Optical Spectrum Based Estimation of Grades in Mineral Flotation

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Abstract— **Mineral enrichment by flotation is one of the hardest industrial processes to monitor and control. The main process measurements collected from a flotation circuit are the metal contents or grades in the different phases of the circuit. To improve the process monitoring capabilities, machine vision systems have previously been developed to characterize the flotation froth properties from digital images of the froth. This study discusses an on-line measurement of the optical froth spectrum in order to improve the slurry grade measurements obtained from the X-ray fluorescence based Courier analyzer. It is shown that the grades of the zinc flotation circuit concentrate can be estimated with a linear multiregression model using the measured froth spectra as input values. The model is then applied to estimate the grades of the concentrate between the originally sparse X-ray fluorescence measurements. Additionally, some preliminary results are presented which suggest that also the spectra measured directly from a slurry flow may correlate with the corresponding grade values.**

I. Introduction

In the mining industry, mineral flotation is a common process which is used to separate valuable minerals from the mined and ground ore. Flotation plants are typically complex structures, consisting of multiple individual flotation cells connected to each other. In order to manage the complete flotation process, it is essential to be able to measure the state of the process accurately enough. However, even a single flotation cell is difficult to model properly because of the stochasticity and complexity of the underlying physical phenomena. Additionally, the current measurement technologies do not provide means to comprehensively determine the state of the cell.

Main measurements obtained from flotation processes are the metal contents or grades of selected slurry flows. Traditional method to measure these grades is to use X-ray fluorescence based analysis. Recently also the machine vision approach has been studied in the context of flotation; froth properties can be analyzed and characterized using RGB cameras located above the cells [1–4]. Despite the developments in flotation measuring, the processes are still typically supervised by human operators, who utilize e.g. the results of X-ray analysis and visual inspections of the froth to determine the process state and required control actions. Thus the primary goal when developing new measurement techniques is to provide the operators with more accurate information on the process state.

So far the machine vision systems used in flotation have mainly been based on ordinary RGB cameras operating in the visual wavelength range. It has been shown that one of the most relevant quantities when considering the froth grade is the color of the froth, even though other properties of it also have correlation with the content values [5]. Also discussions with operators justify that the color of the froth is an important factor for grade estimation [6]. Additionally, studies of spectrum measurements in the previous projects involving our research group have also given encouraging results about the grade estimation based on the color of the froth [7].

In this study an on-line optical spectrum analysis based approach for improving the measurement of grades of the flotation froth overflow is proposed. A spectrophotometer with a wide wavelength range is used to measure the spectrum of the froth, and linear multivariate regression methods are used to map the spectral measurements to the corresponding grade values. Additionally, some preliminary results of the slurry spectrum analysis are discussed.

II. Process

The measurements for the study have been conducted in Pyhäsalmi copper, zinc and pyrite mine. The mine is located in Pyhäjärvi town in central Finland and owned by Inmet Mining Corporation. The concentrator plant of the mine is divided into three consecutive flotation circuits, one for each of the main minerals (copper, zinc and pyrite). Fig. 1 shows the overall structure of the zinc flotation circuit that has been used as a test case for our analysis. Additionally, the location of the cameras of the machine vision system developed earlier by our group [8] is shown. The main metal contents measured in the zinc flotation circuit are zinc, iron and copper.

A. Flotation Cell

The principle of flotation in mineral separation is based on manipulation of the physical properties of the ground mineral particles in the feed flow. By adding suitable mineral-specific chemicals to the slurry, the specific mineral particles are made hydrophobic. When air is fed to
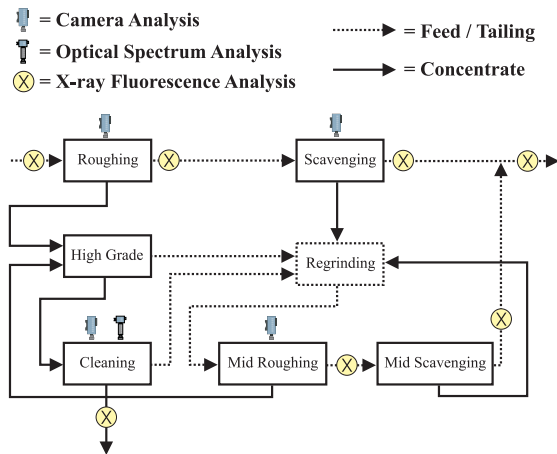
Fig. 1. Structure of the zinc flotation circuit analyzed in the study. The spectrophotometer was located on top of one of the cleaning cells. Each part of the circuit (e.g. Roughing, Scavenging...) consists of multiple flotation cells.
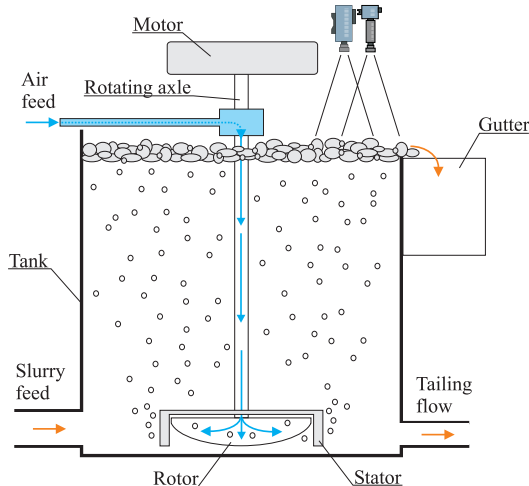

Fig. 2. Cross section of a flotation cell showing also the location of an RGB camera and spectrophotometer.

the bottom of the flotation cell (see Fig. 2), mineral particles attach to the rising air bubbles and drift to the surface of the cell. There the bubbles form a stable froth layer, which is allowed to overflow to a gutter. Typically, the concentrate flow in the gutter has remarkably higher mineral content than the original feed flow led to the cell. Rest of the slurry is continuously removed from the cell as a tailing flow.

B. X-ray Fluorescence Analyzer

The grades of the slurry flows of the flotation process in Pyhäsalmi mine are monitored by Outokumpu Courier 6 SL slurry analyzer, which radiates the slurry sample using a high intensity X-ray tube and measures the emitted fluorescence radiation. The emitted radiation is characteristic to each individual chemical element, thus allowing the determination of the element contents in the sample. A separate branch from each measured slurry flow is continuously led through the analyzer. These branch flows are then sampled so that from each one of them a sample is in turn directed into the jet flow cell of the analyzer. The jet flow cell is designed to maintain a turbulent flow behind the cell window surface, thus providing a representative sample for the X-ray analysis performed through the window.

Because of the sequential measurement of all the important flotation plant flows, the sampling interval for each flow increases. For example, currently the gap between two X-ray measurements of the zinc concentrate flow is about 18 minutes. This motivates the usage of secondary measurements (e.g. optical spectra) to estimate the grade changes in the intermediate time points in order to provide more information for the process operator.

III. FROTH SPECTRUM

Visual analysis of the flotation froth is well justified because other measurements for the flotation cell state determination are hard to conduct. It is also well known that the properties of the froth correspond to the current performance of the cell.

A. Measurements

The optical froth spectrum was measured using a spectrophotometer which consists of a regular monochrome digital camera connected to an imaging spectrograph. The spectrograph captures a line image of the target and disperses the spectrum of each pixel in the line to the vertical axis. Thus an image obtained from the camera contains the line pixels in the horizontal axis and spectrum components (i.e. wavelengths) in the vertical axis. The advantage of the line spectrum is that one image contains multiple spectra from the froth, so that the mean spectrum calculated from the image represents very accurately the current average color of the froth. The wavelength range of the spectrophotometer is from 400 to 1000 nanometers, thus covering the visual range ($400 - 700$ nm) and the lower wavelength part of the infrared range ($700 - 1000$ nm). Fig. 3 shows a typical froth spectrum measured from the cleaning cell of the zinc circuit. The slurry spectrum also present in the figure is discussed in the next section. A more specific description of the measurement system is given in [9].

In order to gather a substantial amount of data for validating the importance of spectral measurements, the spectrophotometer was installed on top of one of the cleaning cells in the zinc flotation circuit and used on-line for a couple of months. During that time the flotation plant was in normal operation. Due to the high variance of the froth color, spectrum images were captured using a sample time of five seconds and the mean spectrum of each image was heavily low-pass filtered (90% exponential filtering) with respect to time. The filtered spectrum was stored once a minute for further off-line analysis. Simultaneously, the X-ray measurements of the cleaning phase concentrate flow were stored with an average sample time of 18 minutes.
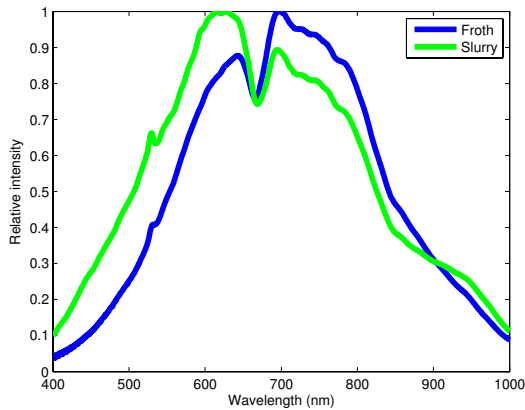
Fig. 3. Typical froth and slurry spectra. The wavelength range of the spectrophotometer covers the visual range as well as the lower part of the infrared wavelengths.

B. Modeling

To reveal the connection between the measured froth spectra and the corresponding grades of the cell overflow as measured by the X-ray fluorescence analyzer, static multivariate regression methods were applied to the data. Originally, the input data (spectra) contained 960 variables (wavelength values) according to the vertical resolution of the camera. To simplify and speed up the modeling process, the input dimension was reduced to 96 by calculating the averages of each ten adjacent spectrum values in the original data. It was observed that the information content of the spectrum was not significantly reduced during this operation. Because of the continuous nature of the spectrum with respect to wavelength, the input variables were highly dependent of each other. Thus the standard *multilinear regression* (MLR) mapping (see e.g. [10]) based on least squares fitting could not be successfully used for the modeling. Instead, the *partial least squares* (PLS) method [11] suited well to the problem; it finds a set of latent variables that explains both input and output data structures, and forms the mapping from input to output using this lower dimensional latent basis.

Generally, the estimation of the PLS model parameters is based on a set of previously gathered data. In this case, the input data consisted of the reduced spectrum values collected in the N rows of matrix $X \in \mathbb{R}^{N \times 96}$. Correspondingly, the output data consisted of the X-ray measurements of the iron, zinc and copper contents of the zinc flotation circuit concentrate flow, collected in the N rows of matrix $Y \in \mathbb{R}^{N \times 3}$. As a standard procedure, the data were mean centered and scaled to unit variance before further analysis. Now the PLS approach decomposes both the input and output data as follows:

$$X = TP^T + E = XW(P^TW)^{-1}P^T + E, \qquad (1)$$
$$Y = TC^T + F = XW(P^TW)^{-1}C^T + F = XB + F, \quad (2)$$

where T is the score matrix of X, and P and C are the loading matrices of X and Y, respectively. W is the weight matrix of X, and E and F are the residual matrices of X and Y, respectively. The commonly used NIPALS-algorithm (see e.g. [12]) was applied to the calculation of the final PLS mapping $B \in \mathbb{R}^{96 \times 3}$. As shown by (2), the mapping matrix B can be used to predict a new grade value vector y when a spectrum measurement vector x is known:

$$\hat{y} = B^T x. \qquad (3)$$

Based on the collected data, the delay from the froth spectrum measurement to the Courier measurement (i.e. time taken by the overflown slurry to transfer from the flotation cell to the X-ray analyzer) was estimated to be approximately four minutes. However, the amount of the delay is not a crucial factor since the spectrum measurement is heavily averaged over time. Additionally, the true delay is slightly varying according to the flow speed of the pipe connecting the flotation cell and the Courier sampler.

It has been detected that the flotation plant data are not necessarily stationary; especially the properties of the input ore can alter the behaviour of the process. Thus it is not possible to form a fixed model structure for predicting the grade values based on the spectra, since the model will not stay valid for a longer period of time. To overcome this phenomena, a rather crude method was applied in which a window of 300 previous samples (about 3.5 days) was used for model calculation, and the obtained model (matrix B) was assumed to hold for the following ten X-ray samples (about three hours). These ten samples were treated as validation data, and the values for them were predicted using the model. After this, a new model was calculated to predict the next ten samples, etc. Because of the sliding nature of the modeling, a continuous data set was required for the analysis. Consequently, a representative data set collected during one week of normal operation of the flotation plant was used in this study.

C. Results

The results of the modeling can be divided into two main parts. Firstly, the modeling approach was evaluated by comparing the measured X-ray values and corresponding predicted metal contents. Secondly, since the X-ray samples were measured with a 18 minute sampling interval, whereas the spectrum was obtained once a minute, it was possible to estimate the behaviour of the grades *between* the X-ray measurements. A detailed analysis of the results is presented in the following.

The modeling performance was evaluated using the linear correlation of the predicted output values and the corresponding X-ray measurements. Based on comparison of different model sizes, a model with six latent variables was selected. When the input loading values (columns of matrix P) of one of the PLS models are drawn (Fig. 4), some analysis can be conducted. Clearly the most important latent variable (no. 1) corresponds to the overall intensity
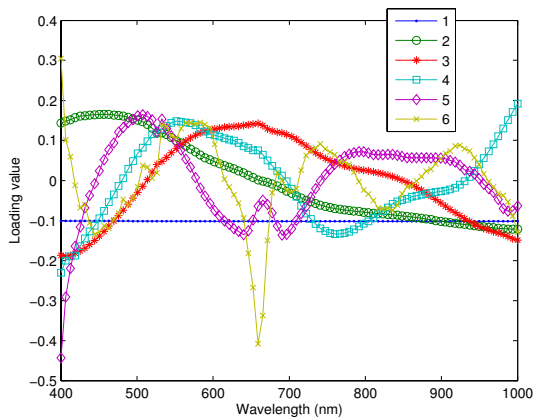
Fig. 4. Input loadings of one of the PLS models. The loadings are numbered according to the importance of the corresponding latent variables.
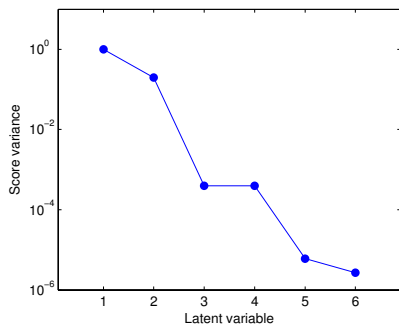

Fig. 5. Input score variances of the PLS model reveal the importance of each latent variable.

of the spectrum, since all wavelengths are equally present in the loading. The second loading captures the proportion of the intensity in the low and high wavelength values of the spectrum, whereas the third loading describes how much intensity the middle part of the spectrum has with respect to the low and high wavelengths. Furthermore, the fourth loading is again emphasizing the difference between the high and low wavelengths. The effect of the last two loadings is quite low as can be seen from the corresponding score variances (Fig. 5). However, all six latent variables are required to maintain the good estimation of the validation data. Slightly surprising is the fact that only the sixth loading seems to emphasize a narrow wavelength range, whereas the other loadings are distributed more smoothly over all the wavelengths. It seems that the overall properties of the spectrum contain most of the relevant information of the froth metal contents.

The correlation coefficients between the predicted and measured metal content values are shown in Table I. For comparison, the metal contents were also predicted using a MLR model calculated from the normalized red, blue and green channels and overall intensity values of an RGB

	Contents		Content changes	
	RGB	Spectrum	RGB	Spectrum
Fe%	0.81	0.82	0.26	0.28
Cu%	0.86	0.95	0.27	0.45
Zn%	0.82	0.83	0.23	0.28

camera located on the same flotation cell as the spectrophotometer (see [9]). It can be noted that especially the copper content is predicted remarkably well based on the spectrum values. To estimate the capability of the models to predict changes in the content values, difference signals (current - previous value) for both measured and estimated contents were formed, and the linear correlation coefficients between these were calculated (Table I). The correlations are clearly smaller, which is partly due to noise, but may also relate to different levels of filtering in the X-ray and spectrum measurements. However, both results show that the more accurate measuring of froth color by the spectrophotometer also provides more accurate grade estimates.

The main advantage of the spectrum measurements is the easy and fast measurement process. Once the camera is installed, it can operate continuously and with a high sampling interval, thus providing a large amount of measurements. To improve the sparse X-ray fluorescence measurements, the more frequent spectrum values were used to predict the changes in the metal contents in the intermediate time points. When a new X-ray measurement was available, the prediction error of the PLS model was calculated and cancelled out of the following predicted values. This way the intermediate estimates are as close as possible to the real content values. Fig. 6 shows the X-ray measurements and corresponding metal content estimates given by the model during a normal operation period of the flotation circuit. Clearly the model can predict the behaviour of the grades well and provides additional information on the process behaviour. Especially interesting is the prediction of rapid changes in the content values.

In some regions the estimates are not so well in line with the X-ray measurements (e.g. in the end of the period shown in Fig. 6). There are a couple of known factors which reduce the modeling accuracy. Firstly, the cleaning part of the zinc circuit is divided into two identical branches, and the camera and spectrophotometer only monitor one of them, while the concentrate flow measured by the X-ray analyzer consists of the total output flow of the circuit. During the measurement period the flow in the other branch was smaller than in the monitored branch, but may all the same have caused disturbance in the modeling results. Secondly, the delay between the flotation cell and the X-ray analyzer was estimated to be constant, even though the
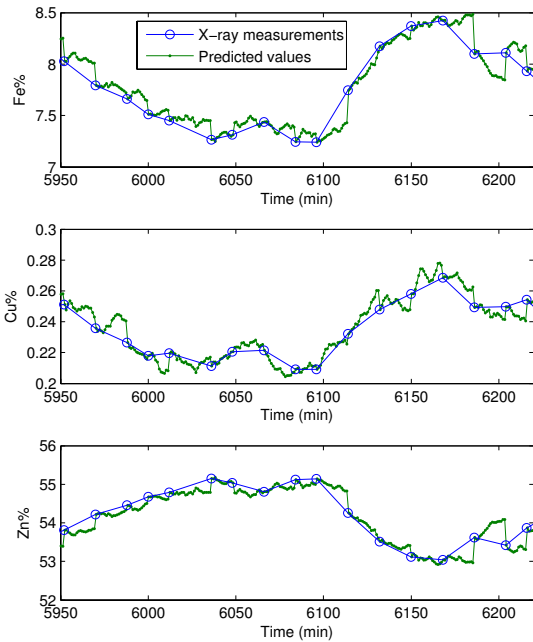
Fig. 6. A short interval of the sparse X-ray measurements and the more frequent metal content value estimates calculated from the optical froth spectrum measurements. Predicted values are level corrected so that the estimation error of each X-ray sample is subtracted from the following predictions. Clearly the PLS model is in most cases able to anticipate the metal content changes before the next X-ray measurement. Thus the spectrum measuring can improve the monitoring of the flotation process.

variance in the concentrate volume flow was in fact almost 50% during the measurement period. For a more accurate analysis this variable delay should be compensated.

IV. SLURRY SPECTRUM

It was shown above that optical spectra measured from the froth surface of a flotation cell have strong correlations with the grades of the cell overflow. However, the improvement of the X-ray measurements based on the spectra suffered from the distance between the flotation cell and the X-ray analyzer, as mentioned before. Consequently, if the spectrum of the slurry fed to the analyzer contained the same information as the froth spectrum, a more accurate estimate of the grades of the slurry could be achieved by measuring the slurry spectrum nearer the analyzer. Additionally, the grades of the tailing flows which cannot be measured from the froth typically tell more about the process performance than the contents of the flotation cell concentrates. This is why the second part of the study focused on analyzing the spectra of the slurry.

A. Measurements

The optical spectrum of the slurry was measured by manually collecting slurry samples from the zinc circuit clean-

ing cell overflow. Twenty samples were collected during 24 hours of normal operation of the flotation process. However, some changes in the cell control variables were made to rise additional variation in the grade levels. The spectra of the samples were measured off-line in laboratory conditions. Each of the about five liter samples was circulated in a closed circuit consisting of a pump and a jet flow cell equal to the one in the Courier analyzer. A halogen light was used to illuminate the cell window and the spectrophotometer was installed to measure the color of the sample through the window. Each sample was measured for twenty seconds at one second sampling interval, and the average of the obtained spectra was calculated to form the final spectrum for the sample. For comparison, the spectrum of the froth was continuously measured during the overflow sampling as described above, and the filtered froth spectrum values at the sampling time points were collected to a set of twenty froth spectra.

B. Analysis

The analysis of the slurry color measurements was based on the comparison of the slurry and froth spectra corresponding to each slurry sample. Fig. 3 shows typical froth and slurry spectra. Clearly, the slurry spectrum has more intensity in the lower wavelengths than the froth spectrum, which is partly explained by the fact that different halogen lamps were used in the froth and slurry measurements. Otherwise the overall shape of the two spectra seem to be quite similar.

To better compare the spectra, the variance of the two spectrum sets were calculated for each wavelength value (Fig. 7). Assuming that variance carries information, this should reveal the possible information content of the spectra. In the visible light range $(400 - 700$ nm) there is a variance peak in both curves, even though the slurry spectrum seems to vary more in lower wavelengths. The other high variance region is located in the infrared range of the both spectra, where the general shape of the two variance curves is almost identical. The similarities of the variance curves suggest that the slurry spectra could contain the same metal content information as the froth spectra.

The similarities of the slurry and froth spectra pairs corresponding to each sample were also investigated. Fig. 8 shows the linear correlation of the normalized spectra pairs for each sample. The overall correspondence of the spectra seems to be quite good, even though there are two samples (5 and 9) with negative correlation values. These could be explained by the fact that the slurry spectra were measured from a single and small slurry sample, whereas the froth spectra were heavily exponentially filtered from multiple measurements taken from the continuously changing froth surface (see above). It is also possible that a human error has taken place in the measurement process or sample processing.

Generally, however, the results of the slurry spectra measurements are promising. It seems very likely that the grade
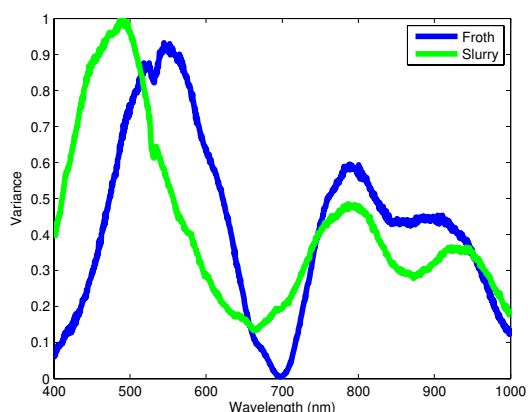
Fig. 7. Normalized variances of the slurry and froth spectra with respect to the wavelength values. The similarities of the variance distributions suggest that the slurry spectrum could contain the same mineral content information as the froth spectrum.
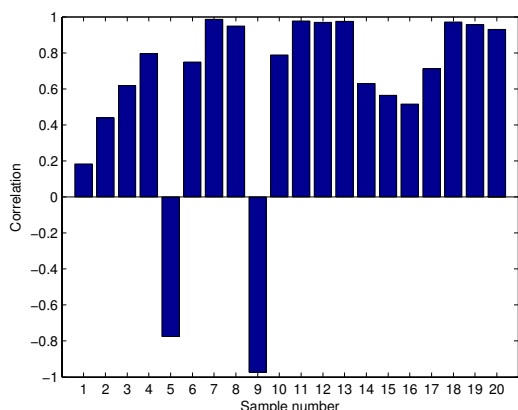

Fig. 8. Correlation of the slurry and froth spectra for each sample. Except for the two negative correlations, the spectra seem to be quite similar.

estimates could be more accurately calculated from slurry spectra measured e.g. from the sampling flow of the X-ray analyzer. The necessary step to be taken in the future research is the development of an on-line slurry spectrum measurement system to provide the required amount of data for proper modeling.

V. Conclusion

This study discussed the possibilities of predicting grades of a mineral flotation circuit by measuring the spectra of the flotation froth and slurry. On-line measurements of the froth spectrum in the zinc flotation circuit of Pyhäsalmi Mine were conducted and a sliding PLS model was calculated to estimate the metal contents of the concentrate flow. It was shown that the model can link the froth spectrum with the metal contents accurately. The main benefit of the modeling is the decreased sampling interval of the concentrate content measurement, which is obtained by the estimation of the metal contents between the sparse X-ray fluorescence measurements. Thus the modeling concept could readily be used to provide the plant operators with more accurate information on the process state.

The second part of the study concentrated on the analysis of the slurry spectrum. It was shown that the variation in the slurry spectra is quite identical with the results obtained from the froth spectra. However, the lack of on-line slurry spectrum measurements prevented the direct modeling of the relation between the spectra and metal contents of the slurry. Because of the promising results, the future efforts will focus on the installation of an on-line slurry spectrum measuring system. This should allow even more precise estimation of the metal content measurements.

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