Determination of Slag Outflow Moment during Steel Teeming using Competitive Neural Network

Automated and information control systems department
Stary Oskol Technological Institute n.a. A.A. Ugarov (branch) National University of Science and Technology
Stary Oskol, Russia
po-dima@yandex.ru

Abstract—The article describes method of competitive neural network usage to process vibration acceleration signal spectrum from a tundish surface in order to determine the moment of slag outflow from the ladle. It is proved experimentally that the neural network is able to recognize the steel teeming process state, which is prior to the slag outflow from the ladle under industrial conditions and influence of disturbances. The research results show the feasibility of the developed approach.

Index Terms—ladle, tundish, steel teeming, spectral analysis, competitive neural network, images classification, vibration acceleration.

I. INTRODUCTION

Steel teeming process is an important one in the metallurgical branch of industry. It greatly affects the quality of the final product. Teeming the molten metal from the ladle, the task is to determine the slag level to close a gate before the slag enters the tundish. The process is monitored by an operator affected by rough conditions. So they can make mistakes causing slag presence in the tundish. It results in breakage of the upper slag crust, which protects the metal from oxidation and cooling. There is also a possibility of slag injection to the cast billet, which can lead to the final product fault. Preventing this, an indirect method for slag mass calculating is used. It allows to close the gate in advance. In most cases it is too much in advance, since if errors in measurements and calculations are only 0.5%, and ladle volume is 150 tons, amount of pure metal losses (not teemed form the ladle) will be approximately 750 kg. If annual production volume is three million tons, then the metal losses will be 14 thousand tons of pure metal. To date, the problem is quite actual due to significant losses incurred by steel enterprises during the process of steel teeming.

Currently, there are four technologies of preventing slag from entering the tundish (slag cutoff).

• Automatic arm (float type) [1]. The advantage of this technology is its low cost and ease of implementation. However, for the plant in question, this technology cannot be applied as it is designed for metal teeming from converter only. It is tiled to pour the metal allowing to place the float just above the gate valve.

• Infrared [2]. The advantage of this technology is its simplicity, lack of massive constructions, which could cause problems during the metal smelting process. However, as far as described above problem is concerned, this technology can not be applied, since it is designed for direct control of an open flow metal by camera shooting in the infrared range.

• Electromagnetic method [3]. A major disadvantage of this technique is its non-universality. Electromagnetic coil should be installed in each steel ladle and protected against excessive temperature by lining. When ladle is relined, coils also need to be changed. This disadvantage could be overcome by the coils installation to the tapping pipe. But then there will be no possibility of early gate closing. It is closed when slag has already entered the pipe. Another disadvantage of this system is expensive electromagnetic coils.

• Vibration method [4-8]. This system has several advantages comparing to other methods. First of all, it is applicable to the plant in question using shroud for liquid metal teeming. Secondly, it has the ability of early slag detection, when it has not approached the gate, but rather close to it. Thirdly, it does not require substantial investment and signal gathering devices design. The disadvantage of this system is the strong exposure to disturbances, which can lead to uncertainty in the slag cutoff control and false alarms.

There are also attempts [9] of experiments with a model of the teeming process, where water is used as steel. Conclusions are made that the vibration method is the most informative and easy to implement comparing to other methods of slag outflow detection. These methods are electromagnetic induction, infrared thermal images, supersonic reflection and weighting method.

Today spectral analysis based on Fourier transform is widely used to solve this problem. It allows to characterize the frequency content of the signal being measured. The method is based on the analysis of the vibration spectrum. This analysis is the identification of the periodicity (frequency) of amplitude spikes occurrence. Using the spectrum frequency analysis, it is possible to identify the state of the many process parameters. Thus, authors of [10] show the results of experiments analyzing the amplitudes of the vibration acceleration spectrum obtained from a manipulator of a shroud, a tundish and a tundish carrier. Graphs show how the ladle gate has been controlled to cutoff slag. However, in most cases ladle gate is controlled to solve the problem of tundish steel level stabilization. This is needed to ensure the required quality of the steel ingot formed by mould. So the gate is permanently being closed or opened.
That undoubtedly causes significant perturbations, which amplitude is even higher than the one of the vibration signal generated by the steel teeming process. It is unclear whether this fact has been taken into consideration in the mentioned research or not.

However, cross-interference of some parameters on the other ones is usually observed in such complex processes. It makes the process significantly nonlinear and uncertain. In its turn, the vibration spectrum becomes difficult to be analyzed due to so-called hidden dependencies between process parameters. As a result, it is almost impossible to find some harmonics or frequency domain in this spectrum characterizing a certain plant parameter.

One of the relatively new and practically applied methods of mathematical processing of vibration signals is a wavelet transform. It shows the change in the value of each harmonic amplitude in the signal over time. Sometimes this analysis provides a qualitatively new diagnostic conclusions in comparison with the spectral analysis.

In [11] the authors propose to analyze together the power spectral density and discrete wavelet decomposition of vibration acceleration signal from shroud manipulator. The most informative ranges in the frequency domain and range of the wavelet transform coefficients are found. Authors note that the results of both approaches are correlated with each other, and it is an indicator of effectiveness. However, the authors have made conclusions on the basis of only one experiment. At the same time, signals spectrum, as practice shows, can vary significantly from one melt to another even if steel grade and teeming speeds are the same. This leads to the fact that the informative ranges for one melt are useless for another.

In recent time, papers related to the neural network processing of the Fourier spectrum and wavelet transform coefficients are occurred. The use of neural networks provides plant state recognition of higher accuracy since existing knowledge about the similar process units functioning are used [12-15].

In this paper we propose to obtain vibration acceleration signal from the tundish, expand it in a finite Fourier series using the fast Fourier transform, and then sent to inputs of a competitive neural network. It will be used to determine the start moment of slag outflow from the ladle into the tundish.

II. DESCRIPTION OF TEST STAND AND EXPERIMENTS

The system "ladle - tundish" is the scope of this research (Fig. 1). The data for the mentioned above method development have been obtained from a real industrial steel teeming process unit at a metallurgical combine.

To obtain the informative signal a vibration sensor was mounted directly to the body of the tundish. It was capable to function at temperatures up to 250°C with axial sensitivity 100 pC / g and a frequency range of 2 ... 7000 Hz. The signal from the sensor was sent to 4-channel, 24-bit analog input module NI 9234, which had four BNC connectors for four analog input channels with simultaneous signal digitation. This module was installed into a special chassis National Instruments cDAQ-9181 to be connected to a PC via the Ethernet interface.

The plant operator reported slag outflow moment during the measurements. It was recorded into the data acquisition system.

ADC and a laptop with the software NI LabVIEW 2013 was set near the steel teeming operator panel. This software was used to record and store data.

Three experiments were made during three teemings in order to determine the general laws for the plant operating under real production conditions. One experiment was one full ladle discharge into the tundish. For each of these experiments the tundish surface vibration acceleration signal was recorded with a frequency of 30 kHz into files <name>.lvm.

III. DESCRIPTION OF PROPOSED INFORMATION PROCESSING METHOD

In this paper we propose to use a competitive neural network to solve the considered problem (Fig. 2). It is a vector classifier. The input vector is classified depending on which previously stored image it is similar to. Also this network using self-learning algorithms can identify and approximate hidden dependencies in the signal spectrum, which in conventional analysis can not be detected.

We propose to obtain the tundish surface vibration acceleration signal (Fig. 3), expand it to the spectrum (Fig. 4.) using Eq. 1.

\[
X(k) = \sum_{n=1}^{N} x(n) \cdot e^{-j2\pi\left(\frac{k-1}{N-1}\right)}
\]

\(X(k)\) – Discrete Fourier image of the acceleration signal (spectrum harmonic amplitude),
\(x(n)\) – measured signal amplitude,
\(n\) – point number from the beginning of the process,
\(k\) – frequency value.
Then send it to the competitive neural network (Fig. 2). It is used to determine moment prior to the time of slag outflow from the ladle to the tundish.

![Diagram of competitive neural network]

**Fig. 2.** General structure of the competitive neural network.

This network consists of two layers. The number of inputs are associated with the vibration acceleration signal spectrum processing specifics, namely with the number of averaging points. These dots (Fig. 5) are calculated by averaging the informative frequency range 40 - 400 Hz of the original spectrum (Fig. 4.) The averaging window width (accuracy) is calculated with Eq. 2.

\[
a(z) = \frac{\sum_{i=(z^1+\Delta z-1)}^{\Delta z} X(i)}{\Delta z}
\]  

\(a\) – vector of measured signal averaged spectrum values, \(\Delta\) – number of harmonics with sampling rate of the spectrum \(X\), which are used for averaging.

\[
z = 1, z_{\text{max}}
\]  

\(z\) – value number of measured signal averaged spectrum, \(z_{\text{max}}\) – total number of values of the measured signal spectrum.

\[
z_{\text{max}} = \frac{(F_{\text{max}} - F_{\text{min}}) \text{length}}{\Delta}
\]  

\(\text{length}\) – number of signal points used for spectrum calculation (number of .lvm files each of which contained 30000 points).

The normalized vector \(a_{\text{norm}}^j = (a_{1}^j, a_{2}^j, a_{3}^j, \ldots, a_{z_{\text{max}}}^j)\) was used as input for network training. This vector corresponds with a certain teeming \(j = 1, M\), where \(M\) is the total number of teemings:

\[
a_{\text{norm}}^j = \frac{a^j}{|a|}
\]

The initial spectrum was obtained using the mentioned above equipment with window width \(\text{length} = 5\) points, removal rate of 30 kHz. It contains 75000 harmonic component values with sampling rate \(\delta = 0.2\) Hz. The spectrum was averaged with \(\Delta = 5\) harmonics (Fig. 5) in order to reduce the amount of information sent to the neural network without loss in quality of its functioning. Thus, the input layer contains \(z_{\text{max}} = 360\) neurons with the distribution functions. The output layer includes three neurons to generate a signal corresponding to a certain steel teeming.

![Graph of vibration acceleration signal](image1)

**Fig. 3.** Vibration acceleration signal.

![Graph of vibration acceleration signal spectrum](image2)

**Fig. 4.** Vibration acceleration signal spectrum.

Having prepared training set, all network weights \(\omega^j = (\omega_1^j, \omega_2^j, \omega_3^j, \ldots, \omega_{z_{\text{max}}}^j)\) were generated randomly and then normalized:

\[
\omega_{\text{norm}}^j = \frac{\omega^j}{||\omega||}
\]

Normalization equalizes the chances of all participants in competition of neurons with different unit weight vector.
Frequency-dependent competitive training was applied to determine the neuron-winner. It was neuron, which had the minimum value of the product of Euclidean distance between the input vector and the weights vector and the number of victories of the neuron:

$$KRIT_j = f_{\text{winnings}_j} \cdot \|p_j - \omega_j\|$$

$KRIT_j$ – criterion estimating the quality of reaction of $j$th neuron to the input vector, $f_{\text{winnings}_j}$ – number of winnings by $j$th neuron according to the criterion $KRIT_p$.

$K_{\text{min}} = p, if KRIT_p \setminus KRIT_j \forall j \neq p$

$K_{\text{min}}$ – index corresponding to the minimal value of $KRIT_j$.

The weights of the neuron-winner were tuned according to the following expressions:

$$\Delta \omega_{\text{norm}}^K = \mu \cdot (\omega_{\text{norm}}^K - \omega_{\text{norm}}^K_{\min}),$$

$\mu$ – learning rate.

$$\omega_{\text{norm}}^K (t + 1) = \omega_{\text{norm}}^K (t) + \Delta \omega_{\text{norm}}^K_{\min}$$

The neural network outputs are calculated according to the following equation:

$$Y_j = \begin{cases} 1, & \text{if } \omega_{\text{norm}}^j \cdot \alpha_{\text{norm}}^j \omega_{\text{norm}}^p \cdot \alpha_{\text{norm}}^p \forall p \neq j \\ 0, & \text{otherwise} \end{cases}$$

IV. RESULTS AND DISCUSSION

Having conducted experiments, the results shown in Fig. 6-8 were obtained.

The graphs depict the functioning of the neural network, namely the weighted sums ($P$) for each of the competitive neurons of the network, on the basis of which the threshold activation function triggers. Each point on the curve is formed by moving a window (5 measurements) in real time on curve obtained from the plant and proposed information processing method application for the data inside the selected window for each of the three steel teemings.

Initially, the neural network has been trained during 60 000 iterations. Data from the real plant containing five measurements preceding the slag outflow to the tundish and defined visually by the plant operator were used as a training set. The cutoff (gate closure) moment is a red vertical line in Fig. 6-8. Having been trained, the neural network learnt to define the state prior to the slag outflow for each of teemings. The first neuron won for the first teeming, the second – for the second and the third – for the third.

The graphs show that for each teeming simulation one of three neurons wins. Moreover the weighted sum was the highest for the neuron responsible for the teeming under consideration. It should be noted that the data for the points of the graphs numbered from 1 to 141 were not involved in the learning process. This suggests that the neural network classifier was able to identify some unique patterns in the spectrums of various teemings and divide data on that basis. At 142th point values of the weighted sums increased significantly indicating the occurrence of the moment prior to the slag outflow. Thus, if the network is modified by introducing logic elements for weighted sums signal level analysis and the threshold of 0.95 is set, it will be possible to obtain the control signal for the slag cutoff preventing it from entering the tundish.

V. Conclusion

Obtained results allow to state that proposed method is able to determine the moment prior to the slag outflow to the tundish. Its implementation will allow to increase the efficiency of steel teeming process and develop an automatic control system to close the gate cutting off the slag. The scope of future research is to optimize the width of the used time window to improve the accuracy and sustainability of the method. Other frequency ranges from the vibration acceleration spectrum from the tundish surface will be investigated.
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REFERENCES


