Chapter 3

Life Cycle Inventory (LCI) Approach Used for Rare Earth Elements (REEs) from Monazite Material, Considering Uncertainty

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Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/intechopen.80261

Abstract

This study describes the development of life cycle inventory (LCI) to rare earth elements (REEs) based on the secondary sources, conducted according to ISO 14040 (2006) guidelines. Monte Carlo (MC) simulation with the Crystal Ball (CB) spreadsheet-based software was employed to stochastic modeling of life cycle inventory. The number of simulations was set at 10,000. The study scope considered LCI associated with REE concentrate production from New Kankberg (Sweden) gold mine tailings production (input gate) to the final delivery of rare earth elements (end gate) to reprocessing/beneficiation for rare earth element recovery. For the presented case, lognormal distribution has been assigned to scandium (Sc), dysprosium (Dy), yttrium (Y), lanthanum (La), cerium (Ce), praseodymium (Pr), neodymium (Nd), samarium (Sm), europium (Eu), gadolinium (Gd), holmium (Ho), erbium (Er), terbium (Tb), thulium (Tm), ytterbium (Yb), and lutetium (Lu). The MC simulation (10,000 trials) for the sum of analyzed REEs used for CB is presented in the form of statistics. Sensitivity analysis (SA) presented in the form of tornado charts and spider charts was performed. The results from this study suggest that uncertainty analysis is a powerful tool that should support and aid decision-making and is more trusted than the deterministic approach.

Keywords: rare earth elements (REEs), life cycle inventory (LCI), life cycle assessment (LCA), Monte Carlo (MC) simulation, Crystal Ball® (CB), sensitivity analysis (SA), uncertainty

1. Introduction

This chapter presents the utility of MC simulation with the Microsoft Excel with a CB extension software used to LCI modeling under uncertainty based on the public dissemination data

from environmentally friendly and efficient methods for extraction of rare earth elements from secondary sources (ENVIREE)—ERA-NET ERA-MIN-funded research project [1]. Recently, rare earth elements (REEs) have received increased attention due to their importance in many high-tech and clean energy applications, although very limited life cycle assessment (LCA) studies have been conducted [2].

Life cycle assessment (LCA) is one of the tools that is increasingly being used to examine the environmental impact of a product through its entire life cycle [3]. Udo de Haes et al. [4] highlighted LCA as a global tool, while a wide range of LCA applications are presented in [5]. The increasing application of LCA as a tool for making policy decisions as well as material and design choice and need for robust and up-to-date information for such studies is also presented in [6, 7].

2. Uncertainty in LCA

Uncertainty is a pervasive topic in LCA and can be defined in various ways [8]. In [9], definition of uncertainty given by [10] is quoted: "Uncertainty is defined as incomplete or imprecise knowledge, which can arise from uncertainty in the data regarding the system, the choice of models used to calculate emissions and the choice of scenarios with which to define system boundaries, respectively."

LCA is an analytical tool which needs intensive data: methodological choices, initial assumptions, and degree of data uncertainty have a profound effect on validity of LCA results [11], and existing quantitative uncertainty methods in LCA require also a huge amount of accurate data [12]. Problem of aleatory uncertainty or "lack of knowledge" and epistemic uncertainty or "variability" [13] is discussed in [14], when it is highlighted that quantification for the aleatory uncertainty is usually performed using the MC. Detailed description of the combination of sources of uncertainty (parameter, model, and scenario uncertainties) and methods (deterministic, probabilistic, possibilistic, and simple methods) to address them is presented by [15]. According to the [16] discussed municipal solid waste incineration model, it is suggested that uncertainty is due to data gap or inaccurate data.

The LCI analysis involved the collection and calculation of data and procedures to quantify the relevant input and output of the product system. Very often large amounts of data required for LCI [17, 18] are affected by uncertainty [19, 20]. The main sources of uncertainty presented in [21, 22] is quoted in [23, 24]. With respect to parameter uncertainty, the common practice in LCA consists in representing uncertainty parameters by single probability distributions, e.g., a normal distribution is characterized by an average and a standard deviation [25, 26], while in [8], uncertainty is defined as geometric standard deviation of intermediate and elementary exchanges at the unit process level. To obtain a result, different statistical methods can be applied. The most well-known sampling method is MC simulation (e.g., [18–26]) easily applied to LCA [27], while a most sophisticated method is the Latin hypercube (LH) method, where the sampling strategy is not entirely random but utilizes stratified probability distributions [27]. MC simulation is also recommended in the IPCC 2006 Guidelines [28, 29]. Most software for LCA is by now able to deal with uncertainties, in most cases on the

basis of MC simulation [27–29]. LH sampling performs better that random sampling when the output is dominated by a few components of the input factor and better that random sampling for estimating the mean and the population distribution function [30]. Moreover, LH sampling (data compression techniques) can reduce computer time [15] and may reduce the required number of simulation [27]. It is important that a sufficient number of replications be used in a simulation. The number of replications of simulation affects the quality of the results. In general, the higher the number of replications, the more accurate will be the characterization of the output distribution and estimates of its parameters, such as the mean [19, 20]. According to [31], it is suggested that statistical accuracy of the simulation increases with an increased number of trials.

As pointed out in, the number of runs will vary from problem to problem, at least 1000 runs (see *Introduction to LCA with SimaPro* [32]) to thousands [23, 24, 30, 33]. In discussion of stochastic flow shop scheduling metaheuristic model for vessel transits in Panama Canal that used 200 runs in MC simulation model, which stated that the change in the 95% confidence interval width for makespan was negligible, is presented.

The problem of number of runs in MC-based approaches was also considered by [34], who analyzed the fuzzy uncertainty propagation using matrix-based LCI and proposed the number of runs between 100 and 10,000. According to [35] in the analysis of the IBM, daily trading volume stocks used a Poisson distribution via the MC simulations based on 1000 repetitions. Also [36] applied 1000 iterations to estimate the uncertainties of life cycle impact assessment (LCIA) results introduced by the statistical variability or temporal, geographical, or technological gaps in the LCI data. In the same work to estimate the combined uncertainty for IPCC-derived greenhouse gas inventory, the MC simulation with 5000 iterations was used [36]. In [36], when probabilistic scenarios are analyzed, using Microsoft Excel with CB for MC method for each scenario, uncertainty analysis involved 20,000 MC simulations. Finally, [37] presented relative results between compact neighborhoods cells in Mexico City involved 100,000 MC simulation.

3. Material and methods

The framework of LCA, structured according to International Organization for Standardization ISO 14040 [38] standard, is described in [39].

3.1. Goal and scope of the study

The goal of this study was to provide LCI under uncertainty calculus on the probabilistic MC approach for the primary data delivered from the secondary REE recovery process following the guidelines in ISO 14040:2006 standard.

3.1.1. Functional unit

The FU, central concept in LCA, is the measure of the performance delivered by the system under study [3, 18]. The FU has been defined as 1000 kg of a secondary source to be excavated and processed as the input for all subsequent processes.

3.1.2. Data quality and collection

As noted above, very often LCI required a lot of data [17, 18] that are well correlated to the study context [40]. Data quality is discussed widely in literature [17, 23, 40–44]. In [45] analyzed uncertainty in a comparative LCA of hand drying systems pointed that data collection is one of the limitations in their LCA analysis. The databases presented in this study are affected to several uncertainties. According to [41], the basic uncertainty in data quality considerations of the inventory of rare earth concentrate processes comes out with data obtained from the literature studies. Large uncertainties exist for the infrastructure and also for particle emissions, fresh water use, and land use [41]. Another reason for the uncertainties is the nature of the chemicals used for the recovery of the REEs from the concentrate after flotation and beneficiation processes (e.g., collector, conditioner, depressant) due to production system characterized by diverse practices and technologies [41, 46], as well as various laboratory methods.

The primary data used in the study is obtained from the Deliverable D1.2 Report on the physical-chemical properties of available materials for the recovery of REE and Deliverable D1.3 chemical and mineralogical data of secondary REE sources [1]. The secondary data used in the study is obtained from the following sources:

- The subject literature—scientific publications
- Expert consultations and knowledge of the process

4. Results and discussion

The MC simulations for evaluation parameter uncertainty involve the following steps [47]:

1. Select a distribution to describe possible values of each parameter.
2. Specify properties of each parameters.
3. Generate data from the distribution.
4. Use the generated data as possible values of the parameter in the model to produce output.

The REEs can be grouped into two different categories based on their atomic numbers. REEs with atomic numbers 57–63 are classified as light-rare earths (LREEs), and REEs with atomic numbers 64–71 are classified as heavy-rare earths (HREEs) [48]. However, the term "rare" earth is a misnomer; they are relatively abundant in the Earth's crust; however, they are typically dispersed and only rarely occur in concentrated and economically exploitable mineral deposits [49].

The literature on the flotation of monazite is rather scarce. The available literature focused on the separation of monazite from xenotime, bastnaesite, rutile, and zircon [50] or on the Rhône-Poulenc liquid-liquid extraction process for separation of the REEs from monazite [51] and the Shanghai Yue Long Chemical Plant monazite concentrate treatment in the process similar to the Rhône-Poulenc process [11], both described in [49].

http://dx.doi.org/10.5772/intechopen.80261

Monazite and xenotime from titania-zircon paleo beach placers in Australia, in the 1980s, were the third most important source of REEs in the world [52]. According to [53], in Australia, monazite typically has associated radioactivity due to thorium content (by substitution up to 30%). Until 1995, rare earth production in Australia was largely a byproduct of processing monazite contained in heavy mineral sands [54].

In addition to Australia, monazite deposits in Brazil, India, Malaysia, Thailand, China, Thailand, Sri Lanka, South Africa, and the United States constitute the second largest segment [49]. Present-day production is from India, Malaysia, Sri Lanka, Thailand, and Brazil [52]. Moreover, approximately 500 t of monazite per year was produced from 1952 to 1994 as a byproduct of titania-zircon production from Pleistocene sands near Green Cove Springs in Florida [52].

The Carolina monazite belt, from which a total of about 5000 t of monazite was produced between 1885 and 1917, has considerable placer reserves that average 0.25 kg/m^3 of monazite [55]. Bear Valley, Idaho, where monazite- and yttrium-bearing euxenite was mined by dredging, contains an estimated 10,000 t of REOs along with significant niobium and tantalum, on the basis of data from [56]. At Baotou, the largest producer of rare earths in China, the bastnesite concentrates contain a small amount of monazite [49].

According to ENVIREE project, flotation tests have been carried out on the flotation tailing from New Kankberg to find out if the REEs can be recovered [57]. The results indicate that most of the REEs are in monazite. *Monazite* is the second most important rare earth, after bastnaesite, and is a rare earth phosphate mineral that contains various amounts of thorium [50]. Sample from the flotation tailing was delivered to the ENVIREE project. After delivery of samples and their homogenization, they were analyzed. As mentioned above, ICP-MS analysis of samples was investigated, in order to test the availability of REE extraction. The results are presented in **Table 1** [1].

In this study we concentrate on a set of 16 REEs, denoted as critical [58] (European Commission 2014), namely, Sc, Dy, Y, La, Ce, Pr, Nd, Sm, Eu, Gd, Ho, Er, Tm, Tb, Yb, and Lu. MC, an uncertainty propagation method [59], required definition of the mean, type of statistical distribution, and standard deviation (SD) for each parameter [59]. In this study, the uncertainty analysis was modeled using probability distributions considered to be lognormal (term *lognormal distribution*) was derived from [60], according to the criteria proposed by [18] that "heavy metals is a sum parameter in the form of Pb, equivalents of following heavy metals: As, B, Cr, Cu, Hg, Mn, Mo, Ni, Pb and Sb," and according to the estimations published by [61], as well as following the [62, 63] indication, that environmental parameters in LCA studies are independent and usually follow the lognormal distribution as do the impact results [59]. Other studies showed that the lognormal distribution has been used by [9] for the variability assessment by means of bootstrap technique (applied for the computation of the median absolute deviation (MAD) for measure of the *variability* in statistical analysis). As pointed out by [62], the lognormal distribution has an upside-down bathtub-shaped hazard rate [64, 65], and no negative values are possible [18]. Lognormal distribution always remains positive, and it is consistent with the data available in the ecoinvent database and the pedigree matrix approach, as suggested by [45]. In addition, it is interesting to note that according to analysis, the trace element concentrations in gold processing have been concluded that concentration distribution of the elements between the grinding stages and the discharge stages was not uniform probably due to the different physical and chemical processes at various stages [64, 65].

REEs	Distribution type	Atomic number	μ_g	σ_g	Quality	Reference
Scandium (Sc)	Lognormal	21	0.41	1.10	0.41	CB® result
Yttrium (Y)	Lognormal	39	3.25	1.10	3.27	CB® result
Lanthanum (La)	Lognormal	57	12.13	1.10	12.19	CB® result
Cerium (Ce)	Lognormal	58	23.86	2.39	23.89	CB® result
Praseodymium (Pr)	Lognormal	59	2.39	1.10	2.4	CB® result
Neodymium (Nd)	Lognormal	60	9.78	1.10	9.83	CB® result
Samarium (Sm)	Lognormal	62	1.74	1.10	1.75	CB® result
Europium (Eu)	Lognormal	63	0.45	1.10	0.45	CB® result
Gadolinium (Gd)	Lognormal	64	1.27	1.10	1.28	CB® result
Terbium (Tb)	Lognormal	65	0.14	1.10	0.14	CB® result
Dysprosium (Dy)	Lognormal	66	0.49	1.10	0.49	CB® result
Holmium (Ho)	Lognormal	67	0.08	1.10	0.08	CB® result
Erbium (Er)	Lognormal	68	0.22	1.10	0.22	CB® result
Thulium (Tm)	Lognormal	69	0.03	1.10	0.03	CB® result
Ytterbium (Yb)	Lognormal	70	0.17	1.10	0.17	CB® result
Lutetium (Lu)	Lognormal	71	0.02	1.10	0.02	CB® result

μ_g = geometric mean value; σ_g = geometric standard deviation.

Table 1. Overview of the rare earths taken into account in the study (all values in ppm).

Finally, in this study to address uncertainty in the inventory data, analyzed REEs were fitted by lognormal distributions based on the real data summarized in **Table 1**. The CB lognormal distribution tab windows included the lognormal distributions of each of the 16 analyzed REEs after defining the geometric mean value (μ_g) automatically which calculated (matches) the standard deviation (σ_g) and lower as well as upper boundaries of lognormal distribution. There is lack of critical details in literature on how experimental data (e.g., σ_g) with regard to probability distributions for the REEs in monazite was calculated. Moreover, lack of expert knowledge and transparency makes it extremely difficult for other researches to carry out their studies [48]. As noted above, *monazite* is the second most important rare earth, after bastnaesite [48]. The results of the performed simulation (10,000 runs) can be presented in the form of frequency charts shown in **Figure 5**.

4.1. Uncertainty analysis: MC simulation results

The literature includes many studies and papers dealing with the uncertainty analysis. According to [66], the uncertainty analysis can vary from a qualitative assessment (where parameters are assigned a low, medium, or high level of uncertainty) to a semiquantitative assessment in which parameter values are bounded [66].

http://dx.doi.org/10.5772/intechopen.80261

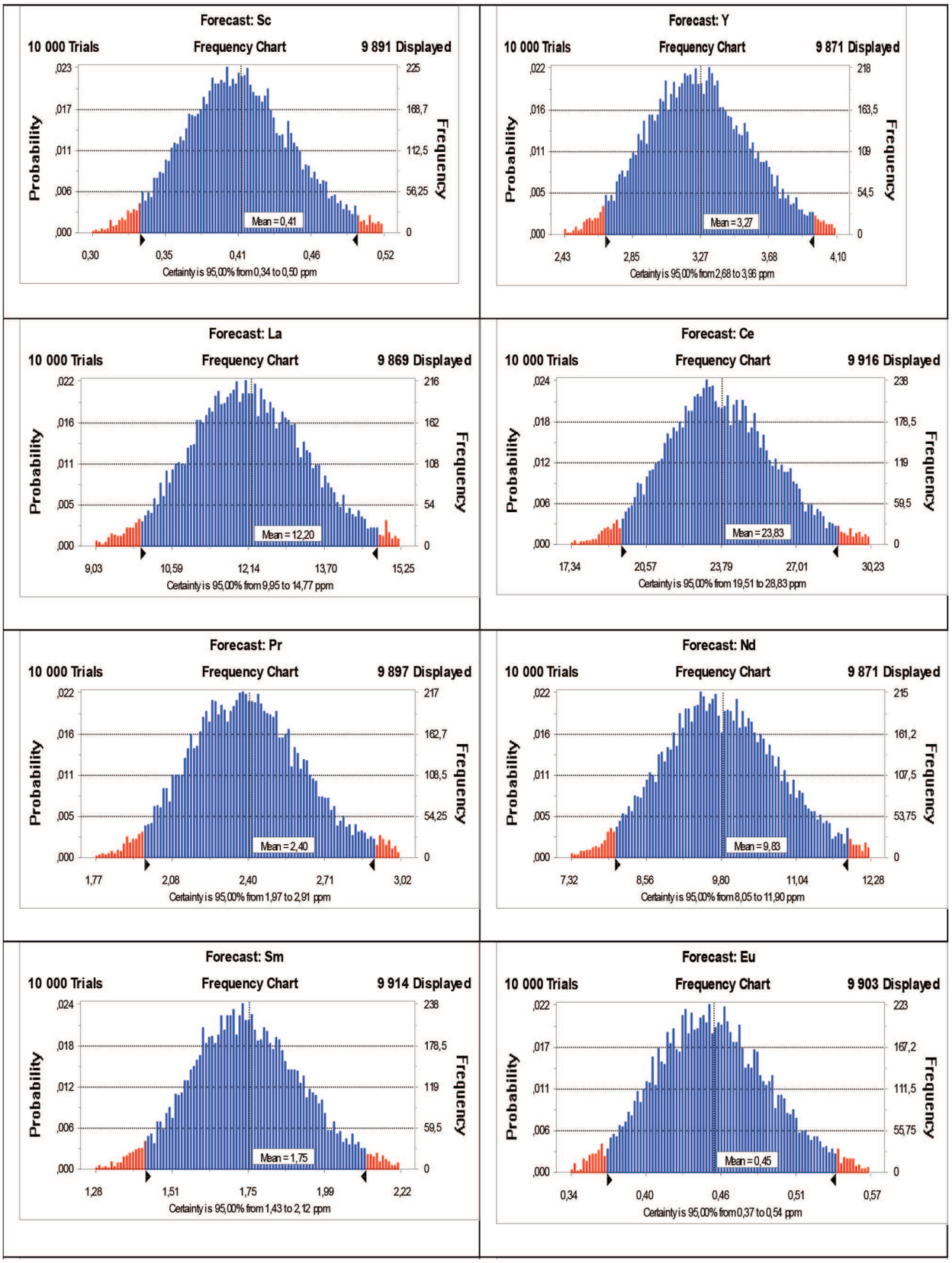
Several studies have presented examples of the utilization of MC simulation in LCA studies; however, according to [67], MC and fuzzy set theory have been applied in a limited number of LCA studies. According to [25] the LCA data, in general, is full of uncertain numbers, and these uncertainties, for instance, are caused by uncertain measurement or uncertainty about how representative a data is for the analyzed problem [25]. Bieda [23] depicted that the reliability of LCA results may be uncertain, to a certain degree, and this uncertainty can be pointed out using MC method. In order to obtain robust conclusions about LCA results, the uncertainty needs to be sufficiently accommodated [68], and in order to apply the MC approach, it is needed to translate own information about uncertainty into a standard distribution type [32].

In this study each REE is independent (uncorrelated) of the others and comes from the same source (i.e., laboratory). Uncorrelated means that deviations for all products (elements) are independent [45]. In carring out the MC simulation used CB (10,000 runs) obtained histograms, shown in **Figure 1**, statistics, as well as percentiles reports presented in **Tables 2** and **3**, respectively, are present the results obtained by MC simulation for the sum (total) of the Sc, Dy, Y, La, Ce, Pr, Nd, Sm, Eu, Gd, Ho, Er, Tm, Tb, Yb, and Lu. The confidence interval is 95%. This means that 95% of the results lay within this range [25]. Total forecast value amounted to the geometric mean value of the 56.59 ppm contained between 51.20 ppm and 62.58 ppm (see **Figure 2**). After 10,000 runs, the standard error of the mean is 0.04. The entire range which expressed the 95% confidence interval is from 45.78 ppm to 69.17 ppm. Range width is 23.38 ppm. The number displayed in the upper right corner of the histogram showed 9887 data points inside 2.6 SD of the mean [19, 20]. Just below the horizontal axis at the extremes of distribution, there are two small triangles, called endpoint grabbers [19, 20]. The certainty range (confidence interval) is displayed at the lower center of the frequency charts—the area of the histograms covered by them is darker [19, 20]. A detailed description of the simulation performed using CB is given in [19, 20, 23, 24]. The outcomes of the MC simulation listed in **Table 3** indicate that, for example, the chance that the total REEs will be less than 56.49 ppm is only 50% [19, 20].

4.2. Sensitivity analysis

The definition of sensitivity analysis (SA) given by [30] is "the study of how the uncertainty in the output of model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input." According to suggestion [45], SA isolates the main drivers of impact (and possibilities for improvement) and should be included in complete assessment of uncertainty. It is worth pointing out that Kolb [69] noted that theoretical methods are sufficiently advanced, so that it is intellectually dishonest to perform modeling without SA (see [30]). According to [70], SA of a result is most often studied parameter by parameter, while according to [71], SA helps decision-makers to understand the impact of chosen allocation method and boundary setting on LCA results.

The result of this SA with the confidence level of 95%, created on the basis of SRCC and sorted in descending order, where positive correlation coefficients indicate that the acceptance of the stricter assumptions can be associated with obtaining the higher forecast probability [23, 24], for the data presented in **Table 1**, is shown in **Figure 3**. Positive coefficient signifies the existence of positive correlation, whereas the negative coefficient signifies negative correlation


Forecast: Sc
10 000 Trials
Frequency Chart
9 891 Displayed
Probability
Frequency
,023
,017
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225
168,7
112,5
56,25
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Mean = 0,41
0,30
0,35
0,41
0,46
0,52
Certainty is 95,00% from 0,34 to 0,50 ppm
Forecast: Y
10 000 Trials
Frequency Chart
9 871 Displayed
Probability
Frequency
,022
,016
,011
,005
,000
218
163,5
109
54,5
0
Mean = 3,27
2,43
2,85
3,27
3,68
4,10
Certainty is 95,00% from 2,68 to 3,96 ppm
Forecast: La
10 000 Trials
Frequency Chart
9 869 Displayed
Probability
Frequency
,022
,016
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,005
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216
162
108
54
0
Mean = 12,20
9,03
10,59
12,14
13,70
15,25
Certainty is 95,00% from 9,95 to 14,77 ppm
Forecast: Ce
10 000 Trials
Frequency Chart
9 916 Displayed
Probability
Frequency
,024
,018
,012
,006
,000
238
178,5
119
59,5
0
Mean = 23,83
17,34
20,57
23,79
27,01
30,23
Certainty is 95,00% from 19,51 to 28,83 ppm
Forecast: Pr
10 000 Trials
Frequency Chart
9 897 Displayed
Probability
Frequency
,022
,016
,011
,005
,000
217
162,7
108,5
54,25
0
Mean = 2,40
1,77
2,08
2,40
2,71
3,02
Certainty is 95,00% from 1,97 to 2,91 ppm
Forecast: Nd
10 000 Trials
Frequency Chart
9 871 Displayed
Probability
Frequency
,022
,016
,011
,005
,000
215
161,2
107,5
53,75
0
Mean = 9,83
7,32
8,56
9,80
11,04
12,28
Certainty is 95,00% from 8,05 to 11,90 ppm
Forecast: Sm
10 000 Trials
Frequency Chart
9 914 Displayed
Probability
Frequency
,024
,018
,012
,006
,000
238
178,5
119
59,5
0
Mean = 1,75
1,28
1,51
1,75
1,99
2,22
Certainty is 95,00% from 1,43 to 2,12 ppm
Forecast: Eu
10 000 Trials
Frequency Chart
9 903 Displayed
Probability
Frequency
,022
,017
,011
,006
,000
223
167,2
111,5
55,75
0
Mean = 0,45
0,34
0,40
0,46
0,51
0,57
Certainty is 95,00% from 0,37 to 0,54 ppm

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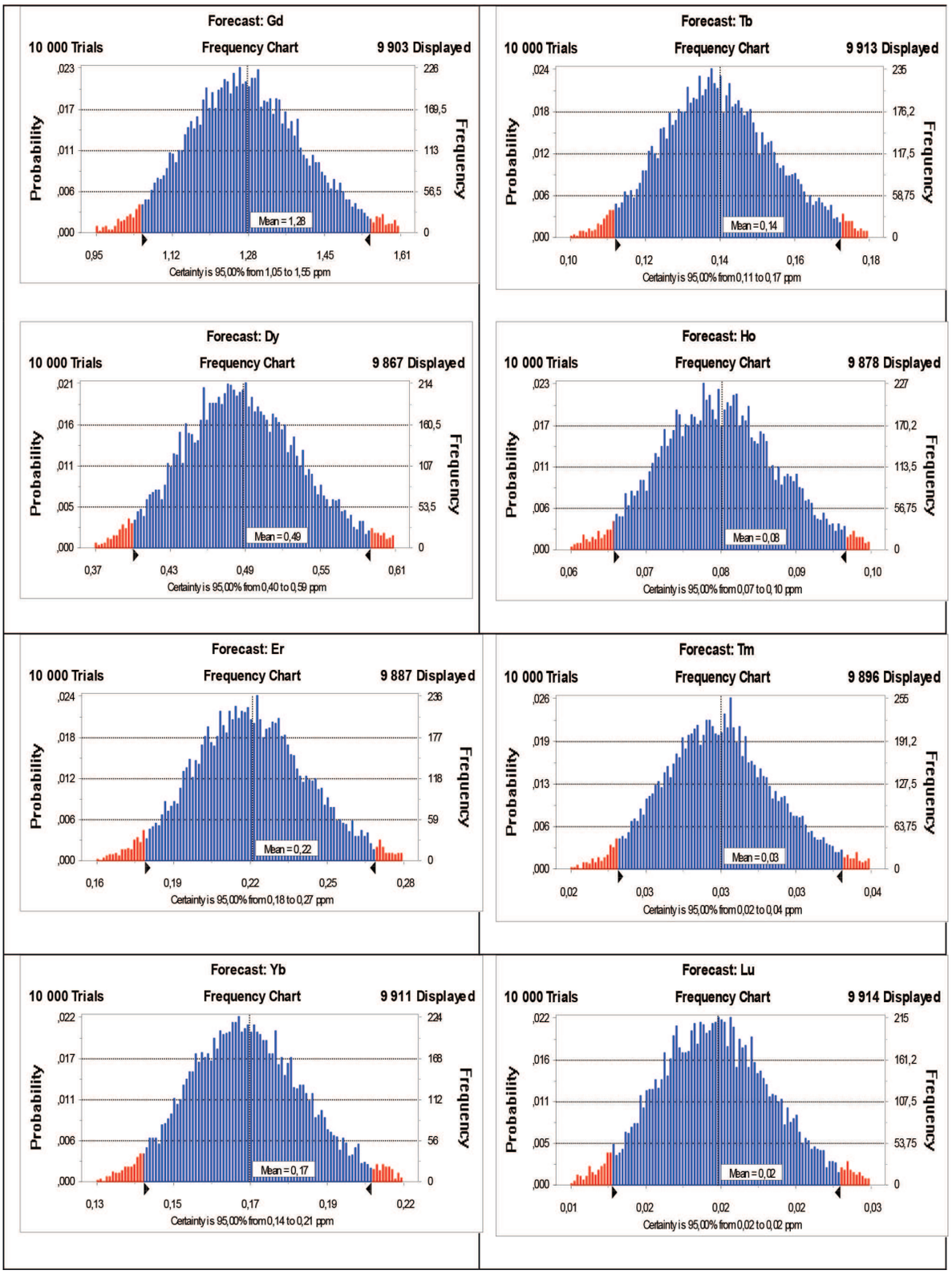

Figure 1. The frequency chart of the 16 analyzed REEs forecasted with 95% confidence level (source: own work).

Statistics	Total (ppm)
Trials	10,000
Mean	56.59
Median	56.49
Mode	—
Standard deviation	2.89
Variance	8.36
Skewness	0.21
Kurtosis	3.11
Coeff. of variability	0.05
Range maximum	45.78
Range minimum	69.17
Range width	23.38
Mean std. error	0.03

Table 2. Statistical report of outcomes from the simulation.

Percentile	Total (ppm)
0%	45.78
10%	53.00
20%	54.16
30%	55.01
40%	55.78
50%	56.49
60%	57.20
70%	58.02
80%	59.00
90%	60.34
100%	69.17

Table 3. Percentile report of outcomes from the simulation.

[23, 24], or in other words, positive coefficients indicate that an increase in the assumption is associated with an increase in the forecast; negative coefficients imply the reverse [19, 20]. The MC simulation results have then been used also to perform the SA, presented in the form of tornado charts (see **Figures 4** and **6**) and spider charts (see **Figures 5** and **7**). According to [72] the concentrate that contains a mix of phosphates (apatite and monazite) can be further enriched through magnetic separation thanks to the paramagnetic property of monazite (apatite is nonmagnetic). Magnetic separation leads to the production of a concentrate containing 17.5% of the initial phosphate content (monazite mainly) and the REE content from 170 ppm to 5,000 ppm for Ce (90 ppm to 2,800 ppm for La and 70 to 2,300 ppm for Nd).

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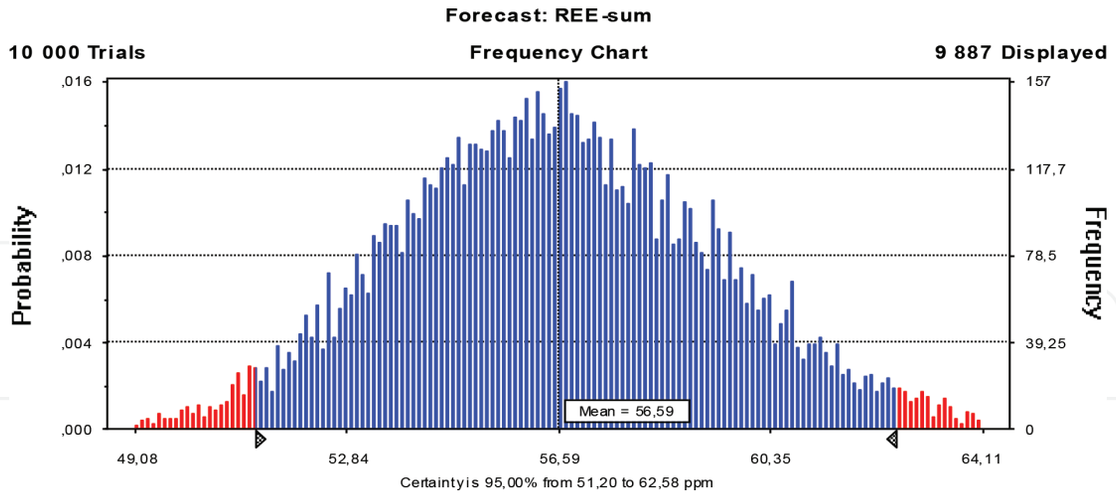

Figure 2. Frequency chart of the total REE forecast expression (95% confidence level), obtained from a MC simulation of 10,000 runs. Certainty range is from 51.20 pm to 62.58 ppm (source: own work).

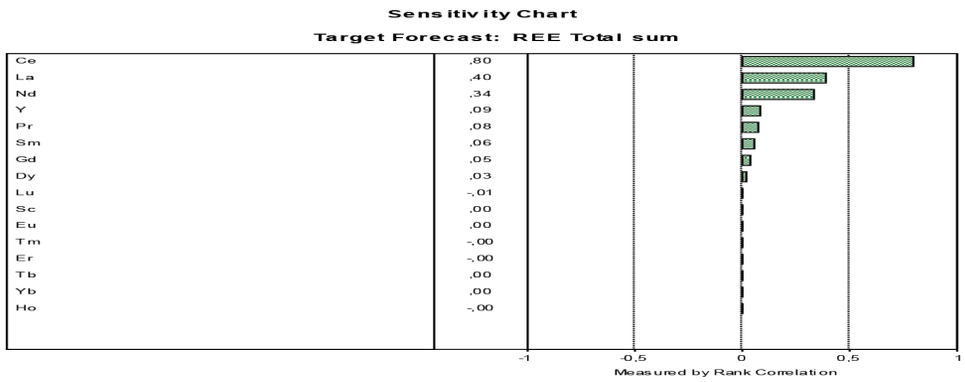

Figure 3. Sensitivity analysis with confidence levels of 95% (created by SRCC) (source: own work).

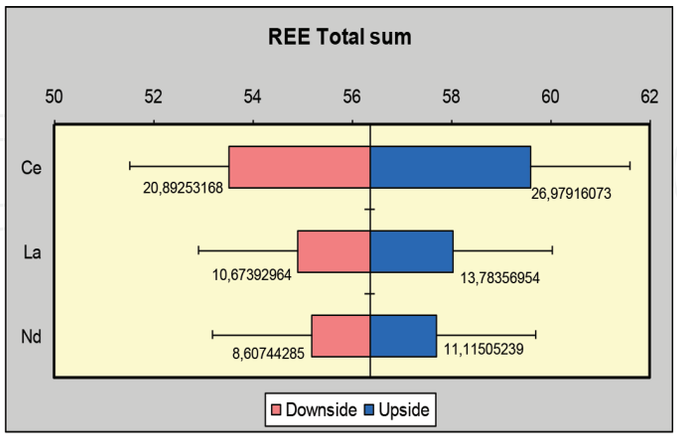

Figure 4. Tornado sensitivity chart of the Ce, La, and Ne scenario based on the percentiles of the variables, testing range of 10–90%. Error bars indicate mean standard errors (source: own work).

The sensitivity analysis demonstrates that Ce, La, and Ne are the most sensitive parameters and will be used for further analysis. The tornado and spider charts have been created on the basis of data included in the newly built tables, **Tables 4–7**, respectively. Tornado chart and spider

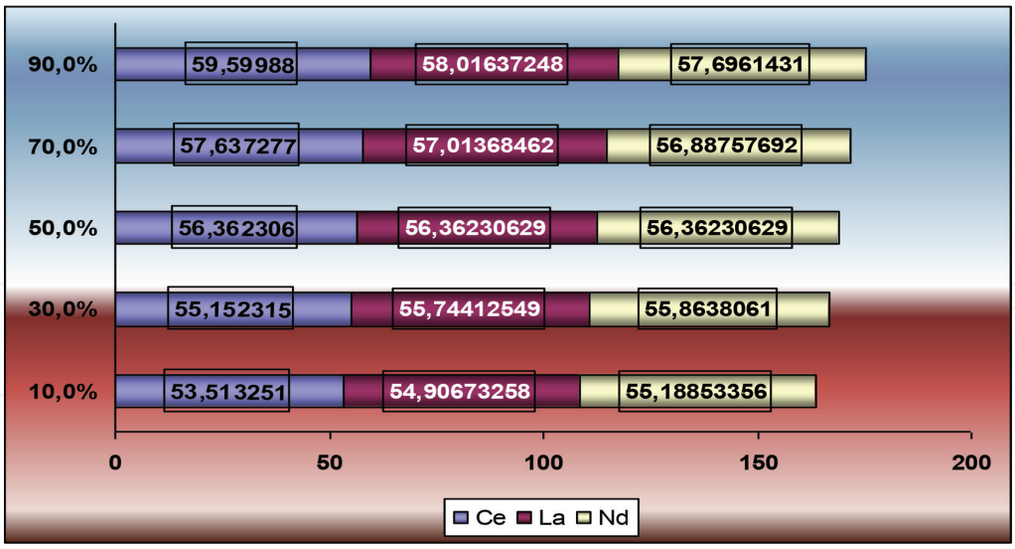

Figure 5. Spider sensitivity chart of the Ce, La, and Ne scenario based on the percentiles of the variables, testing range of 10–90%. Error bars indicate mean standard errors (source: own work).

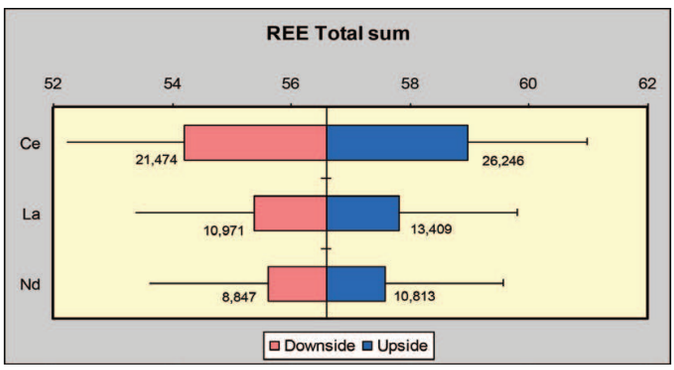

Figure 6. Tornado sensitivity chart of the Ce, La, and Ne scenario based on the percentage deviation from the base case method, testing range from −10% to +10%, using existing cell values (source: own work).

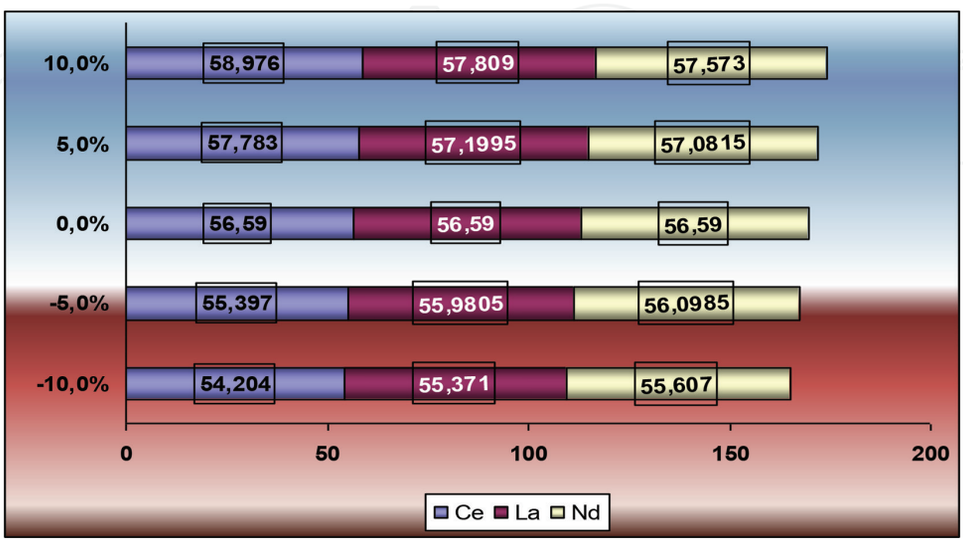

Figure 7. Spider sensitivity chart of the Ce, La, and Ne median value scenario based on the percentage deviation from the base case method, testing range from −10% to +10%, using existing cell values (source: own work).

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	REE total sum			Input		
Variable	**Downside**	**Upside**	**Range**	**Downside**	**Upside**	**Base case**
Ce	53.51325061	59.59987966	6.086629053	20.89253168	26.97916073	23.74158736
La	54.90673258	58.01637248	3.109639906	10.67392964	13.78356954	12.12950335
Nd	55.18853356	57.6961431	2.507609539	8.60744285	11.11505239	9.78121558

Table 4. The MC simulation results, using CB for the tornado sensitivity analysis-sensitivity table.

REE total sum					
Variable	**10.0%**	**30.0%**	**50.0%**	**70.0%**	**90.0%**
Ce	53.51325061	55.15231499	56.36230629	57.63727651	59.59987966
La	54.90673258	55.74412549	56.36230629	57.01368462	58.01637248
Nd	55.18853356	55.8638061	56.36230629	56.88757692	57.6961431

Table 5. The MC simulation results, using CB for the spider sensitivity analysis-sensitivity table.

	REE total sum		Input			
Variable	**Downside**	**Upside**	**Range**	**Downside**	**Upside**	**Base case**
Ce	54.204	58.976	4.772	21.474	26.246	23.86
La	55.371	57.809	2.438	10.971	13.409	12.19
Nd	55.607	57.573	1.966	8.847	10.813	9.83

Table 6. The MC simulation results, using CB for the tornado sensitivity analysis table.

REE total sum					
Variable	**−10.0%**	**−5.0%**	**0.0%**	**5.0%**	**10.0%**
Ce	54.204	55.397	56.59	57.783	58.976
La	55.371	55.9805	56.59	57.1995	57.809
Nd	55.607	56.0985	56.59	57.0815	57.573

Table 7. The MC simulation results, using CB for the spider sensitivity analysis-sensitivity table.

chart of the Ce, La, and Ne median-value base case model for input testing ranging from 10 to 90% that used percentiles of the variables method were presented in **Figures 4** and **5**, while tornado chart and spider chart of the Ce, La, and Ne based on the existing cell-value base case model for input testing ranging from −10% to +90% that used percentage deviation from the base case method were presented in **Figures 6** and **7**, respectively. Red bar indicates that the value was produced by the downside (lower bound), and a blue bar indicates that the value was produced by the upside (upper bound). Error bars indicate mean standard errors. The importance of the examined REEs is illustrated by the length of the associated bar. The rest 13

REEs were not included in the process of generating tornado and spider charts as other thirteen REEs are not in the field of ENVIRRE project research scope and interest.

Spider chart is obtained by perturbing Ce, La, and Nd median values (input variables) at consistent (testing) range from 10 to 90% from the base case, which used percentile of the variables from the base case method. The vertical y-axis maps the location measure of distribution expressed in percentages (percentile of the variables) ranging from 10 to 90% (see **Figure 6**). The variation of each input parameter (Ce, La, and Nd) (e.g., by 10, 50, and 90%) showed how much the output (REE Total sum) changes.

Spider chart is obtained by perturbing Ce, La, and Ne median values (input variables) at consistent (testing) range from 10 to 90% from the base case, which used percentile of the variables from the base case method. The vertical y-axis maps the location measure of distribution expressed in percentages (percentile of the variables) ranging from 10 to 90% (see **Figure 6**). The horizontal x-axis maps the sum of analyzed REEs (in ppm). As a result, the spider chart enables the possibility to simultaneously compare the examined REEs [23, 24].

5. Conclusions

This study refers to uncertainty in the input parameters used to create LCI of REE recovery processes from secondary sources performed according to ISO 14040 (2006). The focus of this study is defined in the goal and scope and was developed using the primary and secondary data.

Due to uncertainty analysis, a final result is obtained in the form of value range. The results from this study suggest that MC simulation is an effective method for quantifying parameter uncertainty in LCA studies.

The analyzed parameters are assigned with lognormal distribution. It is concluded that uncertainty analysis offers a well-defined procedure for LCI studies; early phase of LCA as the deterministic analysis does not include uncertainty in the input data.

The methodological approach regarding databases and boundaries was transparent and fully documented. Moreover, the results of this study can help to assess environmental impacts of rare earth mining, because production of REEs is associated with considerable environmental burdens. Additionally these result inventory data will be available for LCIA and, finally, for full LCA analysis. The obtained results may be also useful and interesting for further studies of REE recovery and could be used to other domestic and international LCA studies, and the study results demonstrate the utility of the MC simulation for a clear interpretation of LCA results. Moreover, they can also help scientist gain a cleaner understanding of the stochastic modeling in the environmental engineering and could be useful tool for decision support methods such as multi-criteria decision analysis.

And finally, consideration of uncertainty in LCA provides additional scientific information for decision-making, as discussed in the work of Romero-Gámez et al. [73].

http://dx.doi.org/10.5772/intechopen.80261

Acknowledgements

The authors are grateful for the input data provided as part of the environmentally friendly and efficient methods for extraction of rare earth elements from secondary sources (ENVIREE) project funded by NCBR within the second ERA-NET ERA-MIN Joint Call Sustainable Supply of Raw Materials in Europe 2014.

Compliance with ethical standards

Conflict of interest: the authors declare that they have no conflict of interest.

Research is not involving human participants and/or animals.

Funding

This work was supported by the Management Department of the AGH University of Science and Technology, Kraków, Poland.

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