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Comparison of sampling methods by using size distribution analysis

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Pierre Gy has derived an equation, which can be used to estimate the relative variance of the fundamental sampling error of size distribution results given as mass fractions for each size class. This theory is used in this study. The Heterogeneity Invariant, *HI*, is the relative variance of the fundamental sampling error extrapolated to a sample size of a unit mass (usually 1 g). *HI* can be estimated from a sieve analysis for each size class *i* from Eq. 1.

$$HI_i = \left(\frac{1}{a_i} - 2\right) v_i \rho_i + \sum_{i=1}^{n} \rho_i a_i v_i \quad (1)$$

Here a_i is the mass fraction of size class *i*, v_i the average particle size in class *i* and ρ_i the density of particles in size class *i*. Given HI_i, the relative variance of the fundamental sampling error, S^2_{FSE} can be estimated for different sample sizes to be sieved from the test material:

$$s^2_{FSE} = HI_i \left(\frac{1}{m_s} - \frac{1}{m_L}\right) \quad (2)$$

Here m_s is the sample size to be sieved and m_L the size of the lot from which the sample is taken.

If the sampling methods performs correctly (unbiased) and is able to minimize the segregation effects, always present when material consisting of fragments or particles having a wide size distribution, the observed variance of replicate samples should be close to that obtained by using the above equations. It is also possible to calculate a confidence intervals for a given size distribution.

In this study a newly developed sampler was tested by sampling blast hole chippings from Northland Resources' Kaunisvaara Iron Ore Mine in northern Sweden and the results were compared to other sampling methods currently in use. A number of the samples were also sent for chemical analysis to see if the analytical results correlate with the size classes. A convenient way to summarize and compare size distribution results and analytical results is to carry out Principal Component Analysis (PCA) on both the size data and the analytical data.

Introduction

Blast hole sampling, especially from large rotary drill holes, is challenging. While the final circumstances depend on the material density and the diameter and depth of the hole, the mass of drill cuttings coming up from the hole is often counted in tons. Once the drill cuttings have settled on the ground, correct sampling is nearly impossible due to segregation and delimitation error. After the cuttings have settled, depth information is lost making sampling per meter impossible. Especially in vein type ores the grade can vary greatly as a function of depth, and sampling each meter would provide more detailed information. In the past, sampler cutters of different types including sectorial samplers and tube samplers have been applied with varying success. Often the practically useful methods does not provide representative samples and the ones that could give correctly cut samples need so much work and preparation that it is not feasible in practice. Above all, the working environment for someone taking samples near the drill is very poor due to excessive noise and dust, and significant health hazards are present in form of heavy moving machinery.

A newly developed sampling device, RAS – Rotary AutoSampler, was designed by IMA Engineering Oy Ltd. (Figure 1). This is an automatic sampling system that collects a sample continuously while drilling and subsequently splits the sample into an adjustable and pre-selected sample size. Depth information is also recorded for each sample. The sampler consists of two main parts, a primary sampling belt and a rotating cone splitter. The basic operation is simple: the primary sampling belt takes a continuous sectorial sample from the original flow of drill cuttings which is then delivered to the cone splitter, which divides the final samples that are collected

Figure 1. RAS – Rotary Autosampler installed in a rotary drill

MOLS Sampled Hole		Hole Number 465100		Iron mine Hole Average
3.55	4	0 -> 1 m	37	
9.14	9	1 -> 2 m	37	
14.60	15	2 -> 3 m	37	
23.50	24	3 -> 4 m	37	
24.90	25	4 -> 5 m	37	
32.30	32	5 -> 6 m	37	
50.21	50	6 -> 7 m	37	
50.21	50	7 -> 8 m	37	36.79275842
54.10	54	8 -> 9 m	37	
40.40	40	9 -> 10 m	37	
40.40	40	10 -> 11 m	37	
42.10	42	11 -> 12 m	37	
30.90	31	12 -> 13 m	37	

Figure 2. Iron content per meter vs. iron content from single pile sample

in transparent plastic sample bags, which are then processed and analysed. This kind of sampling method is new and never been fully tested before. Therefore this research was necessary to examine if the sampling technology is correct, if the samples taken are representative of the original lot and if the method can be applied in practice. Testing was carried out in Northland Resources' Kaunisvaara Iron Ore Mine in northern Sweden and IMA Engineering premises in Espoo, Finland. A certified commercial laboratory Labtium Oy was used to process and analyse the samples obtained.

According to the results, the primary sampling belt collects on average 10% of the total cuttings blown out of the drill hole. The total mass of cuttings from each hole varies greatly and is seldom the theoretical amount calculated from material density and hole dimensions. Often the cuttings also spread unevenly around the hole, which adds to the size variation of the sample. Moreover, the first 1-3 drill meters that penetrate the previous sub-drill yield very little sample which is often originating from the filling material used to level the blast benches for easier drill rig movement. The mass of collectable sample material increases as a function of depth. The last few meters yield the usually the largest sample, so significant part of the lot comes from sub-drilling which represents the next bench instead of current bench (Figure 2).

Design of sampling experiments

Equipment

Sampling Belt

The primary sampling belt is essentially a conveyor belt, which collects drill cuttings as they fly out of the blast hole during drilling (Figure 3). Minor modifications (Figure 6) were made to the dust curtains of an Atlas Copco Pit-Viper 271 (Figure 4) rotary blast hole drill in order to fit the sampler belt next to the drill rod to collect cuttings. The drill was drilling 12-14 meter long blast holes using 251 mm (9 7/8 inch) diameter tricone drill bit.

The collected drill cuttings fall from the conveyor belt through a splitter capable of splitting the feed into samples with the following ratios: 1/8, 1/8, 3/4 (Figure 5). To summarise, drill cuttings flying out from the blast hole would be carried by the conveyor belt and dropped through the splitter, and the final sample is collected in a bucket underneath the splitter (Figure 7).

Figure 3. Primary sampling belt conveyor used in this study. Conveyor width was 400 mm and length 3 meters.

Autosampler

The Autosampler is a rotating cone splitter which divides the drill cuttings feed from the RAS primary sampling belt into 2 samples and a reject pile (Figure 8). The splitting ratio and sample size can

Figure 4. Atlas Copco Pit Viper 271 Rotary drill at Kaunisvaara iron ore mine

Figure 5. A Metzke model MFS 3T32 3C 3-tier splitter was used at the end of the conveyor belt to split collected drill cuttings at ratios 1/8 , 1/8, 3/4, as shown above right.

Figure 6. Modification in Pit Viper's dust curtain for RAS conveyor belt entry.

be adjusted. Autosampler was tested independently of the primary sampling belt test. (Figure 9)

Detailed testing procedures

Primary sampling with belt conveyor (3m samples)

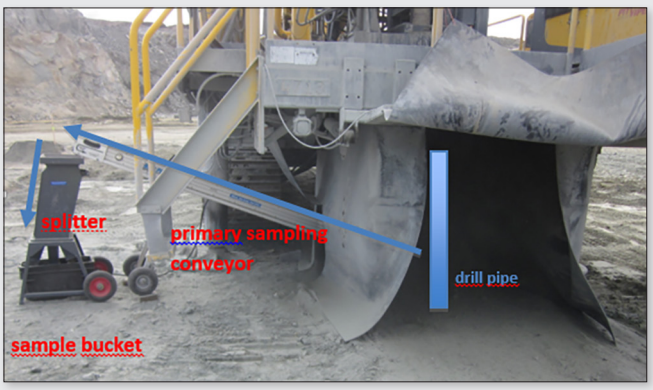

Figure 7. Drill cuttings flow chart

Figure 8. Autosampler system with Softcore™ sample socks attached.

The experiment is designed to collect samples of borehole cuttings from 3 drill meters and compare grain size distribution and chemical properties against the discarded cuttings:

Figure 9. Testing the Autosampler by pouring drill cuttings through it. Two samples are collected in buckets on opposite sides and the reject in the centre.

Figure 10. Tarp laid on the ground around the concrete ring, which surrounds the blast hole.

- Pit Viper 271 drills to 4 m depth. The drill pipe and drill bit is then lifted from the hole, drill cuttings cone already accumulated around the hole is cleared, and a 6m^2 tarpaulin is laid on the ground to surround the drill hole. The tarpaulin prevents contamination of the accumulated cuttings from the ground underneath. A concrete ring is placed around the drill hole on top of the tarpaulin cover to prevent any drill cuttings from being lost under the cover (Figure 10).
- The conveyor belt is then brought through the opening in the helm, to the edge of the drill hole. Drilling is continued. A Sample is continuously collected by the primary sampling conveyor and the drill cuttings from the 3 m drilling from 4–7 m depth accumulate on top of the tarpaulin (Figure 11).

Figure 11. Primary sampling conveyor is pushed through the opening in the dust curtain and placed next to the mouth of the blast hole.

Figure 12. A drill cuttings cone as viewed from under the dust curtain, with the RAS conveyor belt in place.

- The Pit Viper drills for 3 meters. Meanwhile, most of the drill cuttings accumulate as a cone on the tarpaulin. The rest of the drill cuttings are carried out by the conveyor, through the splitter (splitting them at 1/8) and collected in buckets (Figure 12).
- After 3 m has been drilled, the entire cuttings cone left on the tarpaulin is also split with 1/8 ratio, into sample buckets. This was done by shovelling all the drill cuttings from the heap on to the conveyor belt. From the belt the material falls through the splitter, and is collected in buckets beneath the splitter. For practical reasons, splitting was continued until a sample of around 6-10 kg was achieved. This sample is used for comparison with the conveyor sample collected during drilling (Figure 13).
- Samples taken with the sampling belt and the sample collected from the rest of the pile (Figure 14) are sent to a laboratory for sieving and chemical analyses in order to compare the results.

Autosampler (rotating cone splitter)

The Autosampler was tested as follows:

- A bucket of drill cuttings was originally collected from a drill cuttings cone in the Kaunisvaara mine.
- These were then poured through the Autosampler (Figure 9).
- As they fall through, the Autosampler splits the poured bucket of drill cuttings into 3 parts: 2 samples, actual sample and duplicate) (white buckets) and 1 reject pile (pink bucket) in the centre.
- All 3 samples from each pour were sent to a certified laboratory for further analysis (grain-size distribution and elemental contents).
- Grain-size distributions and elemental contents of all the samples were compared and analysed.

Additional testing methods

Some sectorial samples were also taken for comparison. The sectorial sampling boxes shown in Figure 15 were placed next to the hole at the same time than sampling belt, and removed after 3 meters was drilled. The sample was split with riffle splitter until a practical sample size was achieved.

Figure 13. Drill cuttings flow

Estimation of sampling variance from sieve analysis

Pierre Gy[1,2] has derived an equation, which can be used to estimate the relative variance of the fundamental sampling error of size distribution results given as mass fractions for each size class. This theory is used in this study. The Heterogeneity Invariant, *HI*, is the relative variance of the fundamental sampling error extrapolated to a sample size of a unit mass (usually 1 g). For each size class i from a sieve analysis, *HI* is estimated from Eq. 1.

$$HI_i = \left(\frac{1}{a_i} - 2\right) v_i \rho_i + \sum_{i=1}^{n} \rho_i a_i v_i \qquad (1)$$

Here a_i is the mass fraction of size class i, v_i average particle size in class i and ρ_i the density of particles in size class i. Average particle size can be estimated from the upper, d_{iu} and lower d_{il} openings

Figure 14. Visual comparison of primary sampling belt collected drill cuttings pile on the left vs. the remainder of the blast hole cone after 14m drilling.

Figure 15. Triangular sampling trays next to the blast hole prior to drilling 3 meters.

of the sieves:

$$v_i = f_i \frac{d_{iu}^3 + d_{il}^3}{2} \quad (2)$$

f = particle shape factor, which is 1 for cubic particles, 0.524 for spherical particles. For most crushed and ground materials, the factor is close to 0.5 which was used in this study as the default value. If a sample of size m_s is taken from a lot m_L, which is much larger than the sample, the constitution heterogeneity, CH, or relative variance of the fundamental sampling error for each size class is

$$CH_i = s_{FSE}^2 = \frac{HI_i}{m_s}, m_L >> m_s \quad (3)$$

If the sample forms a significant part of the lot from which it is taken, then a correction has to be made in estimating the sample variance

$$CH_i = s_F SE^2 = HI_i(1/m_s - 1/m_L) \quad (4)$$

Often the primary sample is so large that the sample size has to be reduced before sieving. If, e.g., the primary sample m_{s1} is taken from a lot by size m_L, and sample m_{s2} is taken from the primary sample and sample m_{s3} taken from the secondary sample is then sieved the variance of this 3-step process is, if the size distribution is not changed:

$$CH_{TOT} = HI_i\left(\frac{1}{m_{s1}} - \frac{1}{m_L}\right) + HI_i\left(\frac{1}{m_{s2}} - \frac{1}{m_{s1}}\right) + HI_i\left(\frac{1}{m_{s3}} - \frac{1}{m_{s2}}\right) = HI_i\left(\frac{1}{m_{s3}} - \frac{1}{m_L}\right) \quad (5)$$

Constitution heterogeneity is converted to relative standard deviation follows:

$$s_{ri} = \sqrt{CH_i} \quad (6)$$

If the relative standard deviation is given in percentages s_{ri} should be multiplied by 100. Fundamental sampling variance gives the variance of an ideal sampling process, i.e., the material of the lot is a random mixture of its constituents and the sampling process is correct. If there is segregation in the lot or sampling devices are not correctly designed or operated, experimental variances are larger than those calculated from Eq. 1.

Confidence intervals

When HI values from the sieving are available approximate confidence intervals for the size fractions can be estimated. Absolute standard deviations for the size fractions i are, given the sizes of the lot (m_L) and the sample (m_{si}):

$$s_i = \sqrt{HI_i\left(\frac{1}{m_{si}} - \frac{1}{m_L}\right)} \cdot a_i \quad (7)$$

Approximate confidence intervals ci for the size fractions are

$$ci_i = a_i \pm k \cdot s_i \quad (8)$$

The coverage factor $k = 2$ gives theoretically 95% confidence interval, i.e., if the lot is a truly random mixture of fragments and the sampling system is correctly designed and operated, as an average only one value in 20 replicate samples taken from the same lot shows results outside the confidence interval. If the standard deviations are multiplied with a factor of 3, it gives 99.7% confidence interval corresponding as an average to one outlier in 300 observations. In practise, the fragment shape and density values used in calculations are approximate values, not exact. Consequently, the confidence levels are also approximate values. However, significant deviations from these values indicate either a deficient sampling system or material segregation that the sampling system cannot eliminate.

Note: If the sample is so small that only a few fragments, say less than 16, from the coarsest fraction are included in the sample symmetric confidence intervals obtained from Eq. 8 are not valid for this size fraction. Relative standard deviation estimate larger than 25% is an indication that number of these fragments in the sample is smaller than 16.

Minimum sample size for a given precision requirement

Given the lot size and precision requirement, i.e., the required relative standard deviation, , Equation 9 gives the minimum sample size (for an ideal mixture and sampling system)

$$m_s \geq \frac{HI}{s_{r(req)}^2 + \frac{HI}{m_L}} \quad (9)$$

In interpreting experimental results one should remember that the results obtained from FSE calculations are valid for ideal mixtures and sampling equipment designed and operated according to the principles of TOS. In practice parameters, like shape factors and size class densities, are not exact but only approximates. As safety factor it is recommended that the theoretical minimum sample sizes are doubled. In addition, if the sample size needs to be reduced for analysis each new sample should consist of several increments, ideally from as many as is possible without introducing increment *delimitation and extraction* errors. Increasing the number of fragments in the samples reduces the grouping and segregation errors defined in TOS.

Experimental results

Example of calculations

Tables 1 and 2 show the sieve results obtained from one of the experimental drill holes. The sample, 6.053 kg, was taken with the RAS sampler from a 3 m section of the drill hole. Table 1 gives the results of the fundamental sampling error calculations as explained in the previous section. Table 2 gives the average fragment mass, total mass of fragments and the average number of fragments in each of the six size classes sieved from the sample.

Sampling variance of a particle mixture is a function of the number of the analyte particles in the sample. As Table 2 shows, the number of fragments rapidly increases when the particle size is reduced and, consequently, HI decreases. If a reliable result of the coarsest fraction in sample is necessary, then it determines the minimum sample size that should be used. Table 3 shows the confidence intervals for the mass fractions in each size class for 1 kg and 5 kg samples calculated using the experimental HI values (Eqs. 7 and 8). The confidence intervals for the coarsest size fraction are: from 1 kg sample a_i = 5% ± 3.52% and from 5 kg sample a_i = 5% ± 1.50%

Table 4 shows how the theoretical minimum sample size depends on the required uncertainty of sampling given as the relative standard deviation: 1%, 5% and 10%. Sample sizes were calculated for

Table 1. Results from calculating the heterogeneity invariant (*HI*), constitution heterogeneity (*CH*) and relative standard deviation (s_r) from sieving results of 6053 g sample from a 50 kg lot. Shape factor $f = 0.5$ and density 3.2 g/cm^3 were assumed.

Size class d1 (cm)	Size class d2 (cm)	d(nominal)	v_i (cm^3)	a_i	*HI* (g)	*CH*	s_r (%)
1.5	0.8	1.248	0.972	0.050	56.18	0.00816	9.03%
0.8	0.2	0.638	0.130	0.123	2.757	0.0004	2.00%
0.2	0.1	0.165	0.002	0.076	0.288	4.18E-05	0.65%
0.1	0.05	0.0825	0.000281	0.111	0.214	3.1E-05	0.56%
0.05	0.025	0.0413	0.0000352	0.181	0.208	3.02E-05	0.55%
0.025	0.01	0.0203	0.00000416	0.451	0.207	3.01E-05	0.55%

Table 2. Average fragment mass, total mass and number of fragments in each size class in 6053 g sample.

d (nominal)	v_i (cm^3)	fragment mass (g)	Total mass in size class (g)	Av. No. of fragments
1.248	0.972	3.1096	303	97.3
0.638	0.130	0.416	745	1790
0.165	0.002	0.0072	460	63893
0.083	0.000281	0.0009	672	746537
0.041	0.0000352	0.0001125	1096	9738604
0.020	0.00000416	0.0000133	2730	205255865

two different lot sizes: 200 kg (sample taken from a pile) and from a lot much larger than the sample (primary sample taken from a large target). The minimum sample size depends strongly on the required standard deviation: if the uncertainty is reduced by factor 10 the sample size has to be increased by factor of 100 in case the lot is much larger than the sample size. In case that the lot size is 200 kg in order to reduce the sampling standard deviation of the coarsest fraction to 1% 147 kg sample is needed.

Comparison of samples taken from the same lot

In most of the experimental drill holes 3-m sections were taken and sampled with the methods currently in use and with the new test

Table 3. 3 *s* confidence intervals calculated for 1 kg and 5 kg sample sizes from the experimental results.

HI (g)	*s* (mass fraction) m_s = 1 kg	*s* (mass fraction) m_s = 5 kg	a_i	3 *s* conf. interv. (m_s = 1 kg) lower	3 *s* conf. interv. (m_s = 1 kg) upper	3 *s* conf. interv. (m_s = 5 kg) lower	3 *s* conf. interv. (m_s = 5 kg) upper
56.18	0.01173	0.00503	0.050	0.0148	0.0852	0.035	0.065
2.757	0.00639	0.00274	0.123	0.1038	0.1422	0.115	0.131
0.288	0.00128	0.00055	0.076	0.0722	0.0798	0.074	0.078
0.214	0.00161	0.00069	0.111	0.1062	0.1158	0.109	0.113
0.208	0.00258	0.00111	0.181	0.1733	0.1887	0.178	0.184
0.207	0.00643	0.00276	0.451	0.4317	0.4703	0.443	0.459

Table 4. Minimum sample sizes calculated for three different relative standard deviation targets for sampling error; lot sizes m_L = 200 kg and $m >> m_s$.

HI (g)	Minimum sample size (g) s_r = 1% $m_L >> m_s$	s_r = 1% m_L = 200 kg	s_r = 5% $m_L >> m_s$	s_r = 5% m_L = 200 kg	s_r = 10% $m_L >> m_s$	s_r = 10% m_L = 200 kg
56.18	562000	147500	22500	20200	5620	5460
2.757	27600	24230	1100	1100	276	275
0.288	2880	2840	115	115	29	29
0.214	2140	2120	86	86	21	21
0.208	2080	2060	83	83	21	21
0.207	2070	2050	83	83	21	21

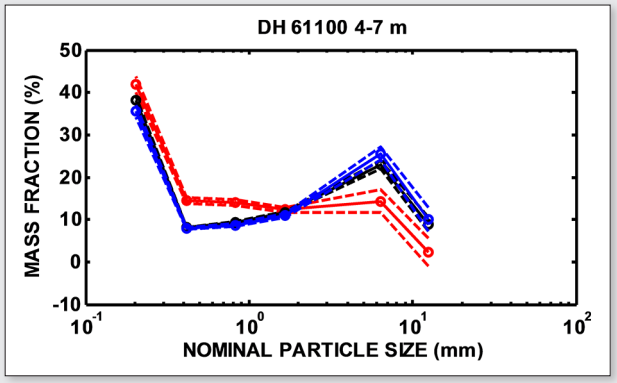

Figure 16. Size fractions with 3 s confidence intervals calculated from data of the test method (red) and from two sampling methods currently used (black and blue). 4–7 m section of the drill hole was sampled.

method. The remaining pile was split in two or three steps using riffle splitter type sampler in order to obtain pile sample weighing less than 10 kg. If necessary, other primary samples taken from the pile were also split. Sample sizes sieved varied from 2 to 9 kg. From the sieve results *HI* values were calculated for each six size fractions obtained in sieve analysis. *HI* values available confidence intervals of the size fractions can be calculated for the used sample sizes. Confidence intervals calculated for the samples obtained by using different sampling methods should overlap, if the sampling methods are correct and can eliminate the effects of segregation. Segregation is caused by variation in the rock that the drill has penetrated and segregation in forming the pile. Significant differences indicate that segregation errors play a significant role, and samples taken with different methods are not comparable. Figure 16 shows an example, where the test method (RAS) was compared with two samples taken with a sectorial boxes, which do not extract a complete sector from the pile. The box samples are comparable but differ significantly from the test sample which has lower concentration of coarse and higher concentration of finer fragments. It is obvious that incomplete extraction of a sample sector increases the risk of segregation error in results.

When all samples taken from the lot (drill section in this case) and the sample taken from the remaining pile are analysed it is possible to calculate reference values for the size distribution as weighted

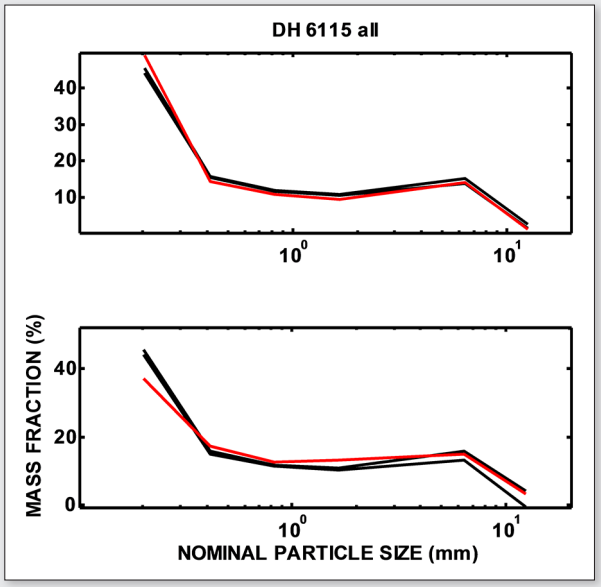

Figure 17. 3 s confidence intervals (black lines) calculated from the weighted averages of the size distribution from all samples for sample sizes of the conveyor and pile sample. Red line shows the observed size distribution of RAS sample (upper panel) and pile sample (lower panel).

average from the analysed samples. The lot mass is the sum of the sample masses (m_j) and the mass of remaining part of the pile (m_R).

$$m_L = \sum_j^n m_j + m_R \tag{10}$$

The reference value for each size class i of this lot thus is:

$$a_i\,(ref) = \frac{\sum_j^n m_j \cdot a_{ij} + m_R \cdot a_{Ri}}{m_L} \tag{11}$$

With these reference values HI_i of each size class of the lot can be calculated. Applying Eqs. 7 & 8 the confidence intervals for each experimental sample size can be estimated. If the experimental results are within confidence interval the sampling method/process can be regarded unbiased. As an example from one of the test

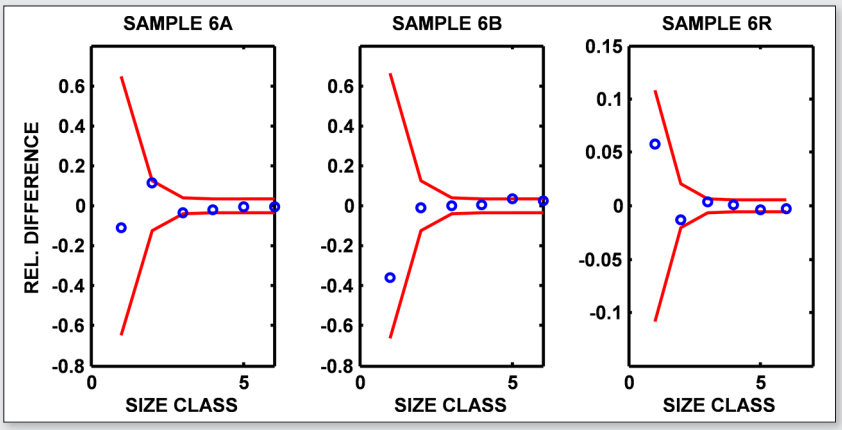

Figure 18. Relative differences (o) of the sieve results from the weighted size class mass fraction values. A and B are duplicates taken with the RAS sampler and R is the sample from the remaining pile. Red lines give the 3 s_r confidence intervals. Size class1 is the coarsest and 6 the finest.

drillings Figure 17 shows the confidence intervals and experimental results of the sample taken from the pile and test method (RAS).

From some of the test piles duplicate samples were taken with the test method (RAS). Pile samples were also analysed, consequently, the reference *HI* values of the lot, and relative deviations of the experimental size distribution from the reference could be calculated. Relative differences of size class *i* in sample *j* from the reference are:

$$dr_{ij} = \frac{a_{ij} - a_i(ref)}{a_i(ref)} \quad (12)$$

Expected confidence intervals of the relative differences are

$$cf_{ij} = 0 \pm k\, s_{ri} \quad (13)$$

and s_{ri} is calculated applying Eq. 6. Figure 18 shows an example from one of the experimental drillings, where duplicate samples were taken with RAS sampler. In general, results of RAS method agreed well with the reference values of the whole pile.

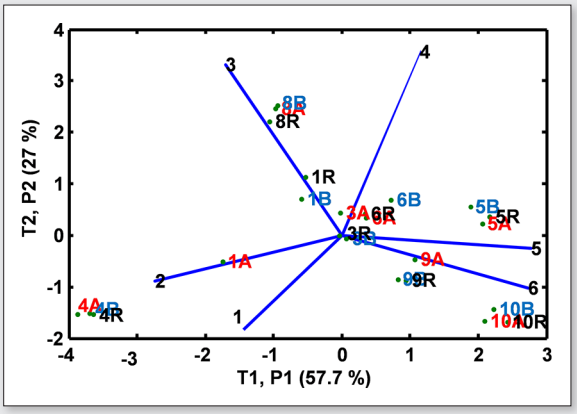

Figure 20. Score and loadings biplot of the two first components of the PCA model. Blue lines show the loadings of the size fractions (1 coarsest, 6 finest) and dots the sample scores. First component explains 57.7% of the total variance of size data (X) and second 27%.

Multivariate analysis of the experimental results

Information available in large data sets consisting of several variables measured on a large number of objects can often conveniently be extracted by using a mathematical tool called principal component analysis (PCA)[3,4]. The principle of the PCA is presented in Figure 19. The data matrix **X** is organised so that the variables (size fractions or analytical results) are on columns of **X,** while objects (samples in this case) are on rows. **X** is usually first auto-scaled, i.e., from each column of **X** its mean value is subtracted and divided by its standard deviation. The first principal component finds the direction of the highest spread of the objects in the multivariate space. The second PC finds an orthogonal direction where the spread of the objects is next highest, etc. *Variable loadings* define the directions of the PC axes and *object scores* are objects projected on these axes. In ideal case the residual matrix **E** contains only noise. Often only a few PC's are needed to extract the useful information contained in **X**. Plotting the scores of two PC's gives a projection of objects from the original multivariate space onto a 2-D plane. Plotting loadings shows which variables are important on these components. Objects grouping close to each other have common features and variables having high correlation have loadings with similar values. Plotting scores and loadings superimposed as so called bi-plots show how objects and variables are related.

PCA was calculated from the size fraction data of the samples as **X** matrix. Figure 20 shows as a bi-plot the two first components of the PCA model. Duplicate RAS samples (A and B) are compared with the pile samples (R). The samples taken from the same drill sections form tight clusters indicating high similarity between samples from the same lot (drill section). The only exception is sample 1A which is far from 1B and 1R and thus an outlier in this group. Samples 10 and 5 have high concentrations in two of the coarsest size fractions and samples 4 are high in finest fraction. Samples 8 have high in middle fractions. The other samples are close to the average sample.

Chemical analyses vs. size distribution

Most of the samples collected in this study were analysed for major and minor elements in a laboratory by using XRF. From one experimental drill hole only composite samples from 1–2 metre sections were analysed and from other hole samples also the size fractions. How the rock breaks in concussion drilling depends on the type and mineral composition of the rock penetrated by the drill. So there is a correlation between size distribution and chemical composition. This is clearly seen in Figure 21. Fe, Al, Ti, V and K show a similar pattern (concentration decreases with increasing fragment size) whereas Mg, Si and to some degree also Ca and Mn show opposite behaviour.

Figure 22 shows the variation of chemical composition of major constituent with increasing depth in one of the drill hole, from which composite samples representing 1 or 2 metre sections were analysed. It is obvious that this kind of variation causes severe segregation (stratification) in the pile. If the sample is taken from the pile it is difficult to eliminate the segregation error. It is easier to eliminate

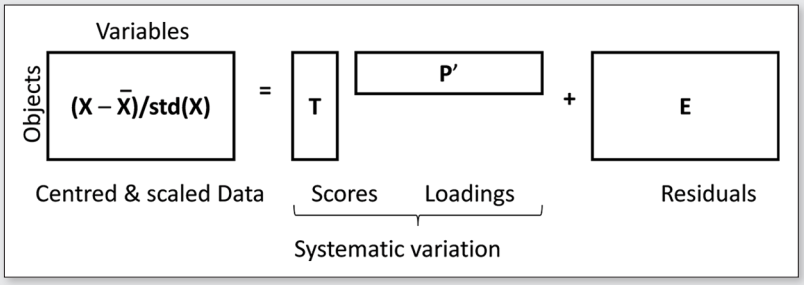

Figure 19. In PCA the original data matrix, which is usually autoscaled, is decomposed into two smaller object score and variable loading matrices and residual matrix.

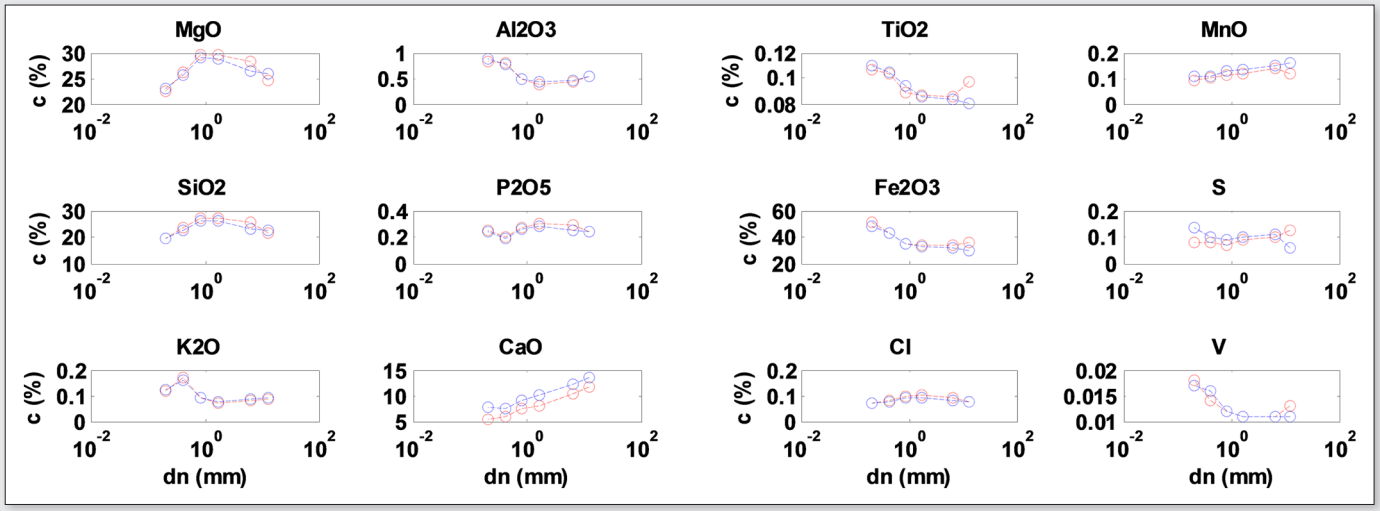

Figure 21. Chemical composition vs. nominal particle size of the size fractions in a 3 metre section of one experimental drill hole. Red dots are RAS samples and blue dots sample taken from the remaining pile.

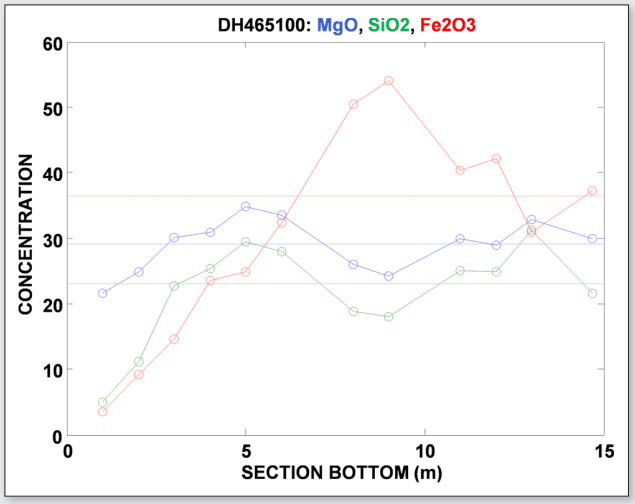

Figure 22. Variation of chemical composition in composite samples with increasing depth.

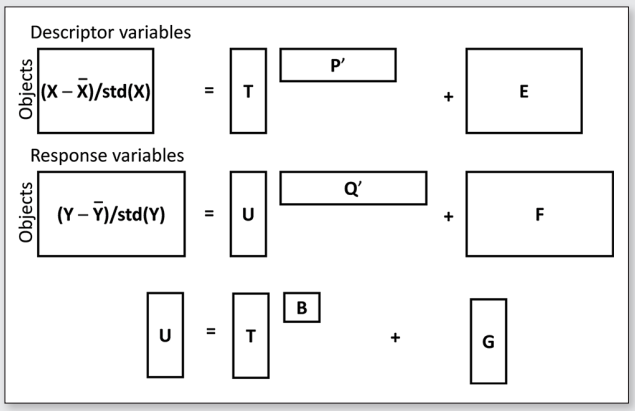

Figure 23. Principle of PLS regression: Descriptor and response variable matrices are decomposed into object and variable score matrices so that when columns of U are regressed on T the fit is optimised (sum of squared residuals G minimised). When descriptor variables on new objects are available T, U and predictions of Y can be calculated.

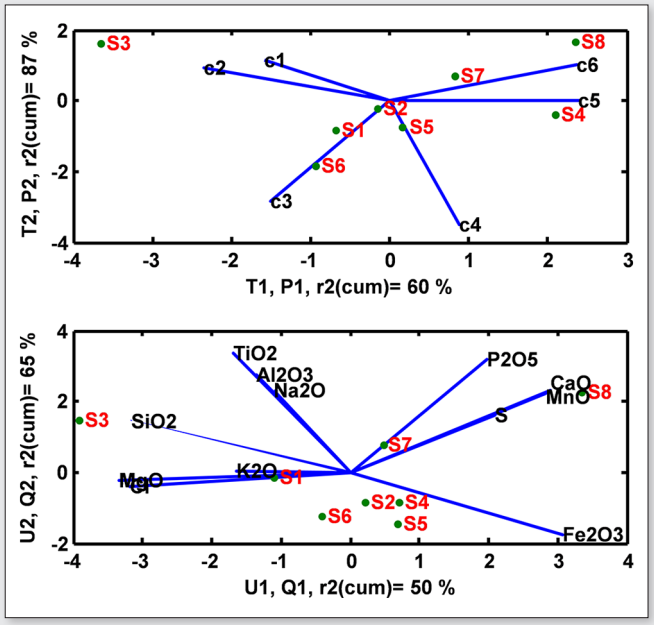

Figure 24. Result of PLS as biplots. Upper panel shows loadings of the size fractions c1 (coarsest) – c6 (finest) and scores of the samples (S1–S8). Lower panel shows s variable loadings of the Y matrix (chemical composition).

segregation error if the composite sample is collected continuously with a correctly designed sampling device, when the drilling progresses.

If two types of variables, descriptor variables **X** and response variables **Y** are measured on the same objects their relationship can be modelled by using Partial Least Squares regression (PLS). PLS is a standard method used in chemometrics[3,4]. The principle of PLS is given in Figure 23. Just like in case of PCA the main features of the data sets can be presented as informative projections. Figure 24 shows an example. Mean values of the size distribution from 8 samples (drill core sections) were used as **X** and chemical composition as **Y**. Two first components explain 87% and 65% of the total variance of **X** and **Y**, respectively. This means that the chemical

composition of the drill sections could be approximately predicted from the sieve results. The plot also shows at a glance the relationship between samples, size distribution and chemical analysis.

Conclusions

Taking representative samples from a pile of blast hole drill chippings is a very difficult task. Variations in mineral composition in the ore body inevitably cause stratification in the pile. Also the pile accumulation process segregates fragments depending on the particle size, shape and density. Here the performance of a new design of a blast hole sampler was tested by comparing the results with samples taken by other sampling methods and also with results obtained by splitting the whole remaining pile (reference). The Theory of Sampling was used to analyse the estimation uncertainty of an ideal (random) mixture of material consisting of particles of different sizes. The results of this study showed that the new design largely eliminates the effect of segregation and gives reliable results.

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