CHAPTER 6.1

Mineral Sorting

Bern Klein and Andrew Bamber

Over the past 40 years, society has put increasing demand on industries to move toward cleaner and more efficient means of production. Industry has generally responded with improved processes and significant increases in efficiency and environmental performance. Over the same period, mining has become a point of focus for governments, nongovernmental organizations (NGOs), and communities as an industry out of tune with this trend. High-grade and easily accessible deposits have become largely depleted, and a large proportion of the remaining deposits are found in either remote locations or at extreme depths or embody other complications such as poor ground conditions, complex structure, adverse mineralogy, or presence of deleterious elements. The grade of new discoveries is declining severely, as is the mined grade at existing operations across most commodities. The general response to this situation is that most companies simply exploit economy of scale to dilute the fixed cost at operations, leading to the prevalence of ever-larger underground and open pit mines (Scoble 1994). Large-scale mining approaches, while improving economics by reducing the contribution of fixed costs and overhead, often incorporate high levels of unit inefficiency, particularly as extraction methods have inherently low levels of selectivity, leading to significant dilution as well as losses. Furthermore, beneficiation processes, particularly grinding, are singularly inefficient; hence, impacts on the efficiency of treating ores with lower grindability, as well as lower value, are particularly acute (Klein et al. 2015). Cost-effectively maximizing the amount of ore extracted while simultaneously reducing the waste content in ore delivered to downstream processes (whether simply transport and crushing or more sophisticated circuits, such as grinding and flotation or leaching) is therefore of key interest for all mining operations and projects struggling with low margins (Scoble et al. 2003; Bamber 2012).

Interest in the preconcentration of ore ahead of transportation and milling, as one way to achieve this, has historically been high. Preconcentration of mined material before it enters the mill reduces waste content and increases the value of ore, reducing overall processing cost (Scoble et al. 2003; Bamber et al. 2005, 2008; Engelbrecht 2012; Robben et al. 2013; Lessard et al. 2014). It may also assist in reducing the capacity required of all downstream processes, including transportation and milling, to deliver equivalent economics (Bamber et al. 2004; Bamber 2008). According to Salter and Wyatt (1991), sorting of ore also helps in providing a more uniform quality feed to the mill, which leads to further improvements in metallurgical recovery. Sensor-based sorting supports efforts to address pressures to transform the mining industry to become safer through mechanization, to improve overall energy efficiency by reducing transport requirements and diverting waste away from comminution, and to become more productive by maximizing resource utilization (Egerton 2004; Klein et al. 2011; Nadolski et al. 2015; Duffy et al. 2015).

There are various benefits to applying sorting in mining, and the best results are observed when it is introduced at very early stages in the mining cycle, potentially as early as the bench or face (Klein et al. 2002; Bamber et al. 2004; Bamber 2008). While several methods of preconcentration are available, including classification by size or density, sorting possibly offers the most potential of all because of its applicability to a wider range of mineralogies and its water- and reagent-free operation benefits.

Electronic sorting of minerals has been commercially available on a small scale since World War II. Early applications were in industrial minerals and more recently, with uranium, gold, diamonds, and massive base metal sulfides. Sensor-based sorting involves the sensing of the quality of granular materials such that the sensor response informs a decision to accept or reject the material. The technology, however, has not been adopted as widely as may be possible for several reasons. These include the traditionally low processing capacity of the technology, resulting in high unit capital and operating costs, limitations on the range of particle sizes that can be treated, as well as pervasive misconceptions about the principles and benefits of sorting among mine operators (Arvidson 2002; Manouchehri 2003; Bergmann 2009; Wotruba 2006; Wotruba and Harbeck 2010). Lack of awareness about what constitutes an opportunity for sorting

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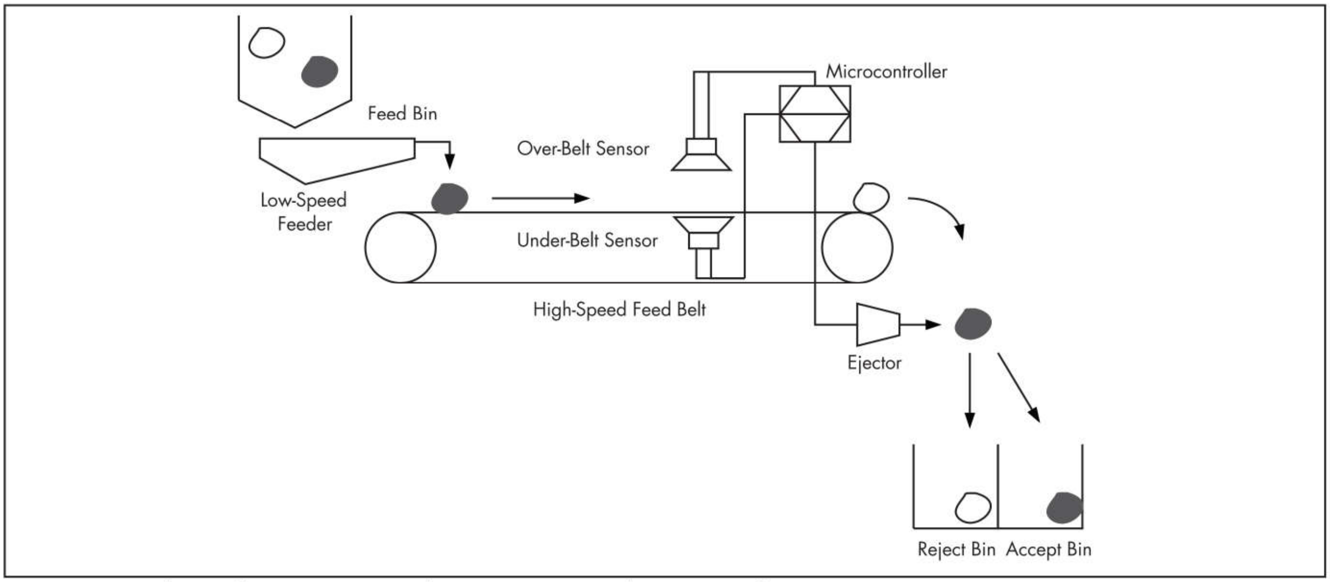

Figure 1 Typical particle sorting system showing sensors and pneumatic diverters

and ignorance of indicators of amenability to sorting has also been a barrier (Klein et al. 2015). However, recent developments in sensor-based sorting, including an increase in the range of applicable sensors, advances in speed, as well as new concepts in bulk- and semi-bulk sorting, have stimulated renewed interest in this unit operation within the industry (Kleiv 2012; Duffy et al. 2015; Bamber et al. 2016). These advances in capacity and range of application suggest that sorting, with its relatively low capital and operating cost, should be considered where good metallurgical response has been indicated, as either a possible final treatment step (in the case of bulk commodities) or a preconcentration step ahead of conventional grinding and flotation or leaching (in the case of base and precious metals).

This chapter seeks to present the current state of sensor-based sorting, the range of sensors, tools for the mineral processor to identify opportunities to sort, approaches to characterize materials for sorting, selection criteria pertaining to the unit operation, circuit designs, capital and operating cost considerations, as well as a range of example applications.

SORTING SYSTEMS

In sensor-based sorting, sensor information is acquired for a material. This information is used in an algorithm to classify the material, for example, according to its value or the concentration of a particular contaminant. Based on the estimated value and comparison of that value to a relevant threshold, the microprocessor informs a mechanical actuator to either accept or reject the material. Sorting can be applied to individual particles (rocks), bulk streams, or batches of material.

Particle Sorting

Sorting has application for a range of deposit types with grades varying from very low to high. For low-throughput high-value operations, particle (rock) sorting can add significant value to the operation by rejecting significant quantities of barren or low-grade waste ahead of more cost- and energy-intensive processes such as grinding (Bamber et al. 2008). In this case, the impact of sorting increases with decreasing grade, because at lower grades, such ore has a greater proportion of waste that can be rejected.

For particle sorting, the material must be prepared through a series of crushing and screening stages to prepare narrowly bounded size fractions, typically 3:1 top-size-to-bottom-size range. Often, washing via sprays or wet screening is needed to clean the particle surfaces for accurate sensing. The sorting systems require feeders that produce a monolayer of spaced particles so that each particle can be sensed and sorted individually.

The most common sorting system involves a belt conveyor, a sensing system to assess the quality of conveyed material, and ejectors consisting of valves delivering compressed air to eject detected waste particles, as shown in Figure 1. Alternative systems sense the rocks while free falling, informing either pneumatic or mechanical deflectors to reject the rock (Figure 2). Sensors used for particle sorting can either detect properties on the surface or assess bulk composition. For some mineralogies, the disposition of surface properties adequately represents the bulk, therefore surface measurement will suffice. This is not true, however, in all cases. Sensing accuracy can be improved by using multiple sensors in different orientations and/or combining responses from more than one type of sensor.

Bulk Sorting

The trend in the mining industry is to mine larger and lower-grade deposits to take advantage of economies of scale. While the throughput of current particle sorters at less than a few hundred metric tons per hour generally prohibits their deployment in such applications, bulk sorting solutions overcome throughput limitations by incorporating sensor systems into the material handling equipment of the mine. While less selective, and delivering generally lower-yield results than rock sorting, bulk sorting has very low cost intensity, and where heterogeneity in the ore is present at a relevant length scale, it can be very effective at delivering increased value. An increasingly wide range of sensors that integrate into conveying equipment, haulage equipment, and more recently into

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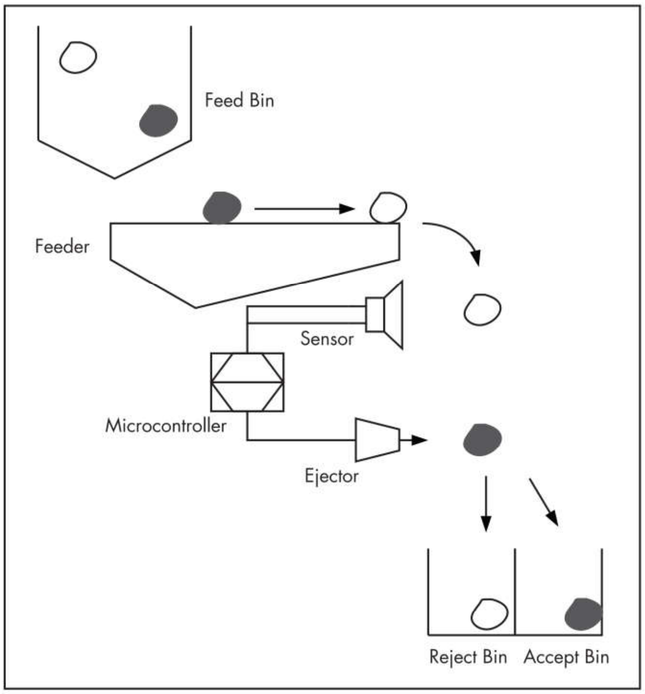

Figure 2 Vibrating feeder system with sensors on falling material and mechanical diversion

Source: Bamber et al. 2016

Figure 3 ShovelSense shovel-based bulk sorting solution at a Cu-Au mine

Source: Nield 2002

Figure 4 Overhead scintillometers (left) used for scanning U_3O_8-bearing trucks (right) at Rossing uranium mine in Namibia

Figure 5 Bulk diversion of nickel laterites via X-ray fluorescence analysis to product stockpile (right) and waste stockpile (left)

loading assets (e.g., mining shovels) is now available to support bulk sorting options where these did not previously exist.

Bulk separation has not been widely contemplated as a method, except in specific situations. For example, LKAB (a Swedish mining company) uses laser-induced fluorescence (LIF) for bulk sorting (Kruukka and Briocher 2002). Recent work, however, indicates that a wide potential for the application exists, therefore bulk sorting, whether on shovel (i.e., bulk-batch sorting) or on belt (bulk or semi-bulk sorting) has a key role to play in ore upgrading, particularly at large-scale open pit and underground mines (Murphy et al. 2012; Duffy et al. 2015; Bamber et al. 2016). Real-time bulk sensing systems can be deployed in several ways: Sensing can simply be used to help mines better execute grade control, or it can provide feed-forward process control information to the flotation or leach plant. Integrated with material routing or other diversion systems, material can be physically upgraded, either by rejecting waste or, more importantly, by recovering high-grade ore that would otherwise have been left in situ or sent to the waste dump. Sensors integrated with loading assets, such as shovels, scoops, backhoes, and loaders, sense the material during loading and can support sorting decisions at the bucket or dipper (i.e., 10–50-t scale; Figure 3).

Sensors integrated with hauling assets, such as trucks, can detect material in transit and support sorting decisions at the truck, for example, on a 300-t scale (Nield 2002; Figure 4). Sensing system deployment for sorting on shovels and trucks can improve the precision, accuracy, and resolution in the routing of material to low-grade stockpiles, leaching heaps, concentrators, or waste dumps.

Sensors installed on belt conveyors with integrated diverters can sense the conveyed material, supporting sorting decisions at a higher resolution than the truck or shovel scales, ranging from metric tons to hundreds of kilograms (Figure 5; Duffy et al. 2015). Probably the best cited example of this type

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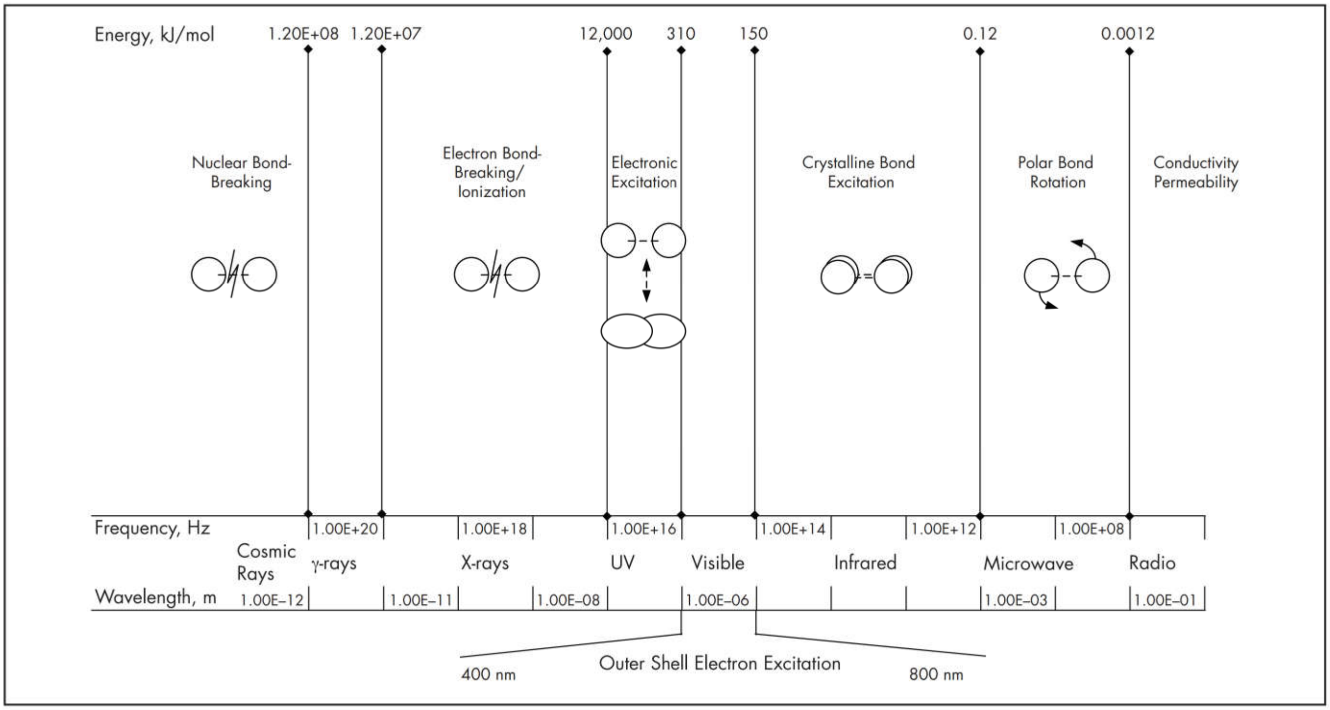

Adapted from Harris 1987

Figure 6 Theoretical potential for analysis using different bands of the electromagnetic spectrum

of sorting is the application of LIF in the bulk sorting of high-phosphorous Fe from low-phosphorous Fe at LKAB iron ore mine in Kiruna, Sweden (Kruukka and Briocher 2002).

MINERAL SENSING TECHNOLOGIES

Most sensors belong to a general class of electromagnetic source–detector combinations, where some form of stimulation using a particular band of the electromagnetic spectrum is used, and the response to that stimulation is recorded by the detector. A summary of the electromagnetic spectrum and its level of interaction with physical materials is shown in Figure 6.

The most common sensor techniques currently used in the industry are optical, conductivity, medium-wave infrared, and X-ray (X-ray transmission [XRT] or X-ray fluorescence [XRF]). Rapidly emerging sensing methods include prompt gamma neutron activation, laser-induced breakdown spectroscopy (LIBS), as well as multispectral reflectance imaging.

A list of sensors that are applicable to ore sorting is presented in Table 1. The sensors can be divided into two broad classes: those that measure properties volumetrically and those that measure surface characteristics only. In general, using a volumetric property to correlate to metal content provides a higher degree of confidence for sorting. For many ores, and particularly in bulk and semi-bulk situations, measuring only surface characteristics can accurately represent the volume characteristic. Sensors also classify according to response type. For example, analytical systems such as XRF or prompt gamma neutron activation analysis (PGNAA) can give a direct measurement of elemental composition, whereas electromagnetic or reflectance-based systems can give only a proxy for material composition. Furthermore, electromagnetic approaches require preexisting conductivity or magnetic susceptibility to be present, whereas other methods, such as PGNAA, have no such prerequisite. There is no general case or rule, however, and it is therefore highly recommended to test the suitability of sensors for each ore type to be sorted (Klein et al. 2002; Fickling 2011; Tong 2012; Altun et al. 2014).

Light-Based Techniques

Light-based techniques are divided into two main categories referred to as photometric and hyperspectral.

Photometric

The most widely known method in mineral sorting is optical sorting. There are many subclasses of photometric sorters, including those that sense visible or near-visible spectrum, minerals that naturally fluoresce under ultraviolet (UV) light, and hyperspectral sensing systems that detect over the visible to shortwave infrared wavelengths.

Visible and near-visible spectrum. Sensors are fundamentally cameras or charge-coupled device (CCD) sensors capturing reflectance phenomena from mineral particles, batches, or flows illuminated by visible wavelengths of light (Figure 7).

Interpretation can be simple, such as aggregate red-green-blue color intensity, or more sophisticated methods can be used, such as image analysis that characterizes texture. Alternate methods of illumination such as UV or near-infrared, coupled with very similar CCD detectors, give capability for characterization and, ultimately, sorting at those wavelengths instead.

Natural fluorescence. Many minerals, such as scheelite and wolframite, are naturally fluorescent under UV lighting conditions and can be sorted, based on responses in the fluorescent spectrum, from non-fluorescing species such as quartz or magnesium aluminosilicates.

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Table 1 Sensor types for mineral sorting

Technology	Physical Property	Principle	Surface or Volume	Ore Types	Sorting Applications	Manufacturer*
Radiometric (scintillometer)	Natural gamma radiation level	Radioactivity	Volume	Uranium, Witwatersrand gold ores	Particle and bulk	TOMRA, Rados
Prompt gamma neutron activation analysis (PGNAA), pulsed fast thermal neutron activation (PFTNA)	Elemental composition	Neutron activation/ gamma energy emission	Volume	Iron ore	Bulk	Scantec, ThermoFisher, PANalytical
X-ray transmission (XRT)	Atomic density	Relative absorption of high energy X-rays	Volume	Base/precious metals, coal, diamonds, sulfides, etc.	Particle	Steinert, TOMRA
X-ray fluorescence (XRF) spectroscopy	Elemental composition	Inner shell electron excitation	Surface	Base/precious metals, metal sulfides	Particle and bulk	MineSense, Rados, Steinert, IMA
Laser-induced fluorescence (LIF)	Visible fluorescence under laser stimulation	High-energy photonic emission	Surface	Diamonds, limestone, iron ore, sulfides	Particle and bulk	IMA, AIS Sommer
Microwave-infrared (MW/IR)	Polar bond excitation	Microwave absorption, heat radiation	Volume	Base metals, carbonaceous materials	Particle	Not applicable
Laser-induced breakdown spectroscopy (LIBS)	Elemental composition	Electron excitation/ light emission	Surface	Base metal oxides, sulfides	Particle	Secopta, LDS, LSA
UV/X-ray luminescence (X-Ray/UV-L)	Photonic emission from outer shells	Luminescence through X-ray or ultraviolet (UV) stimulation	Surface	Diamonds	Particle	TOMRA, De Beers
Photometric	Red-green-blue (RGB) color, gray-scale, surface texture, size/shape	Chromatic reflectance/ absorption	Surface	Industrial minerals, gemstones, diamonds, coal, massive sulfides, phosphates	Particle	Steinert, TOMRA
Hyperspectral analysis	Molecular bonds	Reflectance/ absorption	Surface	Hydrated minerals	Particle	Steinert
Electromagnetic (EM)	Conductivity/ magnetic susceptibility	Electromagnetism/ induction	Volume	Base metal sulfides, native metals, massive oxides	Particle and bulk	TOMRA, Steinert, MineSense
Magnetic resonance spectroscopy (MRS)	Magnetic resonance	Resonant frequency of molecules	Volume	Chalcopyrite	Bulk	CSIRO

*AIS Sommer GmbH, Germany; CSIRO (Commonwealth Scientific and Industrial Research Organisation), Canberra, ACT, Australia; De Beers, Johannesburg, South Africa; IMA Engineering Ltd., Helsinki, Finland; LDS (Laser Distance Spectrometry), Petah Tikra, Israel; LSA Laser Analytical Systems and Automation GmbH, Aachen, Germany; MineSense Technologies Ltd., Vancouver, BC, Canada; PANalytical, Almelo, Netherlands; Rados International, London, UK; Scantec, Camden Park, Australia; Secopta, Berlin, Germany; Steinert Global, Walton, KY, USA; ThermoFisher Scientific, Waltham, MA, USA; TOMRA, Shelton, CT, USA.

Hyperspectral Imaging and Reflectance Spectroscopy

Hyperspectral imaging, also known as reflectance spectroscopy in the visible to shortwave infrared regions of light is a rapid, nondestructive remote sensing technique that requires little to no sample preparation. Imaging spectroscopy of geological materials operates on the premise of absorption of incident light in the visible to shortwave infrared region by minerals, whereby diagnostic absorption features are a function of electronic and vibrational processes specific to that mineral's crystal structure and chemistry. Light reflected by mineral targets is collected by a line-scanning imaging spectrometer, producing an *image cube* where each pixel contains a reflectance spectrum (Figure 8).

Spectrometers sample at upward of 400 frames per second with a spectral range from 400 nm to 2,500 nm and ~3 nm spectral resolution. Spectra are processed through proprietary high-speed digital signal processing, pattern recognition, and identification algorithms, providing information about the structural nature of certain detectable minerals, especially clays, carbonates, and OH-bearing minerals. One variation applies industrial microwave treatment of the rock to enhance the infrared response of metal-bearing conducting minerals, which enhances the ability to discriminate from nonconducting minerals (Van Weert et al. 2011).

X-Ray Techniques

Fluorescence

The composition of minerals can be determined by characteristic X-rays or *fluorescence*, generated when atoms are irradiated with low levels of X-ray energy. When X-ray energy strikes a mineral, the atom absorbs X-rays, and electrons are ejected from the inner shells, creating vacancies. These vacancies present an unstable condition for the atom, and the atom returns to its stable condition by transferring electrons

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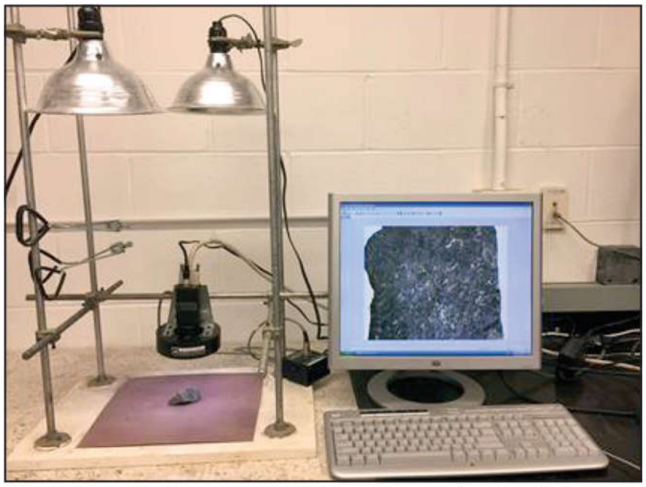
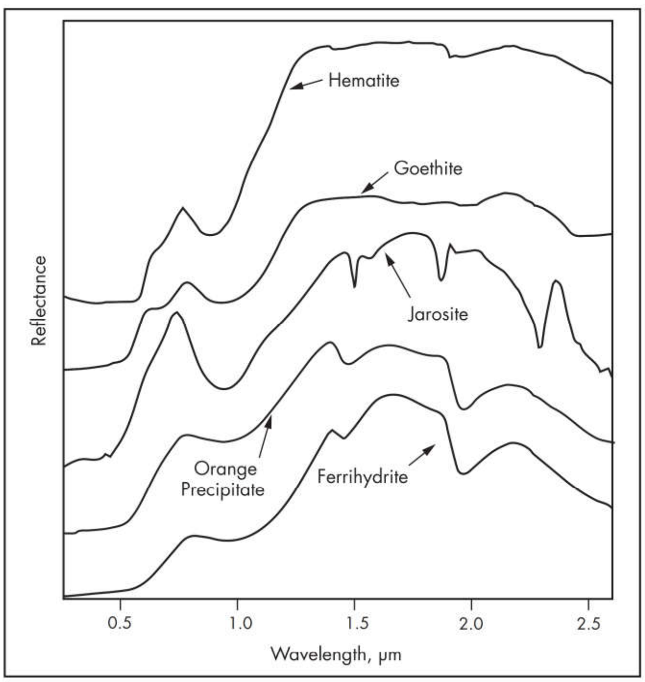


Figure 7 Optical image acquisition system showing lighting (top left), CCD camera with integral ring light (bottom left), and image-processing computer with display (bottom right)



Source: Clark 1999

Figure 8 Example laboratory reflectance spectra of selected iron-bearing geological materials from the visible (~400 nm) to the shortwave infrared (~2,500 nm) light

from the outer shells to the inner shells and, in the process, emits X-rays of characteristic energy related to the difference between the binding energies of the corresponding shells. The X-rays emitted from this process are called *X-ray fluorescence*, or XRF. Emitted X-rays are classified by a spectrometer designed to recognize fluorescence of specific elements in the periodic table. The technology is effective in detecting transition metals and some precious metals (Figure 9).

Mineral samples are irradiated by low-power X-ray energy, and characteristic X-ray backscatter is measured by the spectrometer. Typical deployments require seconds or even minutes for effective detection of mineral composition; in faster approaches, X-ray emissions are sampled more than 60 times per second, with characteristic spectra processed through proprietary high-speed digital signal processing, pattern recognition, and identification algorithms.

Transmission

XRT techniques similarly deploy X-ray sources, but at much higher intensities, which are powerful enough to penetrate the mineral and be captured by an opposing photonic detector (Figure 10).

The method is versatile, and gives an approximation of atomic density based on the degree of X-ray absorption. Principal applications are in coal and fine high-density and low-density minerals. Application is limited, however, as results are compromised in the presence of near-density non-valuable material (e.g., epidote); applications are also limited by limitations in X-ray penetration to ore minerals typically up to 38-mm particle size (Figure 11).

Laser-Induced Sensors

Fluorescence

Several minerals that do not naturally fluoresce can be made to do so under stimulation from coherent light. Typically, a pulsed laser (e.g., an Nd:YAG [neodymium-doped yttrium-aluminum-garnet] laser) is used as a source to illuminate the sample. Fluorescent elements in the sample respond to bombardment by coherent photons and emit fluorescent backscatter, which can be measured again by CCD (Figure 12). The intensity of fluorescent backscatter is proportional to the concentration of the fluorescing element. The technique has been successfully used in bulk analysis of phosphorus in iron ore and disseminated base metal sulfides.

Breakdown Spectroscopy

Chemical analysis of minerals is also possible by use of laser light. A high-powered, short-duration monochromatic laser beam of approximately 3 GW is used to irradiate the sample from a distance of between 150 mm and 1,000 mm. The high-powered laser pulses ionize the atomic structure of the minerals. Between pulses, however, the atom begins to reorder disrupted electron shells, and characteristic breakdown energies are emitted. Characteristic spectra are passed through a spectrometer specifically designed for the wavelengths of interest, delivered to a CCD for digitization, and analyzed in the embedded computer (Figure 13). Typical deployments of LIBS are for gases and pure alloys, however, application has recently been extended to oxides and sulfides of both base and precious metals. Compact, portable LIBS systems (Fortes and Laserna 2010) and advances in the development of systems to analyze rocks (Senesi 2014) enable application to sorting.

Gamma Techniques

Sensing techniques that use gamma radiation are classified as those that use natural gamma radiation and induced gamma radiation.

Natural Gamma Radiation

Many minerals contain concentrations of standard, naturally occurring radioactive elements K, U, and Th. These include uraninite, pitchblende, and most Witwatersrand gold ores where the gold is associated with uraninite. These elements give off a gamma ray of a unique energy when they decay.

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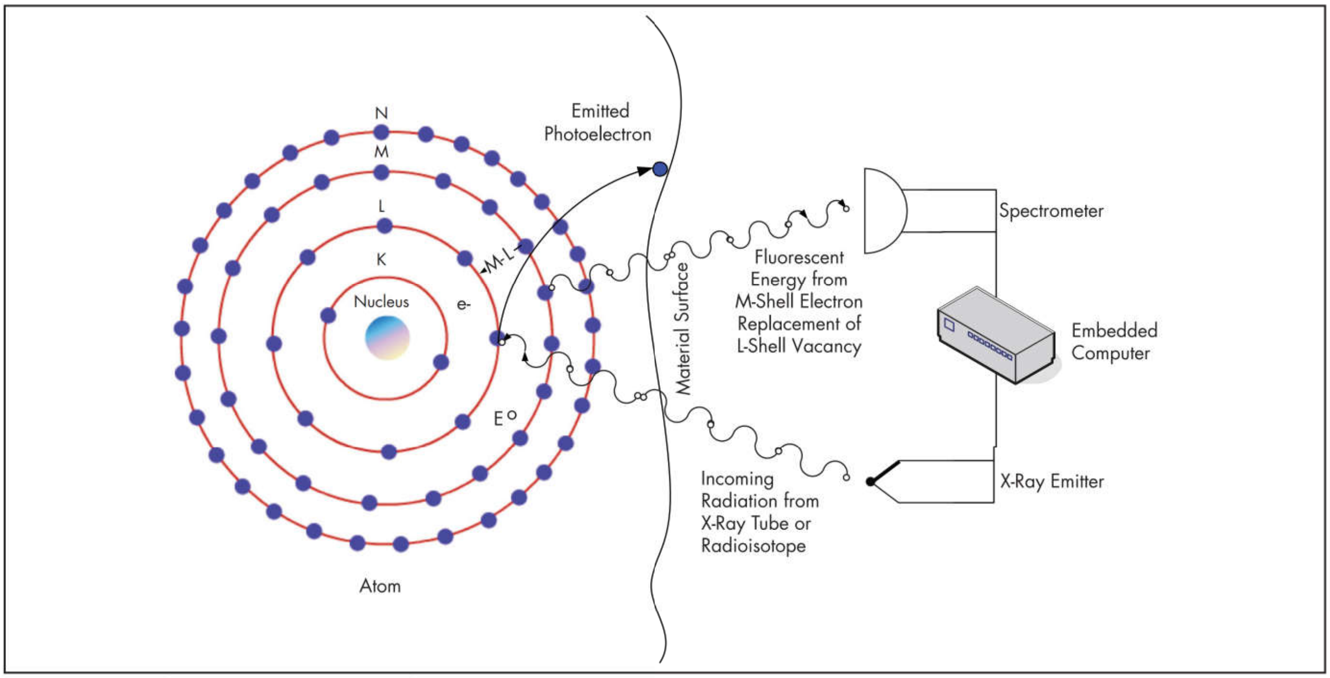


Figure 9 X-ray fluorescence principle of operation

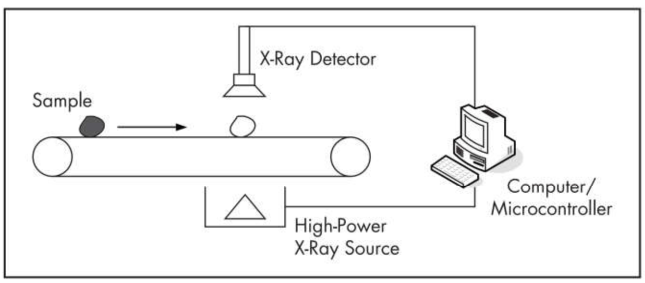
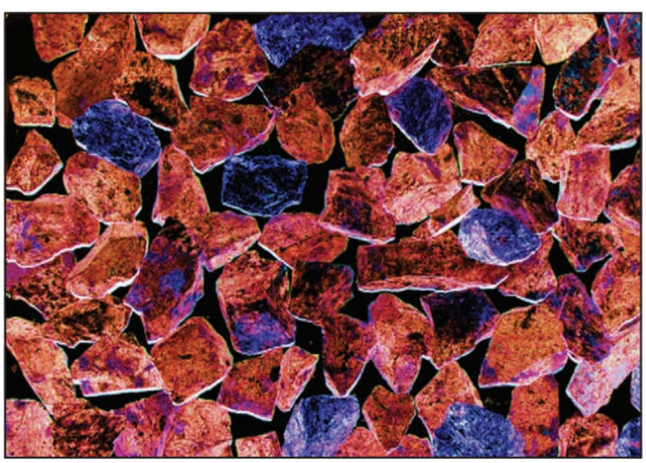


Figure 10 X-ray transmission sensing system



Source: Bamber 2004

Figure 11 False color image for ore minerals in X-ray transmission

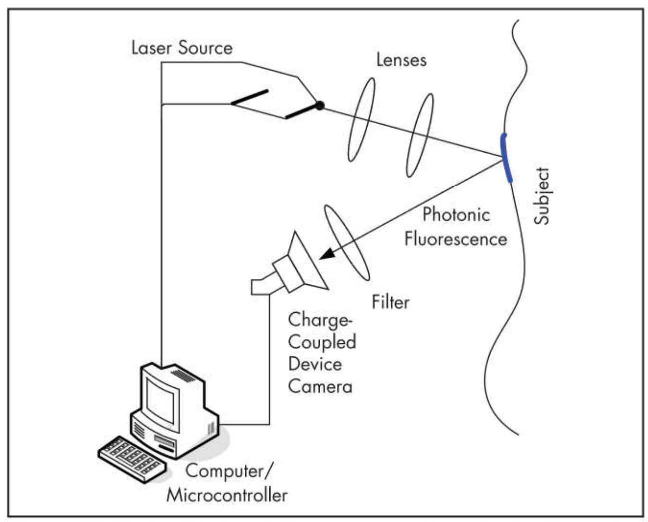


Figure 12 Typical induced fluorescence characterization setup showing source, subject, detector, and analyzer

Natural gamma emissions from these elements are captured in a scintillator crystal, which produces a pulse of visible light whose intensity is proportional to the energy of the gamma radiation. These pulses are in turn detected by a photomultiplier and converted to electrical pulses whose current is proportional to the energy of the gamma ray, and the number of pulses is proportional to the concentration of the emitting element. This is called *pulse-height spectrum analysis* (Figure 14).

Induced Gamma Radiation

PGNAA, pulsed fast thermal neutron activation (PFTNA), and variants are types of analysis that activate neutrons to measure

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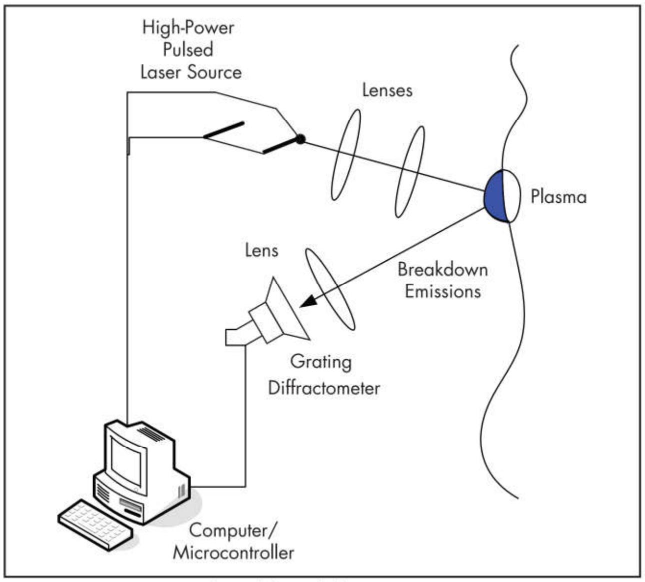


Figure 13 Laser-induced breakdown spectroscopy sensing system

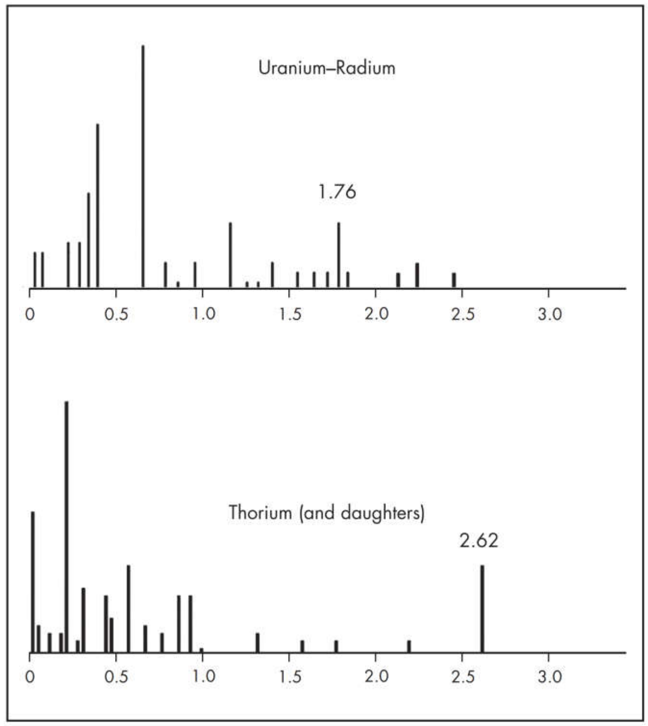
elemental composition. The material is bombarded with neutrons that create artificial radioisotopes that decay, emitting gamma rays characteristic of the element from which they are emitted; the intensity of gamma rays at a given wavelength are related to the elemental concentration. For PGNAA, the gamma rays are measured during irradiation (Figure 15). PFTNA is similar but uses high kinetic energy (fast) neutrons to measure gamma rays during irradiation. Both provide bulk chemical composition and require sensor response periods in the order of minutes, making the approaches unpractical for particle sorting but suitable for some bulk sorting applications when positioned over belts.

Electromagnetic Techniques

Many economic minerals of interest are metallic and therefore either conductive, magnetic, or paramagnetic. These properties can be measured using electromagnetic field devices, which is an established principle in mining exploration as well as sorting. In principle, passing a current through a coiled conductor generates an electromagnetic field. In any conductor, inductance (L) is a measurement of the distribution of the magnetic field. The magnitude and phase of the current is determined by the applied voltage and the coil's impedance (Z), which in turn controls the characteristics of the time-varying magnetic field. Impedance is a measure of two factors: resistance (R) to direct current and reactance (X), where j is the imaginary unit, and Ω, ω represent frequency. Reactance is the frequency-dependent opposition to alternating current and is determined by inductance.

$$Z = R + jX\,[\Omega]$$
$$X_L = j\,\omega\,L \qquad \textbf{(EQ 1)}$$

Time-varying magnetic fields in turn generate time-varying electric fields. Any object within close proximity to the coil encounters these time-varying fields. Conductive and magnetic minerals that are present distort the field and alter the coil's electrical properties proportional to the amount of material present (Figure 16). Conductive material influences the voltage of the current in the conductor (either positive or negative); magnetic material influences the phase of the current flowing in the conductor, again either positively or negatively. A comparator or other bridge circuit measures these changes; in simple systems, responses above a certain predetermined threshold indicate detection of conductive or magnetic material. In more complex systems, frequency-dependent effects can be monitored, enabling the capability to determine concentration of conductive or magnetic mineral as well.



Adapted from SPE 2015

Figure 14 Gamma ray spectral plots for uranium (1.76 MeV) and thorium (2.62 MeV)

ORE SORTABILITY

Ore sorting studies are aimed at determining ore sortability and providing design information for sorting systems. There are four components to evaluating the feasibility of sensor-based sorting: ore heterogeneity, sensor response evaluation, sorting analysis, and feasibility as presented in Figure 17. Ore heterogeneity is a fundamental property of mineral deposits and must be assessed independently of the sensor or sorting method to be used. Sensor response evaluation exposes minerals to sensors relevant to the application and confirms the ability of sensors to detect the property of the minerals in question and the quality of correlations between the sensor response and the property (typically ore grade). Sorting analysis considers—in combination—the levels of grade heterogeneity identified and the quality of sensor response to the grade in order to develop theoretical yield–grade–recovery relationships. Feasibility studies would consider the following: the commercial availability of a sorting product that can meet the requirements of the envisaged application, metallurgical performance of the envisaged sorting stage, downstream impacts on throughput and recovery, and capital and operating costs of the envisaged circuit.

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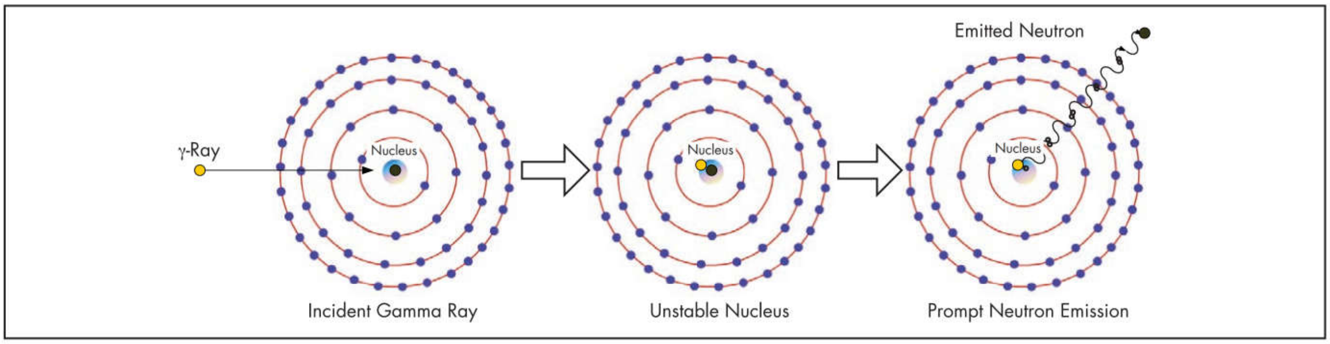
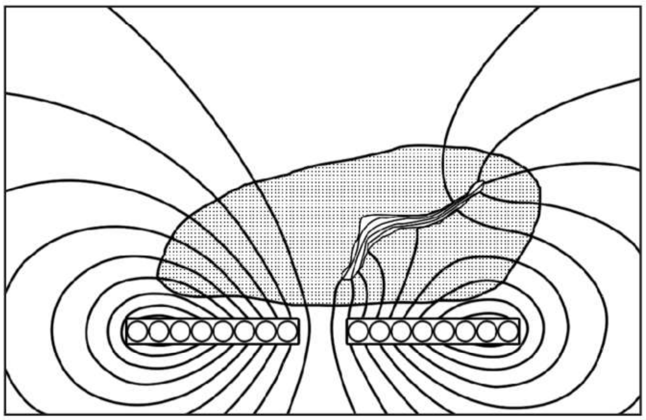


Figure 15 Basic principle of prompt gamma neutron activation analysis



Source: Bamber and Houlahan 2010

Figure 16 Sympathetic fields generated by low concentrations of conductive or magnetic minerals in rock

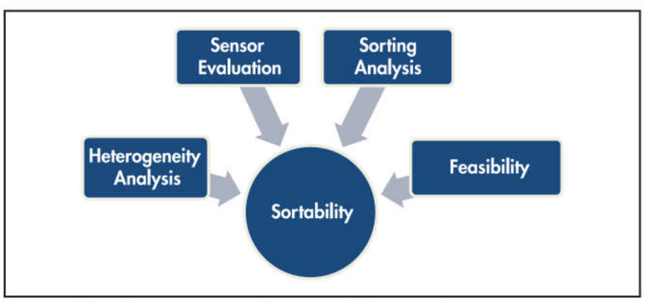


Figure 17 Components of a sortability study

Fundamental Indicators of Sortability in Ores

Ore bodies are complex, highly heterogeneous mixtures of different lithological units with varying mineralogical compositions. A key to successful sorting is knowledge of the lithology, mineralogy, and quantification of levels of heterogeneity as the basis for discrimination.

In mining systems, heterogeneity is generally expressed at the block modeling stage (e.g., 5 × 5-m scale) and is used to distinguish between ore and waste rock, as well as at the beneficiation stage at size ranges where mineral liberation occurs (e.g., 100-mm scale). Sorting is applied at length scales intermediate to these two extremes, and it is therefore important to understand how heterogeneity is expressed between these two size ranges (Figure 18).

Ore Body Lithology and Mineralogy

Much can be learned about heterogeneity and therefore the potential for sorting from knowledge of lithologies within the ore bodies and their mineralogy (Barbanson et al. 2009; Hitch et al. 2015). Preliminary assessment should include a review of reports that describe features of the ore body that would allow sorting (e.g., multiple adjacent lithologies with different metallurgical response). Descriptions of distinctive differences between ore and waste rock lithologies and related mineral associations can provide insights into heterogeneity as well as into physical and chemical characteristics that can be exploited as the basis for sensor discrimination.

Early-stage assessment can come from visual observations of rock or drill core. Providing that samples include a distribution of valuable and non-valuable constituents, a qualitative assessment of sortability is possible and can justify further testing.

When examining the drill core, features that are relevant to sorting are the size of mineralogical features and contacts between valuable and non-valuable constituents (Carrasco et al. 2016). Examination of the drill core, particularly for early-stage projects, reveals the potential for ore sorting (Bamber et al. 2006). Figure 19 shows sharp contacts between ore and waste. It also shows that sections of ore and waste have significant extents, which demonstrates heterogeneity over relatively large sections along the core (5–25 cm). Fragmentation should therefore produce particles that have significant differences in mineralogical and physical properties that are sufficiently heterogeneous to allow sorting.

Simple visual examination of core samples supports early-stage assessments of heterogeneity. For example, within a coarse fraction, such as 5–20 cm, the presence of alternating barren rock and mineralized rock allows conclusion that the rock may be sortable providing a sensor can detect the differences between them. In cases where heterogeneity is not visible, scanning with sensors is required to assess this heterogeneity and the potential for sorting.

Heterogeneity Analysis in Ores

The nature of the distribution of metal grades between individual rocks as well as within and between bulk samples provides an indication of sortability. A wide distribution of grade would suggest that there is potential to beneficially separate at a grade threshold. Conversely, a narrow distribution around a cutoff would indicate that sorting will be difficult. Two additional parameters indicate the potential benefit of sorting. Measures of the constitution heterogeneity (CH) indicate

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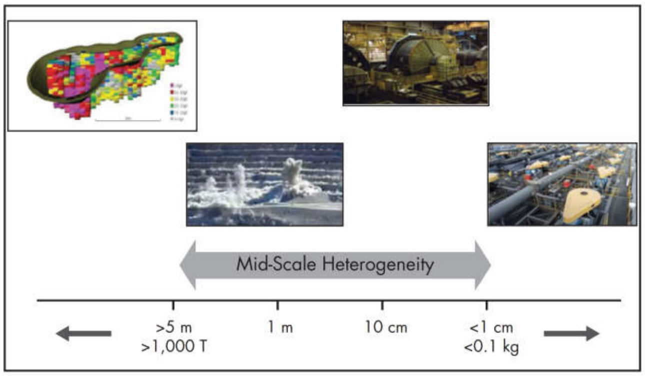

Figure 18 Schematic of mid-scale heterogeneity ranges

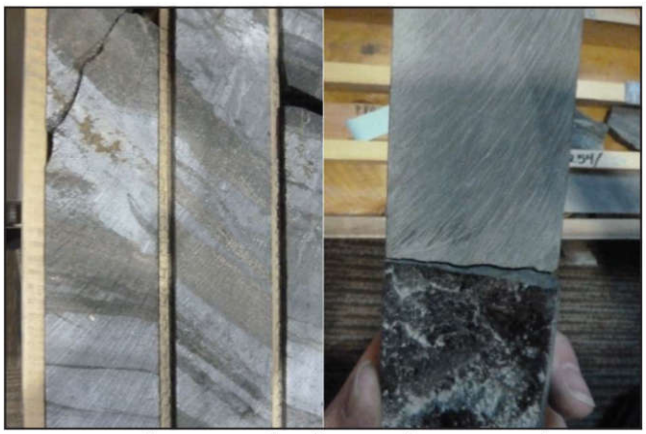

Figure 19 Drill-core samples showing sharp contact between lithological rock types and coarse heterogeneity

potential for rock sorting, and measures of the distribution heterogeneity (DH) indicate potential for bulk sorting.

CH characterizes grade variance of rocks such that a high CH implies the potential for rejecting a large portion of barren rock (or alternately recovering a meaningful proportion of valuable rock). DH (or spatial heterogeneity) indicates potential for bulk sorting in a similar mode. The grade and weights of units (rocks or bulk units) allows determination of the potential grade, mass yield, and recovery relationship.

Constitution Heterogeneity

CH was first introduced by Gy (1992) in his theory of sampling in order to define the uncertainty that is inherent in sampling, represented by the relative, dimensionless variance of the heterogeneities associated with each fragment F_i making up a lot of N_F fragments in a sample as shown in the following equation:

$$CH_L = N_F \Sigma_i \frac{(a_i - a_L)^2}{a_L^2} \cdot \frac{M_i^2}{M_L^2} \quad \text{(EQ 2)}$$

where CH_L is the constitution heterogeneity; α_i and α_L are the grades of the fragment i and the lot, respectively; and M_i and M_L are the masses of fragment i and the lot.

This definition can be easily extended to the heterogeneity of fragments or particles within a lot of particles within a stockpile, for example, or even fragments within the mineral deposit as a whole. By inputting values for the grade of individual particles in a sample and the average grade of the sample as a whole, CH can be calculated for any sample. The CH parameter has elevated relevance with respect to particle sorting applications. A high CH indicates the potential to reject or separate a greater proportion of the feed (Mazhary and Klein 2015).

The particle heterogeneity is most easily evaluated by measuring the grades of individual particles within a sample, and plotting the measured grades in two possible ways.

Weight Distribution by Grade

First, the frequency distribution within the grade range measured (i.e., the weight percent of the sample falling into specific grade ranges) can be evaluated from the data (Figure 20).

A general indicator of sortability can be evaluated graphically in the form of skewness of the distribution (mode ≠ mean). A normal distribution—0 skewness—indicates low sortability. Left skewness (mode < mean) suggests a high proportion of low-grade material in the sample, and therefore potential for rejection of these fractions. Potential for the recovery of small quantities of high-grade material is also suggested when viewing such a distribution. Right skewness (mode > mean) suggests a high proportion of high-grade material in the sample, and therefore potential for recovery of these fractions.

Of course, simpler indications of heterogeneity are available; for example, taking the quotient of the 90th percentile grade value and the 10th percentile grade value, where for g90/g10 > 20 (where g means grade value), good potential for sorting is indicated. The identification of any sensor-based method that can distinguish between the grades of various particles identified in such an evaluation supports application of sensors to the sorting of these materials.

Grade Distribution by Particle Size

Second, where the individual particles in the sample were first separated into size classes before assaying (i.e., size/assay), the distribution of grade by particle size can be evaluated (Figure 21).

Again, a general indicator of sortability can be evaluated graphically in the form of skewness of the distribution (mode ≠ mean) representing a preferential deportment of grade with respect to particle size. A uniform distribution indicates no preferential deportment. A normal distribution indicates preferential deportment to the middlings size class. Left skewness (mode < mean) suggests higher grades in the fine fractions of the sample, and therefore potential for recovery of this high-value material by size classification. Potential for the rejection of small quantities of low-grade coarse material is also suggested when viewing such a distribution. Conversely, right skewness (mode > mean) suggests higher grade in the coarse fractions of the sample, and therefore potential for the recovery of this high-value material by size classification.

Distribution Heterogeneity

DH is a measure of the heterogeneity of parameters associated between fragments or lots of fragments at different locations in the deposit (Equation 3). The definition can be easily extended to a sample within a set of samples, or one lithological or geometallurgical unit among the set of lithological units of interest (i.e., different ore zones within a deposit). Therefore, the DH parameter has elevated relevance to bulk

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sorting applications, although it can further inform applications in particle sorting as well.

$$DH = N_g * (\Sigma\,(a_i - a_L)^2 \times M_i^2) / (a_L^2 \times M_L^2) \quad \textbf{(EQ 3)}$$

where N_g is the number of groups; α_i and α_L are the grades of group i and lot, respectively; and M_i and M_L are the masses of group i and the lot.

Evaluation of DH is much simpler than for CH. When considering a set of units, such that a lot represents a set of units, Gy (1992) refers to the distribution heterogeneity (DH_L) that depends on three factors: (1) the constitution heterogeneity (CH_L), (2) the spatial distribution of the constituents, and (3) the shape of the lot. Lots can vary in scale, ranging from geological units, to blocks within a block model, to shovel loads, to flows along a conveyor. Initial indications can be found in the ore body model where characteristic *steps* in the grade–tonnage curve of the deposit may suggest significant zones of differential grade (or other characteristics), and therefore potential for classification of these zones by sorting into streams for custom processing (Figure 22).

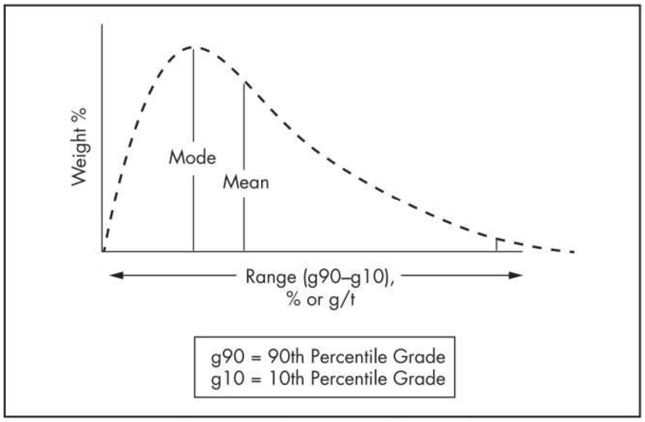

Figure 20 Typical weight distribution by grade

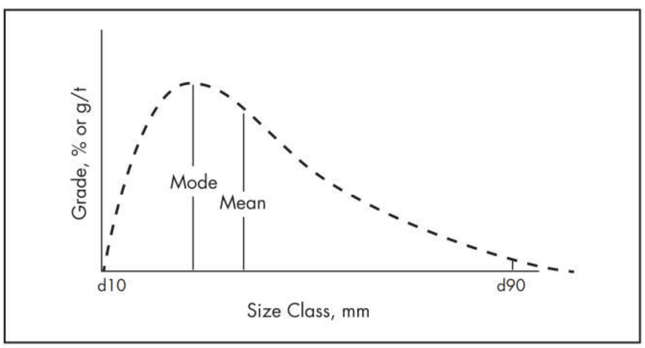

Figure 21 Distribution of grade by particle size

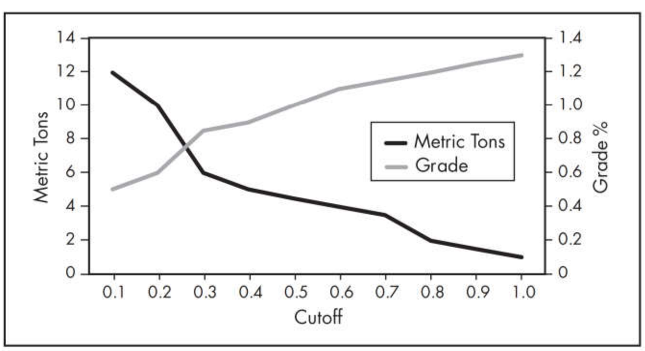

Figure 22 Grade–tonnage curve steps indicating zones of highly differential grade or other characteristics in the deposit

Evidence of DH may be much more elementary. For example, in conventional geological modeling, lithologies of different geological units are usually well defined. These lithologies can and do have widely varying ore and gangue mineralogy, and therefore grade, grindability, and other metallurgical characteristics (thus also making them geometallurgical units). In some cases, heterogeneity between these geometallurgical units can be slight, as in iron ores (Table 2), or distinct, as in highly weathered volcanogenic massive sulfides (VMSs) (Table 3).

Clearly, levels of heterogeneity between the various ore lithologies within the iron ore deposit and between the ore and waste lithologies in the deposit are low; however, separation based on sensor-based characterization may still be possible.

Levels of heterogeneity between the various ore lithologies within the VMS deposit, and between the ore and waste lithologies in particular are high; therefore separation potential based on sensor-based characterization is highly indicated (Bamber et al. 2007).

The identification of any sensor-based method that can distinguish between the various characteristics of such lithological units supports further evaluation of bulk sorting of these materials by the techniques described in the following sections.

Generally, the degree of heterogeneity will increase with the decreasing size of the unit, as shown in Figure 23. However, each ore body will exhibit a different heterogeneity versus unit size relationship, as indicated by the solid and dashed lines. The relationship between DH and unit size range can be estimated from drill-core assay. For example, DH can be calculated from the grades determined at 1-m intervals, 2-m intervals, 3-m intervals, and so on. This approach allows DH assessment from the drill core for early-stage projects.

DH generally decreases as a consequence of the mixing and blending that occurs in material handling (Duffy et al. 2015). Therefore, the greatest heterogeneity and opportunity

Table 2 Low levels of heterogeneity between units in an iron ore deposit

Sample Description	Fe, %	SiO_2, %		Al_2O_3, %	
	Minimum	Minimum	Maximum	Minimum	Maximum
High-grade upper channel iron deposit (CID)	52	0	5.5	0	2.5
Upper CID	52	5.5	11	0	2.5
High-grade detrital	53.5	0	8	0	3
Detrital waste	12	NA*	NA	NA	NA
Blendable upper CID	52	5.5	11	0	2.5
Middle CID	52	6.5	13	0	2
High-grade bedded	52	0	6	0	3

*NA = not applicable.

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for bulk sorting is close to the face. CH is affected by mixing, but to a lesser extent.

Test Programs

Three aspects must be considered when developing test programs. First, if amenability test work is preliminary, the tests should be as nondestructive as possible to preserve as much sample as possible for further testing, whether for more scanning or for downstream test work (e.g., grindability or flotation response).

Second, the choice of assay method is critical. Often, if samples are from an operation, the mine will suggest or recommend a specific or custom assay procedure. If working a greenfield project, or if no guidance is available, the assay lab should be consulted beforehand for recommendations as to the appropriate assay procedure for the ore type in question. Inductively coupled plasma (ICP) whole-rock methods are generally suitable for metal sulfides. Specific digestion methods, however, are recommended for Cu porphyries, and multielement X-ray fluorescence (ME-XRF) methods are recommended for oxides such as ferric oxide (Fe_2O_3) or Ni laterites.

Third, the criticality of developing good sensor–assay correlations must be considered. In rare cases, sensor correlations are simple linear functions with high correlation, therefore fewer assays are required to develop a fit. In this case, hand selection of 60–80 specimens from across the grade range (a visual assessment of mineralization may be required) is sufficient to develop the correlation. In most cases, correlations will be more complex requiring cubic functions or multivariate regression, and more assays will be required to develop a good fit. In equally rare cases, no sensor correlation may be apparent from the data, and CH must be judged solely from the underlying assay data. It is, therefore, possible that the entire 500-particle sample set must be assayed. In such cases, the testing is completely destructive, and any rescanning must be done on a separately procured sample.

Sampling and Sample Preparation

Effective sampling is key in assessing the amenability of ores to sorting. A quick referral to Gy (1992) or Pitard (1993) will reveal that representative sampling at the typical particle size distributions and metal grades in question suggests representative sample sizes in the hundreds of kilograms for high-grade fine samples and thousands of kilograms for low-grade coarse samples. As truly representative sampling is generally unfeasible in this domain, the aim of sampling and test work should be to obtain indicative results from as representative a sample as possible. While geometallurgical approaches can be adopted to include many smaller samples from across the deposit to maximize representivity, the individual samples obtained in this mode are by necessity small and therefore may not be optimal in the assessment of sorting parameters.

The fundamental considerations that are applied to sample selection for conventional metallurgical studies are relevant as presented in Chapter 1.8, "Sampling Practice and Considerations." However, considering the constraints of practical sample size and to ensure the capture of as many relevant features of interest as possible, custom, guided sampling is recommended. Sample bias also needs to be avoided. This can arise from three approaches to sampling:

Table 3 High levels of heterogeneity between units in a polymetallic VMS deposit

	Assay			
Unit	Au, g/t	Ag, g/t	Pb, %	Zn, %
Waste	<1	<50	<3	<2
Oxide	6	200	3	2.5
Inner Peñasco breccia	30	500	4	7
Azul breccia	4	300	3.5	7
Sediments	15	500	4	10

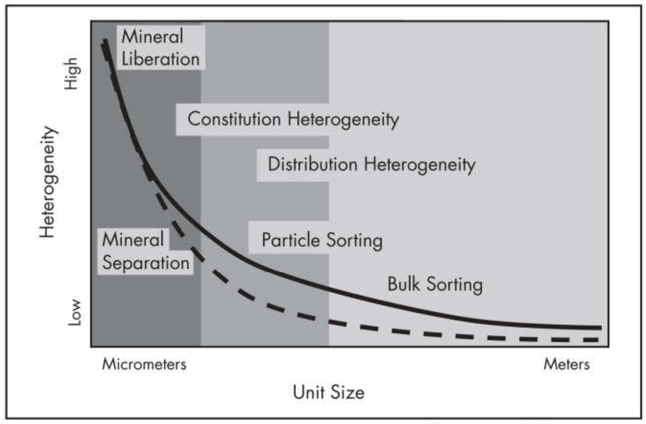

Figure 23 Heterogeneity versus unit size for two different ores represented by solid and dashed lines

1. Preferential exclusion of fines in sampling (fines can be high grade)
2. Preferential exclusion of oversize particles in sampling (oversize particles are difficult to handle)
3. Preferential samplers to prejudge "good" material (bias toward high grade) or "waste" material (bias toward low grade)

Following are three suggested sampling approaches, which are relevant to new (exploration) projects and to surface and underground operations, respectively.

Exploration projects. Where sorting is being evaluated for a new project, and often in underground projects, core samples are the only source of material for testing. In this case, it is not only essential to ensure that samples of every relevant ore type plus waste are sampled but also that a full intersection of ore (i.e., an intersection containing hanging wall, ore zone, and footwall material) is taken. Half-core is generally available and optimal for testing. Quarter-core tends to be too fine at the outset and also tends to break up further during scanning, which is suboptimal. Often, samples provided by geologists or metallurgists for sorting test work are *too good* in that they are too high grade and do not contain relevant quantities of gangue material. Also, diluting *rich* samples with waste will not give meaningful results compared to testing *virgin* samples of similar grade.

Open pit mines. Sampling for sorting test work in open pits is most easily achieved by taking samples directly from the bench or benches in question. Ideally, at least one sample per ore type plus one sample of waste (either overburden or basement material) is recommended. Samples should be full

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Source: Bamber 2008

Figure 24 Classification of samples into size fractions for testing

fraction: To be useful, they should contain the largest feasible particle size as well as a representative measure of fines. In open pits, large run-of-mine (ROM) particle size distributions often prohibit the practical collection of samples, and therefore coarse crushing of samples is often necessary. Optimal samples are taken in either 1- or 2-t bulk bags or if absolutely necessary, 210-L drums (approximately 300 kg each). Belt cuts from overland conveyors post in-pit crushing or from the semiautogenous grinding (SAG) mill feed are admissible. Because this type of sample often cannot be traced back to any particular block in the ore-body model, it must be taken under advisement.

Underground mines. Sampling in underground mines is ideally done by sample collection directly from the blasted muck pile in the stopes. Again, one sample per major ore type, plus a sample of waste material as a control, is recommended. Samples can be taken as subsamples of the contents of scoop buckets or manually by hand shovel from the muck pile. Care should be taken to capture both coarse and fine fractions of the sample to ensure maximum representivity and avoid bias as previously described. In the underground context, samples from ore passes and waste passes are also considered valid, as are belt cuts from underground conveyors where the content of the belt can be traced back to a particular heading or section.

Sample Preparation

Samples are ideally weighed and either wet or dry screened into at least three size fractions (+75 mm, –75+25 mm, and –25 mm) although more fractions can be contemplated. Figure 24 shows multiple size fractions: +125 mm, –125+75 mm, –75+53 mm, –53+38 mm, –38+25 mm, –25+13 mm, –13+9 mm, –9+6 mm, –6+3 mm, –3 mm. To deliver clean, fines-free particles for scanning test work, wet screening is preferred; however, dry screening may be used to more closely simulate the condition of particles in a field situation.

Classification into particular size fractions in this way supports assessment of any characteristics of preferential grade deportment by size. Characterization classification of material also supports complementary characterization, such as assessment of the liberation index at the various particle sizes and observation of preferential breakage (i.e., breakage along grain boundaries or contact lines), which might influence presentation of the valuable minerals to the sensor.

Sensor response evaluation. Samples scanning is done to achieve two objectives: (1) to measure the true heterogeneity of the particles in a sample and (2) to generate data for the correlation of sensor responses to the grade of mineralization in the sample. An additional objective that can be achieved in scanning is to screen into an appropriate number of size classes a priori as previously described, and scan each size class separately. To select a method for scanning, Table 1 should be consulted with consideration of the property of interest.

Rocks (or batches of rocks representing a particular lithology) prepared for analysis are then scanned by the selected sensor. Sensor responses are recorded for individual rocks or the batch sample to determine the sensor response distribution with respect to the heterogeneous property. Sensor response distribution is then correlated to the property described by independent assay of the property (i.e., grade). The results indicate the potential for a specific sensor to classify rock according to value. For example, a narrow sensor response distribution close to a threshold grade along with a low CH indicates a low potential for the sensor to classify the material. Conversely, the opposite would indicate a high potential for sensor classification. Similarly, evaluation of sensor response for bulk samples with consideration of the DH parameter would show the potential of the sensor in a bulk sorting application.

Experimental programs are carried out to determine which sensors are capable of sensing ore and waste qualities within each lithological unit in an ore body. Table 1 lists sensors that could be considered as part of an evaluation of sensor-based sorting. Once the sensor responses are mapped against individual rock types, a sorting strategy and system that applies to selected sensors can be investigated and developed further.

Often, scanning using multiple types of sensors simultaneously (e.g., electromagnetic, photometric, and XRF) is recommended, depending on the expected range of properties that may be exploited. In scanning for characterization purposes, all particles in a given size class should be scanned multiple times. At least four scans per particle (one scan per *face*) is recommended, typically turning the particle 90° between each scan. A greater number of scans per particle is possible, even advisable, in the case of coarse particles (e.g., >125 mm).

Fines <25 mm (in the case of ROM samples) and <13.8 mm (in the case of primary crusher underflow) would generally not be scanned, as these are considered too fine, practically, for particle sorting at scale. For low-tonnage and fine-particle applications, evaluation can be done at these particle sizes if desired. When scanning core, each core piece should be scanned as a single sample; multiple scans (four or six) would again be required for core pieces >100-mm long. Core pieces <25-mm long would generally be considered fines and not scanned. If the sample particle size distribution is relatively fine, a practical limit of 500 particles scanned per size class is suggested. Scan data from the various modes of sensor for each size class should be logged together with a sample number and, ideally, the sample mass in a database for later retrieval and analysis (Table 4).

Sorting analysis requires the assessment of the grade and metal distribution in the unit (e.g., by CH and DH metrics previously described) and the development of algorithms that correlate generated sensor responses to variations in grade. Correlations are demonstrated using sensor calibration curves that relate the grades of rocks as determined by whole-rock assay to sensor-predicted responses. Figure 25 shows an example plot

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Table 4 Typical data from a sensor amenability test program

Sample No.	Date	Weight	Peak 1	Peak 2	Peak 3	Peak 4	Fe	Cu	Pb	Zn
1	2015-11-24	191	270	20	1,650	20	27.0	2.0	16.5	<1
2	2015-11-25	100	300	30	3,900	20	30.0	3.0	39.0	<1
3	2015-11-26	78	100	40	1,599	20	10.0	4.0	16.0	<1
4	2015-11-27	140	120	10	1,299	20	12.0	1.0	13.0	<1
5	2015-11-28	200	400	30	699	20	40.0	3.0	7.0	<1
6	2015-11-29	156	500	20	679	20	50.0	2.0	6.8	<1
7	2015-11-30	130	270	30	400	20	27.0	3.0	4.0	<1
8	2015-12-01	99	300	40	399	20	30.0	4.0	4.0	<1
9	2015-12-02	238	100	10	700	20	10.0	1.0	7.0	<1
10	2015-12-03	340	120	30	200	20	12.0	3.0	2.0	<1
11	2015-12-04	67	400	20	345	20	40.0	2.0	3.5	<1
12	2015-12-05	180	500	30	899	20	50.0	3.0	9.0	<1
13	2015-12-06	200	300	40	1,237	20	30.0	4.0	12.4	<1

of assayed grades for Pb and Zn against XRF sensor responses for those elements showing good correlation (Tong et al. 2015). It can be concluded from the high correlation that this lead-zinc ore is amenable to sorting by XRF. Correlations may be simple $y = mx + c$ relationships; more complex quadratic or cubic functions; or may require more sophisticated methods, such as multivariate regression analysis to generate a usable correlation. Calibrated sensor responses thus developed can then be used to develop grade, mass yield, and metal recovery relationships discussed in more detail in the following section.

Sortability Analysis

The ability to sort materials is based on the ability to correlate elemental/metal grades to sensor responses with consideration of mineralogical properties of the ore and waste. Most commonly, a single sensor response is correlated to a metal grade. Correlations can be improved by application of several approaches, including

- Combining sensor responses to improve accuracy,
- Analyzing proxies for target metals or minerals (multivariable regression),
- Assessing heterogeneity of gangue phases for rock rejection (e.g., detecting the waste for rejection),
- Applying piece-wise regression to focus models to selected grade ranges, and
- Assessing rock size heterogeneity to determine optimum size ranges for sorting.

Test data from sensor studies are used to evaluate each of the approaches to determine potential metal recoveries, product grades, and mass rejections for a range of thresholds. The results can also be used to test the developed algorithms to indicate separation efficiency by determining the proportion of potentially misplaced rocks or bulk material. Algorithms that can be correlated to mineralogical, physical, or geochemical properties are considered more robust than those that are completely empirical. The assay data are required to provide a calibrating data set against which to correlate the average scan result for each particle to first determine the heterogeneity and second, the degree of correlation between sensor response and the elemental (or mineralogical) composition of the sample.

Heterogeneity and Frequency Distributions

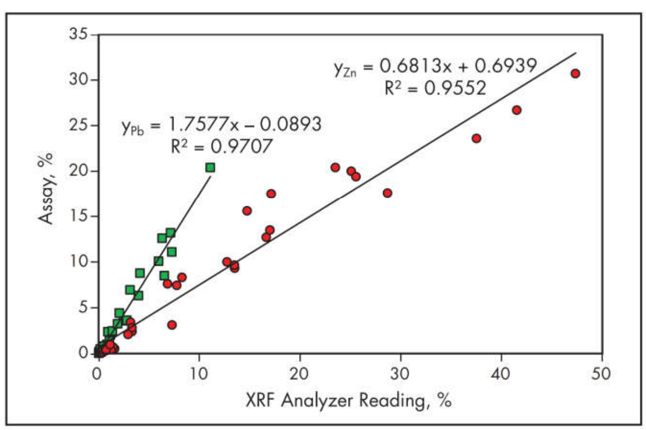
From either the full sample assay data or from calibrated scan data for the sample, a grade distribution can be developed by taking the frequency of occurrence of either grades (in the case of assay data) or magnitudes of sensor response (in the case of scan data) within *bins* of grade or magnitude of response and plotting their relative frequency. Factoring the frequency of occurrence by the mass of particles falling within each bin will give the distribution of sample weight percent in each grade or response interval (Figure 26).

From such results, CH can be calculated using Equation 2. For multiple results across several ore types from the same deposit, DH or spatial heterogeneity (Equation 3) can also be calculated.

Size–Grade Distribution

The size-by-grade distribution can be used to identify the potential for size classification as a means of sorting. The relationship between particle size–grade and metal distribution supports targeting of size classes for sensor-based sorting. Size analysis and assays are shown in Table 5 and are plotted in Figures 27 and 28.

The data clearly suggest that the –75+53-mm and –53+37.5-mm fractions are preferentially carrying the Pb and Zn value. The benefit of recovering by size classification should then be investigated further.



Source: Tong et al. 2015

Figure 25 Correlations between X-ray fluorescence analyzer reading and particle assay

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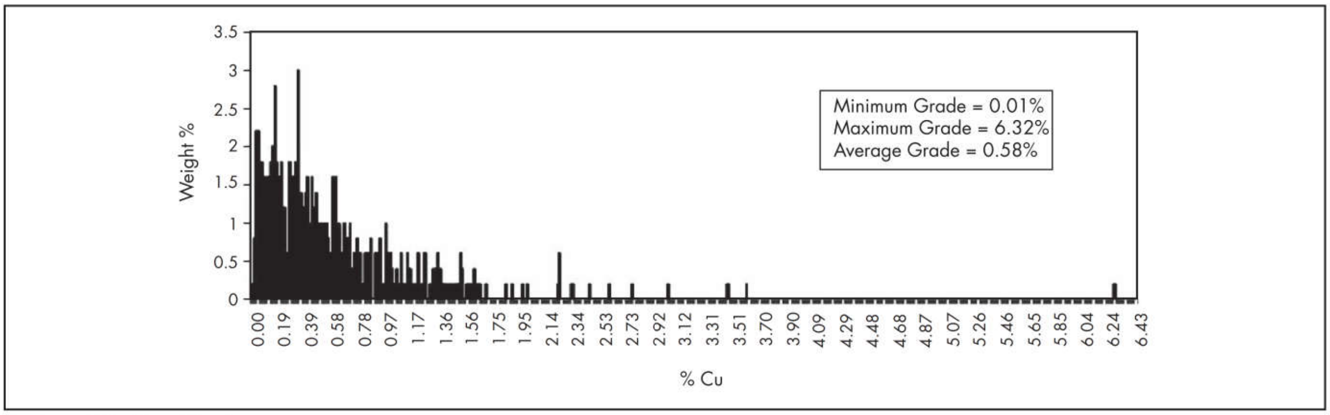

Courtesy of Preetham Nayak

Figure 26 Frequency (wt %) distribution by grade interval in a Cu-porphyry sample

Table 5 Head sample size analysis and assays

Size Fraction, mm	Size Fraction, in.	Weight Distribution, %	Cumulative Weight, % Retained	Cumulative Weight, % Passing	Grade, % Pb	Grade, % Zn	Distribution, % Pb	Distribution, % Zn
+75	+3	24.5	24.5	75.5	2.84	5.58	16.9	14.2
–75+53	–3+2.12	44.9	69.3	30.7	4.66	11.80	50.9	55.1
–53+37.5	–2.12+1.5	14.2	83.6	16.4	5.85	9.97	20.2	14.7
–37.5+26.5	–1.5+1.06	6.3	89.9	10.1	3.65	9.52	5.6	6.3
–26.5+19	–1.06+0.75	2.1	92.0	8.0	1.49	12.80	0.8	2.8
–19+13.2	–0.75+0.5	2.0	94.0	6.0	2.23	7.78	1.1	1.6
–13.2	–0.5	6.0	100.0	0.0	3.10	8.61	4.5	5.3
Total		**100.0**			**4.11**	**9.63**	**100.0**	**100.0**

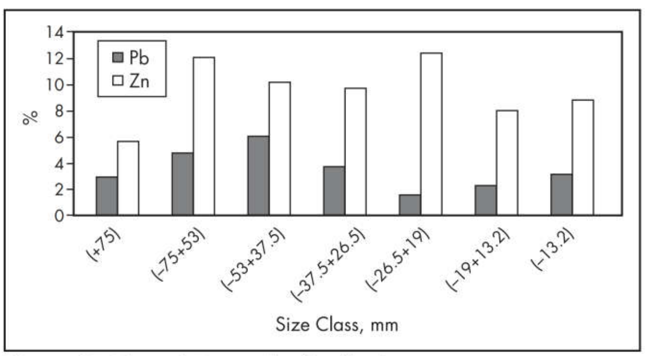

Figure 27 Pb and Zn grade distributions

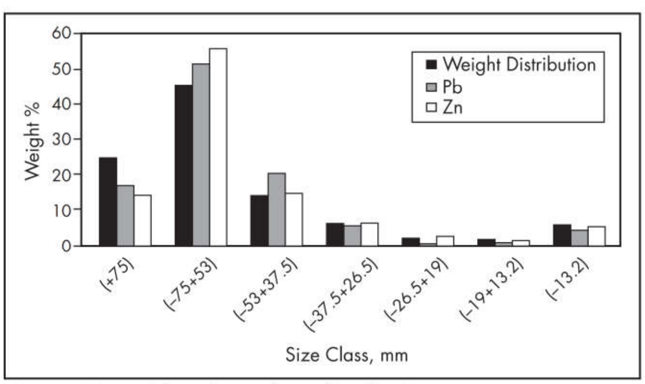

Figure 28 Weight, Pb, and Zn distributions

Grade–Recovery Curves

Theoretical grade–recovery curves for the sorting of the tested sample can be generated from the frequency distribution data. Selective exclusion of the sample mass mathematically by grade, from low to high (or high to low) will generate a theoretical grade–recovery curve for the separation of the sample. Grade–recovery curves can be generated for the ideal case based on the geochemical assay data set, or as derived from calibrated sensor responses.

Relative amenability to sorting can be assessed by examining the yield–grade–recovery characteristics indicated by the curve in question (Figures 29 and 30).

As can be seen, the ideal grade–recovery for the sample with highest CH value is the best; however, even for CH = 4, grade–recovery response may, subject to economic factors, still result in a beneficial outcome in sorting.

Finally, comparison of the ideal grade–recovery relationship as determined by heterogeneity of the sample to the grade–recovery relationship as determined by the sensor method will give an indication of expected performance of the selected sensor in classifying the material according to grade. Figure 31 shows the grade–recovery relationship for Cu, using XRF. It is based on regression models of Cu, Fe, As, and Mo peaks, where Cali-CuFe is calibrated to XRF Cu and Fe, and Cali-CuFeAsMo is calibrated to XRF Cu, Fe, As, and Mo. The figure shows that the regression model based on Cu and Fe alone does not fit the ideal as well as the model based on Cu, Fe, As, and Mo. These elements likely occur in minerals associated with the Cu mineralization.

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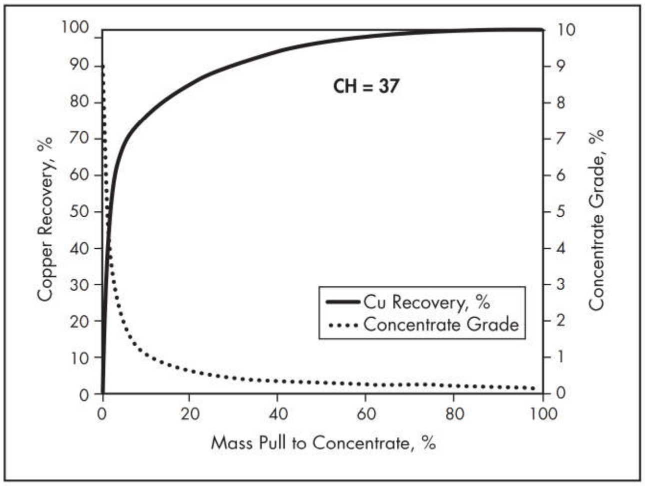

Figure 29 Grade–recovery curve, CH = 37

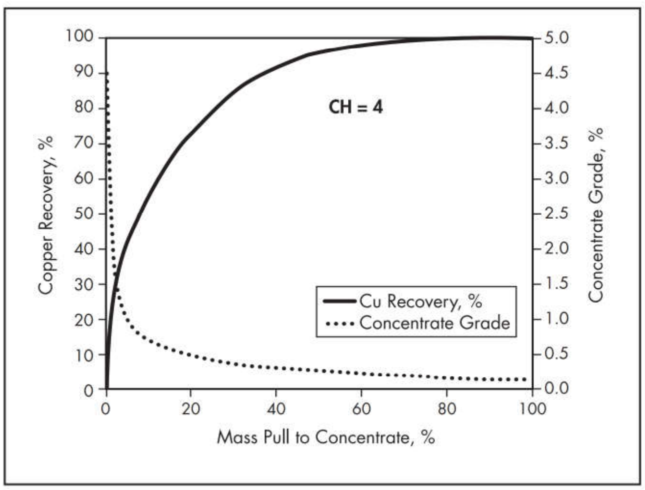

Figure 30 Grade–recovery relationship, CH = 4

SELECTION DATA FOR SORTING SYSTEMS AND CONSIDERATIONS FOR CIRCUIT DESIGN

Selection of an appropriate sorting system is governed by several factors (Klein et al. 2003, 2010). Mineral type, mine type, and application location are primary factors. Mineral type governs both heterogeneity parameters as well as the type of sensor to be deployed. Mine type largely governs the expected feed particle size distribution and capacity required of the circuit. Application location (e.g., in-pit or underground, pre-mill or within the SAG circuit) similarly governs the expected feed particle size distribution and capacity required of the circuit, as well as placing constraints on the type of sorting system (bulk or batch, semi-bulk or particle) that can be deployed. A final consideration is the optimal or desired yield–grade–recovery of the circuit, where the selectivity of bulk or batch systems, for example, may not allow grade or yield requirements to be met. Alternately, particle sorting systems may not meet capacity (or capacity and cost) requirements. Yield–grade–recovery requirements will also govern the selection and number of stages where delivering a final sorting product

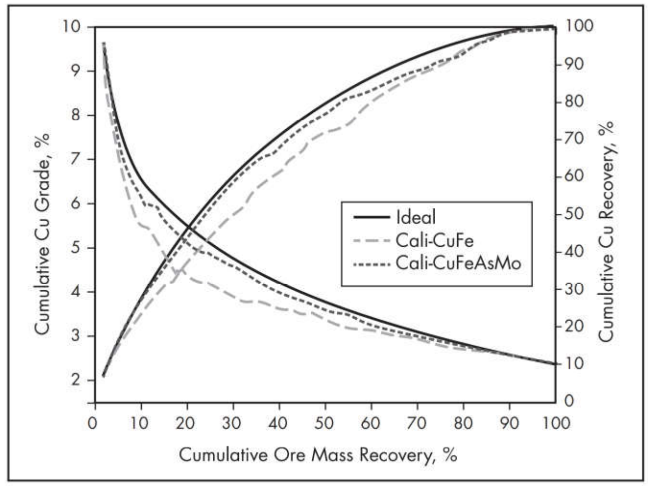

Figure 31 Grade–recovery relationship for Cu by assay and Cu grades estimates

in a single stage of sorting, for example, may not be possible, or meeting capacity requirements with a single unit may not be possible, and multiple lines and stages of sorting may need to be considered. Table 6 presents a range of sorting system options and their relevant capacity and selectivity parameters. A range of selection criteria unique to bulk, semi-bulk, and particle belt/chute sorting systems also pertain. For particle sorting, the belt width, belt speed, and particle size distribution range are primary considerations that affect capacity (Table 7). Other parameters that affect capacity are specific gravity and the amount of material ejected.

Example Circuits

Figures 32 through 35 present typical bulk and particle sorting circuit designs. For bulk shovel and truck systems, in-pit or underground locations are typical. For bulk belt systems, locations can be in-pit (crush/convey) or pre-mill. For particle systems, locations are typically pre-mill or possibly applied to treat the pebble stream of the SAG mill circuit. Alternate deployments of both bulk and particle systems can be on the waste dumps of active or inactive mines.

Indicative Particle Sorting Parameters

Particle sorting is generally used for waste rejection ahead of the mill. Mass yield to concentrate can vary from 40% to 80% (20%–60% waste rejection). Recovery to concentrate can vary from 60% for high weight percent rejected, to 99% for low weight percent rejected, or in the case of waste rejection from unusually well-liberated ores. Table 8 presents a range of achievable particle sorting results based on the literature. The reader is reminded that as sortability is more a function of ore characteristics than machine characteristics, results presented here should be viewed not as representative of the particular technology described, but of the ore treated.

Indicative Bulk Sorting Parameters

Bulk sorting is typically applied further upstream than particle sorting, often as a pretreatment step ahead of other sorting stages, or ahead of flotation or leach processes. Selectivity in bulk sorting is inherently lower, therefore is typically applied

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in either cleaner (removing residual waste from ore material) or scavenger (recovering residual ore from waste material) applications. Mass yield to concentrate typically varies from 85% to 95% (5%–15% waste rejection), although higher rejection rates are possible when entire lithologies must be rejected to waste. It is important to keep in mind that the main value of bulk sorting, particularly shovel-based systems, lies in the ability to recover ore that would otherwise have been left in situ or lost to the waste dump. Recovery rates for ore in waste can be similarly 5%–15%, where ideally, the rate of ore recovery is used to balance the rate of waste rejection to optimize grade and throughput of feed to the mill (or leach). Parameters for bulk sorting often match parameters used in grade control and material routing, as this type of solution is most often deployed in support of those processes at a mine. Two examples of bulk sorting are given in Tables 9 and 10.

Available sorting options are generally traded off against the option of not sorting at all, although several other trade-offs can be considered. In situations where particle sorting is being considered, this option often competes with other coarse gangue-rejection technologies, such as jigging or dense media separation, which can be used in a similar duty with similar effects, or against more selective mining methods where these are possible. A key trade-off is the decision between particle sorting (with higher selectivity and yield–recovery parameters but limited capacity and higher unit capital expenditure [CAPEX] to operational expenditure [OPEX] ratio) and bulk sorting (with lower selectivity and yield–recovery parameters

Table 6 Sorting system selection criteria

Type	Particle Size Distribution Range	Lot Size Range, kg	Capacity, t/h
Fine-particle sorting	4–10 and 10–20 mm	0–0.05	0–40
Coarse-particle sorting	20–80 and 80–300 mm	0.05–6	20–300
Semi-bulk belt sorting	0–300 mm	10–100	100–1,500
Bulk belt sorting	0–600 mm	100–10,000	500–10,000
Bulk sorting shovel	Run-of-mine	10,000–50,000	500–10,000
Bulk sorting truck	Run-of-mine	100,000–300,000	500–10,000

Table 7 Particle sorting system typical selection criteria

Type	Belt Width, mm	Belt Speed, m/s	Particle Size Distribution Range, mm	Capacity, t/h
Ultrafine	600	2.8	0–4	0–10
Fine	600–1,000	2.8–6	4–20	10–60
Standard	1,000–2,000	2.8–6	10–200	20–150
Coarse	2,000–3,000	2.8–6	20–300	40–300

Courtesy of Lütke von Ketelhodt

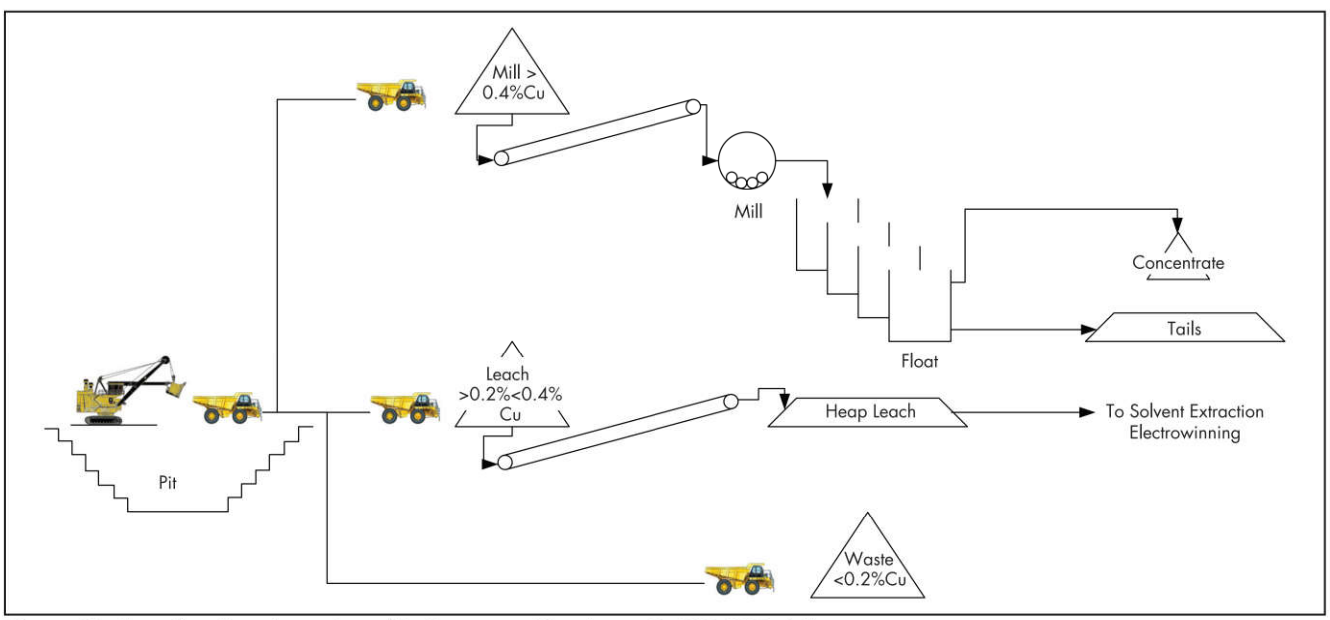

Figure 32 Shovel and truck sorting of bulk commodities (e.g., Cu 100,000 t/d)

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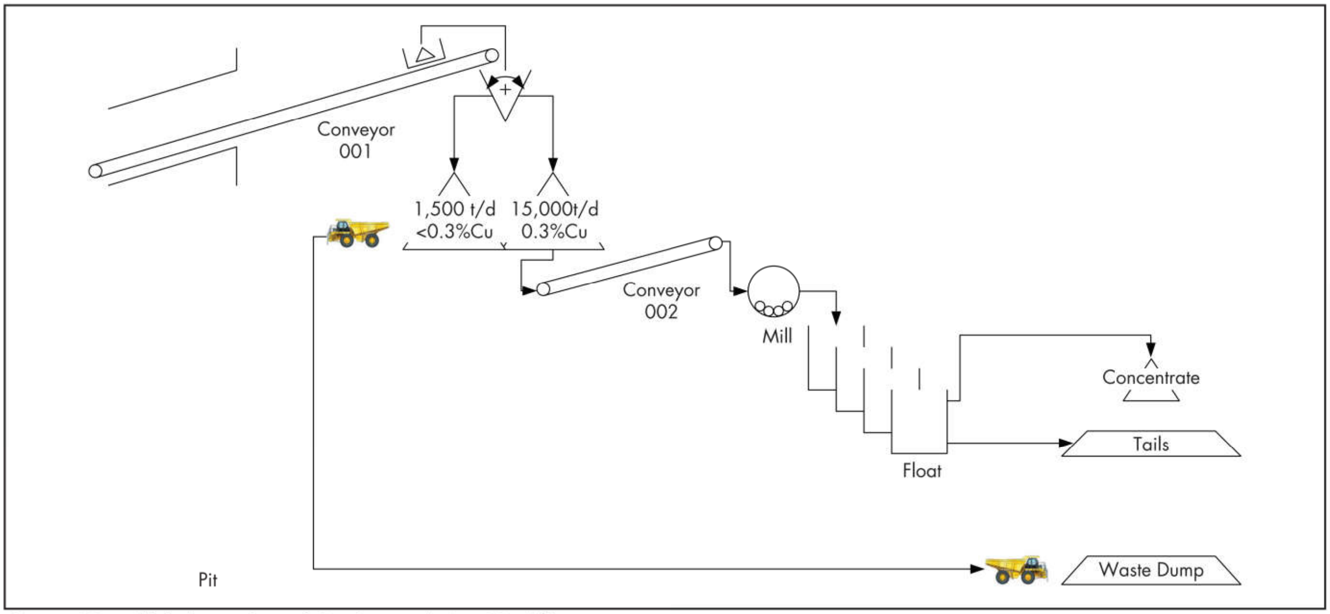

Figure 33 Bulk belt sorting of Cu-Au ore (16,500 t/d)

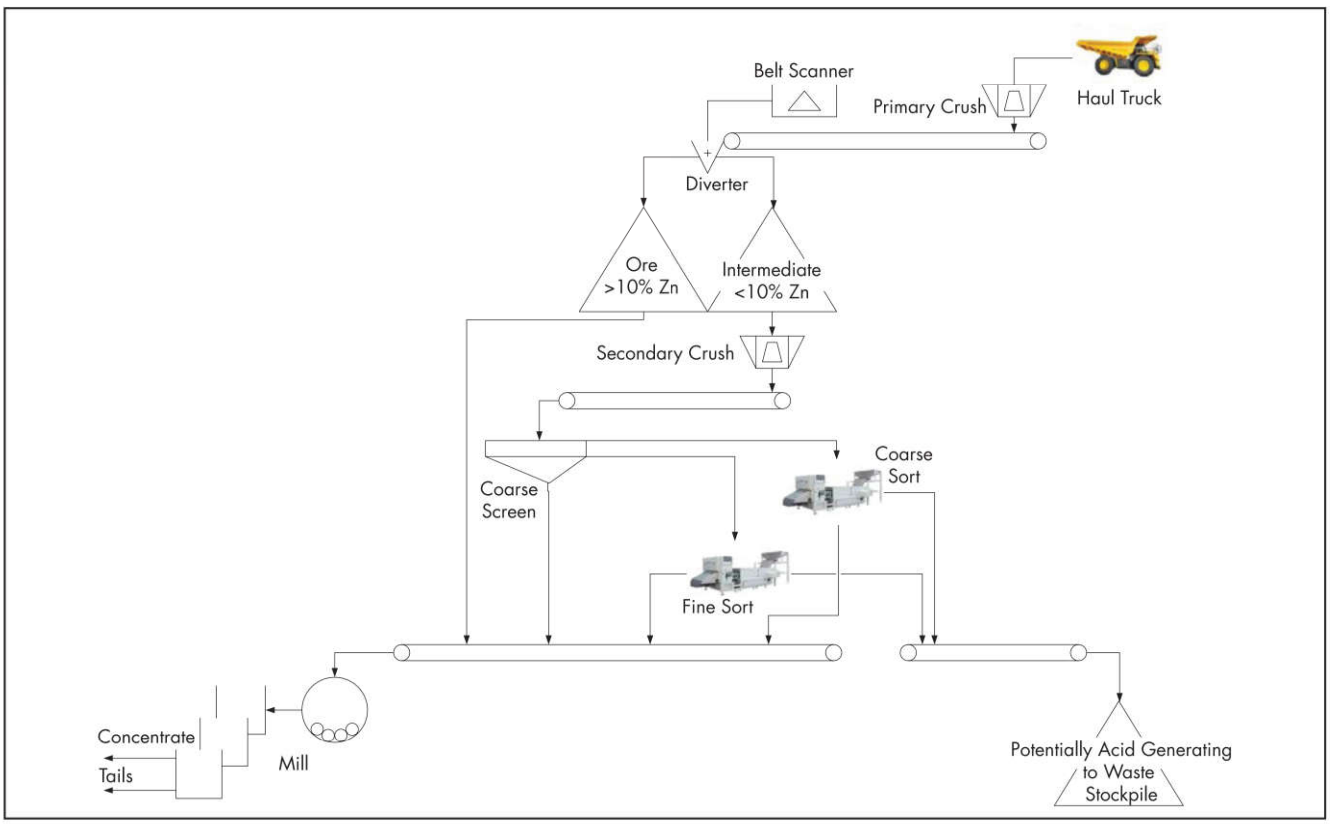

Figure 34 Combination of bulk and particle sorting of Pb-Zn ore (10,000 t/d)

but order of magnitude higher capacity and lower CAPEX to OPEX). In high-capacity (~10,000 t/h) situations, bulk sorting is often the only option. Then, where contemplated, bulk sorting is often traded off against basic capital expansion (pit pushback or plant expansion) options, and commonly against more intensive or sophisticated grade control and material routing strategies. Options are generally constrained by the fundamental degree of heterogeneity in the ore body, the length scale at which this occurs, and the capacity required of the ore recovery or waste rejection solution.

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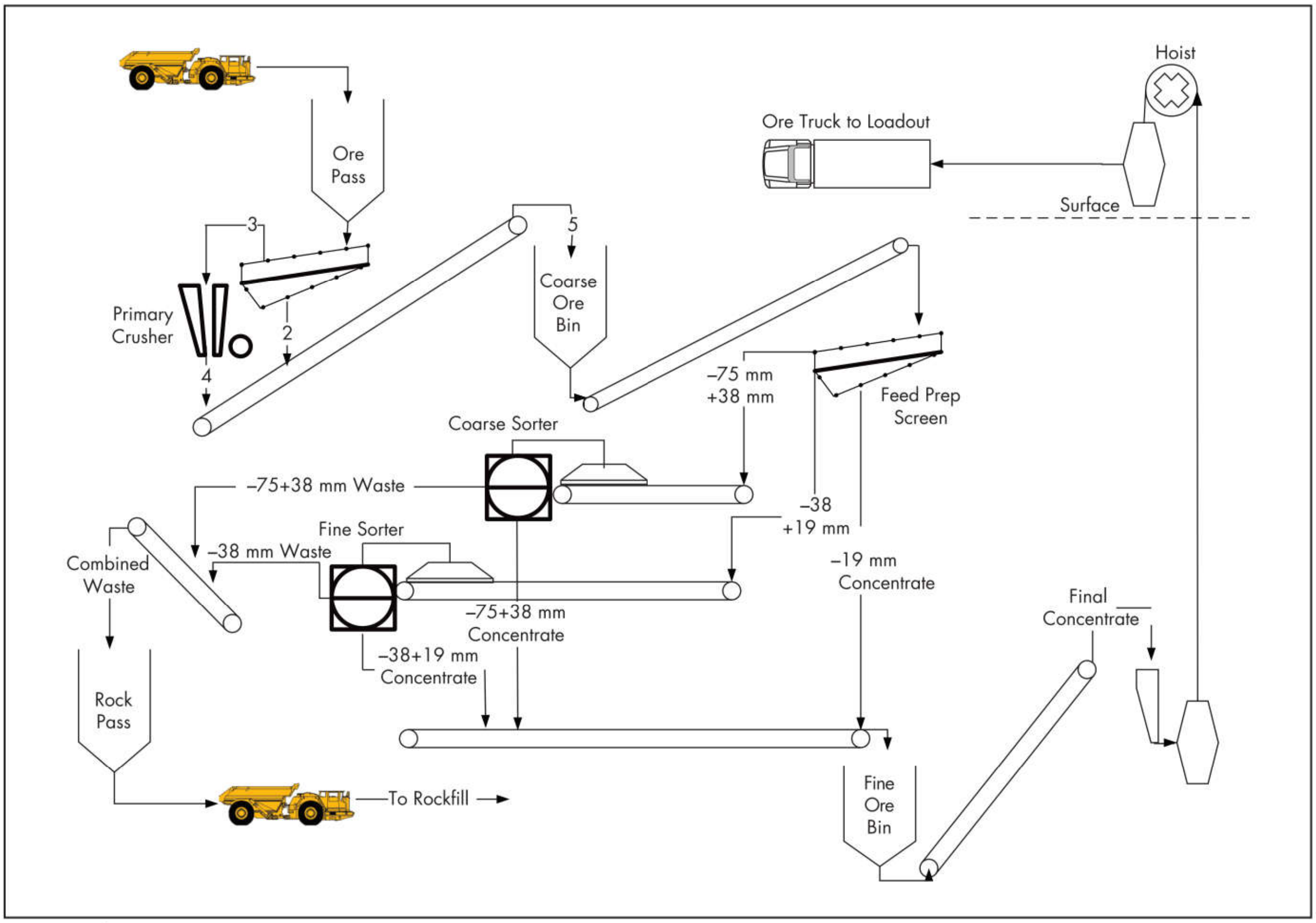

Source: Bamber 2004

Figure 35 Combination design including size classification, coarse and fine-particle sorting for an underground Ni mine (3,000 t/d)

Table 8 Selected published sorting results

Preconcentration Method	Ore Type	Feed Size, mm	Reject, wt %	Metal Recovery	Reference
Model 19 optical	Pb-Zn	150	26.3	94	Collins and Bonney 1995
Model 6 radiometric	U_3O_8	150	39	96.5	
Magnetic	Ni	100	40	96.7	
Radiometric	Au-U_3O_8	50	50	98	Sivamohan and Forrsberg 1991
Conductivity	Ni-Cu	25	80	80	
Conductivity	Ni-Cu	100	60	90	
Conductivity	Ni-Cu	70	27.83	82	
Model 16 optical	Cu	100	32.7	96	
Screening	Cu	100	20	99	
Optical	Au	100	44.8	94.8	Wilkinson 1985
Conductivity sorting	Au	100	54	80.5	
Optical plus conductivity	Au	100	50.2	97.8	
Radiometric	Wits Au	250	44.1	87.9	Kowalcyk 2011
Radiometric	Wits Au	250	29.5	92.6	
Comminution/screening	Cu-Platinum group elements	75	37	99	Bamber 2008
Comminution/screening	Cu porphyry	31.75	54.37	75.75	Burns and Grimes 1986

Adapted from Bamber 2008

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Table 9 In-pit ore recovery/waste rejection at a large-scale open pit Cu mine

	Mill	Leach	Waste
Base Case			
Yield, t	95,000	63,000	160,000
Grade, %Cu	0.48	0.35	0.19
Bulk Sorting Products			
Yield, t	23,750	0	25,600
Grade, %Cu	0.22	0	0.55
Combined			
Yield, t	96,850	63,000	158,150
Grade, %Cu	0.56	0.35	0.14

Capital Costs, Operating Costs, and Economic Analysis

In cases where good sorting potential exists, sorting, whether by particle or in bulk, is generally more attractive from a capital cost point of view than competing alternatives. Bulk sorting, whether shovel, truck, or belt, is attractive from an operating cost perspective. Minimal capital investments are required, particularly for instrumenting existing mobile equipment, such as shovels and trucks, making these options attractive from a cost point of view versus alternatives delivering similar value. Nield (2002) reports four truck scanners generating a value of between US$120,000 and $160,000 per month with payback "in months." For belt installations, CAPEX on new conveyors may be required, however, these are again relatively low capacity per cost compared to alternatives and therefore quite feasible. Based on several case studies, typical payback on belt applications, where feasible, varies between three and six months (Kurth 2015; Hilscher 2016).

Selection of particle sorting, however, does incur capacity and cost issues, as applications are inherently limited to low throughputs and where scaling this option to higher throughput requires increasing numbers of machines and therefore circuit complexity, which must be taken into account (Arvidson 2002; McCarthy 2014). For particle sorting installations, pretreatment as well as product handling circuits are required, which can significantly add to the overall capital cost.

Particle sorting also embodies higher operating costs than bulk sorting. This is particularly true in the case of larger models of conventional sorters deploying compressed air pulses as the method of particle diversion. While the sorter itself may be operated at relatively low cost, compressed air generation significantly adds to the capital and operating cost of the circuit. Despite this, particle sorting does find application in lower throughput, higher value situations.

Indicative capacities for typical particle sorting installations, together with indicative capital and operating costs are presented in Table 11. Figure 36 presents some order-of-magnitude operating cost guidelines for particle sorting circuits to further aid in selection.

Barton and Peverett (1980) quote US$1,450,130 initial cost and US$0.28/t operating for a 90-t/h ore sorter model 19 installation at Driefontein gold mine in South Africa. More recently, Rule et al. (2015) reported overall capital costs of US$5 million for a 30-t/h pilot XRF installation, and up to US$100 million capital overall for a 1,000-t/h production facility. Operating costs at 1,000 t/h were estimated at between US$0.20/t and $0.30/t. Nevertheless, even with higher unit capital and unit operating cost requirements, typical reported payback for particle sorting projects, where ore is amenable, vary from one to two years (Hilscher 2016).

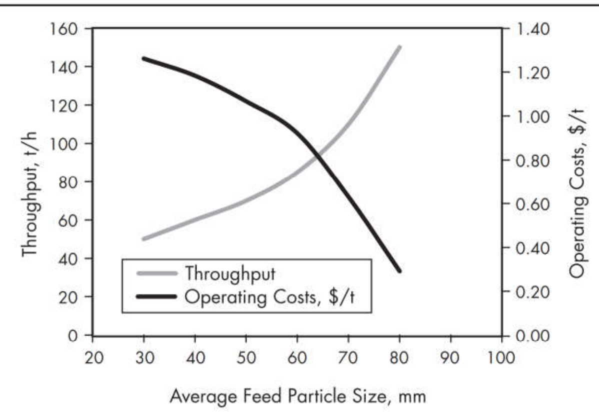
Table 10 Ore recovery from Ni-Cu mine waste dump

Distribution/ Grade	Feed, %	Product, %	Tails, %
Weight %	100	33	68
Ni Grade %	0.67	1.57	0.28
Ni Weight %	100	76	24
Fe Grade %	16.55	18.39	9.04
Fe Weight %	100	40	60

Table 11 Indicative throughputs, capital expenditure (CAPEX), and operational expenditure (OPEX) of particle sorters (in US$)

Top size, mm		25	50	100	200
Throughput, t/h		35	60	120	250
CAPEX	Sorter only	$1,312,500	$1,579,000	$1,875,000	$2,025,000
OPEX	Sorter	$0.33	$0.22	$0.10	$0.08
	Ancillaries	$0.50	$0.25	$0.12	$0.09

Courtesy of Matthew Kowalcyk



Note: Costs adjusted to 2016 costs using capital expenditure cost index.

Adapted from Robben 2014

Figure 36 Relationship between throughput, particle size, and operating cost

Installation, Operating, and Maintenance Considerations

Shovel- and truck-based systems require little overhead in the way of installation, although Nield (2002) describes a requirement for this type of system to be integrated with the mine's grade control and ore routing systems for maximum effectiveness. Bulk systems, whether shovel, truck, or belt, require little in the way of feed preparation, although bulk belt sorting systems do require additional material handling for reject streams that are created. Particle sorting systems require a higher standard of feed preparation, both in terms of crushing and screening the feed within the particle size ranges previously described (3:1 top size to bottom size) as well as in terms of removing adhering fines, for example, by wet screening for better analysis of the particles to be sorted, particularly with use of surface sensing methods. Strict specifications relating to presentation of the feed to particle sorters (monolayer of particles, controlled velocity, particles preferably not

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Figure 37 Provisions for impact and/or abrasion resistance in feed and discharge areas are important in primary applications

touching) also need to be observed in circuit design where not catered for by the vendor. Additionally, particle sorting solutions often implicate multiple units in parallel because of their low unit capacity, therefore the feed preparation circuit, the sorting plant itself, as well as the product handling circuit can be complex and require careful design.

In operations, several considerations pertain. Maintaining calibration of the sensors to grade is key, where either step changes in calibration or drift over time can occur; calibration should be regularly monitored and corrected. Changes in the feed material type over time should also be tracked, particularly where feed transitions to a type not previously characterized for sorting; thus recharacterization by the procedures described would then be required to maintain system performance. Barton and Peverett (1980) note fragmentation of the feed on entering the sorter (as this is typically done at high velocity and can be an area of high impact) can affect system performance. Variations in temperature and humidity of the environment, as well as excess moisture content in the feed itself, should also be monitored and, if required, controlled.

Several maintenance considerations should also be noted. Damage to sensors by direct impact of rocks or other environmental factors relating to the aggressive mine environment should be monitored. Sensor and sorter systems should always be designed to *fail-safe*, that is, to default to normal operation on breakdown as well as cause no direct hazard during failure. Barton and Peverett (1980) note the potential wear in feed and discharge chutes, as these are areas of high impact abrasion as well as potential damage to sorter belts by rocks, as these are often not mining-rated belts (Figure 37). Blockages to air valves in air-actuated machines have been noted, as well as wear and actuator failure on mechanically diverted systems.

Recently Reported Sorting Installations

Hilscher (2016) lists several recent sorting examples, their location, application, and technology. Russia, Australia, and South Africa appear as leading practitioners, with Europe and the Americas currently lagging in adoption (Table 12). Figure 38 shows an example of an XRF sorting plant at a South African platinum mine.

Table 12 Recent ore sorting installations and the technology applied

Year	Country	Segment	Application	Type
2000	Russia	Gold	Ore preconcentration	X-ray fluorescence (XRF)
2000	Russia	Gold	Waste rock removal	XRF
2001	Kazakhstan	Manganiferous	Ore preconcentration	XRF
2001	Russia	Gold	Ore preconcentration	XRF
2001	Russia	Lead/zinc	Ore preconcentration	XRF
2002	South Africa	Platinum	Waste rock removal	Color
2003	Russia	Copper/zinc	Ore preconcentration	XRF
2003	Brazil	Aluminum	Not available	Color
2003	Russia	Nickel	Ore preconcentration	XRF
2004	Russia	Nickel	Ore preconcentration	XRF
2005	Australia	Nickel	Waste rock removal	Electromagnetic (EM)
2005	Russia	Copper/zinc	Ore preconcentration	XRF
2006	Kazakhstan	Chromite	Ore preconcentration	XRF
2006	Russia	Copper/zinc	Ore preconcentration	XRF
2006	Russia	Uranium	Ore preconcentration	XRF
2007	Australia	Nickel	Waste rock removal	EM
2007	Austria	Tungsten	Waste rock removal	X-ray transmission (XRT)
2007	Russia	Gold	Ore preconcentration	XRF
2007	Russia	Fluorite	Ore preconcentration	XRF
2010	South Africa	Gold	Waste rock removal	Color
2010	United States	Gold	Waste recovery	EM
2010	Canada	Nickel	Waste rock removal	EM
2011	Australia	Gold	Waste rock removal	XRT/laser
2011	Australia	Gold	Waste rock removal	Color/laser
2011	Australia	Gold	Waste rock removal	Ultraviolet/laser
2011	Russia	Gold	Waste rock removal	XRT
2011	Russia	Magnesite	Ore preconcentration	EM
2011	United States	Copper	Waste rock removal	Not available
2011	Australia	Tungsten	Ore preconcentration	XRT
2012	South Africa	Platinum	Ore preconcentration	XRF
2012	Australia	Tungsten	Ore preconcentration	XRF
2012	South Africa	Manganiferous	Waste recovery	EM
2012	Austria	Tungsten	Waste rock removal	XRT
2013	South Korea	Tungsten	Waste rock removal	XRT
2013	Russia	Gold	Waste recovery	Laser
2013	China	Gold	Waste rock removal	XRT
2014	Russia	Magnesite	Ore preconcentration	XRF
2014	Namibia	Gold	Ore preconcentration	XRF
2014	Australia	Copper	Preconcentration	XRF
2014	Australia	Copper	Ore preconcentration	XRF
2015	United States	Gold	Waste rock removal	XRT

Adapted from Hilscher 2016

Table 12 demonstrates an extensive range of ores where the technology is now proven, including manganese, lead-zinc, chromite, aluminum, and platinum, in addition to traditional applications in nickel, copper, gold, and diamonds. New applications, such as with rare earth elements, lithium,

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Source: Rule 2012

Figure 38 X-ray fluorescence (XRF)-based platinum sorting plant

molybdenum, and phosphates, are constantly in development. As can also be seen from the table, the pace of implementation has recently accelerated on the back of improvements in capacity and applicability of the technology, as well as an increased understanding by industry practitioners in how to apply sorting to the benefit of selected operations.

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