composition in the manufacturing process of flotation balls based on intelligent soft sensing

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Abstract
This paper presents an application of computational intelligence in modeling and optimization of parameters of two related production processes – ore flotation and production of balls for ore flotation. It is proposed that desired chemical composition of flotation balls (Mn = 0.69%; Cr = 2.247%; C = 3.79%; Si = 0.5%), which ensures minimum wear rate (0.47 g/kg) during copper milling is determined by combining artificial neural network (ANN) and genetic algorithm (GA). Based on the results provided by neuro-genetic combination, a second neural network was derived as an intelligent soft sensor in the process of white cast iron production. The proposed ANN 12-16-12-4 model demonstrated favorable prediction capacity, and can be recommended as an ‘intelligent soft sensor’ in the alloying process intended for obtaining favorable chemical composition of white cast iron for production of flotation balls. In the development of intelligent soft sensor data from the two real production processes were used.

Keywords: wear rate; chemical composition; neural networks; genetic algorithm; optimization.

Quality balls used in ore-grinding mills are important for copper milling. The very nature of the process poses high requirements in respect of ball wear resistance therefore white cast iron is used. Wear resistance directly affects quality of milling copper ore and economical aspect of the production process, hence the adjustment of technology of flotation balls production is of the significant importance for technological process of ore milling. Wear rate of flotation balls on one hand depends on mechanical and chemical properties of the material obtained from the casting process, and ore composition on the other. Technology of flotation balls production and properties of flotation balls, especially hardness (HRC) and chemical composition, can be varied to manage wear rate. On the other hand, due to no uniform behavior of balls during milling, number of uncertainties is introduced in correlations between wear, hardness and chemical composition. In order to avoid these ambiguities different techniques of computational intelligence, like genetic algorithms and neural networks, or their combination, have the great potential to handle problems such as modeling, optimization, prediction, control, estimation and others in complicated nonlinear systems [1–10].

The objective of this work is to establish the relationship between flotation balls wear rate and preparation of white cast iron (chemical composition of white cast iron) used for flotation balls production, using artificial neural networks and genetic algorithms in order to improve processes, both in terms of efficiency and economy. This work follows two production processes, establishes correlation between them, and models and optimizes parameters of the processes monitored. Attainment of objective involves three stages that use computational intelligence techniques. In the first stage, using a neural network, based on experimental results, a non-linear correlation between flotation balls wear capacity on the one hand, and chemical composition and hardness of flotation balls on the other is established. The second stage involves investigation of chemical composition and hardness which ensures minimum wear. For this purpose, a genetic algorithm with neural network as fitness function from the first stage is used. Finally, in the third stage, the preparation of white cast iron for flotation balls is managed using a second neural network aimed to achieve the desired chemical composition given by the genetic algorithm.

Flotation ball wear rate prediction using artificial neural networks

A non-linear correlation between flotation balls wear capacity, chemical composition and hardness of flotation balls, was established using a neural network, based on experimental results.
Experimental setup for flotation balls laboratory testing

In order to develop an artificial neural network (ANN) models, measurements of the chemical composition of the flotation balls, as well as their wear rate during ore milling in an experimental mill were carried out. Every experiment to measure the wear rate of the flotation balls in the laboratory mill was performed with ten balls each with a mass of 0.85 kg, cast from the same batch, and with the same chemical composition. Rockwell hardness testing of the floating balls was performed by the Rockwell "C" method using a 5006-УХЛ 4.2, ТОЧПРИБОРРОСИА appliance. The experimental results gave an average - value of hardness measured for all ten balls on a specially prepared surface. Chemical composition measurements were performed by spectrochemical analysis using a METALLAB 75/80 (GNR-Italia) device.

The milling experiments were carried out to obtain the worn mass of balls per kg of milled ore. Milling experiments were performed in the mill of optimum volumetric filling \( V = 0.0152 \, \text{m}^3 \) with \( \varnothing 60 \, \text{mm} \) diameter balls. During the experiments, the mass of the new balls at charging was 8.5 kg, and the initial mass of copper ore was 2.5 kg. Additional ore mass of 2.5 kg was added into the mill every 12 min. The experiment continued until a sampled ore mass of 500 kg was milled. The difference between mass of new balls and mass of balls after milling, divided by 500 kg of milled ore is the result of the experiment. Based on a repeated set of experiments carried out under the same conditions, 73 experimental results were obtained. The results indicate the abrasive wear rate expressed in grams of worn mass of balls per kilogram of milled ore (g/kg). Some of the experimental results are shown in Table 1.

<table>
<thead>
<tr>
<th>No.</th>
<th>( HRC )</th>
<th>( \text{Mn} )</th>
<th>( \text{Cr} )</th>
<th>( \text{C} )</th>
<th>( \text{Si} )</th>
<th>( P / \text{g kg}^{-1} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>57.17</td>
<td>0.4</td>
<td>2.74</td>
<td>3.57</td>
<td>0.65</td>
<td>0.542</td>
</tr>
<tr>
<td>2</td>
<td>56.59</td>
<td>0.41</td>
<td>2.6</td>
<td>3.33</td>
<td>0.63</td>
<td>0.635</td>
</tr>
<tr>
<td>3</td>
<td>57.95</td>
<td>0.43</td>
<td>2.68</td>
<td>3.35</td>
<td>0.56</td>
<td>0.536</td>
</tr>
<tr>
<td>4</td>
<td>57.29</td>
<td>0.48</td>
<td>2.4</td>
<td>3.52</td>
<td>0.71</td>
<td>0.546</td>
</tr>
<tr>
<td>5</td>
<td>58.72</td>
<td>0.44</td>
<td>2.8</td>
<td>3.41</td>
<td>0.48</td>
<td>0.524</td>
</tr>
<tr>
<td>6</td>
<td>57.39</td>
<td>0.44</td>
<td>2.49</td>
<td>3.58</td>
<td>0.52</td>
<td>0.544</td>
</tr>
<tr>
<td>7</td>
<td>59.06</td>
<td>0.43</td>
<td>2.52</td>
<td>3.48</td>
<td>0.56</td>
<td>0.528</td>
</tr>
<tr>
<td>8</td>
<td>57.71</td>
<td>0.42</td>
<td>2.6</td>
<td>3.59</td>
<td>0.4</td>
<td>0.568</td>
</tr>
<tr>
<td>9</td>
<td>57.32</td>
<td>0.4</td>
<td>2.48</td>
<td>3.51</td>
<td>0.56</td>
<td>0.572</td>
</tr>
<tr>
<td>10</td>
<td>58.17</td>
<td>0.44</td>
<td>2.8</td>
<td>3.95</td>
<td>0.66</td>
<td>0.549</td>
</tr>
</tbody>
</table>

Methodology for wear rate prediction

Artificial neural networks (ANNs) are parallel interconnections of simple neurons that function as a collective system [11]. Figure 1 shows a schematic representation of an artificial neuron with input vector with \( r \) elements \( (r = 5) \), as well as characteristic structure of the feed forward ANN with one hidden layer. Each of the input elements \( x_1, x_2, \ldots, x_r \) is multiplied with the corresponding weight of the connection \( \omega_{1,1}, \omega_{1,2}, \ldots, \omega_{1,r} \). The neuron sums these values and adds a bias \( b_j \) (lacking in some of the networks). The argument of the function (called transfer function) is stated in the following:

\[
 a_j = x_1 \omega_{1,1} + x_2 \omega_{1,2} + \ldots + x_r \omega_{1,r} + b_j
\]

while neuron produces output:

\[
 y_j = f(a_j) = f\left(\sum_{j=1}^{r} x_j \omega_{1,j} + b_j\right)
\]

This output is input to the neurons of another layer, or an element of the output vector of the ANN. In this particular case, input layer of all created ANNs has five neurons: chromium (Cr %), manganese (Mn %), carbon (C %), silicon (Si %) and hardness (HRC), in the way that only one output neuron leads to a predicted wear rate \( (P) \).

Artificial neural networks consist of an arbitrary number of layers and neurons as well. According to the number of layers, number of neurons, transfer function, presence of a bias as well as the way the neurons are connected, the realization of ANN is various (Fig. 1).
and ANN 5-4-2-1 (two hidden layers with 4 and 2 neurons, respectively). The principal aim was to reduce to a minimum the performance function, in this case mean squared error (MSE) function, which was calculated as:

\[
MSE = \frac{1}{Q} \sum_{k=1}^{Q} e(k)^2 = \frac{1}{Q} \sum_{k=1}^{Q} (t(k) - y(k))^2
\]  

(3)

where \( Q \) denotes number of experiments, \( e(k) \) denotes error, \( t(k) \) denotes target values, while \( y(k) \) are predicted values.

The training algorithm used in all cases was Levenberg–Marquardt algorithm which ensures the fast and stable convergence [12]. The neurons in input and hidden layers of ANNs had sigmoid transfer function, while the neurons of the output layer have linear transfer function. Overall number of experiments carried out is 73. The dataset was randomly divided into training, validation and testing sets. The training sample (51 measurements) was presented to the network during training, and the network was adjusted according to its error. The validation sample (11 measurements) was used to measure network generalisation, and to halt training when generalisation stopped improving. Finally, the testing sample (11 measurements) had no effect on training and so provided an independent measure of network performance during and after training.

RESULTS OF WEAR RATE PREDICTION AND DISCUSSION

To test ANN model, mentioned set of 11 measured data (which was omitted in the training phase) was used. The Table 2 shows a maximum and mean error of all proposed networks.

The ANNs prediction, for the set of 11 measured data is given in the Figure 2. Based on the data presented in Figure 2 and Table 2, the ANN 5-5-1 network has been adopted as the one showing the best performance, and was applied after a comparison with other models (Fig. 3).

Table 2. Errors of different ANN models

<table>
<thead>
<tr>
<th>Error, %</th>
<th>ANN model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max.</td>
<td>5-5-1</td>
</tr>
<tr>
<td></td>
<td>5-3-1</td>
</tr>
<tr>
<td></td>
<td>5-5-3-1</td>
</tr>
<tr>
<td></td>
<td>5-4-2-1</td>
</tr>
<tr>
<td>2.49</td>
<td>5.96</td>
</tr>
<tr>
<td>8.94</td>
<td>9.52</td>
</tr>
<tr>
<td>1.78</td>
<td>2.75</td>
</tr>
<tr>
<td>3.55</td>
<td>3.81</td>
</tr>
</tbody>
</table>

Network demonstrated good agreement with experimental data, so it can be used as effective tool to predict wear rate based on hardness and chemical compositions.

Figure 3. Comparison of the measured values with the results of ANN 5-5-1.

Defining optimal chemical composition of balls

Chemical composition of floating balls which ensures minimum wear rate during ore milling process was defined using a genetic algorithm. For this purpose, neural network as fitness function is used with the
genetic algorithm. Genetic algorithms (GAs) are a family of adaptive search algorithms described and analyzed in references [14–18]. GAs derive their name from the fact that they are loosely based on models of genetic change in a population of individuals. These models consist of three basic elements: 1) a Darwinian notion of fitness, which governs the extent to which an individual can influence future generations; 2) a mating operator, which produces offspring for the next generation; 3) genetic operators, which determine the genetic makeup of offspring from the genetic material of the parents [15].

The GA/ANN-based principle of defining optimal chemical composition and hardness of flotation balls is shown in Figure 4. The initial population is generated randomly [18]. The fitness function is a model of superior neural network (ANN 5-5-1) presented in the previous section of the paper. The fitness of each member of the initial population is calculated using the ANN model, and is followed by selection, crossing and mutation as parts of the reproduction process of a new generation. The process is repeated until one of the multiple requirements for termination of GA is satisfied.

Neural network establishes a non-linear correlation between flotation balls wear capacity on the one hand, and chemical composition \(\text{Cr, Mn, C, Si}\) and hardness \((HRC)\) on the other, as the fitness function. The goal is determination of chemical composition and \(HRC\), where fitness function is at minimum. The domain of search values of parameters to optimize corresponds to the domain of neural network inputs given in Table 3. This is based on the expertise of the process.

### Table 3. Domain of optimal values search (%)

<table>
<thead>
<tr>
<th>Bound</th>
<th>Cr</th>
<th>Mn</th>
<th>C</th>
<th>Si</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower</td>
<td>2.0</td>
<td>0.38</td>
<td>3.11</td>
<td>0.3</td>
</tr>
<tr>
<td>Upper</td>
<td>2.8</td>
<td>0.79</td>
<td>3.95</td>
<td>0.88</td>
</tr>
</tbody>
</table>

The population range is 30 individuals, with 50 generations at maximum. Stochastic universal sampling algorithm is used in the selection [18]. Uniform crossover served as the crossing operator. The coefficient of the crossover fraction is 0.8. Crossover fraction defines a portion of the new population derived from a crossing (non-elite individuals), its value being between 0 and 1. Not more than two elite individuals are to be transferred to the next generation. Figure 5 shows the fitness function decline over 50 generations.

Function minimum, generated by the neural network model is approximately 0.47 g/kg. The optimized contents of parameters is presented in Figure 6 which result in minimum flotation balls wear rate are as follows: 1) \(HRC = 58.2\); 2) \(\text{Mn} = 0.69\%\); 3) \(\text{Cr} = 2.247\%\); 4) \(\text{C} = 3.79\%\); 5) \(\text{Si} = 0.5\%\). The contents are to be used as referential values in the following section and will be referred to as the targeted chemical composition.

### Neural network control of chemical composition of batches

In this section ANN-based intelligent soft sensor is introduced, used for control chemical composition of the induction furnace batch so as to obtain the desired chemical composition of white cast iron. Obtaining the targeted chemical composition of white cast iron used for the production of flotation balls is a complex process which involves complex non-linear chemical reactions and observes thermodynamic nature of the process. Optimized chemical characteristics of floating balls described in section „Defining optimal chemical composition of balls“ were used as referential ones in the phase of preparation of data for modelling of the melting process. Neural network is used to establish, through training, mutual correlation between input parameters and deviations from the referential (targeted) chemical composition.
Principles of data collection in the foundry

Data for training and testing of the developed ANN model was collected in foundry, from real production conditions. Quantometer was used for chemical analysis and 8000 kg capacity induction furnace, which operates at a frequency of 50 Hz, was used for melting of white cast iron. Melt temperature was 1500 °C.

The furnace is not fully emptied after melting – about 2500 kg of white cast iron of unknown chemical composition was left inside (based on chemical analysis during the melting process). About 5000 kg of steel scrap of particular chemical composition is subsequently added into the furnace, and chemical analysis using quantometer is done in the following stage. If the desired chemical composition has not been achieved, particular alloys are added into the furnace, which is followed by another chemical analysis. Total performed number of measurements was 120. Only final chemical analysis of white cast iron after alloying were taken into consideration.

Methodology for development of ANN based intelligent soft sensor

As for the prediction of flotation balls wear, feed forward ANN (based on the same principles explained in section „Methodology for wear rate prediction”) was also applied. The total of 120 experimental results (number of batches) was used to build the ANN model. The dataset was randomly divided into training, validation and testing sets. The training sample (84 measurements) was presented to the network during training, and the network was adjusted according to its error. The validation sample (18 measurements) was used to measure network generalisation, and to halt training when generalisation stopped improving. Finally, the testing sample (18 measurements) had no effect on training and so provided an independent measure of network performance during and after training.

The ANN input layer comprises 12 neurons originating from three data sets. The first group includes chemical composition of 2500 kg of cast iron left in the furnace after melting (the input neurons in this group are as follows: 1) C (%), 2) Cr (%), 3) Mn (%) and 4) Si (%), Fig. 7). The second group involves chemical composition of 5000 kg of steel scrap that is added to the furnace anew (input neurons in this group are: 5) C (%), 6) Cr (%), 7) Mn (%) and 8) Si (%), Fig. 8). The third group represents the weight of pure metal that is added within the alloying process (input neurons in this group are: 9) C (kg), 10) Cr (kg), 11) Mn (kg) and 12) Si (kg), Fig. 9).

The output layer of ANN consists of four neurons, respectively ΔC, ΔCr, ΔMn and ΔSi, which represent the deviation from the referential (targeted) values of the chemical composition. This set of data is obtained by

![Figure 5. Evolution of generations to optimize flotation balls wear rate.](image)

![Figure 6. Optimized mechanical and chemical characteristics of floating balls.](image)
subtraction of referential values obtained by GA from the value of the output chemical composition of the white cast iron:

\[
\begin{align*}
\Delta C &= C_{\text{measured}} - C_{\text{ref.}} \\
\Delta Cr &= Cr_{\text{measured}} - Cr_{\text{ref.}} \\
\Delta Si &= Si_{\text{measured}} - Si_{\text{ref.}} \\
\Delta Mn &= Mn_{\text{measured}} - Mn_{\text{ref.}}
\end{align*}
\]  

(5)

Figure 10 presents the data used in the ANN training, validation and test as output values.

Results and discussion regarding intelligent soft sensor

According to the methodology presented in section „Methodology for wear rate prediction“ for prediction wear rate, several different ANN architectures were derived, and the one with the best characteristics was adopted.

To test ANN model, mentioned set of 18 measured data (which was omitted in the training phase) was used. The ANN 12–16–12–4 architecture, presented in Figure 11, demonstrated best characteristics, and can be recommended as a intelligent soft sensor. Maximum
and mean errors are validity measures of the proposed model (Table 4).

Figures 12 and 13 show a comparative survey of the measured contents and the results obtained by the simulation using the ANN 12-16-12-4 network. Results of the testing above suggest that the ANN 12-16-12-4 is a good model for predicting deviations from referential (desired) chemical composition of white cast iron. The quality of predicting can be particularly observed through testing of manganese, although the prediction rate in other chemical elements is also quite satisfactory. Simulation of the proposed model allows management of the alloying process whereby the deviation from the desired chemical composition tends to zero, i.e., the ANN outputs tend to zero (ΔC → 0, ΔCr → 0, ΔMn → 0, ΔSi → 0). It is, thus, possible to determine the amount of pure metal in the alloying process (C (kg), Cr (kg), Mn (kg) and Si (kg)) required for the particular output from the network. This network feature was the origin of the term intelligent soft sensor, which is proposed to describe computationally intelligent sensing of the core process characteristic.

CONCLUSION

This paper presents application of computational intelligence in order to improve two related production processes, namely grinding copper ore and white cast iron production. Connecting these production processes, represents a novelty and a special contribution of this research. Combining ANN/GA/ANN joins these two production processes rendering them more economical and efficient.

The application of the ANN contributed to the modelling of the process of copper milling, aiming at establishing a correlation between mechanical and chemical properties of flotation balls on the one hand, and flo-
The first proposed ANN 5-5-1 model proved to be satisfactory in respect of its ability to predict wearing capacity of flotation balls. Its capacity to predict recommended it as a fitness function in GA. Using GA enabled us to discover some mechanical ($HRC = 58.2$) and chemical features ($Mn = 0.69\%$; $Cr = 2.247\%$; $C = 3.79\%$; $Si = 0.5\%$) which ensure minimum wearing (0.47 g/kg) in flotation balls. The integration of ANN and GA proved to be a good device for prediction and stochastic procedures-based search. The results delivered by the GA were considered as referential ones for managing the production of white cast iron used for casting flotation balls. The application of the new ANN has enabled modelling of the production of white cast iron. The proposed ANN 12-16-12-4 model demonstrated favourable prediction capacity, and can be recommended as an intelligent soft sensor in the alloying process intended for obtaining favourable chemical composition of white cast iron.

Establishing a connection between correlated production processes substantially contributes to the production management and efficiency. The presented computational intelligence techniques are the effective tool for modelling complex non-linear correlations from experimental data as well as for finding optimal solutions. Combination of computational intelligence techniques enables the development different software solutions (in this case 'intelligent soft sensor') with a significant role in the industry. The developed intelligent soft sensor is a highly effective tool in foundry, in the production of flotation balls. The methodology of its development can be used as an idea in intelligent integration of production processes, which will be the subject of further research. Also, further studies will include: the possibility of application of other optimization techniques to a specific problem of finding the optimal chemical and mechanical properties of balls, and consideration of alternative and more sophisticated ANN training algorithms and network topology optimizations as important research directions.

**Acknowledgements**

The paper is the result of the work of the authors on two projects funded by the Ministry of Education, Science and Technological development of the Republic of Serbia: TR35037 and TR35015.
REFERENCES


IZVOD

OPTIMIZACIJA HEMIJSKOG SASTAVA U PROIZVODNJI FLOTACIJSKIH KUGLI ZASNOVANA NA INTELIGENTNOJ SOFTVERSKOJ DETEKCIJI

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² Mašinski fakultet Niš, Univerzitet u Nišu, Niš, Serbia

(Naučni rad)

U radu je predstavljena primena tehnik veštačke inteligencije u modeliranju i optimizaciji parametara dva međusobno zavisna proizvodna procesa – flotacija rude i proizvodnja flotacijskih kugli za mlevenje rude. Kombinacijom neuronske mreže i genetskog algoritma dobijen je željeni hemijski sastav flotacijskih kugli (Mn = 0,69%; Cr = 2,247%; C = 3,79%; Si = 0,5%) za koji je njihovo habanje, u procesu mlevenja rude bakra, minimalno (0,47 g/kg). Na bazi rezultata koje je dala zajednička upotreba neuronske mreže i genetskog algoritma, kreirana je nova neuronska mreža sa ciljem da se koristi kao inteligentni soft sensor, u procesu proizvodnje belog livenog gvožđa. Neuronska mreža arhitekture 12-16-12-4 pokazala je povoljne predikcijske kapacitete i može se koristiti kao inteligentni soft sensor u procesu legiranja radi dobijanja željenog hemijskog sastava belog livenog gvožđa od koga se izrađuju flotacijske kugle. Za izgradnju inteligentnog soft senzora korišćeni su eksperimentalni podaci prikupljeni u realnim proizvodnim uslovima.

Ključne reči: Nivo habanja • Hemijski sastav • Neuronske mreže • Genetski algoritam • Optimizacija