Acoustic emission and machine learning for in situ monitoring of a gold–copper ore weakening by electric pulse

Bastian Meylan a, Sergey A. Shevchik a, Daniel Parvaz b, Abbas Mosaddeghi b, Vladimir Simov b, Kilian Wasmer a,.*

a Federal Laboratories of Material Science and Technology (Empa), Laboratory of Advanced Material Processing, Feurwerkstrasse 39, CH-3602, Thun, Switzerland
b SELFRAZ AG, High Voltage Department, Biberenzalggi 18, CH-3210, Kerzers, Switzerland

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A B S T R A C T

The excessive energy consumption from the mining industry are currently receiving international attention. A promising method able to enhance significantly the comminution process efficiency worldwide is by using electric pulse fragmentation treatment. However, to insure a minimum energy consumption in real scale operation, an online process monitoring is of utmost importance. This work presents an in situ and real-time monitoring method by combining acoustic emission sensor and advanced machine learning algorithms. The proposed method was developed on a gold-copper ore in well-controlled single stone experiments and in semi-continuous process, reproducing a real industrial environment. In single stone experiment, the pulse energies was varied from 200 to 750 J leading to three weakening behaviours; no discharge, surface discharge and fragmentation. Acoustic signals for these categories have been decomposed with wavelet packets, and sub-band energies have been chosen as features. Then, only the most informative features were selected via standard linear principal component analysis. Finally, the classification was performed via a traditional support vector machine. In the semi-continuous experiments, an unsupervised learning method was used for classification task based on Laplacian support vector machine. Results for single stone tests showed accuracy above 90% for the three categories. For semi-continuous tests, we demonstrated that the unsupervised classification can be applied efficiently to estimate the amount of weakening of the passed through ore. We are very confident that the proposed method can be easily industrialised to monitor in situ and in real-time the electric discharge process within a comminution operation.

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1. Introduction

The vast majority of electricity consumed during ore beneficitation is used to reduce rocks in size. This process is known as comminution and this technique is applied in various industries. It includes waste electrical and electronic equipment (Diani et al., 2019), softwood bark (Tudor et al., 2020), daily human household activities (Singh et al., 2018) but predominantly in the mining industry (Bluhm, 2006). In the latter, comminution is, in fact, the most energy intensive process. The results were also confirmed by Andres et al. (2001). Ballantyne et al. (2012) reported that comminution consumes, on average 36%, of the energy utilized by mining industry. It also accounts for a few percent of the total energy consumptions of several mining countries such as Canada, Australia and South Africa (Tromans, 2008). The reason is comminution is an inherently inefficient process when taking into account the ratio of mechanical strain energy input to the fracture surface area generated (Fuerstenau and Abouzeid, 2002). Actually, Bluhm (2006) reported that the energy efficiency of traditional mechanical comminution is in the order of 0.002–1%, depending on the degree of fragmentation. Hence, impact of mining and mineral processing is an increasingly important topic (Farjana, 2019), in particular energy savings in comminution in mineral processing research (Bearman, 2013). In this context, weakening of solid materials prior to conventional crushing using electric pulse has been proven to be a promising technology in reducing the energy needed to process minerals in a complete comminution chain (Shi et al., 2014). But, this method is not destined to substitute completely the traditional milling but replace one step at a specific stone size range. Indeed, this method cannot compete with the traditional crushers for the large stones and it becomes inefficient for small stones and will not replace the traditional milling.

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Electric pulse fragmentation (EPF) uses very high voltage discharges (>90 kV) at short pulse rise times (<500 ns) to cause dielectric breakdown inside dielectric materials such as rocks, ores or concrete. The high electric field is enough to ionize the material and create plasma channels (Shevchik et al., 2018a). The expansion of the plasma channel creates a damage similar to conventional explosive, with crushing localized around the plasma channel and shockwave damage in the surrounding volume (Bluhm et al., 2000; van der Wielen et al., 2013). The main effect is the creation and growth of cracks in the adjacent material. These cracks weaken the treated stones, potentially leading to a reduction in energy consumption in the later stages of comminution (Bluhm, 2006; Cho et al., 2013). Wang et al. (2011) reported an increase in the ore softness indicator values of up to 52% after batch processing in a Lab electric discharge unit from SELFRA G AG, representing a reduced resistance of the ore to breakage. Even higher weakening values of 171% after EPF treatment were reported by Shi et al. (2013) using a single stone testing approach.

The EPF process has also a better efficiency observed for mineral liberation. Andres et al. (2011) shows the potential for EPF to increase concentrate grade and/or recovery of copper, nickel and platinum group elements after flotation, which they attributed to improved liberation. Wang et al. (2012) used a mineral liberation analyser to compare sulphide liberation after EPF to conventionally processed samples using similar energy inputs. They found that sulphide liberation was improved after EPF treatment, with over an order of magnitude more sulphide minerals depleted into >53 µm size fractions.

Despite these advantages, the EPF process is not yet implemented in large scale, high throughput (1000's tph) comminution process for two main reasons. First, the physics of the weakening of solid materials during the EPF process is known to be complex and highly dynamic. Second, the large variability in electrical and mechanical material properties of natural materials (e.g. between ore and waste minerals) results in a lack of process reproducibility and repeatability.

Nowadays, the only process control is made ex situ, either via a Drop Weight Test (DWT) method (Tavares, 1999) or JK Rotary Breakage Tester (Shi et al., 2013). These methods require treating a large amount of samples and several steps of sieving and weighing to measure the size distribution of the broken pieces. The results are, then, compared with a reference sample (not treated by electric pulse) in terms of amount of energy requires to achieved a given particle size distribution. Obviously, these methods are very time consuming and so extremely costly. Thus, an in situ and real-time monitoring system remains an open topic and still is of great demand.

In recent years, an innovative approach that combined acoustic emission (AE) with machine learning (ML) was successfully to highly complex and dynamic processes. It includes 3D reconstruction of cracks in glasses (Shevchik et al., 2019a); detection of scuffing, a sudden friction and wear failure mechanism via support vector machine (Saedi et al., 2016) and Random Forest (Shevchik et al., 2017); laser welding quality monitoring via Laplacian graph support vector machine (Shevchik et al., 2019b) and taking advantage of high speed X-ray radiography to investigate the different process transient (Shevchik et al., 2020); and additive manufacturing quality monitoring via manufacturing using either spectral convolutional neural networks (Shevchik et al., 2018b), deep learning methods such as various convolutional neural networks framework (Shevchik et al., 2019c), or a reinforcement learning approach (Wasmer et al., 2019). Based on the know how acquired, this approach was applied in a previous work (Shevchik et al., 2018a) for in situ and real-time monitoring of weakening of polymer transparent artificial sample. The success of this approach resulted in a granted patent (Vaucher et al., 2016).

The aim of the current study is to explore whether our method combining AE and ML can be reliably implemented as a monitoring system of the EPF process of real mining materials, in particular to gold–copper ore. To address this issue, we performed two type of experiments. To start with, single gold-copper stone experiments were carried out similar to Shevchik et al. (2018a) for polymer transparent artificial sample. Second, to reproduce a real industrial environment, semi-continuous tests were performed. The conclusion of this study is that the approach proposed is a robust and cost-effective in situ and real-time monitoring system able to classify the efficiency of the process and insure that the EPF process gives the correct amount of weakening.

2. Materials and methods

2.1. Materials

The stones used in this study are similar to the ones previously employed by Wang et al. (2011). They originate from a gold–copper mine operation located in New South Wales, Australia. The gold–copper mineralization occurs in quartz veins, sheeted quartz sulphide veins and as disseminations. The gold occurs mainly as free grains in quartz or on the margins of sulphide grains. The principal copper sulphide minerals are chalcopyrite and bornite. The major silicate minerals are quartz, orthoclase, hornblende, chlorite, anorthoclase, and the non-silicate minerals include magnetite, calcite and apatite.

In this contribution, the stone are all coming from the same batch of a single ore. Despite this fact, the stone material is, of course, subject to natural variations so that the amount of impurities in each stone is not known.

2.2. Electric discharge setup

All stones were treated over several days in the pre-weakening test station (PWTs) at SELFRA G AG (Kerzers, Switzerland) (Bru et al., 2018; Selfrag, 2019). A photograph of the installation is shown in Fig. 1a and a schematic representation of the discharge area is shown in Fig. 1b. The setup consists of a high voltage pulse generator (up to 200 kV) with up to 4 stages of capacitors providing from 2.5 to 37.5 nF. The uncertainties of the PWST station being insignificant as compared to the stochasticities of the process and samples, they are not given. The discharge occurs in a so-called process zone, which consists of a water chamber between an electrode and the conveyor belt that acts as the counter-electrode. The large water tank provided a more or less stable temperature throughout the process and over time.

In this contribution, two types of test were performed. First, we carried out a proof of concept demonstrating that AE can be used to monitor the process. To achieve this goal, we performed single stone tests following the method of Shi et al. (2013) using the PWTs instead of the Lab system, with the conveyor belt remaining inoperative. For the single stone tests, the impurities (stone particles) in the water have time to settle between the processing of successive stones and so provide constant process condition. The second series of experiments processed 5 kg batches of material continuously to simulate a real industrial processing environment. For these experiments, the small particles/debris created during the process are still present in the water for the next pulse and their impact on the AE signals will be discussed.

2.2.1. Single stone testing

The stones were sieved into 4 size categories; (i) 25–31 mm, (ii) 31–35 mm, (iii) 35–40 mm and (iv) 40–45 mm. The weight of each stone was recorded before the EPF treatment. For the two smallest size categories, 120 stones were selected and separated in 4 groups.
of 30 stones. For the two large sizes, 80 stones were selected and separated in 4 groups of 20 stones. To achieve different weakening states, each group of stones was treated with various EPF parameters. For all groups, the voltage was set at 200 kV while the capacitance was varied (10, 15, 22.5, and 37.5 nF) giving pulse energies of 200, 300, 450, and 750 J, respectively. The single stone tests were performed by manually positioning each stone on the motionless conveyor belt in the gap below the electrode and applying one pulse with the desired EPF parameters. After each pulse, the largest daughter stone was weighed to assess the percentage of mass loss defined as: weight loss = 1 - \frac{\text{weight final}}{\text{weight prior}}. Then, the stone fragments were collected for drop weight testing.

2.2.2. Semi-continuous stones testing

The semi-continuous tests were made to simulate real industrial operating conditions. Stones were first separated by size in 4 categories: (i) < 25 mm, (ii) 25–35.5 mm, (iii) 35.5–40 mm and (iv) > 40 mm. For each size category, 3 groups of 5 kg were prepared. Similarly to the single stone tests, to have various weakening states, each group was treated at a constant voltage of 200 kV but with three different capacitances (10, 15, and 22.5 nF), producing pulse energy of 200, 300, and 450 J, respectively. Before the semi-continuous tests, 5 kg of stones were spread on the conveyor belt in front of the electrode. The tests were started by moving the conveyor belt at a velocity of 100 mm/s and simultaneously applying electric pulse at 15 Hz. A schematic representation of the semi-continuous tests is shown in Fig. 1b. On the left hand side, the large stones visible are the initial stones that did not receive any pulse. The conveyor belt transported these stones below the electrode where the EPF process occurred and fragmented the stones. The fragments were transported away from the electrode on the conveyor belt (right hand side). The pulses and the conveyor were stopped manually once all stones had passed below the electrode. After the tests, the stone fragments were collected for drop weight testing.

2.3. Drop weight testing

The products of the single stone tests were grouped into sixteen categories of sizes and capacitance. The stones of each group were then separated in three size categories; (i) 14–20 mm, (ii) 20–35 mm, and (iii) > 35 mm for the DWT. The DWT was performed on batches of 10–20 stones for each size fraction. The products of the single stone tests were processed in an Instron CEAST 9350 drop tower impact system. The impactor mass and speed were adjusted per stone to deliver a fixed 0.5 kWh/t energy to each stone. DWT product stones for each batch were combined and sieved to estimate the cumulative distribution of the size of the fragments. Based on these distributions, \( P_{80} \) values were measured. The \( P_{80} \) value is defined as the theoretical sieve diameter size through which 80% of the particles pass. The change in \( P_{80} \) for the untreated and EPF treated material gives an indication of the degree of weakening caused by the electric pulse. EPF treated stones will have greater fracture density than traditionally crushed material that will facilitate the fragmentation of the stone during the DWT. The more cracks (i.e. the higher the weakening), the smaller the DWT product fragments. Smaller fragments imply a reduction of the \( P_{80} \) values. Similarly to the uncertainties in the PWST, the uncertainties of the DWT are insignificant as compared to the stochasticities of the process and samples and so they are not given.

2.4. Acoustic emission signal acquisition

For each electric pulse, the corresponding AE signal was recorded simultaneously. The detection of the acoustic signals was made directly inside the process zone. We used an R30-UC acoustic hydrophone sensor from Physical Acoustics™. Based on the sensitivity curve of the hydrophone (not shown here), it has a high sensitivity between 200 and 400 kHz. The hydrophone was located 30 cm from the electrode gap (See Fig. 1b). Also, the hydrophone was fixed above the conveyor belt to avoid collision with the moving fragments and facing down in the direction of the gap below the electrode. The AE
signals were recorded using an AMSY-6 system from Vallen GmbH with a sampling rate of 10 MHz and duration for each record of 16 ms that was triggered by the voltage pulse start.

3. Signal analysis

3.1. Wavelet decomposition

In this work, we used a sparse signal representation in the time-frequency domain applying a standard wavelet packet transform (Mallat, 2008). The operation used a standard Daubechies wavelet with 10 vanishing moments. The reason is that, after an exhaustive search, it showed the lowest errors in approximation of the collected AE signals. The energies of the narrow frequency bands from the wavelet packet transform were further applied as features of the original signal. More details about this approach can be found in Shevchik et al. (2018a).

3.2. Principle component analysis (PCA)

Before classification, only the most informative features were selected making use of the standard linear principal component analysis (Jolliffe, 2002). The idea behind the method is the projection of the higher dimensional space into a lower dimensional one. This allows disposing of non-informative features components, thus decreasing the noise and additionally reducing the computational complexity (Jolliffe, 2002). In this work, PCA excluded the narrow frequency bands that did not include information about the fragmentation process.

3.3. Support vector machine (SVM) for single stone tests

The classification was performed via a traditional support vector machine, a statistical learning technique, proposed by Cortes and Vapnik (1995). SVM belongs to the supervised learning methods. A supervised learning algorithm learns a mapping function from labelled training data to predict outcomes for unforeseen data. SVM is a margin classifier that operates with the geometrical representations of the data in an abstract feature space. In our case, the feature space was built as in Shevchik et al. (2018a), where the feature coordinates were given by the energy values of the narrow frequency bands. The goal of the classifier is to define the decision cut that separates the data from the different categories in this abstract space. An original SVM realization was employed in this contribution for these purposes (Cortes and Vapnik, 1995).

3.4. Unsupervised learning for semi-continuous tests

The training made for the single stone tests could not be applied to the semi-continuous test directly. The reason is the strong damping of the acoustic signals during the semi-continuous experiments. This will be discussed in Section 4.2.1. To overcome this problem, it was decided that the classification of the AE signals will be made using an unsupervised learning method. It is known that the results of such method is more difficult to interpret as compared to supervised learning method. Still, this method could become more and more precise and provide increasingly interesting information about the process as the amount of signals and tests increases.

The unsupervised classification was performed using Laplacian support vector machine (LapSVM) (Melacci and Belkin, 2011), a recent extension of the original SVM proposed by Cortes and Vapnik (1995). The novelty of LapSVM is in capturing the geometry of the input feature space utilizing the undirected graph Laplacian, which is introduced inside the optimization procedures. The Laplacian graph includes the information about the local connectivity of each individual feature with the neighbours. In this setup, the structure of the input data includes several agglomerations of the features with better internal connectivity as compared to the surrounding neighbourhood. Hereafter, these agglomerations will be referred to as “clusters” and the close relation of all features within an individual cluster may indicate a belonging to the same category. This information captured with LapSVM is employed for unsupervised learning. In this case, the categories are not defined by the user, but they are extracted by the algorithm (Melacci and Belkin, 2011).

4. Results and discussion

4.1. Single stone tests

4.1.1. General observations

The outcome of the single stone tests is varied and reflects the heterogeneity of the ore material and typical examples are shown in Fig. 2. In this figure, 5 stones of the 31 – 35 mm category were treated with a pulse energy of 300 J. The 1st row and 2nd row contain pictures of the same stone before and after being subjected to an electric pulse, respectively. The 3rd row shows the raw AE signals obtained during the electric pulse. Finally, the 4th row are the corresponding wavelet decomposition of the AE signal. In these figures, the x-axes are the time in seconds whereas the y-axes are the channel N’ (See also Fig. 5b and d). In Fig. 2, the columns (stones A, B, C, D, and E, from left to right) illustrate various damage (weakening) states. In fact, damages to the stones are in increasing order from no damage (stone A) to complete fragmentation of the stone (stone E). For stone A, no complete electric discharge was heard during the test. Some indications of a partial discharge are visible at one corner of the stone (red arrow). The corresponding AE signals is much weaker than for the other categories and goes back to noise level (<6 ms) than the other signals. This is confirmed on the wavelet decomposition graph were the higher energy domains are concentrated from 0 to 4 ms (yellow domains). Stone B shows the result of a surface discharge. For this stone, a loud discharge was heard with a corresponding strong AE signal but no weight loss was measured on the stone. This is an indication that the discharge path was either at the surface of the stone or completely inside the water. The AE signal is similar to all other cases and cannot be distinguished from the other discharge category without advance signal analysis methods. Stone C corresponds to a discharge only at the surface of the stone, resulting in only 2.7% weight loss. This means that the stone is mostly intact. Discharge path is also visible on the stone (red arrow). Stone D corresponds to an internal discharge with some moderated fragmentation of the stone. For this stone, the weight loss was 20% and two main fragments were recovered after the discharge (on the right of the stone). Stone E corresponds to a complete fragmentation of the stone with a weight loss of 85%. The main stone was fragmented in 8 fragments of similar size. The fragmentation has also revealed some pyrite minerals exposed on the breakage plane (red arrows), suggesting that the discharge pathway is influenced by the presence of metal rich in minerals (Zuo et al., 2015).

The variability of the results obtained in Fig. 2 proves the stochasticity of the process and samples as well as the necessity for a monitoring method to control the process. The proximity of the AE signals (expect for the no discharge case) confirms that advance signal analysis methods are required to correctly classify the signals.

The relation between the discharge path and the energy level is shown in Table 1 and also illustrated in Fig. 3a. The number of no discharge events is relatively high (24%) for pulses energy of 200 J
and it decreases steadily to only 2% at 750 J. This is explained by the
fact that for a discharge to occur, two conditions must be met. First,
the voltage must overcome the dielectric strength of the material.
Second, for the discharge to bridge the gap between the two
electrodes, the energy must be sufficient to sustain the growth of
the plasma streamer (Bluhm, 2006). When the pulse energy is not
sufficient, a partial discharge can occur as illustrated for the stone A
in Fig. 2. An augmentation of the pulse energy leads to a decrease of
the surface discharge and an increase of internal discharge as
illustrated in Fig. 3a. The reason is that at low pulse energy, the
electrical discharge takes the path requiring the least energy to
reach the counter-electrode, which is in many cases either in the
water or at the surface of the stone. As the pulse energy increases,
the probability of occurrence of the electrical breakdown of the
stone increases. In other words, the probability that the discharge
goesthrough the stone increases. As expected, the average weight
loss follows the same trend as the one of internal discharge (see
Fig. 3a). Indeed, a higher proportion of discharges occurring inside
the stone means more fragmentation and so a higher weight loss
percentage.

Based on Table 1 and Fig. 3b, the influence of the stone size is
less obvious, partly due to the relatively low amount of stones per
size category (30 for the sieving sizes -31.5 + 25 mm and
-25 + 31 mm and 20 for the sieving sizes -40 + 35 mm and
-45 + 40 mm). However, several observations can still be made. The
amount of no discharge is usually higher for the two sieving sizes
-31.5 + 25 mm and -35 + 31 mm as compared to the sieving sizes
-40 + 35 mm and -45 + 40 mm categories. The reason is that the gap between the electrodes was kept constant for all
stones. In other words, the distance between the stone and the
electrode (or “water gap”) is higher for smaller stones. Obviously,
the closer the stone is to the electrode, the more probable is a
discharge to occur. In the opposite, smaller stones are further away
from the electrode, and so experience more no discharge events.
Therefore, a larger water gap requires higher voltage to increase
discharge probability (van der Wielen et al., 2013). Our results
supports this hypothesis since at higher voltages, we observed
fewer no discharge events for similar sized stones (Table 1). To
avoid this issue for industrial processing, the gap between the
electrodes should be reduced proportionally to the size of the
stone. But for this study, this variation provides a variety of signals
and conditions which are highly interesting to validate our
approach and so it is not an issue.

$P_{80}$ data from the experiments (Table 1, Fig. 3b) shows that
smaller feed particles before DWT results in product with lower $P_{80}$
values. The only exception is for the untreated size where the size
categories > 35 mm and 35 – 20 mm have $P_{80}$ values of 12.7 and
12.8 mm, respectively. The increase in fragmentation rates for lager
feed particles is known and discussed by van der Wielen et al. (2013)
as “the feed size effect”. The size 35 mm may be an inflec-
tion point where the effect of increasing the feed size increases the
breakage to the point where the product $P_{80}$ is equal to that of a
finer feed $P_{80}$. This indicates that this feed size range shows a higher
breakage efficiency for this material. The smaller untreated stones
(20 – 14 mm) have a smaller $P_{80}$ value of 9 mm. As for untreated
stones, the smaller stone before DWT will produce smaller frag-
ments after DWT. Another effect explaining the larger $P_{80}$ value for
larger stones is that some larger fragments originate from stone
with partial discharges or surface discharges. Both categories are
expected to produce little weakening of the stones and so lead to a
$P_{80}$ value closer to untreated stones.

As the pulse energy is increased, the $P_{80}$ value decreases for the
three sizes (see Fig. 3b). This is a clear sign that the electric discharge
has weakened the stones since the stones subjected to the electric
discharge break more than an untreated stone. The goal of this
process is to induce a dense microcrack network within the material
to enhance the fragmentation of the stones in the later stages of a
comminution circuit (Wang et al., 2011). A decrease in product $P_{80}$
values for large feed sizes is observed even when a relatively low
mass loss was observed. This indicates pure weakening and no
fragmentation has occurred for these stones. One possible explana-
tion is that surface discharge can lead to weakening of the stone

Fig. 2. This figure shows the variations of the outcome of the discharge treatment. 1st row contains five stones prior electric pulse. 2nd row shows the same stones after one electric pulse of 300 J. A is no discharge, no weight loss; B is a discharge with no weight loss; C has 2.7% weight loss; D has 20% weight loss; and E has 85% weight loss. 3rd row presents the corresponding raw AE signal whereas the 4th row is the corresponding wavelet decomposition of the AE signal.
when shockwaves penetrate inside the material. This was already observed in our previous study on transparent materials (Shevchik et al., 2018a). Moreover, even for an internal discharge, the amount of cracks produced in the stone will be much higher than the actual number of fragments generated. This is due to the fact that fragments are created when a crack propagates from one surface of the stone to another. The generation of a fragment makes use of existing cracks within the stone. Only a small number of cracks achieved this and thus the majority of the cracks remain internal. As the amount and length of the cracks are two important factors determining the mechanical strength of brittle materials, presence of cracks weakens significantly the material (Griffith, 1921). Less than 10% mass loss would normally be classed as a surface discharge, however, the decrease in $P_{80}$ indicates internal fracture generation, meaning the original surface/internal discharge classification based on absolute mass loss must be reconsidered in future work.

### 4.1.2. $P_{80}$ reduction index

As mentioned in the introduction, even though classifications of AE signals using ML is never a trivial task, it has been successfully applied to various industrial processes. However, in this study, the classification of the AE signals is even more challenging. The reason is the available/accessible data to build the training and tests database for the supervised learning approach. In the construction of the database, we have to take into account three characteristics. First, a unique AE signals exists for each pulse. Second, for each stone, the weight loss after discharge is measured. Third, the $P_{80}$ values are measured for groups of fragments of similar sizes issued from different stones treated with the same conditions. The major difficulty is that, as seen before, two stones with a similar weight loss but treated with a different pulse energy will have different $P_{80}$ values. To account for the effect of both, the weight loss and the pulse energy, it is necessary to introduce a new $P_{80}$ index; the $P_{80}$ reduction index. To calculate this value, we assume a reduction of the size equal to the weight loss of the stone whereas the size is related to a length in one dimension of the fragments. Still, in this contribution, this simplification can be used as we are looking for a classification criterion and not a physical criterion. This means that for each signal, we need a unique classification value. This value allows differentiating for two stones of the same size treated at the same pulse energy but with very different outcome like no discharge or complete fragmentation. This value has no direct physical meaning as a fragmented stone will produce for example several fragments that might be separated in different size categories for the $P_{80}$ tests. An example to

### Table 1

The proportion of internal discharge (>10% mass loss); surface discharge (<10% mass loss); no discharge events; average mass loss for stones, and $P_{80}$ values for treated products for each size category in the experiments.

| Pulse Energy | Sieving size | Discharge inside | No discharge | Surface Discharge | Average mass loss | $P_{80}$ >35 [mm] | $P_{80}$ 35-20 [mm] | $P_{80}$ 20-14 [mm] |
|--------------|--------------|------------------|--------------|------------------|------------------|-----------------|-----------------|-----------------|
| 200 J        | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
|              | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
|              | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
|              | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
| 300 J        | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
|              | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
|              | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
|              | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
| 450 J        | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
|              | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
|              | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
|              | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
| 750 J        | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
|              | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
|              | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |
|              | –31.5 + 25 mm | 27%              | 47%          | 27%              | 8.4%             | –               | 8.6             | 6.7             |

Fig. 3. (a) Proportion of the different types of discharge as a function of the pulse energy; (b) Evolution of product $P_{80}$ values for varying different feed size fragments as a function of the pulse energy.
calculate the $P_{80}$ reduction index is shown in Fig. 4. Let’s take a stone from the category 40–45 mm, where the initial size was 45 mm and had a 46.6% weight loss, which corresponds to a 46.6% size loss. Under such circumstances, the size of the largest fragment can be calculated and is equal to 45(1–0.466) = 24 mm (see black arrow on the x-axis in Fig. 4). Then, on the y-axis, we plot the three values of $P_{80}$ calculated for each pulse energy. The reduction of $P_{80}$ value is calculated as $\frac{P_{80} \text{not treated} - P_{80} \text{treated}}{P_{80} \text{not treated}}$. Then, a linear regression is made with the three values with an origin that considers no reduction for no weight loss (for this example, a size of 45 mm in Fig. 4). The $P_{80}$ reduction index is simply the intersection between the size loss (i.e. weight loss) and the linear regression given by the pulse energy of the current stone considered. This is illustrated by the blue arrows in Fig. 4. Considering a stone with the same weight loss of 46.6%, we will have different $P_{80}$ reduction index based on the pulse energy ranging from 24% for a stone treated at 200 J to 42% for a stone treated at 750 J (see red arrows in Fig. 4). This takes into account that stones treated at higher energy have a lower $P_{80}$ value, as more cracks are present inside the stones.

4.1.3. Database preparation of the AE signals for single stone tests

The $P_{80}$ reduction index was calculated for each stone and the AE signals were then separated in 5 categories based on this value as shown in Table 2: (i) no discharge, (ii) $P_{80}$ reduction 0–10%, (iii) $P_{80}$ reduction 10–30%, (iv) $P_{80}$ reduction 30–50% and (v) $P_{80}$ reduction > 50%. The category limits were chosen to have similar number of AE signals in each category (as shown in Table 2). Only the category no discharge has a significantly smaller number of signals as this cannot be influenced. The first category (no discharge) is composed of all pulses where no discharge occurred and so no weakening is observed. The AE signal can be directly classified visually after the test. The second category, $P_{80}$ reduction 0–10%, corresponds with the case of surface discharge where the weight loss is small. The last three categories correspond to various degrees of fragmentation and weakening. As can be seen in Fig. 4, only the stones with a high weight loss and treated with high pulse energy can be classified in the last category ($P_{80}$ reduction > 50%). In contrast, the stones treated at low pulse energy will be classified in the categories $P_{80}$ reduction 10–30% and $P_{80}$ reduction 30–50% depending on the weight loss achieved.

4.1.4. Classification of the AE signals for single stone tests

The classification accuracy for all the categories is shown in Table 2. In this table, on the number of stone for the training data and test data are given in bracket (training/test data). The accuracy is shown in the diagonal in bold highlighted in dark grey, where machine classification matched human classification. Misidentified classifications are in italic without highlighting. For examples, for the category no discharge, the classification accuracy is 99% and there is a 1% misclassification with the category $P_{80}$ reduction 0–10%. The accuracy for the category no discharge is high since those signals are very distinct from the other (Fig. 2). The algorithm is also able to classify with high accuracy the two extreme cases (i.e. surface discharge $P_{80}$ reduction 0–10% and complete fragmentation $P_{80}$ reduction > 50%). The intermediate categories have a worse recognition rate especially the category $P_{80}$ reduction 30–50%. It has to be noted that the boundary of these categories were arbitrarily chosen, and the physical process is expected to be more or less similar for all categories.

From an industrial point of view, the fact that we are able to classify in real-time and with high accuracy the two extreme cases is very important. It allows the operator to know instantaneously whether or not the weakening process is efficient, and if not gives the opportunity to tune the process parameters. Obviously, to be energy efficient, the process must operate in optimum weakening conditions (i.e. > 50%) and not in the categories no discharge and surface discharge where the weakening is not sufficient.

4.2. Semi-continuous tests

4.2.1. Damping of the acoustic emission signals

As mentioned in Section 3.1.4, the training made for the single stone tests could not be applied to the semi-continuous test
directly. The reason is that during the semi-continuous experiments, the relatively high repetition rate of the discharge led to a strong damping of the acoustic signals and evidence of this is in Fig. 5. Fig. 5a is a typical raw AE signal taken at the very beginning of a semi-continuous experiment and Fig. 5b is its corresponding wavelet decomposition. In Fig. 5a, no damping is visible and the signal is back at noise level after 13 ms. Similarly to Fig. 5a and b, Fig. 5c is a typical raw AE signal taken after 100 pulses at a frequency of 15 Hz and Fig. 5d is its corresponding wavelet decomposition. From Fig. 5c, it is evident that the AE signal is highly damped since it is back at noise level after only 4 ms. The damping is thought to be caused by residual air bubbles in the water from the

| Categories (training/testing data) | Observed | $P_o$ red. $0$–$10\%$ | $P_o$ red. $10$–$30\%$ | $P_o$ red. $30$–$50\%$ | $P_o$ red. $>50\%$ |
|---------------------------------|----------|-----------------|-----------------|-----------------|-----------------|
| *No discharge* (40/44)         | 99       | 1               | –               | –               | –               |
| $P_o$ red. $0$–$10\%$ (90/125) | –        | 91              | –               | –               | 9               |
| $P_o$ red. $10$–$30\%$ (70/93) | –        | 9               | 86              | –               | 5               |
| $P_o$ red. $30$–$50\%$ (60/80) | –        | 22              | –               | 63              | 15              |
| $P_o$ red. $>50\%$ (60/84)     | –        | 1               | –               | 7               | 92              |

Table 2
Classification accuracy for the different categories. The accuracy is shown in the diagonal in bold highlighted in dark grey, where machine classification matched human classification. The misclassification are in italic without highlighting.
previous discharge as well as the presence of dust stones suspended in the water as a result of the fragmentation. Therefore, the decision was taken that the classification of the AE signals will be carried out using an unsupervised learning method.

4.2.2. Results of the $P_{90}$ values for the semi-continuous tests

Results of the $P_{90}$ values after electric discharge at different pulse energies are shown for the four size categories in Table 3. As expected, the $P_{90}$ values decrease with increasing pulse energy. Indeed, as the energy increases, the shockwave energy also increases which leads to more damage and cracks in the stones. For all size categories with the exception of $25.0 – 35.5$ mm, the $P_{90}$ reaches a value of around $6$ mm for pulse energy of $450$ J. The decrease of the $P_{90}$ values is not as strong for the $25.0 – 35.5$ mm category where the value is just over $9$ mm. The reason for this higher value is not understood yet and more tests would be necessary to explain this result.

4.2.3. Classification of the AE signals for the semi-continuous tests

The results from the classification are presented in Table 3, along with the $P_{90}$ values. As the exact impact of a single pulse is not known, a clustering method is used as explained in Section 3.1.4. We took 200 signals for each testing condition. The first 100 AE signals of each semi-continuous test, where the transient damping of the signal occurs, are omitted (see Fig. 5) from the analysis. Therefore, only the AE signals of the 101 to 300 pulses from the beginning of the test were analysed. This ensures that all analysed signals are taken from the processing of the ore and not from the first stone has reached the electrode or after all stones have been processed. In this study and based on our experience, we decided to have a 2-levels clustering. The first level separates the signals in 2 categories A and B and then separates both groups in subcategories 1 and 2. For example, for the size – pulse category “35.5 – 40.0 mm – 200 J”, the results of the clustering show that $36.5\%$ of the 200 pulses analysed are classified in the category A1, $39\%$ in A2, $9.5\%$ in B1, and finally $15\%$ in the cluster B2. The repartition of the AE signals for the size $35.5 – 40.0$ mm at different pulse energy are also graphically presented in Fig. 6a. It can be seen that the amount of AE signals in subcategories A1 and A2 drops with an increase of the pulse energy. Concordantly, the amount of signals in category B increases, in this case, it increases in B1 for $300$ J and in B2 for $450$ J. With this first observation, it becomes evident that the ratio of the AE signals of category A over the signals of the category B brings useful information about the process efficiently. Thus, this ratio is given in the last column of Table 3. For example, for the size – pulse category “35.5 – 40.0 mm – 200 J”, the A/B ratio is $3.08 = (A1 + A2)/(B1 + B2) = (36.5 + 39.0)/(9.5 + 15.0)$. Based on Table 3 and Fig. 6b, it can be seen that, apart for the size $25.0 – 35.5$ mm, the ratio A/B decreases as the pulse energy increases. Scrutinizing Table 3 and Fig. 6b, we observe that, actually, the $P_{90}$ values follow the same behaviour as the ratio A/B. Both parameters decreases with increasing pulse energy. The only exception is observed for the size $25.0 – 35.5$ mm where the ratio A/B is more or less constant and does not follow the same trend as the $P_{90}$.

These results seem to indicate that the ratio A/B could be used as a measure of the process efficiency. A simple way to verify this hypothesis is to calculate the correlation coefficient R between the $P_{90}$ values and the ratios A/B. A high R-value indicates a strong relationship between the analysed parameters. On the opposite a low R-values indicate a weak or no relationship. The R-value obtained for all sizes and pulse energy, except the size $25.0 – 35.5$ mm, is has high as 0.91. This proves the hypothesis that the ratio A/B can be as a measure of the process efficiency. For the size $25.0 – 35.5$ mm, the ratio does not vary with pulse energy. This could be a sign that the process is not running as expected. As a consequence, the operator can be warned that the process needs some verifications and/or the process parameter must be changed back to the expected values. These findings are of high importance for industrial application since the ratio A/B can be easily obtained in real-time whereas determining the $P_{90}$ values are highly time consuming and so very costly.

Looking at the A/B ratio, it is found that a low value of the A/B ratio is a clear sign that weakening of the stone is occurring and that the majority of the electric pulses are having the desired effect on the stones. However, at present, the separation of the cluster A and B in subcategories 1 and 2 does not allow improving the monitoring. The fluctuations between the subcategories are not always consistent with an increase of the pulse energy. More work and especially more data are needed to perfectly exploit the full potential of the clustering method.

5. Conclusions

In mining industry, traditional mechanical comminution is the most energy intensive process (avg $36\%$). It is also an inefficient process ($0.002 – 1\%$), depending on the degree of fragmentation. Electric pulse fragmentation (EPF) has proven to reduce significantly energy consumption in comminution process. However, the lack of process reproducibility and repeatability prevent its implementation in mining industries. Hence, an online process monitoring is of utmost importance.

This work address the latter issue and presents a robust and cost-effective in situ and real-time monitoring system able to classify the process efficiency making it industrially sustainable. Our monitoring approach system analyses AE signals produced during EPF with ML in terms of weakening occurring inside the stones. The monitoring system was developed for single stone tests as well as in industrial conditions using semi-continuous testing.

It is found that, the classification accuracy is equal or higher than $91\%$ for the categories with highest industrial perspective (no discharge, surface discharge and complete fragmentation). Two intermediate categories (partial fragmentation) were recognized at $86$ and $63\%$. The relatively low success rate is due to the proximity of the AE signals with the main categories and the arbitrary limits chosen for the different categories. Taking into account the small amount of data available, the stochastic nature of the process and material, the results can considered as outstanding. The results shows that the training of the ML from the single stone experiments cannot be transferred to the semi-continuous tests. This is due to the damping of the AE signals. Consequently, a clustering method based on unsupervised learning was developed. To demonstrate the feasibility of industrialisation of the method, we decided to have two main clusters A and B and 2 subcategories 1 and 2. It is found that the ratio A/B is strongly
correlated with the $P_{80}$ values, which gives an indication of the degree of weakening caused by the electric discharge. This proves that the ratio $A/B$ is a very good measure of the process efficiency. The major advantage of the ratio $A/B$ over the $P_{80}$ value is that it can be calculated in real-time and does not require any time consuming and costly post-processing of the treated stones. In addition, if no variation of the ratio $A/B$ is observed when increasing the pulse energy, it would also point out to potential deviation of the optimal processes. Under such circumstances, an alarm could go off to warn the operator that the process may require adjustments.

In view of these results, we can conclude that the proposed approach is a promising solution to monitor in situ and in real-time the EPF process efficiency. We are also confident that our method can be easily transfer to real industrial comminution process. The reasons are threefold. First, AE is one of the most effective monitoring method. Second, the AE signal acquisition system used is built from "on-the-self" elements. Finally, the ML algorithms developed are based on open access libraries.

Our monitoring system can also be improved in terms of sensor and signal processing. We could employ more sensitive acoustic sensors with a selective filtering on the hardware level. In addition, two improvements are possible for the signal processing part. To start with, additional experiments will improve the classification accuracy as most ML methods require often large amount of data. Additionally, other ML algorithm such as deep neural network may be more efficient in classification tasks.

The prospective of the combination of AE and ML is in the energy consumption optimization of the EPF process. In particular, a fully automatic control unit able to maximise fragmentation with minimum electricity consumption. Taking into account already worldwide energy savings proposed by this technology, such optimization of fragmentation process may even enhance its efficiency and bring it closer to industrialising in mining industry.
CRediT authorship contribution statement

Bastian Meylan: Methodology, Investigation, Supervision, Writing - original draft, Writing - review & editing.

Sergey A. Shevchik: Methodology, Investigation, Software, Data curation, Formal analysis, Writing - original draft.

Daniel Parvaz: Methodology, Investigation, Resources, Writing - original draft.

Abbas Mosaddeghi: Methodology, Investigation, Resources, Writing - original draft.

Vladimir Simov: Investigation, Resources, Writing - original draft.

Kilian Wasmer: Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Nomenclature

Abbreviations

AE Emission Acoustic
DWT Drop Weight Test
EPF Electric Pulse Fragmentation
LapSVM Laplacian Support Vector Machine
ML Machine Learning
PCA Principal Component Analysis
PWTs Pre-Weakening Test Station
SVM Support Vector Machine

Symbols

A1, A2 A indicates the first category of the clustering method based on unsupervised learning for the semi-continuous tests. 1 and 2 are the subcategories of A
B1, B2 B indicates the second category of the clustering method based on unsupervised learning for the semi-continuous tests. 1 and 2 are the subcategories of B
A/B The ratio of the categories A over B which is a measure of process efficiency. A/B is equal to (A1 + A2)/(B1 + B2)
P80 The theoretical sieve diameter size through which 80% of the particles pass
P80_red The P80 reduction index, defined in Section 4.1.2

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