Investigations on the Detectability of Rare-Earth Minerals Using Dual-Energy X-ray Transmission Sorting

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Abstract Mechanical processing of rare-earth ore types typically requires very high-energy consuming steps such as grinding to liberate valuable minerals. In addition, occasionally harmful reagents are used in processes such as flotation to separate the contained minerals. Sensor-based sorting (SBS), a technology used for coarse particle separation (ca. +10–20 mm), can play a key role in reducing mass flows and increase valuable contents at an early stage of the process chain, with positive effects on the following processes. One sensor-technology used in SBS is dual-energy X-ray transmission (DE-XRT) sorting. The principle is known from luggage safety inspections at airports and has already been adapted to the sorting of numerous commodities in the raw materials sector, such as coal, gold ore and tungsten ores. The technical applicability of DE-XRT sorting is limited to ore types for which differences in the valuable/metal contents are detectable, based on an interpretation of recorded X-ray images. Since variations in ore characteristics such as mineralogy, valuable content, and grain sizes of valuable minerals are typical, each ore has to be tested individually for the technical applicability of DE-XRT sorting. In a fundamental research project, influences of specific parameters on the detectability of rare-earth minerals were investigated based on practical test works with artificial samples of defined, simplified composition, followed by an

interpretation of recorded X-ray images. Influences such as rare-earth concentrations, grain sizes and spatial distribution of valuable minerals on the average X-ray attenuation were investigated. Limits and potentials of this fundamental approach are presented. Besides the above, the ability to simulate X-ray absorption characteristics, based on a Monte Carlo simulation approach was tested. X-ray absorption features of defined particle compositions were calculated, and virtual X-ray images were produced. Results of both measurement approaches were compared to assess the general technical feasibility of the computer-based simulation.

Keywords Sensor-based sorting · Dual energy X-ray transmission sorting · Rare-earths

Introduction

As the majority of deposits mined do not have a sufficient purity for direct use of contained valuable minerals, mineral processing steps are necessary to separate non-valuable minerals [1]—this includes rare-earth deposits. State of the art rare-earth mineral processing methods include the crushing and grinding of the entire extracted material down to liberation size of contained valuable minerals, followed by a separation of minerals by mainly wet processes such as flotation [2] [3]. At present, no sensor-based sorting is used in rare-earth mineral processing. The use of SBS, however, enables the rejection of coarse barren particles at an early stage of the process chain [4]. With this, consumptions of energy as well as water and reagents by the following conventional sorting processes can be decreased. In this current study, technical aspects and influences on the technical applicability of dual-energy X-ray transmission sorting were investigated with focus on rare-earth mineral processing.

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Sensor-Based Sorting (SBS)

In mineral processing, sensor-based sorting (SBS) is used as an umbrella term for applications in which the characteristics of particles are detected by suitable sensors. In general, sensor-based sorting can be applied in cases where ore is liberated from gangue particles at coarse particles sizes and individual particles can be differentiated based on detected sensor signals. SBS is generally applicable for particle sizes ranging between +0.5–300 mm [5]. Sortable particle sizes depend on various factors such as the used sensor types as well as on material characteristics (e.g. density and liberation). As an example, if DE-XRT sorting is used for coal, larger particles are sorted due to lower density of coal. If used, for example iron ore, only smaller particle sizes can be sorted by SBS, due to higher density of particles. Detected signals are processed individually for each particle via computer. Based on a previously defined sorting criterion, the particles are characterized and a sorting decision is made, followed by mechanical processes (e.g. high-speed air valves) to separate particles into different material streams [6]. Industrially, two types of sensor-based sorters are used—the belt-type and the chute-type sensor-based sorter [7]. Regardless of the type of sensor-based sorter used, the sorting process can generally be divided into the following five sub-processes: (1) material conditioning, (2) material presentation, (3) detection, (4) data processing and (5) separation.

Figure 1 depicts the basic principle of SBS, based on a chute-type sensor-based sorter. Usually, the material stream is screened to obtain a specific particle size distribution [7] and separate fine particles which are not sorted by SBS. Additional cleaning of the surface of particles becomes necessary in cases where surface properties are detected [7]. Following the isolation of each particle, each object is presented to the detection zone. Here, single sensors or sensor combinations detect the specific material properties. The collected data is then processed using pre-defined algorithms, every particle is characterized and a sorting decision can be made [6]. It is decided, whether particles ejected from the material stream or not, based on the sorting decision. A positively identified particle is separated from the material stream by changing its flight parabola via compressed air from high-speed air valves. In addition, the decision whether a particle is rejected or accepted depends on the type of sorting (positive or negative sorting).

In general, the throughput of sensor-based sorters increases with larger particle sizes. Therefore, SBS is preferably used for the separation of coarse particles. However, applications exist where SBS is used down to particle sizes of 2–3 mm (e.g. gem-stone concentrate cleaning). Besides that, various applications for SBS in the

Fig. 1 Schematic illustration of a chute-type sorter [8]

primary raw material sector exist, including waste rejection, ore-type diversion as well as waste dump re-processing. Usually, with the exception of gemstones, SBS is used as rougher pre-concentration stage for waste rejection [5]. Here, sensor-based sorters are used to separate coarse barren rock at an early stage. This way, particles with low or no valuable content are separated to decrease mass flows into subsequent processes and to increase the valuable content of the material stream. For mineral applications, the run-of-mine stream is usually crushed and screened and only coarse particles (>10–20 mm) are sorted by SBS, whereas fine particles are not sorted by SBS and are directly transported into conventional processing operations (e.g. milling) without prior sorting. The coarse concentrate from SBS is either treated separately in a different process route or is mixed with fines from the foregoing screening stage (e.g. for further milling). A separation of barren rocks has positive impacts on tailing processes such as reduced downstream operational costs as well as a lowered consumption of water, energy and reagents. Figure 2 shows the principle of SBS used as waste rejection stage.

The currently available sensor systems used for SBS in the primary raw materials industry are shown in Table 1. In general, sensors that cover the entire range of the electromagnetic spectrum are used. The best suitable sensor type and the general ability to differentiate between different particle-types based on sensor signals, has to be tested individually for each ore. In this publication, the main focus is laid on the X-ray transmission technique, which principle is explained in the following section.

X-ray Transmission Sorting

The dual-energy X-ray transmission (DE-XRT) technique is well known from airport security scanners. Here, it is used to prevent dangerous materials from reaching

Fig. 2 Schematic principle of sensor-based sorting used for waste rejection [9]

commercial air planes. In the primary raw materials sector, DE-XRT sorting is used to sort individual particles, based on their specific X-ray absorption features [10]. Therefore, DE-XRT sorting is limited to ores in which contained minerals can be classified on basis of different absorptions characteristics. The basic concept of DE-XRT sorting is shown in Fig. 3 on the example of a belt-type DE-XRT sorter. The sorting process is based upon the interaction of X-rays with matter. X-rays are emitted at defined wavelengths by an electrical X-ray source above the conveyor belt (1). As X-rays transmit through the particles in the detection zone (2), an interaction between X-rays and the

Fig. 3 Working principle of X-ray transmission sensing [8]

particles matter takes place. The extent in which X-rays are absorbed depends on the material composition – in which elements of low atomic number absorb less X-rays compared to those of high atomic number. The intensities of transmitted, attenuated X-rays (3) are detected pixel-by-pixel on the opposite side of the conveyor belt by two line-scan scintillators (4). A transformation of received information into electrical signals is used to create grey scale X-ray images. This way, it is possible to look “inside” the particles. Consequently, the characterization is not solely performed based on surface properties, but on an interpretation of the whole particle [11]. With this, inclusions (5) can be detected [11], often referred to as one major advantages of DE-XRT sorting compared to other sensor types. In the projected X-ray images, dark pixels correlate to a relatively strong absorption of X-rays whereas brighter pixels correspond to a relatively low absorption of X-rays.

For DE-XRT sorting, two greyscale images (high energy and low energy) are recorded from the same particle by using a filter (usually aluminium) in between the two line-scan scintillators. By doing so, information about the

Table 1 Selection of sensor systems, detected material properties and exemplary applications

Available sensor technologies	Measured characteristics	Exemplary applications in the minerals industry
Optical sensors–CCD colour camera	Reflection, absorption, brightness and transmission of visible radiation	Industrial minerals, base metal and precious metal ores, diamonds
X-ray transmission	Transmitted X-ray radiation	Coal, industrial minerals, diamonds, base metal and heavy metal ores, precious metal ores
Near infrared (NIR)	Reflection and absorption of NIR-radiation	Industrial minerals, base metal ores
X-ray fluorescence	Reflected x-ray fluorescence under X-ray radiation	Diamonds
Inductive (metal detector)	Electrical conductivity and susceptibility	Base metal sulphide ores
Radiometric	Natural radioactivity	Radioactive ores

Fig. 4 Methodology for the test works

thickness of the scanned particle can be obtained. Changing thicknesses of the scanned particles would cause different X-ray attenuation characteristics in the scanned particles. Using software biases the influence of varying thicknesses of particles. Based on a preceding calibration, false colour pictures are created based on a combination of collected greyscale images. The colouring of greyscale images thereby depends only on differences in the atomic weight of the particles. By doing so, the picture is subdivided into different percentages of previously defined false colour classes by assigning pixels to density intervals (colour classes). Individual colour classes are defined during the initiation of the actual sorting process. This represents the basis of the DE-XRT technique for sorting of particles.

Artificial Samples: Methodology

In 2006, Wotruba and Riedel introduced an approach to produce artificial samples of defined (simplified) compositions. During that study, the detectability of finely disseminated sulphide ore (nickel-ore) by X-ray transmission and electromagnetic sensors was investigated [12]. To do so, mixtures of quartz and nickel sulphide particles at different grain sizes were mixed together with defined Ni-contents into artificial samples. It was determined, whether particles could be differentiated based on their valuable content based on sensor signals from both measurement techniques [12]. This approach was extended to investigate the detectability of rare-earth elements in ores using DE-XRT technology. Aspects that were investigated include the valuable-/REO-content as well as grain sizes of valuable minerals. Artificial samples (cylindrical particles) of varying compositions were produced. Three samples were prepared for each composition and X-ray images were collected for each particle. For this fundamental research approach, exclusively raw image data (greyscale X-ray images) was interpreted, without prior assignment of greyscale brightness values to pre-defined colour classes. To do so, all particles were scanned using a DE-XRT sorter at a belt speed of approx. 3 m/s to record X-ray images.

The mean brightness value (MBV) of three measurements (3 particles per particle type) was utilized for data interpretation. Relationships between single features and the mean greyscale brightness value (mean X-ray absorption) of particles were investigated. Figure 4 depicts the general methodology of the measurement approach.

Bastnaesite $[(\text{Ce}, \text{La})\text{CO}_3\text{F}]$ was used as REO-containing mineral with a REO-content of approx. 59 wt% REO.¹ It was crushed and screened into narrow particle size ranges and was either mixed into a calcite $[\text{CaCO}_3]$ or quartz $[\text{SiO}_2]$ matrix at varying quantities and grain sizes. Quantities of 0.5, 1, 2, 3 and 5 wt% bastnaesite were used. The quantity of matrix mineral was adjusted according to the desired bastnaesite content. Both minerals were mixed for a homogeneous distribution of the mineral grains within the sample volume, followed by a compaction in a press. To ensure a sufficient stability of the samples, a binding agent (sodium silicate) was used. Tested bastnaesite grain size ranges were 0–32, 63–125, 125–250, 250–500 and 500–1000 μm . A particle size range of 63–125 μm for the matrix minerals was used for all samples. With regard to the atomic weights, the rare-earth elements (REE) have a higher value compared to silicon (28.085) and calcium (40.087), which are the main constituents of the minerals, calcite and quartz. The calcium percentage of calcite is approx. 40 %, whereas silicon makes up for approx. 47 % of the elements in quartz. The atomic weights of the lanthanides are in the range of 138.9055–174.967, while those of Scandium and Yttrium are 44.9559 and 88.9059, respectively. The bastnaesite used for the test works contains the full range of REEs at varying concentrations. However, the most prevalent elements in bastnaesite are lanthanum, neodymium and cerium, which make up for approx. 45 % of all the elements contained. Consequently, the bastnaesite minerals should be visible in the collected X-ray images, as the X-ray attenuation is stronger for bastnaesite compared to quartz and calcite.

¹ The REO-contents of both minerals were measured by Lithium Metaborate Fusion ICP-MS analysis.

Fig. 5 Mean brightness values of recorded X-ray images from quartz-based particles

Results and Data Evaluation

In this publication, results from an analysis of calcite- and quartz-based sample types are presented. For data interpretation, the average MBV of three X-ray images (three particles of identical composition) was calculated. For each of the synthetic particles, one X-ray image was recorded at 160 kV. Besides, X-ray images were recorded for each particle at 125 and 90 kV—these results are, however, not included in this publication. At 160 kV, the MBVs of X-ray images from quartz-based sample types for particles of identical composition deviate by an average of 0.54 % and by 0.5 % for calcite-based sample types. The bar chart in Fig. 5 depicts the MBVs from X-ray images of 25 quartz-based sample types (total of 75 artificial samples) with bastnaesite contents of 0.5, 1, 2, 3 and 5 wt%. Reference values from samples with no valuable content are included in the graph (cross-hatched bars). The MBV decreases almost linearly for all samples with the increasing bastnaesite contents in the samples volume, as indicated in Fig. 5. Similar results were obtained for calcite-based sample types, where the average MBV also decreased almost linearly for increasing bastnaesite contents (results are not part of this publication). For the quartz-based samples, the highest MBVs were obtained for samples with a bastnaesite content of 0 wt% (100 wt% calcite). Decreasing MBVs were already noticeable for bastnaesite contents as low as 0.5 wt% (approx. 0.3 wt% REO). Moreover, results indicate that the size of bastnaesite grains only has a minor influence on the MBV for identical bastnaesite-/REO contents. Although the X-ray images show visual differences, there are no considerable changes in the MBV for the respective X-ray images. However, X-ray images from samples with coarser bastnaesite grain sizes (500–1000 μm) show slightly higher MBVs, compared to

Fig. 6 X-ray images from samples with identical bastnaesite content at varying bastnaesite grain sizes

those from the samples with smaller bastnaesite grain sizes.

The bastnaesite grain sizes do not have a significant influence on the average X-ray attenuation (MBV) for identical valuable contents. Consequently, comparable MBVs were obtained for such sample types so that the tested sample types could be differentiated from each other only based on their bastnaesite content.

Collected data from SBS generally contain more complex information than what is actually needed for the sorting decision. Usually filters are used to separate too much data for a fast and accurate sorting decision. In this research approach, it was tested whether supplementary, valuable information could be obtained from a more detailed analysis of recorded X-ray image data. It was tested whether additional statistical indicators could be used to appraise the sizes of contained valuable minerals, based on an interpretation of the collected X-ray image data. Potentially, these data could be used for optimized process control and automation of subsequent processing steps (e.g. milling of ore according to contained grain sizes). Figure 6 depicts exemplary X-ray images from two quartz-based samples with 2 wt% bastnaesite content and bastnaesite grain sizes of 125–250 μm (left) and 500–1000 μm (right). Differences in the visual characteristics are clearly visible—larger bastnaesite grains are especially visible for the 500–1000-μm grains. However, only minor influences of the bastnaesite grains on the MBV were noticeable during practical DE-XRT test works.

An arithmetical combination of two statistical parameters was used as indicator for bastnaesite grains sizes. Under idealized, homogeneous settings, variation between the brightness values of pixels should increase with coarser bastnaesite grain sizes (right image, Fig. 6), whereas a narrower distribution of pixel brightness values is visible for samples with smaller bastnaesite grain sizes (left image, Fig. 6). Consequently, X-ray images of those samples appear more homogeneously (left image, Fig. 6). This feature could be used for an advanced interpretation of

Fig. 7 Quotient of RMS and ω_{BV} , quartz-based sample types

collected X-ray image data. In the current study, the quotient of the Root Mean Square (RMS) value and the percentage of the most abundant brightness value in an X-ray image were used for data interpretation (Eq. 1).

$$\frac{\text{RMS}}{\omega_{BV}} = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2}}{\frac{\mu_{\text{dominant brightness value}}}{\mu_{\text{all brightness values}}}} \cdot 0.01 \quad (1)$$

where RMS is root mean square value, and ω_{BV} is the percentage of the most abundant brightness value.

The RMS value increases with the increasing brightness values in the X-ray image. However, the RMS value solely cannot be used to appraise sizes ranges of bastnaesite grains, because the grain size-dependent increase of the RMS is not very strong. That is why the ω_{BV} -value was introduced additionally for data interpretation. Unlike the RMS value, ω_{BV} decreases with larger bastnaesite grain sizes, which is related to a more heterogeneous distribution of pixel brightness values in the X-ray image. A quotient of both values should increase in case of larger bastnaesite grains, whereas a lower quotient should be the result of reduced bastnaesite grains. This theory was tested on collected X-ray image data from practical DE-XRT rest works.

Figure 7 depicts the calculated values for different quartz-based sample types. The x-axis represents the bastnaesite grain sizes, whereas RMS/ ω_{BV} values are displayed on the y-axis. In general, higher values are found for increasing bastnaesite grain sizes. The effect becomes particularly apparent for increasing bastnaesite contents and larger grain sizes (+125–1000 μm). In the range of 0–125 μm, a relationship between increasing grain sizes and higher RMS/ ω_{BV} -values is not always clearly visible. This

fact is most likely related to bastnaesite agglomerations² of the 0–32-μm size class. Nevertheless, a relationship can be observed, in which coarser bastnaesite grain sizes lead to increased values on the x-axis. Even though, no quantitative determination of individual grain size classes was conducted in this study, qualitative differences between smaller (0–250 μm) and larger (250–1000-μm) grain sizes (at identical grade of the samples) are clearly visible. However, it should indeed be noted that values were observed from simplified compositions of artificial samples. The transferability to more complex particle compositions will be subject of further research. On a long-term perspective, a potential use of a supplementary data interpretation could be the optimized regulation of subsequent grinding processes, based on grain size classes as specified during the sorting process of particles.

Simulation of Average X-ray Attenuation

In the present study, it was tested whether photon interactions can be calculated, based on a Monte Carlo simulation approach. Based on the Monte Carlo N-Particle Transport Code (MCNP), a simplified, virtual DE-XRT sensor system was designed and interactions between X-rays and samples of varying compositions were simulated. The virtual X-ray images were compared to practical DE-XRT test work results for validation of the measurement concept. The simulation was conducted by the Institute of Nuclear Engineering and Technology Transfer (NET) of RWTH Aachen. In this section, fundamentals of the MCNP

² A computer tomography analysis was conducted. Images showed agglomerations of bastnaesite in the 0–32-μm size class.

simulation are presented and results from a comparison of practical test works and the simulation are described.

Monte Carlo N-Particle Transport Code

The origin of the Monte Carlo method goes back to the mid-nineteenth century, when the Monte Carlo method was, e.g. used for an approximate calculation of the number pi [13]. Problems which are difficult or impossible to be solved based on an analytical approach can be numerically approximated with a Monte Carlo simulation. Based on the Monte Carlo method, MCNP is used to describe and study the motion of radiation, often referred to the so-called radiation transport [14]. Among other possible uses, the code can be used to describe stochastic processes such as the transport/propagation of photons and neutrons (particle transport) through matter. In order to describe such processes, each particle is actually followed throughout its entire life (from a source to its death by, e.g. absorption, escape, etc.) [15]. Transport data is used to determine the outcome at each step of a particles life and probability distributions are randomly sampled [15]. Individual probabilistic events that comprise a certain process are simulated sequentially and the probability distributions governing such events are statistically sampled in order to describe the total phenomenon [15]. Random numbers are selected for the sampling process—similar to rolling the dice in casinos, e.g. in Monte Carlo [15]. The statistical accuracy of the simulation increases with an increased number of trials. Applications of MCNP simulations extend from criticality safety, oil-well logging, space exploration, medical technology to radiation protection in nuclear power plants [14].

Methodology

Taking into account the general working principle of a DE-XRT sensor-based sorting system, the measurement system was broken down into three basic components for subsequent simulations: (1) the X-ray source, (2) the particle/sample compositions and (3) the detector system. For all components, simplifications had to be made in order to adhere to specifications and limits of the MCNP simulation tool. For this theoretical approach, particles compositions close to those of practical DE-XRT test works were simulated. One simulation was conducted for each tested sample type, which equals a total number of 12 simulations (10^9 photons for each sample type). The variance of simulation results for identical particle compositions was not determined, as only one simulation was conducted for each

sample type. During the study, it was not possible to use grain size ranges of the contained minerals, so that grain size ranges had to be converted into discrete grain sizes by calculating the mean value of a size range (e.g. 375 μm instead of 250–500 μm). In addition, the matrix mineral was simulated as a block and not as individual grains, in order to not exceed limits of the MCNP tool. A computer model was applied to disseminate bastnaesite grains homogeneously into the sample volumes at previously defined bastnaesite contents. Depending on bastnaesite grain sizes and contents, the dimensions (volume sizes) of simulated samples were adjusted. This was necessary, as simulation efforts increase with increasing valuable contents and reduced bastnaesite grain sizes. The X-ray source was modelled in accordance to characteristics of industrial tungsten-based X-ray sources with an accelerating voltage of 160 keV and a maximum power of 1000 W. Based on these characteristics, an X-ray spectrum was simulated. In order to reduce the necessary simulation effort, this spectrum was used for all simulations conducted. The detector was modelled, based on specification of dual-energy sandwich-type scintillator detectors in a quadratic shape. The spatial resolution was set to $0.8 \times 0.8 \text{ mm}^2$. The detector sizes were adjusted in the MCNP tool in accordance with the specified samples sizes. Considering necessary simplifications, a basic DE-XRT measurement system was modelled, and average X-ray attenuation was calculated for different sample types.

Results of MCNP simulation

Based on MCNP simulations, X-ray intensities were calculated for defined sample types and detector areas. A virtual X-ray image is created to visualize differences in detected X-ray intensities. Besides this, this allows for the comparison of simulations to practical DE-XRT test work results. Properties of computer-generated X-ray images were compared to the recorded X-ray images from DE-XRT test works, in which dark pixels correlate to areas of low detected X-ray intensities (number of detected photons) and brighter areas correlate to regions with more detected photons. A virtual X-ray image, as generated by MCNP simulation, is presented in Fig. 8.

The percentage reductions of MBVs and average X-ray intensities were calculated, as a function of increasing bastnaesite contents and grain sizes. This enables validation of the simulation model. In total, results from an analysis of 12 sample types are presented. MBVs and average X-ray intensities of samples with bastnaesite contents of 1, 2 and 5 wt% were put into relationship with a bastnaesite content of 0.5 wt%. Tested bastnaesite grain sizes were 125–250 μm (187.5 μm), 250–500 μm

Fig. 8 Exemplary virtual X-ray image from MCNP simulation

(375 μm) and 500–1000 μm (750 μm). Figure 9 depicts a comparison of all measurement results. The tested bastnaesite contents are displayed on the x-axis, and the decrease of measured values is shown on the y-axis. Results indicate that for both methodologies, the mean X-ray attenuation—expressed by the MBVs (DE-XRT test work) and average X-ray intensities (MCNP simulation)—is subject to bastnaesite contents present in the sample volumes. For the artificial samples, this was previously shown during practical test works. Compared to these results, influences of increasing bastnaesite contents on the calculated mean X-ray attenuation are stronger for MCNP simulations. Especially for higher bastnaesite contents, deviations between practical test work results and MCNP

simulations increase. With regard to MCNP simulations, effects of bastnaesite grain sizes on the mean X-ray attenuation become increasingly noticeable for higher valuable contents. As can be seen from Fig. 9, the decrease of the mean X-ray intensity for same bastnaesite contents is slightly lower for larger bastnaesite grain sizes—this applies especially for bastnaesite contents of 5 wt%. Here, the minimum reduction of the mean X-ray intensity was calculated for bastnaesite grains of 750 μm , whereas the maximum reduction was analysed for grain sizes of 187.5 μm . As described previously, influences of bastnaesite grain sizes are minor DE-XRT test work results, compared to MCNP simulations. Effects of bastnaesite grain sizes on the mean X-ray attenuation were only visible for bastnaesite contents of 5 wt% and a size range of 500–1000 μm . During MCNP, the lowest decrease of the mean X-ray intensity was also measured for this particular sample type.

Table 2 contains measurement values from MCNP simulations and DE-XRT test work, as depicted in Fig. 9. For identical increases of the bastnaesite content, the decline of MCNP simulation values was around 2.2-fold stronger, compared to those from DE-XRT test work.

Considering the fundamental DE-XRT measurement components, a simplified DE-XRT measurement system was designed for the simulation study. Influences of grain sizes and valuable contents were investigated, based on a simulation of simplified sample compositions and compared to results from practical DE-XRT test works. Although, values from MCNP simulations were not directly transferable to obtained results from DE-XRT measurements; nonetheless, it was demonstrated that qualitative differences in the X-ray attenuation behaviours of varying sample compositions could be calculated, based on a computer-based simulation approach.

Fig. 9 Decreases of MBV and average X-ray intensities

Table 2 Decreases of MBV and average X-ray intensities from MCNP simulation

Bastnaesite grain sizes	Decrease of the MBV and the average X-ray intensity for increasing bastnaesite contents					
	0.5–1 M%		0.5–2 M%		0.5–5 M%	
	DE-XRT	MCNP	DE-XRT	MCNP	DE-XRT	MCNP
125–250/(187.5 μm)	–4 %	–11 %	–29 %	–62 %	–29 %	–62 %
250–500/(375 μm)	–5 %	–10 %	–30 %	–58 %	–30 %	–58 %
500–1000/(750 μm)	–5 %	–11 %	–26 %	–53 %	–26 %	–53 %

Summary and Conclusion

In this current publication, two measurement approaches are presented—the analysis of average X-ray attenuation behaviour based on practical DE-XRT test works and the simulation of X-ray intensities based on a computer-based simulation model.

The general ability to detect low grade REO-contents, based on an interpretation of collected X-ray image data, was evaluated in practical DE-XRT test works. Artificial samples of defined simplified compositions were prepared, and collected X-ray image data were analysed, based on brightness values. By doing so, influences of bastnaesite grain sizes and valuable contents on the average X-ray attenuation (mean brightness value, MBV) of particles were evaluated. Results show that samples with bastnaesite grades of 0.5 wt% (approx. 0.3 wt%) were distinguishable from samples with no valuable content, with a nearly linear correlation between increasing valuable contents and growing X-ray attenuation of the samples. It was also shown that, for identical bastnaesite contents, bastnaesite grain sizes seem to only have a minor influence on the mean brightness value (MBV). In addition, a potential use of an extended interpretation of collected X-ray images was demonstrated. It was shown that, besides the MBV, further statistical values might be applicable to, for example, enable an assessment of bastnaesite grain sizes in particles. Here, qualitative differences in bastnaesite grain sizes were shown based on an additional statistic interpretation of brightness values. A complementary data interpretation of collected X-ray image data may open up new opportunities for an optimized regulation of following processes (e.g. grinding processes), demonstrating the potential of additional interpretation of collected X-ray image data. Subject of further research activities, however, should include the testing of the transferability of the obtained results to more complex particle compositions and real ores.

A computer-based simulation model was used to evaluate the possibility to simulate photon interactions from defined REO-containing sample compositions. The tests were carried out with regard to basic DE-XRT

measurement components and simplified particle compositions. Photon interactions were calculated based on a virtually replicated and simplified dual-energy measurement system. Characteristics of virtual X-ray images were compared to X-ray images from practical DE-XRT test works for similar particle compositions. It was demonstrated that qualitative differences in the X-ray attenuation behaviour between particles of varying compositions could be shown, based on a MCNP simulation, although measurement results were not directly transferable to DE-XRT test work results. Variations between DE-XRT test work results and those from MCNP simulations are most likely caused by a combination of necessary simplifications during the MCNP simulation approach. Nonetheless, investigations have revealed the general technical feasibility of a computer-based simulation to assess average X-ray attenuation behaviours of heavier (bastnaesite) particles in a lighter (quartz) matrix. Further modifications of the tested simulation model could lead to improved comparability of results from both approaches. On a long-term perspective, computer-based simulations could be turned into valuable tools to simulate X-ray attenuation behaviour of even more complex particle compositions. Potential future applications could include the testing of influences on the X-ray attenuation of particles and the assessment of the general applicability of DE-XRT sorting for various ores. Taking into account all these factors, this could lead to an even deeper understanding of dual-energy X-ray transmission sorting of primary raw materials.

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