Bogusław Bieda

Stochastic Analysis in Production Process and Ecology Under Uncertainty

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Summary

The monograph addresses a problem of stochastic analysis based on the uncertainty assessment by simulation and application of this method in ecology and steel industry under uncertainty. The first chapter defines the Monte Carlo (MC) method and random variables in stochastic models. Chapter 2 deals with the contamination transport in porous media. Stochastic approach for Municipal Solid Waste transit time of contaminants modelling, using MC simulation, has been worked out as well. The third chapter describes the risk analysis of the waste to energy facility proposal for the city of Konin, including its financial aspects. Environmental impact assessment of the Mittal Steel Poland (MSP) S.A. Power Plant, in Kraków is given in the fourth chapter. Thus, four scenarios of the energy mix production processes are studied. Chapter 5 contains examples of using Ecological Life Cycle Assessment (LCA) – a relatively new method of environmental impact assessment – which helps in preparing pro-ecological strategies, and which can lead to the reduction of the amount of waste produced in the MSP production processes. Moreover, real input and output data of selected processes under uncertainty, mainly used in the LCA technique, are examined. The last chapter of this monograph contains the final summary.

Log-normal probability distribution, widely used in risk analysis and environmental management with the aim of developing stochastic analyses of the LCA, as well as uniform distribution for stochastic approach of pollution transport in porous media have been proposed.

In order to determine the uncertainty of parameters using MC simulation, two software packages, SimLab® from the European Union's Joint Research Centre (Italy) and Crystal Ball® (an add-on to Excel) from Decisioneering (USA), are employed. Sensitivity analysis is another function of these computer programs and it refers to the amount of uncertainty in a forecast that is caused by both the uncertainty of an assumption and by the model itself.

The distributions employed in this monograph are assembled from site-specific data as well as from data existing in the most current literature, and are based on professional judgment.

Introduction

The aim of this project is to discuss the stochastic analysis, based on the theory of probability and statistical mechanics, using Monte Carlo (MC) simulation, focusing especially on the chosen aspects of ecology management and on the examples of manufacturing processes in the steel industry under uncertainty. The paper includes the identification, the assessment, and the evaluation of uncertainty in the probabilistic analysis of: (1) the diffusion (transport) of polluting substances in homogeneous porous media, (2) the project investment risk in the waste to energy facility in the City of Konin, Poland, (3) the assessment of the environmental impact of the energy production processes in Mittal Steel Poland (MSP) Power Plant S.A. Unit in Kraków, Poland, as well as (4) the life cycle of waste management in MSP. Despite the interdisciplinary nature of the monograph, MC simulation is the common feature across the fields and, consequently, the methodology employed in MC computer simulations, the sensitivity analysis, and the data uncertainty assessment, are all discussed.

In order to conduct all the necessary calculations, two professional software packages are used in this project: SimLab®, developed by the European Commission Joint Research Centre (JRC) in Italy, and Crystal Ball® (CB), a spreadsheet-based application, used for modelling, forecasting, simulation, and optimisation. Due to its wide application in research publications (Evans and Olson 1998; Sonnemann et al. 2004; Bradley, Warith et al. 1999), and its verification in practice (see Sonnemann et al. 2004), more emphasis is placed on CB software. However, both programs offer a large number of statistical distributions that can be applied in the modelling of stochastic systems, and allow for MC simulation, as well as sensitivity and uncertainty analysis, to be performed.

The monograph is comprised of an introduction, five chapters, and a conclusion. The introduction illustrates the origin of the problem and the outline of the relevant subject matter, whereas the conclusion summarises and generalises the final results. Each of the five chapters also ends with a brief conclusion.

The first chapter defines the chosen terms from the scope of probability, concentrating on MC method and random variables. The log-normal probability distribution of continuous random variables is discussed here in greater detail, as it is widely applied in environmental risk analyses and environmental management, in particular in the research on the ecological Life Cycle Assessment (LCA) and uncertainty.

The second chapter focuses on the stochastic model of the diffusion (transport) of polluting substances in homogeneous porous media, with the help of CB computer software. Thanks to its wide range of statistical tools, CB makes it possible to perform sensitivity analyses, among other tasks, and is able to generate tornado charts and spider charts. In addition, the program allows the user to express uncertainty as a probability, which makes it a useful tool in environmental forecasting and management. In the third chapter the emphasis is on the employability of MC simulation, a problem which is analysed with the help of SimLab® professional computer software that performs risk assessments of investment costs management, illustrated with the case study of the waste gasification project in the City of Konin.

The possible applications of stochastic analysis in the LCA studies that determine the potential environmental impact of the energy production processes in MSP Power Plant are discussed in the fourth chapter. The opening paragraphs of the chapter deal with the basic terms used in the LCA method, a method used in environmental management, and defined in the ISO 1404x standard series (Environmental Management – Life Cycle Assessment), published by the International Organisation for Standardisation (ISO). The application of Life Cycle Assessment is recommended in a number of official documents issued by the EU, among which is the Directive 2008/98/EC of the European Parliament and of the Council (of 19 November 2008) on waste (Kulczycka and Henclik 2009). According to the provisions outlined in the standard, the Life Cycle Assessment method can be adopted by identifying and determining the amount of materials and energy used, as well as the quantity of waste discharged into the environment. This is followed by the assessment of the environmental impact of such processes and the interpretation of the obtained results. It is vital to establish both the aim and scope of the analysis, as well as its functional unit and its boundary system. The detailed description of the LCA method can be found in the subsequent chapters of this monograph.

In LCA studies, the emphasis is on a more detailed characterisation of uncertainty, which leads to concentration on uncertainty of source data. The quantitative data analysis, based on MC simulation, is performed, as exemplified by the comparative analysis of the environmental impact of the four scenarios of the energy production processes in the Power Plant, in its annual cycle in 2005. Each of these scenarios is different, due to the change of proportioning ratios of the two types of fuels: hard coal and blast furnace gas. The levels of other fuels, such as natural gas and coke oven gas, are left unchanged. The life cycle processes of energy production in the Power Plant and the existing connections between these processes are illustrated with the help of resources "trees" and processes "trees" generated by SimaPro 7.1 computer software.

The fifth chapter focuses on the LCA methodology with a view to presenting the problem of stochastic analysis of the waste management life cycle in MSP Power

Plant and its impact on the quality of the environment. The uncertainty and sensitivity analyses are performed by looking at the Human Health damage category, measured in Disability Adjusted Life Years (DALY) that help determine the relative amount of time by which human life is shortened as a result of damaging waste management effects of MSP, recognising the category as the most representative type of analysis possible. Other categories, namely Consumption of Resources and Ecosystem Quality, were omitted, since, as is indicated in the Eco-indicator 99 method, the uncertainly analysis is not conducted in the Resources category.

All four chapters (Chaps. 2–5) focus on the application of the MC method in stochastic models.

Both the material balance and the waste management balance in MSP are composed on the basis of information received from MSP and the data obtained from a document about the application for an integrated permit for the fuel combustion for energy production facility in the Mittal Steel Poland S.A. Unit in Kraków – the summary (in non-specialist language), drafted in June 2006 (Wniosek 2006).

All the simulations and recorded findings, which result from these simulations and are presented in the fourth and fifth chapter of this monograph, are performed using the data acquired from the calculations made for the thesis by the Mineral and Energy Economy Research Institute of the Polish Academy of Sciences in Kraków, as part of the order for the papers entitled "Life cycle assessment in the energy production process in MSP Power Plant S.A. in Kraków, Poland" (Ocena 2008) and "Life cycle assessment in the generation processes – the case study of MSP Power Plant S.A. in Kraków, Poland" (Ocena 2009), financed by the research project resources (post doctoral research grant number N115 084 32/4279), allocated for foreign services. All the calculations are made using the SimaPro 7.1 software and its implemented databases (mostly Ecoivnet), and the analysis is based on the Eco-indicator 99 method, a typical example of final element method (Kowalski et al. 2007).

The data gathered from the Power Plant contains the material-energy balance, with its 48 entries, which is shown in an inventory table for the energy production processes in MSP Power Plant. For the purposes of the analysis, an individual process is established, which includes all the entries between entry eighteen (18) and entry forty-two (42) of the inventory table. This process is called Siłownia-E (E-Power-Plant) and its functional unit is based on the entire life cycle of the Plant, from an annual perspective, with 2005 used as its base year.

The scope of the study dealing with life cycle assessment of waste production by individual MSP facilities includes:

- The coke production facility – Coke Plant,
- The ore sintering facility – Sintering Plant,
- The pig iron melting facilities – Blast Furnaces,
- The steel melting facility – Converter Plant,
- The Continuous Steel Casting facility – CSC,

- The facility for hot rolling of ferrous metals – Hot Strip Mill,
- The fuel combustion facility – Power Plant.

Each of the facilities is a source of different types of pollutant emissions: air, water, and solid waste. This analysis focuses on the waste management aspect of the problem.

The waste production by the abovementioned facilities in an annual cycle (based on 2005) is considered to be the chosen functional unit, and the boundaries of the analysed system are labelled as gate to gate. The carried out analysis is based on the balance of the waste produced.

For the purposes of the analysis, some of the types of waste are grouped; for instance, a "dangerous waste" category was created, in which all of the dangerous types of waste produced by the analysed facilities are placed. However, the results, indicated in the analysis, may not be entirely correct, owing to the chosen sludge generated during the production of steel in electric furnace shops equipped with electric furnaces (as there is no other method of steel production available in the database). At present, there are two dominant steel production methods in the world. The first one is based on the production in, the so-called, integrated mills where pig iron is produced in blast furnaces and then is converted into steel using oxygen converters with the help of scrap metal. The second method of steel making is based on using scrap metal in an electric process in steel plants equipped with arc furnaces. The use of all-European data may further damage the credibility of the results, as this type of data is not always adequate to Polish conditions.

This monograph would have been impossible to complete without the help of, and the fruitful collaboration with, the Department of Environmental Protection and MSP Power Plant that have made some necessary data available for this experimental research. The permission to use the appropriate data needed to complete this project has been given by the Managing Director of ArcelorMittal Poland S.A. Unit in Kraków (the letter no. DN/327/2007 of 25.05.2007). The financial help offered by the Ministry of Science and Higher Education in Warsaw in the form of a postdoctoral research grant (no. N115 084 32/4279) has been very important as well.

Contents

List of Main Symbols

a	Minimum value
MSP	Mittal Steel Poland S.A. unit in Kraków Poland
b	Maximum value
C_E	Exit concentration of a dissolved contaminant (mg/ton)
$C(z,t)$	Concentration of a dissolved contaminant in the direction of the z-axis (mg/m^3)
C_0	Concentration of a dissolved contaminant in the direction of the z-axis on the surface of the liner (mg/m^3)
CB	Crystal ball®
cm	Centimetre
d	Day (from the 1st to the 31st)
D	Diffusion coefficient (m^2/s)
exp	The Napierian base ($e = 2.71828\ldots$)
E(X)	Expected value
EDC	Diffusion coefficient (m^2/s)
erfc	Error function
f(x)	Density function (for $x > 0$)
g	Hour (from 0 to 23)
HC	Hydraulic conductivity (m/s)
HG	Hydraulic gradient (dimensionless)
LCA	Life cycle assessment
LCI	Life cycle inventory
Ln(X)	Natural logarithm of variable x
m	Metre
mg	Milligram
$M_0(X)$	Modal value (dominant)
MC	Monte Carlo
POROS	Porosity coefficient (dimensionless)
R_d	Retardation coefficient (dimensionless)
t	Time (s)

TH	Design life of landfill (in years)
VS v_s	Seepage velocity (initial condition) (m/s)
X	Random variable
$x_{0,5}$	Median
y(t)	Stochastic process as a function depending on the time parameter *t* whose values always take the form of random variables
z	Coordinate of the accepted reference system – direction of the diffusion of a contaminant (m)
μ	Mean value
μ_g	Geometric value
σ	Standard deviation
σ_g	Geometric standard deviation

Chapter 1

Introduction to Monte Carlo (MC) Method: Random Variables in Stochastic Models

According to its definition, stochastic simulation model should contain at least one random variable (Snopkowski 2007). Random variable, being a numerical representation of the outcome of a random experiment, is a key term in statistical analysis (Barańska 2008) and, as observed by Snopkowski (2007), is an essential element of every stochastic simulation. In literature, there are a number of different definitions of a random variable. Stanisz (2006) defines random variable as a "function determined on an elementary event space, which assigns a real number with defined probability to every elementary event. Therefore, this value cannot be predicted in advance, as it depends on a random event." A similar definition is provided by Barańska (2008). As claimed by Benjamin and Cornell (1977), random variable is "a variable that assumes numerical values whose outcome cannot be predicted with complete certainty." Bobrowski (1980), on the other hand, defines random variable as "a variable that, as a result of an experiment, can assume, with defined probability, one of the values of a certain set of real numbers", and Aczel (2000) states that "random variable is a variable whose assumed values depend on chance". Sokołowski (2004), however, apart from quoting a popular definition of random variable, analyses the instances of carelessness and errors that he has encountered in many other studies, regarding random variables.

As far as the argument about the probability distribution used in stochastic simulations is concerned, this thesis limits its focus to the graphs of density function, as it is assumed that all necessary formulas and mathematical descriptions concerning these distributions are not the focus of this thesis and can be found in the extensive literature dealing with this subject (other aspects are therefore not analysed here).

With respect to the random simulation technique, simulation can be carried out using Monte Carlo (MC) or Latin Hypercube (LH) method. The difference between the two simulation methods lies in the fact that uncertainty distribution of every single parameter in MC method must be specified, whereas in LH method the distribution is divided into a series of non-overlapping intervals of equal probability (Kowalski et al. 2007).

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While working on computer procedures for generating random variables with different distributions, Janicki and Izydorczyk (2001) draw attention to the fact that these are based on algebraic methods of generating pseudo-random numbers. The authors confirm the statement that computer MC methods for constructing random samples from the distribution data attract a large number of supporters. The United States Environmental Protection Agency (EPA) recognises the MC simulation method as the sole method permitted to undertake risk assessments in ecology and environmental protection (Smith 2006). Polak (2007) describes the results of a study, where the application of a neural network taught with synthetic data allows to reduce the systematic error, of a resistance estimator and susceptibility of the respiratory system, estimated with the help of the MC method on the basis of 100 elements of a testing sequence, approximate to zero, and the mean squared error, from 34% and 56% to 6.5% and 22%, respectively (for more information see Polak et al. 2001).

The advantage of the random simulation technique is the relative ease with which parameters of different distributions can be used. Stochastic simulation may be described as static or dynamic, or continuous or discrete (Snopkowski 2007). Fishman (1973) believes that if stochastic simulation is of static nature (time plays no role), then the term "MC simulation" is used. Oftentimes, however, terms such as "stochastic simulation" and "MC simulation" (the expressions "MC method" or "MC methods" are also applied) are treated as synonymous (Ripley 1987).

The history of MC simulation, as a research method, dates back to the World War II and the Manhattan Project – the construction of the American atomic bomb (Snopkowski 2007). MC method involves presenting a solution to a posed problem in the form of a parameter of a certain hypothetical population and using random number sequences to create a sample of such a population, on the basis of which, one can statistically estimate the value of the studied parameter described in an incomplete and inaccurate way. The name, MC method, originates from Monte Carlo, the city in the Principality of Monaco. According to some sources (Hall 1997), the history of the MC method traces back to 1768 when Buffon,[1] a French mathematician, experimentally calculated the value of pi $= 3.14$. The development of this method was possible due to the contribution of Lord Rayleigh[2] (1899 – the solution to the parabolic differential equation), W.S. Gosset-Student (1908 – Student's t-Distribution), E. Fermi[3] (1930 – the splitting of the neutron), A.N. Kolmogorov[4] (1931 – demonstrating the connection between stochastic Markov processes and some integro-differential equations), J. Von Neumann[5] (1940 – mathematical

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[1] George-Louis Leclerc, de Buffon (1707–1788).

[2] John William Strutt, Lord Rayleigh (1842–1919), the Nobel Prize in Physics (1904).

[3] Enrico Fermi (1901–1954), the Nobel Prize in Physics (1938).

[4] Andrej Nikołajewicz Kolmogorov (1903–1987).

[5] John von Neumann (born as Johann von Neumann 1903–1957).

definition of PDF), and S.M. Ulam[6] (1946 – the MC method used to finding solutions to mathematical problems with the help of random numbers), among others, and due to the contribution of IBM, a computer company that pioneered the work on random number generators. Simulation is a process of building a mathematical or logical model of a system or a decision problem, and then conducting experiments on this model with a view to reaching a solution to the abovementioned problem (Kaczmarek 1999). The aim of the MC method is to calculate the values that appear as a result of integration. Heerrmann (1997) exhaustively explains the fundamentals of the MC method – method that because of its stochastic nature is based on random numbers. In addition, he presents a wide range of random number generators, as well as prepares a general definition of the MC method: "the MC method involves presenting a solution to a posed problem in the form of a parameter of a certain hypothetical population and using random number sequences to create a sample of such a population, on the basis of which one can statistically estimate the value of the studied parameter".

A more detailed description of the MC method is not provided in this thesis. Therefore, for instance, the problem of the evaluation of the method by one-dimensional integration analysis, named by Heermann as direct sampling (1997), is addressed by the author in a different project (Bieda 2000). The outline of random number generators can be found in the work of Hoła and Mrozowicz (2003), and Koleśnik et al. (1976); for a more in-depth study of discrete generators and continuous random number generators see Snopkowski (2007).

The distribution of probability demonstrates, for every possible event, the probability of that event happening (Williams et al. 2002).

A number of commercial computer software programs, assisting the uncertainty assessment of parameters with the use of MC simulations, exist on the software market. Among the well-known programs, one could include (Sonnemann et al. 2004) the following:

- Crystal Ball®[7]
- Risk®[8]
- Analytica®[9]
- Stella II®[10]
- PRISM®[11]

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[6] Stanisław Marcin Ulam (1909–1984).

[7] A registered trademark of Decisioneering, Inc., Denver, Colorado, USA.

[8] A registered trademark of Palisade Corporation, Newfield, NY, USA.

[9] A registered trademark of Decisioneering, Inc. Z Denver, Colorado, USA.

[10] A registered trademark of High Performance Systems, Inc., Lebanon, NH, USA.

[11] A registered trademark of SENES Oak Ridge, Inc., Oak Ridge, TH, USA.

- SusaPC®[12]
- SimLab[13]

When the U.S. Environmental Protection Agency (EPA) recommended the application of the MC method as being a reliable statistical tool capable of analysing uncertainty in risk assessment (Abbott 2009), it published a 33-page document that includes the application rules of this method, as well as a comprehensive technical guide to the analysis, and evaluation of variability and uncertainty (EPA 1997). Nevertheless, there are other methods of uncertainty propagation in numerical calculations, apart from the MC method. Among the most frequently used ones are:

- Interval analysis – described more thoroughly by Ryder (1951), Moore (1966), Alefeld and Hertberger (1983), and Neumaier (1990), and recognised as one of the easiest mathematical methods of portraying uncertainty. It uses calculations on real number intervals.
- Delta method – based on the application of the Taylor series, to approximate the variance and covariance of a function of random variables (Seber 1973; Kirchner 1992).
- Laplace transform and Melin transform (Springer 1979) – the standard methods for probability distribution employed to solve the problem of additive and multiplicative convolutions with the help of simple addition. This approach is used only in distributions with known transformation.
- Fuzzy arithmetic (Kaufmann and Gupta 1985) – the generalisation of interval analysis based on the theory of probability (Zadeh 1978; Dubois and Prade 1988).

Extensive literature on interval estimation is available worldwide (Pawłowski 1976; Aczel 2000; Hoła and Mrozowicz 2003; Snopkowski 2007; Barańska 2008). Pawłowski (1976), for instance, proposes a number of interval estimation theories. Apart from the theory of Jerzy Spława-Neyman, an eminent Polish statistician, Pawłowski also mentions the R.A. Fisher's fiducial interval and Bayes estimation.

In recent years there has been a growing interest in the use of the MC method in stochastic modelling describing various phenomena in ecology, in the risk analysis related to human diseases, and in the assessment and verification of health statistics. Additional information regarding these uses can be found in the work of: Nadal et al. (2008), Smith (2006), Sanga et al. (2001), Price et al. (1996), Öberg and Bergbäck (2005), Sonnemann et al. (2004), and Wajs (1999).

Different descriptions of simulation can be encountered in the subject literature. Łukaszewicz (1975) states that "simulation represents the behaviour of the original,

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[12] A registered trademark of Gesellchaft für Anlagenund Reaktorsicherhet (GRS) mbh, Kőln, NRF.

[13] A software program developed by the European Commission Joint Research Centre (JRC) in Italy.

through the behaviour of the model". Yet, Naylor (1975) describes simulation as "a numerical technique employed in experiments carried out on mathematical models that illustrate, with the help of a computer, the behaviour of a complex system in a long time interval". Simulation, as defined by Zdanowicz (2002), is a technique used to conduct experiments on certain types of models; it can also be understood as a form of model manipulation, leading to the recognition of the behaviour of the system. Snopkowski (2007) discusses the evolution of the definition of simulation in the last few decades. And so, simulations are used especially when solving a problem in an analytical way may be too difficult. Recent research suggests that in management studies the use of simulation methods and statistical research outweighs the use of other available methods and tools in the ratio of 2:1 (Evans and Olson 1998). In a traditional model built using spreadsheets, the variables and the results are deterministic and are surrounded with a degree of uncertainty. Snopkowski (2007) quotes the notion of simulation, presented by Jan Gajda (2001), as "setting the model in motion". According to Róg (2010), simulation began its development stage in the 1970s when first computers, efficient enough and cheap enough to have practical applications, appeared on the market. Apart from solving deterministic modelling problems, simulation immediately began to be used in order to solve problems, in which particular system parameters were of uncertain size. In addition, a probabilistic approach was adopted, and very soon it revealed its weaknesses: the amount of time needed to make calculations, the difficulty and the cost of obtaining accurate data on the simulated system, a highly limited set of functions describing uncertain system parameters, and a whole series of internal problems of stochastic methods that hinder their effective practical applications. The incoherence principle proposed by Zadeh (1978) was the nail in the proverbial coffin of simulation. According to this rule, the more complex the simulation model, the lower is our ability to formulate, on the basis of the simulation, vital statements on the modelled system. Additionally, after crossing a certain boundary in the complexity of the model, the detail and the significance become virtually mutually exclusive.

Simulation has its advantages, among which is the fact that it provides knowledge and proposes a system without interference, construction or modification of the existing system. Moreover, simulation models are generally easier to understand than analytical deliberation. As far as simulations' flaws are concerned, they require a certain amount of time in order to not only prepare a suitable input database, but also to develop a model and its associated computer programs, and to interpret the results.

Chapter 2
Stochastic Model of the Diffusion of Pollutants in Landfill Management Using Monte Carlo Simulation

2.1 Introduction

Hazardous waste landfills, as well as landfills for other than hazardous or inert waste, require the application of technical solutions that comply with the Regulation of the Minister of Environment of 24 March 2003 on the detailed requirements regarding the location, construction, operation and closure, that should to be met by the particular types of landfills (D.U. 2003) (Official Journal "Dz. U." No. 61, item 549). In line with the requirements of the abovementioned regulation, it is necessary to isolate the deposited waste from the subsoil with a natural geological barrier. This applies to the other than hazardous or inert waste with the thickness no less than 1 m (for the hazardous waste it is 5 m) and the filtration coefficient (diffusion) $k \leq 1.0 \times 10^9$ m/s. If artificial geological barrier is to be used, its thickness cannot be less than 0.5 m and the permeability cannot be greater than that of the natural barrier. Synthetic isolation needs to supplement the natural or artificial geological barrier, depending on which one is used. The shape of the basin needs to make it impossible for the precipitation water from the surrounding area to flow into the basin. A drainage system should be built at the bottom and on the slopes of the landfill that would ensure its reliable functioning during the service life of the landfill and during the period of 30 years after its closure. Uncertainty can be described with the help of parameters such as variance (informing about the distribution of a random variable value) or standard deviation, or with the help of other statistical methods, e.g. the MC method. The employment of MC simulation for the modelling of propagation delay of waste in porous media is a very useful tool that can be used to assess the life cycle of a modern landfill.

One of the advantages of one-dimensional modelling is the ability to change the concept of calculations relatively quickly (Elmore 2007; Hritonenko and Yatsenko 1999; Szymkiewicz 2009). The general scheme of mathematical modelling described by Hritonenko and Yatsenko (1999), is shown in Fig. 2.1. The reviewed domestic and international specialist literature suggests that transportation of waste in water, air, and soil, as well as transportation of contaminants between water and

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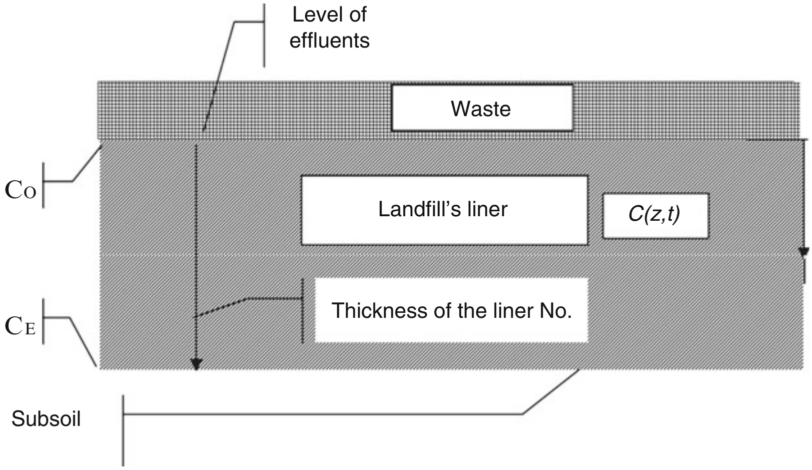

Fig. 2.1 One-dimensional model of contaminant diffusion. C_O – concentration of the dissolved contaminant on the surface of the liner (mg/t), on entry, C_E – concentration of the dissolved contaminant on the surface of the liner (mg/t), on exit

water slurry, are most often described by adsorption-desorption processes (see Van Genuchten 1985; Lunn et al. 1996; Khandelwal and Rabideau 1999; Unice and Logan 2000; Bear 1972; Goodall and Quigley 1977; Freeze and Cherry 1979; Crooks and Quigley 1984; Shackelford and Daniel 1991; Shackelford 1990, 1994; Rowe 1994; Russo 2002; Nima 2003; Bedient et al. 1999; Yeh and Yeh 2007; Domenico and Schwartz 1990; Schwartz and Zhang 2003; Bieda 2002). The three-dimensional (3D) model of the transport of contaminants in hydrous media is presented and evaluated by Li and Wu (1999). Modelling the dynamics of water flow and transport of deposit in unsaturated porous media is examined by (Zhiang et al. 2001; Warith et al. 1999), and transport of dissolved heavy metals (Cd^{2+}, Pb^{2+}, Cu^{2+}, and Zn^{2+}) is presented and evaluated in (Du et al. 2009). As Chu and Mariño point out (2006), the description of the pollutant transport in the insulating layer of various types, and the simulation of the migration of naphthalene through the MICROBIAL filter, is given using the application of FLOTRANS, a two-dimensional (2D) model based on the advection-dispersion equation, which is based on the Finite Element Method (FEM). A similar two-dimensional (2D) advection-dispersion model is described, in the work of Chang and Latif (2010), as a deterministic model of conservative pollutant transport in the environment. The Nonlinear Extended Kalman Filter is applied as a forecast tool that helps determine the contamination area and, as a result, the prognosis error can be reduced by a margin of 74–91%, compared to the prognosis error when the problem is solved using numerical methods. By looking at specific examples of the subject literature it can be observed that there are two methods employed in stochastic modelling of transport of contaminants in groundwater: the MC method and the Exodus method (Aniszewski 1998, 2001; Bear 1972; Bear and Bachmat 1990;

Dagan 1982, 1985a, 1985b; Zaradny 1990). The modelling of transit time of contaminants in porous media is a valuable tool when assessing the life cycle of a modern landfill (municipal, industrial, as well as hazardous) that can be helpful when it comes to determining the thickness of subsoil that constitutes a natural, artificial, or synthetic geological barrier (Crooks and Quigley 1984; Shackelford 1990; Shackelford and Daniel 1991; Chu and Mariño 2006; Rooy 1977). The results achieved by Shackelford and others (Crooks and Quigley 1984; Shackelford and Daniel 1991) suggest that diffusion is an important, if not a dominant, mechanism in the transport of contaminants through the subsoil of a landfill. The details regarding the cohesive impact (clay and silt) of the insulating system of a landfill on the quality of groundwater, are provided by Du et al. (2009) and by Li and Wu (1999). Aniszewski (2001) thoroughly examines the migration modelling of contaminants in the ground, taking into account the process of adsorption. In addition, he defines the mathematical model of the contaminant transport processes in groundwater as a "system of mathematical equations resulting from basic principles of behaviour with information on area and its properties, as well as with both initial and boundary conditions".

2.2 Aim and Scope of the Project

Landfills are engineering structures that are especially arduous for the natural environment; consequently, they need to be designed in a certain way and constructed using the best available technology (BAT), under strict supervision. The purpose of every landfill is the isolation and safe storage of waste with a guarantee that its negative impact on natural environment is minimised. It is established that a landfill should be equipped with a protective liner that ensures it is leak-proof and groundwater is not contaminated by pollutants from effluents. Thus, landfill areas, whose geological barriers in the ground are not impermeable enough, have to be additionally sealed with the help of a mineral isolation layer (Majer et al. 2007).

After considering the conclusions drawn from the review of the literature devoted to the model of transport of contaminants in the ground, the author has stated the aims and formulated the following scope of the project:

- The development of a MC simulation model by using CB® software based on the simplified one-dimensional (1D) advection–diffusion equation of the transport of contaminants, as worked out by Acar and Haider (1990),
- The presentation of the simulation results,
- The analysis of the results.

The model demonstrated in the quoted work has been verified on the basis of the actual data acquired from the observations and measurements made by Cokca (1999).

This project benefits from the application of a one-dimensional (1D) advection-dispersion model[1] of the diffusion of a contaminant dissolved in saturated soil, developed by Acar and Haider (1990), with a view to calculating the optimum liner thickness of a landfill during its desired operational life. All the necessary calculations are made using the CONTRANS program, written in the MATLAB environment. The source code of the program can be accessed in (Bieda 2002). The program is based on the block diagram proposed by Cokca (1999) and adapted here for the purposes of this monograph.

The abovementioned one-dimensional (1D) model, developed by Acar and Haider (1990), of the diffusion of a contaminant dissolved in saturated soil takes the following form (Cokca 1999):

$$R_d \frac{\partial C_z}{\partial t} = D_p \frac{\partial^2 C_z}{\partial z^2} - v_s \frac{\partial C_z}{\partial z} \tag{2.1}$$

where:

R_d – retardation coefficient,[2]
C_z – solute concentration – concentration of a dissolved contaminant in the direction of the z-axis,
D_p – dispersion coefficient,[3]
v_s – percolation velocity with initial condition of:

$C_z = 0$ for $z \geq 0$ and $t = 0$;
and boundary conditions of:
$C_z = C_0$ for $z \leq 0$ and $t > 0$ and
$C_z = 0$ for $z = 0$ and $t > 0$.

The program calculates the diffusion (transfer) time of a dissolved contaminant in relation to the liner thickness of a landfill [38–39]. The liner consists of clay with low conductivity coefficient of the aquiferous layer of the tank ($\leq 1.0 \times 10^{-9}$ m/s) (Raport 2007; Majer et al. 2007). In a situation where the calculated diffusion time is shorter than the planned service life of a landfill (in years), the program demands the increase of the liner thickness.

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[1] Advection – the horizontal transfer of air mass properties by the velocity field of the atmosphere, of the soil (different to convection, which describes the predominantly vertical movements). Dispersion – mixing.

[2] Retardation coefficient – the movement velocity of the separation surface of mass zone.

[3] Dispersion consists of two elements: hydronomic-mechanic dispersion and molecular diffusion.

The solution of (2.1), included in the work of Cokca (1999), takes the form of:

$$C(z,t) = (C_0/2) \times \left\{ erfc\left[(R_d z - v_S t)/2(DR_d t)^{0.5}\right] + \exp(v_S z/D) erfc\left[R_d z + v_S t)/2(DR_d t)^{0.5}\right]\right\} \tag{2.2}$$

where:

$C(z, t)$ – concentration of a dissolved contaminant in the direction of the z-axis (mg/m^3);
t – time (s);
z – direction of the diffusion of the contaminant (m);
C_0 – concentration of a dissolved contaminant in the direction of the z-axis on the surface of the liner (mg/m^3);
erfc – error function;
R_d – retardation coefficient[4] (dimensionless);
v_s – seepage velocity (initial condition) (m/s);
D – diffusion coefficient (m^2/s).

In order to solve (2.2), a diagram, depicted in Fig. 2.1, has been applied. The calculations are made on the following assumptions:

- The liner layer is homogeneous,
- The dissolved contaminant is saturated,
- The diffusion is one-dimensional in the direction of the z-axis.

Equation 2.2 can be rearranged to the following form:

$$C/C_0 = 0.5[erfc(z_1) + \exp(z_2) erfc(z_3)] \tag{2.3}$$

where:

erfc – error function;
z_1, z_2 and z_3 are arguments described in the following way:

$$z_1 = (R_d z - v_S t)/2(DR_d t)^{0.5} \tag{2.4}$$

$$z_2 = v_S z/D \tag{2.5}$$

$$z_3 = (R_d z + v_S t)/2(DR_d t)^{0.5} \tag{2.6}$$

---

[4] Retardation coefficient – the movement velocity of the separation surface of the mass zone.

2.2.1 Constructing the Model: Defining Input Data

In order to demonstrate the simulation model using Crystal Ball software, a certain simplification has been made; namely, the adaptation of a single equation (2.5) in this simulation. This equation takes the form of:

$$\mathrm{Z2} = (\mathrm{VS}{*}\mathrm{TH})/\mathrm{EDC} \tag{2.7}$$

where:

VS – seepage velocity (initial condition) (m/s);
TH – design life of landfill (in years);
EDC – diffusion coefficient (m^2/s).

This equation is part of the computer software demonstrated in the Appendix VIII, found in Bieda (2002).

The Z2 expression is part of the algorithm of the CONTRANS calculating software, presented in Fig. 2.2 (Bieda and Wajs 2002; Bieda 2004c).

VS can be described in the following form:

$$\mathrm{VS} = \mathrm{HG}{*}\mathrm{HC}/\mathrm{POROS} \tag{2.8}$$

where:

HG – hydraulic gradient;
HC – hydraulic conductivity (m/s);
POROS – porosity coefficient.

Equation 2.7, after considering the expression (2.8), takes the following form:

$$Z2 = (\mathrm{HG}{*}\mathrm{HC}/\mathrm{POROS})^{*}\mathrm{TH}/\mathrm{EDC} \tag{2.9}$$

where:

TH – design life of landfill (in years);
EDC – diffusion coefficient (m^2/s).

The numerical data and the types of probability distribution used in random estimation of the parameters of the Z2 expression that take part in MC simulation using Crystal Ball, along with the distribution parameters, are presented in Table 2.1. These are: hydraulic conductivity – HC, hydraulic gradient – HG, diffusion coefficient – EDC, the thickness of the isolation barrier – TH, and porosity – POROS. The stochastic model includes five random variables in its description, listed above, which can be characterised by two probability distributions: log-normal distribution and uniform distribution (Zdanowicz 2002), sometimes also known as symmetrical or rectangular. The in-depth analysis of log-normal probability distribution, assigned to hydraulic conductivity (HC), performed by Bear and Cheng, can be

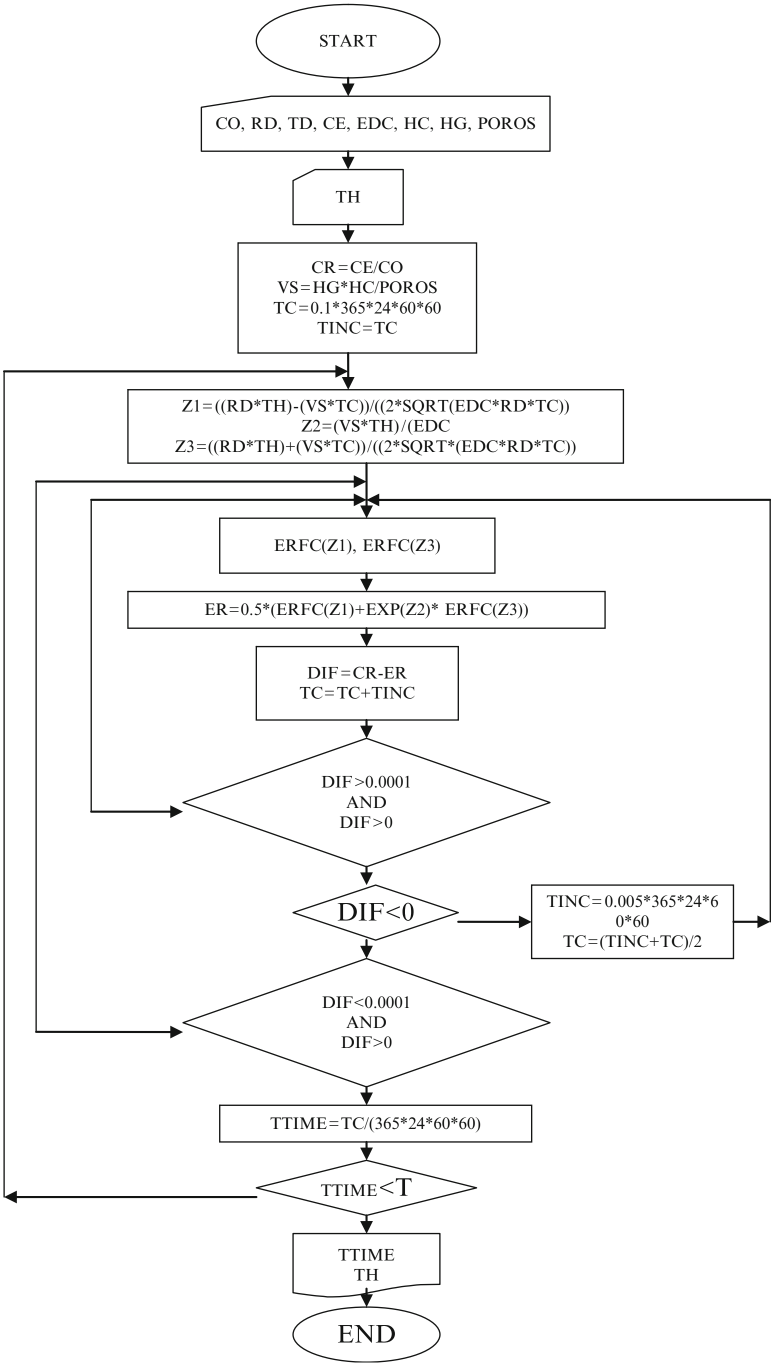


Fig. 2.2 General algorithm of the calculating program CONTRANS

Table 2.1 The values and types of probability distribution of the parameters in the Z2 expression, used in MC simulation with the help of Crystal Ball® program along with the distribution parameters

Parameter	Type of parameter distribution	ED	μ_g	σ_g	Sources
Hydraulic gradient – HG (dimensionless)	Log-normal	1.35	1.34	1.10	Majer et al. (2007)
Hydraulic conductivity – HC (m/s)	Log-normal	1E-9	9.95E-10	1.0E + 0	Raport (2007)
Porosity – POROS (dimensionless)	Uniform	0.35 –	0.31[a]	0.38[b]	Majer et al. (2007)
Thickness of isolation barrier – TH (m)	Uniform	1.0	0.90[a]	1.10[b]	Raport (2007)
Diffusion coefficient – EDC (m^2/s)	Log-normal	1E-10	9.95E-11	1.10E + 0	Majer et al. (2007)

ED – experimental data (ED = μ (mean value)), μ_g – geometric mean, σ_g – geometric standard deviation

[a] Minimum value

[b] Maximum value

found in their recent publication (2010). In their work the attention is drawn to numerous studies and observations in situ, which lead to log-normal distribution of the hydraulic conductivity value (Gelhar 1986, 1993; Freeze 1975; Hoeksema and Kitanidis 1985). The authors also point out to the fact that different units describing hydraulic conductivity can be found in the subject literature. Some hydrogeologists prefer to use meters per day (m/d), while certain scientists and geotechnical engineers use centimetres per second (cm/s). The International System of Units (SI) uses metres per second (m/s) as a standard unit (Bear and Cheng 2010).

The approximation of the three Z2 parameters (i.e. HC, HG, and EDC) with log-normal probability distribution and the establishment of the magnitude characterising the functions of this distribution has been performed (geometric mean μ_g and geometric standard deviation σ_g).

The two remaining parameters: the thickness of the isolation barrier – TH and porosity – POROS, have been subjected to uniform distribution. The mean values μ characterising this distribution have been accepted on the basis of the analysis of the available literature data (DE), included in these publications (Raport 2007; Majer et al. 2007).

Crystal Ball® software (Bieda 2000) allows for defining the input parameters of a model as random data containing assumed features of probability distribution. In its professional version, the program offers 12 different types of probability distributions, including: normal, log-normal, uniform, exponential, Poisson, and Weilbull distribution (Evans and Olson 1998).

Decisioneering Inc., an American company from Denver, has developed the CB software, which is based on a model built using the functions of a spreadsheet application (Evans and Olson 1998; Crystal Ball 2010), and it utilises the development of simulation (stochastic) models.

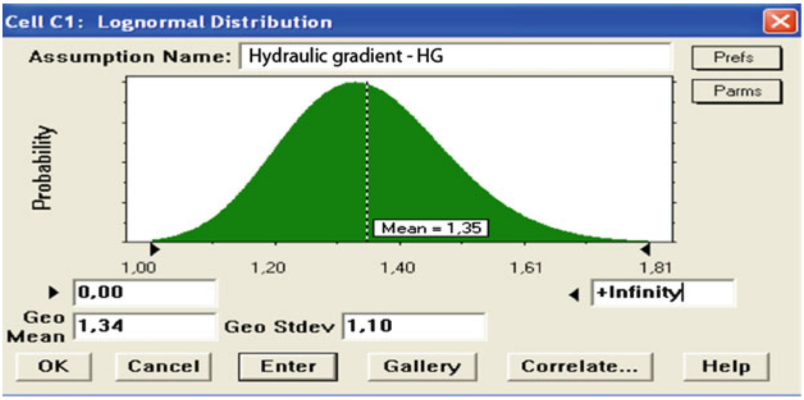
To use CB we must perform the following steps:

Step 1. The development of the simulation model using the spreadsheet function.
Step 2. The definition of variables, which are to become probabilistic variables. Thus, particular variables need to be approximated with an appropriate distribution of probability.
Step 3. The selection of a spreadsheet cell, in which the forecast will be inserted.
Step 4. The process of running the simulation. The maximum number of trials is 10,000 (ten thousand) (Evans and Olson 1998).

CB software has a very attractive feature that allows the user to graphically demonstrate the results of the simulation in the form of frequency charts, cumulative charts, sensitivity analyses, as well as statistic reports. The reports are presented using tables.

2.3 Activating the Model: Simulation

CB software is used to run the simulation. The Distribution Gallery feature (Evans and Olson 1998) allows the user to make the correct choice of probability distribution, in a given research situation. The log-normal distribution curve, being an asymmetrical distribution (positive asymmetry), of the analysed variable, is described by two parameters: the geometric mean μ_g and the geometric standard deviation σ_g. In the subsequent chapters of this monograph, the following terminology is used: in the case of log-normal distribution – geometric mean μ_g and geometric standard deviation σ_g; and as far as the normal distribution is concerned – mean value μ (instead of: the scale parameter, the expected value of the random variable X, the mean population value), and standard deviation σ (instead of: the population standard deviation, shape parameter). Log-normal probability distributions (Figs. 2.3, 2.4, and 2.7) are chosen for approximation of hydraulic gradient (HG), hydraulic conductivity (HC), and diffusion coefficient (EDC), whereas random porosity values (POROS) and the thickness of the isolation barrier (TH) are described using uniform distributions (Figs. 2.5, 2.6). Mean values μ are consistent with the deterministic values of the variables HC, HD, EDC, TH, and POROS (Table 2.1). The decision to choose log-normal distribution, described using the density function with a range of zero to infinity, is based on the work of Schenker et al. (2009), Sonnemann et al. (2004), Rabl and Spadaro (1999), as well as Spadaro and Rabl (2008), and the bibliographies included in the abovementioned publications. Crystal Ball automatically calculates the remaining parameters of log-normal distribution, and these may include: geometric mean μ_g, geometric standard deviation σ_g, and minimum as well as maximum values of uniform distributions. The dialog boxes, namely: Log-normal Distribution and Uniform Distribution, and their parameters, which are used in this project, are presented in Figs. 2.3, 2.4, 2.5, 2.6, and 2.7. As can be noticed, the mean value μ is higher than the geometric mean value μ_g of log-normal distribution, a fact thoroughly analysed by Spadaro and Rabl (2008).



Cell C1: Lognormal Distribution

Assumption Name: Hydraulic gradient - HG

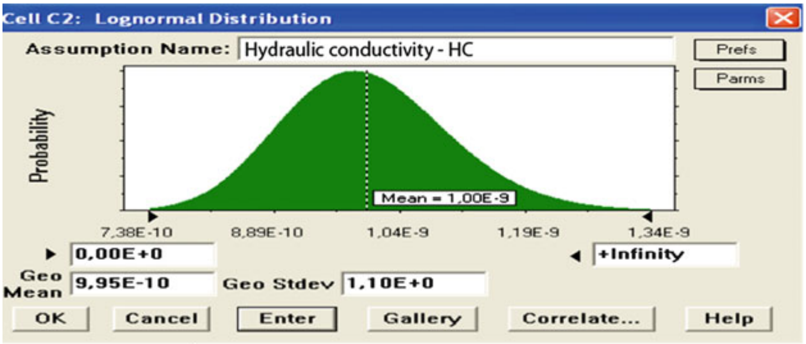
▶ 0,00

◀ +Infinity

Geo Mean 1,34

Geo Stdev 1,10

Fig. 2.3 Dialog box – log-normal distribution for the hydraulic gradient variable – HG (Source: Own work)



Cell C2: Lognormal Distribution

Assumption Name: Hydraulic conductivity - HC

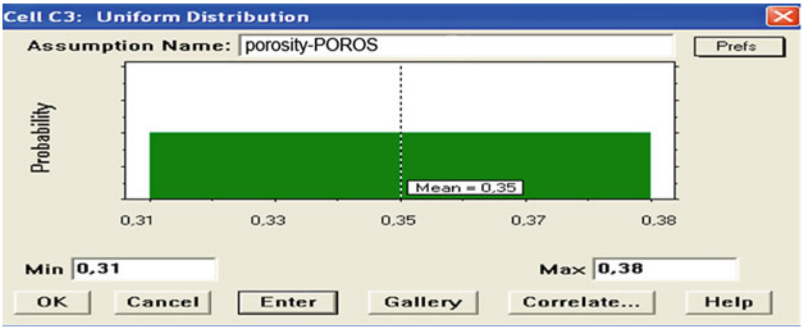
▶ 0,00E+0

◀ +Infinity

Geo Mean 9,95E-10

Geo Stdev 1,10E+0

Fig. 2.4 Dialog box – log-normal distribution for the hydraulic conductivity variable – HC (Source: Own work)



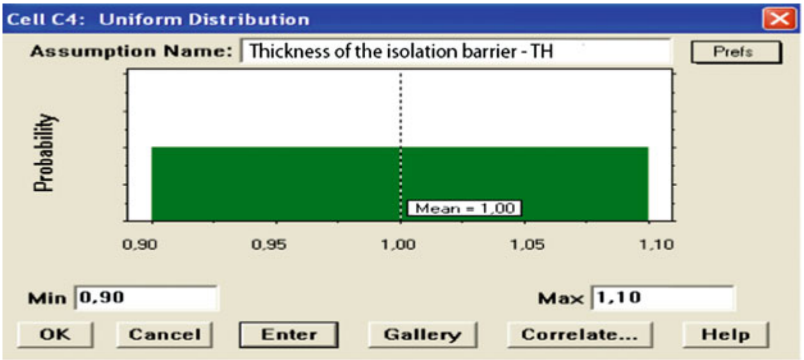
Cell C3: Uniform Distribution

Assumption Name: porosity-POROS

Min 0,31

Max 0,38

Fig. 2.5 Dialog box – log-normal distribution for the porosity variable – POROS (Source: Own work)

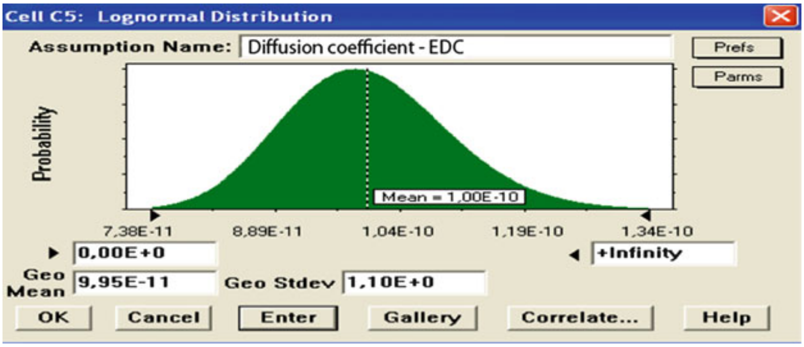


Assumption Name: Thickness of the isolation barrier - TH

Min 0,90

Max 1,10

Fig. 2.6 Dialog box – log-normal distribution for the thickness of isolation barrier variable – TH (Source: Own work)



Assumption Name: Diffusion coefficient - EDC

▶ 0,00E+0

◀ +Infinity

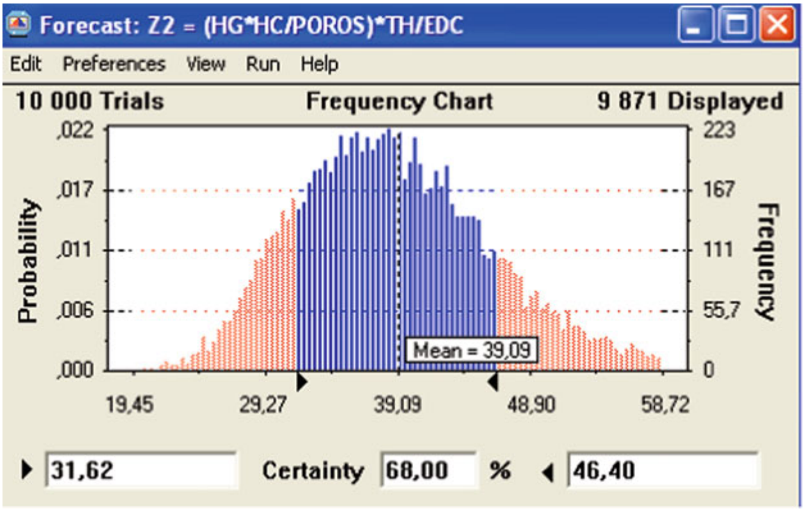
Geo Mean 9,95E-11

Geo Stdev 1,10E+0

Fig. 2.7 Dialog box – log-normal distribution for the diffusion coefficient variable – EDC (Source: Own work)

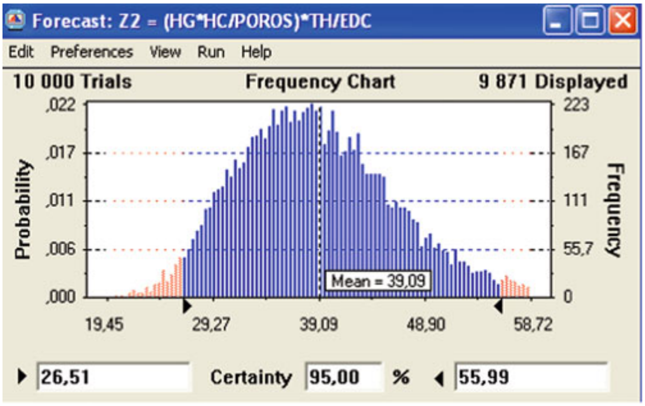
2.4 The Results of the Simulation

After activating the simulation, according to the algorithm (2.1) (having previously set the randomisation cycle, which, in the analysed case, has 10000 trials), the numerical results of the Z2 forecast calculations are presented in the form of frequency charts (Figs. 2.8, 2.9) and statistic reports (Figs. 2.10, 2.11). The results of MC simulation with different confidence levels are shown in Figs. 2.8 and 2.9. In the uncertainty analysis connected to LCA methodology, the 68% confidence levels are used quite frequently (Sonnemann et al. 2004; Rabl and Spadaro 1999; Spadaro and Rabl 2008). In the Forecast window, one can notice a frequency chart along with some tools that modify it. These modifiers, or grabbers, presented in the form of small black triangles, indicate where, after a finished simulation, is the right and left end of the confidence interval. In the frequency chart (Figs. 2.8 and 2.9) the confidence interval span is highlighted with a darker colour marker (the probability



31,62 Certainty 68,00 % 46,40

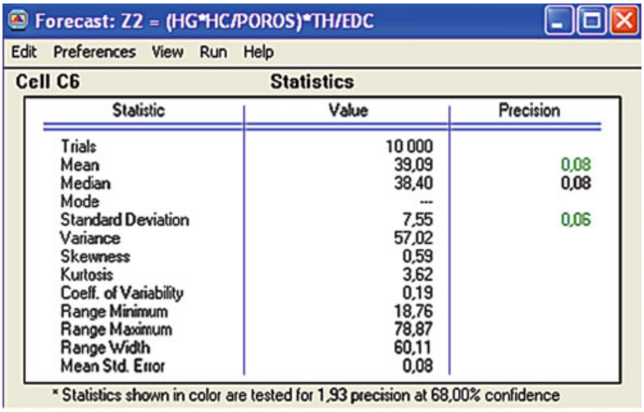
Fig. 2.8 Frequency chart of the Z2 forecast expression (68% confidence level) (Source: Own work)



26,51 Certainty 95,00 % 55,99

Fig. 2.9 Frequency chart of the Z2 forecast expression (95% confidence level) (Source: Own work)

that *X* assumes the values in the confidence interval, is equal to the measure of the cell under the darker part of the frequency chart). By writing: Z2 = (HG*HC/POROS)*TH/EDC in the Certainty edit field of the Forecast dialog box, and by

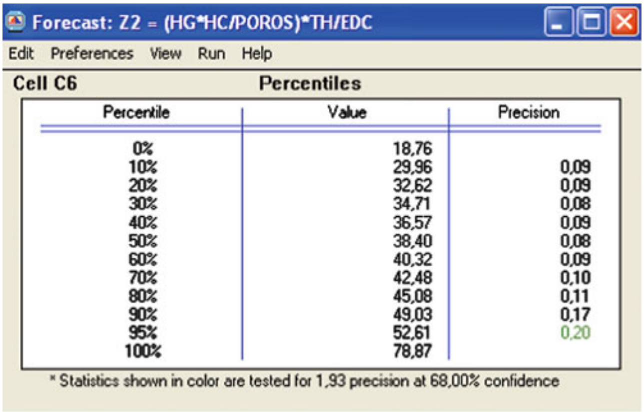


Cell C6 Statistics

Statistic	Value	Precision
Trials	10 000	
Mean	39,09	0,08
Median	38,40	0,08
Mode	---	
Standard Deviation	7,55	0,06
Variance	57,02	
Skewness	0,59	
Kurtosis	3,62	
Coeff. of Variability	0,19	
Range Minimum	18,76	
Range Maximum	78,87	
Range Width	60,11	
Mean Std. Error	0,08	

* Statistics shown in color are tested for 1,93 precision at 68,00% confidence

Fig. 2.10 Statistical report of the Z2 expression forecast – *Statistics*



Cell C6 Percentiles

Percentile	Value	Precision
0%	18,76	
10%	29,96	0,09
20%	32,62	0,09
30%	34,71	0,08
40%	36,57	0,09
50%	38,40	0,08
60%	40,32	0,09
70%	42,48	0,10
80%	45,08	0,11
90%	49,03	0,17
95%	52,61	0,20
100%	78,87	

* Statistics shown in color are tested for 1,93 precision at 68,00% confidence

Fig. 2.11 Statistical report of the Z2 expression forecast – *Percentiles* (Source: Own work)

setting the values to 68% and 95%, respectively,[5] the span of the confidence intervals is set automatically by the grabbers, and the corresponding numerical values are entered in the edit fields in the bottom part of the dialog boxes of the Forecast tab: Z2 = (HG*HC/POROS)*TH/EDC.

Confidence interval, theoretical basis of which was postulated in 1993 by a Polish statistician, J. Spława-Neyman, defines the probable scope of calculation deviation from the real value (Stanisz 2006). In other words, the simulation results provide an opportunity to realise the span of the random confidence intervals that will cover the estimated values of the Z2 forecast. Additionally, the author wishes

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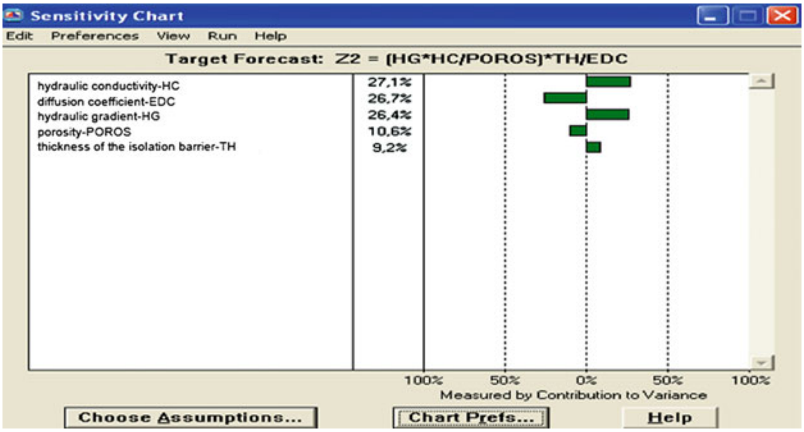
[5] The 68% confidence interval is synonymous to an interval equivalent of the 68% confidence level.

to present, for comparison purposes, the results of uncertainty analysis for the 95% confidence level, which is quoted in the literature as being the "classic" amount (Tadeusiewicz 1999). The 95% confidence level's recommendation can be found, among others, in the Eco-indicator method (Eco-indicator 99 2009) and in the Regulation of the Minister of Environment of 12 September 2008 on the means of monitoring emission levels of substances covered by the emission allowance trading scheme of the Community (D.U. 2008). As a result of the carried out simulation, the confidence intervals, equivalent to the 68th and 95th percentage level of confidence, are equal to [31,62; 46,40] and [26,51; 55,99], respectively (Figs. 2.8, 2.9).

2.4.1 Sensitivity Analysis

Sensitivity analysis of input data is extremely useful both in environmental testing and in investment processes. In the subject literature, one can encounter different versions of its definition (de Koning et al. 2010) and it is perceived, by some sources, as the most important outcome of MC simulations using CB software (Bradly 1999; Gaudet 1997; Lorance and Wendling 1999; Warith et al. 1999; Yenni 1999; Saltelli et al. 2004, 2008). The method indicates which input parameter of a model is of greatest influence on the final result of the simulation, or, in other words, it demonstrates the usefulness of particular critical variables, i.e. the ones that significantly influence the value of an expression. Depending on the choice in the drop-down menu in the Sensitivity Chart tab and the View command, the diagram will be created by comparing Spearman's rank correlation coefficients, 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. On the other hand, negative correlation coefficients point to an opposite tendency, or the measured contribution of the model's entry variables on variance, or to put it differently, the definition of the involvement, of critical variables in the model, in the variation of the dependent variable's mean value (the Z2 expression). Evans and Olson (1998), by briefly outlining the problems associated with MC simulation, have formulated a statement that correlation coefficients combine hypotheses with forecasts. Suh and Rousseaux (2002) have used sensitivity analysis in LCA studies, the aim of which is to compare the environmental impact of five sludge management methods in France (see Kowalski et al. 2007). The graphic presentation of sensitivity analysis is most effective when, at most, 10 (ten) parameters are analysed; if there are more, it becomes unpractical (Uncertainty 2008).

Crystal Ball has integrated statistical, optimisation, and prognostic tools; this results in the elimination of both the uncertainty element and the lack of confidence in the deterministic values of parameters that form the Z2 expression (Bieda 2002). The sensitivity analysis shown in Fig. 2.12 suggests that hydraulic conductivity (HC) has the most significant influence on the variability of the Z2 expression.



Target Forecast: Z2 = (HG*HC/POROS)*TH/EDC

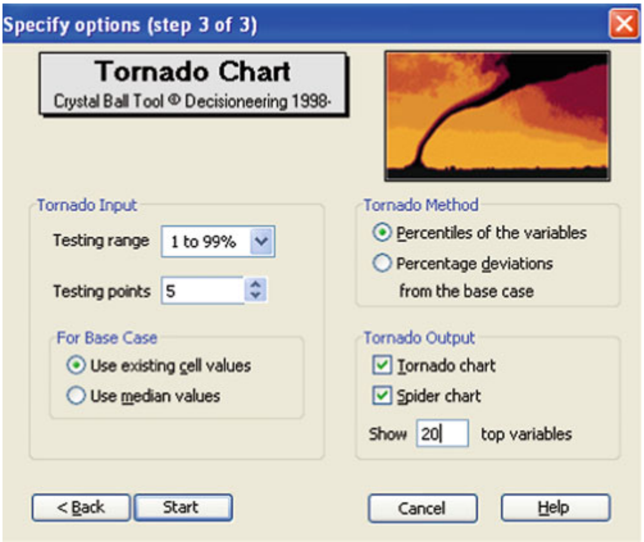
hydraulic conductivity-HC	27,1%
diffusion coefficient-EDC	26,7%
hydraulic gradient-HG	26,4%
porosity-POROS	10,6%
thickness of the isolation barrier-TH	9,2%

Fig. 2.12 Sensitivity analysis of the Z2 expression forecast (Source: Own work)

Hydraulic gradient (HG) as well as the thickness of the isolation barrier (TH) are next in line. Their respective variance share is: 27.1%, 26.4%, and 9.2%. When it comes to diffusion coefficient (EDC) and porosity (POROS), however, their influence is negative and amounts to 26.7% and 10.6%, respectively (Li and Wu 1999).

The recommended method of the model's analysis of its sensitivity to the change of value of individual variables is the graphic method of evaluating the analysed model's sensitivity to individual variables, for the specified type of distribution. Crystal Ball offers the ability to generate tornado charts and spider charts. In order to create the abovementioned charts, the Tornado Chart option needs to be picked from the drop-down CB Tools menu, which can be found on the main menu bar of the CB program. The Specify Options dialog box, in the third step (Fig. 2.13), allows the user to enter individual quantities, characteristic of the creation of tornado and spider charts. The following elements are used in this process: input data (Tornado Input), the method of creating the chart (Tornado Method), the type of input data used to create the chart (Use existing cell values), and the types of charts (Tornado Output). After making the choice, the program runs the procedure of constructing sensitivity analysis in the form of a tornado and/or a spider chart. The outcome of the analysis in the form of a tornado chart is shown in Fig. 2.14. This diagram has been constructed on the basis of data included in the sensitivity Table 2.2. The values of the impact of the analysed variables on the value of the Z2 expression (forecast) is presented in the form of horizontal bars, bearing in mind that the most crucial ones are at the top of the chart and the less important ones at the bottom. Next to each bar there is a calculated value of the parameters within the upper and lower interval ranges for the defined probability distribution. The error bars indicate standard errors.

An alternative way of presenting output data is the use of line graphs, also known as spider charts. These have five series of data containing reporting for individual input variables of the Z2 value. The horizontal x-axis maps the location measure of



Specify options (step 3 of 3)

Tornado Chart

Crystal Ball Tool ® Decisioneering 1998·

Tornado Input

Testing range: 1 to 99%

Testing points: 5

For Base Case

● Use existing cell values

○ Use median values

Tornado Method

● Percentiles of the variables

○ Percentage deviations from the base case

Tornado Output

☑ Tornado chart

☑ Spider chart

Show 20 top variables

Fig. 2.13 The Tornado Chart dialog box with the options to create tornado and spider charts

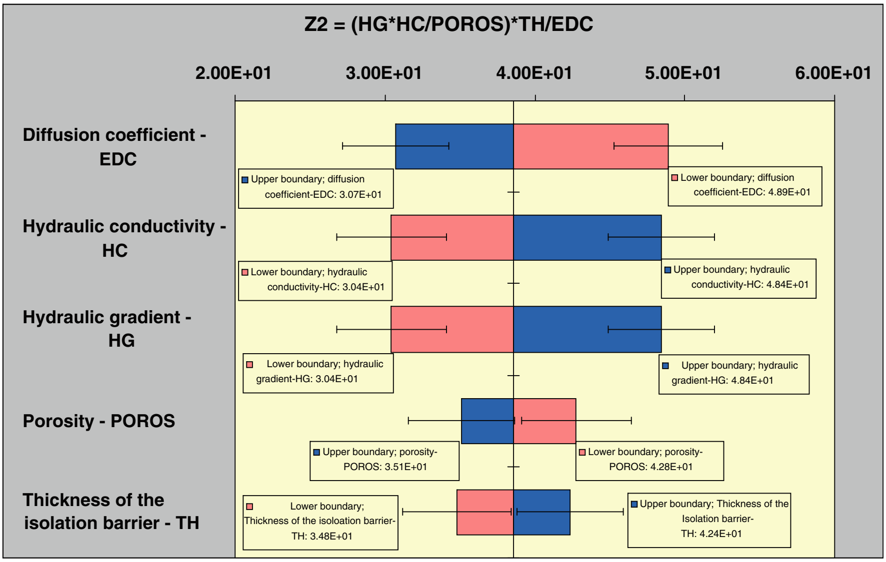


Fig. 2.14 Tornado sensitivity chart. The error bars indicate mean standard error (*Source*: Own work)

distribution ranging from the 1st to the 99th percentile of data (it measures the concentration of units, as percentages). The location measures point to the placement of the value that represents the variable values in the best way possible

Table 2.2 The MC simulation results, using CB software, of the sensitivity analysis of the diffusion of contaminants – sensitivity table (table of data) of the tornado chart

Parameter	Z2 = (HG*HC/POROS)*TH/EDC			Input parameters		
	Lower boundary	Upper boundary	Range	Min.	Max.	Base value
Diffusion coefficient – EDC	4.89E + 01	3.07E + 01	1.82E + 01	7.89E-11	1.25E-10	1.00E-10
Hydraulic conductivity – HC	3.04E + 01	4.84E + 01	1.80E + 01	7.89E-10	1.25E-09	1.00E-09
Hydraulic gradient – HG	3.04E + 01	4.84E + 01	1.80E + 01	1.065104692	1.694157822	1.35
Porosity – POROS	4.28E + 01	3.51E + 01	7.63E + 00	0.3157	0.3843	0.35
Thickness of the isolation barrier – TH	3.48E + 01	4.24E + 01	7.56E + 00	0.902	1.098	1

Table 2.3 The MC simulation results, using CB software, of sensitivity analysis of the diffusion of contaminants – sensitivity table (table of data) of the spider chart

Parameter	Z2 = (HG*HC/POROS)*TH/EDC				
	1.0%	25.5%	50.0%	74.5%	99.0%
Diffusion coefficient – EDC	48.89	41.40	38.76	36.30	30.74
Hydraulic conductivity – HC	30.43	35.94	38.38	40.99	48.40
Hydraulic gradient – HG	30.43	35.94	38.38	40.99	48.40
Porosity-POROS	42.76	40.56	38.57	36.77	35.13
Thickness of the isolation barrier – TH	34.79	36.68	38.57	40.46	42.35

(Ostasiewicz et al. 1995; Stanisz 2006). The y-axis, on the other hand, denotes the values of Z2. These statements can be understood, statistically speaking, on the basis of porosity, as: the value of POROS reaching 99% of population is less than or equal to 35.13, the value of POROS reaching the half (50%) of population is less than or equal to 38.57, while the value of POROS reaching just 1.0% of population is less than or equal to 42.76. The graph has been constructed using the data included in Table 2.3, generated by Crystal Ball during the process of making the sensitivity analysis spider charts. The line graph is shown in Fig. 2.15. The process of performing multiple calculations of the Z2 expression value can create this type of a graph, and the value that it assumes for different tested variables, for instance, is 1%, 25%, 50%, etc., of population (i.e. the population being above or below this observation, or in other words, the set of all the measurement results that are of interest to us). It is said that, for instance, the 25th percentile divides the population into two parts resulting in a situation where 25% of population units have values no greater than the threshold value of Z2, and 75% of population units have values no smaller than the threshold value of Z2. The greater the incline of the line describing the value of the Z2 expression, the more critical the input variable becomes.

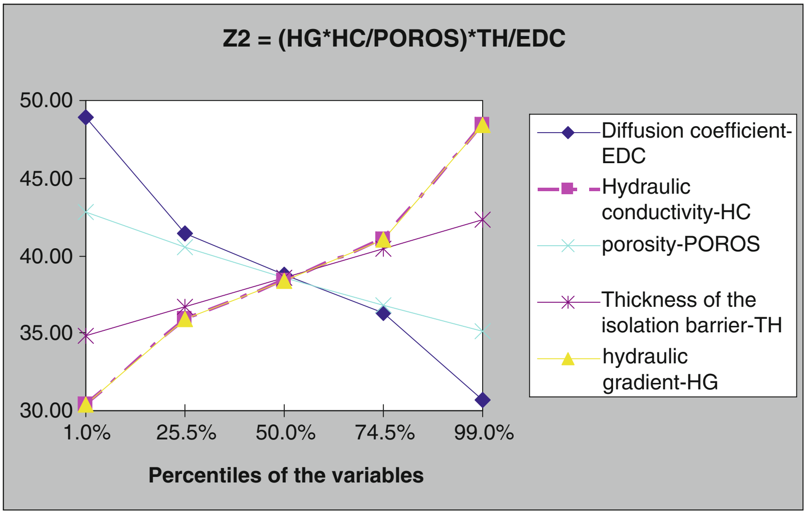


Fig. 2.15 The sensitivity line graph (*spider chart*). (Source: Own work)

2.5 The Results

Based on the obtained results, the following conclusions can be reached (Bieda 2000).

From the analysis of the frequency charts shown in Figs. 2.8 and 2.9, it appears that intervals equivalent to the 68th and 95th percentage level of confidence are equal to [31.62; 46.40] and [26.51; 55.99], respectively. The range width between the left and the right edge of the frequency chart (Figs. 2.8, 2.9) is 60.11 (Fig. 2.10); this is equivalent to the difference between the 0th and the 100th percentile, as can be seen in Fig. 2.11. The display range is between 19.45 and 58.72.

The evaluated value of the final result of the Z2 expression, of 38.5714 (from a deterministic perspective, described as evaluated – see Biegus 1999), from the formula (2.9), after substituting the experimental data presented in Table 2.1, is smaller than the estimated forecast value of $Z2 = 39.09$, calculated with the help of Crystal Ball (from a probabilistic perspective, described as estimated – see as above). The expectation that the final result's value of the Z2 expression will be within the assigned confidence intervals is fulfilled. Therefore, the result of the stochastic analysis can be seen as confirmation that the confidence intervals of [31.62; 46.40], respectively, with the probability of $p = 0.95$, indicated using MC method and Crystal Ball software, cover the mean value of Z2 (i.e. the value of Z2 is within these intervals). The application of computer simulation results in the information regarding MC method and the dynamics of the process becoming available.

2.6 Summary and Conclusion

The simulation results demonstrate that MC method, employed to solve stochastic models that describe the transport of contaminants in porous media, is a very useful tool applied to determine the life cycle of a modern landfill, and may be valuable when it comes to simulation studies of modelling waste management, the two aspects that are extremely important in environmental management (Bieda 2004b, 2004d, 2006c). Previously, deterministic models were used in such cases. Yet, as is noted by Snopkowski (2007), one needs to realise that by using stochastic values, it should not be expected that the results are going to be too accurate. What is very beneficial, when it comes to stochastic simulation (and other types of simulations for that matter), is its ability to compare the values calculated under defined real conditions, with the values of the same attributes obtained by the means of simulation of this process. However, in the presented case of calculating the optimum liner thickness of a landfill during its desired operational life, the modelled process will take place in the future and verification of such comparisons may be difficult, if not impossible (Bieda 2007b). Majer et al. (2007), draw attention to the fact that construction of landfills in recent years has grown to become an independent business. This work can, therefore, constitute a helpful method during the design and construction process of, for example, mineral liners. There are few publications and little research done in this area and the procedures described in international subject literature are not always adequate to Polish conditions. Another issue that needs recognition is the fact that many countries use different methods of how, for instance, soil properties are defined, and these inconsistencies may sometimes lead to conclusions that cannot be compared (Canarache and Simota 2002). Pilkey and Pilkey-Jarvis (2007), in their description of the Total System Performance Assessment (TSPA) model, a very sophisticated model whose architecture consists of 286 sub-models, applied in the study of radioactive waste, stored at Yucca Mountain in Arizona, USA, strongly emphasise the fact that if an assumption is made about a low value of rock permeability – a parameter that is involved in risk assessment of waste storage – then after a long period of time the numerical value of this parameter ought to be analysed due to the fact that during rainy seasons water filters through from desert regions to underground repositories. Consequently, the results achieved on the basis of the TSPA model used, may be unreliable. According to Moczko (1999), even a correct interpretation of obtained results would not improve the badly gathered experimental data. Moreover, the values of parameters published in the subject literature are often equivalent only to the conditions in which the research has been conducted. Empirical formulas, mentioned in literature, are characterised by large discrepancies. Nevertheless, simulation enhances understanding of what changes can be caused by a change of certain quantities taking part in simulation modelling. Deterministic analysis is based on an analytical description, or on a numerical approximation, of phenomena connected to transport and accumulation of pollutants. Stochastic analysis, however, makes use of the data that display the relations between available data and measurement values. The abovementioned simulation method of transport of contaminants in porous media may, in addition, have practical significance in measuring the range of safety zones surrounding industrial plants, landfills, etc., in order to avoid contamination and degradation of the ground, a situation that occurred in the former Huta im. Lenina (Lenin's Steel Plant), in Kraków (today, ArcelorMittal Steel Poland), which was a cause of a serious source of contamination of the surrounding area (e.g. cadmium contamination in Kokotów, which is situated in the Kraków area (Gawęda 2009)). The application of a computer simulation method offers more possibilities, as it allows the ability to analyse a model in a situation where its parameters are assigned other probability distributions, such as normal distribution.

Chapter 3

The Role of Risk Assessment in Investment Costs Management, Based on the Example of Waste Treatment (Gasification) Facility in the City of Konin

3.1 Introduction

The technology behind converting, disposal, and destruction of waste is constantly being modernised. The United States Environmental Protection Agency (EPA) sponsors competitions and finances a considerable number of innovative scientific-research studies in this field. As a result, various project ideas can be realised and the most interesting solutions can be turned into real technology, thanks to EPA funding. In Poland, the Article 1 of the Waste Management Act of 27 April (Official Journal 'Dz. U.' No. 62 2001) and the Directives 91/156/EEC, 91/689/EEC, and 94/67/EEC of the European Parliament and of the Council (Dyrektywa 2010), state the rules regarding waste procedures which ensure human life and health safety, as well as environmental protection, in accordance with the rules of sustainable development, and especially the rules establishing how waste production can be avoided, or rules limiting the amount of waste and its negative impact on the environment, as well as the waste recovery or waste neutralisation rules.

This chapter does not provide a more detailed description of risk management, and the nine theories, discussed by Hall (1997), which are of fundamental importance to risk management, are presented elsewhere (Bieda 2002, 2004e, 2006e), and their inclusion in this chapter goes beyond the framework of this project.

3.2 Risk in Waste Management (Environmental Protection) in European Union and International Legislation

The main aim of the legislation is the minimisation of risk in the field of environmental protection and public health. Thus, it is crucial to differentiate between 'danger' and 'risk'. In the context of waste management, a threat is a possible source of danger, whereas risk indicates the possibility of causing a threat

B. Bieda, *Stochastic Analysis in Production Process and Ecology Under Uncertainty*,
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(Bradly and Goldman 2010; Champy 1995). The definition of risk consists of two elements: the threat, and the possibility of its occurrence. Consequently, the same level of risk may be resulting from a combination of high threat and low probability of its appearance, or low threat but with high probability of it being real. The United States Environmental Protection Agency (EPA) has developed the Waste Resource Allocation Program (WRAP), whose aim is to analyse the risk involved in transport, utilisation, and storage of hazardous waste (Nema and Gupta 1999). The function of the model's aim is to minimise the cost and the risk, while dealing with a range of restrictions (the waste's mass, the processing power of a waste treatment facility, utilisation technology, etc.) The definition of risk is similar to the definition of banking risk. It is measured by a product of:

- The probability of an event happening (the generation of hazardous waste),
- The consequence of an event happening.

In addition, the United States Environmental Protection Agency (EPA), in 1989, developed a Stochastic Risk Assessment model for hazardous waste (Valdés et al. 1998). This model was built using Excel spreadsheet and Crystal Ball software (CB 2010).

3.3 The Application of MC Simulation, Using Simlab® Software, in the Analysis of Investment Risk: Probabilistic Cost Model of the Construction Project of the Waste Treatment Facility in the City of Konin

Certainty is no doubt. In Webster's New Collegiate Dictionary, one of its definitions of the word 'certainty' is that it is a state of 'having no doubt', a definition that can be treated as sufficient when it comes to studying risk management. The antonym of certainty is uncertainty, which is defined as 'doubting in the ability to predict the consequences of current actions' (Williams et al. 2002). Risk is the potential changeability of events. Risk is an objective term and, as such, it can be measured. The discussed problem of investment risk in the project of the Waste Treatment Facility in the City of Konin is based on the utilisation of theoretical distributions used in probability theory and in statistics. Probability is about evaluating the proportions of results concerning the given events' chance of happening. The knowledge of the described probability distribution allows a probability assignment procedure to be applied in specific stages of risk management procedures, in order to set the overall budget of the project investment and construction of the Waste Treatment Facility in the City of Konin, as well as to predict the future effects of today's decisions. If the person responsible for risk management knows the probability distribution of costs, the estimation of the investment's budget at completion becomes a simple calculation (Bieda 2000; Williams et al. 2002). There is, however, little evidence in support of the statement that costs have a known theoretical distribution. In this chapter, the role of risk analysis in investment costs management is described, based on the example of the project of the Waste Treatment Facility using pyrolysis method with energy recovery for the City of Konin and Konin district (Oferta 2002). The Waste Treatment Facility was supposed to be built based on American technology introduced by a consortium of the following companies: IESSCO Inc., NORCON INTERNATIONAL Inc., SIMONDS MFG. Corp., BECO ENGINEERING Co., CP. Mfg. Inc., MARATHON EQUIP. Inc., and FOSSIL ENERGY GOV. The facility was set to include two complete units, responsible for the pyrolysis and gasification of municipal waste, with a daily output of 200 metric tons of waste.

3.4 Developing the Model

The six stages of the Waste Treatment Facility Project as well as the total value of the projected investments costs (TOTAL – see Table 3.1) have been taken into consideration during the analysis. The simulation has been conducted using Simlab® software – a simulation package that is equipped with features such as: full visualisation of the performed simulation and clear methods for inputting data and recording obtained results. In addition, Simlab® offers a range of distribution types (normal, log-normal, uniform, etc.).

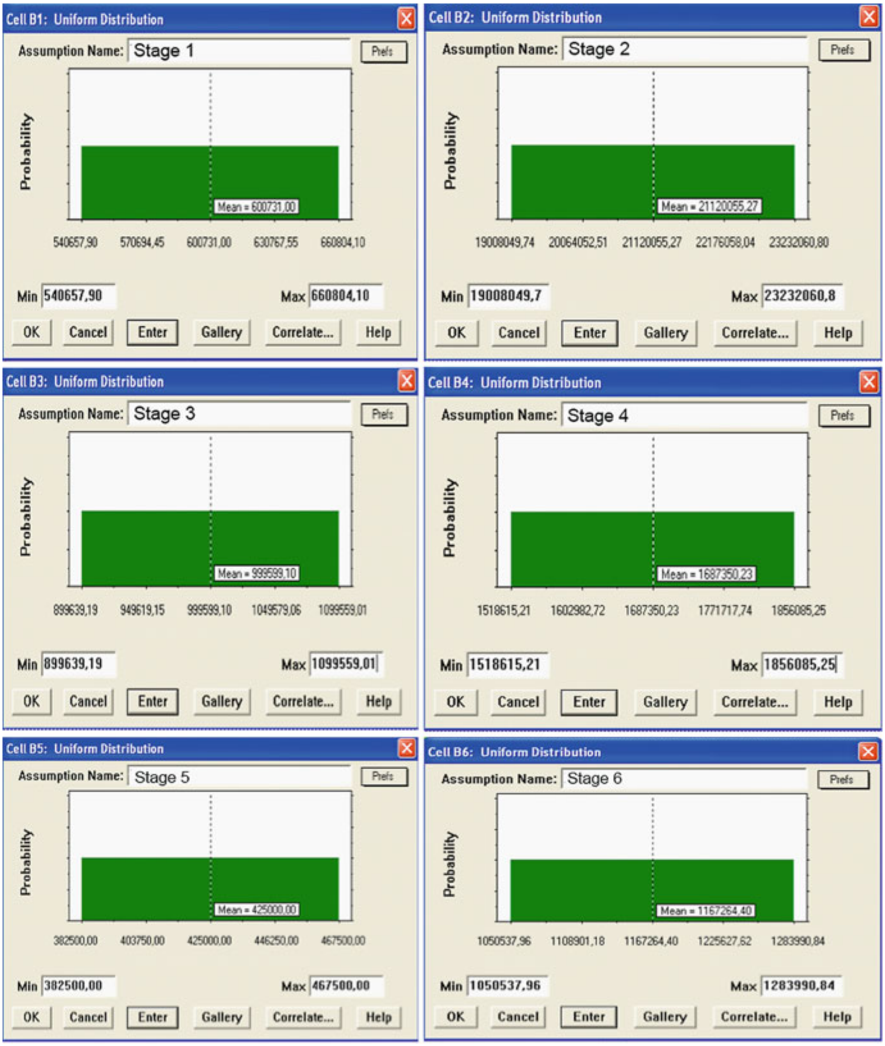
The specification of investment costs is shown in Table 3.1. The values are given in US Dollars (USD), since the presented offer was originally drawn up based on that currency. In this thesis, it is established that random cost values of the investment, in its individual stages, may be described using uniform distribution, based on the work of Liberman (2003) who, in his economic analysis of the

Table 3.1 The projected investment costs, based on the American project (values shown in USD), along with parameters of uniform distribution

City of Konin

The Waste Treatment Facility project

	Investment stages	Partial cost (in USD)	a – lower interval value	b – higher interval value
1	Stage 1 – management, investment, design, permissions	600731.00	540657.90	660804.10
2	Stage 2 – the waste gasification facility building, gasification facility (boilers, transport, permissions, assembly)	21120055.27	19008049.70	23232060.80
3	Stage 3 – monitoring of gas emission	999599.10	899639.19	1099559.01
4	Stage 4 – conveyor belts, automatic loading system, design supervision, engineering, start-up	1687350.23	1518615.21	1856085.25
5	Stage 5 – office equipment, computers, transport facilities, lifts, etc.	425000.00	382500.00	467500.00
6	Stage 6 – investment reserve	1167264.40	1050537.96	1283990.84
	Total cost – TOTAL	26000000.00		



Cell B1: Uniform Distribution
Assumption Name: Stage 1
Min 540657,90
Max 660804,10

Cell B2: Uniform Distribution
Assumption Name: Stage 2
Min 19008049,7
Max 23232060,8

Cell B3: Uniform Distribution
Assumption Name: Stage 3
Min 899639,19
Max 1099559,01

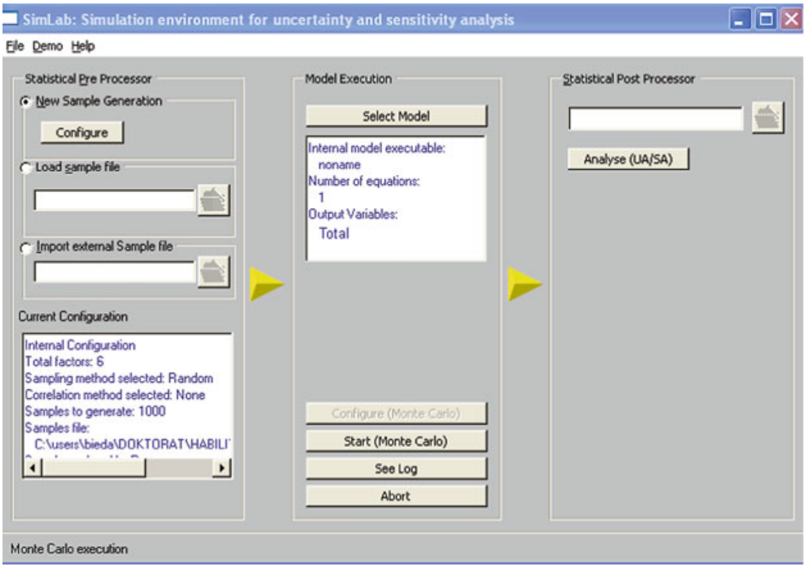
Cell B4: Uniform Distribution
Assumption Name: Stage 4
Min 1518615,21
Max 1856085,25

Cell B5: Uniform Distribution
Assumption Name: Stage 5
Min 382500,00
Max 467500,00

Cell B6: Uniform Distribution
Assumption Name: Stage 6
Min 1050537,96
Max 1283990,84

Fig. 3.1 Graphical presentation of the density function of random input parameters of model approximation using uniform distribution, in Crystal Ball software (Source: Own work)

construction of wind power plants in the United States, has used uniform distribution in the approximation of random cost values in the investment's budget. As is argued by Snopkowski (2007), uniform distribution, despite its limited capabilities in terms of modelling of real processes, has a wide range of applications in stochastic simulation algorithms. Interval values [a, b] of uniform distributions, estimating the random cost values of the investment (Stage 1–Stage 6), can be found in Table 3.1. The values of a and b are calculated on the basis of automatic estimation using CB, following the steps given in Chap. 2 (see Chap. 2). Mean values (Fig. 3.1) are equivalent to deterministic costs of separate investment stages presented in Table 3.1.

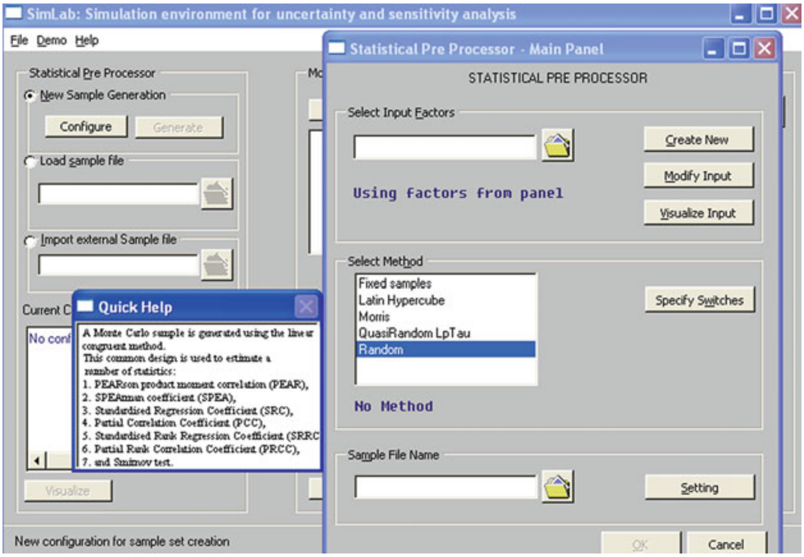


Internal model executable:
noname
Number of equations:
1
Output Variables:
Total

Internal Configuration
Total factors: 6
Sampling method selected: Random
Correlation method selected: None
Samples to generate: 1000
Samples file:
C:\users\bieda\DOKTORAT\HABILI

Monte Carlo execution

Fig. 3.2 The main screen of the Simlab® program



No conf

Using factors from panel

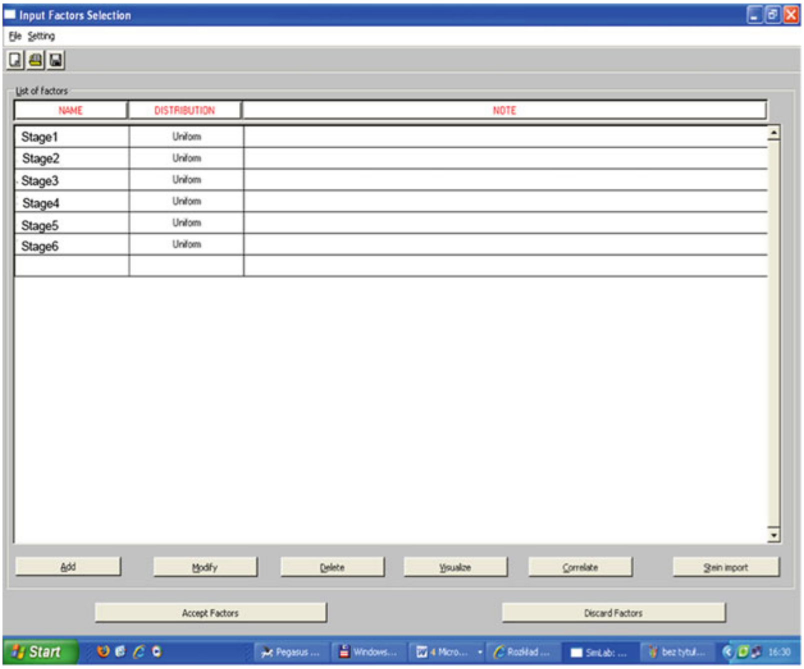
No Method

A Monte Carlo sample is generated using the linear congruent method.
This common design is used to estimate a number of statistics:
1. PEARson product moment correlation (PEAR),
2. SPEArman coefficient (SPEA),
3. Standardised Regression Coefficient (SRC),
4. Partial Correlation Coefficient (PCC),
5. Standardised Rank Regression Coefficient (SRRC
6. Partial Rank Correlation Coefficient (PRCC),
7. and Smirnov test.

New configuration for sample set creation

Fig. 3.3 Main Panel window

The main screen of the Simlab® program is shown in Fig. 3.2. The construction of the model can be started by clicking on the Configure button, seen on the main screen of the program (Fig. 3.2). Once clicked, a new window appears (Main Panel), as presented in Fig. 3.3. After clicking on the Create New button, another



NAME	DISTRIBUTION	NOTE
Stage1	Unifom	
Stage2	Unifom	
Stage3	Unifom	
Stage4	Unifom	
Stage5	Unifom	
Stage6	Unifom	

Fig. 3.4 Input Factors Selection window

window appears (Input Factors section), a representation of which can be seen in Fig. 3.4, which serves as a tool for creating distributions estimating input parameters of the model.

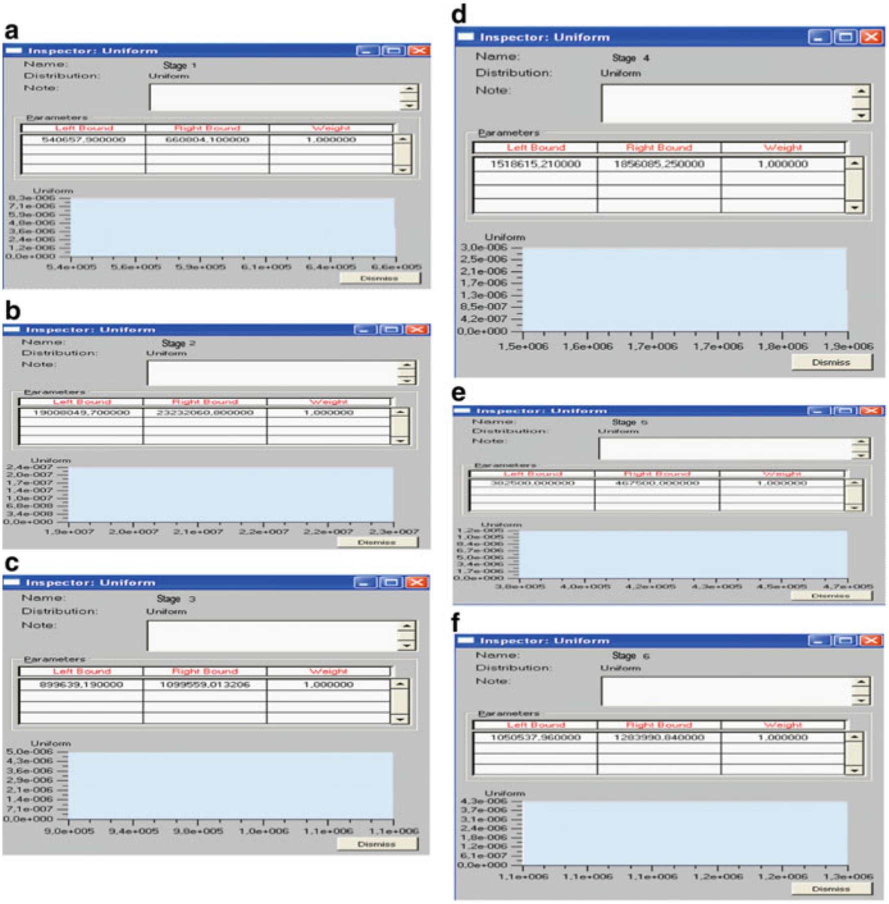
3.5 Defining Input Data: Organising the Simulation

Before running the simulation, the input data, received in the graphic form presented in Fig. 3.5 (a–f) (Bieda 2010), is defined.

The model constituting the total cost – TOTAL, characteristic due to its six stages (Stage 1–Stage 6), is shown in Fig. 3.6.

3.6 Activating the Model: The Results of the Simulation

In order to start a model it is required to first use the Random option, which can be selected from the Main Panel window (Fig. 3.3) that serves as a starting point for MC simulation. After choosing the Random option, a new Quick Help window appears to the left of the Select Method dialog box, which informs us about the



a

Inspector: Uniform

Name: Stage 1

Distribution: Uniform

Note:

Parameters

Left Bound	Right Bound	Weight
540657,900000	660804,100000	1,000000

b

Inspector: Uniform

Name: Stage 2

Distribution: Uniform

Note:

Parameters

Left Bound	Right Bound	Weight
19008049,700000	23232060,800000	1,000000

c

Inspector: Uniform

Name: Stage 3

Distribution: Uniform

Note:

Parameters

Left Bound	Right Bound	Weight
899639,190000	1099559,013206	1,000000

d

Inspector: Uniform

Name: Stage 4

Distribution: Uniform

Note:

Parameters

Left Bound	Right Bound	Weight
1518615,210000	1856085,250000	1,000000

e

Inspector: Uniform

Name: Stage 5

Distribution: Uniform

Note:

Parameters

Left Bound	Right Bound	Weight
382500,000000	467500,000000	1,000000

f

Inspector: Uniform

Name: Stage 6

Distribution: Uniform

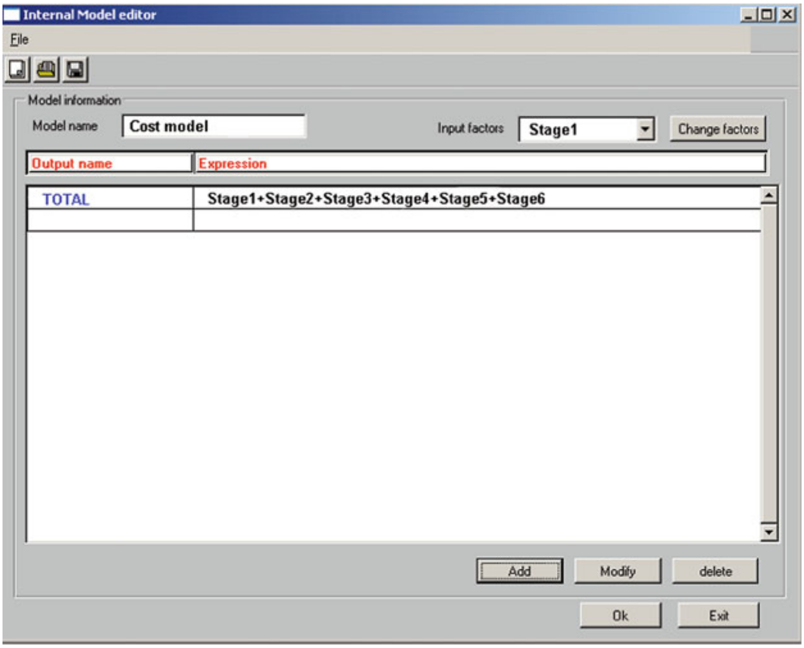
Note:

Parameters

Left Bound	Right Bound	Weight
1050537,960000	1283990,840000	1,000000

Fig. 3.5 Graphical presentation of the density function of random input parameters of model approximation using uniform distribution, in SimLab software (Source: Own work)

availability of possible data analysis methods based on randomness. The Specify Switches button takes us to a new window, which is used to specify different parameters of the simulation (such as the number of randomisation steps). By clicking on the Configure (Monte Carlo) button (Fig. 3.7) and then in turn on the Select Model and Start (Monte Carlo), as is shown in Fig. 3.8, Monte Carlo simulation begins to run. The results of the simulation can be presented in the form of sensitivity analysis (SA) and uncertainty analysis (UA) by clicking on the Analyse (UA/SA) button (Fig. 3.8) and by clicking on the UA or SA button, available from the Statistical Post Processor – Main Panel window (Fig. 3.9), launched automatically once the abovementioned Analyse (UA/SA) button is activated. Sensitivity analysis with the confidence level of 95%, created on the basis of Spearman Rank Correlation coefficients (SCR), for the data presented in Table 3.1, is shown in Figs. 3.10 and 3.11. In Fig. 3.11 the chart's vertical axis is

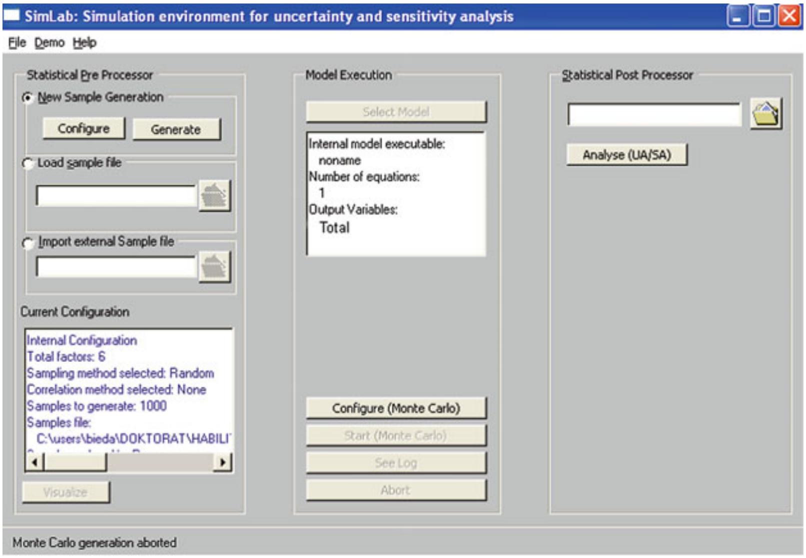


Model name: Cost model

Input factors: Stage1

Output name	Expression
TOTAL	Stage1+Stage2+Stage3+Stage4+Stage5+Stage6

Fig. 3.6 Internal Model editor window (Source: Own work)



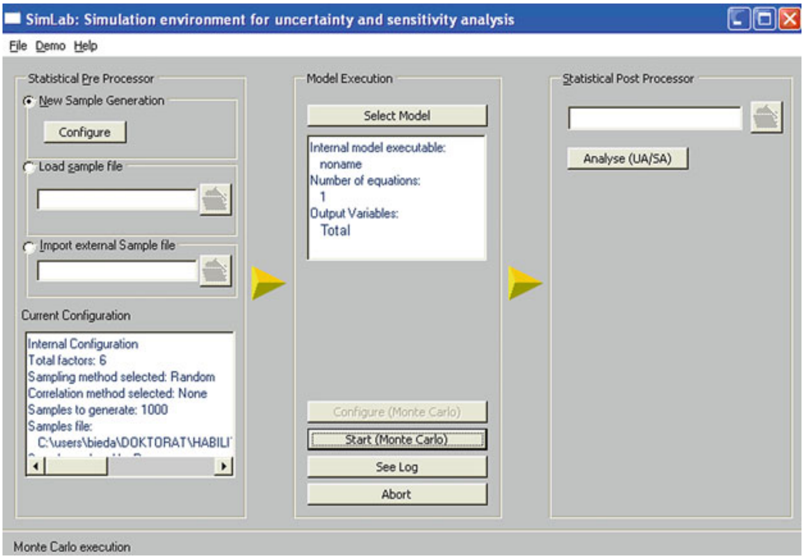
● New Sample Generation
○ Load sample file
○ Import external Sample file

Internal Configuration
Total factors: 6
Sampling method selected: Random
Correlation method selected: None
Samples to generate: 1000
Samples file:
C:\users\bieda\DOKTORAT\HABILI

Internal model executable:
noname
Number of equations:
1
Output Variables:
Total

Monte Carlo generation aborted

Fig. 3.7 The sensitivity and uncertainty analysis window: Monte Carlo configuration

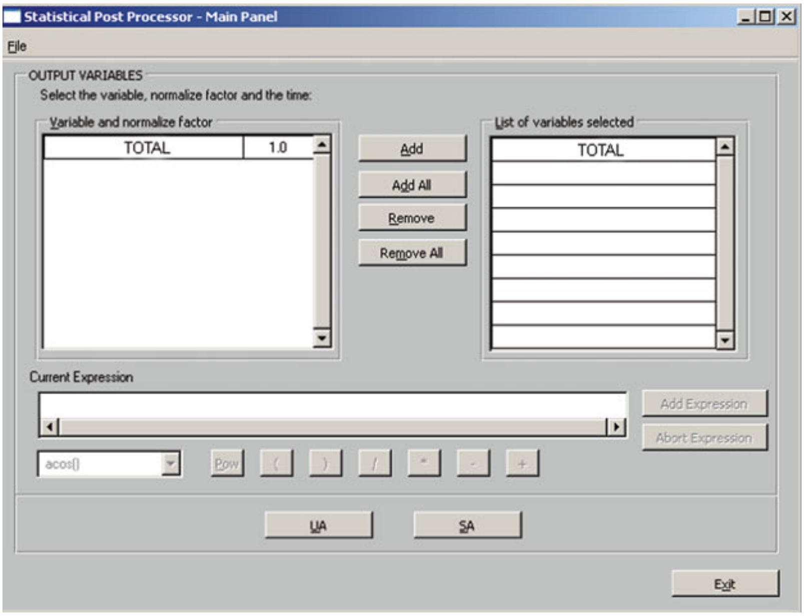


● New Sample Generation

Internal Configuration
Total factors: 6
Sampling method selected: Random
Correlation method selected: None
Samples to generate: 1000
Samples file:
C:\users\bieda\DOKTORAT\HABILI

Internal model executable:
noname
Number of equations:
1
Output Variables:
Total

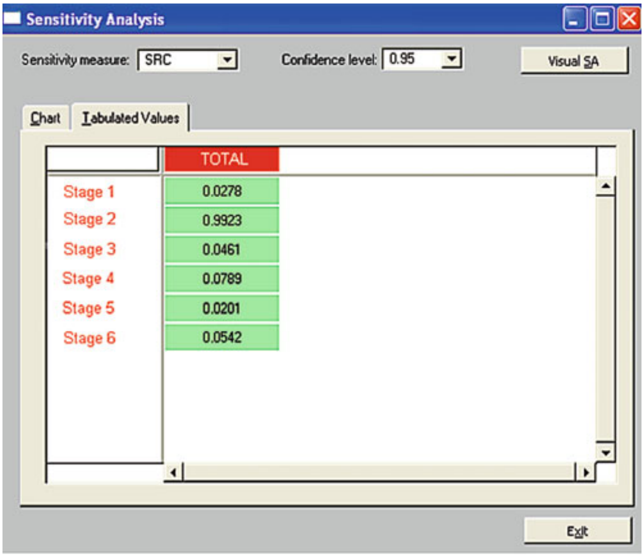
Fig. 3.8 The sensitivity and uncertainty analysis window: Start Monte Carlo



Variable	Normalize factor
TOTAL	1.0

List of variables selected
TOTAL

Fig. 3.9 Statistical Post Processor – Main Panel window with a list of uncertainty (UA) and sensitivity analysis (SA) buttons (Source: Own work)

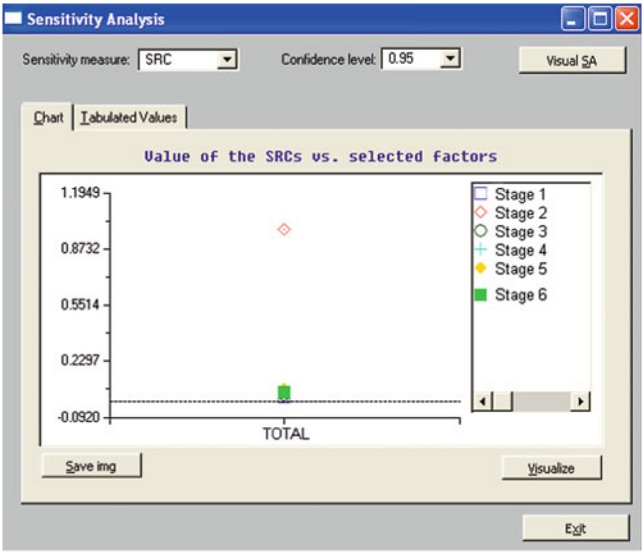


Sensitivity measure: SRC

Confidence level: 0.95

	TOTAL
Stage 1	0.0278
Stage 2	0.9923
Stage 3	0.0461
Stage 4	0.0789
Stage 5	0.0201
Stage 6	0.0542

Fig. 3.10 Sensitivity analysis with confidence levels of 95% (SRC – Spearman Rank Correlation) – tabular form (Source: Own work)



Sensitivity measure: SRC

Confidence level: 0.95

Fig. 3.11 Sensitivity analysis with confidence levels of 95% (SRC – Spearman Rank Correlation) – dot diagram (Source: Own work)

scaled according to the values of Spearman Rank Correlation coefficients, but at the same time it is worth remembering that the rank correlation coefficient's values are within the specified range of [-1; 1]. It can be concluded, from the analysis of

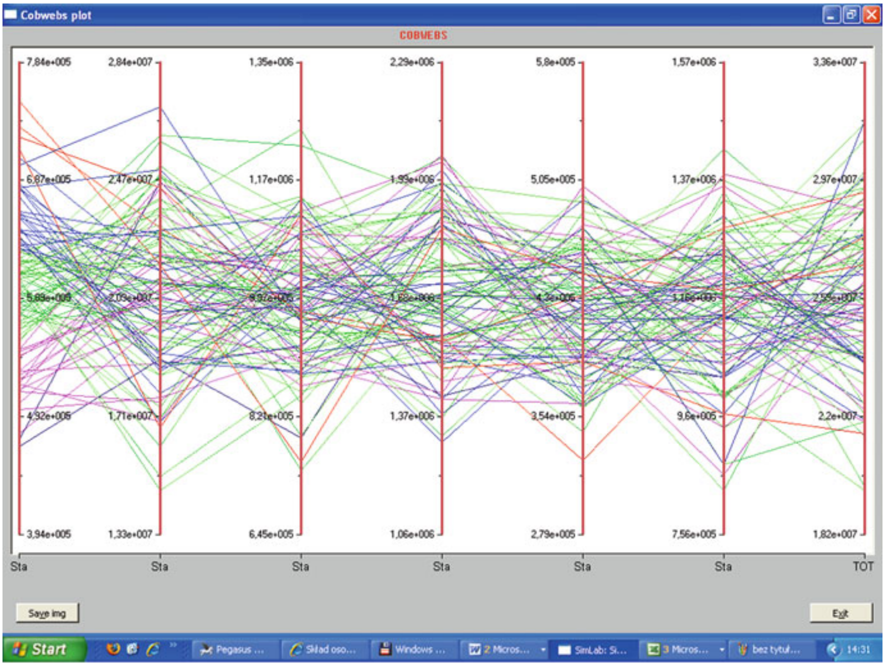


Fig. 3.12 Cobwebs plot sensitivity analysis under confidence levels of 95% (SRC – Spearman Rank Correlation) (Source: Own work)

the chart that the key variable, which influences the total cost of the project the most, is Stage 2 (correlation coefficient = 0.9923). The positive sign of the coefficient signifies the existence of positive correlation, whereas the negative sign marks negative correlation. While evaluating the results it is important to draw one's attention to whether correct requirements have been met regarding the number of randomisation steps in the cycle. The green colour of cells in the TOTAL column, containing the values of Spearman Rank Correlation coefficients, means the randomisation has been performed correctly. A flawed randomisation (too few steps) generates results, which are inserted in the TOTAL column cells and are coloured red (Saltelli et al. 2004).

The instruction – Visual SA – allows the user to present the simulation results in a graphic form. An example of a visualisation in the form of the Cobwebs plot can be seen in Fig. 3.12. This graph helps us better understand the state of the model's certain parameters, while the simulation process is underway. In Fig. 3.12, the chart's horizontal axis is labelled with both the symbols of different stages (1–6) that appear in the cost model, and the symbol of total cost – TOTAL. The range of confidence intervals can be read from the frequency charts, shown in Figs. 3.13–3.19, built as a result of uncertainty analysis performed using MC simulation.

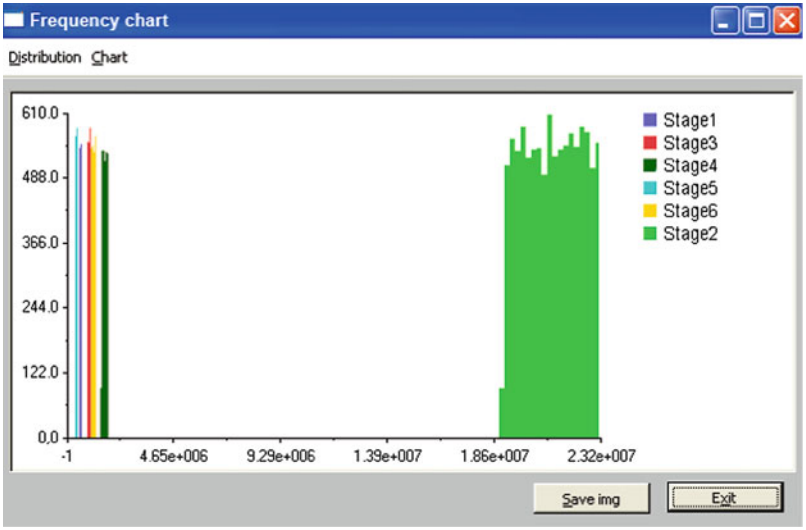
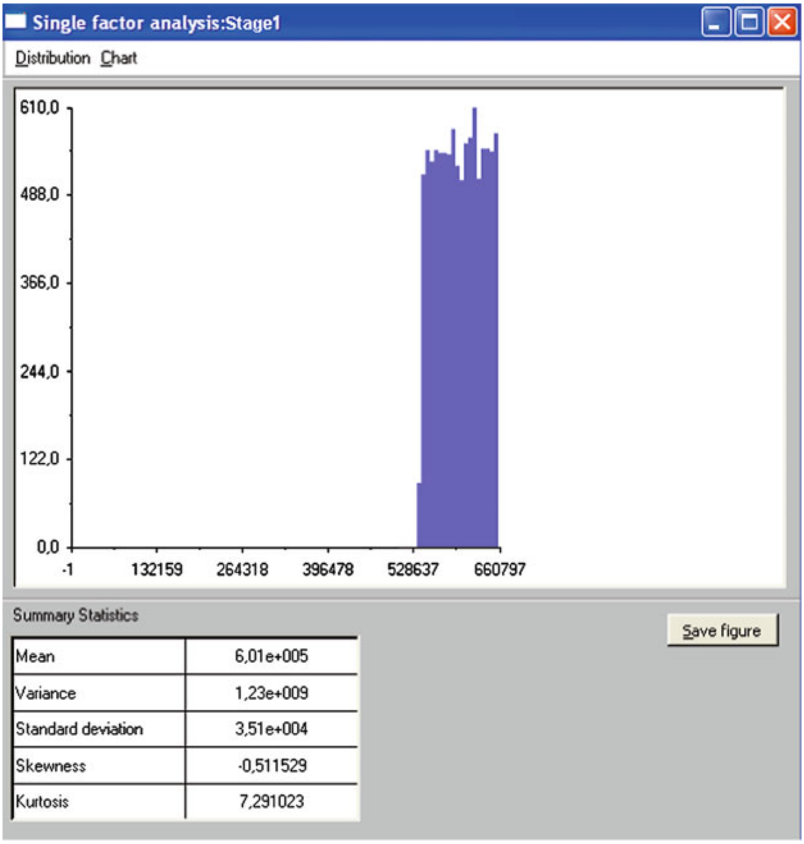


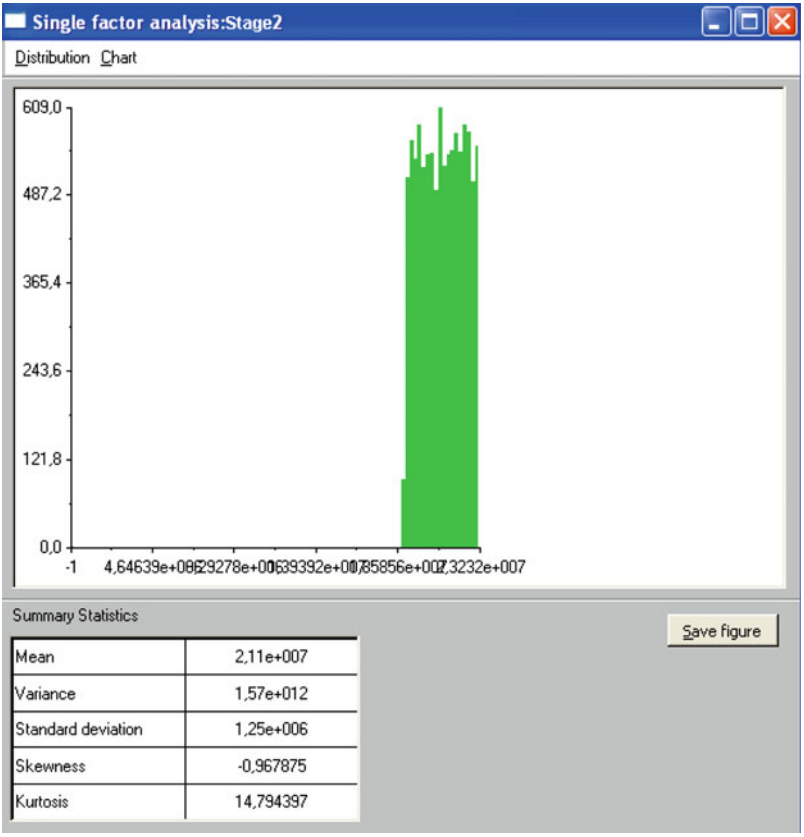
Fig. 3.13 Uncertainty analysis frequency chart – cumulative, of all six stages (Source: Own work)



Summary Statistics

Mean	6,01e+005
Variance	1,23e+009
Standard deviation	3,51e+004
Skewness	-0,511529
Kurtosis	7,291023

Fig. 3.14 Uncertainty analysis frequency chart – Stage 1 (Source: Own work)

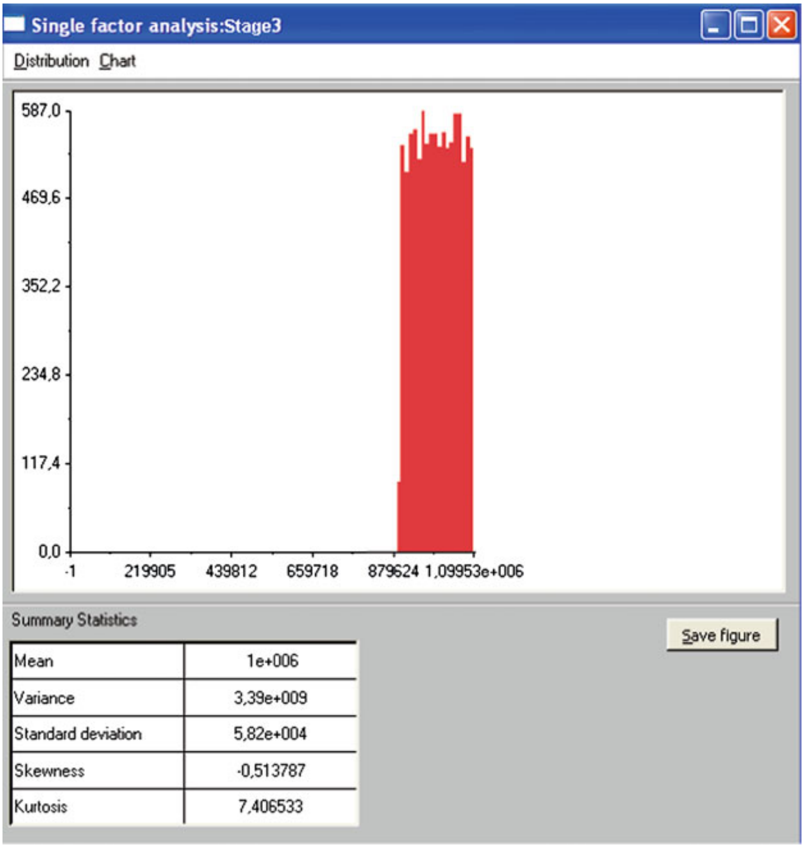


Summary Statistics

Mean	2,11e+007
Variance	1,57e+012
Standard deviation	1,25e+006
Skewness	-0,967875
Kurtosis	14,794397

Fig. 3.15 Uncertainty analysis frequency chart – Stage 2 (Source: Own work)

The results of the uncertainty analysis, obtained after using the UA button (Fig. 3.8), are shown in Figs. 3.20 and 3.21 in the form of frequency charts (confidence level of 95%). The frequency chart along with the statistic report, received after the activation of the TOTAL field (a square in the top right hand corner of the chart (Fig. 3.21)) is presented in Fig. 3.21. Both figures display a horizontal axis, which is labelled with the total investment cost values TOTAL (shown in USD). The mean value, which is equal to 2.6E + 7, is equivalent to the deterministic total cost of the investment – TOTAL (Table 3.1). It can be observed, by analysing Table 3.2 that, starting from zero, the higher the frequency (the second column) the higher the increment (the third column). The read value of x = TOTAL equals 2.45E + 7. When frequency reaches the value of 614, which is equivalent to the value of x = 2.1E + 7, its value begins to fall, until it reaches zero (its increment falls and gets close to zero as well), while its corresponding value is



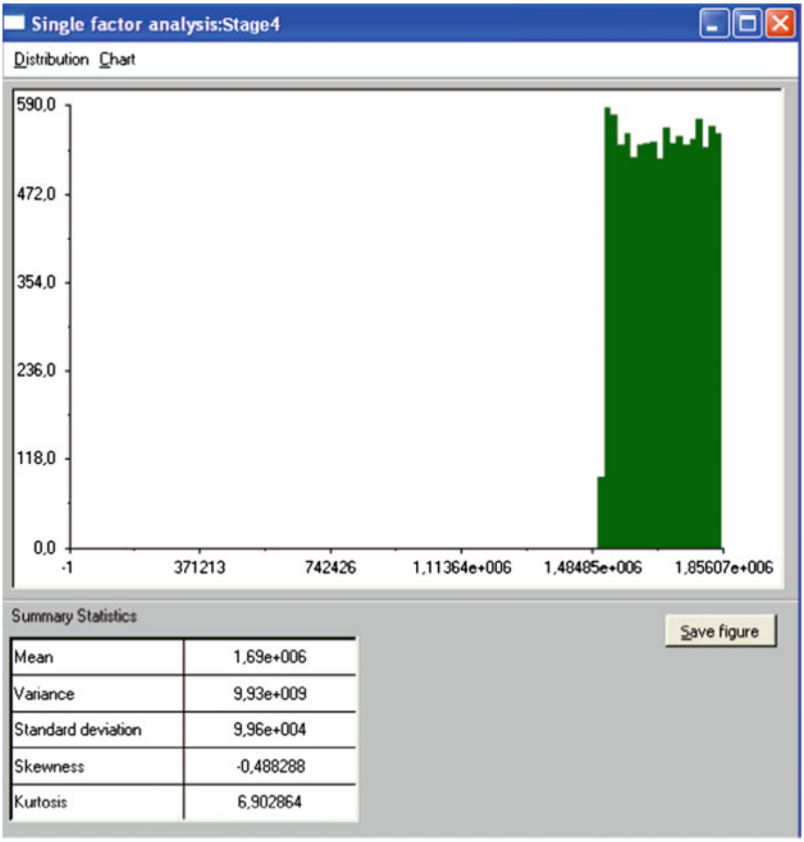
Summary Statistics

Mean	1e+006
Variance	3,39e+009
Standard deviation	5,82e+004
Skewness	-0,513787
Kurtosis	7,406533

Fig. 3.16 Uncertainty analysis frequency chart – Stage 3 (Source: Own work)

x = 2.98E + 7. Thus, it can be noted that the obtained confidence interval is described with the values of [2.454E + 7; 2.98E + 7] (shown in USD), and its span can be expressed by the number 5.3E + 6.

The total (deterministic) value of investment costs, presented in the row 'Total' in the Table 3.1, amounts to 2.6E + 7 USD. In the stochastic approach to design, however, the mean random value of the total investment costs, worked out as a result of the simulation, amounts to 2.73E + 7 USD. Therefore, we may be 95% confident that the confidence interval covers the mean value of the total investment costs, or in other words, the mean value of the total investment costs is between the number 2.45E + 7 USD and the number 2.98E + 7 USD, with the same 95% confidence level.



Summary Statistics

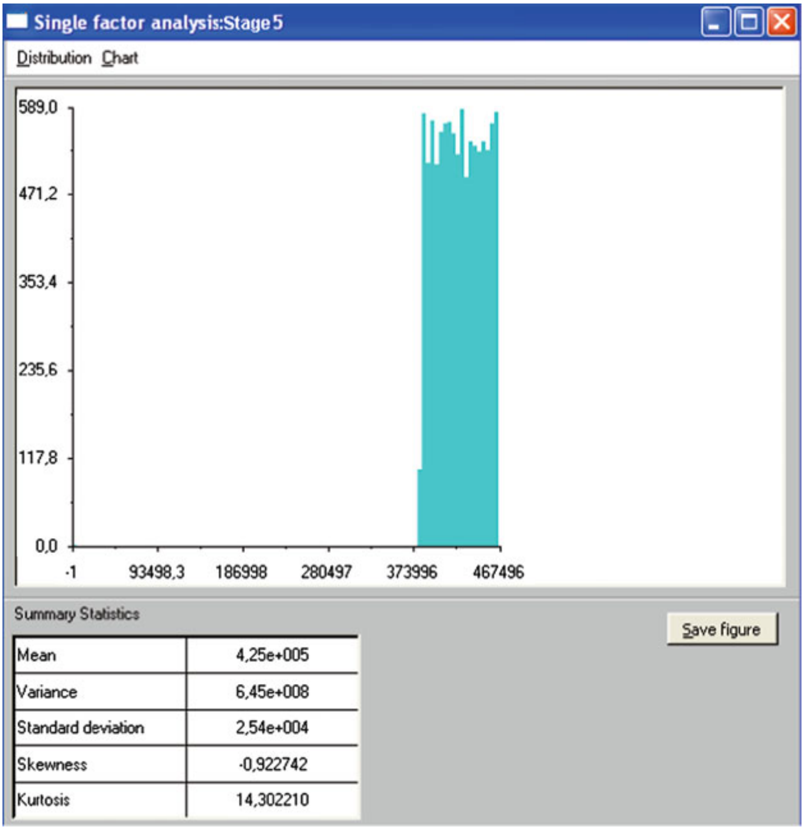
Mean	1,69e+006
Variance	9,93e+009
Standard deviation	9,96e+004
Skewness	-0,488288
Kurtosis	6,902864

Fig. 3.17 Uncertainty analysis frequency chart – Stage 4 (Source: Own work)

3.7 Summary and Conclusion

In the deterministic approach to investment design, a costs model is created by assuming constant values of individual elements in the financial plan. In the stochastic method of estimating the investment costs, the knowledge of probability distribution is required, as it is used to approximate the random values of partial costs, whose sum is the final cost of the investment. In order to describe the random nature of the elements in the financial plan (Stage 1–Stage 6), uniform distribution has been applied, based on the work of Liberman (2003).

When examining a given investment project, it is necessary to include the analysis and presentation of investment costs. The traditional methods of estimating costs do not provide answers to the following questions (Bieda 2005a, 2006a, 2006f, 2007a):



Mean	4,25e+005
Variance	6,45e+008
Standard deviation	2,54e+004
Skewness	-0,922742
Kurtosis	14,302210

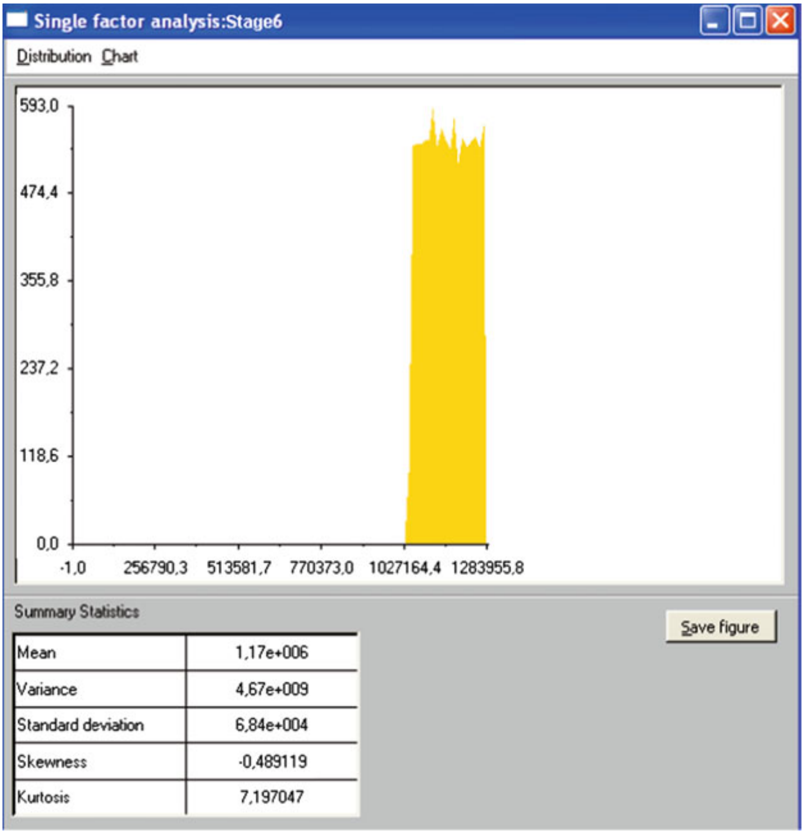
Fig. 3.18 Uncertainty analysis frequency chart – Stage 5 (Source: Own work)

1. What is the danger of cost overruns?
2. What can be considered as risk in both the project and the realisation of the investment?

The aim of the analysis of investment risk (of the total investment costs) is to deliver tools to the investment manager that would help them manage the risk.

The above example illustrates that by employing Monte Carlo simulation, it becomes possible to include uncertainty in the evaluation of investment costs, consequently, the risk in the decision making process is considered as well (Bieda and Tadeusiewicz 2008). Moreover, on the basis of the same simulation results, each of the decision-makers is able to make an individual, and yet separate, decision.

If an assumption is made that the estimated values of the investment project's partial costs (Stage 1–Stage 6) can be described with the help of uniform distribution, the total investment cost TOTAL is transformed from a specific deterministic



Mean	1,17e+006
Variance	4,67e+009
Standard deviation	6,84e+004
Skewness	-0,489119
Kurtosis	7,197047

Fig. 3.19 Uncertainty analysis frequency chart – Stage 6 (Source: Own work)

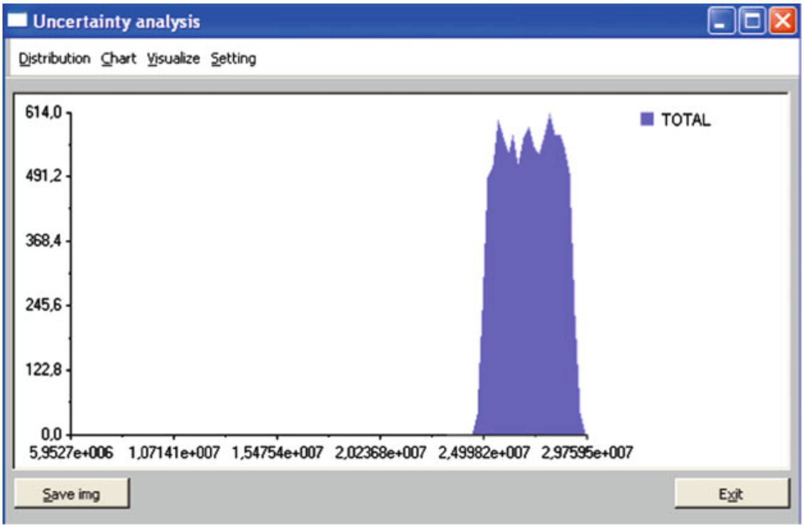
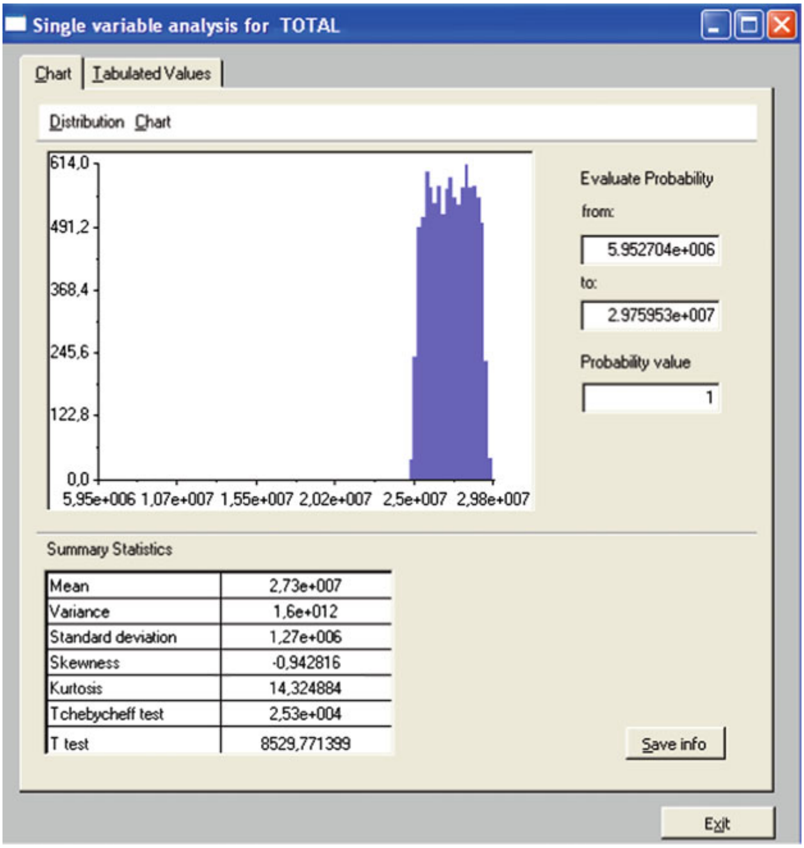


Fig. 3.20 Uncertainty analysis with 95% confidence level (Source: Own work)



Evaluate Probability

from:

5.952704e+006

to:

2.975953e+007

Probability value

1

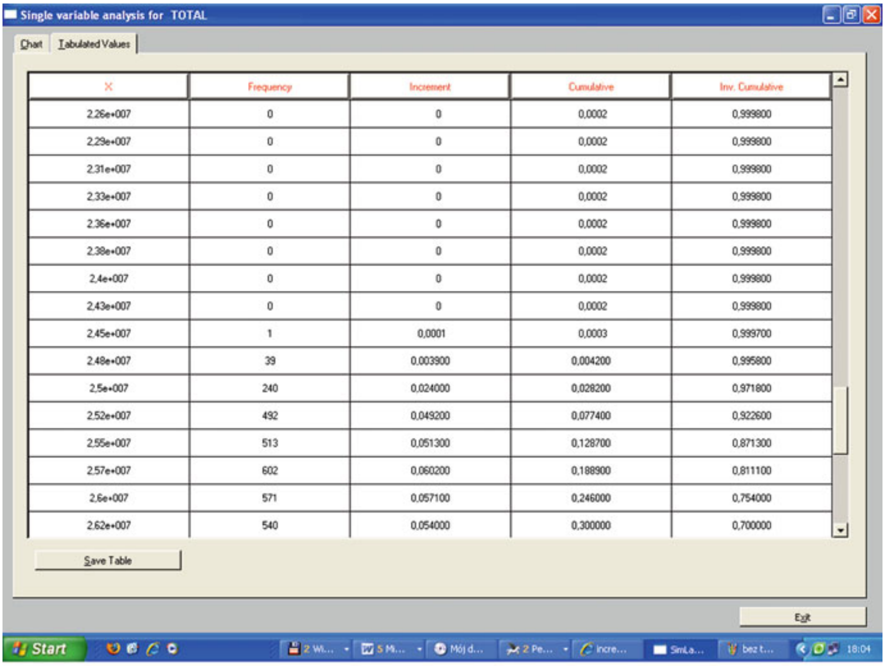
Summary Statistics

Mean	2,73e+007
Variance	1,6e+012
Standard deviation	1,27e+006
Skewness	-0,942816
Kurtosis	14,324884
Tchebycheff test	2,53e+004
T test	8529,771399

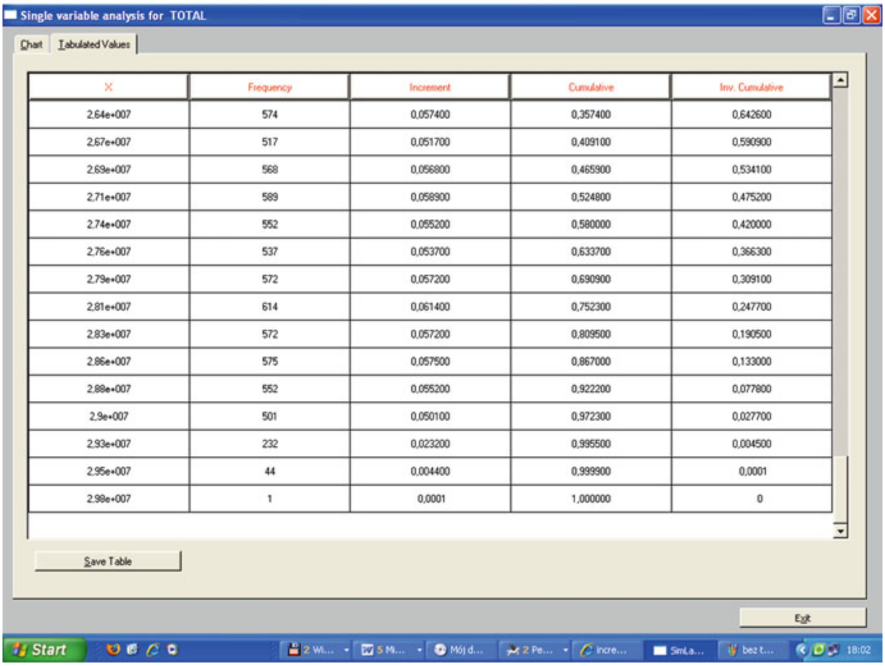
Fig. 3.21 Uncertainty analysis and distribution parameters with 95% confidence level (Source: Own work)

value into its probable distribution around the mean value. The probability distribution achieved in this way allows for a better understanding of the uncertainty level, which covers the interval range established using MC method with the help of SimLab® (see Fig. 3.12).

Table 3.2 Supportive calculations made in the process of creating the uncertainty analysis charts. Stages of statistical calculations require verification



X	Frequency	Increment	Cumulative	Inv. Cumulative
2,26e+007	0	0	0,0002	0,999800
2,29e+007	0	0	0,0002	0,999800
2,31e+007	0	0	0,0002	0,999800
2,33e+007	0	0	0,0002	0,999800
2,36e+007	0	0	0,0002	0,999800
2,38e+007	0	0	0,0002	0,999800
2,4e+007	0	0	0,0002	0,999800
2,43e+007	0	0	0,0002	0,999800
2,45e+007	1	0,0001	0,0003	0,999700
2,48e+007	39	0,003900	0,004200	0,995800
2,5e+007	240	0,024000	0,028200	0,971800
2,52e+007	492	0,049200	0,077400	0,922600
2,55e+007	513	0,051300	0,128700	0,871300
2,57e+007	602	0,060200	0,188900	0,811100
2,6e+007	571	0,057100	0,246000	0,754000
2,62e+007	540	0,054000	0,300000	0,700000



X	Frequency	Increment	Cumulative	Inv. Cumulative
2,64e+007	574	0,057400	0,357400	0,642600
2,67e+007	517	0,051700	0,409100	0,590900
2,69e+007	568	0,056800	0,465900	0,534100
2,71e+007	589	0,058900	0,524800	0,475200
2,74e+007	552	0,055200	0,580000	0,420000
2,76e+007	537	0,053700	0,633700	0,366300
2,79e+007	572	0,057200	0,690900	0,309100
2,81e+007	614	0,061400	0,752300	0,247700
2,83e+007	572	0,057200	0,809500	0,190500
2,86e+007	575	0,057500	0,867000	0,133000
2,88e+007	552	0,055200	0,922200	0,077800
2,9e+007	501	0,050100	0,972300	0,027700
2,93e+007	232	0,023200	0,995500	0,004500
2,95e+007	44	0,004400	0,999900	0,0001
2,98e+007	1	0,0001	1,000000	0

Source: Own work

Chapter 4
Stochastic Analysis of the Environmental Impact of Energy Production Processes, Based on the Example of MSP Power Plant

4.1 Introduction

This chapter deals with the application of the stochastic method, used to analyse the environmental impact of the manufacturing processes, namely the energy production in the MSP Power Plant. The quantitative analysis of uncertainty of this kind has been proposed, based on the case of comparative analysis of four scenarios of the power plant's annual work cycle, taking into consideration that the scenarios differ only in the change of proportioning ratios of the two types of fuels: hard coal and blast furnace gas (the remaining fuels, such as natural gas and coke oven gas are left at their current levels – they are used as start-up gas, owing to their higher heating value). The MC methodology, because of its stochastic nature, has been applied for the quantitative analysis (Heermann 1997). There is little mention, in the subject literature, of research carried out in the area of the application of stochastic analysis in the manufacturing industry, let alone steel industry. In the work of Marice et al. (2000) an effort is made to apply the stochastic method in the Life Cycle Inventory analysis (LCI) in order to evaluate uncertainty of cumulated emissions and necessary materials to conduct the assessment of, e.g., the influence of the energy produced in coal power plants.

In current industry practice, manufacturing processes exert potentially considerable impact on environment. The environmental impact of the Power Plant is examined by employing the ecological life cycle assessment, one of the fastest developing assessment methods, in literature more commonly known as Life Cycle Assessment (LCA). It is, especially in Poland, a relatively new technique of environmental management that in recent years has attracted more and more interest. The reliability of LCA results may be uncertain, to a certain degree, and this uncertainty can be noticed with the help of MC method, for instance. This methodology has not yet been used in Polish steel industry. The International Iron and Steel Institute in Brussels, Belgium, in 2002 undertook a study (IISI 2002) focused on data inventory, based on the material-energy balance in the Life Cycle Inventory (LCI) procedure, which is the second phase in LCA, on the basis of data

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gathered from 28 steel plants from across Europe and Asia (excluding China and former USSR countries), North America, and South America. The steel power plants from the Mittal Steel Group were not included in the study (Arcelor Group was not part of Mittal Steel Group at the time). This is one of the reasons why this monograph discusses the LCA method so extensively (see Sects. 4.1, 4.2 and 4.3). The analysis introduced in this chapter is supported by a presentation of the life cycle of the process in the form of process trees, presented as boxes; each element of the tree includes a piece of information regarding the involvement of the processes and materials, proportionate to the value of indicators. In addition, it is possible not only to determine which process/material has the greatest influence on the product, but also to describe the involvement of a single element in the entire life cycle.

4.2 Origin and Development of the LCA Method

Life Cycle Analysis is an environmental management technique, which has very wide application (Kulczycka and Henclik 2009). It is a relatively new (Kowalski et al. 2007) and developing (Finnveden et al. 2009) environmental management technique described in international ISO standards, which has been developing since the mid-1980s. As is demonstrated by Kulczycka (2009), the first research in the area of LCA application in the study of machines and devices, conducted in Poland (since 1986), was undertaken by Prof. Zbigniew Kłos (1990) at Poznań University of Technology, resulting in the publication of the first book in 1990 and the first doctoral thesis about LCA (in Poland and in the former people's democracy countries), defended by Grzegorz Laskowski in 1999 (Kłos 2000). More information regarding the application of the LCA method in Poland can be found in other publications (Kłos and Kurczewski 2007; Merkisz et al. 2007).

A definition of Life Cycle Analysis, provided by Kulczycka and Henclik (2009), and based on the official definition given by the European Commission, states that it is a "process of collection and assessment of not only the input and output data of the manufactured product, but also of the potential impact on the environment in its entire life cycle (production, usage, and utilisation)". In accordance with the recommendations described in the standards, the assessment using the LCA technique can be carried out by identifying and determining the amount of materials and energy used, as well as the amount of waste discharged into the environment, and then by evaluating the impact of these processes on the environment and interpreting the obtained results. It is vital to establish the aim and scope of the analysis, the functional unit, and its boundary system.

LCA is an effective tool used in the evaluation of current technology, and it can be employed in, for instance, the decision-making processes in the introduction of new technology solutions, and in modernisation or liquidation of processes, among others. The LCA method can be applied in individual production or service facilities (irrespective of their size) and in all types of industries (extractive, food, waste management, etc.).

In the work of Assies (1991), Vignon et al. (1993), Pedersen (1993), Boustead (1992) as well as Castells et al. (1997), one can come across general descriptions of the origin of the LCA technique. According to Vignon et al. (1993), the LCA method was first introduced by Harold Smith who, in 1969, presented the results of his research at the World Energy Conference. His research, carried out in 1969, was on the calculation of energy demand in chemical industry manufacturing public-use products (Sonneman et al. 2004). The complete theoretical bases of the LCA method were formed at a conference in Vermont. It was then that the name Life Cycle Assessment (LCA) was introduced (Kulczycka 2001). After the conference in Vermont the interest surrounding LCA issues began to grow. As a result of the efforts to standardise the Ecological Life Cycle Assessment technique (LCA), the ISO 14040–14044 standards, describing the issues connected to LCA, were introduced in the ISO 14000 series. In recent years, governments of different countries have begun to implement programmes where the solutions to certain undertakings are based on the application of the LCA method. In Japan a 5-year programme has been developed, entitled: the Development of Assessment Technology of Life Cycle Environment Impact of Products and so Forth (Itsuba and Inaba 2003). In Netherlands, the programme has involved waste management, with special emphasis on sewage-treatment plants (Bieda 2007b).

In the European Union membership countries, more and more companies use or introduce an integrated management system, known as Environmental Management System (EMS). This norm aims at ensuring the general effectiveness of the system – not necessarily in all areas of environmental activity, but in accordance with the ecological policies of a company, which is dealt with by Subcommittee 1 (Bizan-Gatys 1997; Kowalski et al. 2007). As far as the standardisation in the field of Ecological Life Cycle Assessment is concerned, however, Subcommittee 5 – Life Cycle Assessment (LCA) deals with it. The principles and framework of the LCA technique are thoroughly explained and provided in the following standards: ISO 14040 (1997), ISO 14041 (1998), ISO 14042 (2000), ISO 14043 (2000) (Kulczycka 2001). In accordance with the recommendations described in the standards, the assessment using the LCA technique can be carried out by identifying and determining the amount of materials and energy used, as well as the amount of waste discharged into the environment, and then by evaluating the impact of these processes on the environment and interpreting the obtained results. It is vital to establish the aim and scope of the analysis, the functional unit, and its boundary system.

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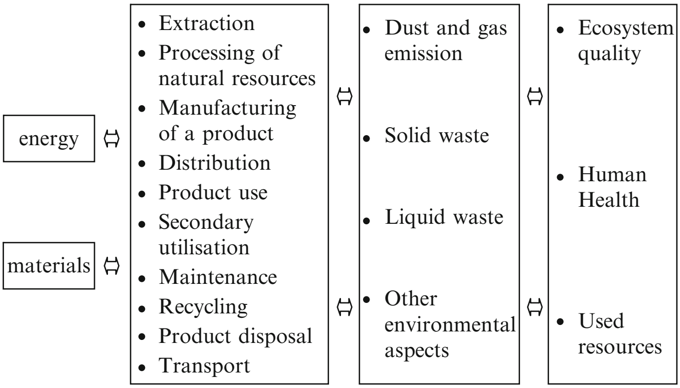

Fig. 4.1 Definition of ecological life cycle assessment (Source: Kulczycka (2001))

4.3 Defining the LCA Method

The definition of Ecological Life Cycle Assessment is shown in Fig. 4.1 (Kulczycka 2001).

The application of the Ecological Life Cycle Assessment technique is carried out in four distinct stages (PN-EN ISO 14040, 2009; PN-EN ISO 14041, 2002; PN-EN ISO 14042, 2002; PN-EN ISO 14043, 2002):

1. The goal and scope of study (ISO 14040)
    - Setting out the aims of the study
    - The choice of the functional unit
    - The setting of the system boundaries
    - The database of quality requirements
2. Life Cycle Inventory – LCI (ISO 14041)
    - Creation of the life cycle flow chart
    - The database – data on inputs and outputs
    - Catalogue construction – the sum of individual functional units
    - The analysis of input and output data
3. Life Cycle Impact Assessment – LCIA (ISO 14042)
    - Selection of impact categories
    - The classification stage – the definition of catalogue elements that have an impact on the environment
    - Characterisation – defining their impact on the environment
    - Measurement – assigning the significance of each impact category

4. Interpretation of the results (ISO 14043)
    - Identification of strong and weak points of the analysed cases
    - Systematic analysis of the study's goals
    - The evaluation of the study considering its consistency with the goals and scope of the study, by:
        - Creating additional databases
        - Analysing sensitivity and different scenarios
        - Thoroughly analysing the system boundaries
        - By recommending other possible solutions (e.g. ecolabelling – environmental labelling)

4.4 Uncertainty and Random Variables in LCA Research

The uncertainty of source data included in LCA research concerns the measurement or the predictions regarding the size of the results (Bieda 2005b, 2006b). Uncertainty of data can be expressed through a definition of probability distribution of that data (e.g. through standard deviation or variance), which in turn makes it possible to define the range of values that the data can take. To achieve this, different statistical methods can be applied, including MC simulation (Bieda 2007c, 2007d). The United States Environmental Protection Agency (EPA) recommends the MC simulation method as the only effective method that should be used in risk assessment (Smith 2006).

The advantage of MC simulation is its time and cost effectiveness; moreover, thanks to Crystal Ball, there is no need to conduct numerous complicated and expensive analytical calculations using many different spreadsheet applications (Wajs et al. 2000a, b, 2001). Yet another advantage of using MC simulation with the help of CB is its ability to determine the confidence level. Oftentimes, manual adjustment of mini-sliders (or grabbers) with a view to defining the certainty level can be onerous. Grabbers react in a rough way and it may be difficult to move them with a high degree of precision. Therefore, a more comfortable method, thanks to which the same results can be achieved more quickly and precisely, is to provide the parameters of confidence interval by inserting the appropriate values in the edit field, which can be found at the bottom of the frequency chart forecast window (see Fig. 2.9).

It is also possible to perform a reverse operation. By setting the value of confidence levels, one can define its corresponding interval value. Simulation models are generally easier, when it comes to their interpretation and understanding, than a number of analytical solutions (Evans and Olson 1998).

Deterministic approach and the description of processes in the studies of Ecological Life Cycle Assessment do not properly reflect the reality (Canarache and Simota 2002). In the face of the existence of many diverse and random factors influencing these processes, it is sometimes more adequate to use a stochastic model, i.e. a model based on the theory of probability (Trybalski 1999). Essential theoretical information about probability can be found in many different monographs. Janicki and Izydorczyk (2001), believe that the stochastic model is a mathematical model of a special type, i.e. a formula – most often a system of stochastic differential equations – that makes it possible to explicitly define the stochastic process, which describes the evolution of the observed or researched phenomenon that is subject to random disturbances. As is maintained by Zdanowicz (2002), a stochastic process is a function *y(t)*, which depends on the time parameter *t*, whose values always take the form of random variables. He distinguishes between two basic classes of stochastic processes: Markov processes and stationary processes. The latter are defined on the basis of other studies (Benjamin and Cornell 1977; Bobrowski 1980), and the probabilistic relations between the realisation values in different moments in time depend solely on the placements of each of the moments, and not on their placement on the time axis. Zdanowicz also points out, when describing the issues connected to stochastic processes, that the central problem in the theories of stochastic processes is the finding of the appropriate probability distribution of the random variable *y(t)* in a certain moment in time *t*. Probability distribution is defined as an arranged data set. Filipowicz describes stochastic models in operational research used in the analysis and synthesis of service and queuing systems. Holnicki-Szulc (2006) has observed that despite the sudden boom in computer technology, numerical methods, and their applications – all very notable in recent years – uncertainty in mathematical description of phenomena occurring in natural environment still plays a significant role.

Uncertainty in the studies dealing with the application of LCA methodology may cause doubt being raised as to whether the obtained final values of the indicators (eco-indicators), describing the potential impact of the manufactured product or process on the environment, are reliable (Kowalski et al. 2007).

There are three types of uncertainty:

- Uncertainty of data,
- Uncertainty connected with the correctness (representativeness) of the applied model,
- Uncertainty caused by incompleteness of the model (Goedkoop et al. 2000).

In the uncertainty analysis of data, performed by Lewandowska and Fołtynowicz (2004), the main assumption is that the more important the input data, the better the quality that it should demonstrate. It was proposed that the quality of data be analysed after the environmental impact phase. Since the evaluation of the impact is conducted for the entire system, as part of the precisely set boundaries, the final result is not only about the input of the main data, but also about all the processes that it represents. However, in the case of the analysis of data, obtained with the help of questionnaires or through interviews, the data is often unavailable and its interpretation is impossible. According to Kowalski et al. (2007), in a situation when it proves difficult to employ a unified approach to uncertainty in LCA, the best solution is to combine MC analysis with sensitivity analysis, with the aim of assessing the model's uncertainty. As observed by the authors (Kowalski et al. 2007), uncertainty of the source data can be applied to the measurement of, or forecasting, the size of the results. This type of uncertainty is relatively easy to evaluate and may be measured with statistical parameters (standard deviation, variance, etc.). On the other hand, however, the uncertainty of the model is much more difficult to evaluate. In the literature, quoted above, a differentiation exists between absolute and relative uncertainty. The values of the latter can be much lower than the values of the former, as they may be mutually correlated and may show tendencies towards mutual compensation. The problem of absolute uncertainty applies to nearly all influences on human health and to the majority of ecosystems or even to expert panel assessments. In addition, there is no sufficient data regarding the certainty of assessments of acidification, eutrophication, consumption of resources, or standardisation data. In accordance with the ISO 14043 (PN-EN ISO 14043 2002) series, four types of information are required, and these include: the quality of data, methodological choices (e.g. allocation rules), the scale value used, and application.

Heijungs (1996), when researching the impact of input data uncertainty on output data uncertainty, defined the main sources of uncertainty, and so obtained a set of results that proved to be key for future research. The aim was to find the main factors, defined as the LCA aspects for which more thorough research is needed if solid and appropriate results are to be formulated. The base for the search of the key factors was the uncertainty analysis of principal results for which standard statistical and mathematical methods were applied. In order to describe to credibility of data and the model used in LCA, one could and should introduce appropriate methods of assessing the results' uncertainty, such as the analysis of contribution, perturbation, sensitivity, and others. Contribution analysis and perturbation analysis are elaborated on in greater detail in the work of Guinee et al. (2001) and in ISO 14042 series (2002). Sensitivity analysis, however, provides an opportunity to consider the usefulness of particular input variables, by indicating the variables that can be omitted without the loss in quality, and the key variables that cannot be omitted. Sensitivity analysis has been used in financial analyses for years now (Woodward 1995). Saltelli et al. (2004, 2008), and Funtowicz et al. (1990) draw attention to the fact that some researchers consider sensitivity analysis as a prerequisite in modelling and computer simulation. According to Kolb, quoted by Rabitz (1989), in today's state of scientific research, modelling without sensitivity analysis is considered intellectually dishonest. In LCA methodology, sensitivity analysis may apply to both input data and to study results, as oftentimes a large number of input data has to be dealt with and the results are characterised by a certain degree of uncertainty. In this case, uncertainty may be assessed with the help of statistical parameters defined on the basis of probability distribution of data (Kowalski et al. 2007; Sonnemann et al. 2004). Due to the complexity of calculations, uncertainty connected to LCA results is extremely difficult to present in the form of a single equation that describes probability distribution of the calculated values. Thus, numerical simulations are also performed in order to assess these uncertainties. Steen (1997) points out that sensitivity analysis makes it possible to express uncertainty in the form of probability; hence, the degree of uncertainty as well as probability distribution have to be assessed. As far as more detailed LCA is concerned, Kowalski et al. (2007) recommend performing a more detailed sensitivity analysis or, if possible, a partial uncertainty analysis in relation to the chosen results and parameters, whose uncertainty ranges are known, e.g. by employing MC simulation. They also draw attention to the fact that in the studies on the application of LCA methodology, one can encounter uncertainty, which may cause doubt as to whether the obtained final values of the indicators (eco-indicators), describing the potential impact of the manufactured product or process on the environment, are reliable. The authors have analysed the uncertainty, of the model's manufactured product, which may apply to, for instance, the model of environmental damage and issues of whether or not certain effects, whose existence is not proven due to incomplete scientific basis, should be included in the model.

According to the ISO 14041 series (PN-EN ISO 14041 2002), sensitivity analysis is a requirement. Guinee et al. (2001), in performing comparison analyses, using LCA methodology without sensitivity (or uncertainty) analysis, base their work on the following methods:

- The measurement of extreme values (e.g. by including the highest and lowest values of each of the parameters, so that the interval value of the final result is calculated).
- Formal statistics, uncertainty propagation (e.g. a statement such as: with the 95% confidence level, the emission of sulphur dioxide from facility A is greater than from facility B).
- Empirical statistics, random simulation.

Klopffer and Hutzinger (1993) describe three types of models that can be found in the literature in the field of LCA methodology:

- The black box. It is the most commonly used model in LCA research, as it is the easiest method of modelling processes.
- Models defined using linear dependence functions. This idea deals with the description of dependence between input and output data, as well as dependence between input data – a description given using linear functions.
- Models defined using non-linear and linear dependence functions. This idea deals with the description of dependence between input and output data, as well as dependence between input data – a description given using non-linear and linear functions.

In the Eco-indicator 99 methodology (2009), used in LCA analysis, three fundamentally different types of uncertainty are presented:

- Operational, or data uncertainty – expressed using geometric standard deviation squared, which expresses the variance between the higher and lower confidence limit (97.5% and 2.5%). Statistical methods, such as Monte Carlo method, are used to achieve this.
- Fundamental, or uncertainty caused by correctness (representativeness) – the decision to choose of the model is often subjective.
- Uncertainty caused by incompleteness of the model.

Hauschild (2005), by contrast, distinguishes between two types of uncertainty:

- Uncertainty of the model and its parameters.
- The interpretation of the results uncertainty.

Uncertainty about the correctness of the model results from the fact that it is never a real model that we deal with. Every LCA examination is burdened with uncertainty resulting from the subjectivity of decisions made to build a model. Examples of such subjective decisions are given by Kowalski et al. (2007):

- Representativeness – very often data about different processes is used that comes from various sources, e.g. data on cotton crops in Pakistan is used to analyse crops in India (data on cotton crops in India should be used).
- The basis of allocation – there is no single allocation procedure.
- The analysis of future events – a lot of LCA analyses deal with products with a long life cycle.
- The decision regarding a functional unit[1] – occasionally it is not clear what is the basis on which different products are compared.

The authors emphasise that uncertainty, caused by the incompleteness of a model, most of the time applies to the lack of cohesion between individual, analysed elements or appears because of the incompleteness of data. Moreover, the authors analyse the problem of uncertainty of a decision involving a model with the choice of time horizon. Among the different theories, three archetypes of time perspective deserve attention (individualist, egalitarian, and hierarchist), adopted in Eco-indicator 99 methodology, and first presented in a monograph by Thompson et al. (1990). In the study (Ocena 2008), a hierarchist model of assessment is adopted (the archetype of time perspective of ecological effects), in which the balance between short and long term effect is maintained, making it possible, if management is appropriate, to avoid numerous problems. One has to deal with many different models in LCA examination. As explained in the subject literature, a model constitutes a certain simplification of reality and this already becomes the first source of uncertainty. Currently, the most popular model in Poland is the model that can be characterised as: “a formal, balanced, one- or multi-structural model with linear dependencies between parameters, statistical model, solved with the help of mathematical programming methods with a deterministic set of information” (Kisielnicki 1993; Kacperska and Słota 2000). A definition, quoted after Łukasiewicz, states that a model is a “certain representation of the researched system used to describe, explain, and predict its behaviour in different environmental conditions” (Łukaszewicz 1975). Maciejewski (1980) argues that “a model does not deal with the reality, but our image of it”. The correct interpretation of a model described using incomplete information and the interpretation of the obtained results are crucial when it comes to making an optimal decision. In management

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[1] Cieślak A. Ekologiczna ocena cyklu życia produktu. in: Zapobieganie stratom w przemyśle, Białystok, 1999.

systems there is very often no complete information available, or there is no information available regarding the subject of the decision making process. There are different ways of specifying incomplete information and of making decisions under uncertainty. Different management models are used in order to solve the problem of the decision making process, among which the most important ones are (Bubnicki 1993):

- Relational models,[2]
- Probabilistic models,[3]
- Game theory models,[4]
- Fuzzy models.[5]

As a supplement to the discussion on uncertainty, it may be worth quoting the definition of uncertainty provided in the Regulation of the Minister of Environment of 12 September 2008 (D.U. 2008): "uncertainty can be understood as a parameter, connected with the result of quantity assessment, characterising the diffusion of values, which can be rationally attributed to a given quantity, while considering the impact of both systematic and random factors, and is expressed in percentages of the confidence interval of a mean value equal to 95%, with the inclusion of all asymmetries in the distribution of values".

4.5 Types of Random Variables in Uncertainty Analysis in LCA Studies

By reviewing international subject literature (Frischknecht and Rebitzer 2005; Rabl and Spadaro 1999; Spadaro and Rabl 2008; Hofstetter 1998) and Polish domestic subject literature (D.U. 2008), one could conclude that it is assumed that in the analysis of environmental risk as well as of environmental management, and especially in ecological life cycle assessment, normal distribution and logarithmic-normal distribution, or logarithm-normal, or simply log-normal distribution (Biegus 1999), is used as a characteristic of random variables. The term – log-normal distribution – was first used by Gaddum in 1945 (Statistica 2010; Gaddum 1945; Hofstetter 1998). Since a considerable research potential, dealing with engineering and environmental management, is directed towards analysing

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[2] The relational model specifies the dependence of the decision on its results with the help of certain dependencies, known as relational.

[3] The probabilistic model uses probability distributions and information regarding the model's stochastic nature.

[4] The game theory model (or the "gaming model" – according to Bubnicki) treats the decision-maker and their parameters as members of a certain game, using the theory of games.

[5] The fuzzy model formalises inaccurate and fuzzy information.

data, approximated using log-normal distribution, the decision was made to include this distribution in the mainstream of this thesis.

Weidema (1999) draws attention to the fact that random variables that exist in stochastic analyses and studies in environmental protection and economics are usually subject to normal, log-normal, bi-normal, triangular, and uniform distributions. The computer program, offered in the ecoinvent database package (Overview 2007), includes four types of probability distributions: normal, log-normal, triangular, and uniform, while random variables are characterised with the following parameters: mean population value μ, standard deviation σ (with the 95% confidence level), and diffusion, defined by the range of 2.5–97.5 percentile (Iwasiewicz and Paszek 2004).

In the subject literature, it is possible to come across different approaches to the problem of selecting the probability distribution (function) of variables. For some variables, it is possible to empirically determine probability distributions, whereas for others, such an evaluation is not possible due to the lack of data. It is suggested that probability distributions should be attributed arbitrarily but this solution is met with criticism (Finley et al. 1994; Haimes et al. 1994). At times, it is possible to let the experts decide which probability distribution curve they approve of, yet still, such a decision is a subjective one and provokes controversy (Valopi 1995). A possible solution to the above-mentioned problem may be the employment of the principle of maximum entropy (Jaynes 1957), which has its roots in Laplace's principle of insufficient reason. It is about defining the probability distribution on the basis of Shannon-Weaver entropy, thanks to which, on the basis of acquired knowledge, one can define the possible shape of the probability distribution curve. This approach does not define the assumptions about the shape of the probability distribution curve, but it chooses the optimal input probability distributions on the basis of limited information in relation to random variables (Tilwari and Hobbie 1976; Lee and Wright 1994). Piórecki (1973) proposes log-normal distribution as a solution to the problems connected with working time for it approximates the random variable better (working time being the random variable) than normal distribution, because of the reasons mentioned above.

Log-normal distribution is closely connected to normal distribution (Zdanowicz 2002), and it often offers a better approximation of feature distribution than normal distribution, in which the ratios between the values are more important than the differences between them (Morgan and Henrion 1990). The random variable X of the continuous type has a log-normal distribution with parameters μ and σ with density function (for $0 < x < \infty, \mu > 0, \sigma > 0$) when its density takes the form of (see Snopkowski 2007; Zdanowicz 2002; Hoła and Mrozowicz 2003):

$$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left[-\frac{(\ln(x) - \mu)^2}{2\sigma^2}\right] \tag{4.1}$$

where:

μ – the mean value
σ – standard deviation.

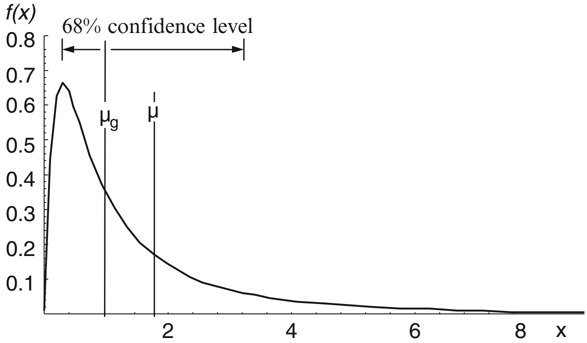
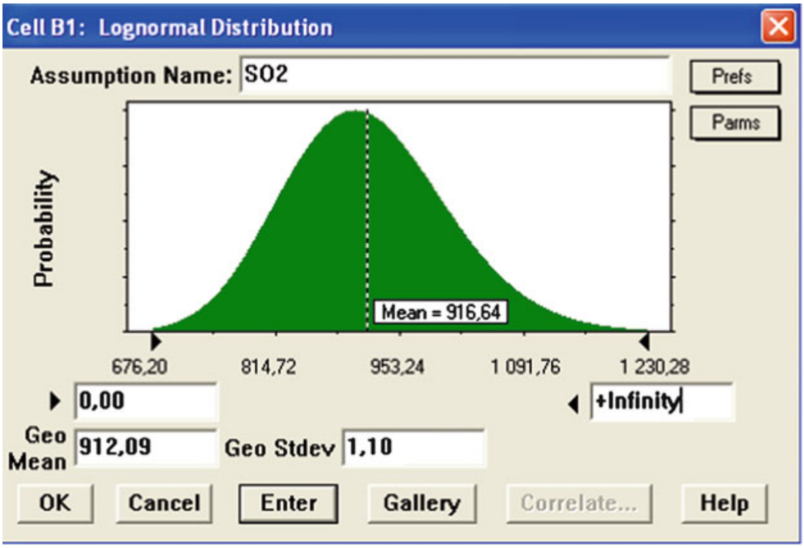


Fig. 4.2 An example of a density function of a log-normal distribution ($\mu_g = 1$, $\sigma_g = 3$, $\mu = 1.83$). The *arrows* point to a 68% confidence level, geometric mean is denoted as μ_g, geometric deviation is denoted as σ_g, and population mean as μ (Source: Spadaro and Rabl 2008)

The work of Rabl and Spadaro are of great importance here (Rabl and Spadaro 1999; Spadaro and Rabl 2008), as they thoroughly analyse log-normal distributions. An example of a density function of a log-normal distribution ($\mu_g = 1$, $\sigma_g = 3$, $\mu = 1.83$) can be found in the work of the above-mentioned authors (Fig. 4.2). The arrows point to a 68% confidence level. The geometric mean μ_g is equal to the median.

As has already been mentioned, log-normal distribution can be very useful in ecological research (risk analysis) or humanities studies, among others (Spadaro and Rabl 2008). It is believed that log-normal distribution is stable, in relation to multiplication (division) of random variables, which means that the distribution of products (quotients) of random variables remains log-normal but with different parameters (Spadaro and Rabl 2008). Log-normal distribution is called by the name of "model of products", in which the product of random variables X, after finding the logarithm, on the basis of the central limit theorem, provides an expression, in which the sum of these variables will approximately have a normal distribution (logarithms of these variables are random variables as well), and ultimately, the random variable X, whose natural logarithm is subject to normal distribution, has a log-normal distribution (Snopkowski 2007; Benjamin and Cornell 1970). The central limit theorem deserves attention, since it states the measurement of the distribution of an average from a sample for normal distribution independently of population distribution from which the sample was taken (Aczel 2000). Log-normal distribution can also be useful in economic research where variables with positive values are located asymmetrically, in such a way that the values lower than the mode are more clustered while the values higher than the mode are more scattered (Snopkowski 2007). The knowledge of geometric mean, μ_g, and geometric standard deviation, σ_g, of probability distributions of input data, may prove useful during the process of defining the confidence intervals. Effective formulas for the multiplicative confidence intervals are provided in the work of other researchers (Sonnemann



Assumption Name: SO2

0,00

+Infinity

Geo Mean 912,09

Geo Stdev 1,10

Fig. 4.3 Parameters of log-normal distribution approximating SO_2 emissions (Source: Own work)

et al. 2004; Rabl and Spadaro 1999; Spadaro and Rabl 2008; Rabl et al. 2005), and they take the following forms:

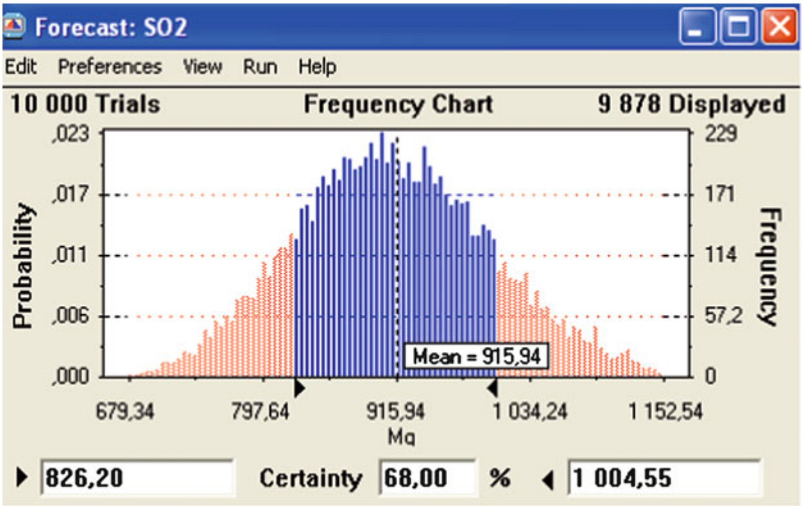
$$\left[\mu_g/\sigma_{g,}\ \mu_{g*}\sigma_g\right] \text{ for confidence interval of } 68\% \tag{4.2}$$

$$\left[\mu_g/\sigma^2_{g,}\ \mu_g * \sigma^2_g\right] \text{ for confidence interval of } 95\% \tag{4.3}$$

where:

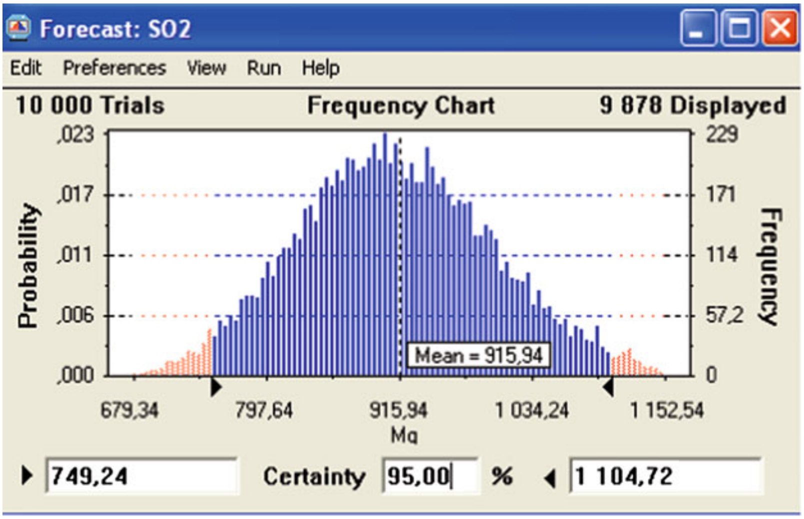
μ_g – mean geometric value
σ_g – standard geometric deviation.

This approach is illustrated below, based on the example of the emission of SO_2, generated during energy production in MSP Power Plant. The data was obtained in 2005. By approximating the SO_2 emissions with log-normal distribution, with a range of zero to infinity and its parameters set to the levels shown in Fig. 4.3, where the mean value corresponds to an annual deterministic SO_2 emission level amounting to 916.64 Mg, CB software automatically selects the remaining parameters (geometric standard deviation, $\sigma_g = 1.1$, and geometric mean values, $\mu_g = 912.09$ Mg), which can be entered in the Lognormal Distribution edit window. The results of the MC simulation, with a 10,000-trial randomisation cycle, are shown in Figs. 4.4 and 4.5, respectively, and in the form of statistical reports in Figs. 4.6 and 4.7.



826,20 Certainty 68,00 % 1 004,55

Fig. 4.4 Frequency chart of the SO_2 emissions forecast, with 68% confidence interval (Source: Own work)



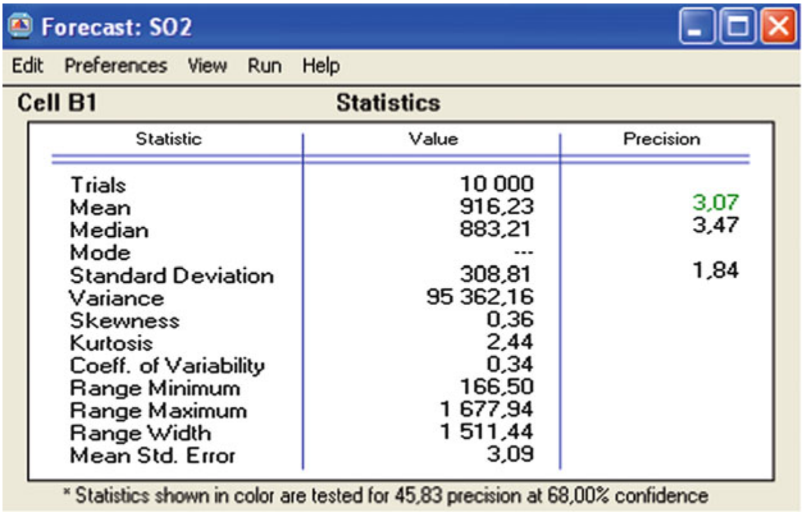
749,24 Certainty 95,00 % 1 104,72

Fig. 4.5 Frequency chart of the SO_2 emissions forecast, with 95% confidence interval (Source: Own work)

The intervals corresponding to the 68% and the 95% confidence level are equal to, respectively:

$$[826.20; 1004.55] \text{ and } [749.24; 1004.72] \text{ Mg.}$$

The intervals corresponding to the 68% and 95% confidence level, calculated with the help of formulas (4.1) and (4.2), are equal to, respectively:

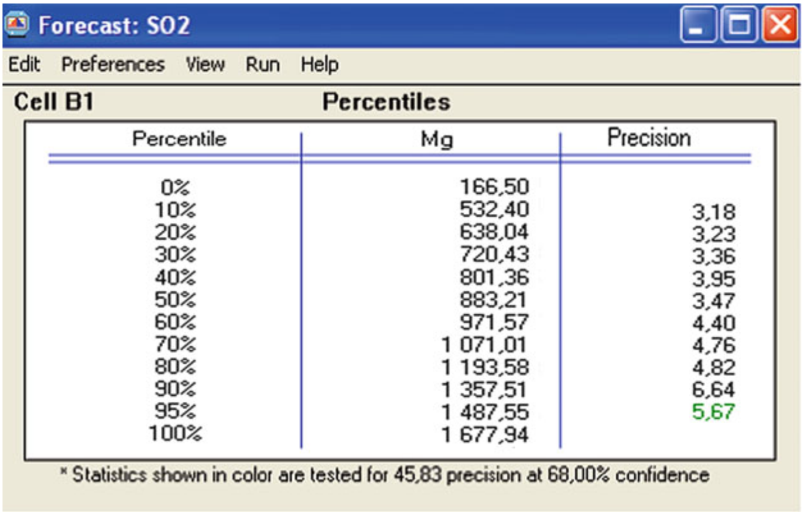


Cell B1 Statistics

Statistic	Value	Precision
Trials	10 000	
Mean	916,23	3,07
Median	883,21	3,47
Mode	---	
Standard Deviation	308,81	1,84
Variance	95 362,16	
Skewness	0,36	
Kurtosis	2,44	
Coeff. of Variability	0,34	
Range Minimum	166,50	
Range Maximum	1 677,94	
Range Width	1 511,44	
Mean Std. Error	3,09	

* Statistics shown in color are tested for 45,83 precision at 68,00% confidence

Fig. 4.6 SO_2 emissions report – Statistics (Source: Own work)



Cell B1 Percentiles

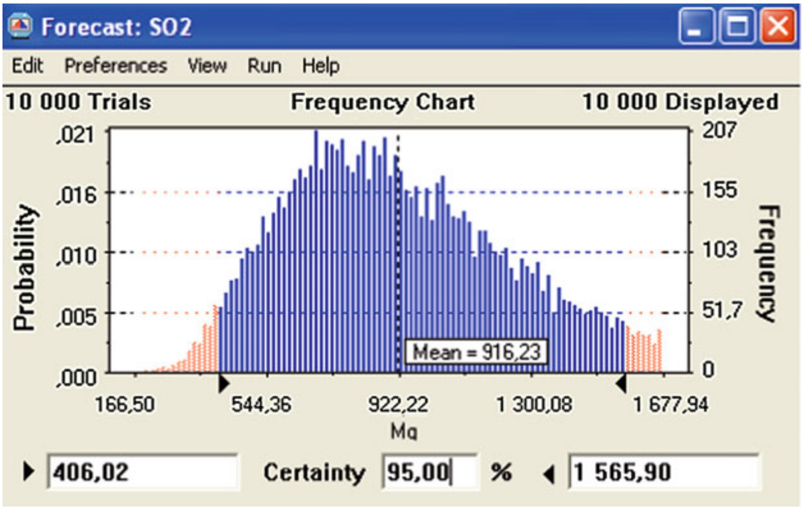
Percentile	Mg	Precision
0%	166,50	
10%	532,40	3,18
20%	638,04	3,23
30%	720,43	3,36
40%	801,36	3,95
50%	883,21	3,47
60%	971,57	4,40
70%	1 071,01	4,76
80%	1 193,58	4,82
90%	1 357,51	6,64
95%	1 487,55	5,67
100%	1 677,94	

* Statistics shown in color are tested for 45,83 precision at 68,00% confidence

Fig. 4.7 SO_2 emissions report – Percentiles (Source: Own work)

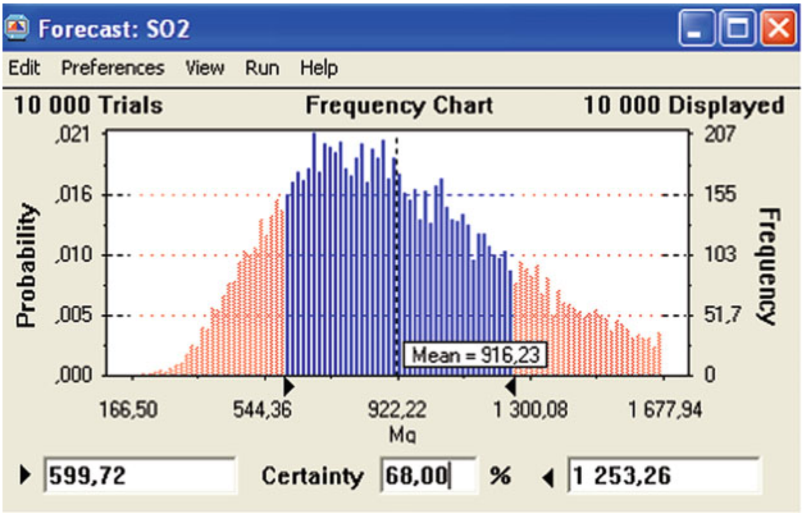
$$[829.17; 1003.30] \text{ and } [753.80; 1103.63] \text{ Mg}.$$

It is worth mentioning that, after analysing the results, it can be noted that seven out of eight values describing the span of the confidence intervals, calculated by employing MC simulation with the use of CB package, are smaller than the same values calculated analytically with the help of formulas (4.1) and (4.2). According to Sonneman et al. (2004), dynamic characteristics of a stochastic model can be an explanation of these differences.



406,02 Certainty 95,00 % 1 565,90

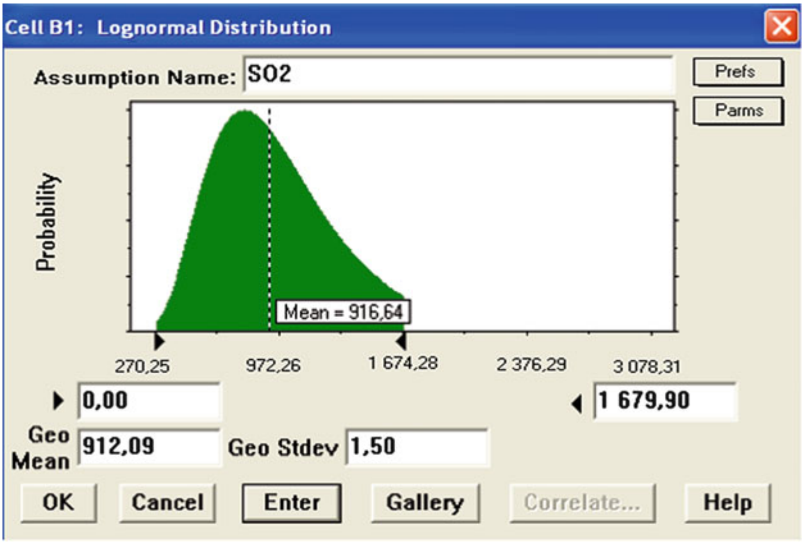
Fig. 4.8 Frequency chart of the SO_2 emissions forecast, with 95% confidence interval (Source: Own work)



599,72 Certainty 68,00 % 1 253,26

Fig. 4.9 Frequency chart of the SO_2 emissions forecast, with 95% confidence interval (Source: Own work)

Simulation results, with geometric standard deviation, $\sigma_g = 1.5$, suggested in literature, for the emission of SO_2, are presented in Figs. 4.8 and 4.9 (Sonneman et al. 2004; Rabl and Spadaro 1999). The parameters of the distribution are shown in Fig. 4.10.



Assumption Name: SO2

0,00

1 679,90

Geo Mean 912,09

Geo Stdev 1,50

Fig. 4.10 Parameters of log-normal distribution approximating SO_2 emissions (Source: Own work)

The intervals corresponding to the 68% and the 95% confidence level (Figs. 4.8 and 4.9) are equal to, respectively:

$$[599.72;\ 1253.26] \text{ and } [406.02;\ 1565.90] \text{ Mg.}$$

The intervals corresponding to the 68% and 95% confidence level, calculated with the help of formulas (4.2) and (4.3), are equal to, respectively:

$$[608.06;\ 1368.135] \text{ and } [405.37;\ 2052.203]$$

The influence of dynamic characteristics of a stochastic model can be noticed here as well.

Log-normal distribution has been used in numerous studies and reports, written by Hofstetter (1998), describing the environmental risk analysis and drawing one's attention to the fact that this distribution is better at characterising changeability and uncertainty in fate assessment than normal distribution for it cannot take negative values, and so, it can be widely used in LCI analyses, as part of the LCA methodology (e.g. measurements of emissions are never negative – see Hoła and Mrozowicz 2003; Piórecki 1971; Sonnemann et al. 2004). In order for the significance of this problem to be properly illustrated, the research results concerning the contamination with hazardous waste of the area of a former U.S. Army military base in Ford Ord, California, produced by Valopi (1995), are presented in this monograph. Normal distribution of random variables, such as heavy metals, and especially lead, was used in the simulation. It became clear that, from a statistical point of view, the result of the simulation (variance), regarding the concentration of lead, was correct, but from an ecological point of view it was unacceptable. The area of the local fauna was much smaller than the research area hence the results were unrepresentative (e.g. negative values were obtained regarding the concentration of the above-mentioned lead). Consequently, the MC simulation results (sensitivity analysis, frequency charts of hazardous substances, etc.), based on the assumptions made and included in the work of Burmaster and Anderson (1994) were questioned and rejected. The decision to use normal distribution was proven incorrect.

Sonneman et al. (2004), in their examination of uncertainty in LCA research, such as the one in the processes of thermal waste utilisation in Tarragona, Spain, in the analysis of input and output sets and in the assessment of the life cycle impacts (impact assessment), make use of normal and log-normal distribution. Tarantola et al. (2008) draw attention to the fact that in the case of domestic data concerning the emissions of industrial gases, approximated with normal distribution, due to the lack of information regarding standard deviation $\sigma = 0.1$ of the mean value μ can be assumed in statistical calculations. In the work of the Society of Environmental Toxicology and Chemistry, SETAC, one can encounter examples of risk assessment in environmental management under uncertainty, for which normal and log-normal distributions are used. Normal and log-normal distributions are used in the description of other processes. Zdanowicz (2002) investigates probability distributions applied in modelling in the Taylor's program, used, for instance, in simulation modelling of flexible manufacturing cells, and provides examples of application of log-normal distribution in the examination of up time of objects whose defects are caused by gradually increasing fatigue cracks, and used as random models of grain sizes included and seen in a fracture of a metal sample. Log-normal distribution is among these distributions. Biegus (1999) employs normal and log-normal distribution in the probabilistic analysis of load bearing capacity and safety of steel constructions. Layton and Breamer (2009) demonstrate a probabilistic model of transport of contaminants in subsoil using log-normal probability distribution to assess the concentration of microelements (such as lead or arsenic). Crow and Shimizu (1988) analyse and compare computer simulations, which make use of random variables with log-normal, Weibull, and gamma distributions. Tomazi (2004) analyses the problem of deterministic and stochastic optimisation of the production of peptides, used in processes such as the production of synthetic human insulin. In modelling of the kinetic processes of producing peptides under uncertainty, normal and log-normal distributions are employed for the analysed parameters (these are random numbers). The same distributions are chosen for approximation of parameters in modelling of DDT concentration in the environment, using the CliMoChem model for each of the 47 input parameters of the model (Schenker et al. 2009). As mentioned above, log-normal distribution is called by the name of "model of products". It is calculated on the basis that the random variable, whose natural logarithm is subject to natural distribution, has log-normal distribution (Morgan and Henrion 1990; Snopkowski 2007; Schenker et al. 2009).

In a log-normal distribution, with a positive asymmetry, there are three characteristic values of the random variable X: the modal value (dominant) $M_0(X)$, the median $x_{0,5}$, and the expected value $E(X)$, all of which satisfy the inequality (Tumidajski and Saramak 2009; Hoła and Mrozowicz 2003):

$$M_0(X) < x_{0,5} < E(X) \tag{4.4}$$

The log-normal curve of the distribution, being an asymmetrical distribution (positive asymmetry) of the analysed variable, is defined using two parameters: geometric mean μ_g and geometric standard deviation σ_g. In the subsequent sections of this thesis, in the case of log-normal distribution, the following definitions are used: μ_g – geometric mean and σ_g – geometric standard deviation; and in the case of normal distribution: μ – mean value (instead of the expected value, the mean population value) and σ – standard deviation. Parameters of log-normal distributions are very useful in uncertainty analyses, as they correspond with mean value μ and standard deviation σ of the normal distribution that describes many processes, despite the fact that the field of density functions of probability distribution is the interval of minus to plus infinity (Snopkowski 2007). Historically speaking, one of the first studies dealing with log-normal distributions were presented by Kołmogorow (1941) and Epstein (1947) who worked on theoretical approach to defining the distributions of grain sizes of product size reductions.

Different definitions of simulation can be found in the subject literature. Łukaszewicz (1975), quoted above, states that "simulation represents the behaviour of the original, through the behaviour of the model". Naylor (1975), on the other hand, defines simulation as "a numerical technique employed in experiments carried out on mathematical models that illustrate, with the help of a computer, the behaviour of a complex system in a long time interval". According to Zdanowicz (2002), simulation is a technique used to conduct experiments on certain types of models; it can also be understood as a form of model manipulation, leading to the recognition of the behaviour of the system. Snopkowski (2007) discusses the evolution of the definition of simulation in the last several tens of years. And so, simulations are used especially when solving a problem in an analytical way may be too difficult a process.

As far as normal distributions are concerned, work published by Meier (1997) and the databases developed by the Swiss Federal Institute of Technology in Zurich (ETH), built for Europe, offer normal distributions for the analyses of phenomena occurring in the processes of energy production, such as gas emissions or products or media used in these processes, having the following values of coefficients of variation (CV), serving as relative measures of dispersion (covering the dispersion proportionate to the mean):

- For the data obtained using stochastic methods, $\mathrm{CV} = 2\%$
- For, e.g. emission, $\mathrm{CV} = 10\%$
- For the remaining data, $\mathrm{CV} = 20\%$ or 30%.

In their work, Lessmann et al. (2005), propose the coefficients of variation $CV = 0.58$, when calculating the integrated risk index in environmental management of contaminated areas in the chemical/petrochemical industrial zone in Tarragona, Catalonia, in Spain. In carcinogenic toxicity research of the above-mentioned industrial zone, Lessmann (2002) proposes to use a conservative coefficient of variation $CV = 0.9$. However, when it comes to the analysis of environmental persistence of chemicals for the same industrial zone, described using triangular distribution, log-normal distribution is used, achieved from triangular distribution approximation based on standard deviation, calculated on the basis of triangular distribution parameters, described by Florito (2006).

In the MC simulation of input data in the LCA analysis of biopolymers, known for sugar or vegetable oil processing technology and created as part of the processes of generating renewable energy on the basis of biomass originating from cereal grains, Kim and Dale (2008) use standard deviation equal to 10% in a situation where there is not enough sufficient data defining the standard deviation of analysed input quantities in the process of generating renewable energy. The selection of standard deviations used in the simulation research of production and consumption of biofuels can be found in the Economic Research Service (Economic 2009).

95% confidence intervals are universally used in many different applications of statistics. This thesis focuses on the so-called classical interpretation of confidence intervals, as opposed to the so-called Bayesian approach, which makes it possible to treat the unknown population parameter as a random variable. Then it may be said that the unknown population parameter will be included in a given interval, with a probability of 0.95 (Aczel 2000).

There are a number of publications, which can be found in international literature, discussing the application of Bayesian inference in uncertainty analysis of simulation models in ecology. It is possibly worth quoting a statement made by Rubin (1970), mentioned in Smith's publication (1995), which says that, "a good Bayesian does better than a non-Bayesian but a bad Bayesian gets clobbered".

4.6 Life Cycle Assessment of the Impact on Natural Environment of Energy Generation Processes in MSP S.A., Unit in Kraków, Poland

4.6.1 Aim and Scope of the Project

The LCA analysis of the energy generation processes, based on the example of MSP Power Plant, has been performed, for the purposes of the postdoctoral thesis, by the Mineral and Energy Economy Research Institute of the Polish Academy of Sciences (PAN), in Kraków (Ocena 2008). It contains the material-energy balance (LCI) and the result expressed in the form of: characterisation, normalisation, and measurement stage results – values of which are given in eco-points (Pt) for individual impact categories. The analysis has been performed in accordance with the international standards PN-EN ISO 14040:2006 (Environmental Management – Life Cycle Assessment – Principles and Framework) and PN-EN ISO 14044:2006 (Environmental Management – Life Cycle Assessment – Requirements and Guidelines).

The result of the LCA analysis is used here to present the stochastic comparative analysis of the environmental impact of the four scenarios of the energy generation processes in MSP Power Plant, in an annual cycle in 2005. The emphasis is on a more thorough characterisation of uncertainty in LCA studies, focusing on the uncertainty of source data. The quantitative data analysis has been performed based on MC simulation (Bieda 2008e, f, 2009a, b).

4.7 Description of Energy Generation Processes in MSP S.A., Unit in Kraków, Poland

In MSP Power Plant, in its power plant department (hereinafter referred to as "the power plant"), a fuel combustion for energy generation facility can be found. During the production activity the facility consumes non-renewable energy sources (hard coal) and water, it is a source of emissions into the atmosphere, and it generates various types of waste as well as noise emissions (Bieda 2007f, 2008c). In the examined year (2005), the Power Plant was using its seven steam boilers of the following power ratings, calculated using the heating value of fuels processed in the facility:

- TP 230 Boilers (4 units): $4 \times 157\ \mathrm{MW_t} = 628\ \mathrm{MW_t}$,
- OPG-220 Boilers (2 units): $2 \times 149\ \mathrm{MW_t} = 298\ \mathrm{MW_t}$,
- OP 230 Boiler (1 unit): $177\ \mathrm{MW_t}$.

These boilers were used to produce superheated steam of high parameters (pressure 9.0 MPa, temperature 510–540°C). The productivity of the entire facility amounted to 1,360 t/h and the installed power (attainable) – 977 MW, including: $4 \times 138 = 552$ MW (TP 230 Boilers), $2 \times 131 = 262$ MW (OPG 220 Boilers), and 163 MW (OP 230 Boiler). The steam produced in the facility was later used to generate the following: electric energy, blast furnace wind, process steam, 1.6 and 0.8 MPa, heat in the heating water, gas-free and heated softened water, and heated demineralised water. The above-mentioned manufacturing processes, as they are technologically strictly connected with the production of steam, 9 MPa, are an integral part of the facility.

The productivity of all of the boilers (superheated steam at the temperature 510–540°C, and pressure 9.0 MPa) in 2005 was equal to 1,360 t/h and the total installed power (attainable) to 977 MW. The production size of steam, 9.0 MPa, in the years 2003–2005 was formed in the following way:

- The year 2003: 3,633,000 t,
- The year 2004: 3,000,000 t,
- The year 2005: 3,690,000 t.

The produced steam, 9.0 MPa, was used to feed four turbo-generators (station number 3, 4, 5, and 6), three turbo-blowers (no. 1, 6, and 7), as well as reduction-cooling stations – 9/3 and 9/0.8 MPa. The steam, after underexpansion or reduction, turns to steam that is consumed by the needs of the power plant – entirely (3.0, 0.12 MPa) or partially (0.8 MPa).

The steam with the pressure of 3.0 MPa, and temperature of 400°C (the source of which is the turbo-generator no. 4 and – as a reserve – the reduction-cooling station 9/3 MPa), is used to feed the turbo-blower no. 4, as well as the reduction stations 3/1.6 MPa, three top feedwater heaters, and turbo-blowers' and turbo-compressors' auxiliary devices.

The controlled bleeder valves of the turbo-generators no. 5 and 6, and (as a reserve) the three reduction-cooling stations 9/0.8 MPa, as well as the second uncontrolled bleeder valve of the turbo-generator no. 3 are the source of steam, 0.8 MPa. The consumers, within the plant, of this steam are the top feedwater heaters of the central heating system (networked), the reduction-cooling stations 0.8/0.12 MPa, secondary degasifiers (feeders), and a facility for emergency and periodical steaming of gas piping of the Power Plant.

The controlled bleeder valves of the turbo-generators no. 3, 5, and 6, the three reduction-cooling stations 0.8/0.12 MPa, the expanders of periodic desludging, the secondary expanders of constant desludging, the expanders of dehydration in the turbo-blowers and turbo-generators house, and the third bleeder valves of turbo-blowers turbines (no. 1, 6, and 7), are the source of steam, 0.12 MPa. This steam is used to feed basic feedwater heaters of the central heating system, raw water heaters of ChOW, as well as degasifiers (preliminary, evaporator-based and linked).

The following energy carriers are the final products of the power plant:

- Electric energy (maximum power: 96 MW), used by separate objects at the Mittal Steel Poland S.A. Power Plant in Kraków (including the power plant);
- Blast furnace wind (the output of the facility when two out of four turbo-blowers are in operation: 522,000 m^3/h), generated to meet the needs of the blast furnaces department at the Mittal Steel Poland S.A. Power Plant in Kraków;
- Process steam with the pressure – 1.6 MPa, generated to meet the technological needs of individual plants at Mittal Steel Poland S.A. Power Plant in Kraków;
- Process steam with the pressure – 0.8 MPa, generated to meet the technological needs of individual plants at Mittal Steel Poland S.A. Power Plant in Kraków and of the Power Plant itself;
- Heat in the heating water with the temperature of 150°C (the return temperature of 70°C), generated first and foremost to meet the heating needs at the Mittal Steel Poland S.A. Power Plant in Kraków, and partially to meet the heating needs of the part of the Nowa Huta district;
- Gas-free and heated softened water (of parameters: 1.5–1.8 MPa, temperature 103–105°C), generated to meet the needs of evaporative cooling systems of

pusher furnaces of the Hot Rolling Mill and Strip Mill, as well as used as water feeding waste-heat boilers in the Converter Plant and the boilers in the Dry Quenching of Coke facility, WK-1 (in the Coke Plant), and to meet the own needs of the power plant – to make-up for the losses incurred in the heating cycle;

- Demineralised water (produced in ChOW-1 and heated in the system of raw water heaters to the temperature of 20°C), used to make-up for the losses of water used in the boiler house cycle of the power plant, and used in the cooling cycle of the Continuous Casting Machine (CCM) and – sporadically – in the cooling cycle of the electro-galvanising facility.

MSP was in possession of all licences necessary to carry out economic activity within the Energy Regulatory Office’s field of activity, including:

- Heat generation,
- Transfer and distribution of heat,
- Electric energy generation,
- Transfer and distribution of electric energy,
- Electric energy turnover,
- Transfer and distribution of fuel gas,
- Fuel gas turnover.

The data used in this project comes from the following sources:

- Information materials provided by Mittal Poland S.A. Power Plant in Kraków from the period of 2003–2005.
- Investment and modernisation plans in MSP, including environmental protection requirements, for the years of 2006–2016 (Mittal Steel Poland).
- The Study by the Mineral and Energy Economy Research Institute of the Polish Academy of Sciences in Kraków, ordered by the Faculty of Management at AGH University of Science and Technology as part of the post doctoral research grant awarded by the Ministry of Science and Higher Education to the AGH University of Science and Technology for the completion of the author’s research project (grant number N115 084 32/4279) (Ocena 2008).
- An application for an integrated permit for the fuel combustion for energy production facility in the Mittal Steel Poland S.A. Unit in Kraków, drawn up by a team of contractors lead by M. Mazur from the Department of Management and Protection of Environment and the Department of Mechanics and Vibroacoustics at AGH University of Science and Technology (Wniosek 2006).
- The data obtained from the Department of Environmental Protection at the Power Plant.
- The subject literature.
- The balance data are from the year 2005.

The permission to use the appropriate data needed to complete this project was given by the Managing Director of MSP S.A. Unit in Kraków.

4.8 Description of the Functional Unit of the Boundary System of the Performed Analysis: Inventory Analysis

Functional unit is defined as a quantitative effect of a manufacture system applied as a reference unit in life cycle research. The application of a functional unit ought to be clearly defined and measurable (Kowalski et al. 2007; ISO 14041, 2002). A single product, a group of products, a manufacturing process, or a whole system can be used as a functional unit (Kulczycka and Henclik 2009). The functional unit chosen here is the Power Plant, being a production facility working in an annual cycle. Within the boundaries of the analysed system, the life cycle of the Power Plant presented from the point of view of an annual cycle based on the year 2005 is included. The compiled material-energy balance, shown in Table 4.1, is the basis of the analysis.

The system boundary is set to establish the source of the materials and the energy that are employed in different individual stages of the process. A precise definition of the system boundary very much depends on the access to data. This knowledge is one of the elements of uncertainty in LCA research. In the case analysed in this section of the thesis, the system boundary is presented in Fig. 4.11.

For the purposes of this analysis some types of waste have been grouped – e.g. worn out devices, elements removed from worn out devices, and insulating materials (not including hazardous substances) have all been categorised as other waste.

In order to define the Power Plant's environmental impact, the LCA technique has been employed. The LCA issues are currently addressed by more than 40 versions of commercial computer programs. The development of the forecasting model using the LCA technique is supported by SimaPro 7.1 software, developed by a Dutch company – PRé Consultants (Goedkoop et al. 2000), and by databases implemented in the software – mostly Ecoinvent. It is one of the best computer software programs on the market that deals with examinations using the LCA technique in terms of its application possibilities and its price (Adamczyk 2004). The program makes use of the concept of components in modelling the life cycle of a product. A component may describe a single part or an entire product comprised of a few components. Eco-indicator 99 has been chosen as an analysis method and, for the purposes of the analysis, own processes have been built as well. The positions 18–43 (inventory table), of the so-called exit, have been defined as Siłownia-E (E-Power-Plant). The remaining entries (positions 44–49) have been described using other processes. For the purposes of the analysis, some types of waste have been grouped – e.g. worn out devices, elements removed from worn out devices, and insulating materials (not including hazardous substances) have all been categorised as other waste.

The analysis does not include methane – emitted to the atmosphere in large quantities during the energy generation processes at the Power Plant complex. Methane is a greenhouse gas mentioned in the emissions trading act; nevertheless, in the analysed period (i.e. the year 2005), methane was not subject to European

Table 4.1 Inventory table for the energy generation processes in the Power Plant Department at the MSP S.A. in 2005

No.	Minerals and emissions (input and output)	Quantity
1.	Hard coal	315,680 Mg
2.	Blast furnace gas	4.16 mln GJ
3.	Coke oven gas	0.80 mln GJ
4.	Natural gas	0.08 mln GJ
5.	Electric energy	133,628 MWh
6.	Demineralised water	12,384,404 m^3
7.	Tap water	30,205 m^3
8.	Gear oil	0.80 Mg
9.	Solid oil	0.18 Mg
10.	Kotamina	8.75 Mg
11.	Sodium phosphate	12.4 Mg
12.	Hydrated lime	284.2 Mg
13.	Sulphur	100 Mg
14.	Hydrochloric acid	215 Mg
15.	Sodium hydroxide	219 Mg
16.	Conveyor belts	500 m
17.	Land use	93,055 m^2
18.	Carbon dioxide	1,802.902 Mg
19.	Sulfur dioxide	3,138.1 Mg
20.	Nitrogen dioxide	2,648.5 Mg
21.	Dust	622.1 Mg
22.	Chromium	10.4 kg
23.	Cadmium	1.0 kg
24.	Copper	21.3 kg
25.	Lead	22.8 kg
26.	Nickel	19.6 kg
27.	Manganese	274.0 kg
28.	Carbon monoxide	48.1 Mg
29.	Hydrogen chloride	117.2 Mg
30.	Fluorine	9.36 Mg
31.	Aliphatic hydrocarbons	67.5 Mg
32.	Water from cooling cycles	3,316,958 m^3
33.	Municipal sewage	30,205 m^3
34.	Water decarbonisation sediments	2,289.5 Mg
35.	Solutions and sludge from the regeneration of ion-exchange units	1,528.7 Mg
36.	Other sludge and preventive sediments	10.0 Mg
37.	Other engine, gear, and lubricating oils	15.24 Mg
38.	Mineral oils and liquids used as electric insulators and heat carriers not containing chloro-organic compounds	2.98 Mg
39.	Worn out devices containing hazardous substances	0.132 Mg
40.	Lead-acid accumulators and batteries	2.18 Mg
41.	Copper, bronze, brass	9.842 Mg
42.	Aluminium	0.199 Mg
43.	Cables containing crude oil, tar, and other hazardous substances	11.768 Mg
44.	Worn out devices	3.25 Mg
45.	Elements removed from worn out devices	0.003 Mg
46.	Insulating materials	19.5 Mg
47.	Coal fly-ash	11,272.0 Mg
48.	Slag-ash mixtures from liquid drainage of furnace waste	53,078.1 Mg
49.	Unsegregated (mixed) solid municipal waste	102.0 Mg

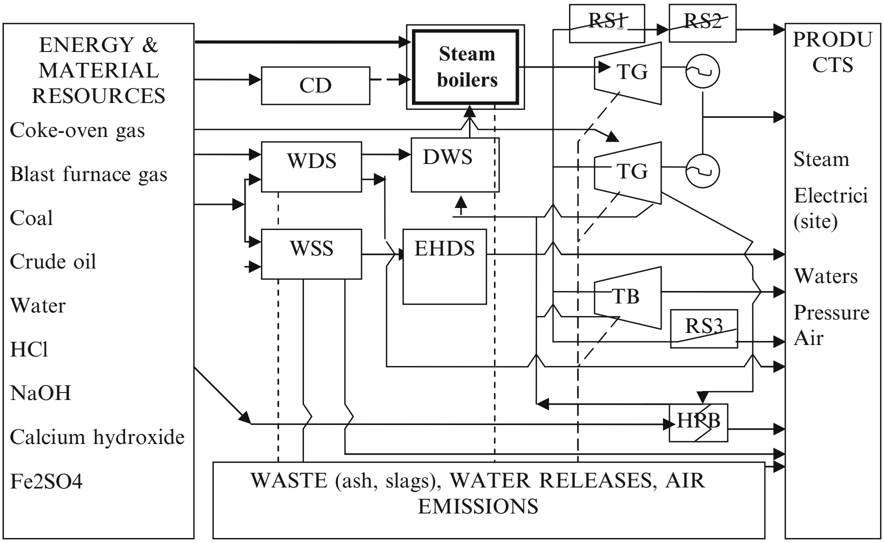


Fig. 4.11 A simplified production diagram of the Power Plant department – an element of the boundary system of the energy generation life cycle. *CD* Coal Deposit (yard) – input: coal, output, conveyor belt, *WDS* Water Demineralizing Station – input: water, HCl, NaOH, output: demineralizing water, *DWS* Degassing of the Water Supply – input: condensation water from turbogenerators, *WSS* Water Softening Station – input: water, output: softening waterm, *EHDS* Evaporator & Heat network Degassing Station installation – input: degassing water, output: degassing softening water, *TG* Turbogenerator – input: turbine oil, output U=6 KV, *RS1* Reducing Station nr 1 – output: steam 3 MPa, *RS2* Reducing Station nr 2 – output: steam 1.6 MPa, *RS3* Reducing Station nr 3 – output: 0.8 MPa, *TB* Turbo blower – output: blow to blast furnace, *HPB* Heat Power Blanks – output: Steel Plant & Krakow city heating, *Steam boilers* input: coal from CD, blast furnace gas, coke oven gas, output: steam 9 MPa

trade regulations. If the European Commission recognises the need to limit methane's emissions, it will then publish the allocation of emissions and the percentage of reduction in the next stage of trade. In addition, methane is not limited in the scope of the allowed emissions levels from individual emission sources and facilities hence it is not included in the application for an integrated permit. It is only subject to charges for the economic use of the environment – for the emissions to the atmosphere. According to the information received from the Department of Environmental Protection at MSP Poland S.A., the amount of methane emitted by the Power Plant complex in 2005 was measured to be 575.08 Mg.

In this analysis it has been taken into consideration that approximately 95% of sewage is recycled and returned to the process.

The amount of energy consumed by the Power Plant is not included in the analysis, as it uses the energy that the Plant itself generates; if that energy were included in the analysis, it would lead to doubling the calculations of the environmental impact of the electric energy generation, since the entire life cycle of the materials and energy sources included in the analysis is taken into account here.

The Life Cycle Inventory analysis (LCI) of the input output set is believed to be one of the most important phases in the LCA method, because in this phase the aim, the scope, the functional unit, the system boundary, and the assumptions are all defined (Roy et al. 2009). The functional unit here applies to the entire manufacture system and the process of production. Defining the system and its boundaries makes it possible to establish the flux of input energy and the materials needed in particular phases of the process.

A simplified production diagram of the Power Plant department is presented in Fig. 4.11.

4.9 The Life Cycle Impact Assessment LCA

SimaPro software and the databases (mostly Ecoinvent) implemented in the program have been used in the LCA analysis. Eco-indicator 99 (version H/A) has been the chosen method for the analysis. This method is based on assigning significance to each of the impact categories, which include: carcinogenic agents, climate change, radiation, ozone layer depletion, ecotoxicity, acidification, or eutrophication. Every impact category is assigned with a relevant damage category:

- Consumption of Resources – R,
- Ecosystem Quality – EQ,
- Human Health – HH.

The Eco-indicator method is based on the assumptions similar to the philosophy of G. Taguchi. Here, the losses are replaced by environmental damage caused by the influence of a process or production (Adamczyk 2004). According to G. Taguchi, each quality symbol or parameter may in the case of the process, reach a level where it fulfils the consumer's expectations to the best of its ability, or, in other words, reaches the optimum quality level. This assumption is also true when it comes to ecological features of a product or environmental parameters. Taguchi uses the so-called loss function, which measures the deviation from its optimum state (Adamczyk 2004; Taguchi and Clausing 1990; Taguchi 1999). In accordance with international standards ISO, every examination employing the LCA technique must include at least the characterisation phase – a phase that is compulsory in the LCA method (Guinee et al. 2001).

The optional elements include: normalisation (calculation of the value of a category indicator in relation to reference information), grouping, measurement, and data quality analysis. These are described in detail in the standard PN-EN ISO 14042 (Environmental Management – Life Cycle Assessment – Life Cycle Impact Assessment – see PN-EN ISO 14042 2002).

The outcomes are presented in the form of results in the following phases:

- Characterisation – it relies on the calculation of the value of a category indicator for the LCI results and makes it possible to evaluate the influence level of the method in a quantity dealing with the given impact category. The characterisation parameter in the Eco-indicator 99 method is defined on the basis of the so-called intermediate points. This method relates the impact of harmful activity on natural environment to three damage categories: Human Health, Ecosystem Quality, and Consumption of Resources (Simapro 2007). Damage to human health is expressed in DALY units – they describe Disability Adjusted Life Years. Murray and Lopez introduced DALY units in 1996 for the World Bank and World Health Organisation (WHO). They allow us to determine the relative amount of time by which human life is shortened as a result of damaging waste management effects. The analysis of harmfulness involves making a connection between the health impact and the final value of the DALY indicator, considering the number of years lost due to disability (YLD) and the number of years of life lost (YLL) (Adamczyk 2004).

The damage to the quality of the ecosystem (eco-toxicity) is expressed as a percentage of species disappearing from a given area, as a result of the influences on the environment. The reference unit used here is the Potentially Affected Fraction (PAF), expressed as a percentage. If there is a need to express acidification and eutrophication, the Potentially Disappeared Fraction units are used (PDF). The unit that expresses the damage done to the ecosystem is PDF, related to the area of the ground in a year: PDF*m^2*year (Adamczyk 2004). The reduction of natural resources is assessed by analysing the quality of the natural sources that have not yet been extracted, including fossil fuels. The surplus energy (MJ) is necessary to access the useful minerals, which may be extracted at a lower cost. An in-depth description of the Eco-indicator 99 method can be found in the work of: Kowalski et al. (2007) and SimaPro (2007).

- Normalisation – it relies on the division of the value of the impact category by the impact on the environment per 1 European inhabitant in a year, i.e. non-designated values. Normalisation facilitates interpretation and understanding of measurement.
- Weighting – the result of normalisation is multiplied by the appropriate subjective significance coefficient – significant values are expressed in eco-points [Pt] and in submultiples [mPt] – mili-points.

Eco-point is a unit that informs us of the effects that one (on average) European inhabitant has on the environment in 1 year. It is calculated by dividing all of the European emissions by the number of its inhabitants. It is worth mentioning the fact that the value of an eco-point [Pt] should be a dimensionless number and that it is created by dividing the entire environmental load, shared by the European continent, by the number of its inhabitants, and multiplying the obtained answer by 10^3 (Goedkoop et al. 2000).

By presenting the outcomes of the analysis one may wish to relate them to the three damage categories:

- Human Health, part of which are factors, such as the number and duration of diseases, premature deaths caused by the environmental impact, as well as effects such as climate change, ozone layer depletion, carcinogenic agents, influence of radiation, or difficulties with respiratory processes.
- Ecosystem Quality, which includes the influence on the variety of species, especially vascular or smaller plants, and on the following effects: eco-toxicity, acidification, eutrophication, and land use.
- Consumption of Resources, which includes the surplus energy needed in the past to extract minerals and fossil resources of worse quality; on the other hand, the impoverishment of building minerals, such as gravel or sand, is treated as land exploitation (Adamczyk 2004).

or to 11 impact categories which add up to the relevant damage categories, i.e. carcinogenic agents, the effects on respiratory systems of organic compounds, the effects on respiratory systems of non-organic compounds, climate change, radiation, ozone layer depletion (Human Health), eco-toxicity, acidification/eutrophication, land use (Ecosystem Quality), mineral and fossil fuel consumption (Consumption of Resources).

The process of defining the eco-point [Pt] is carried out in three steps, according to the diagram proposed by Adamczyk (2004). In inventory analysis new processes are established or existing processes, included in SimaPro 7.1 library, are used. Complete results of the performed LCI analysis (presented here – Ocena 2008), take the form of the following types of frequency charts: characterisation (in a division into 11 impact categories), normalisation (in a division into 3 damage categories), and measurement (in a division into 11 impact categories).

4.10 Stochastic Analysis of the Environmental Impact of the Four Scenarios of Energy Generation Processes in MSP Power Plant

The results of the LCA analysis have been used here to present the stochastic analysis of the environmental impact of the four scenarios of energy generation processes in MSP Power Plant. In order to assess the credibility of the LCA results, which are burdened with a certain degree of uncertainty, the probabilistic analysis, based on the combination of MC simulation as well as sensitivity and uncertainty analysis, has been used with the aim of evaluating the uncertainty in LCA. This thesis is of methodical nature and the simulation results presented here are of cognitive and applied importance. Therefore, it is worth supporting this work with complete results of the LCA analysis (in which the author took part in the inventory phase), which form the basis for the subject analysis, demonstrated in this work.

A fundamental element of the LCI life cycle phase in SimaPro 7.1 is the creation of the tree of processes, depicting all of the vital life cycle processes and the correlations between them. The tree of resources and processes is presented in the form of boxes; each tree element includes a piece of information regarding the involvement of the processes and materials, proportionate to the value of indicators – it is possible to determine which process/material influences the product the most; it is also possible to define the participation of a single element in the entire life cycle. The structure of the tree allows the user to see a detailed review of the resources and their participation in the processes. Each tree box is equipped with a bar chart (or thermometer), which indicates the participation of resources in relation to the value of indicators (Kulczycka 2001). The thickness of the arrows, as well as the height of the bars, is connected to the size of the environmental impact. The trees may be presented separately for each of the damage categories or together as a single score.

By using the process trees one can examine positive impacts on the environment – these, in SimaPro 7.1, are represented by green bars next to the given elements of the process tree. The red bars, on the other hand, indicate that the impact on the environment is negative (Kulczycka 2001; Goedkoop et al. 2000).

In this analysis, the data presented in Table 4.2, showing measurement results, is employed. The table has been created using the data obtained from SimaPro 7.1 library, which makes use of the coefficients included in the Eco-indicator 99 method, the data from the inventory table for the energy generation processes in the Power Plant department, included in Table 4.1. It also includes processes mentioned above, created for the purposes of the analysis, and originating from the LCA study designed for the purposes of the postdoctoral thesis by the Mineral and Energy Economy Research Institute of the Polish Academy of Sciences in Kraków (Ocena 2008).

A comparative analysis for the four scenarios of the Power Plant's annual work cycle has been performed, taking into consideration that the scenarios differ only in the change of proportioning ratios of the two types of fuels: hard coal and blast furnace gas (the remaining fuels, such as natural gas and coke oven gas are left at their current levels – they are used as start-up gas owing to their higher heating value). The simulation has been conducted with an assumption that 1 GJ of energy from coal is equal to 1 GJ of energy from other fuels:

- Scenario S1 – in 2005 – 62% of energy comes from hard coal, 38% from blast furnace gas,
- Scenario S2 – an assumption that 100% of energy comes from hard coal,
- Scenario S3 – an assumption that the percentages of fuels are even,
- Scenario S4 – an assumption that 30% of energy comes from hard coal, 70% from blast furnace gas.

In order for a cumulative impact factor to be determined, a summary of all indicators has been performed, and is included in the TOTAL column. The results of the analysis are expressed using eco-points [Pt], a unit accepted in the LCA method (see Sect. 4.9 for more information) that explicitly defines the measurement of environmental impacts. As is emphasised by Merkisz et al. (2007), the positive

Table 4.2 The results of the LCA analysis in the four scenarios of the Power Plant's annual work cycle, divided into 11 impact categories

Impact category	Unit	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Carcinogenicity	Pt	5,436,453.7	8,648,551	4,367,048.9	2,654,440
Respiratory system – organic compounds	Pt	14,024.572	15,912.46	13,396.037	12,389.466
Respiratory system – non-organic compounds	Pt	14,680,447	20,792,656	12,645,508	9,386,634.4
Climate change	Pt	10,448,258	7,001,483	11,595,807	13,433,532
Radiation	Pt	16,528.649	24,134.59	13,996.4	9,941.1081
Ozone layer	Pt	499.6735	635.9435	454.30506	381.6494
Eco-toxicity	Pt	316,502.38	485,314.1	260,299.82	170,293.71
Acidification/eutrophication	Pt	1,514,979.8	2,116,324	1,314,774.5	994,153.29
Land use	Pt	242,279.63	336,367.2	210,955.03	160,789.98
Minerals	Pt	22,744.293	23,468.29	22,503.256	22,117.237
Fossil fuels	Pt	3,855,978.8	5,544,591	3,293,788.3	2,393,463.6
TOTAL – summary of influence	Pt	36,548,696.5	44,989,437	33,738,532	29,238,136
TOTAL – summary of influence = μ_g	Pt	36,510,598.74	44,953,891.94	33,699,465.59	29,200,035.13
$x_{0,5}$	Pt	36,419,105.46	44,793,382.60	33,607,403.62	29,121,534.18

μ_g – geometric mean
$x_{0,5}$ – median

value of eco-points indicates a negative impact on the environment (the higher the value expressed in [Pt] the greater the negative impact), while the negative values mean environmental benefits.

In the S1 scenario, which describes the present state (and in 2005), where 62% of energy comes from hard coal and 38% from blast furnace gas, the Power Plant's environmental impact in a 1-year production cycle is potentially high – 36,548,697 Pt.

The S2 scenario is a theoretical scenario, in which the only boiler that is heated with coal is boiler no. 8, produced in Poland (OP-230 Boiler). In this scenario the cumulative impact factor of the Power Plant amounts to 44,989,437 Pt.

In the third scenario (S3) based on an assumption that the fuels are dosed equally, the total influence of the Power Plant amounts to 33,738,532 Pt.

The fourth and final scenario (S4) assumes minimal amount of energy involved that comes from hard coal. This is due to the fact that the majority of the boilers are adapted to burn pulverised coal (or coal dust), and such boilers cannot work under a certain critical amount of dust, as it would lead to boiler shutdown. In this scenario the cumulative impact factor of the Power Plant is 29,238,136 Pt.

This means that the energy generation processes during a 1-year cycle of the Power Plant cause the same amount of pollution as 36,548.7 Europeans (scenario 1), 44,989.4 Europeans (Scenario 2), 33,738.5 Europeans (Scenario 3), and 29,238 Europeans (Scenario 4) cause in a year.

The process trees are presented in Figs. 4.12–4.15 (Ocena 2008). The tree boxes also show the share of each of the processes in the total impact on the environment

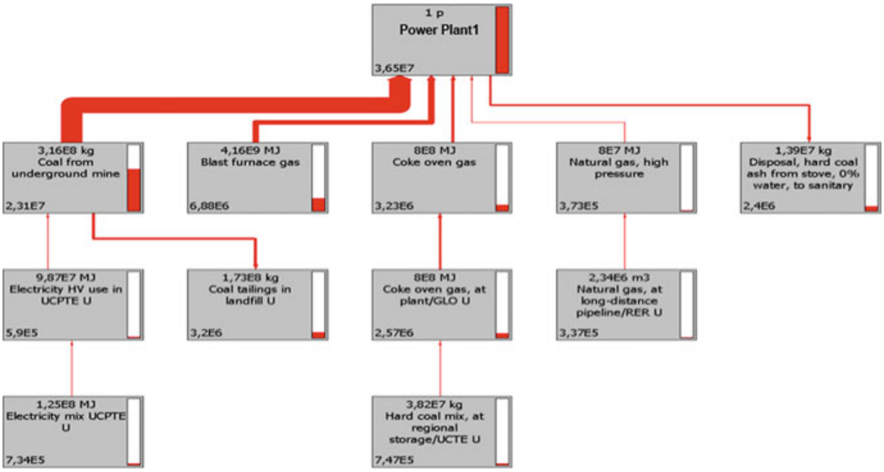


Fig. 4.12 The developed view of the resources and processes tree for the Power Plant (annual data) – scenario S1 – present state – 62% of energy comes from hard coal, 38% from blast furnace gas. In Figs. 4.12–4.14, the E5, E6, and E7 symbols mean 10^5, 10^6 and 10^7 (Source: Ocena (2008) based on data from MSP)

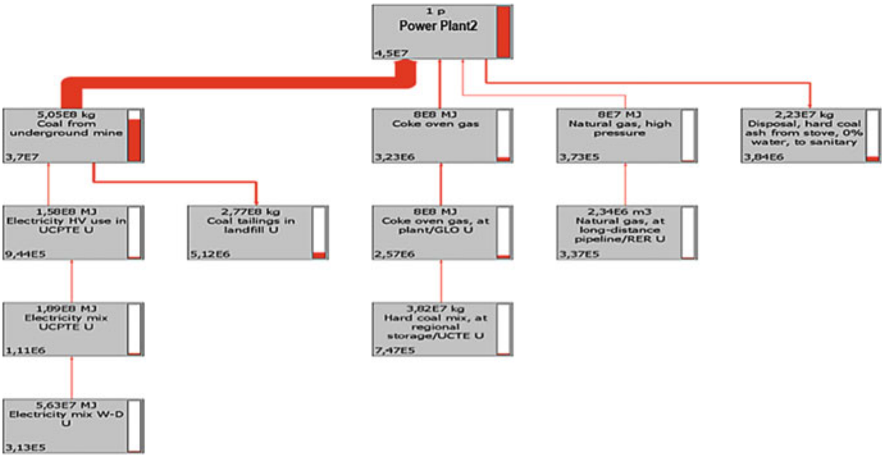


Fig. 4.13 The developed view of the resources and processes tree for the Power Plant (annual data) – scenario S2 – an assumption that 100% of energy comes from hard coal. There is no box containing blast furnace gas (Source: Ocena (2008) based on data from MSP)

(in the bottom left corner), as well as simultaneously present these data on a bar chart, which can be found in each of the boxes. The total result of such influences is given in the first box.

The allocation of emissions has been made on the basis of data received from both the Department of Environmental Protection at MSP S.A. Power Plant (Wniosek 2006) and the subject literature data (Lorenz 1999).

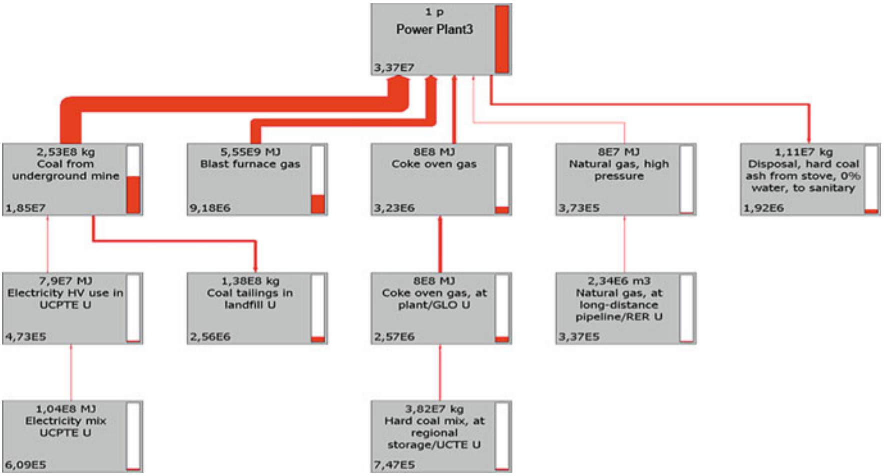


Fig. 4.14 The developed view of the resources and processes tree for the Power Plant (annual data) – scenario S3 – an assumption that fuels are dosed in equal percentages (Source: Ocena (2008) based on data from MSP)

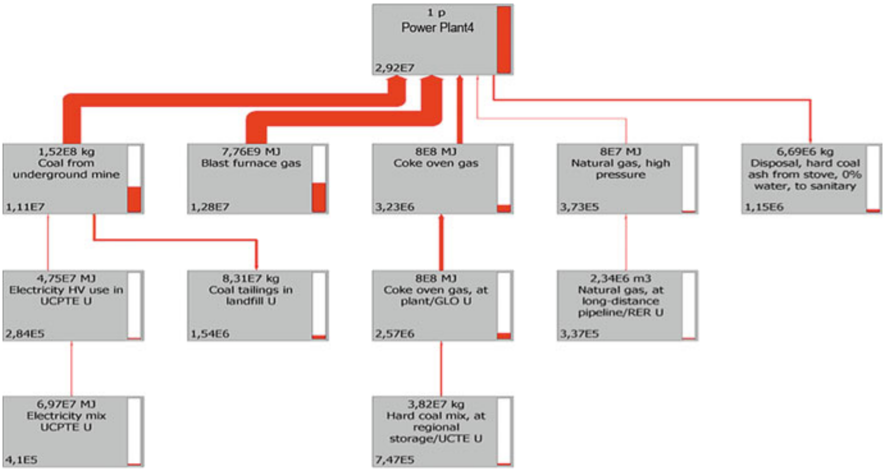
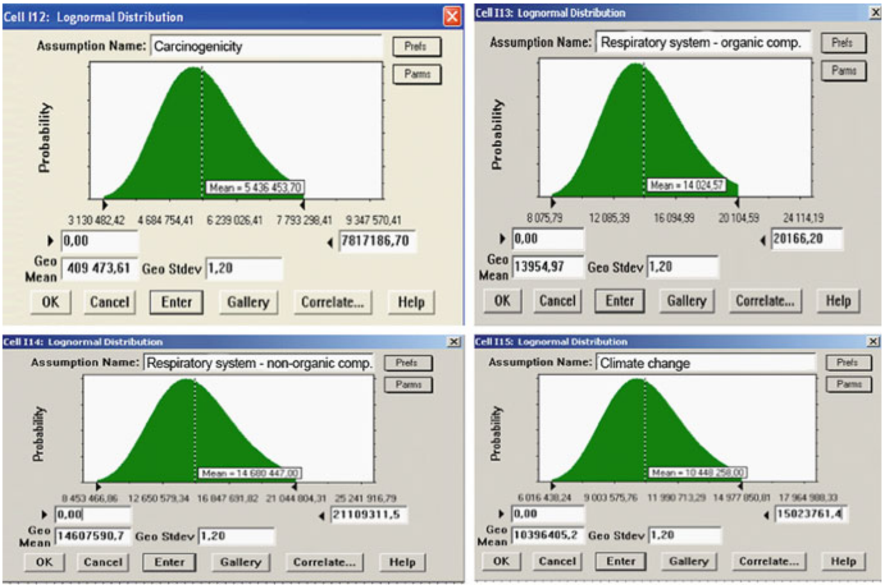


Fig. 4.15 The developed view of the resources and processes tree for the Power Plant (annual data) – scenario S4 – an assumption that 30% of energy comes from hard coal, 70% from blast furnace gas (Source: Ocena (2008) based on data from MSP)

4.11 Defining Input Data: Organising the Simulation

Before a simulation can be run it is necessary to define input information received in graphic form. The analysis consists of 11 impact categories (influences) and their total impact on the environment (Table 4.2).

In all of the discussed scenarios (1–4), the simulations have been performed using Crystal Ball software, in accordance with the steps discussed in Chap. 2. In order for the algorithm to be run, it is necessary to be aware of probability distribution, which is applied in stochastic analysis of environmental impact of energy production processes at MSP, thanks to which at least a theoretical reflection of the analysed real process can be performed. In the field of statistical analysis of uncertainty in the problems of ecology, the most important work has bee published by Sonnemann et al. (2004), Rabl and Spadaro (1999), Spadaro and Rabl (2008), and the Eco-indicator 99 method developed by a Dutch company PRé Consultants. From the analysis of the above-mentioned projects, it can be concluded that random values of the impact category, in stochastic LCA analysis defining the impact of the energy production processes in the Power Plant on the environment, may be described using log-normal distribution with standard geometric deviation $\sigma_g = 1.2$. The Lognormal Distribution tab windows that contain log-normal distributions of each of the eleven impact categories of the analysed scenarios, are presented in Figs. 4.16–4.19, respectively. The distribution tabs define the standard geometric deviation σ_g and the mean value μ that correspond to the random values of the impact category (Table 4.2), which are approximated with log-normal distributions. CB program automatically "matches" the distribution, calculating its remaining parameters: geometric mean μ_g and the upper boundary of log-normal distribution. The lower boundary = 0. As can be observed in Figs. 4.16–4.19, log-normal distributions are cut off on the right-hand side.

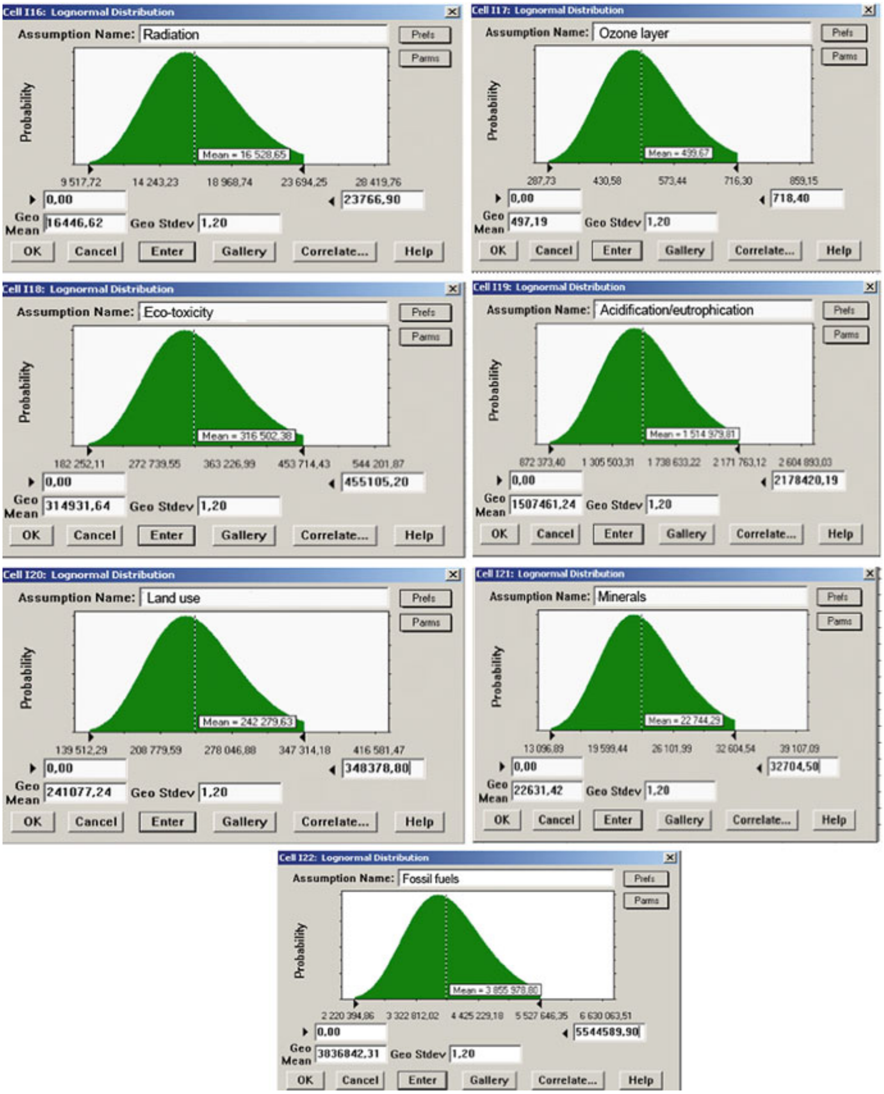

Cell I12: Lognormal Distribution
Assumption Name: Carcinogenicity
0,00
7817186,70
Geo Mean 409 473,61
Geo Stdev 1,20

Cell I13: Lognormal Distribution
Assumption Name: Respiratory system - organic comp.
0,00
20166,20
Geo Mean 13954,97
Geo Stdev 1,20

Cell I14: Lognormal Distribution
Assumption Name: Respiratory system - non-organic comp.
0,00
21109311,5
Geo Mean 14607590,7
Geo Stdev 1,20

Cell I15: Lognormal Distribution
Assumption Name: Climate change
0,00
15023761,4
Geo Mean 10396405,2
Geo Stdev 1,20

Fig. 4.16 (continued)



Cell I16: Lognormal Distribution
Assumption Name: Radiation
0,00 – 23766,90
Geo Mean 16446,62 Geo Stdev 1,20

Cell I17: Lognormal Distribution
Assumption Name: Ozone layer
0,00 – 718,40
Geo Mean 497,19 Geo Stdev 1,20

Cell I18: Lognormal Distribution
Assumption Name: Eco-toxicity
0,00 – 455105,20
Geo Mean 314931,64 Geo Stdev 1,20

Cell I19: Lognormal Distribution
Assumption Name: Acidification/eutrophication
0,00 – 2178420,19
Geo Mean 1507461,24 Geo Stdev 1,20

Cell I20: Lognormal Distribution
Assumption Name: Land use
0,00 – 348378,80
Geo Mean 241077,24 Geo Stdev 1,20

Cell I21: Lognormal Distribution
Assumption Name: Minerals
0,00 – 32704,50
Geo Mean 22631,42 Geo Stdev 1,20

Cell I22: Lognormal Distribution
Assumption Name: Fossil fuels
0,00 – 5544589,90
Geo Mean 3836842,31 Geo Stdev 1,20

Fig. 4.16 The log-normal probability distributions tabs for the 11 impact categories, available in Crystal Ball software for the S1 scenario (Source: Own work)

Scenario S1 – present state – 62% of energy comes from hard coal, 38% from blast furnace gas.

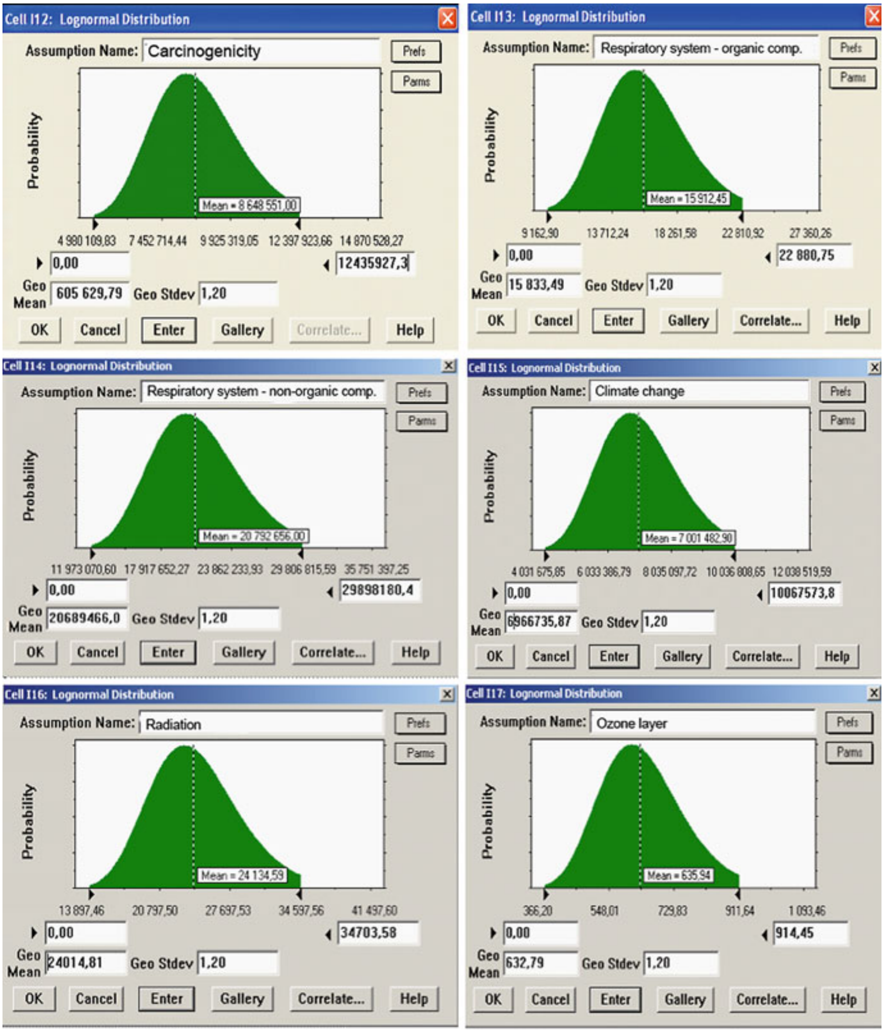
Scenario S2 – an assumption that 100% of energy comes from hard coal.

Scenario S3 – an assumption that fuels are dosed in equal percentages.

Scenario S4 – an assumption that 30% of energy comes from hard coal, 70% from blast furnace gas.

4.12 The Results of the Simulation

The results of the performed simulation (10,000 trials) can be presented in the form of frequency charts, reports, and sensitivity analyses. Below one can find frequency charts of the Forecast (Forecast TOTAL) as a summary of influence of the 11 impact categories on the environment, respectively, in Figs. 4.20–4.23 (68% confidence interval), and Figs. 4.24–4.27 (95% confidence interval). The sensitivity analysis and statistics reports as well as percentiles in the form of tables, are shown in Figs. 4.28–4.31, and in Figs. 4.32–4.35, respectively.


Cell I12: Lognormal Distribution

Assumption Name: Carcinogenicity

0,00 12435927,3

Geo Mean 605 629,79 Geo Stdev 1,20

Cell I13: Lognormal Distribution

Assumption Name: Respiratory system - organic comp.

0,00 22 880,75

Geo Mean 15 833,49 Geo Stdev 1,20

Cell I14: Lognormal Distribution

Assumption Name: Respiratory system - non-organic comp.

0,00 29898180,4

Geo Mean 20689466,0 Geo Stdev 1,20

Cell I15: Lognormal Distribution

Assumption Name: Climate change

0,00 10067573,8

Geo Mean 6966735,87 Geo Stdev 1,20

Cell I16: Lognormal Distribution

Assumption Name: Radiation

0,00 34703,58

Geo Mean 24014,81 Geo Stdev 1,20

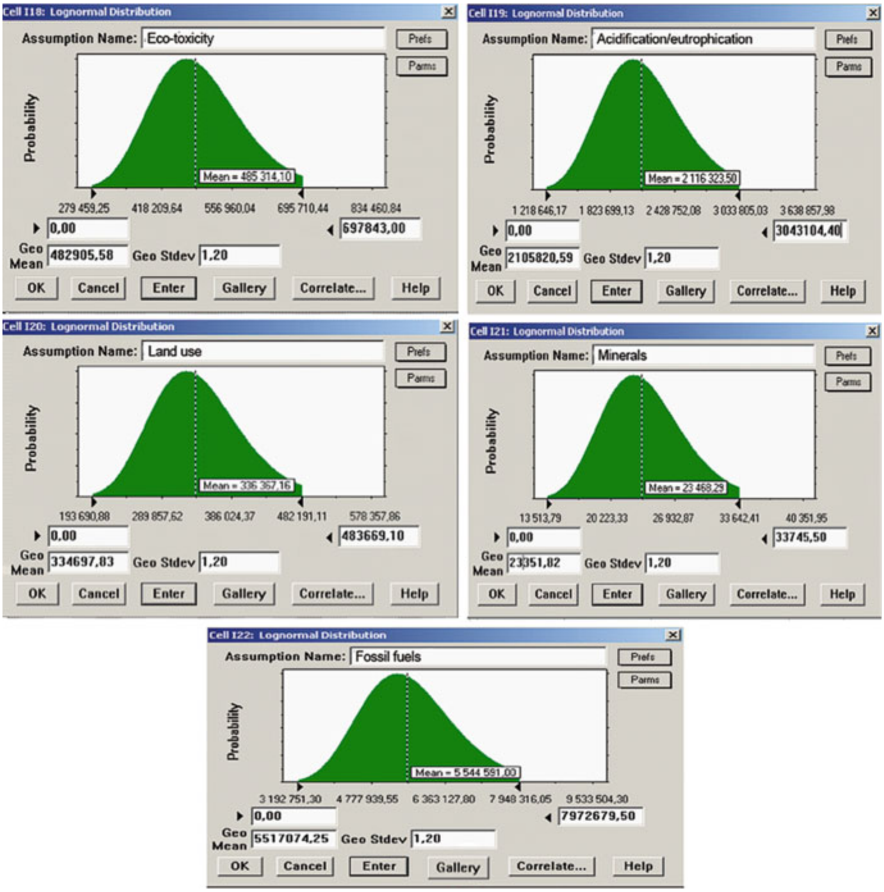
Cell I17: Lognormal Distribution

Assumption Name: Ozone layer

0,00 914,45

Geo Mean 632,79 Geo Stdev 1,20

Fig. 4.17 (continued)



Assumption Name: Eco-toxicity
0,00
697843,00
Geo Mean 482905,58
Geo Stdev 1,20

Assumption Name: Acidification/eutrophication
0,00
3043104,40
Geo Mean 2105820,59
Geo Stdev 1,20

Assumption Name: Land use
0,00
483669,10
Geo Mean 334697,83
Geo Stdev 1,20

Assumption Name: Minerals
0,00
33745,50
Geo Mean 23351,82
Geo Stdev 1,20

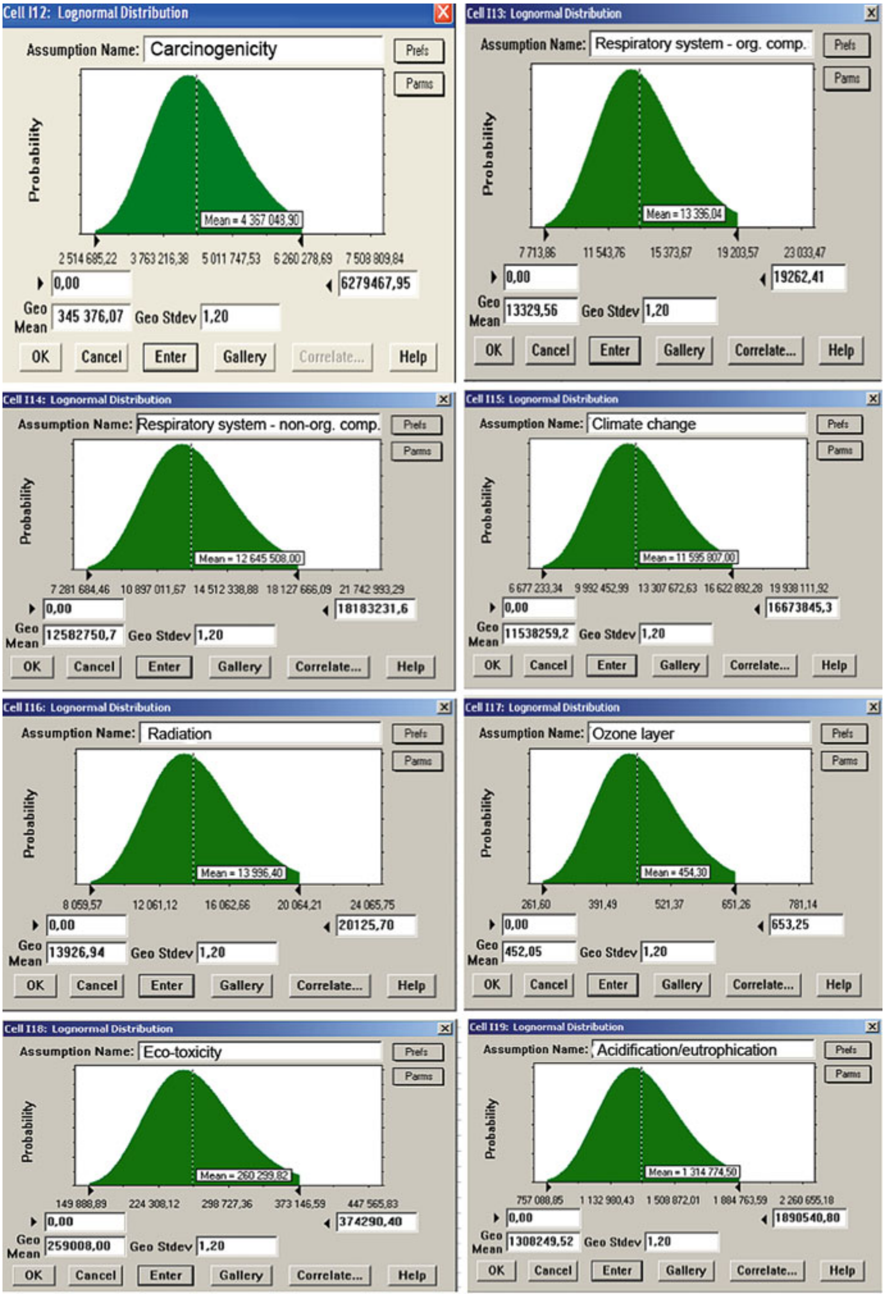
Assumption Name: Fossil fuels
0,00
7972679,50
Geo Mean 5517074,25
Geo Stdev 1,20

Fig. 4.17 The log-normal probability distributions tabs for the 11 impact categories, available in Crystal Ball software for the S2 scenario (Source: Own work)

As a result of the MC simulation, confidence intervals that estimate the values of the total influence of the impact category on the environment are formed, approximated with log-normal distribution at the significance level of 0.05. The confidence limits, presented in the frequency charts, are fixed using the mini-sliders, or grabbers (the area of the frequency chart covered by them is of a darker shade). The values of the obtained confidence intervals are shown below:

68% confidence interval

- Scenario S1: [33,227,982.17; 39,845,407.56] Pt
- Scenario S2: [40,789,087.31; 49,201,184.30] Pt
- Scenario S3: [30,645,422.13; 36,803,304.14] Pt
- Scenario S4: [26,311,943.73; 32,277,038.83] Pt



Cell I12: Lognormal Distribution
Assumption Name: Carcinogenicity
0,00
6279467,95
Geo Mean 345 376,07
Geo Stdev 1,20

Cell I13: Lognormal Distribution
Assumption Name: Respiratory system - org. comp.
0,00
19262,41
Geo Mean 13329,56
Geo Stdev 1,20

Cell I14: Lognormal Distribution
Assumption Name: Respiratory system - non-org. comp.
0,00
18183231,6
Geo Mean 12582750,7
Geo Stdev 1,20

Cell I15: Lognormal Distribution
Assumption Name: Climate change
0,00
16673845,3
Geo Mean 11538259,2
Geo Stdev 1,20

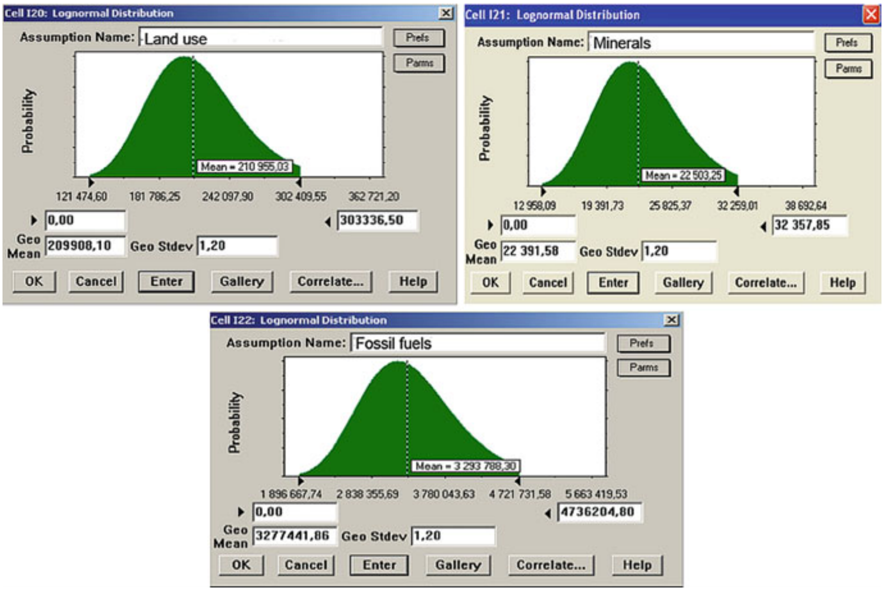
Cell I16: Lognormal Distribution
Assumption Name: Radiation
0,00
20125,70
Geo Mean 13926,94
Geo Stdev 1,20

Cell I17: Lognormal Distribution
Assumption Name: Ozone layer
0,00
653,25
Geo Mean 452,05
Geo Stdev 1,20

Cell I18: Lognormal Distribution
Assumption Name: Eco-toxicity
0,00
374290,40
Geo Mean 259008,00
Geo Stdev 1,20

Cell I19: Lognormal Distribution
Assumption Name: Acidification/eutrophication
0,00
1890540,80
Geo Mean 1308249,52
Geo Stdev 1,20

Fig. 4.18 (continued)

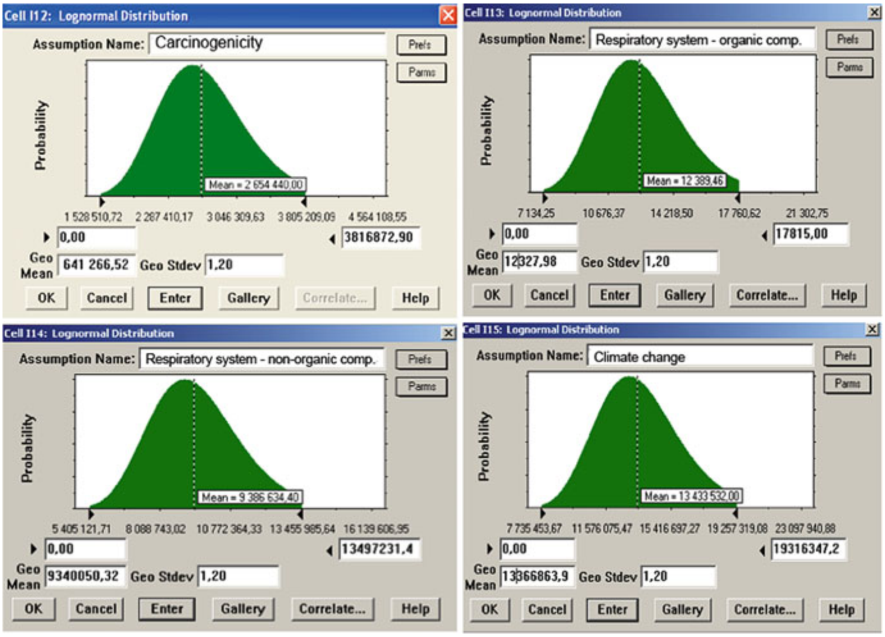


Cell I20: Lognormal Distribution
Assumption Name: Land use
0,00
303336,50
Geo Mean 209908,10
Geo Stdev 1,20

Cell I21: Lognormal Distribution
Assumption Name: Minerals
0,00
32 357,85
Geo Mean 22 391,58
Geo Stdev 1,20

Cell I22: Lognormal Distribution
Assumption Name: Fossil fuels
0,00
4736204,80
Geo Mean 3277441,86
Geo Stdev 1,20

Fig. 4.18 The log-normal probability distributions tabs for the 11 impact categories, available in Crystal Ball software for the S3 scenario (Source: Own work)



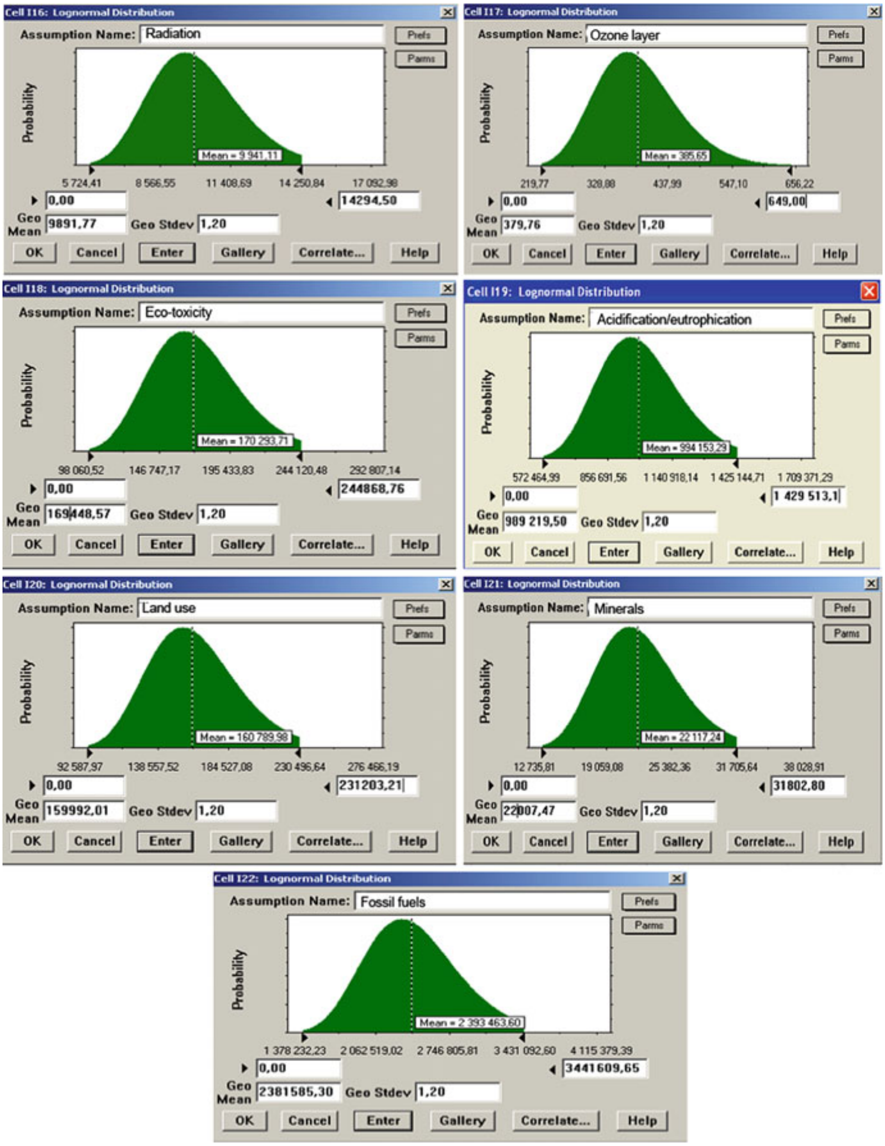
Cell I12: Lognormal Distribution
Assumption Name: Carcinogenicity
0,00
3816872,90
Geo Mean 641 266,52
Geo Stdev 1,20

Cell I13: Lognormal Distribution
Assumption Name: Respiratory system - organic comp.
0,00
17815,00
Geo Mean 12327,98
Geo Stdev 1,20

Cell I14: Lognormal Distribution
Assumption Name: Respiratory system - non-organic comp.
0,00
13497231,4
Geo Mean 9340050,32
Geo Stdev 1,20

Cell I15: Lognormal Distribution
Assumption Name: Climate change
0,00
19316347,2
Geo Mean 13366863,9
Geo Stdev 1,20

Fig. 4.19 (continued)



Cell I16: Lognormal Distribution
Assumption Name: Radiation
0,00
14294,50
Geo Mean 9891,77
Geo Stdev 1,20

Cell I17: Lognormal Distribution
Assumption Name: Ozone layer
0,00
649,00
Geo Mean 379,76
Geo Stdev 1,20

Cell I18: Lognormal Distribution
Assumption Name: Eco-toxicity
0,00
244868,76
Geo Mean 169448,57
Geo Stdev 1,20

Cell I19: Lognormal Distribution
Assumption Name: Acidification/eutrophication
0,00
1 429 513,1
Geo Mean 989 219,50
Geo Stdev 1,20

Cell I20: Lognormal Distribution
Assumption Name: Land use
0,00
231203,21
Geo Mean 159992,01
Geo Stdev 1,20

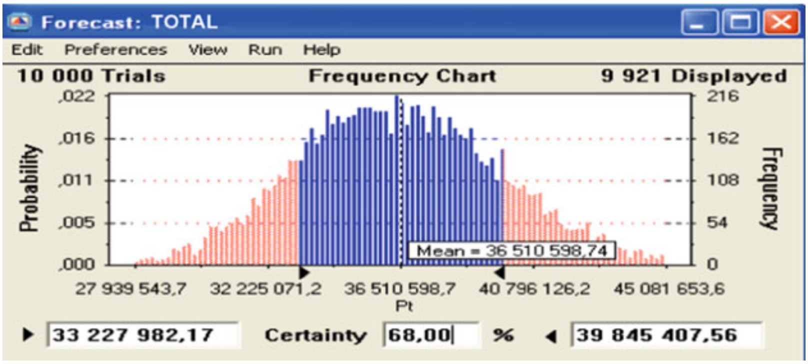
Cell I21: Lognormal Distribution
Assumption Name: Minerals
0,00
31802,80
Geo Mean 22007,47
Geo Stdev 1,20

Cell I22: Lognormal Distribution
Assumption Name: Fossil fuels
0,00
3441609,65
Geo Mean 2381585,30
Geo Stdev 1,20

Fig. 4.19 The log-normal probability distributions tabs for the 11 impact categories, available in Crystal Ball software for the S4 scenario (Source: Own work)

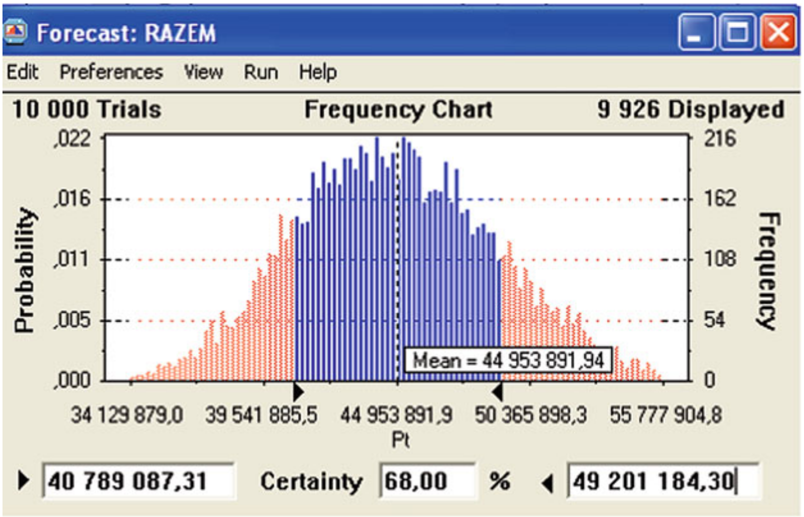
95% confidence interval

- Scenario S1: [30,373,471.47; 43,138,235.52] Pt,
- Scenario S2: [37,234,891.94; 53,336,194.13] Pt
- Scenario S3: [27,933,420.50; 39,941,034.25] Pt
- Scenario S4: [23,719,134.55; 35,258,203.00] Pt



▶ 33 227 982,17 Certainty 68,00 % ◀ 39 845 407,56

Fig. 4.20 The Forecast frequency chart: S1 scenario TOTAL (68% confidence level) (Source: Own work)



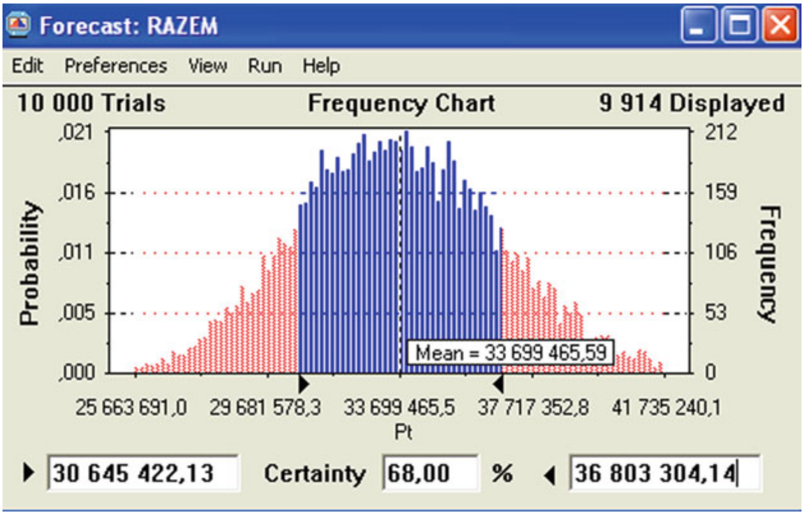
▶ 40 789 087,31 Certainty 68,00 % ◀ 49 201 184,30

Fig. 4.21 The Forecast frequency chart: S2 scenario TOTAL (68% confidence level) (Source: Own work)

4.13 Sensitivity Analysis

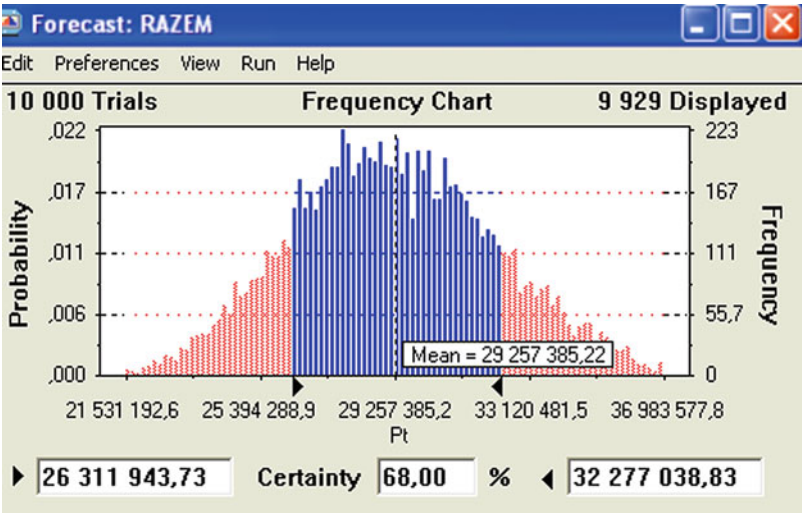
The results obtained in MC simulation have been used to carry out analysis in three different formats:

- Clustered bar charts (Sensitivity Chart)
- Tornado charts (Tornado Chart)
- Spider charts (Spider Chart).



30 645 422,13 Certainty 68,00 % 36 803 304,14

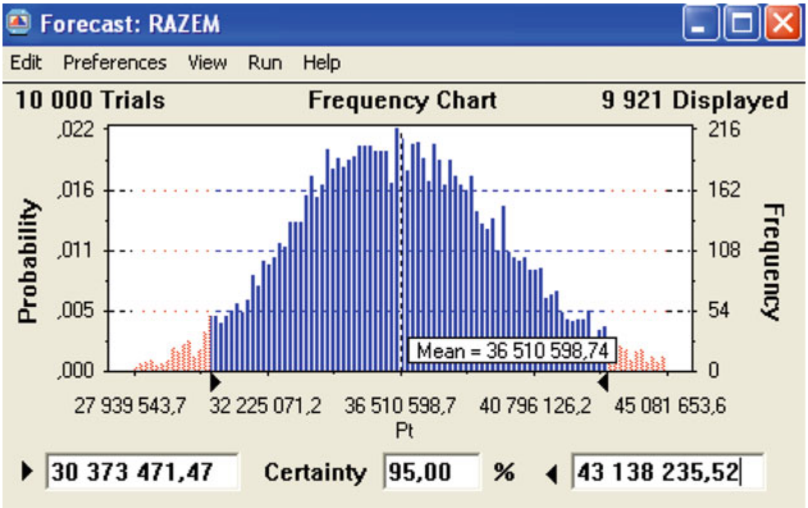
Fig. 4.22 The Forecast frequency chart: S3 scenario TOTAL (68% confidence level) (Source: Own work)



26 311 943,73 Certainty 68,00 % 32 277 038,83

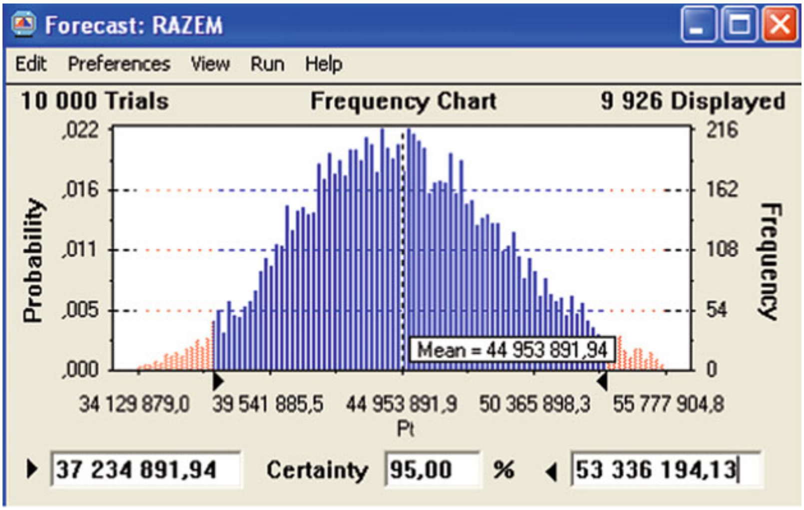
Fig. 4.23 The Forecast frequency chart: S4 scenario TOTAL (68% confidence level) (Source: Own work)

For an easier comparison of the sensitivity analyses in all of the four scenarios, the clustered bar charts of the scenarios mentioned above are shown in Figs. 4.36–4.39.



30 373 471,47 Certainty 95,00 % 43 138 235,52

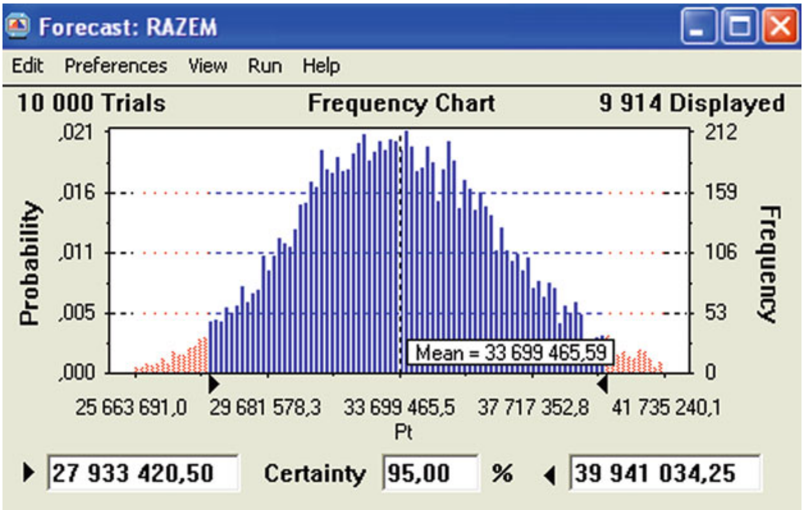
Fig. 4.24 The Forecast frequency chart: S1 scenario TOTAL (95% confidence level) (Source: Own work)



37 234 891,94 Certainty 95,00 % 53 336 194,13

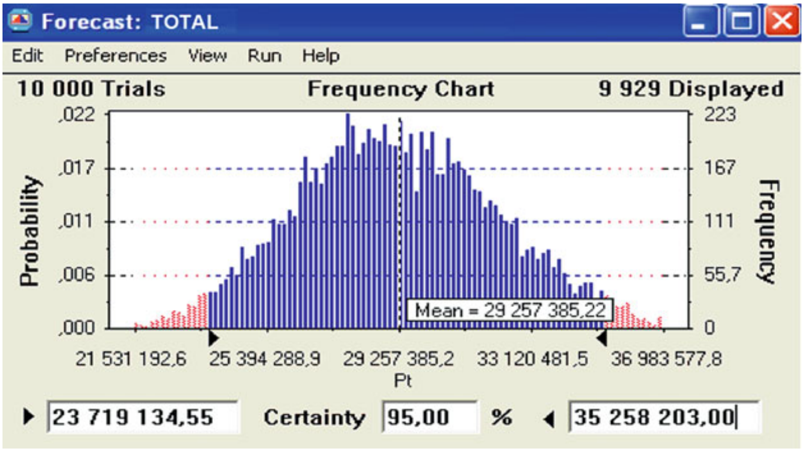
Fig. 4.25 The Forecast frequency chart: S2 scenario TOTAL (95% confidence level) (Source: Own work)

The MC simulation results have then been used to perform tornado sensitivity analyses, presented in the form of tornado charts (Figs. 4.40–4.43) and spider charts (Figs. 4.44–4.47). By presenting the usefulness of individual input variables, the sensitivity analysis indicates which variables can be omitted, without the loss of quality, and which cannot be omitted. A more in-depth analysis of the problem can



27 933 420,50 Certainty 95,00 % 39 941 034,25

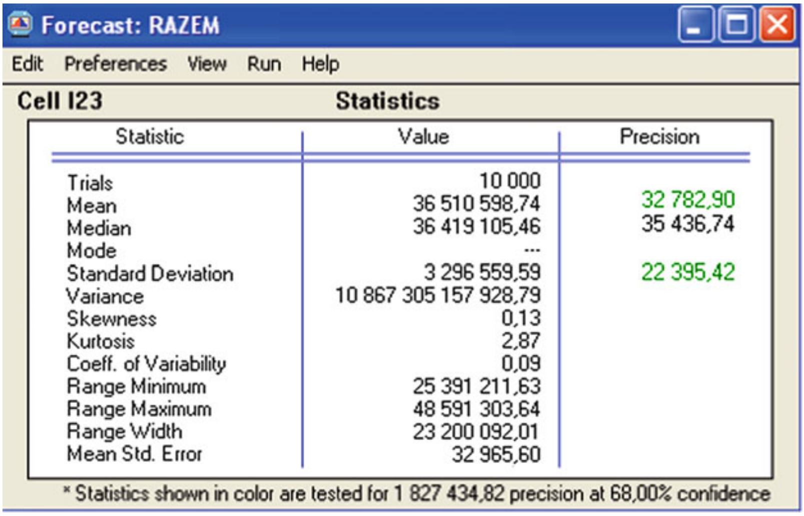
Fig. 4.26 The Forecast frequency chart: S3 scenario TOTAL (95% confidence level) (Source: Own work)



23 719 134,55 Certainty 95,00 % 35 258 203,00

Fig. 4.27 The Forecast frequency chart: S4 scenario TOTAL (95% confidence level) (Source: Own work)

be found in ISO 14041 series (Kowalski et al. 2007). The variables with zero per cent usefulness, as indicated by sensitivity analysis (Figs. 4.36–4.39), are not included in the construction of tornado and spider charts. In all of the scenarios, this relates to: Respiratory system – organic compounds, Eco-toxicity, Ozone layer, Minerals, and Radiation.

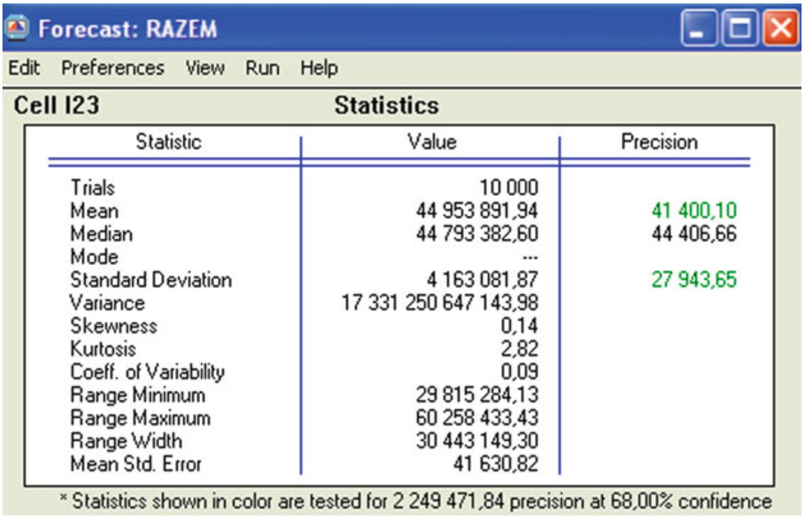


Cell I23 Statistics

Statistic	Value	Precision
Trials	10 000	
Mean	36 510 598,74	32 782,90
Median	36 419 105,46	35 436,74
Mode	---	
Standard Deviation	3 296 559,59	22 395,42
Variance	10 867 305 157 928,79	
Skewness	0,13	
Kurtosis	2,87	
Coeff. of Variability	0,09	
Range Minimum	25 391 211,63	
Range Maximum	48 591 303,64	
Range Width	23 200 092,01	
Mean Std. Error	32 965,60	

* Statistics shown in color are tested for 1 827 434,82 precision at 68,00% confidence

Fig. 4.28 The Forecast statistics report: S1 scenario TOTAL – *Statistics* (Source: Own work)



Cell I23 Statistics

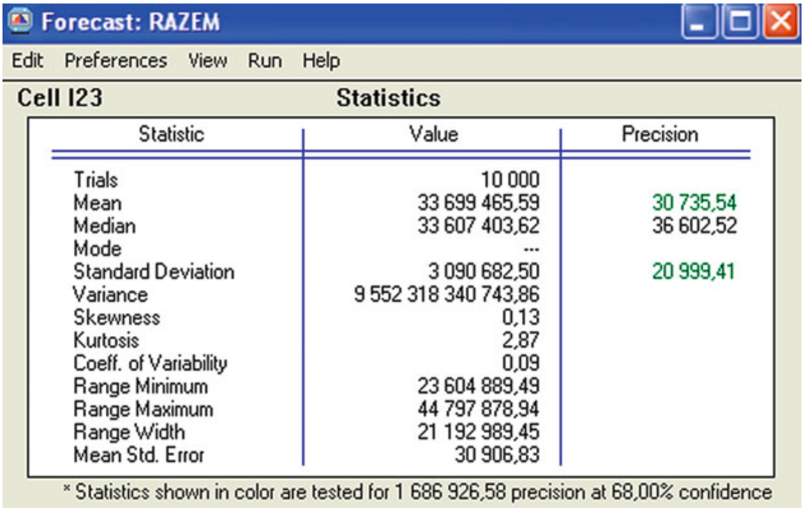
Statistic	Value	Precision
Trials	10 000	
Mean	44 953 891,94	41 400,10
Median	44 793 382,60	44 406,66
Mode	---	
Standard Deviation	4 163 081,87	27 943,65
Variance	17 331 250 647 143,98	
Skewness	0,14	
Kurtosis	2,82	
Coeff. of Variability	0,09	
Range Minimum	29 815 284,13	
Range Maximum	60 258 433,43	
Range Width	30 443 149,30	
Mean Std. Error	41 630,82	

* Statistics shown in color are tested for 2 249 471,84 precision at 68,00% confidence

Fig. 4.29 The Forecast statistics report: S2 scenario TOTAL – *Statistics* (Source: Own work)

4.13.1 Tornado Chart

In order to construct tornado charts, certain parameters in the Tornado Chart dialog window need to be set by activating the two buttons (“use existing cell values” and

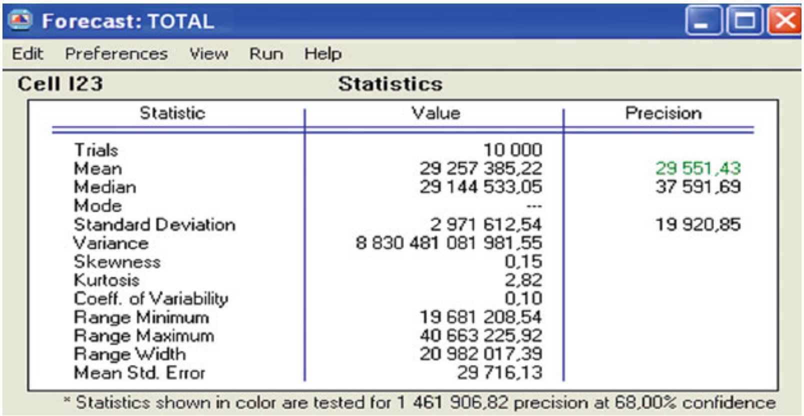


Cell I23 Statistics

Statistic	Value	Precision
Trials	10 000	
Mean	33 699 465,59	30 735,54
Median	33 607 403,62	36 602,52
Mode	---	
Standard Deviation	3 090 682,50	20 999,41
Variance	9 552 318 340 743,86	
Skewness	0,13	
Kurtosis	2,87	
Coeff. of Variability	0,09	
Range Minimum	23 604 889,49	
Range Maximum	44 797 878,94	
Range Width	21 192 989,45	
Mean Std. Error	30 906,83	

* Statistics shown in color are tested for 1 686 926,58 precision at 68,00% confidence

Fig. 4.30 The Forecast statistics report: S3 scenario TOTAL – *Statistics* (Source: Own work)



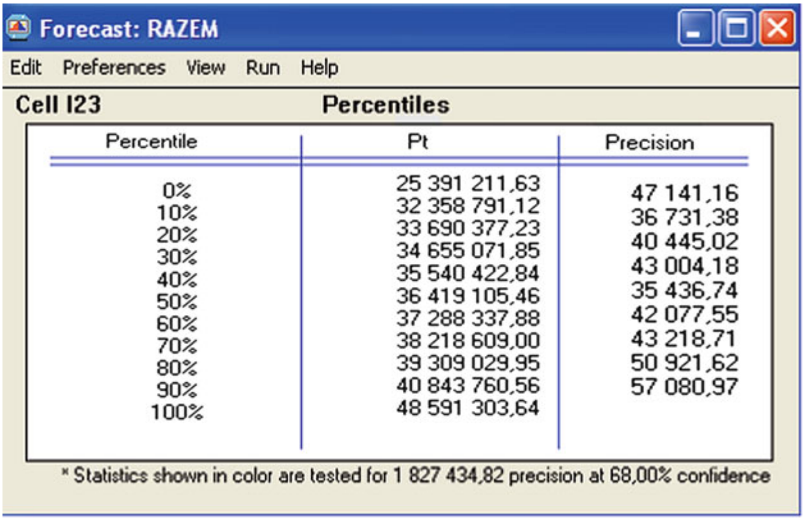
Cell I23 Statistics

Statistic	Value	Precision
Trials	10 000	
Mean	29 257 385,22	29 551,43
Median	29 144 533,05	37 591,69
Mode	---	
Standard Deviation	2 971 612,54	19 920,85
Variance	8 830 481 081 981,55	
Skewness	0,15	
Kurtosis	2,82	
Coeff. of Variability	0,10	
Range Minimum	19 681 208,54	
Range Maximum	40 663 225,92	
Range Width	20 982 017,39	
Mean Std. Error	29 716,13	

* Statistics shown in color are tested for 1 461 906,82 precision at 68,00% confidence

Fig. 4.31 The Forecast statistics report: S4 scenario TOTAL – *Statistics* (Source: Own work)

"percentiles of the variables"), as can be seen in Fig. 4.48, which shows the last, third, step, in modelling the process of building charts. When interpreting the charts presented in Figs. 4.36–4.39, it has been decided that impact categories, with zero per cent usefulness, are not included in further calculations. Tornado charts, presented in Figs. 4.40–4.43, have been constructed using data included in sensitivity tables (Tables 4.3–4.6). The wider the variability interval of the impact category, presented in different charts (horizontal bars), the greater the influence of that factor on the total value of the impact on the environment. Next to each bar



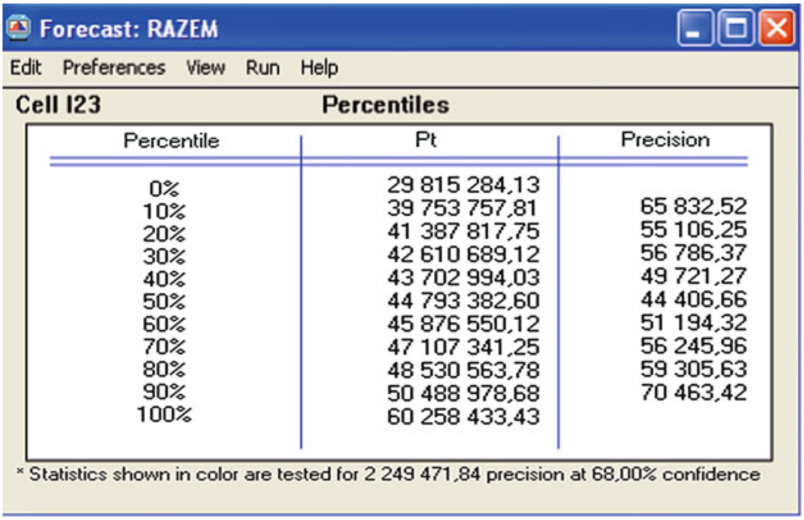
Cell I23

Percentiles

Percentile	Pt	Precision
0%	25 391 211,63	
10%	32 358 791,12	47 141,16
20%	33 690 377,23	36 731,38
30%	34 655 071,85	40 445,02
40%	35 540 422,84	43 004,18
50%	36 419 105,46	35 436,74
60%	37 288 337,88	42 077,55
70%	38 218 609,00	43 218,71
80%	39 309 029,95	50 921,62
90%	40 843 760,56	57 080,97
100%	48 591 303,64	

* Statistics shown in color are tested for 1 827 434,82 precision at 68,00% confidence

Fig. 4.32 The Forecast statistics report: S1 scenario TOTAL – *Percentiles* (Source: Own work)



Cell I23

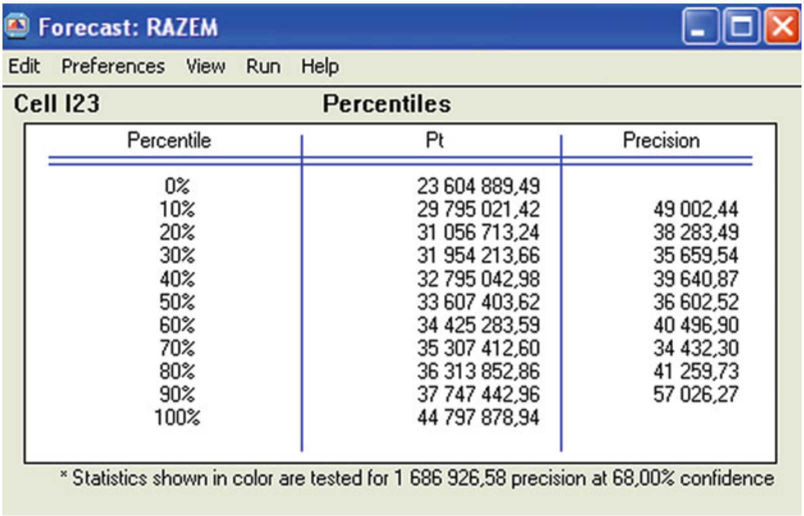
Percentiles

Percentile	Pt	Precision
0%	29 815 284,13	
10%	39 753 757,81	65 832,52
20%	41 387 817,75	55 106,25
30%	42 610 689,12	56 786,37
40%	43 702 994,03	49 721,27
50%	44 793 382,60	44 406,66
60%	45 876 550,12	51 194,32
70%	47 107 341,25	56 245,96
80%	48 530 563,78	59 305,63
90%	50 488 978,68	70 463,42
100%	60 258 433,43	

* Statistics shown in color are tested for 2 249 471,84 precision at 68,00% confidence

Fig. 4.33 The Forecast statistics report: S2 scenario TOTAL – *Percentiles* (Source: Own work)

there is a calculated value of the parameters within the upper and lower interval ranges, calculated from the base value of individual impact categories, for the defined probability distribution. The explanation of the different colours of horizontal bars is included in Chap. 2. The red intermittent line points out the base value of the TOTAL expression – total influence on the environment. Error bars indicate standard error.

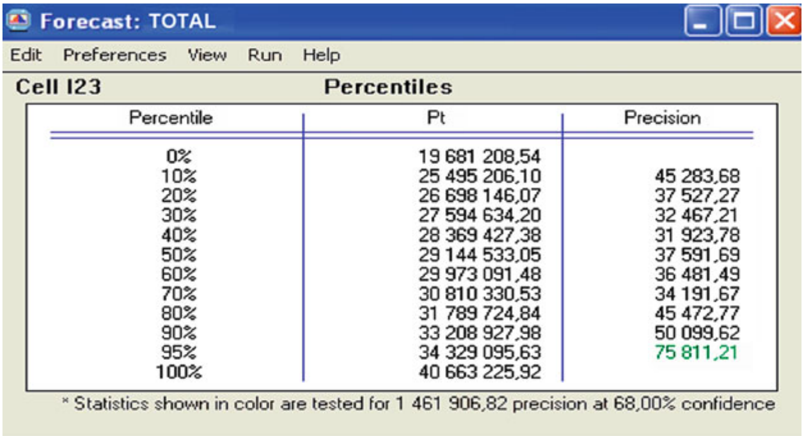


Cell I23 Percentiles

Percentile	Pt	Precision
0%	23 604 889,49	
10%	29 795 021,42	49 002,44
20%	31 056 713,24	38 283,49
30%	31 954 213,66	35 659,54
40%	32 795 042,98	39 640,87
50%	33 607 403,62	36 602,52
60%	34 425 283,59	40 496,90
70%	35 307 412,60	34 432,30
80%	36 313 852,86	41 259,73
90%	37 747 442,96	57 026,27
100%	44 797 878,94	

* Statistics shown in color are tested for 1 686 926,58 precision at 68,00% confidence

Fig. 4.34 The Forecast statistics report: S3 scenario TOTAL – *Percentiles* (Source: Own work)



Cell I23 Percentiles

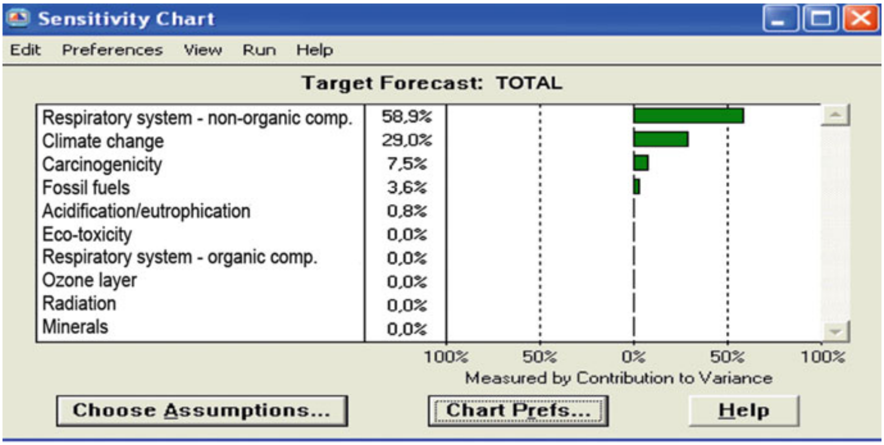
Percentile	Pt	Precision
0%	19 681 208,54	
10%	25 495 206,10	45 283,68
20%	26 698 146,07	37 527,27
30%	27 594 634,20	32 467,21
40%	28 369 427,38	31 923,78
50%	29 144 533,05	37 591,69
60%	29 973 091,48	36 481,49
70%	30 810 330,53	34 191,67
80%	31 789 724,84	45 472,77
90%	33 208 927,98	50 099,62
95%	34 329 095,63	75 811,21
100%	40 663 225,92	

* Statistics shown in color are tested for 1 461 906,82 precision at 68,00% confidence

Fig. 4.35 The Forecast statistics report: S1 scenario TOTAL – *Percentiles* (Source: Own work)

4.13.2 Spider Chart

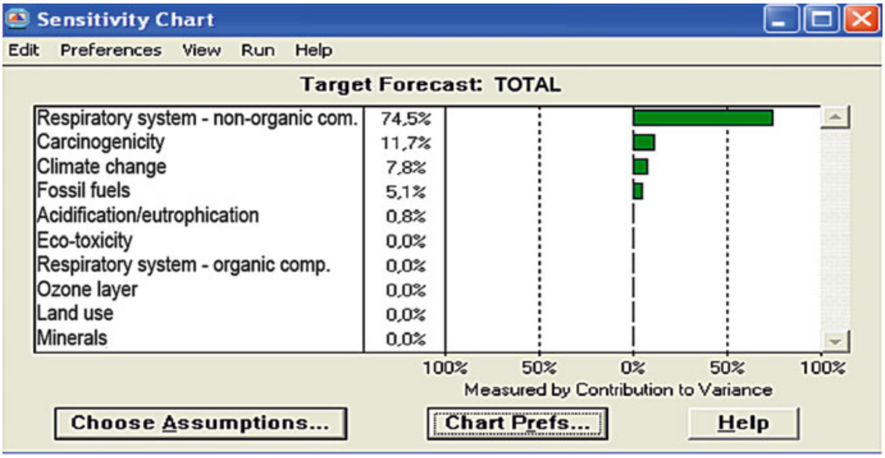
Spider charts are created using the database, included in Tables 4.7–4.10, which have been completed with the results obtained in the MC simulation, after activating the button (Spider chart) in the Tornado chart dialog window (Fig. 4.16). The charts consist of five series of data. The reported key impact categories (excluding the impact categories of zero per cent usefulness that can



Target Forecast: TOTAL

Respiratory system - non-organic comp.	58,9%
Climate change	29,0%
Carcinogenicity	7,5%
Fossil fuels	3,6%
Acidification/eutrophication	0,8%
Eco-toxicity	0,0%
Respiratory system - organic comp.	0,0%
Ozone layer	0,0%
Radiation	0,0%
Minerals	0,0%

Fig. 4.36 Sensitivity analysis for the S1 scenario – present state – 62% of energy comes from hard coal, 38% from blast furnace gas (Source: Own work)



Target Forecast: TOTAL

Respiratory system - non-organic com.	74,5%
Carcinogenicity	11,7%
Climate change	7,8%
Fossil fuels	5,1%
Acidification/eutrophication	0,8%
Eco-toxicity	0,0%
Respiratory system - organic comp.	0,0%
Ozone layer	0,0%
Land use	0,0%
Minerals	0,0%

Fig. 4.37 Sensitivity analysis for the S2 scenario – an assumption that 100% of energy comes from hard coal (Source: Own work)

be omitted without any loss of quality) constitute these data series. They can be found in Figs. 4.44–4.47. The horizontal x axis maps the location measure of distribution expressed in percentages (it measures the concentration of units, as percentages) ranging from 10% to 90%. The greater the incline of the line describing the value of the total environmental impact, the more critical the input variable becomes.

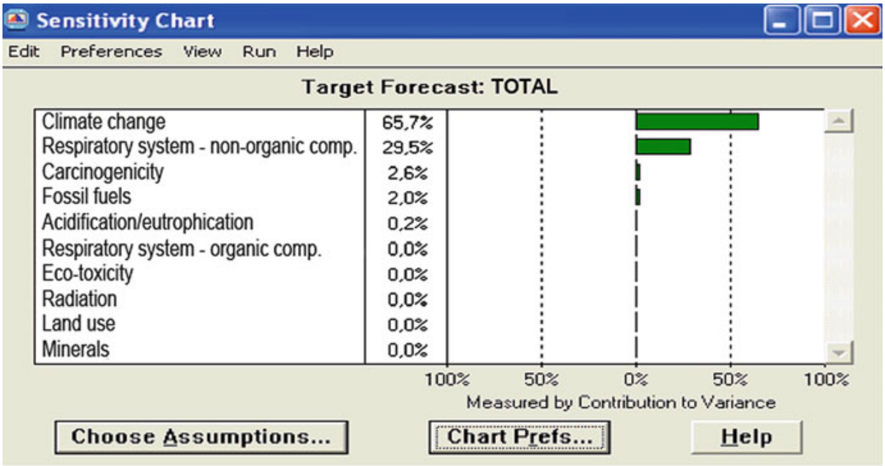
Yet another form of graphic presentation of variables is a spider chart, or diagram, also known as radar chart or M^2 chart, presented in Figs. 4.49 and 4.50. These charts

Target Forecast: TOTAL

Respiratory system - non organic comp.	39,0%
Climate change	33,2%
Carcinogenicity	24,1%
Fossil fuels	3,1%
Acidification/eutrophication	0,6%
Land use	0,0%
Eco-toxicity	0,0%
Radiation	0,0%
Ozone layer	0,0%
Respiratory system - organic comp.	0,0%

Measured by Contribution to Variance

Fig. 4.38 Sensitivity analysis for the S3 scenario – an assumption that fuels are dosed in equal percentages (Source: Own work)



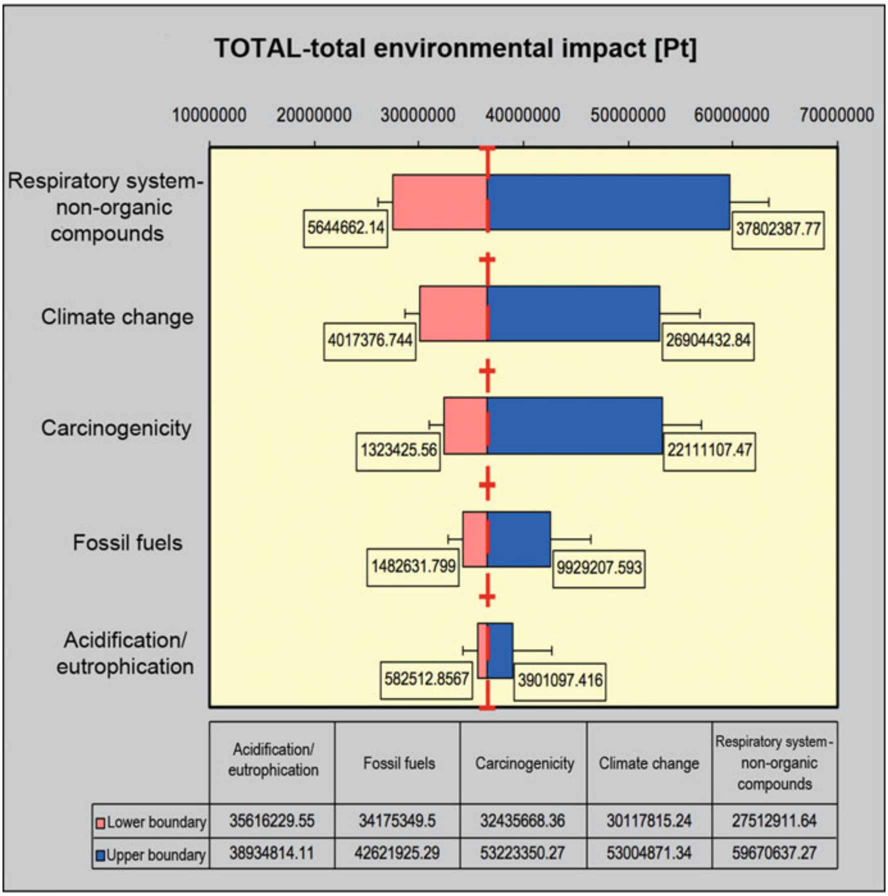
Target Forecast: TOTAL

Climate change	65,7%
Respiratory system - non-organic comp.	29,5%
Carcinogenicity	2,6%
Fossil fuels	2,0%
Acidification/eutrophication	0,2%
Respiratory system - organic comp.	0,0%
Eco-toxicity	0,0%
Radiation	0,0%
Land use	0,0%
Minerals	0,0%

Measured by Contribution to Variance

Fig. 4.39 Sensitivity analysis for the S4 scenario – an assumption that 30% of energy comes from hard coal, 70% from blast furnace gas (Source: Own work)

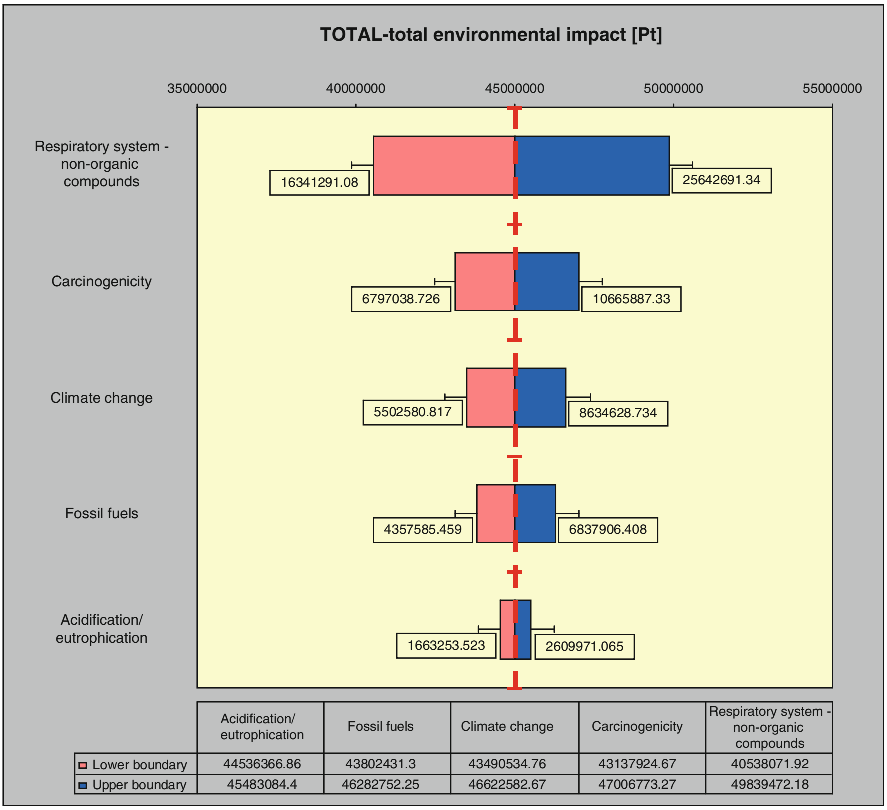
consist of four series of data including the total values of environmental impact in each of the four individual scenarios (scenario S1–scenario S4). The application of spider charts makes it possible to compare the four areas (scenarios) by simultaneously employing five key impact categories (Fig. 4.49) as well as all eleven (Fig. 4.50) impact categories (Keeshley et al. 1996). According to Ziębicki (2005), this type of diagram was first used by Eastman Kodak, a company that received the International Benchmarking Clearinghouse award for the development and pioneering application of the diagram (Bogan and English 1994). In the analysed



	Acidification/ eutrophication	Fossil fuels	Carcinogenicity	Climate change	Respiratory system-non-organic compounds
🟥Lower boundary	35616229.55	34175349.5	32435668.36	30117815.24	27512911.64
🟦Upper boundary	38934814.11	42621925.29	53223350.27	53004871.34	59670637.27

Fig. 4.40 Tornado sensitivity chart of the S1 scenario. Error bars indicate mean standard error (Source: Own work)

diagram the vertical lines describe measuring instruments (impact categories), criteria whose number can be anything between 4 and 16 (Harrington 1996). The lines shaping the "spider web" function as a scale that demonstrates the achieved value of a given criterion (main grid lines of the value's axis). In the next step, the data concerning the given process's scenario is placed in the graph and joined together. As a result, the spider chart enables the possibility to simultaneously compare the examined impact categories for all four scenarios. In a spider chart, the greater the distance between the lines representing different scenarios, the higher the sensitivity of the total environmental impact on the given input variable (in Fig. 4.49 the difference between scenario S2 and scenario S4 is the biggest for that category (the variable: Respiratory system – non-organic compounds)).



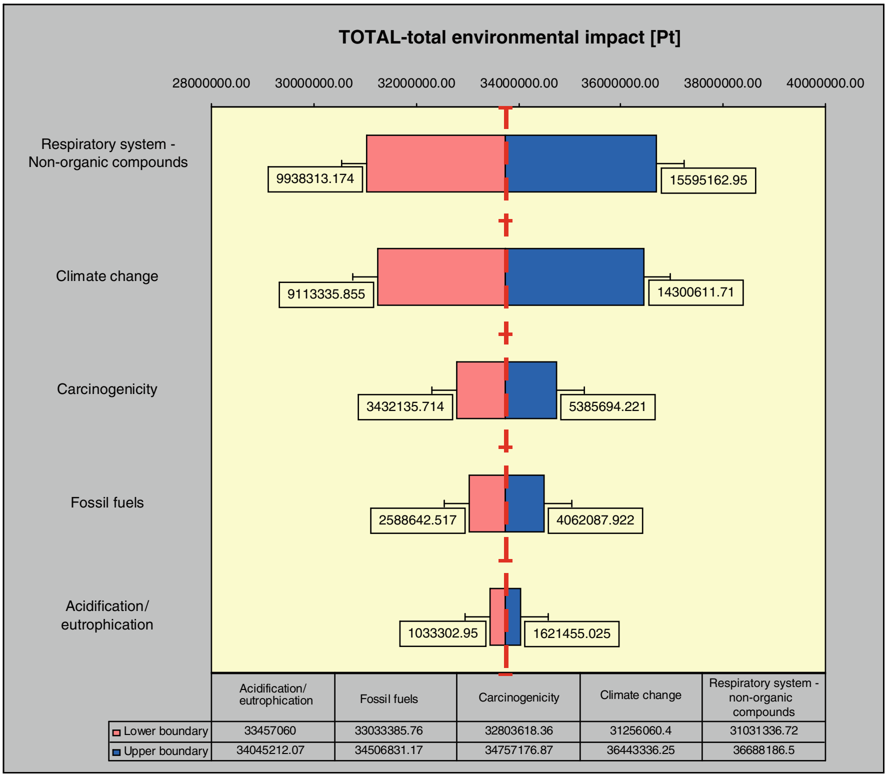
	Acidification/ eutrophication	Fossil fuels	Climate change	Carcinogenicity	Respiratory system - non-organic compounds
🟥 Lower boundary	44536366.86	43802431.3	43490534.76	43137924.67	40538071.92
🟦 Upper boundary	45483084.4	46282752.25	46622582.67	47006773.27	49839472.18

Fig. 4.41 Tornado sensitivity chart of the S2 scenario. Error bars indicate mean standard error (Source: Own work)

The conducted LCA analysis has made it possible to determine to what extent the energy production processes in the Power Plant are affecting the environment. It is worth remembering that the processes chosen from the database and used during the analysis do not relate to Polish conditions and have been subjected to averaging, which may at times be a cause of incorrect results.

The potential environmental strain is the greatest when it is caused by the sulphur dioxide (SO_2) and nitric oxide (NO_x – when expressed in nitrogen dioxide) emissions – this has a negative impact on the respiratory system – non-organic compounds category. This concerns the S1, S2, and S3 scenarios and is connected to coal combustion (by burning less coal the SO_2 emissions are reduced). The SO_2 emitted from the Power Plant comes from two sources (Wniosek 2006):

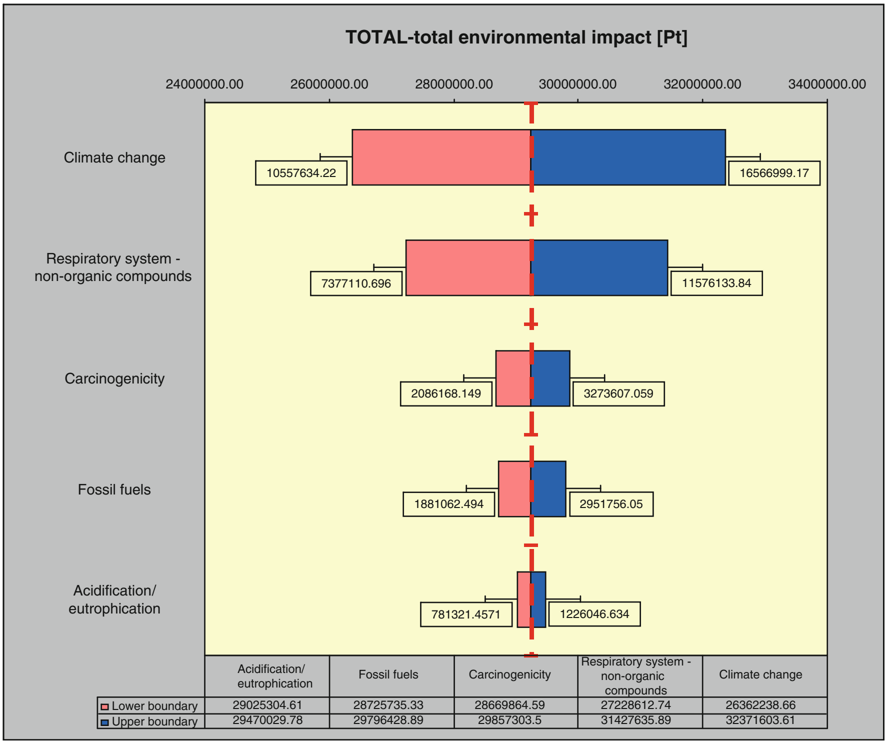
1. Desulfurised hard coal with an average content of 0.7% S (according to an administrative decision coal with a content of 0.8% S should be burned)
2. Purified coke oven gas, containing approximately 0.5 H_2S/Nm_3. SO_2 from coke oven gas constitutes the trace values (majority of which comes from coal).



	Acidification/ eutrophication	Fossil fuels	Carcinogenicity	Climate change	Respiratory system - non-organic compounds
🟥 Lower boundary	33457060	33033385.76	32803618.36	31256060.4	31031336.72
🟦 Upper boundary	34045212.07	34506831.17	34757176.87	36443336.25	36688186.5

Fig. 4.42 Tornado sensitivity chart of the S3 scenario. Error bars indicate mean standard error (Source: Own work)

As far as the S4 scenario is concerned, the large percentage share of combusted blast furnace gas increases the emissions of carbon dioxide (CO_2), the factor influencing climate change, which leads to a situation where the climate change category in fact becomes a key impact category. In the case of S1 and S3, the climate change category is the second most important one. The second type of gas influencing the climate change impact category is methane (CH_4), which is not included in the LCA analysis, as, despite the fact that it is a greenhouse gas mentioned in the emissions trading act, in the analysed period (i.e. the year 2005), methane was not subject to European trade regulations and was not mentioned in the application for an integrated permit (Wniosek 2006). If the European Commission recognises the need to limit methane's emissions, it will then publish the allocation of emissions and the percentage of reduction in the next stage of trade. In addition, methane is not limited in the scope of the allowed emissions levels from individual emission sources and facilities. It is only subject to charges for the economic use of the environment – for the emissions to the atmosphere. According to the information received from the Department of Environmental



	Acidification/ eutrophication	Fossil fuels	Carcinogenicity	Respiratory system - non-organic compounds	Climate change
🟥 Lower boundary	29025304.61	28725735.33	28669864.59	27228612.74	26362238.66
🟦 Upper boundary	29470029.78	29796428.89	29857303.5	31427635.89	32371603.61

Fig. 4.43 Tornado sensitivity chart of the S4 scenario. Error bars indicate mean standard error (Source: Own work)

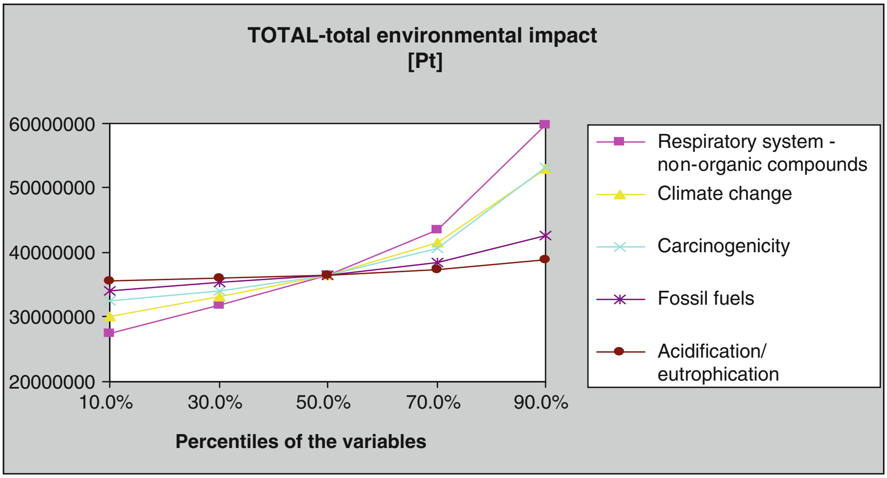


Fig. 4.44 Spider sensitivity chart of the S1 scenario (Source: Own work)

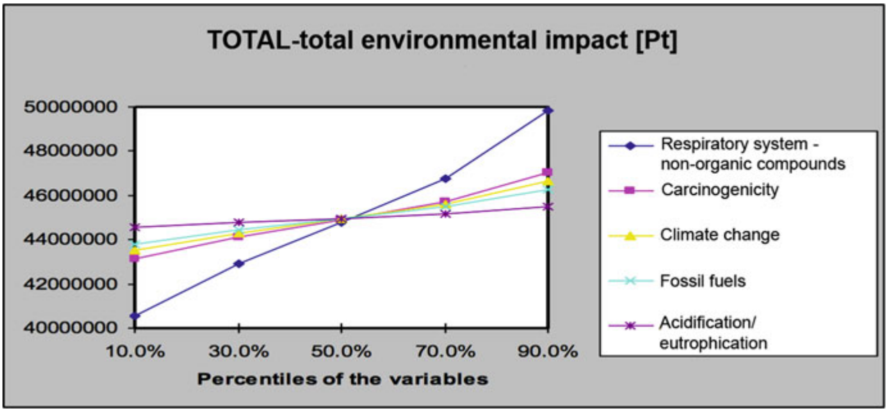


Fig. 4.45 Spider sensitivity chart of the S2 scenario (Source: Own work)

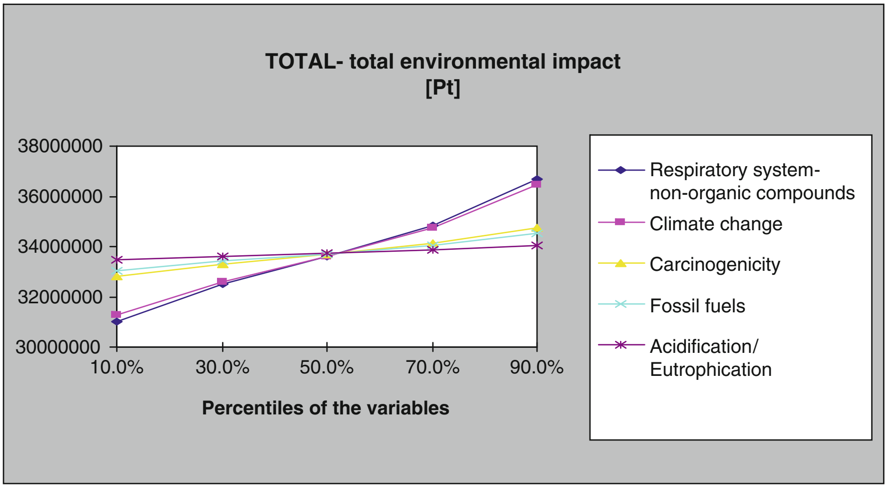


Fig. 4.46 Spider sensitivity chart of the S3 scenario (Source: Own work)

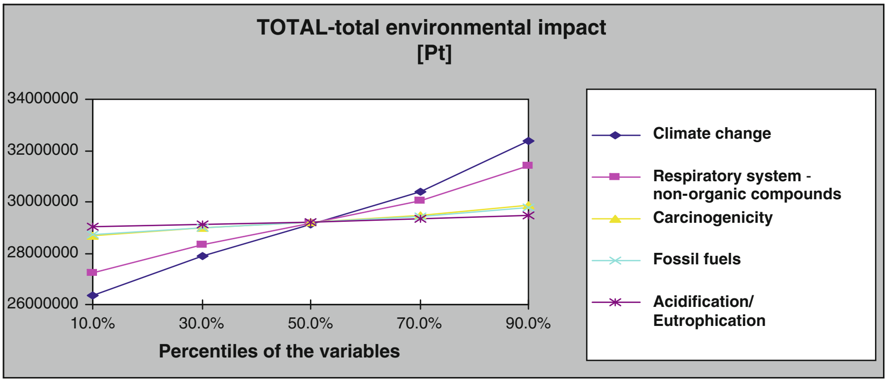
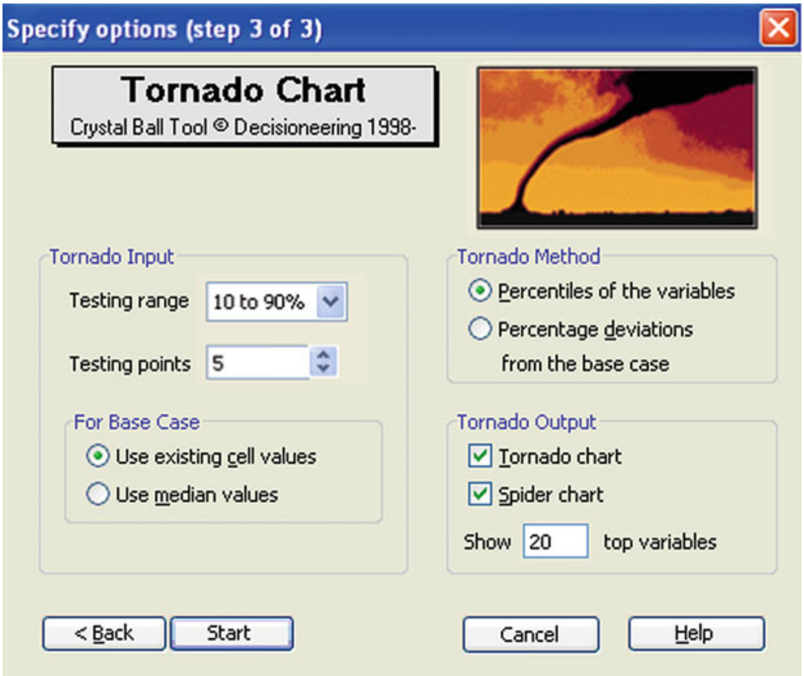


Fig. 4.47 Spider sensitivity chart of the S4 scenario (Source: Own work)



Specify options (step 3 of 3)

Tornado Chart

Crystal Ball Tool © Decisioneering 1998-

Tornado Input

Testing range 10 to 90%

Testing points 5

For Base Case

● Use existing cell values

○ Use median values

Tornado Method

● Percentiles of the variables

○ Percentage deviations from the base case

Tornado Output

☑ Tornado chart

☑ Spider chart

Show 20 top variables

Fig. 4.48 The final view of the Tornado Chart dialog window in the process of entering sensitivity analysis parameters with the Tornado chart and Spider chart options ticked

Protection at MSP, the amount of methane emitted by the Power Plant complex in 2005 was measured to be 575.08 Mg.

The category that is next in line, in terms of its size, which can be potentially affected by the energy production processes in the Power Plant, is the carcinogenicity category. In this case, most of the influence comes from the application of a certain type of hard coal in the analysis – the choice of another type of coal would lead to different results being achieved. Nevertheless, hard coal is the chosen type of fuel picked from the database, as it seems to refer to Polish conditions very well. Hard coal is extracted in Eastern Europe from underground mines and in its inventory table it has: explosive materials, steel, wood, fuel for coal mining machines, methane emission, dust, etc. The difference lies in the methods of its enrichment – in the coal chosen from the database enrichment by floatation is used, whereas in Poland dense liquid separation is used that does not generate flotation tailings. What influences carcinogenicity the most is arsenic – included in coal and ash. Arsenic and nickel are among the trace elements. Olkulski (2004) quotes Jasieńko et al. (1995) that according to Goldchmidt (1952), trace elements, also known as microelements, could occur in coal as a result of the vegetation period of plants that formed coal during the decomposition of plants in the biochemical process or during the decomposition in the geochemical stage.

Table 4.3 The MC simulation results, using CB® software, of the S1 scenario's sensitivity in the tornado analysis – sensitivity table

Variable	Total – environmental impact			Input parameters		
Impact category	Lower boundary	Upper boundary	Range	Lower boundary	Upper boundary	Base value
Respiratory system – non-organic compounds	27,512,911.64	59,670,637.27	32,157,725.63	5,644,662.14	37,802,387.77	14,680,447
Climate change	30,117,815.24	53,004,871.34	22,887,056.1	4,017,376.744	26,904,432.84	10,448,258
Carcinogenicity	32,435,668.36	53,223,350.27	20,787,681.91	1,323,425.56	22,111,107.47	5,436,453.7
Fossil fuels	34,175,349.5	42,621,925.29	8,446,575.794	1,482,631.799	9,929,207.593	3,855,978.8
Acidification/eutrophication	35,616,229.55	38,934,814.11	3,318,584.56	582,512.8567	3,901,097.416	1,514,979.8

Table 4.4 The MC simulation results, using CB® software, of the S2 scenario's sensitivity in the tornado analysis – sensitivity table

Variable	Total – environmental impact			Input parameters		
Impact category	Lower boundary	Upper boundary	Range	Lower boundary	Upper boundary	Base value
Respiratory system – non-organic compounds	40,538,071.92	49,839,472.18	9,301,400.267	16,341,291.08	25,642,691.34	20,792,656
Carcinogenicity	43,137,924.67	47,006,773.27	3,868,848.605	6,797,038.726	10,665,887.33	8,648,550.9
Climate change	43,490,534.76	46,622,582.67	3,132,047.917	5,502,580.817	8,634,628.734	7,001,482.9
Fossil fuels	43,802,431.3	46,282,752.25	2,480,320.949	4,357,585.459	6,837,906.408	5,544,591
Acidification/eutrophication	44,536,366.86	45,483,084.4	946,717.5422	1,663,253.523	2,609,971.065	2,116,323.5

Table 4.5 The MC simulation results, using $CB^{®}$ software, of the S3 scenario's sensitivity in the tornado analysis – sensitivity table

Variable	Total – environmental impact			Input parameters		
Impact category	Lower boundary	Upper boundary	Range	Lower boundary	Upper boundary	Base value
Respiratory system – non-organic compounds	31,031,336.72	36,688,186.5	5,656,849.78	9,938,313.174	15,595,162.95	12,645,508
Climate change	31,256,060.4	36,443,336.25	5,187,275.85	9,113,335.855	14,300,611.71	11,595,807
Carcinogenicity	32,803,618.36	34,757,176.87	1,953,558.507	3,432,135.714	5,385,694.221	4,367,048.9
Fossil fuels	33,033,385.76	34,506,831.17	1,473,445.405	2,588,642.517	4,062,087.922	3,293,788.3
Acidification/eutrophication	33,457,060	34,045,212.07	588,152.0745	1,033,302.95	1,621,455.025	1,314,774.5

Table 4.6 The MC simulation results, using $CB^{®}$ software, of the S4 scenario's sensitivity in the tornado analysis – sensitivity table

Variable	Total – environmental impact			Input parameters		
Impact category	Lower boundary	Upper boundary	Range	Lower boundary	Upper boundary	Base value
Climate change	26,362,238.66	32,371,603.61	6,009,364.942	10,557,634.22	16,566,999.17	13,433,532
Respiratory system – non-organic compounds	27,228,612.74	31,427,635.89	4,199,023.149	7,377,110.696	11,576,133.84	9,386,634.4
Carcinogenicity	28,669,864.59	29,857,303.5	1,187,438.91	2,086,168.149	3,273,607.059	2,654,440
Fossil fuels	28,725,735.33	29,796,428.89	1,070,693.556	1,881,062.494	2,951,756.05	2,393,463.6
Acidification/eutrophication	29,025,304.61	29,470,029.78	444,725.1773	781,321.4571	1,226,046.634	994,153.29

Table 4.7 The MC simulation results, using CB® software, of the S1 scenario's sensitivity in the spider analysis – sensitivity table

Variable	Total – environmental impact				
Impact category	10.0%	30.0%	50.0%	70.0%	90.0%
Respiratory system – non-organic compounds	27,512,911.64	31,767,598.27	36,475,840.23	43,423,375.18	59,670,637.27
Climate change	30,117,815.24	33,145,929.01	36,496,843.78	41,441,491.42	53,004,871.34
Carcinogenicity	32,435,668.36	34,152,794.35	36,521,716.41	40,736,287.75	53,223,350.27
Fossil fuels	34,175,349.5	35,292,889.14	36,529,560.01	38,354,405.5	42,621,925.29
Acidification/eutrophication	35,616,229.55	36,055,300.95	36,541,177.94	37,258,143.52	38,934,814.11

Table 4.8 The MC simulation results, using CB® software, of the S2 scenario's sensitivity in the spider analysis – sensitivity table

Variable	Total – environmental impact				
Impact category	10.0%	30.0%	50.0%	70.0%	90.0%
Respiratory system – non-organic compounds	40,538,071.92	42,935,284.94	44,783,780.61	46,783,169.02	49,839,472.18
Carcinogenicity	43,137,924.67	44,135,027.64	44,903,895.71	45,735,526.52	47,006,773.27
Climate change	43,490,534.76	44,297,745.05	44,920,186.5	45,593,437.85	46,622,582.67
Fossil fuels	43,802,431.3	44,441,674.58	44,934,596.34	45,467,755.31	46,282,752.25
Acidification/eutrophication	44,536,366.86	44,780,360.62	44,968,504.69	45,172,006.96	45,483,084.4

Table 4.9 The MC simulation results, using CB® software, of the S3 scenario's sensitivity in the spider analysis – sensitivity table

Variable	Total – environmental impact				
Impact category	10.0%	30.0%	50.0%	70.0%	90.0%
Respiratory system – non-organic compounds	31,031,336.72	32,489,254.19	33,613,457.22	34,829,428.96	36,688,186.5
Climate change	31,256,060.4	32,592,956.45	33,623,839.61	34,738,873.79	36,443,336.25
Carcinogenicity	32,803,618.36	33,307,101.25	33,695,337.9	34,115,266.31	34,757,176.87
Fossil fuels	33,033,385.76	33,413,131.01	33,705,953.31	34,022,678.71	34,506,831.17
Acidification/eutrophication	33,457,060	33,608,642.1	33,725,527.36	33,851,953.96	34,045,212.07

Table 4.10 The MC simulation results, using CB® software, of the S4 scenario's sensitivity in the spider analysis – sensitivity table

Variable	Total				
Impact category	10.0%	3.0%	50.0%	70.0%	90.0%
Climate change	26,362,238.66	27,911,008.47	29,105,267.91	30,397,014.78	32,371,603.61
Respiratory system – non-organic compounds	27,228,612.74	28,310,810.33	29,145,295.02	30,047,898.71	31,427,635.89
Carcinogenicity	28,669,864.59	28,975,898.51	29,211,881.87	29,467,128.56	29,857,303.5
Fossil fuels	28,725,735.33	29,001,680.94	29,214,463.14	29,444,614.76	29,796,428.89
Acidification/eutrophication	29,025,304.61	29,139,921.87	29,228,303.46	29,323,899.64	29,470,029.78

Entries 18–43 create a new process – Siłownia-E (E-Power-Plant)

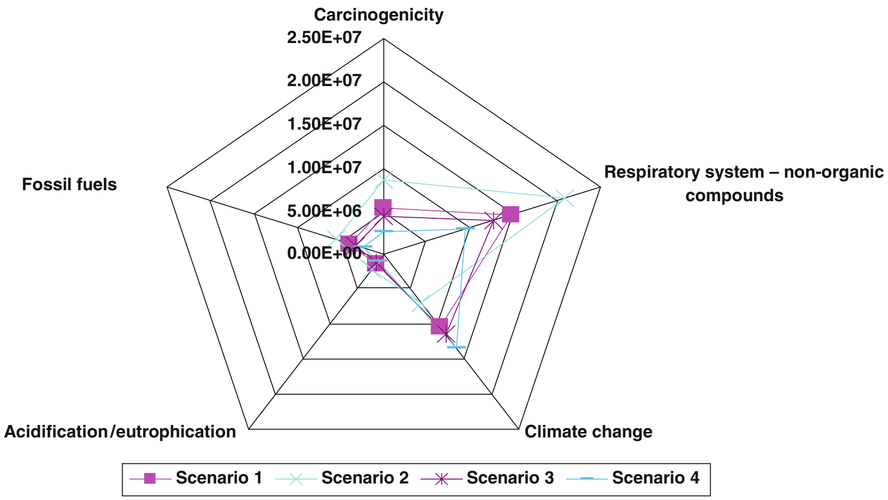


Fig. 4.49 The sensitivity spider chart of four key impact categories (Source: Own work)

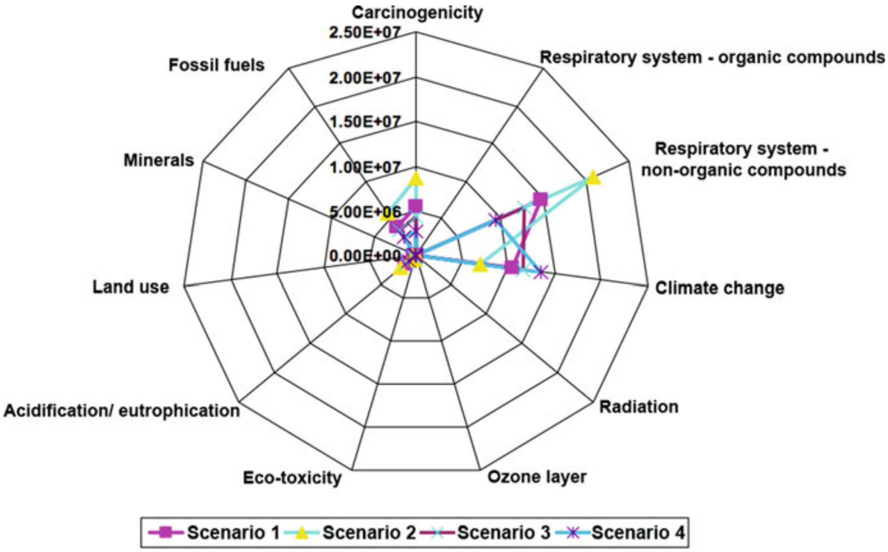


Fig. 4.50 The sensitivity spider chart of (all) 11 impact categories (Source: Own work)

The direct use of hard coal and natural gas, as well as partially the use of natural gas and crude oil in energy production processes constitutes the considerable strain on the fossil fuel impact category.

In the fourth place, in all of the four scenarios, is the fossil fuel impact category. The last place is occupied by acidification/eutrophication category. The acidification/ eutrophication category is largely influenced by the emission of sulphur and nitric oxide – the causes of the so-called acid rain.

Among the most commonly popularised contaminants in fossil fuels, is sulphur (S). According to the information received from the Department of Environmental Protection at MSP, the dust emitted from MSP Power Plant comes from hard coal, with a year-average content of 21% of ash. The power coal for the Power Plant comes from the mines that belong to Katowicki Holding Węglowy, a coal producer based in Katowice, Poland. During the coal burning process, in the boiler, 20% of ash is converted into slag and 80% in the form of fly-ash goes electrostatic precipitators (each of the seven boilers has its own electrostatic precipitator). The average effectiveness of the electrostatic precipitators is around 99.3%; thus, 0.7% of fly-ash is emitted. It is argued (Kucowski et al. 1997) that the arsenic (As) and nickel (Ni) content in coal is shaped accordingly within the boundaries from 1.0 to 7.0 g/Mg (As) and from 6.0 to 48.0 g/Mg (Ni). During the burning processes some of the trace elements are converted to ash and some join the group of ashes and gases that are emitted to the atmosphere (Okulski 2004). The acidification/eutrophication category is largely influenced by the emission of sulphur and nitric oxide – the cause of the so-called acid rain.

The remaining categories constitute less than 5% of the impact.

4.14 Summary and Conclusion

In conclusion, after analysing Figs. 4.22, 4.26, 4.30, 4.34 and 4.27, 4.31, 4.35, 4.36, 4.37, 4.38, 4.39, 4.48 it is safe to evaluate that the respiratory system – non-organic compounds category has the greatest potential impact on the environment during the energy production processes in the Power Plant in scenarios S1, S2, and S3. In the S4 scenario, it is the second most influential category that has an impact on the environment.

The climate change category has the greatest environmental impact in the S4 scenario, while in the scenarios S1 and S2 it is the second most influential category that has an impact on the environment. In the S3 scenario, it is the third biggest category, in terms of its impact on the quality of natural environment.

The carcinogenicity category in the S2 scenario is the second biggest category influencing the environment, while in the S1, S3, and S4 scenarios it occupies the third position.

The fossil fuels and the acidification/eutrophication categories are the fourth and fifth impact categories that influence the quality of natural environment in all four scenarios (S1–S4).

What causes serious difficulty in the field of correct interpretation of acidifying effects of emissions is the awareness of the common nature of this type of a process and the users' disregard for the natural tendencies such as soil washing, which are climate-conditioned, presented in the context of the process's results being less visible due to the well-buffered soil in this area. The fact that this region is largely loessic, generally means that strong decalcification occurs, often below the depth of 70–80 cm, which signifies that the natural carbohydrates content is significantly reduced as a result of the effects of acidifying factors that over the years have affected this area; factors that are not necessarily of industrial nature. To sum up these comments, a conclusion might be reached that the acidifying effects of industrial emissions have very limited importance in the chemism of soils, especially since they are balanced by the addition of alkalising substances.

Chlorine is a contaminant whose average concentration in coal amounts to 0.15%. Burning of coal results in the emissions of hydrogen chloride (HCI). During the process of burning nitrogen (N_2), present in the atmosphere in large quantities, it oxidises to NO_x – a mixture of nitric oxide (NO) and nitrogen dioxide (NO_2). The amount of NO_x, created in this way, can be compared to the amount of SO_2 obtained from fuel with a high content of sulphur. As mentioned above, nitric oxides are emitted to the atmosphere mostly in the form of NO, as it is more reactive, as a reducing agent, than SO_2, and under the influence of ozone it undergoes oxidation to become nitrogen dioxide (NO_2). NO_2 is not as reactive as NO, but more reactive than SO_2 for its half-life is approximately 1 day. The three, among the most important, pollutant gases: SO_2, NH_3, and O_3 interact with the plants' outer surfaces. Dry deposition of ozone (O_3) on the land surface is the main process of removing O_3 from the boundary layer. NO_x is the symbol used to mark contamination that has nowadays spread in the majority of urbanised regions in the world, where x is an unknown, when it comes to the involvement of NO and NO_2, and its value differs depending on place and time. Most of the experimental data currently available concerns the influence of NO_2. In reality however, the majority of oxidised nitrogen present in the atmosphere is emitted as NO. Sulphur (S) is an important bio-component necessary for a normal growth and development of plants to take place – a fact known for 200 years (Duke 1986). It has also been known for many years that the atmosphere including gaseous compounds of sulphur may have a negative impact on plants (Evelyn 1661). Among these gases SO_2 is believed to be the most important phytotoxic compound (Legge 1998). Runeckles (2004) emphasises that low concentration of SO_2, which positively affects the nutrition status of plants, coupled with the increased content of CO_2, may bring double benefits. The increase of concentration of CO_2 might compensate for the effect of negative influence of close to optimum temperature on the growth of some species of plants, on the grounds of the increased catabolic losses, because of the increased rate of photosynthesis. On the other hand however, the increase in temperature may decrease the protective role of CO_2 from O_3.

The necessity to employ stochastic analysis of environmental impacts of the four scenarios of energy production processes in MSP Power Plant seems to be justified. On the basis of the conducted MC simulation, the uncertainty in the LCA results can be noticed. Thanks to uncertainty analysis, a final result, in the form of value range of the total impact of damage category, expressed in [Pt], is obtained. Nevertheless, this fact is not properly reflected in the deterministic approach to environmental impact analysis of industrial processes. In addition, the MC simulation results have been used in the running of sensitivity analysis, which facilitates the interpretation of the results hence may be very helpful in the simulation research on the environmental impact of industrial processes (in this case the energy production processes in the steel industry), by contributing additional information supporting environmental management.

Chapter 5
Stochastic Analysis, Using Monte Carlo (MC) Simulation, of the Life Cycle Management of Waste, from an Annual Perspective, Generated by MSP

5.1 Introduction

This chapter deals with the application of the MC technique, of stochastic nature, in the description of negative effects of waste produced by MSP facilities on the environment. The ecological life cycle assessment of waste management from an annual perspective has been conducted on the basis of the computer-assisted LCA method. The LCA analysis has been performed for the purposes of the postdoctoral thesis by the Mineral and Energy Economy Research Institute of the Polish Academy of Sciences (PAN), in Kraków (Ocena 2009). The analysis has been compiled by using the generated waste's balance. The findings are expressed in the form of: characterisation, normalisation, and measurement stage results. The analysis has been conducted, similarly to what is described in Chap. 4, in accordance with PN-EN ISO 14040:2006 and PN-EN ISO 14044:2006 series.

The results of the LCA analysis are used to present the stochastic environmental impact analysis of MSP complex, in an annual cycle in 2005. The emphasis is on the more detailed characterisation of uncertainty in LCA studies, by concentrating on the uncertainty of source data. The quantitative data analysis has been performed on the basis of MC simulation.

As far as the chapter's subject matter is concerned, to begin with, the analysis of life cycle management of waste, generated by MSP facilities, is presented in order to show the course of the LCA (Bieda 2008b, d). As is argued by Hoła and Mrozowicz (2003), the realisation of production processes proceeds in time. The Kraków's unit manufactures coke, pig iron and steel (oxygen converters), semi-finished products manufactured by Continuous Casting Machines (CCM), hot and cold rolled sheets, electrogalvanised and hot-dip galvanised sheets, in coils and sheets, longitudinal slit strips, black, electrogalvanised and hot-dip galvanised seamed tubes, black profiled and hot-dip galvanised tubes, but also electric energy, wind of blast furnaces, process steam, heat in heating water, softened water and heated demineralised water (the last six are produced mostly to meet the own needs of MSP).

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The permission to use the appropriate data needed to complete this project was given by the Managing Director of MSP. Unit in Kraków.

5.2 Characterisation of Waste Management in the Discussed Facilities

5.2.1 The Coke Production Facility: Coke Plant

The Coke Production Department includes: a coal processing plant, two coke ovens, a dry coke quenching facility, a boiler house facility, a coke sorting plant, central dust removal machines along with dust monitoring stations, and coke-quenching towers.

The Coke Plant generates the following types of waste: acid tars, liquid waste containing phenols, quick coke from decanters, a mixture of molecular salts and autoclaving condensate, tar deposits from tank cleaning (the above types of waste in the past were treated as waste – they are included in the analysis nonetheless – now they are treated as by-products), sorbents, filtering media, wiping cloths, protective suits, rubber, canvas covers, ink, toners, cases, oven linings and refractory materials from metallurgical processes, concrete waste and concrete waste from demolitions and repairs, mixed waste from concrete, crushed bricks, waste ceramic materials and equipment elements, wood, copper, bronze, brass, iron and steel, mixtures of metals, insulating materials, sludge from biological treatment of industrial sewage, waste that undergoes biodegradation, unsegregated (mixed) solid municipal waste, as well as waste generated during street and site cleaning.

The waste produced in the Coke Plant is re-used, by the Plant itself, whenever possible, in MSP facilities. If however, MSP is unable to recycle waste, it is then forwarded to external buyers (for recycling or neutralisation) or neutralised by depositing it in a landfill.

5.2.2 The Ore Sintering Facility: Sintering Plant

The Sintering Plant produces blast furnace and converter sinters and utilises ferruginous waste generated by the other departments within the Plant.

The following types of waste are produced in the Sintering Plant: solid waste from smelter gases cleaning, sludge and filter cake from smelter gases cleaning, sorbents, filtering media, wiping cloths, protective suits, rubber, canvas covers, worn out devices containing hazardous substances (devices containing mercury, used lamps, fluorescent lamps, sodium-mercury discharge lamps), ink, toners, cases, copper, bronze, brass, aluminium, iron and steel, cables, and unsegregated (mixed) solid municipal waste.

The waste produced in the Sintering Plant is re-used, by the Plant itself, whenever possible, in MSP facilities. If however, MSP is unable to recycle waste, it is then forwarded to external buyers (for recycling or neutralisation) or neutralised by depositing it in a landfill.

5.2.3 The Pig Iron Melting Facility: Blast Furnaces

The pig iron melting facility is part of the Steel Plant – Blast Furnaces Department. The main task of the Blast Furnaces Department is to prepare blast-furnace charges, to produce pig iron in blast furnaces, and to transfer pig iron to the Converter Plant.

Slag is the by-product of blast-furnace processes, which is converted into a granulated product and sold to external buyers. Here, however, it is classified as waste for it received such a classification in the source materials.

The following types of waste are produced in the discussed Department: slag from iron-making processes, solid waste from smelter gases cleaning, sludge and filter cake from smelter gases cleaning, melting losses from ferrous metallurgy, production scrap, engine, gear, and lubricating oils, sorbents, filtering media, wiping cloths, protective suits, rubber, canvas covers, worn out devices containing hazardous substances (devices containing mercury, used lamps, fluorescent lamps, sodium-mercury discharge lamps), oven linings and refractory materials from metallurgical processes, concrete waste and concrete waste from demolitions and repairs, mixed waste from concrete, crushed bricks, waste ceramic materials and equipment elements, copper, bronze, brass, iron and steel, mixtures of metals, insulating materials, and unsegregated (mixed) solid municipal waste.

The waste produced in the pig iron melting facility is re-used, by the Plant itself, whenever possible, in MSP facilities. If however, MSP is unable to recycle waste, it is then forwarded to external buyers (for recycling or neutralisation) or neutralised by depositing it in a landfill.

5.2.4 The Steel Melting Facility: Converter Plant

The steel melting facility is part of the Steel Plant – Steel Converter Plant Department and its aim is to produce liquid steel and ingot steel. The activity of the Converter Plant consists of the following: accepting and storage of charge materials, preparing the charges for converters, production of liquid steel in the converter, casting the steel into ingot moulds or transferring it to the Continuous Steel Casting Department (CSC).

The following types of waste are produced in the Converter Plant: slag from steel-melting processes, unprocessed slag from other processes, solid waste from smelter gases cleaning, sludge and filter cake from smelter gases cleaning, melting losses from ferrous metallurgy, production scrap, engine, gear, and lubricating oils, sorbents, filtering media, wiping cloths, protective suits, rubber, canvas covers, worn out devices containing hazardous substances (devices containing mercury, used lamps, fluorescent lamps, sodium-mercury discharge lamps), lead-acid accumulators and batteries, oven linings and refractory materials from metallurgical processes, mixed waste from concrete, crushed bricks, waste ceramic materials and equipment elements, copper, bronze, brass, aluminium, iron and steel, cables, biodegradable waste, unsegregated (mixed) solid municipal waste, and other unmentioned waste.

The waste produced in the Converter Plant is re-used, by the Plant itself, whenever possible, in MSP facilities. If however, MSP is unable to recycle waste, it is then forwarded to external buyers (for recycling or neutralisation) or neutralised by depositing it in a landfill.

5.2.5 The Continuous Steel Casting Facility: CSC

The Continuous Steel Casting facility is part of the Steel Plant – Continuous Steel Casting Department and its aim is to produce slabs. The facility uses liquid steel from the Steel Converter Plant Department as its resource, and slabs are its final products.

The following types of waste are produced in the discussed Department: melting losses from ferrous metallurgy, paper packaging, plastic boards, sorbents, filtering media, wiping cloths, protective suits, oven linings and refractory materials from metallurgical processes, copper, bronze, brass, iron and steel, and other unmentioned waste.

The waste produced in the Continuous Steel Casting facility is re-used, by the Plant itself, whenever possible, in MSP facilities. If however, MSP is unable to recycle waste, it is then forwarded to external buyers (for recycling or neutralisation) or neutralised by depositing it in a landfill.

5.2.6 The Facility for Hot Rolling of Ferrous Metals: Hot Strip Mill

The facility for hot rolling of ferrous metals – Hot Strip Mill is used to produce hot-rolled steel sheets:

- Sheets made of carbon constructional steel,
- Formed sheets designed for further cold rolling,
- Shipborne sheets,
- Sheets made of low-alloyed constructional steel with microadditives,
- Sheets made of silicon steel (transformer and dynamo).

The following types of waste are produced in the Hot Strip Mill: mill scale and silt, production scrap, sludge from metalworking, grinding waste, engine, gear, and lubricating oils, mineral oils and liquids used as electric insulators and heat carriers, sorbents, filtering media, wiping cloths, protective suits, rubber, canvas covers, worn out devices containing hazardous substances (devices containing mercury, used lamps, fluorescent lamps, sodium-mercury discharge lamps), worn out electronic and electric devices, engine scrap, ink, toners, cases, lead-acid accumulators and batteries, oven linings and refractory materials from metallurgical processes, concrete waste and concrete waste from demolitions and repairs, mixed waste from concrete, crushed bricks, waste ceramic materials and equipment elements, wood, glass, and plastic waste, tar paper waste, copper, bronze, brass, aluminium, iron and steel, mixtures of metals, cables, biodegradable waste, and unsegregated (mixed) solid municipal waste.

The waste produced in the Hot Strip Mill is re-used, by the Plant itself, whenever possible, in MSP facilities. If however, MSP is unable to recycle waste, it is then forwarded to external buyers (for recycling or neutralisation) or neutralised by depositing it in a landfill.

In this project's LCA research, the characterisation and balance data used (for the year 2005), come from the old Hot Strip Mill. Currently, production processes are carried out in the new Hot Strip Mill.

5.2.7 The Fuel Combustion Facility: Thermal-Electric Power Station (Power Plant)

The main purpose of the Power Plant is the production of electric energy, blast furnace wind, process steam (1.6 and 0.8 MPa), heat in heating water, as well as the production of gas-free heated softened water, and heated demineralised water. These products are mostly used to cover the own needs of Mittal Steel Poland S.A.

The following types of waste are produced in the Power Plant: coal fly-ash, slag-ash mixtures from liquid drainage of furnace waste, sludge and preventive sediments, engine, gear, and lubricating oils, mineral oils and liquids used as electric insulators and heat carriers, worn out devices containing hazardous substances (devices containing mercury, used lamps, fluorescent lamps, sodium-mercury discharge lamps), worn out electronic and electric devices, engine scrap, ink, toners, cases, lead-acid accumulators and batteries, copper, bronze, brass, aluminium, cables, insulating materials, water decarbonisation sediments, solutions and sludge from the regeneration of ion-exchange units, and unsegregated (mixed) solid municipal waste.

The waste produced in the Power Plant is re-used, by the Plant itself, whenever possible, in MSP facilities. If however, MSP is unable to recycle waste, it is then forwarded to external buyers (for recycling or neutralisation) or neutralised by depositing it in a landfill. In 2005 the Power Plant used 133,628 MWh, for its own purposes. The missing electric energy, equivalent to 686495.027 MWh, required for production activity, was bought from ZEK S.A. (currently Enion S.A.). The Power Plant is equipped with on-site power, independent of the off-site power, coming from the on-site switching station, which receives its power from the main switching station, and is produced by the generators. Off-site power is used only in a situation when electric power shortages in the Power Plant occur (in the last 10 years such an occurrence happened twice, but not in the year 2005).

5.3 Aim and Scope of the Analysis

The aim of the life cycle analysis of the monograph is to define the potential environmental impact of the management of waste, in an annual cycle, generated by the Power Plant's facilities.

Waste management is currently one of the most difficult environmental and economic problems that need dealing with. It is not only the economic aspects that matter, but also the protection of human health, and the environment, from harmful effects caused by transportation, recycling, neutralisation, and storage of waste (Pietrzyk-Sokulska 2009). In this project, the LCA environmental management methodology (Life Cycle Assessment) is proposed with a view to conducting comprehensive environmental impact analysis of the management of waste, in an annual cycle, generated by the Power Plant's facilities:

- The coke production facility – Coke Plant,
- The ore sintering facility – Sintering Plant,
- The pig iron melting facilities – Blast Furnaces,
- The steel melting facility – Converter Plant,
- The Continuous Steel Casting facility – CSC,
- The facility for hot rolling of ferrous metals – Hot Strip Mill,
- The fuel combustion facility – Thermal-Electric Power Station (Power Plant).

Each of the facilities is a source of different types of pollutant emissions: air, water, and solid waste. This analysis focuses on the waste management aspect of the problem. The waste production by the abovementioned facilities, in an annual cycle (based on 2005), is considered to be the chosen functional unit, and the boundaries of the analysed system are labelled as gate to gate. The carried out analysis is based on the balance of the waste produced.

The LCA environmental management methodology makes it possible to conduct the assessment from a holistic perspective, which allows to avoid the spreading of the environmental threats from one phase of the process to another (Kowalski et al. 2007). Moreover, the LCA environmental management methodology also makes it possible to determine the eco-points quantifying the environmental impact of individual production processes described above.

The aim of the life cycle analysis of the monograph is to define the potential environmental impact of the management of waste, in an annual cycle, generated by the Power Plant's facilities.

5.4 Waste Management Balance, Analysis Assumptions

The waste management balance in the MSP Power Plant has been drawn up using provided materials. The types of waste generated during the operation of the facilities, are included in Table 5.1, and divided into sections – each with an analysed facility.

For the purposes of the analysis some types of waste are grouped – e.g. one category with hazardous waste has been created, where all kinds of waste of this type, generated by the analysed facilities, are included.

The following types of waste have been grouped:

- Sludge, waste, and sediments from smelter gases cleaning,
- Construction waste,
- Electronic and electric devices along with their equipment,
- Quick coke from decanters, a mixture of molecular salts and autoclaving condensate, grinding materials, rubber, canvas covers, and other mentioned waste are categorised as the "remaining" waste,
- Slag-ash mixtures from liquid drainage of furnace waste are added to coal fly-ash, and based on the information found in the source materials, their chemical constitution is the same as the constitution of the ashes.

Due to the limitations of the life cycle assessment program's database, the analysis is carried out by assuming that the majority of the generated waste is stored. It is assumed that hazardous waste is stored in an underground mine. However, the results, indicated in the analysis, may not be entirely correct, owing to the chosen sludge generated during the production of steel in electric furnace shops equipped with electric furnaces (as there is no other method of steel production available in the database). At present, there are two dominant steel production methods in the world. The first one is based on the production in, the so-called, integrated mills where pig iron is produced in blast furnaces and then is converted into steel using oxygen converters with the help of scrap metal (MSP). The second method of steel making is based on using scrap metal in an electric process in steel plants equipped with arc furnaces. The use of all-European data (the database found in SimaPro program) may further damage the credibility of the results, as this type of data is not always adequate to Polish conditions. Exchange of energy between the EU countries may be an example here. Western European countries are associated in the Union for the Co-ordination of Production and Transmission of Electricity (UCPTE), and in the database (mostly Ecoinvent) electric energy appears as Electricity HV use in UCPTE (see Figs. 4.11, 4.12, 4.13, 4.14).

Table 5.1 Inventory table of analysed processes – waste [Mg]

No.	Type of waste	Hot strip mill	CSC	Converter plant	Blast furnaces	Sintering plant	Coke plant	Power plant	Total
1.	Acid tars						500.00		500.00
2.	Liquid waste containing phenols						498780.00		498780.00
3.	Other unmentioned waste (e.g. quick coke from decanters, a mixture of molecular salts and autoclaving condensate)						28995.70		28995.70
4.	Other unmentioned waste (sulphur waste)						956.00		956.00
5.	Coal fly-ash							11272.00	11272.00
6.	Slag-ash mixtures from liquid drainage of furnace waste							53078.10	53078.10
7.	Slag from melting processes			245796.00	408500.30				654296.30
8.	Unprocessed slag from other processes			30913.64					30913.64
9.	Solid waste from smelter gases cleaning (other than mentioned in 10 02 07)			3025.00	11845.40	537.05			15407.45
10.	Mill scale	3932.50							3932.50
11.	Mill scale and silt	15522.40							15522.40
12.	Sludge and preventive sediments from smelter gases cleaning (other than mentioned in 10 02 13)			16749.00	7119.00	5023.92			28891.92
13.	Other sludge and preventive sediments							10.00	10.00
14.	Melting losses from ferrous metallurgy		3189.84	12035.74	7385.80				22611.38
15.	Other unmentioned waste (e.g. production scrap)	37286.50		2583.25	14.00				39883.75
16.	Sludge from metalworking containing hazardous substances	33.00							33.00
17.	Grinding waste containing hazardous substances	136.54							136.54
18.	Used grinding waste	1.40							1.40
19.	Other engine, gear, and lubricating oils	9.32		0.72	3.95			15.24	29.23
20.	Mineral oils and liquids used as electric insulators and heat carriers not containing organochlorinated compounds	43.60						2.98	46.58

21.	Paper and cardboard packaging		25.50						25.50
22.	Plastic packaging		5.70						5.70
23.	Sorbents, filtering media, (including oil filters not mentioned in other groups), wiping cloths (e.g. rags, floor cloths) and protective suits contaminated with hazardous substances (e.g. PCB)	19.40	4.50		0.88	1.82	0.76		27.35
24.	Sorbents, filtering media, wiping cloths (e.g. rags, floor cloths) and protective suits	0.00		6.50	0.71	0.14	3.40		10.75
25.	Other unmentioned waste (e.g. rubber, canvas covers)	2.70			12.24	10.90	22.58		48.42
26.	Worn out devices containing hazardous substances (devices containing mercury, used lamps, fluorescent lamps, sodium-mercury discharge lamps)	4.77		0.01	0.15	0.06		0.13	5.13
27.	Worn out devices (worn out electronic and electric equipment, engine scrap)	733.61						3.25	736.86
28.	Elements removed from worn out devices (ink, toners, cases)	0.02				0.00	0.00	0.00	0.03
29.	Lead-acid accumulators and batteries (removed from battery-electric trucks)	0.72		1.30				2.18	4.20
30.	Oven linings and refractory materials from metallurgical processes (e.g. chamotte bricks)	37.50	1424.16	4435.78	2754.10		10.00		8661.54
31.	Concrete waste and concrete waste from demolitions and repairs	1463.00			4463.18		14.00		5940.18
32.	Mixed waste from concrete, crushed bricks, waste ceramic materials and equipment elements	110.80		68.00	187.20		119.50		485.50
33.	Other unmentioned waste		115.22	1635.84					1751.06
34.	Wood	0.00					70.80		70.80
35.	Plastics	2.00							2.00
36.	Wood, glass, and plastic waste containing or contaminated with hazardous substances (wood waste)	2.70							2.70

(continued)

Table 5.1 (continued)

No.	Type of waste	Hot strip mill	CSC	Converter plant	Blast furnaces	Sintering plant	Coke plant	Power plant	Total
37.	Tar paper waste	2.00							2.00
38.	Copper, bronze, brass	123.60	0.26	45.10	0.88	0.78	0.18	9.84	180.63
39.	Aluminium	8.30		2.69		0.16		0.20	11.35
40.	Iron and steel (repair scrap, worn out machines, machine parts, roll scrap)	34047.10	22407.80	24532.04		331.49	4 050.740		81318.43
41.	Mixture of metals	957.20			1390.40		1.63		2349.23
42.	Cables containing crude oil (wet cables)	109.69		19.14				11.77	140.60
43.	Cables	99.80		2.17		4.10			106.07
44.	Insulating materials	0.00			1.00		22.00	19.50	42.50
45.	Sludge containing hazardous substances from biological treatment of industrial sewage						470.00		470.00
46.	Water decarbonisation sediments							2289.50	2289.50
47.	Solutions and sludge from the regeneration of ion-exchange units							1528.70	1528.70
48.	Biodegradable waste	14.00		7.00			53.60		74.60
49.	Unsegregated (mixed) solid municipal waste	145.50		49.82	6.00	7.00	47.30	102.00	357.62
50.	Waste generated during street and site cleaning						41.09		41.09
	Total	94849.67	27172.98	341908.74	443685.19	5917.42	530108.54	68345.39	1511987.93

Source: Own work on the basis of data received from AMPSAK

5.5 The Life Cycle Impact Assessment: Interpretation

The Eco-indicator 99 method is used in the life cycle impact assessment of the management of waste generated by MSP. Power Plant (Ocena 2009). The analysis has been carried out with the help of SimaPro 7.1 software, using the databases implemented in the program (mostly Ecoinvent). The findings are expressed in the form of: characterisation, normalisation, and measurement stage results. Each stage is thoroughly described in the fourth chapter. In order to supplement the Eco-indicator 99 method, it is worth mentioning that the impact category indicators, defined with reference to final elements (three of them, in the case of Eco-indicator 99), are defined, so that their units are the same, which makes it possible to add them within groups (Kowalski et al. 2007). When presenting the results of the analysis, one can refer to three damage categories, namely:

- Human Health
- Ecosystem Quality
- Consumption of Resources

or to 11 impact categories, which can be added to relevant damage categories, i.e.:

- Carcinogenic agents, the effects on respiratory systems of organic compounds, the effects on respiratory systems of non-organic compounds, climate change, radiation, ozone layer depletion (Human Health),
- Eco-toxicity, acidification/eutrophication, land use (Ecosystem Quality),
- Mineral and fossil fuel consumption (Consumption of Resources).

The findings of the analysis are based on the results shown in Tables 5.2, 5.3 and 5.4 and presented in the form of histograms of: characterisation (divided into 11 impact categories – see Fig. 5.1, Table 5.3), normalisation (divided into 3 damage categories – see Fig. 5.2, Table 5.3), and weighting (divided into 11 impact categories – see Fig. 5.3, Table 5.4).

Characterisation, being the compulsory element of impact analysis, deals with calculating the value of impact categories of the results in the inventory table. For characterisation, the value of every impact category is determined in a different unit, thus, it is not possible to compare them directly; however, on the basis of characterisation data, one can determine the involvement of individual processes in a given impact category by scaling it to 100% – is not described, however, whether the 100% refers to high or low potential environmental impact.

The analysis has been carried out for 11 impact categories and, in the majority of cases, the factor that potentially mainly strains the environment, is the generated hazardous waste:

- In the "impact on the respiratory system of organic compounds" category, mostly the non-methane volatile organic compounds (76.6%) and aliphatic hydrocarbons (10.3%), created during the production of hazardous materials, are the emissions that can potentially strain the environment

Table 5.2 The characterisation of individual category indicators of waste generated during the operation of the Power Plant's facilities, grouped for the purposes of the analysis

Impact category	Unit	Total	Solid municipal waste	Remaining waste	Sludge and sediments from the cleaning of gases	Hazardous waste	Slags	Aluminium
Carcinogenic agents	DALY	6.43E + 01	3.48E-01	5.08E-03	1.00E + 01	4.78E + 00	1.50E-01	2.35E-03
Respiratory system – organic compounds	DALY	1.03E-01	1.23E-04	6.64E-04	6.56E-03	6.80E-02	2.16E-02	4.87E-07
Respiratory system – non-organic compounds	DALY	1.46E + 02	8.53E-03	3.13E-01	4.43E + 00	1.31E + 02	8.21E + 00	2.42E-04
Climate change	DALY	2.11E + 01	5.13E-02	4.92E-02	3.10E + 00	1.52E + 01	1.46E + 00	5.10E-05
Radiation	DALY	2.41E-01	7.17E-05	4.52E-04	2.78E-02	1.87E-01	1.58E-02	2.46E-06
Ozone layer	DALY	6.70E-03	1.42E-06	7.42E-05	7.56E-04	2.60E-03	2.68E-03	4.94E-08
Eco-toxicity	PDF*m2year	2.00E + 08	8.81E + 04	3.46E + 03	5.86E + 05	2.07E + 06	1.96E + 08	4.16E + 01
Acidification/ eutrophication	PDF*m2year	2.01E + 06	2.97E + 02	1.21E + 04	1.75E + 05	1.40E + 06	3.15E + 05	9.48E + 00
Land use	PDF*m2year	9.95E + 06	6.99E + 02	−1.69E + 04	2.54E + 05	7.97E + 06	1.75E + 06	2.11E + 01
Minerals	MJ surplus	1.61E + 07	2.50E + 02	3.71E + 03	9.93E + 04	1.58E + 07	1.15E + 05	8.19E + 00
Fossil fuels	MJ surplus	1.09E + 08	1.59E + 04	8.36E + 05	8.26E + 06	6.40E + 07	2.96E + 07	6.03E + 02

Impact category	Unit	Total	Iron, steel, scrap, scale	Biodegradable waste	Cables	Construction waste	Wood	Refractory materials	Paper and cardboard
Carcinogenic agents	DALY	6.43E + 01	2.53E-02	1.97E-02	9.79E-03	3.97E-05	3.00E-03	1.96E + 00	3.89E-06
Respiratory system – organic compounds	DALY	1.03E-01	3.31E-03	1.18E-05	2.42E-05	1.83E-05	4.31E-06	1.28E-03	5.09E-07
Respiratory system – non-organic agents	DALY	1.46E + 02	1.56E + 00	3.36E-03	2.69E-02	6.15E-03	1.15E-03	8.66E-01	2.40E-04
Climate change	DALY	2.11E + 01	2.45E-01	1.28E-02	2.90E-02	7.50E-04	1.13E-03	6.06E-01	3.77E-05
Radiation	DALY	2.41E-01	2.25E-03	4.14E-05	5.17E-04	3.12E-06	3.37E-06	5.43E-03	3.46E-07
Ozone layer	DALY	6.70E-03	3.69E-04	5.39E-07	3.06E-06	4.98E-06	2.29E-07	1.48E-04	5.69E-08
Eco-toxicity	PDF*m2year	2.00E + 08	1.72E + 04	2.07E + 02	1.46E + 05	2.87E + 01	1.10E + 02	2.24E + 04	2.65E + 00
Acidification/ eutrophication	PDF*m2year	2.01E + 06	6.00E + 04	3.34E + 02	8.47E + 02	2.40E + 02	4.22E + 01	3.41E + 04	9.24E + 00

Land use	PDF*m2year	9.95E + 06	−8.42E + 04	5.47E + 01	4.00E + 02	5.48E + 03	1.23E + 02	4.97E + 04	−1.30E + 01
Minerals	MJ surplus	1.61E + 07	1.85E + 04	1.04E + 02	1.37E + 03	8.10E + 00	3.15E + 01	1.94E + 04	2.85E + 00
Fossil fuels	MJ surplus	1.09E + 08	4.16E + 06	8.19E + 03	3.68E + 04	6.32E + 03	2.74E + 03	1.62E + 06	6.40E + 02

Impact category	Unit	Total	Plastics	Ashes	Textiles	Electric and electronic	Copper, bronze, brass	Water decarbonisation sediments
Carcinogenic agents	DALY	6.43E + 01	4.24E-02	4.68E + 01	1.28E-04	1.17E-01	0.00E + 00	3.49E-04
Respiratory system – organic compounds	DALY	1.03E-01	4.81E-07	7.88E-04	1.18E-06	8.91E-05	0.00E + 00	4.57E-05
Respiratory system – non-organic compounds	DALY	1.46E + 02	1.26E-04	2.29E-01	2.80E-03	7.05E-02	0.00E + 00	2.16E-02
Climate change	DALY	2.11E + 01	1.29E-04	1.93E-01	3.17E-03	1.67E-01	0.00E + 00	3.38E-03
Radiation	DALY	2.41E-01	4.33E-07	7.68E-04	1.99E-06	3.71E-04	0.00E + 00	3.11E-05
Ozone layer	DALY	6.70E-03	2.50E-08	4.64E-05	6.95E-08	7.83E-06	0.00E + 00	5.11E-06
Eco-toxicity	PDF*m2year	2.00E + 08	7.19E + 02	8.56E + 05	6.78E + 01	1.59E + 05	0.00E + 00	2.38E + 02
Acidification/ eutrophication	PDF*m2year	2.01E + 06	4.67E + 00	8.46E + 03	1.75E + 02	3.16E + 03	0.00E + 00	8.29E + 02
Land use	PDF*m2year	9.95E + 06	1.34E + 01	2.43E + 04	5.19E + 00	8.07E + 02	0.00E + 00	−1.16E + 03
Minerals	MJ surplus	1.61E + 07	3.50E + 00	6.43E + 03	1.57E + 01	1.68E + 03	0.00E + 00	2.56E + 02
Fossil fuels	MJ surplus	1.09E + 08	2.98E + 02	5.50E + 05	1.12E + 03	9.47E + 04	0.00E + 00	5.75E + 04

Source: (Ocena 2009) based on data received from AMPSAK

Table 5.3 Impact assessment – bringing the impact indicators to the form of three damage categories (after the normalisation step)

Damage category	Solid municipal waste	Remaining waste	Sludge and sediments from the cleaning of gases	Hazardous waste	Slags	Aluminium	Iron, steel, scrap, scale	Biodegradable waste	Cables	Construction waste
Human health	26.55911	24.017235	1144.872	9827.3618	597.5586	0.172335	119.5098	2.335817	4.308515	0.45365922
Ecosystem quality	17.37071	−0.27492936	197.9385	2231.0585	35929.56	0.014059	−1.368049	0.116228	28.79743	1.1208961
Consumption of resources	1.922454	99.899481	995.1087	9498.7488	3296.794	0.072718	497.1001	0.987452	4.546332	0.75331516

Damage category	Wood	Refractory materials	Paper and cardboard	Plastics	Ashes	Textiles	Electric and electronic	Copper, bronze, brass	Water decarbonisation sediments
Human health	0.344529	0.2237982	0.0184008	2.7795456	3076.9096	0.397505	23.119946	0	1.6521046
Ecosystem quality	0.053674	0.0207152	−0.000211	0.14366268	173.25951	0.048371	31.69021	0	−0.018911925
Consumption of resources	0.329544	0.1945226	0.076538	0.035905125	66.255151	0.134867	11.473772	0	6.8719147

Source: (Ocena 2009) based on data received from AMPSAK

Table 5.4 Impact categories including the weight indicator (after the weighting step)

Impact category	Solid municipal waste	Remaining waste	Sludge and sediments from the cleaning of gases	Hazardous waste	Slags	Aluminium	Iron, steel, scrap, scale	Biodegradable waste
Carcinogenic agents	9061.3096	132.22974	260919.01	124533.6	3644.153	61.22368	657.9756	513.4515
Respiratory system – organic compounds	3.199981	17.298201	170.79486	1770.985	523.7339	0.012669	86.0759	0.306712
Respiratory system – non-organic compounds	222.1315	8163.2056	115410.1	3403964	199098.5	6.305323	40620.13	87.40992
Climate change	1335.0967	1280.4658	80706.414	395726.6	35308.23	1.3271	6371.601	332.066
Radiation	1.8682829	11.761713	722.85753	4882.243	383.8528	0.063964	58.52632	1.078466
Ozone layer	0.036885547	1.9330733	19.681426	67.80958	64.9201	0.001287	9.618978	0.014031
Eco-toxicity	6870.5655	269.58088	45721.963	161568	14222045	3.241874	1341.435	16.14456
Acidification/europhication	23.186177	940.49105	13612.505	109437.7	22854.65	0.739282	4679.886	26.08394
Land use	54.533276	−**1320.0437**	19840.941	621417.7	126924	1.64247	−**6568.54**	4.262735
Minerals	5.9608276	88.40987	2362.9387	376834.4	2538.792	0.194855	439.9277	2.469071
Fossil fuels	378.53001	19891.486	196658.8	1522915	656819.9	14.34873	98980.09	195.0213
Total impact of waste management life cycle	**17956.41874**	**29476.81823**	**736146,0055**	**6723118**	**15270206**	**89.10124**	**146676.7**	**1178.308**
Impact category	Cable	Construction waste	Waste	Refractory materials	Paper and cardboard	Plastics	Ashes	Textiles
Carcinogenic agents	254.9684	1.032794	78.24064	51.00412	0.101308	1105.143	1219747	3.329309
Respiratory system – organic compounds	0.629318	0.475501	0.112329	0.033387	0.013253	0.012531	20.52764	0.030755
Respiratory system – non-organic compounds	700.1876	160.2202	29.83694	22.56022	6.254244	3.291425	5956.699	72.99762
Climate change	754.0756	19.52408	29.52778	15.77639	0.981029	3.359262	5018.347	82.59078
Radiation	13.46517	0.081369	0.087762	0.141303	0.009011	0.011281	19.99526	0.051716
Ozone layer	0.079755	0.129716	0.00597	0.003847	0.001481	0.000651	1.208357	0.001811
Eco-toxicity	11421.7	2.237988	8.587553	1.746654	0.20654	56.0575	66749.94	5.28976
Acidification/europhication	66.08253	18.71004	3.292343	2.660955	0.720558	0.364114	660.1428	13.65379
Land use	31.1927	427.4104	9.589632	3.878482	−**1.01135**	1.043455	1893.725	0.404766
Minerals	32.67816	0.192768	0.749218	0.461904	0.067735	0.083398	153.1198	0.374699
Fossil fuels	876.5882	150.4703	65.15965	38.44262	15.23987	7.097627	13097.91	26.59868

(continued)

Impact category	Cable	Construction waste	Waste	Refractory materials	Paper and cardboard	Plastics	Ashes	Textiles
Total impact of waste management life cycle	**14151.65**	**780.4852**	**225.1898**	**136.7099**	**22.58368**	**1176.464**	**1313319**	**205.3237**
Impact category	Electric and electronic	Copper, bronze, brass	Water decarbonisation sediments	Value [Pt]				
Carcinogenic agents	3059.007	0	9.095858	**1623832**				
Respiratory system – organic compounds	2.319592	0	1.189914	**2597.7509**				
Respiratory system – non-organic compounds.	1834.905	0	561.533	**3776919.8**				
Climate change	4341.881	0	88.08106	**531415.91**				
Radiation	9.66277	0	0.809068	**6106.5669**				
Ozone layer	0.203856	0	0.132973	**165.78378**				
Eco-toxicity	12367.01	0	18.54401	**14528467**				
Acidification/eutrophication	246.1455	0	64.69477	**152651.74**				
Land use	62.93157	0	**−90.8036**	**762692.91**				
Minerals	40.07799	0	6.081564	**382506.98**				
Fossil fuels	2254.677	0	1368.301	**2513754.1**				
Total impact of waste management life cycle	**24218.82**	**0**	**2027.66**	**24281111**				

Source: (Ocena 2009) based on data received from AMPSAK

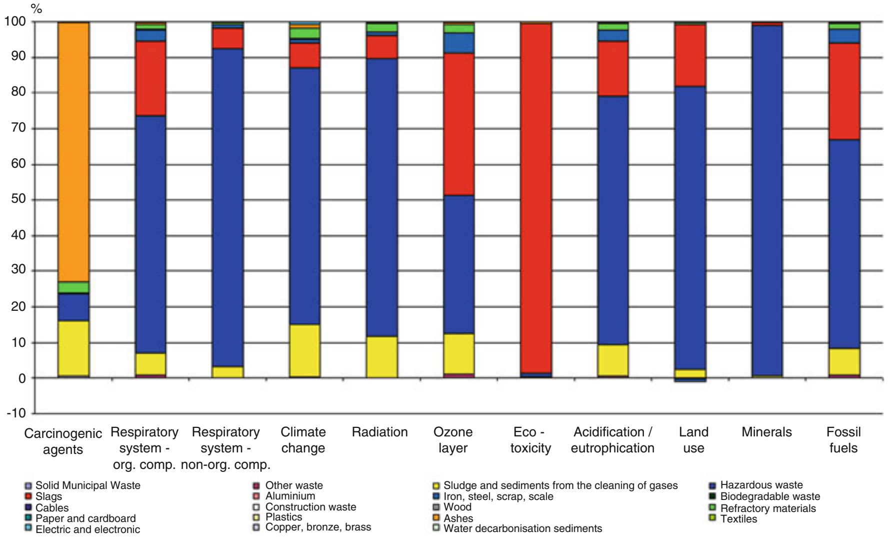


Fig. 5.1 Characterization histogram of the management of waste produced by the MSP facilities in 2005. Source: The Polish Academy of Sciences study (Ocena 2009)

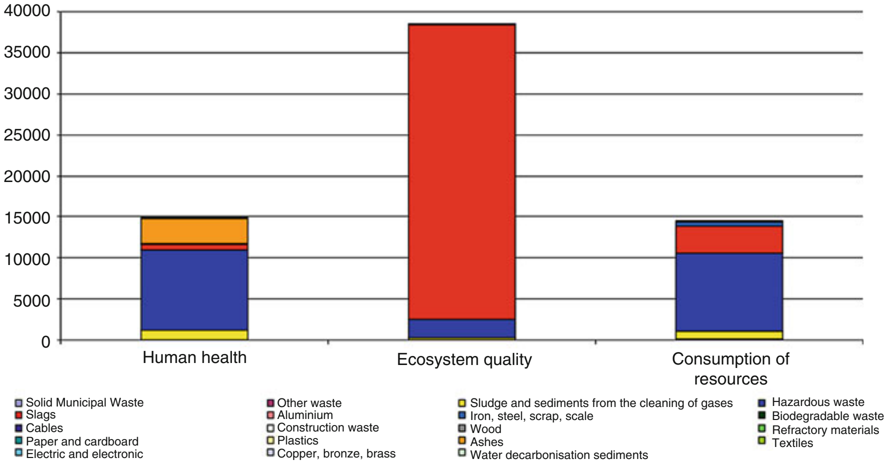


Fig. 5.2 Normalisation histogram in the MSP facilities in 2005. Source: The Polish Academy of Sciences study (Ocena 2009)

- In the “impact on the respiratory system of non-organic compounds” category, the emission of ashes is the factor that mostly strains the environment (in more than 78%)
- What influences the “climate change” category is carbon dioxide

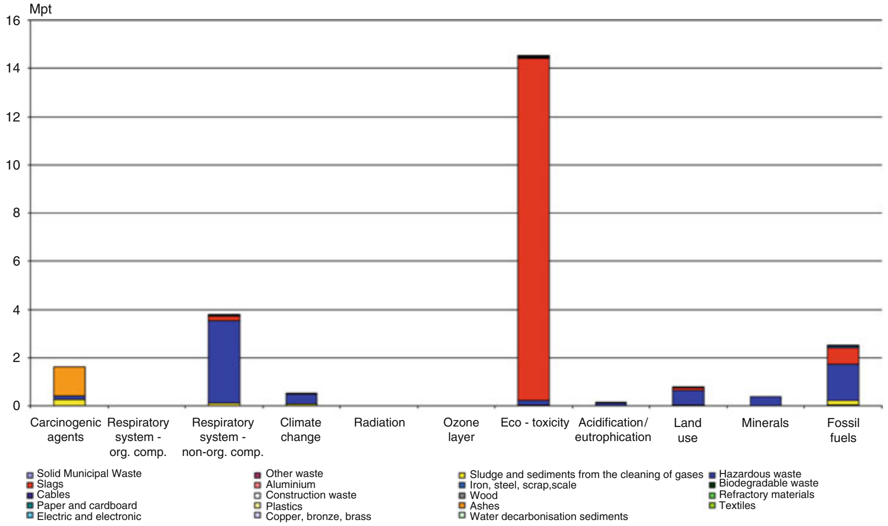


Fig. 5.3 Weighting histogram in the MSP facilities in 2005. Source: The Polish Academy of Sciences study (Ocena 2009)

- In the “radiation” category, the factors that strain the environment are the emissions of radon-222 and the radioactive carbon isotope C-14, created during the production of electric energy used in the production of products that later generate hazardous waste (carbon may be radioactive)
- In the “acidification/eutrophication” category, the potentially harmless emissions that affect the environment are, in the majority of cases, nitric oxides (80%), but also carbon (14%), and ammonia (less than 6%)
- The “land use” category is affected by the conversion of land into industrial areas (for the construction of factories), but also by the utilisation of wooden materials in steel product (goods) packaging
- In the “minerals” impact category, the factor that potentially strains the environment is the diminishing of natural resources, especially iron ore, which is used mostly in construction of production infrastructure (e.g. factories)
- The “fossil fuels” category is affected by the depletion of the reserves of crude oil (51.7%), natural gas (36.4%), and hard coal (around 12%) that are used directly or indirectly in the production of goods, which at the end of their service life become hazardous waste
- The “fossil fuel” category is affected by the depletion of the reserves of natural gas and hard coal.

All of the abovementioned emissions are created during the manufacturing of products that later generate hazardous waste.

The type of emission that is created during the storage of hazardous waste (according to the Ecoinvent database) is waste heat. The influence of hazardous waste on other impact categories ranges between a few to around 40%.

The type of waste that is next in line, in terms of its size, which has a potentially negative impact on the environment, is slag. Slag constitute a strain on the environment mostly in the "eco-toxicity" category and subsequently in "ozone layer", "fossil fuels", and the "impact on the respiratory system of organic compounds" categories. The influence of slag on the remaining impact categories does not exceed 20%. In the case of "eco-toxicity", the emissions that strain the environment are light metals (calcium) and whitewash. The "ozone layer" category is affected by the use of blast furnace gas, coke oven gas, and natural gas. For the "fossil fuels" category, the use of natural gas is a strain. The emission of non-methane organic compounds, on the other hand, affects the "respiratory system diseases caused by organic compounds".

However, it should be noted that the analysis uses (due to the lack of other processes) slag, chosen from a database, which are created after the production of steel in electric furnaces where their composition is most probably different to the slags created in blast furnaces and converter plants – this may generate incorrect results.

Cadmium compounds, created during the processes of fuel combustion (mostly hard coal), which penetrate into the water environment, influence the "carcinogenic agents" category.

The types of waste that affect the chosen categories in more than 10% are sludge and sediments from the cleaning of gases. Emissions that potentially affect the categories are, respectively:

- For "carcinogenic agents" – emissions of arsenic into water,
- For "climate change" – emissions of carbon dioxide into air,
- For "radiation" – emissions of radioactive carbon isotope C-14 into air,
- For "ozone layer" – emissions of halogenated organic compounds into air.

The above emissions are not the direct emissions created during the storage of sludge and sediments from the cleaning of gases, but the indirect ones created during the production of substances used in the cleaning of gases. The impact of the sludge and sediments management on the environment in the remaining categories does not exceed 10%.

The next step in the analysis is normalisation. Adamczyk (2004) emphasises that normalisation points out the relative degree of influence; however, if the gravity of the influences is to be presented, it is necessary to perform measurements – this means that the results need to be converted by applying weight coefficients that are equivalent to the severity of the influence. The normalisation histogram divided into three damage categories is presented in Fig. 5.2. In the case of normalisation, it is possible to determine the potential impact magnitude and to compare them in the three damage categories. Since these are non-designated units, they indicate the involvement and not the magnitude of damage (Table 5.3).

The greatest potential strain to the environment, caused by the waste management in the Power Plant, is its management of slags and hazardous waste when it comes to storage.

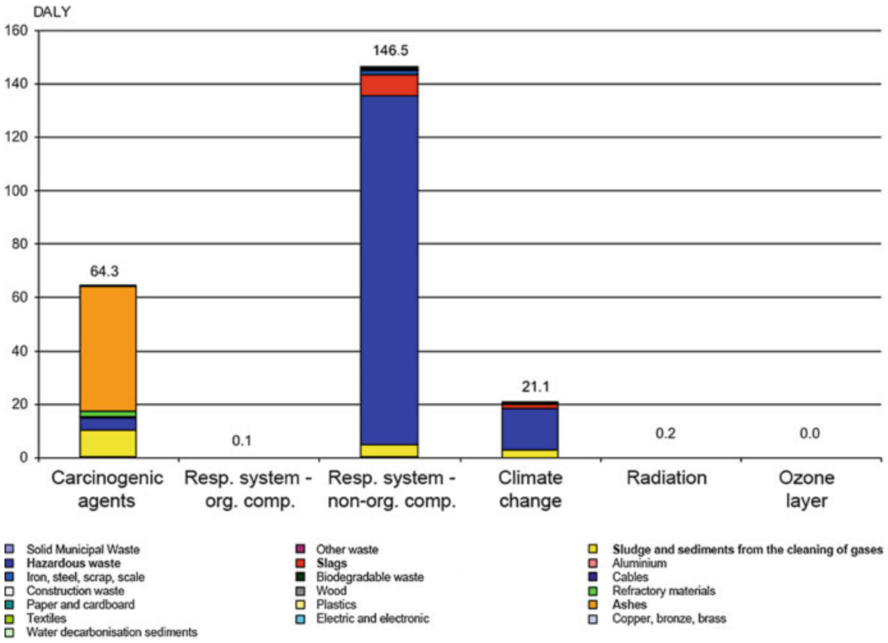


Fig. 5.4 The results of the analysis after the characterization step modelled in the human health damage category. Source: Own work based on data from the study (Ocena 2009)

Slags cause the, potentially, greatest impact on the environment in the "ecosystem quality" category. The stored hazardous waste has the decisive impact on both the "human health" and the "consumption of resources" categories. As far as the "human health" category is concerned, this impact is caused by ashes, as well as nitric and sulphur oxides; the impact on the "consumption of resources" category, on the other hand, is caused by the depletion of natural gas and metal ore (iron). The abovementioned emissions are created indirectly – during the manufacturing of goods that after the end of their service life turn to hazardous waste.

The next stage in the LCA analysis is the weighting step (Fig. 5.3 and Table 5.4). The results here are expressed in millions of Pt for 11 impact categories.

After the weighting step, the aspect of the storage of slag is still the most important type of impact on the quality of the environment – the "eco-toxicity" impact category. The value of the discussed category, expressed in eco-points, amounts to 14.5 million Pt [MPt], which means that the waste economy in the "eco-toxicity" category causes the same amount of pollution as do 15,500 Europeans. It is mostly the emissions of suspended matter and heavy metals into water that affects this situation. These types of emissions are created during the direct storage of slag. Characterization step is presented in the Figs. 5.4, 5.5, 5.6, normalization and weighting steps are given in the Figs. 5.7 and 5.8, respectively.

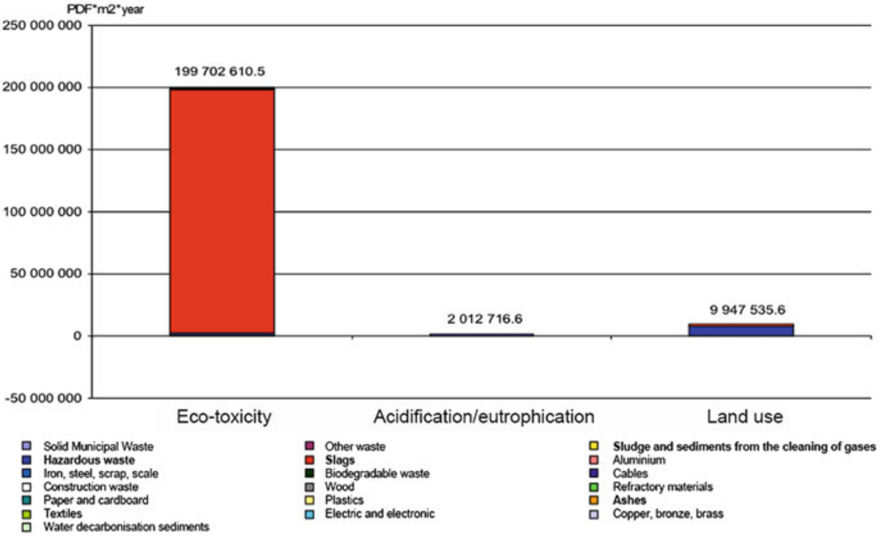


Fig. 5.5 The results of the analysis after the characterization step modelled in the ecosystem quality damage category. Source: Own work based on data from the study (Ocena 2009)

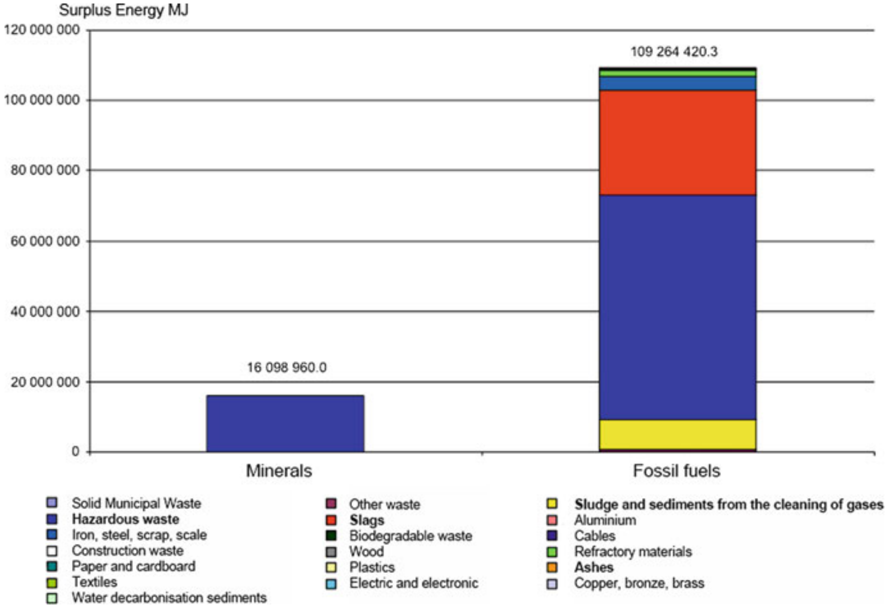


Fig. 5.6 The results of the analysis after the characterization step modelled in the consumption of resources damage category after the normalization step. Source: Own work based on data from the study (Ocena 2009)

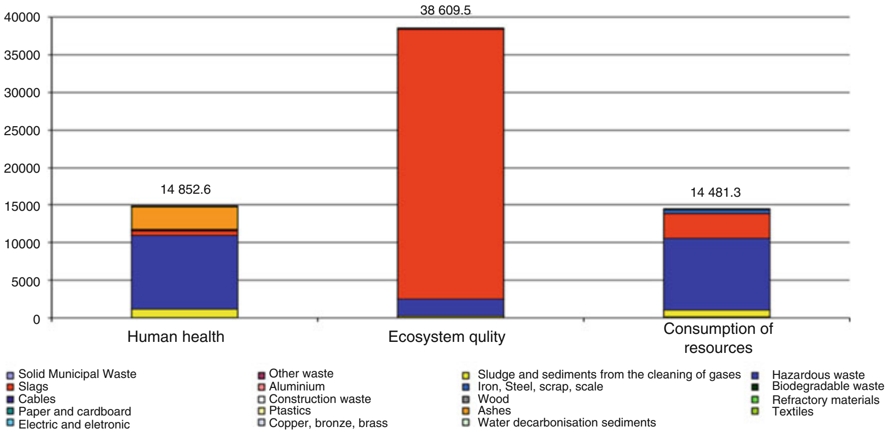


Fig. 5.7 The results of the analysis after the normalization step. Source: Own work based on data from the study (Ocena 2009)

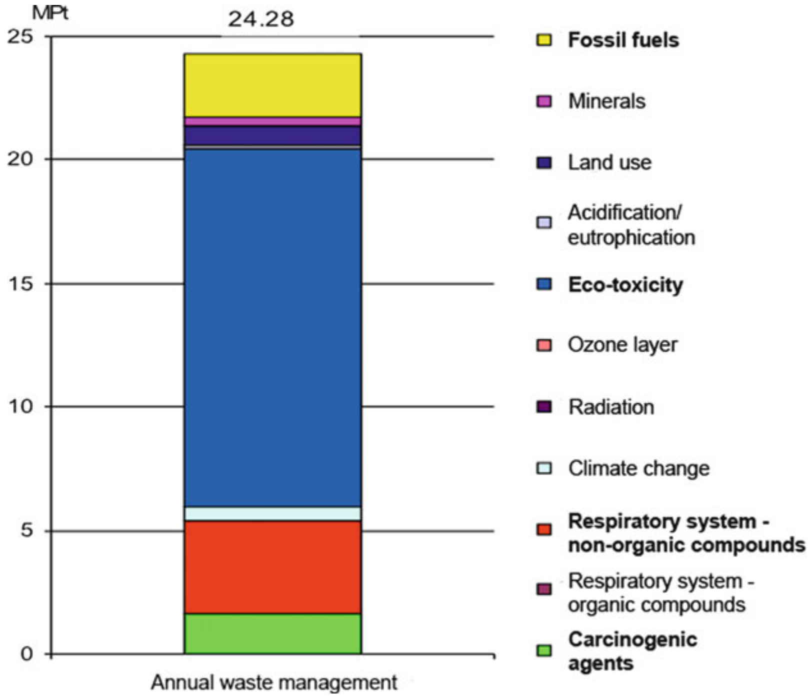


Fig. 5.8 The results of the analysis after the weighting step [MPt]. Source: Own work based on data from the study (Ocena 2009)

5.6 The Analysis of the Results

The performed LCA analysis makes it possible to determine the environmental impact of the management of waste generated by MSP. The fact that the individual waste types are grouped and that the processes chosen from a database and used during the analysis are not adequate to Polish but to European conditions, which may generate inaccurate or even incorrect results, should be taken into consideration here.

The total life cycle impact of the management of waste produced by MSP Power Plant, from an annual perspective, expressed in eco-points, amounts to 24.28 MPt (see Table 5.5 and Fig. 5.8).

The greatest potential environmental strain (approximately 63%) is caused by the storage of slag. The less straining impacts are caused by the storage of hazardous waste (27.7%) as well as coal fly-ashes and slag-ash mixtures (5.4%). The environmental impact of the remaining types of waste does not exceed 3.5%. The results of the analysis are presented in the tree form in Fig. 5.9. The tree boxes

Table 5.5 The LCA analysis results of the management of waste produced in the MSP Power Plant, divided into 11 impact categories

No.	Impact category	Value [Pt]	Share [%]
1.	Carcinogenic agents	1623832.0	6.69
2.	Respiratory system – organic compounds	2597.8	0.01
3.	Respiratory system – non-organic compounds	3776919.8	15.55
4.	Climate change	531415.9	2.19
5.	Radiation	6106.6	0.03
6.	Ozone layer depletion	165.8	0.00
7.	Eco-toxicity	14528467.0	59.83
8.	Acidification/eutrophication	152651.7	0.63
9.	Land use	762692.9	3.14
10.	Consumption of resources (minerals)	382507.0	1.58
11.	Fossil fuels	2513754.0	10.35
12.	Total	24281111	100

Source: The Polish Academy of Sciences study (Ocena 2009)

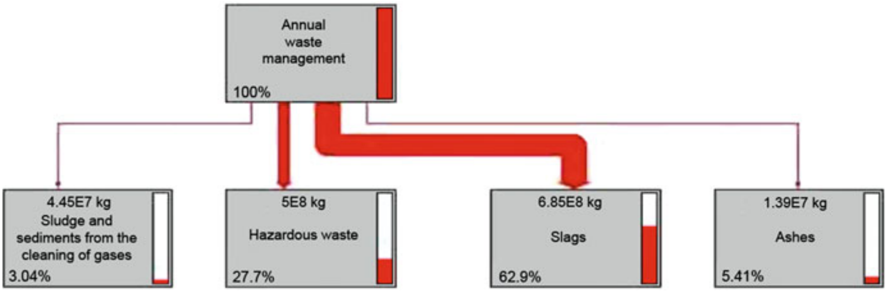


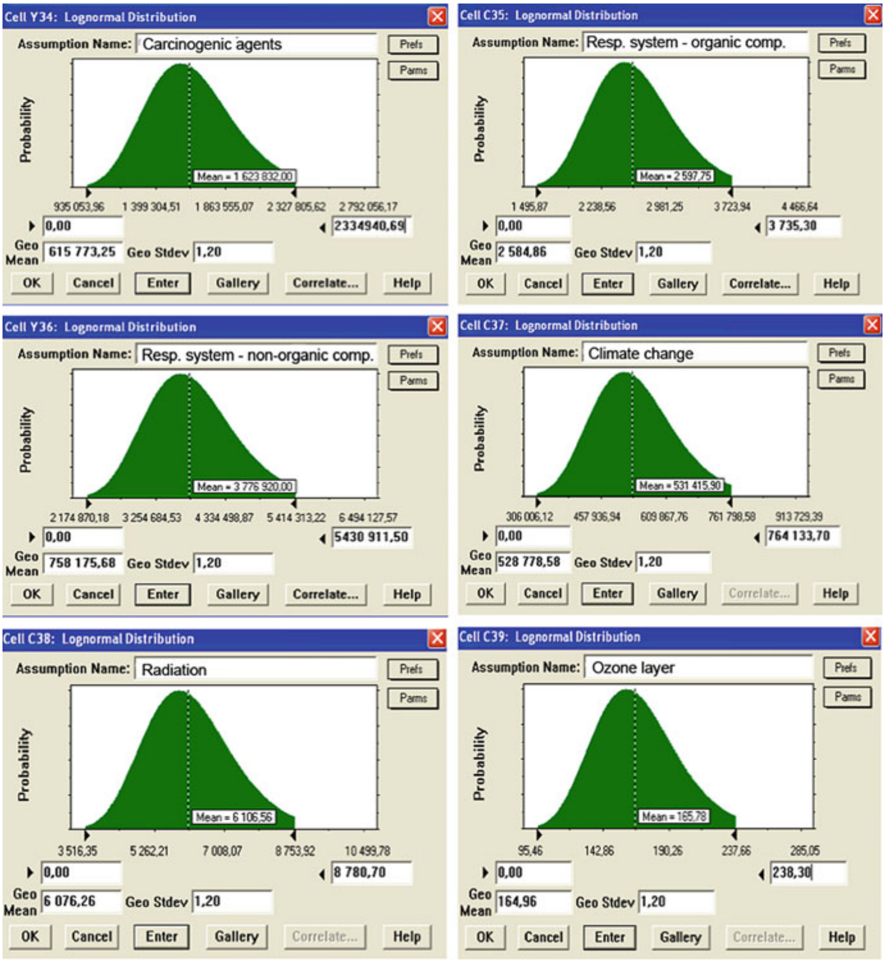
Fig. 5.9 The simplified tree graph, concerning waste management, presenting life cycle impact of the management of waste produced by MSP. Power Plant, from an annual perspective, expressed in percentages. Source: The Polish Academy of Sciences study (Ocena 2009)

detail the percentages of impact environments, which are equivalent to the values presented in brackets.

The specific values of the impact of individual categories, are presented in Table 5.5.

5.7 Stochastic Analysis as an Uncertainty Calculation Tool in the LCA Study

The LCA analysis overlaps with a stochastic compound, which is an outcome of the uncertainty of data included in the Eco-indicator 99 method. Kowalski et al. (2007) describe stages of data uncertainty and their origin. Some data are based on Western European averages and are scaled towards the Eastern European ones. A degree of



Cell Y34: Lognormal Distribution
Assumption Name: Carcinogenic agents
0,00 / 2334940,69
Geo Mean 615 773,25 Geo Stdev 1,20

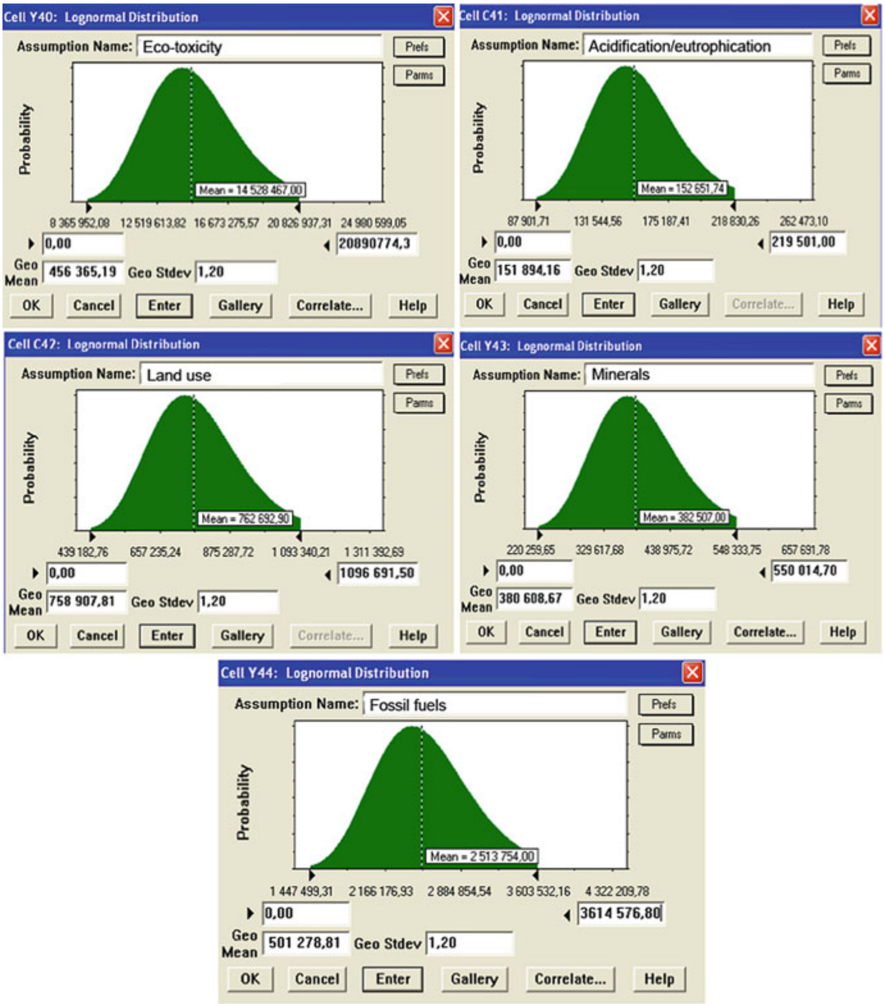
Cell C35: Lognormal Distribution
Assumption Name: Resp. system - organic comp.
0,00 / 3 735,30
Geo Mean 2 584,86 Geo Stdev 1,20

Cell Y36: Lognormal Distribution
Assumption Name: Resp. system - non-organic comp.
0,00 / 5430 911,50
Geo Mean 758 175,68 Geo Stdev 1,20

Cell C37: Lognormal Distribution
Assumption Name: Climate change
0,00 / 764 133,70
Geo Mean 528 778,58 Geo Stdev 1,20

Cell C38: Lognormal Distribution
Assumption Name: Radiation
0,00 / 8 780,70
Geo Mean 6 076,26 Geo Stdev 1,20

Cell C39: Lognormal Distribution
Assumption Name: Ozone layer
0,00 / 238,30
Geo Mean 164,96 Geo Stdev 1,20



Cell Y40: Lognormal Distribution

Assumption Name: Eco-toxicity

0,00 20890774,3

Geo Mean 456 365,19 Geo Stdev 1,20

Cell C41: Lognormal Distribution

Assumption Name: Acidification/eutrophication

0,00 219 501,00

Geo Mean 151 894,16 Geo Stdev 1,20

Cell C42: Lognormal Distribution

Assumption Name: Land use

0,00 1096 691,50

Geo Mean 758 907,81 Geo Stdev 1,20

Cell Y43: Lognormal Distribution

Assumption Name: Minerals

0,00 550 014,70

Geo Mean 380 608,67 Geo Stdev 1,20

Cell Y44: Lognormal Distribution

Assumption Name: Fossil fuels

0,00 3614 576,80

Geo Mean 501 278,81 Geo Stdev 1,20

Fig. 5.10 The dialog windows of log-normal probability distribution of 11 impact categories, offered in CB software, for the LCA analysis of waste management in MSP (Source: Own work)

uncertainty, in such a situation, may reach 50% (e.g. in the case of pesticides). As uncertainty can be quite substantial and its level may be difficult to assess, it is crucial to apply different types of statistical methods, e.g. MC method. Uncertainty can be detected with relative ease through standard deviation range if appropriate statistical information is available. Even the authors of the Eco-indicator 99 methodology claim that it is not a perfect approach; nevertheless, the best possible scientific data was used in its development (Kowalski 2005). The use of all-European data (the database found in SimaPro program) may further damage the credibility of the results, as this type of data is not always adequate to Polish conditions.

The LCA results, which include the sum of the 11 impact categories, presented in Table 5.5, have been used in the MC simulation. Assuming that in order to assess the impact categories different log-normal distributions may be used, in accordance with the studies cited in Chap. 4, the geometric standard deviation $\sigma_g = 1.2$ is defined for all 11 distributions. The graphic illustration of log-normal probability distributions used to assess each of the 11 random impact categories, offered in CB software (Lognormal Distribution tab windows), are shown in Fig. 5.10. Mean values μ are consistent with the deterministic values of the impact category variables (Table 5.5). With the standard geometric deviation σ_g, the upper boundary of log-normal distribution needs to be "adjusted" (by sliding the mini-grabbers, placed on the right-hand side of the window, accordingly), so that the mean values μ correspond to the deterministic values of the impact category variables (Table 5.5). The obtained upper boundary of the distribution is then automatically entered in the edit box placed on the right in the Log-normal Distribution dialog window. The lower distribution value = 0.

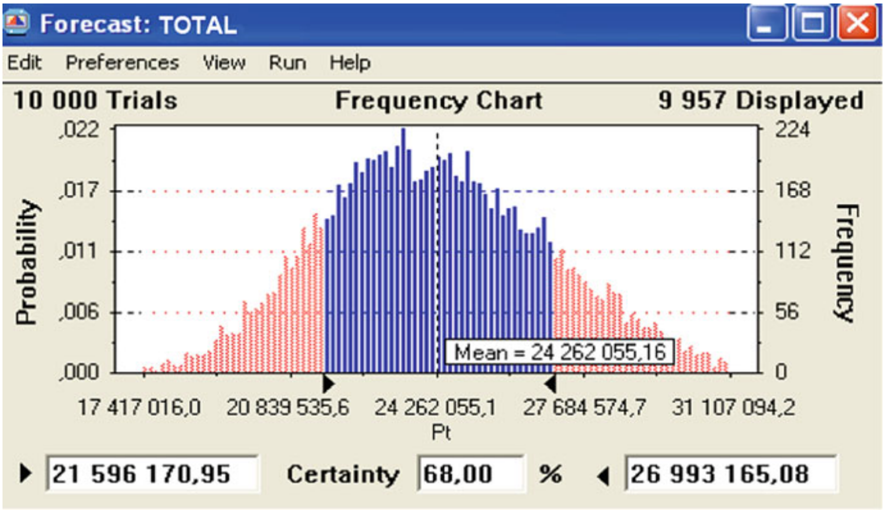
5.8 The Results of the Simulation

The obtained simulation results, in the defined 10,000-randomisation cycle, presented in the graphic form (forecast frequency charts – *Forecast: TOTAL*), are shown in Figs. 5.11 and 5.12. During the simulation, different statistical data has been obtained (*Statistics*, *Percentiles*), which is shown in Figs. 5.13 and 5.14. The dialog windows – *Forecast: TOTAL* of the frequency charts, make it possible to assess certainty intervals. By inputting a defined value of the uncertainty level in the edit field (*Certainty*), Crystal Ball automatically performs the interval estimation. The confidence limits are marked with mini-sliders and their corresponding numerical values can be entered in the edit fields placed at the bottom of the *Forecast: TOTAL* dialog windows.

The confidence intervals corresponding to the 68th and 95th percentage point, respectively, of the confidence level of the estimated value of the total life cycle impact of the management of waste generated in an annual cycle (in 2005) are equal to, respectively:

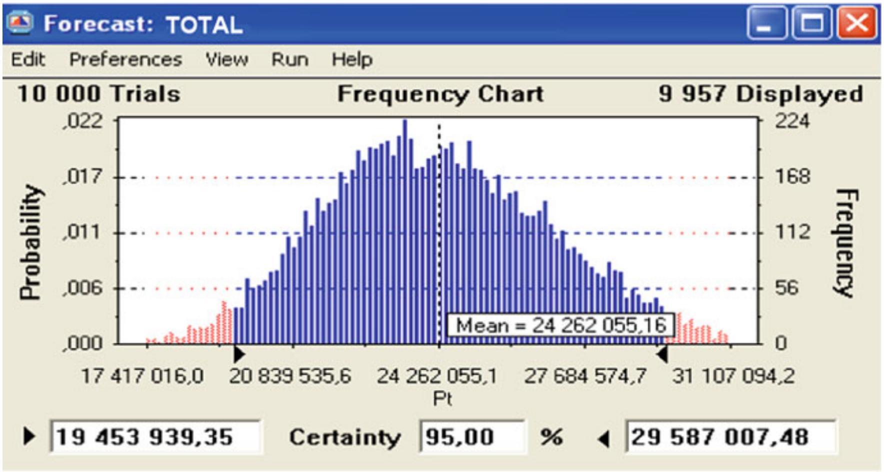
[21596170.95; 26993165.08] Pt
confidence level of 68%
[19453939.35; 29587007.48] Pt
confidence level of 95%

The entire range width between the left and the right edge of the frequency chart (Figs. 5.11, 5.12) is 16423946.56 Pt (Fig. 5.13); this is equivalent to the difference between the 0th and the 100th percentile, as can be seen in Fig. 5.14. The display range is between 15993187.84 Pt and 32417134.40 Pt (Fig. 5.14).



▸ 21 596 170,95 Certainty 68,00 % ◂ 26 993 165,08

Fig. 5.11 Frequency chart of the TOTAL forecast, with 68% certainty level (Source: Own work)

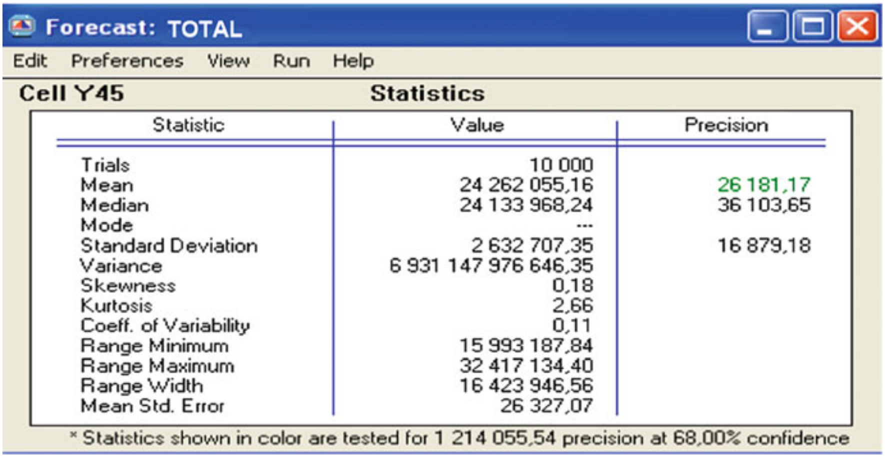


▸ 19 453 939,35 Certainty 95,00 % ◂ 29 587 007,48

Fig. 5.12 Frequency chart of the TOTAL forecast, with 95% certainty level (Source: Own work)

5.9 Sensitivity Analysis

The data sensitivity analysis has been carried out. The data consists of impact categories characterising the total life cycle impact of the management of waste produced in MSP Power Plant, in an annual cycle. The procedure has been conducted by taking into account the variability of the analysed parameters and

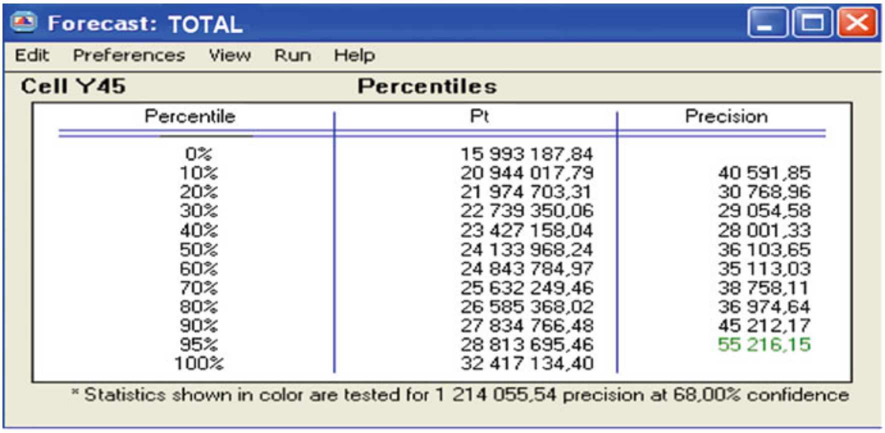


Cell Y45 Statistics

Statistic	Value	Precision
Trials	10 000	
Mean	24 262 055,16	26 181,17
Median	24 133 968,24	36 103,65
Mode	---	
Standard Deviation	2 632 707,35	16 879,18
Variance	6 931 147 976 646,35	
Skewness	0,18	
Kurtosis	2,66	
Coeff. of Variability	0,11	
Range Minimum	15 993 187,84	
Range Maximum	32 417 134,40	
Range Width	16 423 946,56	
Mean Std. Error	26 327,07	

* Statistics shown in color are tested for 1 214 055,54 precision at 68,00% confidence

Fig. 5.13 The statistics report of the forecast of the total life cycle impact of the management of waste generated in the MSP Power Plant, from an annual perspective – Statistics (Source: Own work)



Cell Y45 Percentiles

Percentile	Pt	Precision
0%	15 993 187,84	
10%	20 944 017,79	40 591,85
20%	21 974 703,31	30 768,96
30%	22 739 350,06	29 054,58
40%	23 427 158,04	28 001,33
50%	24 133 968,24	36 103,65
60%	24 843 784,97	35 113,03
70%	25 632 249,46	38 758,11
80%	26 585 368,02	36 974,64
90%	27 834 766,48	45 212,17
95%	28 813 695,46	55 216,15
100%	32 417 134,40	

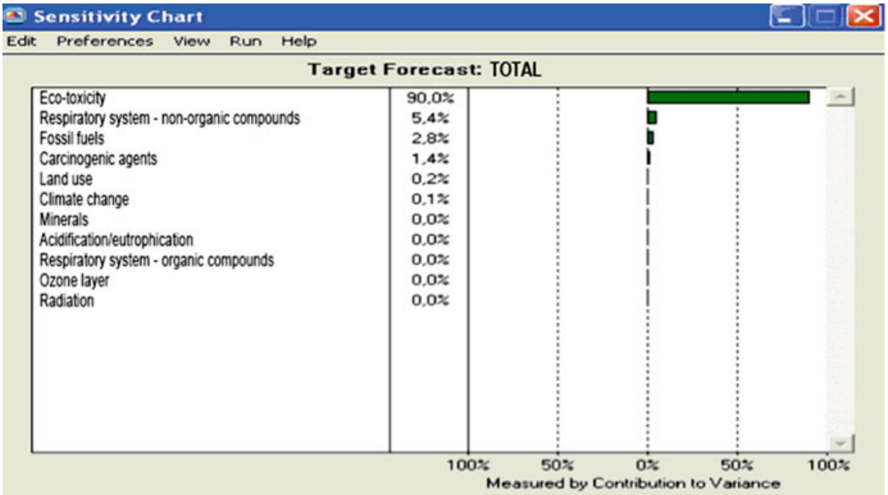
* Statistics shown in color are tested for 1 214 055,54 precision at 68,00% confidence

Fig. 5.14 The statistics report of the forecast of the total life cycle impact of the management of waste (TOTAL) generated in the MSP Power Plant, from an annual perspective – Percentiles (Source: Own work)

using MC simulation based on CB program. The sensitivity analysis is presented using the following three formats:

- Clustered bar chart (Fig. 5.15)
- Tornado chart (Fig. 5.16)
- Spider chart (Fig. 5.17).

A conclusion can be drawn from Fig. 5.15 that the greatest impact, 90% share in the total life cycle impact of waste management, expressed in eco-points and equal

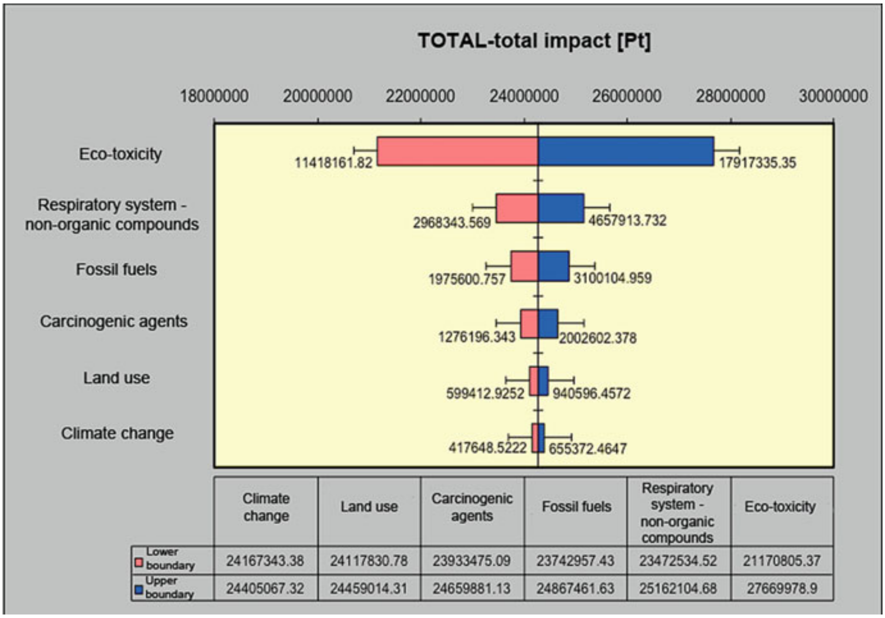


Sensitivity Chart

Target Forecast: TOTAL

Eco-toxicity	90,0%
Respiratory system - non-organic compounds	5,4%
Fossil fuels	2,8%
Carcinogenic agents	1,4%
Land use	0,2%
Climate change	0,1%
Minerals	0,0%
Acidification/eutrophication	0,0%
Respiratory system - organic compounds	0,0%
Ozone layer	0,0%
Radiation	0,0%

Fig. 5.15 The sensitivity analysis of the TOTAL forecast (Source: Own work)



	Climate change	Land use	Carcinogenic agents	Fossil fuels	Respiratory system - non-organic compounds	Eco-toxicity
🟥 Lower boundary	24167343.38	24117830.78	23933475.09	23742957.43	23472534.52	21170805.37
🟦 Upper boundary	24405067.32	24459014.31	24659881.13	24867461.63	25162104.68	27669978.9

Fig. 5.16 Tornado sensitivity chart of the TOTAL forecast. The error bars indicate mean standard error (Source: Own work)

to 24.3 Mpt, on the LCA analysis results of the management of waste produced in 2005 in MSP Power Plant, divided into 11 impact categories, is created by *eco-toxicity*. The second most influential impact category – *respiratory system – non-*

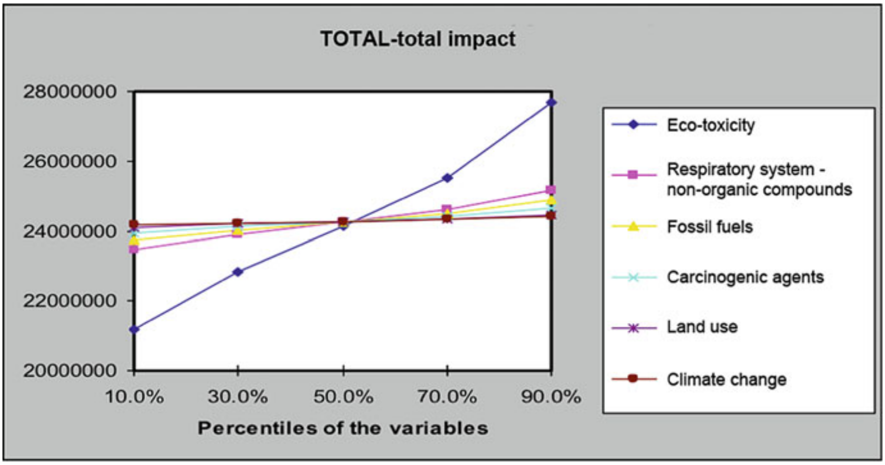


Fig. 5.17 Tornado sensitivity chart of the TOTAL forecast – the total life cycle impact of the management of waste generated in the MSP Power Plant, from an annual perspective (Source: Own work)

organic compounds – has only 5.4% share. The influence of the remaining impact categories does not exceed 2.8% share. The analysis has been performed using a method that defines the contribution of input variables of the model to variation, described in Chap. 4.13.

The tornado and spider charts have been created on the basis of data included in the newly built tables (Tables 5.6, 5.7), which are filled in with values resulting from an MC simulation performed after the activation of two decision fields (found in the Tornado Chart dialog window – see Fig. 4.15), respectively: *Tornado chart* and *Spider chart*. The impact categories, with the 0% share in the total life cycle impact of waste management on the results of the LCA analysis, are not included in the process of generating charts (Fig. 5.15). By analysing the charts shown in Figs. 5.16 and 5.17, it seems that *eco-toxicity* has the widest variability interval presented in the chart (Fig. 5.16) and is the most critical input variable – it corresponds to the line, which has the greatest incline towards the x axis, described in percentiles, which is mapping the location measure of distribution, presenting the total value of the life cycle impact of waste management.

In the fourth chapter of this monograph the Eco-indicator 99 method is described (see Chap. 4.7), which refers the impact of different damaging actions on natural environment to three types of damage categories: *Human Health*, *Ecosystem Quality*, and *Consumption of Resources* (SimaPro 2007). This chapter deals with the stochastic analysis used to calculate uncertainty of six impact categories (*Carcinogenic agents*, *Respiratory system – organic compounds*, *Respiratory system – non-organic compounds*, *Climate change*, *Radiation*, and *Ozone layer*), whose sum, 232.26 DALY, creates the *Human Health* damage category. Damage to human health is expressed in DALY units – they describe Disability Adjusted

Table 5.6 The MC simulation results, using CB software, of the tornado sensitivity analysis of the TOTAL forecast – the total life cycle impact of the management of waste generated in the AMPSAK Power Plant, from an annual perspective – sensitivity table

Variable	TOTAL – the total life cycle impact of waste management			Input parameters		
Impact category	Lower boundary	Upper boundary	Range	Lower boundary	Upper boundary	Base value
Eco-toxicity	21170805.37	27669978.9	6499173.534	11418161.82	17917335.35	14528467.21
Respiratory system – non-organic compounds	23472534.52	25162104.68	1689570.163	2968343.569	4657913.732	3776919.81
Fossil fuels	23742957.43	24867461.63	1124504.202	1975600.757	3100104.959	2513754.09
Carcinogenic agents	23933475.09	24659881.13	726406.0352	1276196.343	2002602.378	1623832.015
Land use	24117830.78	24459014.31	341183.532	599412.9252	940596.4572	762692.9055
Climate change	24167343.38	24405067.32	237723.9425	417648.5222	655372.4647	531415.9085

Table 5.7 The MC simulation results, using CB software, of the spider sensitivity analysis of the TOTAL forecast – the total life cycle impact of the management of waste generated in the MSP Power Plant, from an annual perspective – sensitivity table

Variable	TOTAL – the total life cycle impact of waste management				
Impact category	10.0%	30.0%	50.0%	70.0%	90.0%
Eco-toxicity	21170805.37	22845811.69	24137412.33	25534446.33	27669978.9
Respiratory system – non-organic compounds	23472534.52	23907980.67	24243754.06	24606936.67	25162104.68
Fossil fuels	23742957.43	24032771.48	24256247.65	24497966.17	24867461.63
Carcinogenic agents	23933475.09	24120688.84	24265049.74	24421194.81	24659881.13
Land use	24117830.78	24205762.66	24273567.11	24346906.43	24459014.31
Climate change	24167343.38	24228611.02	24275854.63	24326954.73	24405067.32

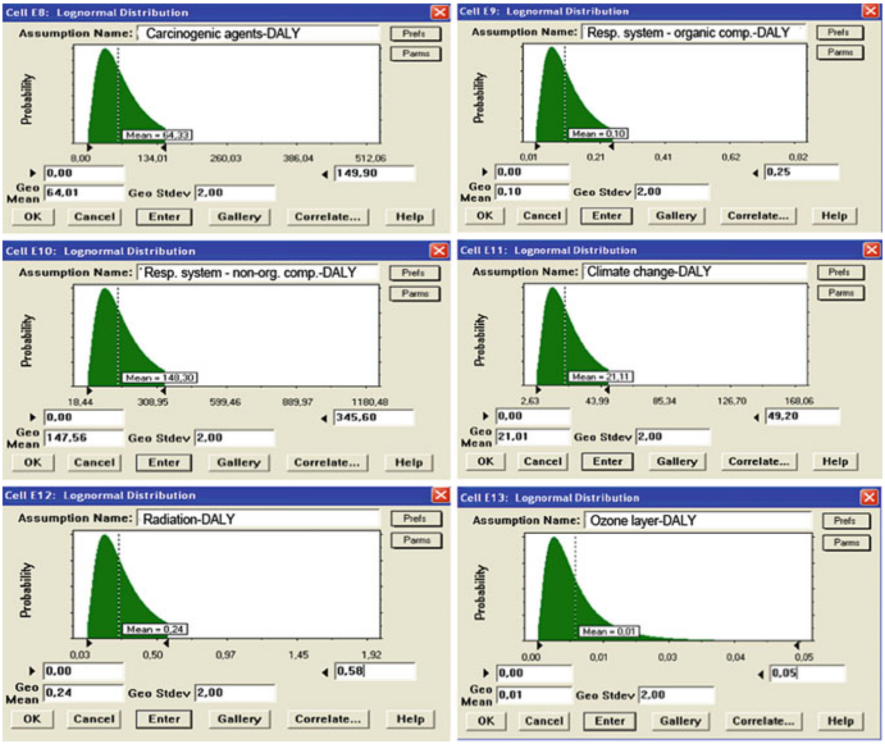
Table 5.8 The LCA analysis results for the management of waste generated by the MSP facilities in 2005 – brought to the form of human health damage category

Impact category	Unit	Total
Carcinogenic agents	DALY	64.33
Respiratory system – organic compounds	DALY	0.10
Respiratory system – non-organic compounds	DALY	146.47
Climate change	DALY	21.11
Radiation	DALY	0.24
Ozone layer	DALY	0.01
Total	DALY	232.26

Source: The Polish Academy of Sciences study (Ocena 2009)

Life Years. According to Adamczyk (2004), the DALY damage unit indicates a stream of hazardous substances in tonnes, in a year. The estimation scale of disability ranges between 0 and 1 and may be expressed in percentages. Zero refers to a full ability, whereas one means death. The details of the damage estimation can be found in Goedkoop et al. (2000), for instance.

The Eco-indicator 99 methodology, by relating the impact of the damaging effects on natural environment to one of the three impact categories, namely the human health damage category, allows to determine the relative amount of time by which human life is shortened, as a result of damaging waste management effects, and the number of deaths as well as the number of life years spent with disability (Kulczycka and Henclik 2009). These involve the following impact categories: *carcinogenic agents*, *respiratory system – organic compounds*, *respiratory system – non-organic compounds*, *climate change*, *radiation*, and *ozone layer*, which may be added up. Damage categories (not impact categories) are normalised on the European level (the damage caused by one European per year), on the basis of data collected in 1993 (the base year). This data has been updated for the most important types of emissions (Kulczycka and Henclik 2009). The data needed for the analysis can be found in Table 5.8. As far as the *consumption of resources* category is concerned, uncertainty analysis is not carried out (Eco-indicator 99). The process of



Cell E8: Lognormal Distribution
Assumption Name: Carcinogenic agents-DALY
0,00
149,90
Geo Mean 64,01
Geo Stdev 2,00

Cell E9: Lognormal Distribution
Assumption Name: Resp. system - organic comp.-DALY
0,00
0,25
Geo Mean 0,10
Geo Stdev 2,00

Cell E10: Lognormal Distribution
Assumption Name: 'Resp. system - non-org. comp.-DALY
0,00
345,60
Geo Mean 147,56
Geo Stdev 2,00

Cell E11: Lognormal Distribution
Assumption Name: Climate change-DALY
0,00
49,20
Geo Mean 21,01
Geo Stdev 2,00

Cell E12: Lognormal Distribution
Assumption Name: Radiation-DALY
0,00
0,58
Geo Mean 0,24
Geo Stdev 2,00

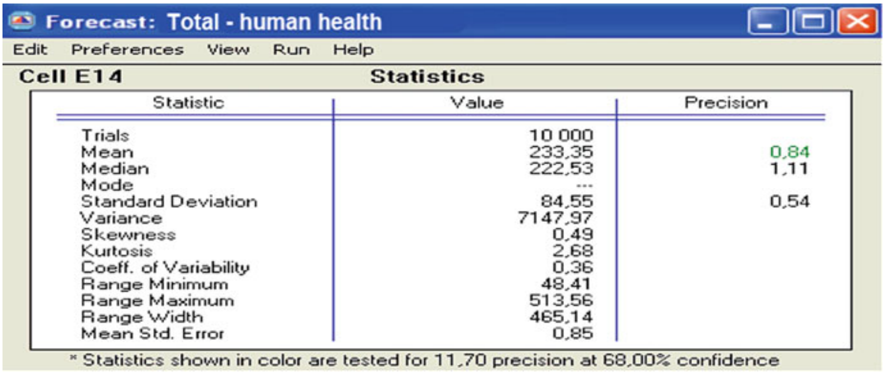
Cell E13: Lognormal Distribution
Assumption Name: Ozone layer-DALY
0,00
0,05
Geo Mean 0,01
Geo Stdev 2,00

Fig. 5.18 The log-normal probability distributions tab windows of six impact categories, available in CB program, that form the human health damage category of the LCA analysis for the management of waste in the MSP Power Plant (Source: Own work)

estimating the impact categories, which are mentioned in Table 5.8 and form the damage category (*human health*) – expressed in DALY units – is assigned with log-normal probability distribution along with the quantities describing the functions of this distribution (geometric mean μ_g and geometric standard deviation σ_g with a 68% confidence level). Due to the lack of Polish data, geometric standard deviations that describe log-normal distribution are chosen in accordance with the data that can be found in the following: Sonnemann et al. (2004), Hofstetter (1998), Rabl and Spadaro (1999), and Hofstetter (1998). Different scenarios (chronic and protracted) of YOLL (Years Of Life Lost) are thoroughly analysed in the above-mentioned publications, and especially in Rabl and Spadaro (1999), and in Friedrich et al. (2001). The recommended extreme values of geometric standard deviation σ_g are between 1.2 and 4. This study assumes that the value of geometric standard deviation is $\sigma_g = 2.0$, similarly to what is suggested in one of the most detailed and extensive work of Rabl and Spadaro (1999). The remaining simulation output data is included in Fig. 5.18 (Table 5.9).

Table 5.9 The MC simulation results, using CB software, of the tornado sensitivity analysis, of the human health damage category, on the change of input parameters (impact categories) of the characterisation model – sensitivity table

	TOTAL – human health			Input parameters		
Impact category	Lower boundary	Upper boundary	Range	Lower boundary	Upper boundary	Base value
Respiratory system – non-organic compounds	217.613138	246.9073692	29.29423119	131.8240404	161.1182715	146.471156
Carcinogenic agents	225.8276374	238.6928698	12.86523238	57.89354573	70.75877811	64.32616192
Climate change	230.1489832	234.371524	4.22254086	19.00143387	23.22397473	21.1127043



Cell E14

Statistics

Statistic	Value	Precision
Trials	10 000	
Mean	233,35	0,84
Median	222,53	1,11
Mode	---	
Standard Deviation	84,55	0,54
Variance	7147,97	
Skewness	0,49	
Kurtosis	2,68	
Coeff. of Variability	0,36	
Range Minimum	48,41	
Range Maximum	513,56	
Range Width	465,14	
Mean Std. Error	0,85	

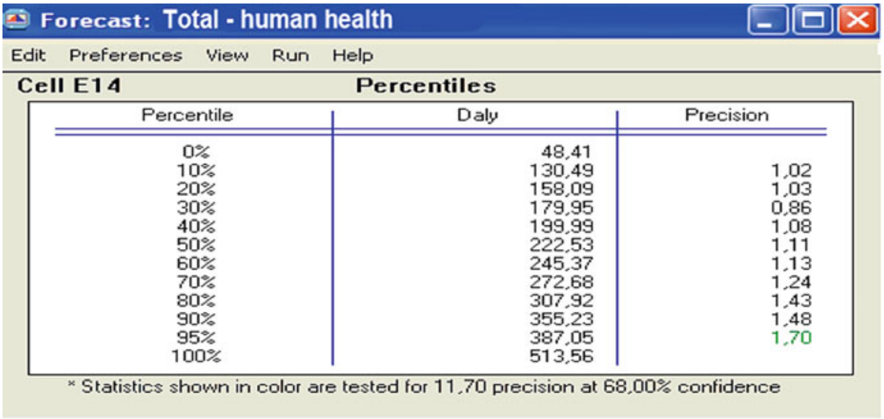
* Statistics shown in color are tested for 11,70 precision at 68,00% confidence

Fig. 5.19 The statistics report of the forecast of the total of six impact categories, that form the human health damage category, of the LCA analysis of waste management in the MSP Power Plant, in an annual cycle – *Statistics* (Source: Own work)

5.10 The Results of the Simulation

The simulation results, in the defined 10,000-randomisation cycle, are shown in Figs. 5.19 and 5.20. Figures 5.21 and 5.22 show the forecast frequency charts (*Forecast: TOTAL – human health*), which are the sum of six impact categories (*carcinogenic agents*, *respiratory system – organic compounds*, *respiratory system – non-organic compounds*, *climate change*, *radiation*, and *ozone layer*). This sum, equal to 232.26 DALY, forms the human health damage category. By setting the confidence levels to 68% and 95%, respectively, the obtained confidence intervals for the human health damage category amount to, respectively:

[148.02; 325.09] DALY
confidence level of 68%
[98.47; 417.47] DALY
confidence level of 95%

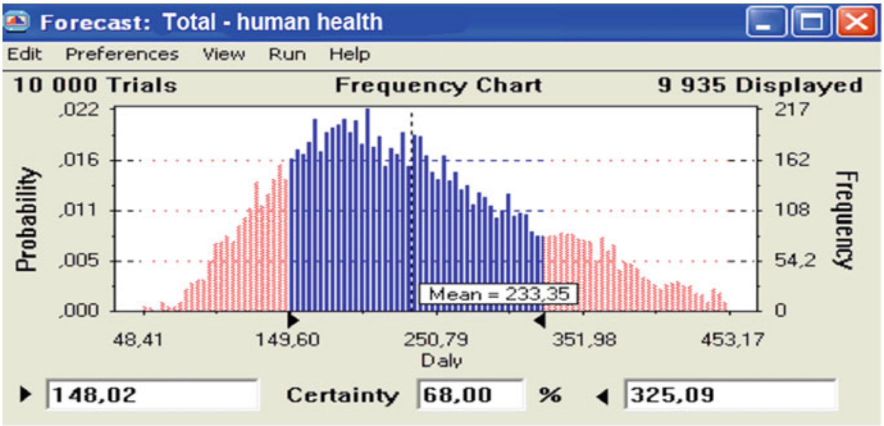


Cell E14 Percentiles

Percentile	Daly	Precision
0%	48,41	
10%	130,49	1,02
20%	158,09	1,03
30%	179,95	0,86
40%	199,99	1,08
50%	222,53	1,11
60%	245,37	1,13
70%	272,68	1,24
80%	307,92	1,43
90%	355,23	1,48
95%	387,05	1,70
100%	513,56	

* Statistics shown in color are tested for 11,70 precision at 68,00% confidence

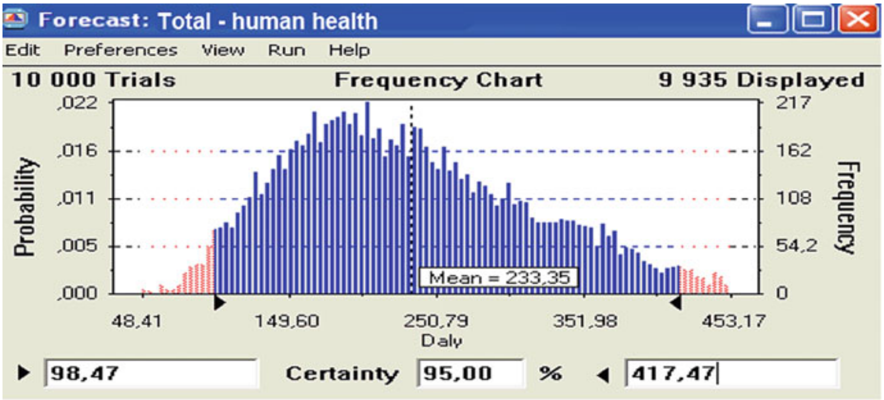
Fig. 5.20 The statistics report of the forecast of the total of six impact categories, that form the human health damage category, of the LCA analysis of waste management in the MSP Power Plant, in an annual cycle – *Percentiles* (Source: Own work)



▸ 148,02 Certainty 68,00 % ◂ 325,09

Fig. 5.21 The frequency chart of the TOTAL forecast – human health (confidence level of 68%) (Source: Own work)

The range width of the set confidence interval, after rounding the values determining the intervals, is 465.14 DALY (Fig. 5.19) – this is equivalent to the difference between the 0th and the 100th percentile, as can be seen in Fig. 5.20. The display range is between 48.41 DALY and 513.56 DALY. Spadaro and Rabl (2008) bring our attention to the fact that in a probabilistic analysis of the damage category (and human health is such a category) interval estimations are usually based on a confidence interval of 95%.



98,47 Certainty 95,00 % 417,47

Fig. 5.22 The frequency chart of the TOTAL forecast – human health (confidence level of 95%) (Source: Own work)

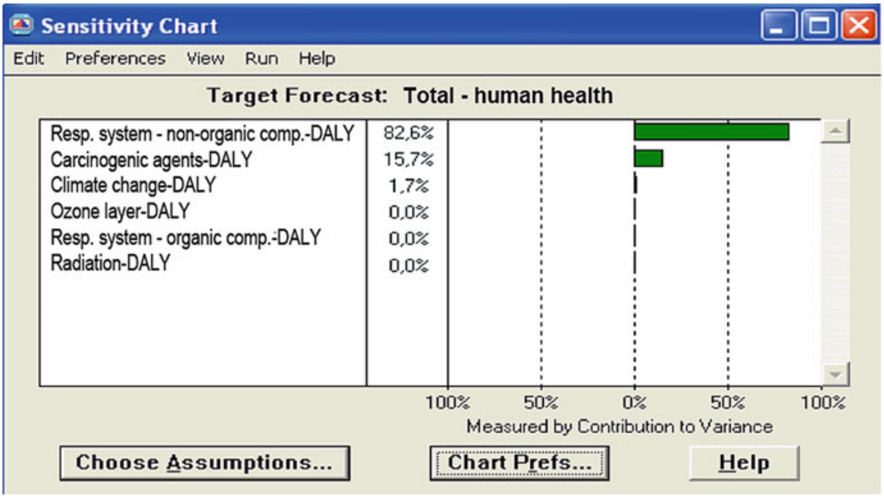
5.11 Sensitivity Analysis

The data sensitivity analysis has been carried out. The data consists of impact categories characterising the *human health* damage category. The procedure has been conducted by taking into account the variability of the analysed parameters and using MC simulation based on CB program. The sensitivity analysis is presented using the following three formats:

- Clustered bar chart (Fig. 5.23),
- Tornado chart (Fig. 5.24),
- Spider chart (Fig. 5.25).

A conclusion can be drawn from Fig. 5.23 that the greatest impact, 82.6% share, in the *human health* damage category, has the r*espiratory system – non-organic compounds*, expressed in DALY. The second and third most influential impact categories – *carcinogenic agents* and *climate change* – have only 15.7% share and 1.7% share, respectively. The influence of the remaining impact categories does not exceed 0% share.

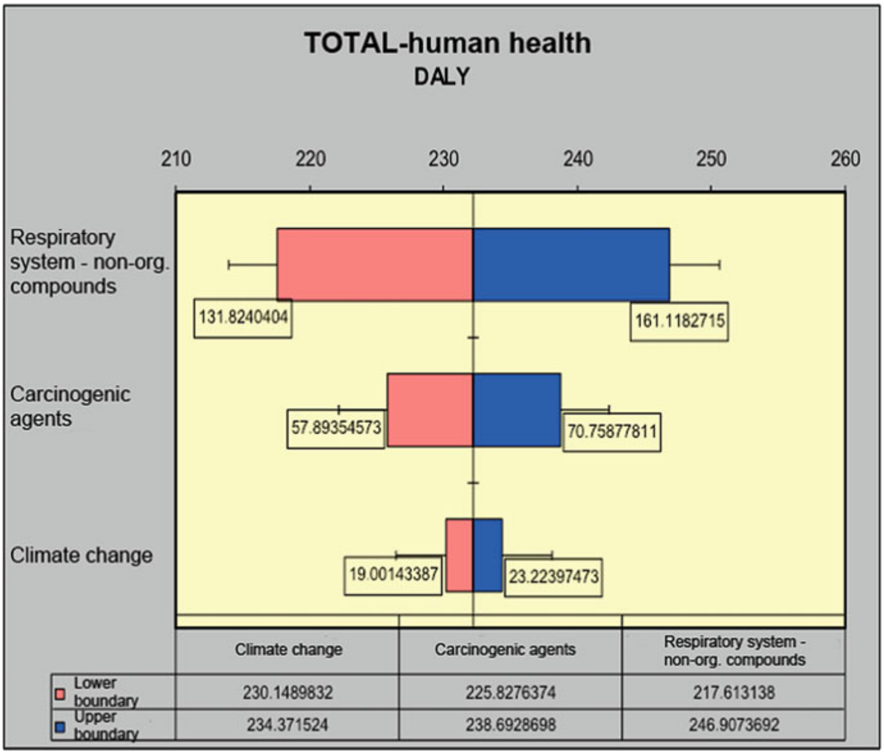
The tornado and spider charts have been created on the basis of data included in the newly built tables (Tables 5.9 and 5.10), which are filled in with values resulting from an MC simulation performed after the activation of two decision fields (found in the Tornado Chart dialog window – see Fig. 4.15): *Tornado chart* and *Spider chart*, respectively. The impact categories, with the 0% share in the *human health* damage category are not included in the process of generating charts (Fig. 5.23). By analysing the charts shown in Figs. 5.24 and 5.25, it seems that r*espiratory system – non-organic compounds* has the widest variability interval presented in the chart (Fig. 5.24) and is the most critical input variable – it corresponds to the line, which has the greatest incline towards the x axis, described in percentiles, which is



Target Forecast: Total - human health

Resp. system - non-organic comp.-DALY	82,6%
Carcinogenic agents-DALY	15,7%
Climate change-DALY	1,7%
Ozone layer-DALY	0,0%
Resp. system - organic comp.-DALY	0,0%
Radiation-DALY	0,0%

Fig. 5.23 The sensitivity analysis of the TOTAL forecast – human health (Source: Own work)



	Climate change	Carcinogenic agents	Respiratory system - non-org. compounds
🟥 Lower boundary	230.1489832	225.8276374	217.613138
🟦 Upper boundary	234.371524	238.6928698	246.9073692

Fig. 5.24 Tornado sensitivity chart of the human health damage category. The error bars indicate mean standard error (Source: Own work)

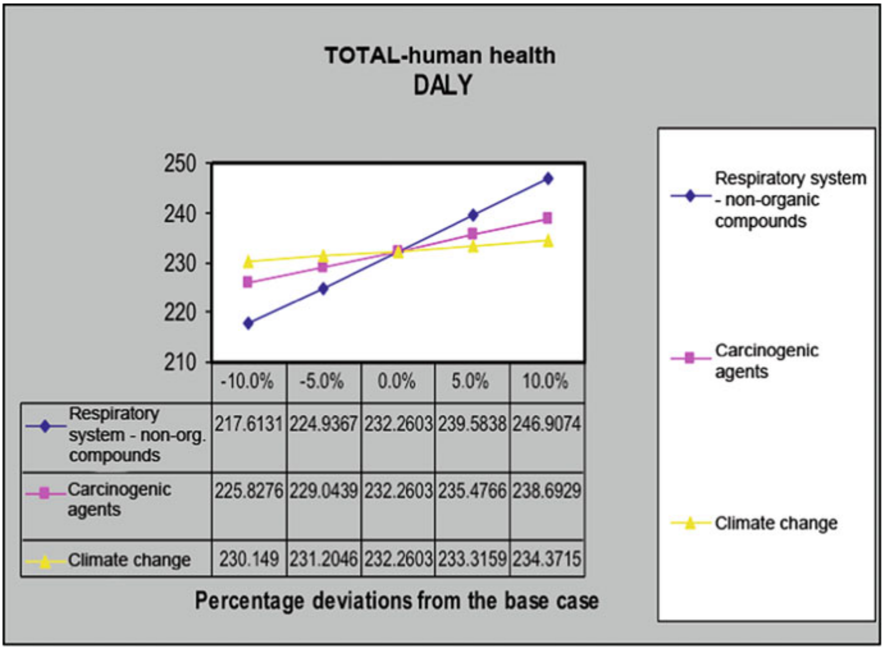


Fig. 5.25 Spider sensitivity chart of the *human health* damage category (Source: Own work)

Table 5.10 The MC simulation results, using CB software, of the spider sensitivity analysis, of the *human health* damage category, on the change of input parameters (impact categories) of the characterisation model – sensitivity table

Variable	TOTAL – human health				
Impact category	−10.0%	−5.0%	0.0%	5.0%	10.0%
Respiratory system – non-organic compounds	217.613138	224.9366958	232.2602536	239.5838114	246.9073692
Carcinogenic agents	225.8276374	229.0439455	232.2602536	235.4765617	238.6928698
Climate change	230.1489832	231.2046184	232.2602536	233.3158888	234.371524

mapping the location measure of distribution, presenting the total value of the *human health* damage category (Table 5.10)

5.12 Summary and Conclusion

The performed LCA analysis makes it possible to determine the environmental impact of the management of waste generated by MSP. The fact that the individual waste types are grouped and that the processes chosen from a database and used during the analysis are not adequate to Polish, but to European conditions, which may generate inaccurate or even incorrect results, should be taken into consideration here (this is the case, for example, when it comes to the emission of radon-222, which is practically absent in the coal burned in MSP Power Plant. This coal, as is mentioned in Chap. 4.13, which comes from the mines that belong to Katowicki Holding Węglowy, a coal producer based in Katowice, should not contain radon-222. Yet, the electric energy produced in MSP Power Plant does not cover the total needs of the mentioned industrial complex. The missing energy is bought elsewhere – see Chap. 5.2).

The performed life cycle analysis of waste management has, in addition, made it possible to:

- Identify waste, whose contribution to the total level of influence is the biggest. The greatest potential environmental strain (approximately 63%) is caused by the storage of slags. The less straining impacts are caused by the storage of hazardous waste (27.7%) as well as coal fly-ashes and slag-ash mixtures (5.4%). The influence of the remaining types of waste does not exceed 3.5% (Fig. 5.9),
- Identify waste, whose contribution to the 11 impact categories is the biggest. In the majority of cases, the factor that is the main potential environmental strain is the produced hazardous waste,
- Identify environmental benefits – by analysing the *land use* impact category (see Fig. 5.1 and Table 5.4), the negative level of environmental influence (the darker cells in Table 5.4) that deals with the remaining waste from iron, steel, scrap and silt, paper and cardboard, as well as water decarbonisation sediments, may be noticed. This is caused by the utilisation and recovery of the products that bring environmental benefits.

The results of the LCA analysis, presented in Table 5.5, which include the total life cycle impact of waste management in an annual cycle, for the examined functional unit, expressed in eco-points and amounting to 24.3 Mpt, are employed here with a view to presenting the stochastic analysis of life cycle waste management in MSP.

The stochastic analysis, used to calculate uncertainty of the six impact categories (*carcinogenic agents*, *respiratory system – organic compounds*, *respiratory system – non-organic compounds*, *climate change*, *radiation*, and *ozone layer*), whose sum, 232.26 DALY, forms the *human health* damage category, has been performed on the basis of data included in Table 5.8. The results of the analysis, presented in graphic form and in the form of reports, are shown in Figs. 5.11, 5.12, 5.13, 5.14, 5.15, 5.16 and 5.17 and in Figs. 5.20, 5.21, 5.22, 5.23, 5.24 and 5.25.

The LCA analysis has been performed, for the purposes of the postdoctoral thesis, by the Mineral and Energy Economy Research Institute of the Polish Academy of Sciences (PAN), in Kraków (Ocena 2009). It contains the result expressed in the form of: characterisation, normalisation, and measurement stage results – values of which are given in eco-points Pt for individual impact categories. The analysis has been performed in accordance with the international standards PN-EN ISO 14040:2006 (Environmental management – Life cycle assessment –

Principles and framework) and PN-EN ISO 14044:2006 (Environmental management – Life cycle assessment – Requirements and guidelines). The material-energy balance (LCI) is based on data provided by the AMPSAK industrial complex (Wniosek 2006).

After a detailed study of the available subject literature (see Chap. 4.4), an assumption has been made, based on the Distribution Gallery tab found in Crystal Ball program, that the simulation should employ log-normal probability distributions with a geometric standard deviation of $\sigma_g = 1.2$ for all parameters of the analysis.

To summarise, normalisation indicates the relative extent of the influences' impact; however, if the gravity of the influences is to be presented, it is necessary to perform measurements – this means that the results need to be converted by applying weight coefficients that are equivalent to the severity of the influence (Adamczyk 2004). The measurement procedure has always been considered as controversial not only due to its subjectivity, but also because it involves social, political, and ethical values (Finnvenden 1997). Nevertheless, it is widely applied in practice, despite the controversies (Hansen 1999). The wider debate on the subject of measurement can be found in Finnvenden et al. (2002), Kowalski et al. (2007), Simapro (2007).

Chapter 6
Summary

This monograph is an outcome of many years of research carried out by the author in the last decade. The presented methodology of research and its findings not only have been published a number of times in reviewed magazines and journals, but also have been discussed in prestige all-Polish as well as international conferences, including the following: International Federation of Operational Research (IFORS2002, IFORS2005, IFORS2008), *VIII Międzynarodowej Konferencji Naukowej* (an International Scientific Conference), *ZARZĄDZANIE PRZEDSIĘBIORSTWEM – TEORIA I PRAKTYKA – 2005* (Enterprise Management – Theory and Practice – 2005), International Business & Economics Research (IBER 2006), 21st European Conference on Operational Research (EUROXXI 2006), Life Cycle Management (LCM2007, LCM2009, LCM 2011) 11th World Multi-Conference on Systemics, Cybernetics and Informatics (WMSCI-2007), R'07 World Congress 2007, The 2007 Crystal Ball user Conference, Global Waste Management Symposium 2008, and Sixth International Conference on Sensitivity Analysis of Model Output, SAMO, in 2010. A number of publications, included in this monograph, are taken from a postdoctoral research grant number N115 084 32/4279, financed between 2008 and 2010 by the Ministry of Science and Higher Education, entitled "Zastosowanie Ekologicznej Oceny Cyklu Życia (LCA) do tworzenia zintegrowanych strategii gospodarki odpadami w warunkach niepewności z użyciem symulacji Monte Carlo" (The application of Ecological Life Cycle Assessment (LCA) in the creation of integrated strategies of waste management under uncertainty using Monte Carlo simulation). The work of the author in the discussed field is also well documented in individual chapters of this monograph; these include (Bieda 2000, 2002; Bieda and Wajs 2002; Bieda 2003, 2004a, b, c, d, e; Bieda 2005a, b; Bieda 2006a, b, c, d, e, f; Bieda 2007a, b, c, d, e, f; Bieda and Tadeusiewicz 2008a; Bieda 2008b, c, d, e, f, g; Bieda 2009a, b; Bieda 2010).

Ecological Life Cycle Assessment method is one of the developing assessment methods, which in literature is more commonly known as Life Cycle Assessment (LCA). It is a relatively new technique, especially in Poland, that deals with environmental management, which in recent years have attracted more and

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more interest. The reliability of LCA results may be uncertain, to a certain degree, but this uncertainty can be noticed with the help of Monte Carlo method, for instance. This methodology has not yet been used in Polish steel industry and this is one of the reasons why this monograph discusses the LCA method so extensively (Chaps. 4 and 5). As is mentioned in the introduction to Chap. 4 (4.1), the International Iron and Steel Institute in Brussels, Belgium, in 2002 undertook a study focusing on data inventory, based on the material-energy balance in the Life Cycle Inventory (LCI) procedure, on the basis of data gathered from 28 steel plants, excluding the steel power plants from the Mittal Steel Group – a fact that is mentioned in the supplementary paper to the study (IISI 2002).

It has been proven that (1) log-normal distribution can be practically applied in the assessment of impacts on the quality of natural environment of manufacturing processes, e.g. in steel industry, (2) uniform distribution can be practically applied in the analysis or risk investment, and, finally, (3) log-normal and uniform distribution can be used in modelling of waste propagation in the management of environmental quality (the transport model of polluting substances in homogeneous porous media). When analysing the subject literature describing the application of uncertainty analysis, the work of Pappenberger and Beven (2006), on the modelling of hydraulic and hydrological phenomena under uncertainty, can attract one's attention for the authors provide seven reasons as to why uncertainty analysis should not be used. First of all, a group of modellers exist who believe that their physical models are (or will be) of static nature, i.e. time is of no relevance. They claim that all parameters, boundary conditions, etc., can be defined a priori, and so, uncertainty analysis is not necessary. Moreover, another group of researchers state that it is enough to alter the model's parameters in the strictly defined range. Second of all, the testing of models can be conducted using non-statistical methods, by eliminating the models that cannot deliver satisfactory results. Thirdly, many researchers claim that the decision-makers and the management personnel are not properly mathematically prepared to carry out their duties, as the notions of risk and uncertainty are understood differently and are oftentimes confused. Furthermore, uncertainty cannot be integrated into decision-making processes that on many occasions are binary. In addition, uncertainty analysis should be disregarded due to its excessive subjectivity and the difficulty with which it is performed. Lastly, the seventh, and final reason emphasises the lack of real impact of uncertainty on the process of reaching the final decision.

The author hopes that the monograph will be helpful in explaining the problems of stochastic analysis to students (at postgraduate level), scientific researchers, and to industry managers. This thesis is of methodical nature, and the simulation results presented here are of cognitive and applied importance. It is the intention of the author to continue the cooperation with other domestic and international scientific centres (e.g. with the EU Joint Research Centre, in Italy, where the discussion regarding SimLab® program took place, in which the author participated during his visit).

It may seem that the proposed problems concerning the application of computer simulation techniques in stochastic analyses, alongside the cognitive values, can also constitute a practical tool, which may make it possible to explain, for example, the problem of uncertainty in LCA studies. The author of this monograph expects this kind of practical and creative application in other technological processes to take place.

Numerical stochastic analysis has been rapidly developing as well, as more powerful computers become available. The focus here has been on the more general, constructive methods of obtaining information regarding stochastic processes with log-normal distributions.

To sum up, a statement may be made, to quote after Snopkowski (2007), that stochastic simulation allows to answer the question of what happens to a process (and its chosen features) if different conditions in its course do occur? Many a time a situation occurs when stochastic simulation is the only research method that makes it possible to find an answer to such a formed question.

It needs to be said that this monograph would have been impossible to complete without the help of, and the fruitful collaboration with, the MSP's Department of Environmental Protection.

The conclusions have been included in the summaries of individual chapters of this thesis.

6.1 General Conclusion

The aim of the thesis was to present and emphasise the versatility of Monte Carlo method in the assessment of uncertainty in stochastic analysis of chosen manufacturing processes and ecology. The interdisciplinary nature of the monograph means that the following aspects need to be linked together:

- The technical aspects – the stochastic model of the diffusion of polluting substances applied in the management of landfills, by using MC simulation, makes the simulation of contaminant transport more detailed in comparison to the simulation based on transportation models available to date, resulting in a better, more practical, assessment of the current state. This is of practical importance in the case of measuring the range of safety zones surrounding industrial plants, landfills, or ground water intakes.
- The ecological aspects – the application of LCA techniques offers important and notable benefits (e.g. of financial nature) to industrial companies or service providers who are interested in limiting the negative environmental impact caused by their activity.
- The economic aspects – the stochastic analysis of investment decisions is a valuable addition to the process of searching for solutions to financial questions regarding investment management, in situations where typical assessment methods cannot provide explicit answers.

The connection made between the manufacturing processes and the management of the LCA technique may be perceived as a methodological goal that has been achieved. The fact that the application of LCA, a technique that is still under development, in the assessment of impact of manufacturing processes on natural environment, which has been included in the research methodology, constitutes a significant progress in relation to the analyses that have been used so far.

The data and parameter values present in the analysis have been determined mainly on the basis of in situ measurements.

The stochastic analyses of manufacturing processes, based on the steel industry case study, and ecology, using Monte Carlo method, presented in this monograph, can be, according to the author, an effective tool supporting not only the environmental management under uncertainty, but also the interpretation of results in environmental economy and engineering.

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