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## STOCHASTIC ASSESSMENT BY MONTE CARLO SIMULATION FOR LCI APPLIED TO STEEL PROCESS CHAIN: THE ARCELORMITTAL STEEL POLAND S.A. IN KRAKOW, POLAND, CASE STUDY

### SYMULACJA MONTE CARLO W STOCHASTYCZNEJ ANALIZIE ZBIORU WEJŚĆ I WYJŚĆ LCI PROCESU PRODUKCJI STALI NA PRZYKŁADZIE KOMBINATU METALURGICZNEGO ARCELORMITTAL POLAND S.A. W KRAKOWIE

#### Abstract

The aim of the paper is stochastic approach for LCA/LCI probabilistic conception with uncorrelated input/output data in steel process chain with six processes (including Coke Plant, Iron Blast Furnace, Sintering Plant, BOF, Continuous Steel Casting and Hot Rolling Mill) applied to the ArcelorMittal Steel Poland (AMSP) S.A. in Krakow, Poland, case study. Uncertainty assessment in LCI based on a Monte Carlo simulation with the Excel spreadsheet and CrystalBall® (CB) software was used to develop scenarios for uncertainty inputs. The economic and social criteria and indicators will not be further discussed in this paper. The framework of the study was originally carried out for 2005 data. Uncertainty of these parameters reflects directly on the outcome of LCA method. The LCI study was conducted in accordance with all requirements of the International Standards ISO 14040:2006. The use of stochastic model helps to characterize the uncertainties better, rather than pure analytical mathematical approach. In this case study only the following substances have been taken in account: hard coal, blast furnace gas, coke oven gas, lubricant oil, cadmium (Cd), carbon monoxide (CO), carbon dioxide (CO<sub>2</sub>), nitrogen dioxide (NO<sub>2</sub>), hydrochloric acid (HCl), sulfur dioxide (SO<sub>2</sub>) and lead (Pb).

*Keywords: Life Cycles Assessment (LCA), Life Cycle Inventory (LCI), Stochastic approach, Monte Carlo simulation, Crystal Ball®*

#### Streszczenie

Celem artykułu jest przedstawienie stochastycznej analizy drugiego etapu oceny cyklu życia (LCA), jakim jest analiza inwentarzowa (LCI), dotyczącej procesu produkcji stali w kombinacie metalurgicznym ArcelorMittal Steel Poland S.A. w Krakowie. Kombinatu obejmuje: koksownię, wielkie piece, aglomerownię, stalownię konwertorową (BOF), ciągłe odlewanie stali oraz walcownię gorącą. Kryteria ekonomiczne i społeczne nie są przedmiotem analizy w prezentowanym artykule. Analiza LCI w warunkach niepewności została przeprowadzona z zastosowaniem programu CrystalBall® (CB), współpracującym z arkuszem kalkulacyjnym Excel, w oparciu o symulację Monte Carlo. Dane wzięte do analizy dotyczą roku 2005. Analiza LCI została przeprowadzona zgodnie z normą ISO 14040:2006. Do analizy wybrano takie wielkości, jak: węgiel kamienny, gaz wielkopiecowy, gaz koksowniczy, oleje, kadm (Cd), tlenek węgla (CO), dwutlenek węgla (CO<sub>2</sub>), dwutlenek azotu (NO<sub>2</sub>), kwas solny (HCl), dwutlenek siarki (SO<sub>2</sub>) oraz ołów (Pb).

*Słowa kluczowe: Ocena cyklu życia (LCA), Analiza inwentarzowa (LCI), analiza stochastyczna, symulacja Monte Carlo, Crystal ball®*

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## 1. Introduction to AMSP Power Plant in Krakow, Poland

AMSP consists of four plants located in Dabrowa, Krakow, Sosnowiec and Swietochlowice. It boasts a full production system – from pig iron to final, highly processed steel products – producing around 6.5 million tons of crude steel annually. Today, AMSP is the only truly global steel maker - with operations in the USA, Canada, Mexico, Trinidad, France, Germany, the Czech Republic, Poland, Romania, Bosnia, Macedonia, Kazakhstan, Algeria and South Africa [2]. The overview of the AMSP is given in Figure 1.

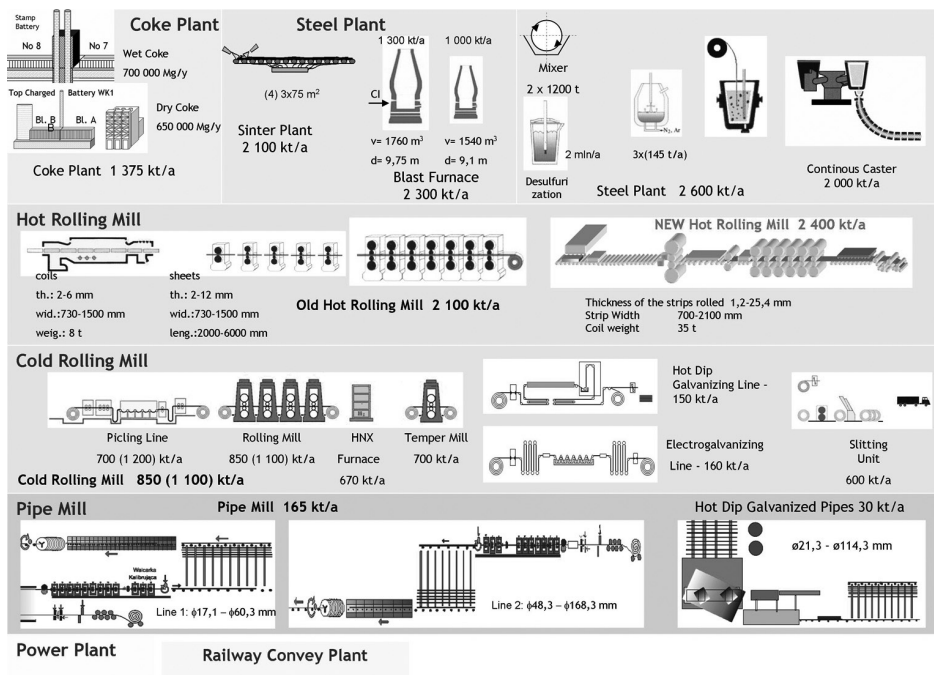


Fig. 1. General view of the ArcelorMittal Steel Poland in Krakow

Rys. 1. Schemat ogólny cyklu produkcyjnego stali w AMP w Krakowie

## 2. Goal, Scope, Terminology and Definitions

Goal definition and scoping is perhaps the most important component in LCA because the study is carried out according to the statements made in this phase, which defines the purpose of the study, the expected product of the study, system boundaries, functional unit (FU) and assumptions [3]. Although many analytic models for managing inventories exist, the complexity of many practical situations often requires simulation [4]. MC simulation with the CB analysis tool, spreadsheet add-in software, is a practical methodology for determining the uncertainty of LCI parameters.

The goals of this study were to:

- develop a stochastic approach for a Life Cycle Assessment (LCA) technique limited to a Life Cycle Inventory (LCI) study for the AMSP steel process chain from Coke Plant and Sinter Plant to Hot Rolling Mill with scope to facilitate the range of emerging impact assessment methods in future studies,
- produce national and regional LCI data for energy generating industry,
- promote the development of LCI and /or LCA research and application in Poland.

The study comprises the inventory corresponding to all the process stages including the Coke Plant, Iron Blast Furnace, Sintering Plant, BOF, Continuous Steel Casting and Hot Rolling Mill. The complete inventory was integrated by main environmental loads (inputs, outputs): energy and raw materials consumed, waste produced, and emissions to air, water and soil [5].

The functional unit in this study, the central concept in LCA, is defined as “steel process chain [which] includes all activities linked with steel production from Coke Plant and Sinter Plant to Hot Rolling Mill in 2005”. System boundaries of this study were presented in Fig. 2. It does not include the manufacture of downstream products, their use, end of life. For the AMSP power plant, mining and transportation of raw coal, crude oil and natural gas were not included. Key characteristics for the AMSP are shown in Tab. 1 [1].

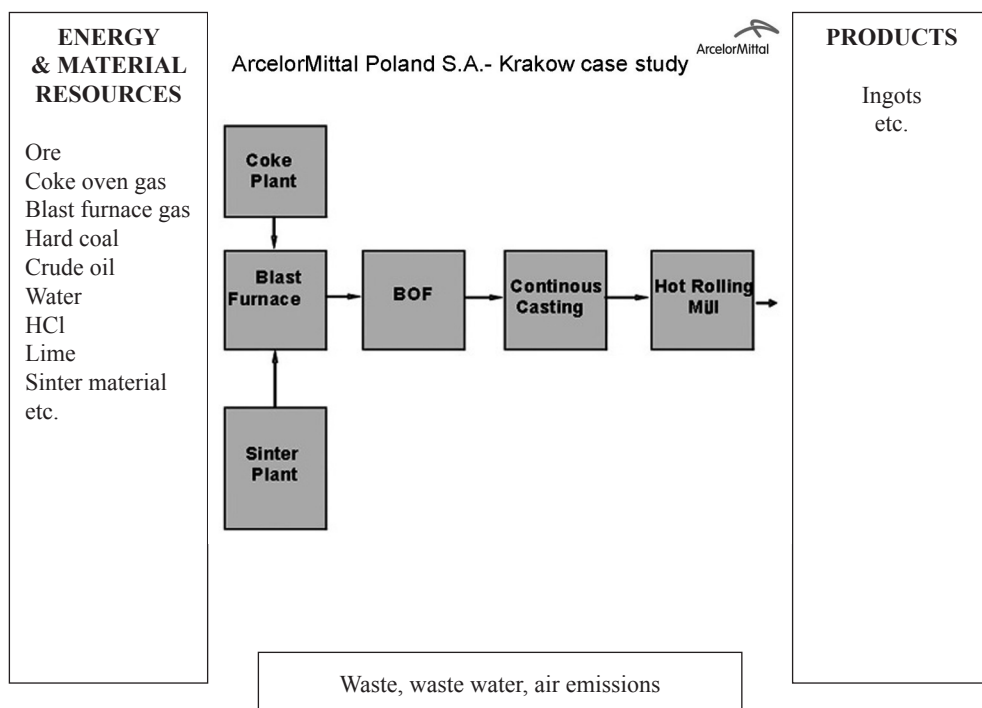


Fig. 2. System boundaries of the study

Rys. 2. Granice analizowanego procesu produkcji stali

### 3. Uncertainty Assessment in LCI

In the Commission Decision of 18 July 2007 establishing guidelines for the monitoring and reporting of greenhouse gas emissions pursuant to the Directive 2003/87/EC of the European Parliament and of the Council, uncertainty means: “a parameter, associated with the result of the determination of a quantity, that characterizes the dispersion of the values that could reasonably be attributed to the particular quantity, including the effects of systematic as well as of random factors and expressed in per cent and describes a confidence interval around the mean value comprising 95% of inferred values taking into account any asymmetry of the distribution of values” [6]. Usually the overall uncertainty of the LCI is dominated by a few major uncertainties. Likewise, the overall uncertainty of a specific process is typically dominated by one source of uncertainty and other sources of uncertainty may be ignored [7]. Information about uncertainty in the LCI results cannot be fully captured within the LCI database, because a significant share of this uncertainty arises in practice, based on relationship between the data [8]. When the main determining parameters of an uncertainty is known, it can be eliminated or at least reduced to the uncertainty by modelling.

Three types of process modelling can be identified in LCA studies [9]:

- black box models of processes. This is the mostly used type in LCA because this is the easiest way of process modelling.
- models of processes with linear functional relations. In this concept linear relations (functions) between each input and output as well as between the different inputs are defined.
- models of processes with non-linear and linear functional relations. In this concept linear or non-linear relations (functions) between each input and output as well as between the different inputs are defined.

In Eco-indicator 99 [10] three fundamentally different types of uncertainty were presented:

- operational, or data uncertainties – the squared geometric standard deviation expressed the variation between the best estimate and the upper and lower confidence limits (97.5% and 2.5%). The uncertainties are intended for use in software tools that apply Monte Carlo analysis
- fundamental, or model uncertainties – many modelling choices are often rather subjective,
- uncertainty due to the incompleteness of the model.

The overall uncertainty of the assessment includes [11]:

- uncertainty of models and parameters,
- uncertainty of the indicators interpretation.

### 4. The benefit of MC simulation

The uncertainty stems from partial ignorance or lack of perfect knowledge. Based on the experiences regarding uncertainty in LCA/LCI studies, it seems that LCI must be performed from a probabilistic point of view, rather than by considering deterministic aspects. Among the probabilistic tools, in order to include the above aspects the use of MC analysis has been increasing in recent years, and is one of the most widespread stochastic

model uncertainty analyses. This effect has been widely studied (e.g. [12, 13]). The MC simulation uses these distributions, referred to as “assumptions”, to automate the complex “what-if” process and generate realistic random values. The benefits of a simulation modelling approach are:

- 1) an understanding of the probability of specific outcomes,
- 2) the ability to pinpoint and test the driving variables within a model,
- 3) a far more flexible model,
- 4) clear summary charts and reports [14].

One of the problems associated with traditional spreadsheet models is that for variables that are uncertain. Without the aid of simulation, a spreadsheet model would only reveal a single outcome. Spreadsheet uncertainty analysis uses a spreadsheet model and simulation to analyze the effect of varying inputs or outputs of the modelled system automatically. With CB, a commercially available software, we have the ability to replace each uncertain variable with a probability distribution, a function that represents a range of values and the likelihood of occurrence beyond that range.

The MC sampling was done using an Excel® spreadsheet modified to develop scenarios for inputs given the probability distributions, means values, etc. and CB, a software package offered by Decisionnering, generating random numbers for a probability distribution beyond the entire range of possible values, based on the assumption variables. For this reason, a large number of trials are required to obtain accurate results for the true shape of the distribution results and probabilities for those results. The MC analysis-simulation is the only acceptable approach for U.S. Environmental Protection Agency (EPA) risk assessments [15]. CB contains 12 distribution types [6].

#### 4.1. Data Sources Choosing Input Distributions

The data collection for the core of the AMSP power plant generating processes has been performed rigorously, with appropriate checks on consistency and completeness. The data used in the study are obtained from the following sources:

- site-specific measured or calculated data [1],
- LCA study carried out on behalf of the AGH-University of Science and Technology’s Management Department by the Polish Academy of Arts and Sciences in Krakow [5],
- value based on literature information,
- AMSP Environmental Impact Report [1],
- data obtained from other sources e.g. personal communication (AMSP Environmental Department director).

For some variables, there may be enough empirical information to fit parametric distributions or even specify empirical histograms. For other variables, the available data may be very limited or completely absent. Sometimes it is reasonable to let experts define the shapes of the input distribution subjectively, but this is not always a workable strategy and often leads to more controversy [16]. Use of default (i.e. arbitrary) input distributions is sometimes suggested, but this approach can be criticized easily [17-18].

The probability distributions for the hard coal, blast furnace gas, coke oven gas and natural gas were considered to be normal with coefficient of variation (CV) of 0.10 according to the [18, 19]. The probability distributions for the lubricant oil were considered

to be normal with CV of 0.1, according to the estimations published by Weidema and Wesnaes [20]. The proper determination of the log-normal probability distributions in the case of SO<sub>2</sub> (emissions), CO (emissions), NO<sub>2</sub> (emissions), Cr, Cd, Ni and HCl data with a geometric standard deviation ( $\sigma_g$ ) between 1.5 and 2.2 is possible according to the estimations published by Sonnemann et al. [14] based on Rabl and Spadaro [21] and STQ [22], as well as the data taken from Kulczycka, Henclik study [5]. It was possible to simulate the following parameters emitted in air (e.g. lack of information regarding geometric standard deviation,  $\sigma_g$ ): Cu, Mn, S and Pb, because according to the criteria proposed by Sonnemann et al. [14] 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”, the log-normal probability distributions with a geometric standard deviation ( $\sigma_g$ ) equal 2.5, were selected from STQ [22]. The geometric standard deviations consideration as well as normal standard deviations were done due to the lack of Polish data applied to the concentrations in emissions of the AMSP steel processes. In the study presented by Sonnemann et al. [14] related to the uncertainty assessment by Monte Carlo simulation for LCI applied to waste incinerator in Tarragona, the data were obtained from the ETH database [19]. These data have been collected from a Swiss perspective on a European scale. The probability distributions for other elements of Site-Specific Data had to be derived from the CB analysis experimental results. The confidence level is specified as 95%.

Meier [18] proposed to assume classes of normal probability distributions with the following CVs:

- for data obtained by stoichiometric determination, a CV of 2% needs to be considered,
- for actual emission measurements or data computable in well-known process simulation, a CV of 10% is expected,
- for well-defined substances or summed parameters, a CV of 20% can be assumed,
- for data taken from specific compounds by an elaborated analytical method, a CV of 30% is expected.

According to [23], and [26] several reports in risk assessment and impact pathway analysis have shown that the log-normal distribution seems to be a more realistic approximation for the variability in fate and effect factors than the normal distribution. The 50<sup>th</sup> percentile of a log-normal distribution is related to the mean of its corresponding normal distribution. The log-normal distribution is calculated assuming that logarithm of the variable has a normal distribution. The geometric mean,  $\mu_g$ , and the geometric standard deviation,  $\sigma_g$ , of the sample is very practical and correspond to the mean and coefficient of variation for the normal distribution. Moreover, they provide multiplicative confidence intervals such as:

$[\mu_g / \sigma_g, \mu_g \cdot \sigma_g]$  for confidence interval (level) of 68%.

$[\mu_g / \sigma_g^2, \mu_g \cdot \sigma_g^2]$  for confidence interval of 95% [14].

The complete inventory was integrated by main environmental loads (inputs, outputs): energy and raw materials consumed, waste produced, and emissions into the air for the year 2005 with their distribution type and deviations are presented in [5].

In this case study only the following substances have been taken in account: hard coal, blast furnace gas, coke oven gas, lubricant oil, cadmium (Cd), carbon monoxide (CO),



carbon dioxide ( $\text{CO}_2$ ), nitrogen dioxide ( $\text{NO}_2$ ), hydrochloric acid ( $\text{HCl}$ ), sulfur dioxide ( $\text{SO}_2$ ) and lead ( $\text{Pb}$ ).

Figures 3-5 show the results of 10000 replications of the CB screenshot (define assumption dialogue box for normal and log-normal distributions as well as the final provision) related to the data given in [5].

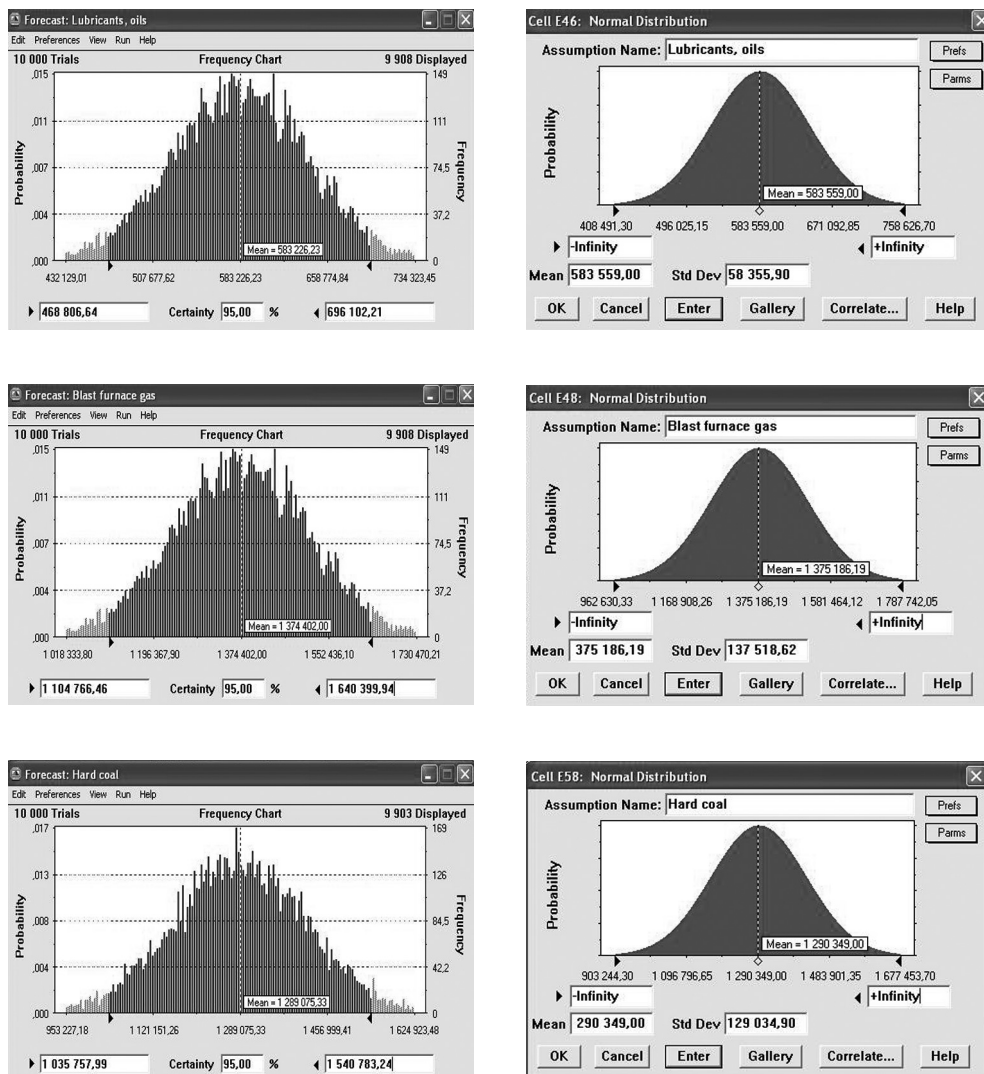


Fig. 3. Steel process chain includes all activities linked with steel production from Coke Plant and Sinter Plant to Hot Rolling Mill in 2005

Rys. 3. Rozkłady prawdopodobieństwa oraz wyniki symulacji MC (histogramy) przeprowadzone dla różnych produktów przyporządkowanych procesowi produkcji stali (koksoznia-walcownia gorąca) w 2005

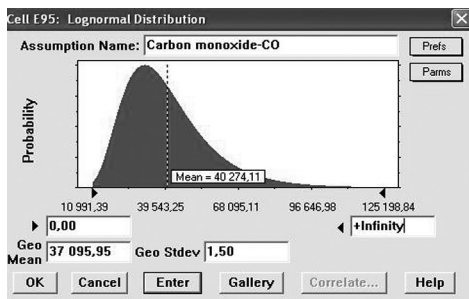
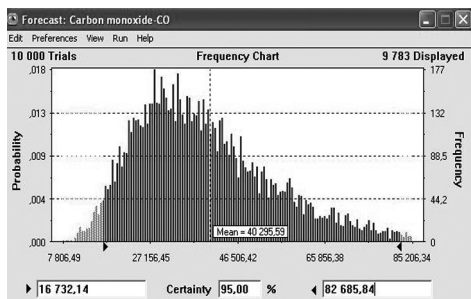
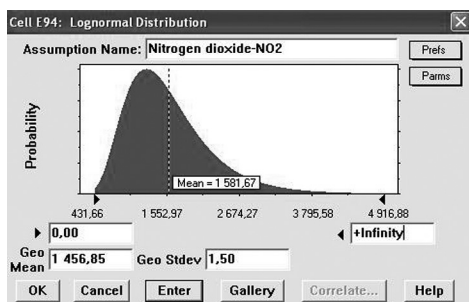
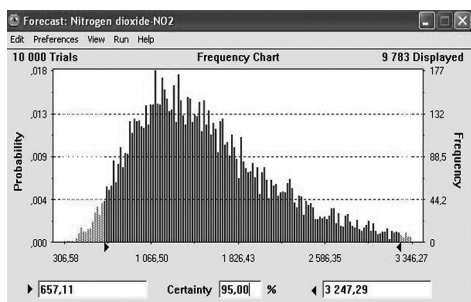
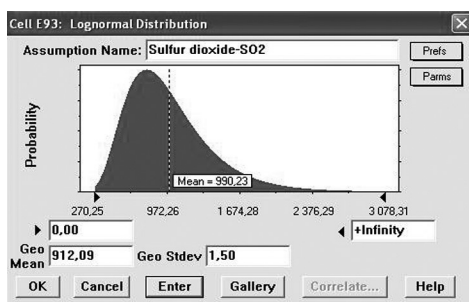
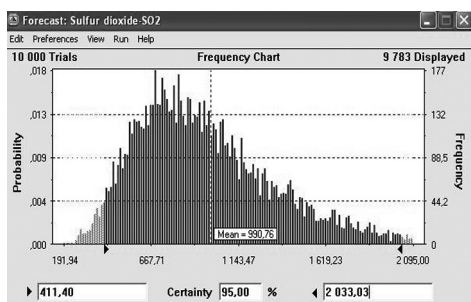
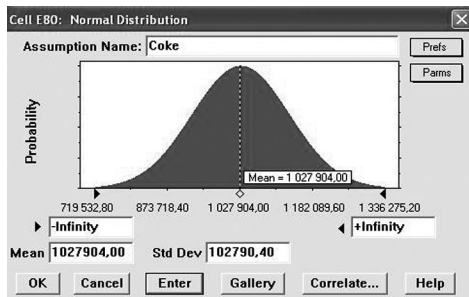
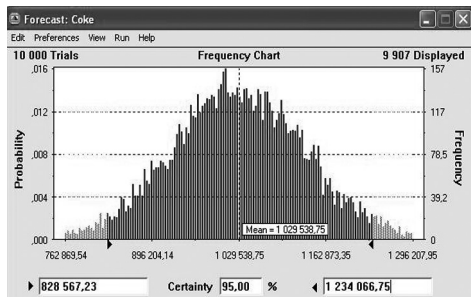


Fig. 4. (continued) Steel process chain includes all activities linked with steel production from Coke Plant and Sinter Plant to Hot Rolling Mill in 2005

Rys. 4. (cd.) Rozkłady prawdopodobieństwa oraz wyniki symulacji MC (histogramy) przeprowadzone dla różnych produktów przyporządkowanych procesowi produkcji stali (koksownia-walcownia gorąca) w 2005



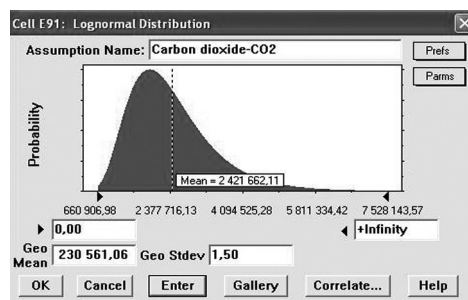
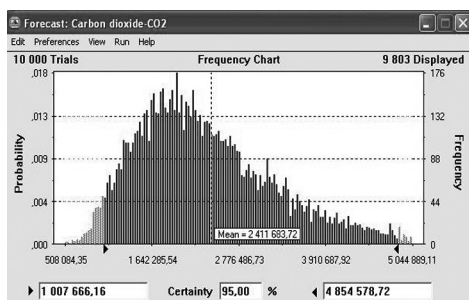
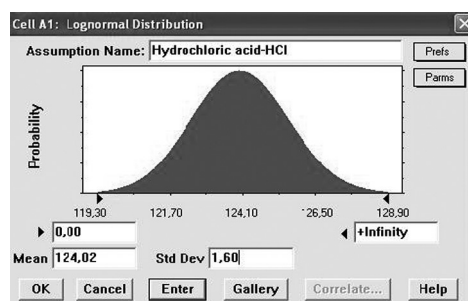
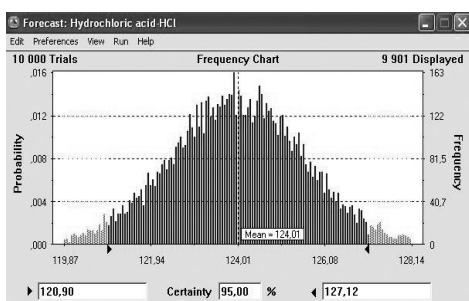
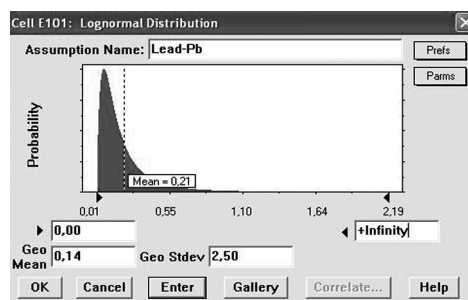
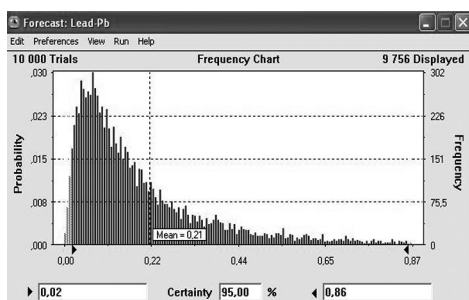
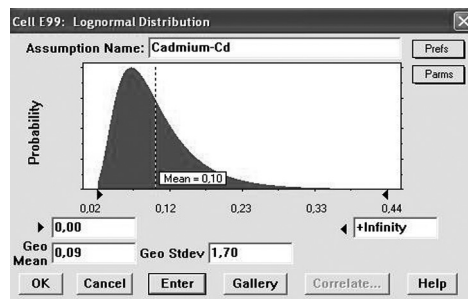
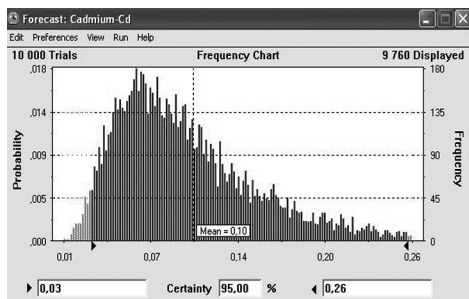


Fig. 5. (continued) Steel process chain includes all activities linked with steel production from Coke Plant and Sinter Plant to Hot Rolling Mill in 2005

Rys. 5. (cd.) Rozkłady prawdopodobieństwa oraz wyniki symulacji MC (histogramy) przeprowadzone dla różnych produktów przyporządkowanych procesowi produkcji stali (koksownia-walcownia gorąca) w 2005

## 4.2. Discussions

Several LCA studies have been proposed in the literature to present and to compare many techniques to compute uncertainty propagation. Simulation models are generally easier to understand than many analytical approaches [4]. Usually the overall uncertainty of an LCI is dominated by a few major uncertainties [24]. One of the most interesting experiences is that reported by Rabl and Spadaro [21]. They evaluated the uncertainty and variability of damage and costs of air pollution by means of analytical statistical methods. Monte Carlo Simulation in LCA approach used for airborne emissions of biomass-based ethanol products from different feedstock planting areas in China is presented in [27], as well as Monte Carlo Simulation on the uncertainties in transportation distance and moisture content is studied in [28]. For the uncertainty analysis of LCI, Hanssen and Asbjornsen [19] used statistical analysis. Ros [30] proved the fuzzy logic, and Maurice et al. [31] as well as Meier [18] decided in favour of the stochastic methods [14]. Benetto et al. [32] have presented the possibility theory approach in uncertainty analysis. The uncertainty analysis in ecological risk assessment is found in the 24<sup>th</sup> Pellston Workshop on Uncertainty Analysis in Ecological Risk Assessment [33], and discussion about the uncertainty and error calculation in LCA is presented in 14<sup>th</sup> SETAC Europe Annual Meeting [34]. An adaptation of the procedure for the uncertainty and variability assessment in the LCI has been presented in [14]. LCI of GHG emission for electricity power plants in Thailand using the LCIA was developed in [35].

## 5. Conclusions

The aim of the study is the use of a stochastic assessment by Monte Carlo Simulation for LCI applied to steel process chain: the AMSP in Krakow, Poland, case study and to promote the use of uncertainty estimation as routine in environmental science. Uncertainty analysis in the LCA methodology has received increasing attention over the last years. The functional unit in this study, the central concept in LCA, is defined as “steel process chain [which] includes all activities linked with steel production from Coke Plant and Sinter Plant to Hot Rolling Mill in 2005”. The economic and social criteria and indicators have not been further discussed in this paper.

LCA/LCI data are full of uncertain numbers. The benefits of Monte Carlo Simulation save time and resources. CB eliminates the need to run, test, and present multiple spreadsheets. With the CB analysis we can show the benefit of investing more on a monthly basis.

The use of stochastic model helps to characterize the uncertainties better than the pure analytical mathematical approach. The created inventories using the probabilistic approach facilitate the environmental damage estimations for industrial process chains with complex number of industrial processes (e.g. steel production). Consequently, the Monte Carlo analysis is a powerful method for quantifying parameter uncertainty in LCA studies. For example, in this study the most likely SO<sub>2</sub> emission values ranged between 411.40 Mg and 2,033.03 Mg. The certainty level is 95%. The quantity of the SO<sub>2</sub> emissions used in the model calculation was 916.64 Mg.

## 6. Outlook

The research described in this paper can also serve as the basis for future work. The data obtained from the Monte Carlo Simulation, presented in Figures 3-5, will be used in the next step of the LCA analysis, in the Life Cycle Impact Assessment (LCIA). A potential direction for the future research is the integrated LCA and risk assessment for industrial processes, based on the probabilistic and statistical modelling for decision making under risk analysis as this technique accounts for uncertainties in the assumptions. The baselines presented in this study use deterministic input values. In a deterministic model, all data are known, or assumed to be known, with certainty. In a probabilistic model, some data are described by probabilistic distributions. Simulation models are generally easier to understand than many analytical approaches.

## References

- [1] Mittal Steel Poland, Environmental Impact Report, 2007 b.
- [2] Mittal Steel Poland (<http://www.mittalsteel.com/Facilities/Europe/Mittal+Steel+Poland>), 2007 a.
- [3] Roy P., Nei D., Orikasa T., Xu Q., Okadome H., Nakamura N., Shiina T., *A review of life cycle assessment (LCA) on some food products*, Journal of Food Engineering 90, 2009, 1-10.
- [4] Evans J.R., Olson D.L., *Introduction in Simulation and Risk Analysis*, Prentice Hall, New Jersey 1998.
- [5] Kulczycka J., Henclik A., *Ocena wpływu cyklu życia procesów wytwórczych na Wydziałach Surowcowych i Wytwarzania Stali Huty ArcelorMittal Steel Poland SA, Oddział w Krakowie*, Polish Academy of Science, Kraków 2009.
- [6] Commision Decision, *Establishing guidelines for the monitoring and reporting of greenhouse gas emissions pursuant to Directive 2003/87/EC of the European Parliament and of the Council*, 2007 (<http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2007:229:0001:0085:EN:PDF>).
- [7] Fress N., Petersen E.H., Olgaard H., *Reducing Uncertainty in LCI*, Environmental, Project No. 862 2003, Danish Environmental Protection Agency, 2003.
- [8] Goedkoop M., De Schryver A., Oele M., *SimaPro 7.1 Tutorial. Pré Consultants*, Report version 3.2, Netherlands 2003.
- [9] Klopffer W., Hutzinger O., *Life Cycle Assessment: State-of-the Art and research priorities, results of LCA NET*, A Concerted Action in the Environment and Climate Programme (DGXII), Vol. 1, LCA Documents, Eco-Informa Press 1997.
- [10] Eco Indicator 99 method (<http://www.pre.nl/eco-indicator99/default.htm>).
- [11] Hauschild M., *Assessing Environmental Impacts in a LIFE-CYCLE Perspective*, Environmental Science & Technology, vol. 39, No. 4, 2005, 905-912.
- [12] Nadal M., Kumar V., Schumacher M., Domingo J.L., *Applicability of a Neuroprobabilistic Integral Risk Index for the Environmental management of Polluted Areas: A Case Study*, Risk Analysis, Vol. 28, No 2, 2008, 271-286.

- [13] Spath P.L., Lane J.M., Mann M.K., Armos W.A., *Update of Hydrogen from Biomass-Determination of the Delivered Cost of Hydrogen*, 2000 ([http://www.cbpredictor.com/articles/download/biomass\\_to\\_hydrogen.pdf](http://www.cbpredictor.com/articles/download/biomass_to_hydrogen.pdf)).
- [14] Sonnemann G., Castells F., Schumacher M., *Integrated Life-Cycle And Risk Assessment For Industrial Processes*, Lewis Publishers: Boca Raton, London, New York, Washington, D.C. 2004.
- [15] Finley B., Proctor D., Scott P., Harrington N., Pasutenbach D., Price P., *Recommended distributions for exposure factors frequently used in health risk assessment*, Risk Analysis 14, 1994, 533-553.
- [16] Haimes Y.Y., Barry T., Lambert J.H., *When and how can you specify a probability distribution when you don't know how much?*, Risk Analysis 14, 1994, 661-706.
- [17] *The Engineering index*, American Society of Mechanical Engineers, The Engineering index inc., Michigan University, 1972, 2865.
- [18] Meier M., *Eco-Efficiency Evaluation of Waste Gas Purification Systems in the Chemical Industry*, LCA Documents, Vol. 2, Ecomed Publishers, Landsberg, Germany 1997.
- [19] Frischknecht R., Bollens U., Bosshart S., et al., *Okoinventare von Energiesystemen – Grundlagen für den ökologischen Vergleich von Energiesystemen und den Einbezug von Energiesystemen in Okobilanzen für die Schweiz*, 3<sup>rd</sup> ed. ETH Zürich, Gruppe Energie-Stoffe\_Umwelt, PSI Villingen, Sektion Ganzheitliche Systemanalysen, 1996.
- [20] Weidema B., Wesnaes M.S., *Data quality management for life-cycle inventories – an example of using data quality indicators*, J. Cleaner Prod. 4 (3-4), 1996, 167-174.
- [21] Rabl A., Spadaro J.V., *Environmental damages and costs – an analysis of uncertainties*, Environ. Int. 25(1), 1999, 29-46.
- [22] STQ (Servei de Tecnologia Química), *Análisis del ciclo de vida de la electricidad producida por la planta de incineración de residuos urbanos de Tarragona*, technical report, Universitat Rovira i Virgili, Tarragona, Spain 1998.
- [23] Hofstetter P., *Perspective in Life Cycle Impact Assessment: A structured approach to combine models of the technosphere, ecosphere and valuesphere*, Kluwer Academic Publishers: Boston, Dordrecht, London 1998.
- [24] Bieda B., Tadeusiewicz R., *Decision support systems based on the Life Cycle Inventory (LCI) for Municipal Solid Waste (MSW) Management under Uncertainty*, International Transaction in Operational, 2008.
- [25] Doka G., Hischier R., *Waste Treatment and Assessment of Long-Term Emissions*, Int. J LCA 10 (1), 2005, 77-84.
- [26] Frischknecht R., Rebitzer G., *The ecoinvent database system: a comprehensive web-based LCA database*, J. Cleaner Prod. 13, 2005, 1337-1343.
- [27] Yu S., Tao J., *Simulation based life cycle assessment of airborne emissions of biomass-based ethanol products from different feedstock planting areas in China*, J. Cleaner Prod. 17, 2009, 501-506.
- [28] Dowaki K., Genchi Y., *Life Cycle Inventory analysis on Bio-DME and/or Bio-MeOH products through BLUE tower process*, DOI 10.1007/s1367-009-0092-6.
- [29] Hanssen O.J., Asbjornsen A.A., *Statistical properties of emission data in life-cycle assessment*, J. Cleaner Prod. 4, 1996, 149-157.

- [30] Ros M., *Unsicherheit und Fuzzyiness in ökologischen Bewertungen – Orientierungen zu einer robusten Praxis der Ökobilanzierung*, PhD Thesis, ETH Zürich. Switzerland 1998.
- [31] Maurice B., Frischknecht R., Coehlo-Schwitz V., Hungerbühler K., *Uncertainty analysis in life-cycle inventory – application to the production of electricity with French coal power plants*, J. Cleaner Prod. 8, 2000, 95-108.
- [32] Benetto E., Dujet C., Rousseaux P., *Possibility Theory: A New Approach to Uncertainty Analysis?*, Int. J LCA 11, 2006, 114-116.
- [33] Uncertainty Analysis in Ecological Risk Assessment, Warren-Hicks W., Moore D.R. (eds). A Special Publication of SETAC, SETACPRESS, 1995.
- [34] Scharnhorts W., Köhler A., Rebitzer G., Hischier R., Jolliet O., *Progress in Modern Life Cycle Assessment: Practice and Research*, Int. J LCA 9, 2004, 143-151.
- [35] Sate S., Seizo K., Naoki M., Akira N., Tanongkiat K., Anugerah W., *LCA-NETS Evaluation for GHGs of Power Generation Plants in Thailand*, 2005 ([http://www.etseq.urv.es/aga/lcm2005/99\\_pdf/Documentos/AE12-4.pdf](http://www.etseq.urv.es/aga/lcm2005/99_pdf/Documentos/AE12-4.pdf)).