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Applications of variography to process control using an iron ore case study

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ABSTRACT

Bulk commodities such as iron ore moving on a conveyor belt represent a one-dimensional lot providing an ideal opportunity for probabilistic cross-belt or cross-stream sampling at regular time intervals. The quality of such materials is measured by the mean, but the variability in the analyses arises from a variety of sources and is aggregated in a single figure for the standard deviation. The application of variography to a time-series of data analyses from a moving conveyor provides an effective means of analysing and disaggregating the sources of variability captured in the standard deviation of the data. Each component of variability leaves a distinctive fingerprint on the variogram, allowing its magnitude and contribution to the overall variability to be identified. Identifying sources of variability also enables one to make suggestions as to what aspect of the sampling protocol and sampling equipment requires improvement. The terms Sampling Capacity, Sampling Capability and Sampling Guidelines and their information content in the establishment of customer specification limits, in keeping with process plant capability, is described. Sources of variability arising from the Fundamental Sampling Error and Grouping and Segregation Error give rise to random variability that must be minimised through careful heterogeneity tests. Non-random variability due to plant process and biases associated with Delimitation Error, Extraction Error, Preparation Error and Weighting Error are identified and mitigated and may be eliminated by reducing the sampling interval and ensuring that sampling equipment recovers a correct sample. Cyclical variability in process streams is particularly detrimental to consistency in the grade of the product and its sources and methods for mitigation by reducing the sampling interval, are discussed. Reduction of large-scale variability provides significant opportunities to improve the product specifications and probably improve costs effectiveness through a less demanding blending routine. Determination of more appropriate specification limits can improve throughput and resource utilization.

1. Introduction

Pierre Gy addressed problems associated with incremental sampling of flowing streams during ship loading and mineral processing and applications of variography to the understanding large-scale variability in process plants and process control in the period 1960–1962. However, it was only in 1977 that he identified and quantified the rules regarding the shape and width of cutter openings, and their velocity through the material streams. More importantly, he found that samples collected at regular intervals from a moving conveyor belt, are "*not independent from one another*" (Gy, 2004, p54). Instead, he found a strong correlation between one sample and the next, and that the strength of the correlation declined as the samples became further and further apart. Hence, the statistical proviso that samples should be random and independent no longer held. Having heard about the work of Matheron (1965) in geostatistics through the writing of Michel David (1988), Pierre Gy borrowed the concept of the variogram for characterising the autocorrelation between samples taken from flowing streams. This opened to him the new area of research he called chronostatistics (Gy, 2004)

Control charts (or Shewhart charts) in plant process control for solids, slurries, liquids and powders provide a graphical representation of the history of process variation in intermediate or final product composition with time (Nelson, 1984). They give the plant superintendent information helping him to decide on how to react to changes in the process. Walter Shewhart (1931), inventor and pioneer of the use of control charts found that tampering with a process only makes things worse if the source of variability is not well understood. Statistical control of processes aims to ensure that the grade of a particular product lies within stated limits, that the process is statistically stable over time, and that a statement of uncertainty about product quality is valid. Random variability arises from natural variability in inputs to the process and is present to some extent in all processes. Because it is inherent in the inputs to the process, trying to identify its causes is futile. It can never be eliminated and can only be reduced by changing the system in some fundamental way. Non-random or cyclical

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variability however, can be significantly reduced, even eliminated if the right point sources of such variability can be identified and engineered out of the process.

Pierre Gy's 1960–1962 research into flowing streams of materials on conveyor belts and liquid launders brought to his attention the importance of sampling the "whole stream" for a fraction of the time, i.e. any increment must be a physical full slice of the stream. He identified the issues in regard to cross-stream sampler operation, namely that the cutter velocity through the stream, the width of the cutter opening and the shape of the cutter are all important, but it was first in 1977 that these issues were scientifically resolved. He also recognised that increments extracted at constant intervals from a flowing stream are correlated (Gy, 1992). As early as 1962 Gy published his work on chronostatistics, as it later became known, borrowing the idea of spatial correlation between samples using concepts from the semi-variogram proposed by Matheron (1965) and later David (1988) for geostatistics and transferring it to linear auto-correlation of time series data (Minnitt and Esbensen, 2017). In the Theory of Sampling, Quality Fluctuation Errors (QFE_1 and QFE_2) refer to errors that arise from processes and procedures in a plant. QFE_1 arises from long-range, non-random changes in composition and correlation between one increment and the next, while QFE_2 arises from non-random cyclical variations in material composition on the conveyor belt due to the extraction of different zones of mineralisation in the mining operations (Pitard, personal communication, 2017).

Sampling variability arising from selection of materials in a one-dimensional lot, the so-called Quality Fluctuation Errors are difficult to resolve into different components of variability, since one easily masks another. The variability arises due to the heterogeneity in a system or stream. Pitard (2006a, 2006b) explained that the three main components of stream variability are the integrated accumulation of three kinds of heterogeneity, each with independent sources, and is expressed as:

$$h_T = h_1 + h_2 + h_3$$

Where, Heterogeneity h_T = Total heterogeneity, Heterogeneity h_1 = Random, discontinuous heterogeneity that is a property of the materials, Heterogeneity h_2 = Non-random, continuous heterogeneity that is a function of time, Heterogeneity h_3 = Cyclic, continuous heterogeneity that is a mechanical function of the system.

This particular case study uses 150 data from a time series in excess of a thousand data. The choice of the number of data may depend on the time interval between samples, but more often than not about 150–200 data will provide the necessary information. The target average (TA) is the minimum acceptable grade prescribed by a customer whose requirements in terms of average grade and acceptable specification limits are a function of the plant feed for his processes or the maximum grade in the case of a contaminant. The difference between the target average required by a customer and the grade of ore delivered by a processing plant may be relatively small, in the order of 1–2 per cent, with the only consideration of the variability in the product stream being a calculation of the standard deviation of the analyses. A vast number of variables in Nature approximate a Gaussian or normal distribution in which the frequency of values is highest in the centre and tapers off symmetrically on either side of the centerline to extreme values (Fig. 1). In their natural settings, sample data collected from precious and base metal deposits such as gold silver, lead, copper zinc and nickel, usually display a lognormal distribution. Samples from a coal deposit or alumina deposit will usually have a normal distribution, while bulk commodities such as iron, manganese, vanadium and chromite ores, usually have negatively skewed distributions. Even if the nature of the true parent distribution from which the samples are collected is unknown, comminution and mixing the ores means that principles of the Central Limit Theorem overtake the natural ore characteristics, causing the distributions of samples of processed ores to be normally distributed. Thus the mean and standard deviation calculated from the sample data, completely define the distribution, even if the distribution of the sample data is unknown. Symmetry of the standard deviations in the Normal distributions makes it useful for forecasting, controlling or fixing the limits of quality in processes (Myers, 1997; Rossi and Deutsch, 2014) (Fig. 1).

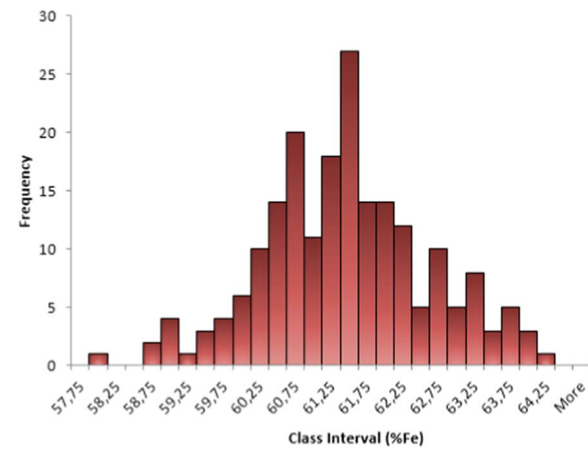

Fig. 1. Histogram of 150 iron ore data in % Fe showing a normal distribution.

Descriptive statistics for these data, provided in Table 1, indicate that the ores are relatively high grade, 61.56%Fe with relatively low standard deviation, 1.07%Fe.

The value of the variogram lies in its simplicity as an effective tool for identifying the components of process variability (h_1, h_2, and h_3) in time-series data and conveying components of variability to the superintendent information about plant behaviour that is otherwise not obtainable. While attendees of the world conferences on sampling have reported on the applications and usefulness of chronostatistics, the ideas and acceptance of these methods by industry has generally been slow. This would seem to be because the interpretation and usefulness of variographic information for informing one about "in control" or "out of control" processes is poorly understood. According to Pitard (2006a, 2006b), conventional statistics and statistical process control (SPC) fail to address the concept of stream heterogeneity, and therefore fail to identify and distinguish between the various sources of variability in a process stream. Types of process variability match different types of stream heterogeneity, but principally the distributional heterogeneity is due to segregation in the process related to size or composition distribution of the material on a local scale (Lyman, 2007). Many plant superintendents fail to appreciate the value of variography and the benefits of the Theory of Sampling as suggested by Gy (1979, 1988, 1992, 2004). The move to continuous on-line monitoring of such process streams provides a momentary view of process variability and changes, allowing plant superintendents to make instantaneous changes

Table 1
Descriptive statistics for the 150 iron ore analyses used in the case study.

Statistic	%Fe
Mean	61,56
Standard Error	0,09
Median	61,68
Mode	62,36
Standard Deviation	1,07
Sample Variance	1,14
Kurtosis	−0,24
Skewness	−0,28
Range	5,37
Minimum	58,48
Maximum	63,85
Sum	9295,71
Count	150,00

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