Applying traceability to grinding circuits by using Particle Texture Analysis (PTA)

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ABSTRACT

LKAB has started a new pelletizing plant at Malmberget, where the raw material will be a mix of ores from Kiruna and Malmberget. The new plant necessitated an investment in a new grinding section in the concentrator. As usual, the new section has larger mills. It also lacks the wet cobbing stage present in the old sections.

Comparing the results from the new section with the old sections show that they give similar results. There are slight variations; the older mills produce a steeper final particle size distribution. Also, it appears that the new mills are more efficient, since they have higher calculated grindability indices.

To better understand the differences between the sections, and the process implications of the new grinding section, a combination of Particle Texture Analysis (PTA) and the statistical method Multivariate Analysis (MVA) is used. It shows that it is possible to identify and follow systematic changes in the particle morphology of the mill products. Also, that there are differences between the old and new grinding sections.

Keyword: Traceability; Grinding; Multivariate analysis

1. Introduction

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2 LKAB has since the beginning of the 1900's produced iron ore from mines in Kiruna and
3 Malmberget and is today one of the world's leading producers of highly refined iron ore
4 products. The main product is pellets, for blast furnaces and direct reduction furnaces. Today
5 there is a higher demand from the customers and to obtain a good quality it is important to
6 have good control over the process and the raw material used.

7 LKAB started the new pelletization plant at Malmberget (MK3) in November 2006. The
8 raw material will be a mix from Kiruna and Malmberget, i.e., different ores having different
9 Fe-content and levels of contaminants (Martinsson and Wanhainen, 2000).

10 That is why the traceability of the continuous process is one of the crucial factors for
11 future development of granular product(s). Traceability gives the advantage to have a better
12 control over the material through the process and there can be adjustments taken, if needed. It
13 can show "the current" values of different parameters and how much we have to adjust to
14 achieve the goals. In food and pharmacy industries it is very common to use different
15 traceability tools but in the mining industry, which is mostly a continuous process, traceability
16 is an untouched area.

17 As mentioned earlier, traceability is common in part or batch production and often
18 relatively easy to achieve, since different kinds of identification markers can be attached to a
19 unit or different parameter can be measured at different process stages. In continuous
20 processes on the other hand the main part of the collected data relate to process variables that
21 are frequently measured, while product data are limited and infrequently measured (Hild et
22 al., 2000).

Also, the literature dealing with traceability is dominated by applications from parts production. However, creating traceability in continuous processes implies vast challenges: process flows can be parallel, serial and circular; sub-processes can be continuous as well as batch-wise; have large buffers or no interruptions in product handling. The purpose of this paper is to compile and describe how process mineralogy could be used for achieving traceability in continuous processes. In this case the grinding sections are in focus, and multivariate data analysis is used to interpret the mineralogy and textures of the minerals in this section.

2. MATERIAL

Most iron ores contain significant amounts of gangue minerals that need to be eliminated to produce iron concentrates. At Malmberget, the dominant iron mineral is magnetite but also hematite occurs. Gangue minerals are mostly quartz, pyroxene, apatite, and feldspar (Geijer, 1930).

Material from the mine is sent to the concentrator plant which separates the minerals into two parts, tail and product (Kvarnström and Oghazi, 2008).

The samples that are used in these studies are from the concentrator's, old section 5 and the new section 6.

2.1 Flowsheet

Figure 1 shows a typical flowsheet for concentrating iron ore at LKAB. The coarse material at 10-15 mm in size is fed to a wet magnetic cobbing separator (M1). The magnetic concentrate is discharged into a primary ball mill (#1), and the ground product (pulp) is transferred to a primary magnetic separator (M2). The resultant magnetic concentrate is then pumped into a secondary ball mill (#2). A secondary magnetic separation unit (M3) finally upgrades the ground product and the concentrate is used as feed for the tertiary grinding stage (#3) (Tano et al., 2005).

Fig.1. Flowsheet for grinding section 5.

The flowsheet for the new grinding section 6 resemble the one for section 5, the only difference is that there is no wet cobbing stage before the primary mill. Here, ball mill grinding is used in three consecutive steps with wet low intensity magnetic separators in between. It is important to grind to, approximate 68% < 45μm to liberate gangue minerals, and to reach the desirable size distribution for the pellets feed. In the result part there is a complete data of how each mill performs (Table1).

3. EXPERIMENTAL

3.1 Sampling

Feed samples were taken manually when the material was in motion at a point of free fall, by making a cut at right angle through the falling stream. The other samples were taken as manual pulp samples with pear shaped scoop throughout the circuit before and after each grinding stage. The samples were weighted and then filtrated at Malmberget. In the laboratory at LTU the samples were dried and then cut by a Jones splitter into suitable proportions. The dry material was sieved with a Rot-Tap shaker down to 75 μm and wet sieved further to 38 μm .

3.2 Particle Texture Analysis

It is important that the liberation data for minerals in a sample come from a sieve fraction. Test and comparisons have shown that measured liberation of specific size particles in unsieved samples are not the same as the sieved sample. For unsieved samples, the result is not correct (Petruck, 2003).

To have a good view over the different samples, Particle Texture Analysis (PTA) was done at NTNU, Trondheim, Norway. The PTA data system is based on the Oxford Inca Feature software and an existing scanning electron microscope (Moen, 2006). Using Back Scattered Electrons (BSE) the images are analysed by means of grey level and every grain of interest is analysed with X-rays. With the Inca data information the images will be processed and calibrated (grey-scale and binary images); and the grains will be identified and evaluated if they are liberated or in composite particles and which minerals occur in the composite mineral. When all particles is analysed, the data will be imported to the PTA software. The PTA software gives plots and thumbnail images regarding mineral liberation, mineral association analysis and intergrowth analysis.

3.3 Multivariate Data Analysis

For achieving good control and having better overview of the process data it is necessary to collect data with many variables and many properties from the process. By using multivariate data analysis (MVDA) these variables will be explained and expressed and condensed into a few latent variables or principal components so it will be easier to understand the importance and contribution of each variable.

Multivariate data analysis is based on projection methods. One, Principal Component Analysis (PCA) is a projection method of the original variables onto new ones, orthogonal and arranged according to their eigenvalue. This is done on all the data contained in a matrix X , where T represents the score matrix and P represents the loading matrix (Wold et al., 1984).

$$X = TP^T + E$$

Other MVDA techniques are PLS (projection to latent structures), SIMCA (soft independent modelling of class analogies), and MSPC (multivariate statistical process control) are not used here, since this contribution is centred on pattern recognition. The MVDA is run with the software program SIMCA-P+, version 11.5 (Eriksson et al., 2006).

4. Result

4.1. Size analysis

The size distributions of particles in the material for both sections (Sections 5 and 6) are shown in Figures 2 and 3 respectively.

Fig. 2. Particle size distribution Section 5.

The particle size analyses of the feed and the products in the grinding process show the reduction of particle size (d_{80}) from 4700 μm in the feed to 70 μm in the final product.

By comparing section 5 and 6 there are slight variations in the results, the finer feed to section 5 is due to the wet cobbing preceding the primary mill. The older mills in this section produce a steeper final particle size distribution. It is, however, too early to say if this is linked to mill size, or if it is the result of a better, worn in, graded charge.

Fig. 3. Particle size distribution Section 6.

The particle size analysis from section 6 gives similar results compared with the results of section 5. The grinding ratio in the primary mill is dramatically higher than the secondary and tertiary mills, which is due to the well known fact that the larger particles grind easily. Size distribution analyses from the output of the primary mill and the input to the secondary mill indicate that the LIMS mainly eliminates smaller gangue minerals fractions. This may explain why the feed to the secondary mill is coarser than the discharge from the primary mill. On the other hand, the analysis from output of the secondary mill reveals that the magnetic separator does not change the particle size for the feed to the tertiary mill.

4.2. Mill efficiency

There are two major ways to easily compare operating mills: grind-ability and apparent work index (Tano, 2005). Grind-ability index (G_i) showing the produced amount of material finer than 45 μm is calculated according to equation (1).

$$G_i = \frac{(S_D^{45\mu\text{m}} - S_F^{45\mu\text{m}})}{100} * \frac{1000 * F}{P} \quad (1)$$

Where $S_D^{45\mu\text{m}}$ and $S_F^{45\mu\text{m}}$ is the percentage of material finer than 45 μm in discharge and feed, respectively. F is the amount of feed [tonne/h] and P is the mill power [kW].

The apparent-Work index (W_{app}) is shown in equation (2).

$$W_{app} = \frac{P}{10 * F} * \frac{1}{\left(\frac{1}{\sqrt{d_{80out}}} - \frac{1}{\sqrt{d_{80IN}}} \right)} \quad (2)$$

Where P is mill power [kW], F is the amount of feed [tonne/h] and d_{80} is the 80% passing size [μm] for discharge and feed, respectively.

Table 1. Grindability and Apparent-work index.

06KV003	42.0	63.0	125	77	2728	335	25.8	33.21
Section 6	Feed	Disch.	d_{80} in	d_{80} out	Power	feed	Grindability	Apparent-Work
Section 5	Feed	Disch.	d_{80} in	d_{80} out	Power	feed	Grindability	index W_{app}
	[% <45 μm]	[% <45 μm]	[μm]	[μm]	[kW]	[t/h]	[kg <45 μm /kWh]	[kWh/ton]
	[% <45 μm]	[% <45 μm]	[μm]	[μm]	[kW]	[t/h]	[kg <45 μm /kWh]	[kWh/ton]
06KV001	4.0	23.0	3 250	315	1918	350	34.7	14.12
06KV002	13.0	41.0	320	125	3419	343	28.1	29.72

05KV001	3.0	19.0	4 780	315	1461	292	32.0	11.95
05KV002	12.0	37.0	330	143	2573	274	26.6	32.86
05KV003	38.0	60.0	140	74	2463	268	23.9	28.96

The result gives that all mills in the new section 6 has a better grindability compared to the old section. However, for the coarse end of the particle size range it is not that clear, since there is no consistent difference between the sections.

4.3. Particle Texture Analysis (PTA)

The PTA gives us information of how different minerals are distributed at different fractions. As it is shown in Figure 4 it is clear that the magnetite content decrease with fraction size. This is due to the sugar grain structure of the Malmberget magnetite, which easily breaks along grain boundaries. Feldspar and pyrox/amphibole are more evenly distributed over the size fractions, while apatite occurs largely below 100µm.

Fig. 4. Content of minerals in different fractions from section 6 (06KV001 in).

The PTA also shows how minerals are liberated in different fractions. In this case magnetite is overall well liberated in the fractions examined, but there is also some other minerals that are associated with magnetite. In the largest fraction, associated minerals are plagioclase and ilmenite.

With PTA it is also possible to have a good overview over the mineral liberation. It is calculated by the area method, an area of mineral in interest is measured and also the host particle in the polished section, and calculating the percent of mineral in the particle. However, the liberation result is not shown here, since the liberation was 90% or better in all cases.

4.4. Multivariate analysis

All the data from the PTA were collected and arranged in different Excel files, and then imported into the software SIMCA. Each particle was an observation in a data file with variables according to Table 2. A typical PTA data for one sample contained of 7000-10000 observations/particles. PCA-models were created to check for pattern in the data. Here, the score and loading plots are used. They give important information about variables that are responsible for the pattern seen among the observation and how they are related to each other.

Table 2. List of mineral identifications and parameters which were extracted from PTA and used for analysis. (The morphology parameters are written *Italic*.)

<u>Minerals:</u>	<u>Parameters:</u>
Magnetite	<i>Area</i> ; (Area of whole feature in square microns)
Ilmenite	<i>Length</i> ; (Max fert)
Rutile	<i>Breadth</i> ; (Min feret)
Plagioclase	<i>Perimeter</i> ; (Perimeter of whole feature in microns)
Quartz	<i>Aspectratio</i> ; $\frac{Length}{Breadth}$
Pyroxene/Amphibole (Pyx/Amf)	<i>Direction</i> ; (Angle)
Biotite	<i>Shape</i> ; $\frac{Perimeter^2}{4\pi \times Area}$
K-feldspar	ECD; $\sqrt{\frac{4 \times Area}{\pi}}$
Enstatite	Mean grey level; (Mean image grey level for each particle)

1	Apatite	% Element (wt %)
2	Titanite	
3	Calcite	
4	Sulphides	
5	Unclassified	

4.4.1 Overview

The first analysis is run to get an overview based on all identifications and parameters in Table 2.

Table 3. Overview of R2 and Q2 for the model of feed to section 5.

PCA-X Observations (N)=9964, Variables (K)=65 (X=65, Y=0)						
Components	R2X	R2X(cum)	Eigenvalues	Q2	Limit	Q2(cum)
0	Cent.					
1	0.174	0.174	11.3	0.112	0.0153	0.112
2	0.157	0.33	10.2	0.161	0.0155	0.256

R2X (cum) explains the cumulative of the sum of squares of all the X's explained by the extracted components. Q2 (cum) explains the total variation of the X's that can be predicted by a component.

The score plot shows the relationship among the observations (minerals). This plot can be seen as window in the X space, where the objects (particles) are projected on a 2 dimensional hyperplane in the 65 variable space. In figure 5 it is shown there is a separation between the magnetite and the gangue minerals in the second direction. There is also a separation between the gangue minerals which put them in different groups.

Fig. 5. Score plot coloured according to mineral identifications for feed material in to section 5 (38 μ m).

In the first PCA overview the material is clearly spread out in the first direction.

In figure 6 which is a loading plot, show the importance of different variables in the X matrix.

It explains how different variables contribute to the model which is shown in the score plot.

Fig. 6. Loading plot for the PCA model, feed material to section 5.

As it show in figure 6 gangue and magnetite are positioned in opposite direction, this explain why the gangue and magnetite are so well separated in the score plot (figure 5). On the top right side of the loading plot the morphology variables are gathered. It is these variables which need to be investigated more.

4.4.2 Comparison of feed and discharges to a mill

The first analysis aimed to compare the feed and discharge for each mill. By excluding all variables except the morphology ones (those in upper right red ring in figure 6), the model was improved.

Table 4. Overview of R2 and Q2 for the developed models for section 5.

PCA-X Observations (N)=20083, Variables (K)=8 (X=8, Y=0)						
Components	R2X	R2X(cum)	Eigenvalues	Q2	Limit	Q2(cum)
0	Cent.					
1	0.627	0.627	5.02	0.581	0.111	0.581
2	0.183	0.81	1.46	0.109	0.125	0.626
3	0.117	0.927	0.936	-	0.143	0.589
4	0.055	0.982	0.439	0.693	0.167	0.874

Fig. 7. Score plot for the PCA model of incoming and outgoing material, section 5

The loading plot in Figure 8 shows that size parameters carry most of the information in the first direction while mean grey have a great influence in the third direction. The first direction is length information.

Fig. 8. Loading plot for the PCA model, section 5.

With the same model and the score plot coloured according to mineral classification it is possible to see how the minerals differentiate. The main parameter pulling magnetite away appears to be Mean grey. This is what to be expected.

Fig. 9. Score plot with mineral identification for feed and discharge to the primary mill material, section 5 (38 μ m).

However if the same plot is stripped to leave only magnetite information, sub-populations of magnetite emerges, cf. Figure 10.

Fig. 10. Score plot for magnetite for feed and discharge to the primary mill material, section 5 (38 μ m).

To this moment it is not entirely clear what causes the split on sub-populations. The lower value of Mean grey and shorter length indicates that the two minor groups may constitute of mixed particles.

The loading plot for the primary mill section 6 is very similar to the loading plot from section 5, and therefore not shown. This proves that the pattern found is systematic. PC direction 1 carries length/size information, while PC3 is mostly Mean grey.

Table 5. Overview of R2 and Q2 for the developed models in Section 6.

PCA-X Observations (N)=16050, Variables (K)=8 (X=8, Y=0)						
Components	R2X	R2X(cum)	Eigenvalues	Q2	Limit	Q2(cum)
0	Cent.					
1	0.623	0.623	4.98	0.575	0.111	0.575
2	0.185	0.808	1.48	0.127	0.125	0.629
3	0.113	0.92	0.902	-	0.143	0.592
4	0.0579	0.978	0.464	0.666	0.167	0.864

Fig. 11. Score plot for the PCA model for feed and discharge of material to primary mill, section 6.

4.4.3 Gangue mineral changes in the sections

To understand the beneficiation process, it is necessary to investigate the gangue minerals more carefully. Usually iron ores occur in formation with siliceous rocks, and other minerals such as apatite and feldspar are also present. The section 5 results for apatite and feldspar are shown in Figures 12 and 13 respectively.

Fig. 12. Score plot for incoming and outgoing apatite in section 5.

Most of the particles are distributed in the first direction; it is the morphology parameters that affect most in first direction cf. figure 8. In the score plot some particles are found outside the confidence interval and are marked with a red circle, by investigating this group with a contribution plot in SIMCA it shows that these particles are larger than average apatite particles.

Fig. 13. Score plot for incoming and outgoing feldspar in section 5.

Almost all of the feldspar are absent from the system after the first magnetic separator. It indicates there are no mixed particles in the system.

Fig. 14. Score plot for incoming and outgoing apatite in section 6.

1

2 The score plot for apatite in section 6 is very similar to section 5, but there are some
3 differences. It is obvious that there is more apatite in section 6 after the last mill compared to
4 section 5. A significant factor is that there is no cobbing stage before section 6, and it is also
5 important to have control over all reflux flows and other flows that are connected to this
6 section.

Fig. 15. Score plot for incoming and outgoing feldspar in section 6.

5. Conclusion

The main benefit of multivariate analysis on particle texture data is that it simultaneously compares several thousand particles. This kind of investigation is state of the art in this area and it can provide unambiguous of information about how each process step influences the material.

The combination of PTA and MVDA seems to be a promising development. Further refinements would be to use MVDA models to discriminate between “good” and “bad” feed materials using SIMCA classification techniques.

By comparing different sections and different minerals it can be shown how the cobbing stage affect the circuit. By comparing the feldspar and apatite it is obvious that the apatite continue to exist during the whole circuit, while most of the feldspar is separated after the first separation stage. It seems that the free particles disappear while mixed particles continue to exist in the circuit.

By comparing section 5 and 6, a direct similarity is found between the two section but also some divergences, which can depend on the cobbing stage or other factors that the grinding mill differs from each section.

It would be interesting to further investigate the material from both sections by using optical microscopy. Optical analysis will better identify the intergrown minerals.

However, more samples are taken from all reflows and they need to be analysed, it will show us how different flows affect the product flow.

Acknowledgements

Financial support from LKAB Research and Development is gratefully acknowledged. We would also like to thank Johan Bucht for valuable ideas regarding the multivariate analysis.

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