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Use of time series event classification to control ball mill performance in the comminution circuit – a conceptual framework

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ABSTRACT:

Metallurgical attributes are often omitted from the mine to metal valuation models since they are either absent or unreliable. However, recent developments in sensor technology indicate the potential to collect information on metallurgical properties directly or by measurement of proxies. Integrating this information back into the resource model would provide the necessary means to move towards a more comprehensive and reliable evaluation model. To obtain truly optimized mining decisions it is necessary to consider the metallurgical attributes since they are indicated as root cause of changing plant performance. Therefore, a better metallurgical characterization of the plant feed over time is required, which allows for a more optimal selection of process control settings. Different material types have varying effects on machine performance in the comminution circuit. This makes it possible to refer a performance change as a response to different geological attributes. Hence, the corresponding geological machine behaviour can be controlled by defining effects of behavioural geology. This paper introduces a framework containing data fusion of sensor responses which resemble geological attributes and subsequent multivariate time series machine behaviour characterization for improved process control in the comminution circuit. The conceptual framework's approach is that process control in future will be supervised by profound knowledge from sensor data indicating geological behaviour. The use of multivariate time series deep learning is proposed to create innovative process control. This innovative control is then a response to a combination of advanced sensor data (XRF, LIBS, FTIR, etc.) with more traditional sensor data (throughput, density, etc.). These advanced sensors provide more knowledge about material specific properties in the form of discoverable events. This new knowledge is important in the vision of behavioural geology, to better understand the influence of geological behaviour on machine performance.

1 Introduction

A reason that machine performance optimisation in the comminution circuit is so important for mining companies, is that the crushing and grinding units are among the most energy-demanding machines (Jeswiet & Szekeres, 2016). A key aspect for optimisation is modelling of the metallurgical behaviour of the plant feed on, for instance, the ball mill performance. This might be challenging due to the lack of knowledge on how different types of materials react to different operational settings (Suriadi, et al., 2018). Therefore, to obtain optimized mining decisions it is necessary to consider metallurgical attributes which affect the comminution circuit. Optimisation can improve the recovery and reduces the energy utilization as well as the chemical usage per ton of processed material (lower the environmental footprint). Consequently, overall operation expenditures will drop making lower grade ore economic while increasing the mineral resources that are available for conversion to ore reserves. Traditional geometallurgy requires a lot of metallurgical laboratory testing of secondary rock attributes (e.g. strength, hardness), what results in a low number of data points and from which plant performance is modelled and designed. The metallurgical test data are generally not indicative of the root cause affecting plant performance (e.g. presence/absence of certain material types).

This root cause in geometallurgical variation is clearly found in the chemical composition, mineralogy, texture and fracturing of plant feed. These primary rock attributes define the secondary material attributes, are spatially abundant and can be cheaply measured in very large quantities from available sensor technology (e.g. hyperspectral, FTIR, XRF, LIBS, Raman, etc.). Use of this data provides the means to link geometallurgical variation with machine behaviour due to geological changes. Therefore, if geological behaviour due to variation is understood then machine performance can also be understood and controlled.

An attempt to find the effect of geological attributes from feed material on the machine performance by a machine learning process is shown in (Tessier, et al., 2007). They used a machine vision approach for on-line estimation of rock mixture composition and linked this to grindability. Although this methodology allows for the recognition of the type of rock, no further effort was done to implement the conceptual workings in practice. That means that there is still no understanding by the resource model from the process, and thus a ball mill does not know what type of material it gets as feed. Therefore, development of an implementable system for machine performance control is critical to take the next step in an optimized comminution circuit.

Nowadays, abundant real-time sensor data are collected which is available for use**.** Initial work by Benndorf, et al., (2014) and Wambeke, et al., (2017) already indicated the importance of combining high density time series data. Their work indicated that correlated measured variables should be jointly considered to update the resource models (Benndorf, et al., 2014) and geometallurgical models (Wambeke, et al., 2018). Neglecting these correlations will result in a loss of information. The geological attributes of plant feed data are key for the ball mill performance, so if it is possible to have data fusion of various sensors responses that could resemble all the material, then it could give insight in the ball mill behaviour. Note that machine behaviour determines the machine performance and is therefore in this paper used interchangeably in the context of the ball mill.

The largely unexplored machine learning techniques area of mineral processing, geological and mineralogical data and time series data is interesting to consider in future research (McCoy &

Auret, 2019). A recent study had focus on the analysis of impact of secondary rock properties and operational settings on key performance indicators of interest. They used regression and classification techniques to separate the influence of rock characteristics from operational settings on plant's performance, and found operating parameters that affected the plant performance, independent of material properties (Suriadi, et al., 2018). Contrary to this, the proposed framework described later, does not separate geometallurgy and operational settings to find the similar relations with ball mill performance for instance. This will be done with a deep neural network which explores the source of changing ball mill behaviour, the geological attributes. Eventually, it finds the interrelation of sensor data, and combines this in a behaviour label. This is possible, because specific domain knowledge about the geological attributes is obtained by sensors. Using the classified label results, it is possible to adapt the process control settings for the incoming material.

This paper introduces an innovative conceptual framework which aims that process control for the comminution circuit in future will be supervised by profound knowledge from sensor data measuring mainly primary geological attributes of plant feed. The expected success of this framework is due to the gained knowledge in the field of domain specific sensor data. This helps to design and develop an integrated and data-driven framework to control machine performance in the comminution circuit. It consists of an approach where sensor data is combined and consequently resembles the geological attributes of the feed. This input is classified by a deep neural network, which determines the optimum control settings in the comminution plant. First, the layout of the conceptual framework is described. Then, the concept and recent developments are elaborated within the three major pillars of the framework. Thereafter, design challenges are discussed. The concept presented here is part of an ongoing research work.

2 Towards geological behaviour based process control

Figure 1 illustrates the geological behaviour based process control framework, wherein future process control settings can be predicted and adjusted based on the defined effects of behavioural geology. This is achieved by the following seven steps:

1. Sensor data from measurements of metallurgical primary and secondary attributes from a feed batch are collected based on timestamps from the appropriate data. Combing the right data from the right moment relies on work done by material tracking. In this stage this work is in progress, but further excluded from the framework.
2. These data are combined and resemble the incoming plant feed for a selected time frame. This data combination contains the data from geological attributes of the feed.
3. A trained deep neural network (DNN) model uses the results of step 2 as input to characterize the corresponding machine performance behaviour. Attached with this label are model-based predictions for the control settings of the machine.
4. Due to the obtained knowledge on geological plant behaviour, process control settings can be suggested and adjusted.
5. The feed material is processed and the actual plant performance is recorded.
6. Comparison of the model-based predicted performance (step 3) and actual measured performance (step 5) can result in two outcomes. The predicted behaviour corresponds with the actual behaviour; assume that the geological attribute classification was correct. The actual

behaviour differs from the predicted behaviour; assume a misclassification. These test data should be stored for future model updating.

7. At regular intervals, the DNN prediction model should be retrained. The new training samples should initially consist of correct and misclassified samples. In later stages mainly misclassified samples from step 6 should be considered.

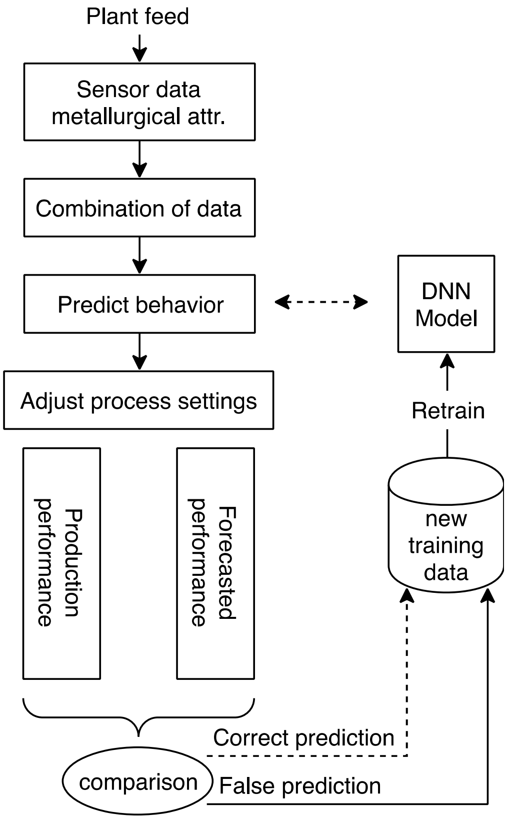

Figure 1: Flowchart of geological behaviour based process control.

The success of implementing this geological behaviour based process control framework lies in the foundation of the three main pillars which characterize the work:

1. Sensor based material characterization; from raw sensor data to fused data and input for a deep neural network.
2. Multivariate time series analysis applied on sensor combinations; create a link between geological attributes and machine performance label.
3. Material behaviour based process control; the effects on process settings.

The following sections provide an overview of recent developments in these three pillars, and describe the new concepts and proposed way of implementation.

3 Raw sensor data fusion

Geological attributes are identified as source of changing plant behaviour. Therefore, they can act as key characteristics to resemble material. The occurring differences can be found for example in lithology, mineralogy, texture, fracturing, degree of alteration, degree of ore mineralization. These profound differences can be found due to recent developments in sensor technology which have shown the potential to collect information on metallurgical properties directly or by measurement of proxies.

Recently, the use of RGB imaging and FTIR sensors were combined in mapping an underground mine wall section (Desta & Buxton, 2017). The following conceptual framework that they developed, indicated that the use of sensor combinations for a raw material characterization in mining is still very limited. Automation of the material identification process by combing sensors signals is not defined at all. The proposed framework was focused on data fusion at three different levels for classification and prediction of mineral properties (Desta & Buxton, 2018). To resemble material, a hierarchical high-level data fusion method of different sensors is proposed, where no specific interpretation of the data (related to material characterization) is required. Since the characteristic attributes of minerals are encapsulated in the fused response, it is expected that fused data can characterize the typical plant behaviour. The rational for data fusion is because of importance of the effect of the material attributes on machine behaviour. When understanding is necessary, it can be found by the underlaying characteristics found in the fused data and can tell more about categorical variables, such as ore types or lithologies. No statement is made that understanding the fused data is not important, it is more seen as a validating tool of the data that is worked with. Therefore, material characterization in this framework is based on the formation of multivariate time series, which are derived from fusion of sensor response data, what results in a quantitative treatment.

Selecting the type of sensor data to characterize material depends on discoverable events in the sensor response data. Several sensor technologies that have the potential to indicate visible events include Raman and Laser-induced breakdown spectroscopy (LIBS), Visible Near Infrared (VNIR) and Short Wave Infrared (SWIR) hyperspectral imagery for determining textures and mineralogy, Mid-Wave Infrared (MWIR) and Long-Wave Infrared (LWIR) for assessing silica content and X-Ray Fluorescence (XRF) for geochemistry.

The main work in this pillar results in a training dataset for the deep neural network. The approach to achieve this is shown in Figure 2, and indicates how it represents multivariate time series data and event labels. a) Displays sensor measurements of plant feed at different locations. By means of material tracking the time-moments of similar material measurements can be linked (not part of this framework, but ongoing research). b) Indicates data fusion from specific sensor responses and how that results in multivariate time series data, that provides the input for the DNN and used to extract features. c) Plant feed is processed by the ball mill and the corresponding performance is obtained in the form of time series data. Changes in the performance behaviour can be indicated as events which, therefore resemble the response of the performance behaviour of the ball mill due to changing geological attributes. Domain knowledge can give insight into the cause of plant behaviour changes, but is expected to not be necessary for indicating behaviour changes. The event labels are combined with the input time series data to form a training dataset, which will be used as input for the deep neural network.

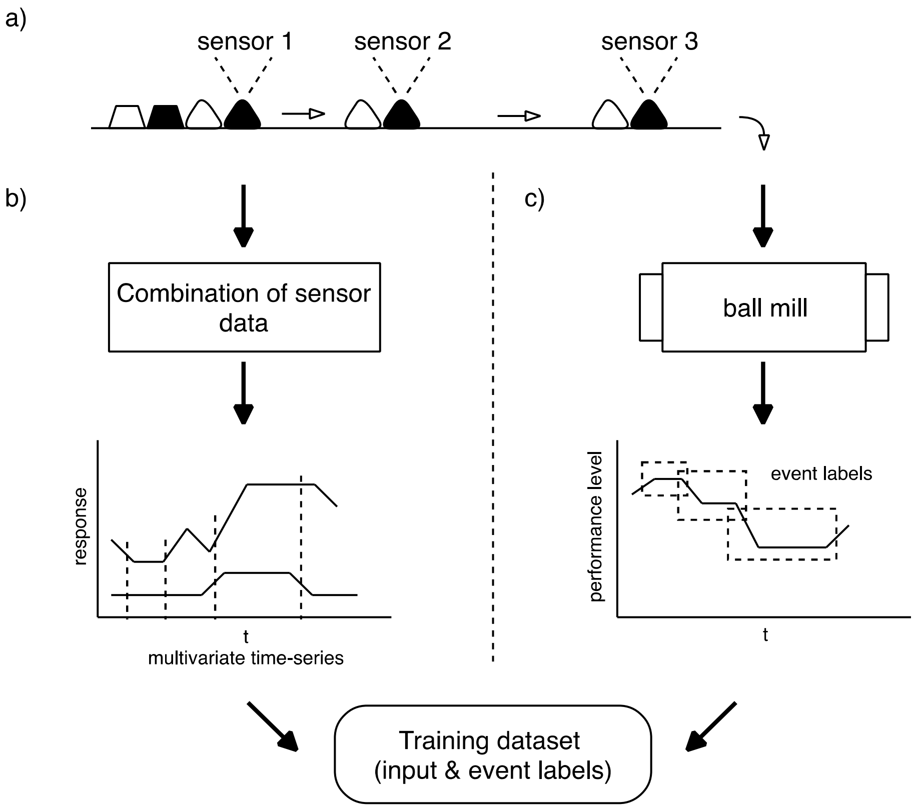

Figure 2: Construction of a training dataset for DNN.

4 Multivariate time series analysis for behaviour prediction

The sensor responses from the plant feed contain the relevant information to identify the root cause of measured differences in plant behaviour. Therefore, the combined sensor responses resemble the plant feed at t, a specific moment in time and changes per sensor update. Geological behaviour is now resembled by multiple univariate time series, $\boldsymbol{x} = \{x_1, \ldots, x_L\}$, where x_i is a measurement of time series $\boldsymbol{x}$ at timestamp i, and L is the total number of timestamps for this time series (Wang, et al., 2016). Each new sensor update will provide a new set of data points in time.

A specific sequence in one of the responses of the multivariate time series data could indicate a changing ball mill performance and can be labelled as an event which characterizes the ball mill behaviour. Therefore, these responses are subject to time series event classification. The approach is that from the multivariate time series data (Fig. 2b) and corresponding event labels (during training, obtained after processing), a classifier is trained which can map from the space of possible inputs a probability distribution over the event label set. Following, the highest probability will determine the label type y_i, that corresponds to a certain type of (predicted) ball mill behaviour. If no clear quantitative relationship between material sensor data and equipment performance can be found, then this label approach should be more generalized. This resorts to a more qualitative approach and, for instance, focusses on low, medium or high performance classes.

To accomplish this goal, this paper proposes the use of machine learning techniques to suggest and train predicted relationships between fused data as input variables and predicted ball mill performance as output. It is suggested to use a deep learning framework for multivariate time series classification to create a deep neural network (DNN) model. The trained model is then able to delineate the root cause of performance change. The choice and design of this neural network is subject to the problem of machine behaviour control and to our best understanding no such operational mining related problem is currently solved by a deep learning framework. Therefore, no existing train and test data sets exists and no definite design choice is made yet. Note that this model might be material type dependent. The development in this pillar mainly consists of building the framework around a data set $D = \{(\boldsymbol{X}_1, y_1), (\boldsymbol{X}_2, y_2), \dots, (\boldsymbol{X}_N, y_N)\}$, where $\boldsymbol{X}_i$ are the fused data time series (set of $\boldsymbol{x}$), y_i is the predicted ball mill performance event-label from the event set Y, and N is the data set size. A DNN-based model is excellent in finding the relationship (features) between the time series and labels. It can design the representable features from the raw data automatically by self-learning hierarchical feature representations. A bigger test dataset ensures higher classification accuracy.

A model is created and trained with the training set to learn feature representations. Within the DNN architecture for time series data, possibly a Convolutional Neural Network (CNN) which generally composes of two parts is suitable. The first part consists of alternating convolution and pooling layers, which generate and learn features from raw data automatically. A simple mechanism explanation is that, after the weight initialization of the model, a forward pass through the model is applied to the first convolutional layer. There the time series is passed through different filters which each is designed (unique weights) to extract a characteristic behaviour of the time series. The second part, uses the learned features from the previous part to either train a fully connected multilayer perceptron (MLP) for classification purpose (Zheng, et al., 2016) or directly classify it by pooling (Zhao, et al., 2017) and softmax operations (Wang, et al., 2017). After the model is trained it can be tested and validated with a test data set. For the working of CNN models the interested reader is referred to (LeCun, et al., 2015).

Time series have dynamic properties, because new time series data $\boldsymbol{X}_i$ are generated when time passes. This creates new data sequences from which the label y_i is characterized by the DNN. Therefore, this framework results in a direct data-fused-driven transition from sensor measurements to predicted behaviour (informed by the actual machine response data). Note that besides the implementation of sensors that measure primary attributes, it should be encouraged that more traditional sensor data that measure for example secondary rock attributes (e.g. throughput, material density) are also used to improve the prediction capabilities of the model. The predicted behaviour will be used as input for process control.

5 Behaviour based process control

From a machine performance perspective, the goal of, for instance, the ball mill is to maintain complex unit operating conditions. Maintaining is satisfied by containing operating conditions at values where the ball mill is optimized and can be measured by key performance indicators. Process control is often simulated in a model during the design phase with the use of control variables (Sbárbaro & del Villar, 2010). During operation the conventional process control then consists of translating secondary rock attributes based on an empirical incompletely validated relationship to predicted behaviour and process variables. Once the framework of this research is implemented in an operational system it will substantiate that an innovative way of process control is possible. This control is based on data assimilation of primary material attributes of the feed and secondary rock attributes. Additionally, it is informed by the actual plant response data.

From the fused data the behaviour (label y_i) of the machine is predicted by the model. This model-based behaviour is an indicator of how the ball mill would perform by processing this material, but this might not be the optimal process option for this material. The development in this pillar aims to find a fitting control setting (adjustment) which can be linked with this label and ensures that for the incoming material the optimal machine control settings is set. This could also mean that relative to the current setting, no change of control settings is needed. Once initialized in a running system a change in control settings can take place. This results in, for example, a better grindability in the ball mill. If not initialized, the material corresponding to the sensor responses will be processed with the ongoing control settings.

While processing the feed material, the actual plant performance is recorded. Comparison of the model-based predicted performance (and possible associated control setting change) and the actual performance can result in two outcomes. The predicted behaviour corresponds with the actual behaviour, and the actual behaviour differs from the predicted behaviour. The first case considers correct classification of the time series data and should be assumed in the early stages of research. However, it could also be due to a misclassification and a not found machine behaviour relation. Additionally, as mentioned in Wambeke, et al., (2017), it could also be because equipment performance measurements might start to drift as critical components are wearing out (e.g. liners in the ball mill). If due to these factors the behaviour by chance resulted in the predicted behaviour, classification was not correct. The second case indicates that the model had a misclassified label, because the accuracy of the model is not high enough. Another reason is that there is possibly a small difference in the type of materials and where this slight difference is key for a performance change.

To get a robust model, which is driven by behaviour caused by geological attributes it is key that the model (initially) makes mistakes, and that all data should be stored regardless the classification. After using the model some time, it can be retrained to improve the classification accuracy. In later stages, it is more important to do this for misclassified data sets only. In the future, the model could be extended with a machine learning system focussed on the effect of its own critical components on equipment performance. This can provide an adjustment factor for the event's label control settings to account for the state of the machine.

Future prospect is seen in providing new information about misclassified material to locally improve the geometallurgical model (Wambeke, et al., 2018), which will improve performance forecasts and more accurate and reliable resource models.

6 Focus areas for design realization

- The characterized material presented to the sensors might represent a blend of material, which might result in quick changes in sensor responses. Decisions should be made when a setting control change is required. For example, what to do in the case of a continuous change vs a discrete change in material.
- The moment of fused data analysis is important to consider in order to make the right process control decision. If the location of the material is still outside the plant, material can be blended, disregarded as ore or processed later to acquire a better plant behaviour. If the mate-

rial is within the comminution circuit, then decisions should have a direct (reactive) impact on process control, because this material will be processed next.
- Generating the fused data response may not be straightforward. The defined set of variables that characterize the process state are subject to each process and must be found in order to correctly characterize the process. Material type characteristic features might need to be identified before correct fused data can be generated.
- Construction of a database where sensor responses are related to performance might be challenging and depends on available data. Additionally, the appropriate CNN model should be selected by testing different deep neural networks. Possible future use could be an early awareness multiscale neural network (Wang, et al., 2016), where behaviour changes can be discovered even earlier.
- If a quantitative prediction of plant behaviour is not possible, predictions should be resorted to a more qualitative approach (low, medium, high performance).
- Validating the framework and predictions might need to rely on prior extensive metallurgical test work.

7 Conclusion and future outlook

Comminution circuit performance is likely to be influenced by the primary material attributes of the blended feed. These attributes can be measured by sensors and the data accordingly contain the geologically influenced behaviour. This implies incorporating direct data-fused-driven characterization into decision making to control machine performance in the comminution circuit. This promises a large potential to improve recovery and reduce energy utilization. Future decisions can be made on multiple continuous measured variables which are analysed together using time series event classification by a deep neural network. Additionally, comparing geometallurgical model and sensor-based behaviour predictions with actual plant behaviour can provide interesting information for resource model updating, what can extend the work of (Benndorf, et al., 2014) and (Wambeke, et al., 2018). Depending on the physical material location (stockpile or plant), early decisions can be made on different blending strategies or reclassification of material.

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