SILESIAN UNIVERSITY OF TECHNOLOGY PUBLISHING HOUSE

SCIENTIFIC PAPERS OF SILESIAN UNIVERSITY OF TECHNOLOGY 2023
ORGANIZATION AND MANAGEMENT SERIES NO. 187

KNOWLEDGE MANAGEMENT IN ORGANISATION ON THE BASE OF USING THE HYBRID METHODS OF UNSERTAINTY ANALYSIS

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Purpose: The purpose of this study is to formalize knowledge management based on the use of methods of uncertainty analysis in the organization, which will allow collecting missing or incomplete information, as well as finding appropriate management solutions.
Design/methodology/approach: The methodology consists of three stages: (1) analysis and evaluation of description of uncertainty in LCA; (2) recommendation of the most appropriate measures of uncertainty; (3) construction of a new hybrid method for LCA based on the fuzzy theory.
Findings: Alternative ways of modeling of uncertainty, such as Monte Carlo (MC) and fuzzy sets (FS) (possibility distributions) are discussed. Based on literature data on hybrid LCA and uncertainty in LCA an overview has been developed. It is concluded that given possibility to analyze different situations creates knowledge experience and its usage due to the knowledge management process.
Research limitations/implications: given research propose the new approach on the environment investigation that forms additional knowledge for making decision support in management process. But additional investigation must be completed and should include suggestions for future research on the implementation of knowledge management in the decision support system of organization.
Practical implications: the study examines the practical results of applying the proposed approach to uncertainty analysis using specific methods that reflect the impact of risk on the consequences of the commercial results of a mining company's project implementation.
Social implications: Proposed research could be impactful to the society by giving methods of environmental investigation with possibility of accounting the factors of uncertainness.
Originality/value: the new hybrid LCA method is proposed when uncertainty is due to both randomness and the lack of, or incomplete, information. The development of such methods is necessary for the appropriate uncertainty analysis in LCA. A set of such techniques are knowledge management tools that support the decision-making process through a clearer understanding of the situation and its implications.

Keywords: knowledge management, life cycle assessment (LCA), uncertainty, fuzzy logic, Monte Carlo (MC) method.

Category of the paper: conceptual paper, case study.

1. Introduction

Modern civilization progress is based on the application of the concept of knowledge management. Its main postulate is the formation and use of unique knowledge, which allows to transform the potential opportunities of organizations into its driving forces of development. And these opportunities are manifested not only in material assets, but are significantly dependent on their intangible component, formalized in the results of intellectual work. Thus, the study of the peculiarities of the implementation of knowledge management in enterprises is relevant. Consideration of this issue will allow us to highlight the basic elements of knowledge management, which should be given primary attention when implementing the mentioned concept in practice.

Today, issues related to the relevance of knowledge management concept in the practice of domestic enterprises are widely discussed. In literary sources, knowledge management is considered in various planes of practical application. This can be attributed to the fact that this concept quickly evolved from a theoretical discipline (the beginning of the 90s of the last century) to its versatile practical application. When considering knowledge management from interdisciplinary positions, the following basic approaches to defining its essence are distinguished: the best practical change transformer based on benchmarking; information and resource management; organizational learning and organizational memory; electronic performance support systems (EPSS); knowledge economy and knowledge as a corporate value; Internet and Web portals (Regan, 2007). In our opinion, such a wide range of definitions of this concept allows us to cover various spheres of the organization's activities that are related to knowledge management processes and allows us to develop directions for the practical implementation of accumulated knowledge. At the same time, it complicates the procedure of identifying the possibilities of implementing knowledge management in the activities of a separate enterprise and identifying practical ways of implementing this concept.

2. Literature review

Despite this, the use of knowledge as a unique resource that forms the competitive advantages of the enterprise within the existing approaches to defining the essence of this category requires the selection of those key provisions of the management activity of the organization that allow bringing the concept closer to real business conditions. In our opinion, knowledge management is a modern concept of enterprise development, which is based on the purposeful activity of people, which ensures the processes of generation, accumulation, storage and use of knowledge in the organization to support the processes of current functioning and long-term development, and is based on the optimal combination of it (knowledge) economic and informational context. Such a combination will allow to increase the quality and efficiency of management decisions, speed up reactions to changes in the organization's environment, and improve the quality of customer service. When studying the peculiarities of the development of the concept of knowledge management in practice, it is necessary to pay attention to the distinction between the concepts of knowledge management, under which a functional task is considered, and knowledge management as a purposeful activity of a person and a company, which determines the philosophy of the development of the ability to learn. It is also important to note that in literature, knowledge management is considered as an economic category related to the development of methods of optimal use of the organization's intellectual potential (Wing, 1997), and information technologies designed to optimize work with knowledge (Mahdi et al., 2020). The choice of the allocation method has a strong correlation with the aims of the study as defined by decision makers. This allows practitioners to both justify their choice and discuss and discuss the results with alternative scenarios for sensitivity analysis (Ijassi, 2021). Qualitative methods are growing the more and more important, because in numerous decision-making situations, uncertainty of economic and environmental parameters is not of probabilistic in nature, but it results from insufficient or vague information and is epistemologically indeterminate Mohamed and McCowan (Mohamed, McCowan, 2001). Moreover, sometimes, as pointed by Gupta (1993), it happens that uncertainty is probabilistic, but the available information is fuzzy. In practice, quite often it is not possible to determine probability distribution because of not sufficient volume of data (and there is no possibility to get enough data) facilitating execution of statistic tests. On the other hand, assumption of "no data available at all" is also not true. In general, there is always some information available, e.g., experts' estimates of unknown values. A good example is the LCA model. By the meaning of LCA or Life cycle assessment it is considered the methodology of environment assessment on all stages of product or service life cycle. The main difficulty in this case stems from the uniqueness of case and the time interval between the moment of studies on a project and its realization and exploitation. Usually, only experts' opinions and subjective probability distributions of the possible values of parameters can be used. The estimation of LCA model parameters from historical data is much more difficult because of the specifity and uniqueness of each case. It is not possible to obtain perfectly reliable information regarding similar past cases. The lack of enough information causes that it is necessary to use subjective probability distribution. The estimation of subjective probability is based on the experience of a person that determines the probabilities of occurrence of individual events. The level of subjectivity depends on the way of estimation and on the knowledge of other similar events. In practice, an arbitrary probability distribution between minimal and maximal estimation is usually adopted. The evaluation of effectiveness of LCA projects using subjective probability distributions is related, among others, to the problem of estimating these distributions. Choobineh and Behrens (1992) and Kuchta (2001) point out these difficulties. Moreover, Kuchta says that sometimes a decision-maker does not know how to answer the question on the probability of the unique, unrepeatable event. The question about frequency has not much sense. A decision-maker can have, however, some opinion on the degree of possibility of occurrence of respective values. Moreover, the subjective probability distribution must have the same properties as any probability distribution. For example, the sum of probabilities of all elementary events must sum up to one and the probability of the simultaneous occurrences of two independent events is the product of the probabilities of each event. It is extremely difficult to maintain these properties in expert judgments about subjective probability of future values Kuchta (2001). This problem can be partially solved by modeling uncertainties using, e.g., fuzzy numbers.

Uncertainty is a pervasive topic in LCA (Heijungs, Lenzen, 2014). In fact, data uncertainty is often mentioned as a crucial limitation for a clear interpretation of LCA results (Sonnemann, 2003). However, uncertainty analysis is not commonly performed in LCAs (Huijbregts et al., 2001; Bjorklund, 2002; Ross et al., 2002), although great efforts have been made on classification, definition, and sources of uncertainty as well as on methodological aspects for expressing uncertainty (Guo, Murphy, 2012). Classification of methods for uncertainty characterization, uncertainty analysis, as well as sensitivity analysis are discussed in detail in (Igos et al., 2019).

Uncertainty is present in many forms (Yen Le, Hendriks, 2014) and shows up in many ways (Heijungs and Lenzen, 2014) in all stages of an LCA. So, it's critical for LCA that the input data is accurate and current. Unfortunately, the available data is usually burdened with uncertainty due to measurement errors, incomplete knowledge, or variability. Therefore, the key stage in the process of LCA assessment is the choice of an appropriate method for describing uncertainty.

The Table 1 present the essential approaches to uncertainness description are considered, on the base of which the methods of uncertainness assessment are variated and suggested to be used for. Currently, the researchers on uncertainty analysis mainly consist of two parts. One is to explore new two main methods to improv the uncertainty estimate: one is the qualitative assessment, and other is the quantitative assessment proposed to use data quality indicators to describe the different magnitudes of influence on the overall uncertainty of a data (e.g., completeness, temporal correlation, etc.).

Table 1.
Methods of uncertainness description and assessment

Approaches to uncertainness description	Methods of uncertainness assessment	Authors	Limitations of methods
Hybrid description of uncertainty	The hybrid description of uncertainty is useful and also suitable for alternative ways - the uncertainty modelling of an LCA results which can be built using the variance and entropy of fuzzy numbers.	Scope et al., 2016	Not all fuzzy numbers equally suited to address different categories of uncertainty. The validity of LCA strongly depends on the validity of the input data (Grant, Horne, 2009).
Expression of uncertainty through a probability distribution	To obtain a result, different statistical methods can be applied including well-known sampling method as Monte Carlo (MC) simulation.	Igos, 2019; Huijbregts et al., 2001; Warren-Hicks, 1998; Bieda, 2012; Sonnemann et al., 2004	High cost of data preparation and difficulties with determining probability distributions of parameters (e.g., economic) significantly limit the usage of this approach; randomness, imprecise or incomplete information is an important source of uncertainty
Risk assessment	Software for LCA based on MC simulation. Methods for propagation uncertainties, apart from MC, as Latin hypercube sampling, quasi-Monte Carlo sampling, analytical uncertainty propagation and fuzzy interval arithmetic. Alternative ways of modeling of uncertainty, such as fuzzy sets or interval numbers. MC simulation with the mathematical description of imprecise or vague information, with information visualization Science-based and practical application of uncertainty analysis integrated within risk management in accordance with ISO 3100 (2009) and IEC 62198 (2013)	The United States Environmental Protection Agency (EPA), Smith, 1994, Heijungs, Lenzen, 2014; Bisinella et al., 2016; Groen et al., 2014; Skalna et al., 2015; Baudrit et al., 2006; Scope et al., 2016	In the risk assessment (including risk identification, risk analysis, and risk evaluation), no distinction is traditionally made between types of uncertainty, both being represented by means of a single probability distribution provided guidance for a science-based and practical application of uncertainty analysis integrated within risk management in accordance with ISO 3100 (2009) and IEC 62198 (2013).
Transformation of a probability distribution into a possibility distribution	The methods which allow different representations of uncertainty (e.g., by probability distributions, fuzzy numbers of interval numbers) to be processed according to their nature and only finally combine them into a synthetic easy-to-interpret measure of environmental impact; sampling method	Groen et al., 2014	Causes the loss of information, whereas the opposite one requires additional information to be introduced. This eventually leads to systematic errors in risk assessment, i.e., overestimation or underestimation of the risk

Cont. table 1.

Random variability, referred to as „objective uncertainty”. Imprecision referred to as “subjective uncertainty”	Deterministic, probabilistic, possibilistic, and simple methods	Ferson, Ginzburg, 1996	Weaknesses or limitations of the semi-quantitative approach are discussed (one being that uncertainty is always considered as following a lognormal distribution) implemented in Eco invent v2, based on the use of a pedigree matrix which considers two types of uncertainties
The basic uncertainty as the epistemic error	New methodology developed to apply the semi-quantitative approach to distributions other than the lognormal	Ciroth et al., 2016; Muller et al., 2016	
The additional uncertainty as the uncertainty due to using imperfect data	Procedure geometric standard deviation, used as the uncertainty measure, is essential to overcome scaling effects; it should therefore also be used if the analyzed data do not follow a lognormal distribution	Zhang et al., 2016; Weidema, Wesnaes, 1996	

Source: worked on the base of literature review.

Most of the real decision-making problems contain a mixture of quantitative and qualitative data. Due to the above, conventional probabilistic approach appeared to be insufficient for modelling of numerous decision-making problems, in particular problems related to LCA. Many authors have applied the alternative description of the uncertainty. The investigations performed for the purposes of this article indicate that fuzzy numbers are the mostly used.

So, the complexity and variety of uncertainness cause the demand on Hybrid LCA enhancing for the better integration between the different methods of uncertainness assessment. Hybrid LCA in this article is proposed to be considered through the combining Monte Carlo (MC) simulation and fuzzy set theory (FST) while taking advantage of its process specificity.

3. Article purpose

The purpose of this study is to show the background of knowledge management functioning at an organization on the base of investigation the theoretical and practical aspects of getting substantiated information on uncertain conditions of organization’s activity with help of the expanding the view of the hybrid LCA method, which is based on the application of uncertainty analysis to the LCA method. This will allow the description and processing of uncertain data in a situation where uncertainty arises from randomness and lack of or incomplete information, using a broad overview of scientists’ views on uncertainty assessment problems regarding new combinations of different methods. Alternative methods for modeling uncertainty, such as Monte Carlo (MC) and fuzzy sets (FS) (probability distributions), are discussed. The process of knowledge management at mining organization is considered with proper recommendation according to the uncertainness analysis results implementation.

4. Methods description

Fuzzy sets were introduced by Lofti Zadeh in 1965. They generalize classical set theory by replacing the binary membership function with a real function taking values in the interval [0, 1].

The fuzzy set theory can be used in a wide range of domains in which information is incomplete or imprecise and are recommended in the case of intangible data (but not limited to) (Scope et al., 2016). A fuzzy subset $\tilde{A}$ of universe $\mathcal{X}$ is a set of pairs $\tilde{A} = \left\{ \left(x, \mu_{\tilde{A}}(x) \right) : x \in \mathcal{X} \right\}$ where $\mu_{\tilde{A}} : \mathcal{X} \to [0,1]$ is any function defined in $\mathcal{X}$ and is called a membership function of the fuzzy subset (Zadeh 1965). Fuzzy subset can be unambiguously determined by a sequence of ordinary subset of set $\mathcal{X}$ called α-levels of subset $\tilde{A}$ (Zadeh). These are classic subsets of $\mathcal{X}$ given by $A_\alpha = \left\{ x \in \mathcal{X} : \mu_{\tilde{A}}(x) \ge \alpha \right\}$, where $\alpha \in$ (0.1]. The fuzzy set can be treated as a family of α-levels. The closed subset $A_0 = \left\{ x \in \mathcal{X} : \mu_{\tilde{A}}(x) \ge 0 \right\}$ is called the support of the fuzzy set $\tilde{A}$ and is denoted by $\sup\left(\tilde{A}\right)$.

The fuzzy subset $\tilde{A}$ can be identified with the approximate value of element x_o. This can occur when x_o is any element of universe $\mathcal{X}$ and $\tilde{A}$ such a fuzzy set, that $\mu_{\tilde{A}}(x_o) = 1$. In general, fuzzy numbers are used for modeling values which are approximate, imprecise, or not clearly defined. The membership function of the fuzzy number is then given by Jorba and Adillon (2017):

$$\mu_{\tilde{A}}(x) = \begin{cases} f(x), & x \in [a_1, a_2] \\ 1, & x \in [a_2, a_3] \\ g(x), & x \in [a_3, a_4] \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

where a_1, a_2, a_3 *and* a_4 are real numbers such that $a_1 < a_2 \le a_3 < a_4$; f(x) is a real-valued strictly increasing and right-continuous function; and g(x) is a real-valued strictly decreasing and left-continuous function (Jorba, Adillon, 2017). Moreover, researchers detailed discuss and propose a generalization of trapezoidal fuzzy numbers based on modal interval theory, which named *modal interval trapezoidal fuzzy numbers*. Trapezoidal fuzzy numbers are a special class of fuzzy numbers.

Possibility distribution was first introduced by Zadeh (1965). The fuzzy set $\tilde{A}$ generates two functions defined on a family of subsets of some space $\mathcal{X}$: a measure of possibility *Pos* and a measure of necessity *Nec*. These measures are defined for every classic set $X \subset \mathcal{X}$ by the formulae:

$$\begin{aligned} Pos(X) &= \sup\left\{ \mu_{\tilde{A}}(x) : x \in X \right\}, \\ Nec(X) &= \inf\left\{ 1 - \mu_{\tilde{A}}(x) : x \notin X \right\} \end{aligned} \tag{2}$$

Their definitions are associated with a well-known interpretation of a fuzzy set given by Zadeh. It assumes that the fuzzy set $\tilde{A}$ is a fuzzy restriction of a certain variable *X*, which takes values in space $\mathcal{X}$. It is assumed that the only information about the variable is that „*X* is $\tilde{A}$". In this case, the variable *X* is characterized by a fuzzy set membership function which describes the possibility of *X* taking values of $x \in \mathcal{X}$, i.e., it induces a possibility distribution in space $\mathcal{X}$. Such a defined variable *X* is called a fuzzy variable with a possibility distribution of $\pi_X(x) = \mu_{\tilde{A}}(x)$. It can be determined how possible is the event that the value of variable *X* belongs to set *X* using the possibility distribution (Gonzàlez et al., 2002):

$$\pi(\boldsymbol{X} \in X) = \sup\{\pi_X(x) : x \in X\} = \sup\{\mu_{\tilde{A}}(x) : x \in X\} = \pi(X) . \tag{3}$$

Such a defined quantity does not have complementary characteristics, i.e. $\pi(\boldsymbol{X} \in X)$ is not necessarily equal to $1 - \pi(\boldsymbol{X} \in X^c)$, where X^c is the absolute complement of *X.* Liu (2006) introduces the concept of credibility measure. The degree of credibility that the value of variable *X* belongs to the set *X* can be defined as follows:

$$Cr(\boldsymbol{X} \in X) = \frac{1}{2}\left(\pi(\boldsymbol{X} \in X) + (1 - \pi(\boldsymbol{X} \in X^c))\right). \tag{4}$$

The quantity defined in this way has complementary characteristics (Cravleuret et al., 2013; Liu, 2006; Cruze et al., 2013; de Figueiredo, Stolfi, 1996). Moreover, when the grade of credibility reaches a value of 1, there is confidence that the fuzzy event will occur. On the other hand, when the degree of possibility reaches a value of 1, such confidence does not exist.

Liu (2006, 2014) define the concept of credibility distribution $\Phi(x)$. The distribution function $\Phi(x)$ determines the grade of credibility, that the fuzzy variable *X* will have a value equal to or less than x. If μ is a membership function of fuzzy variable *X* then the credibility distribution function $\Phi(x)$ is expressed by:

$$\Phi(x) = \frac{1}{2}\left(\sup_{y \le x} \mu(y) + 1 - \sup_{y > x} \mu(y)\right) \quad \forall x \in \Re , \tag{5}$$

where $\Re$ denotes real numbers.

Effective processing of data expressed in the form of fuzzy numbers requires the properly defined arithmetic operations on such numbers. Operations on arbitrary fuzzy numbers can be defined, in line with Zadeh's extension principle (Klir, 1990; Zadeh, 1965), by performing operations on α-levels using interval arithmetic. If $\tilde{A}$ and $\tilde{B}$ are two fuzzy numbers, A_α, B_α their α-levels and $\circ$ any arithmetic operator (+, –, ∗, /), then operations on these numbers can be defined as:

$$\tilde{A} \circ \tilde{B} = \bigcup_{\alpha \in [0,1]} \alpha(\tilde{A} \circ \tilde{B})_\alpha , \tag{6}$$

where $(\tilde{A} \circ \tilde{B})_\alpha = \{ A_\alpha \circ B_\alpha \}, \alpha \in [0, 1]$ and $\circ$ is the respective operation on intervals (Kuchta, 2001).

This definition allows all combinations of values belonging to the respective intervals (α-levels) (Klir, Yuan, 1995; Klir, 1990; Rębiasz, 2011). However, this is not always true. Let, for example, one number represents the price of hot rolled sheets and the second, the price of cold rolled sheets. These quantities are dependent since high prices of hot rolled sheets will generally result in high prices of cold rolled sheets and combinations of low prices of one product and high prices of the other will probably never occur. Thus, the main stress is put on modeling the dependencies between parameters. Interval regression and affine forms will be used to handle these dependencies. However, other methods, identified during the literature study, will be considered as well.

Fuzzy regression is identified when parameters of regression equation are expressed in form of fuzzy numbers. Interval regression is a specific case of fuzzy regression. Tanaka and Lee (Tanaka et al., 1982; Tanaka, Lee, 1998) were among the first authors reported that parameters of regression equation are in this case expressed in form of bounded interval. Interval and fuzzy regression are used in solution of numerous practical problems (Hladík, Černy, 2012). Several methods are used for estimation of the parameters of interval regression equations. The best-known method uses linear programming for this purpose (Tanaka, Watada, 1988). However, these methods are criticized because of many faults (Tran, Duckstein, 2002). Many authors present alternative solutions, e.g. (1) quadratic programming methods in combination with the least squares method (Tanaka, 1987; Tanaka, Watada, 1988), (2) use of Minkowski distance (Fuller, Majlender, 2003) or (3) multi-criteria programming (Tran and Duckstein, 2002). Those modified methods provide more balanced intervals representing the coefficients of interval regression equations. Nevertheless, these require longer computation time and estimation of weigh coefficients by experts, thus they become heuristic methods (Hladík, Černy, 2012).

The major drawback of these methods is that often some of the estimated regression parameters tend to be crisp; it even happens that the method produces only a few unexpectedly wide interval parameters while all the remaining regression parameters are crisp. This drawback is called unbalancedness.

The second drawback is non-centrality property, i.e., the method might produce interval regression parameters, the center of which only poorly fits the data with respect to traditional non-parametric goodness-of-fit tests (such as R-squared, Chi-squared and/or Kolmogorov-Smirnov tests).

The third drawback relates to high sensitiveness to outliers. One of the most promising methods for determining parameters of interval regression equations was developed by Hladik and Černy (2012). They proposed a method based on sensitivity analysis of linear systems. The most appropriate approach will be selected and used to model dependencies between fuzzy numbers. As it was mentioned above, arithmetic operations on fuzzy numbers implicitly assume independence of the operands, thus it is necessary to define new arithmetic on fuzzy numbers which will enable the dependencies to be considered. To reach this goal, nonlinear programming and affine forms will be used. The latter being rarely used in problems of assessing risk in a company.

Affine arithmetic (AA) was first introduced by Comba and Stolfi in 1993 as a new self-validated model for numerical computation. It was designed to eliminate the main weakness of standard interval arithmetic (Moore, 1996), that is the tendency to produce intervals which are often much wider than the true range of the corresponding quantities, especially in long computation chains. AA is like standard interval arithmetic in that it keeps track of input, truncation, and rounding errors. In addition, it considers correlations between computed and input quantities, and is, therefore, able to provide much tighter bounds on computed quantities than standard interval arithmetic.

In affine arithmetic (De Figueiredo, Stolfi, 1997; 2003) an unknown ideal quantity x is represented by an affine form:

$$\hat{x} = x_0 + x_1\varepsilon_1 + \ldots + x_n\varepsilon_n , \tag{7}$$

which is a degree 1 polynomial.

The *central value* x_0 and the *partial deviations* x_i are finite floating-point numbers; the *noise symbols* ε_i are unknown but assumed to vary within their domains, i.e., intervals [–1, 1]. Affine forms sharing the same noise symbols are partially correlated through them (de Figueiredo, Stolfi, 1997). All possible pairs ($\hat{x}$, $\hat{y}$) (if each ε_i vary independently within the interval [–1, 1]) lie in a convex polygon (*zonotope*) which is called a *joint range* and is denoted by $\langle \hat{x} , \hat{y} \rangle$.

Every affine form $\hat{x}$ implies the range $[\hat{x}] = [x_0 - r_x,\ x_0 + r_x]$ for an unknown ideal quantity x, which is the smallest interval that contains all possible values of $\hat{x}$, if each ε_i varies independently within the interval [–1, 1]. The radius $r_x = \sum_{i=1}^{n} |x_i|$ is called the *total deviation* of $\hat{x}$ (Comba, Stolfi, 1993). Conversely, if an ideal quantity x belongs to an interval $x = [\underline{x}, \overline{x}]$, then x can be represented by an affine form $\hat{x} = \breve{x} + \mathrm{r}(x)\varepsilon_i$, where $\breve{x} = (\underline{x} + \overline{x})/2$ is a midpoint of x, $\mathrm{r}(x) = (\overline{x} - \underline{x})/2$ is a radius of x, and ε_i is a noise symbol not occurring in any previous computations (de Figueiredo, Stolfi, 1996; 2003).

Affine-linear operations on affine forms result straightforwardly in affine forms. Non-affine operations must be approximated by affine forms. An extra term must then be added to bound the error of this approximation (this extra term usually also includes round-off errors). Selecting appropriate affine approximation might reduce this error.

Given a non-affine function of two variables $z = f(x, y)$ and two affine forms $\hat{x}$ and $\hat{y}$ representing x and y, an affine form $\hat{z}$ representing z must be computed. It is desirable that $\hat{z}$

is consistent with $\hat{x}$ and $\hat{y}$, and that it preserves the information provided by them as much as possible. It can be easily seen that $z = f(\hat{x}, \hat{y})$ is a function of the noise symbols ε_i:

$$z = f(x_0 + x_1\varepsilon_1 + \ldots + x_n\varepsilon_n, y_0 + y_1\varepsilon_1 + \ldots + y_n\varepsilon_n) = f^*(\varepsilon_1, \ldots \varepsilon_n), \quad (8)$$

where $f^*:[-1, 1]^n \to R$ is generally a non-affine function. An affine approximation f^a of f^* can be then written in the form:

$$f^a = z_0 + z_1\varepsilon_1 + \ldots + z_n\varepsilon_n + z_k\varepsilon_k, \quad (9)$$

where the last term $z_k\varepsilon_k$ represents the *residual* or *approximation error*.

It is assumed that ε_k is a new noise symbol independent from $\varepsilon_1, \ldots \varepsilon_n$ (de Figueiredo, Stolfi, 1996; 1997; 2003).

The quality of the approximation depends on the selection of a central value z_0 and partial deviations z_i. This means that there is n+1 degrees of freedom for the choice of an affine approximation f^a. In fact, two basic approaches to compute affine approximation are used the most frequently (Figueiredo, Stolfi, 2004). The first one is to minimize the approximation error z_k *(Chebyshev approximation)*, the second one is to minimize the range [$\hat{x}$, $\hat{y}$] (*minimum range* or shortly *min-range* approximation).

5. Research results

The transformation of the organization's knowledge into its asset is based on the consistent execution of processes related to their formalization, creation of conditions for access to users, distribution, storage, and application. Key characteristics of knowledge are concepts that significantly distinguish it from data and information. Knowledge is inseparable from the subject who possesses it, has a holistic nature and a dynamic character. This characteristic complicates knowledge management procedures, since knowledge management is directly related to the presence of people, and therefore is accompanied by the appearance of a subjective factor. At the same time, we can generalize that knowledge management at the enterprise requires the organization of the following processes: creation or acquisition of knowledge; modification of knowledge in order to meet the current and future needs of consumers; using knowledge for certain purposes; archiving of knowledge for future access to it by users in an accessible form and format; transfer of knowledge; transformation of knowledge; user access; disposal. So, considering the peculiarities of the category of knowledge and its differences from such key concepts of the concept of knowledge management as data and information, it is possible to distinguish the following approaches to the formation of a knowledge management strategy at the enterprise. The first approach is based on the application of IT systems with different types of knowledge structures, which may include:

document structures (forms, templates, reports, graphs, charts); images (photos and graphic files), video (presentations and video files), sounds and signals, data, cases (case studies, best practices, lessons learned), processes (resources, specifications), models. Knowledge management strategies based on management information systems outline the possibilities of creating, storing, exchanging, and using the organization's documentary knowledge. Such strategies are accompanied by the need to codify and store knowledge with the help of information technologies and create opportunities for the reuse of knowledge.

As the example we made the analysis of the huge industrial company dealing with mining equipment. These studies were carried out as part of an investment project for one of the companies that conducts its production activities in Western Donbas in Ukraine (Dychkovskyi et al., 2013). An industrial enterprise is going to rent new high technological equipment. The cost of rent is 500 thousand euros per year. The contract must be signed for several years, therefore, even before reaching the break-even point, you will not be able to immediately return the equipment. You are going to sign a contract, hoping that modern equipment will save on labor and raw materials costs, and think that the logistics of new equipment will be cheaper. The ranges of expected savings and annual production are given in Table 2.

Table 2.
Initial data for analysis

Parameters	Value
Maintenance savings, MS	5-15 Euro per unit
Labor savings, LS	0-6 Euro per unit
Raw materials savings, RMS	4-12 Euro per unit
Production level, PL	20 000-40 000 units per year
Break-even	500 000 Euro

The mean annual saving is:

$$(MS + LS + RMS)\cdot PL = (10 + 3 + 8)\cdot 35\ 000 = 630\ 000 \text{ Euro.}$$

It looks like we not only broke even, but also made some profit, but remember, there are uncertainties. So, we had to provide the riskiness of these investments. Let's determine the probability that we will not break even, that is, that our savings will be less than the annual cost of renting equipment. Monte Carlo simulation is an excellent way to solve such problems. We will randomly select values in the specified intervals, substitute them into the formula for calculating the annual savings and calculate the total. Some results will exceed the calculated mean value of 630,000 euros, while others will be lower. Some will even be below the €500,000 required to break even.

In this study, we use a normal distribution with 90% confidence intervals and 10 000 scenarios. The simulation result is represented in Table 3. Distribution of annual savings by value ranges is presented in Fig. 2.

Table 3.
The simulation result for the riskiness evaluation

Scenario	MS	LS	RMS	PL	Annual saving	Break-even
90% CI	5-15	0-6	4-12	20 000-40 000		> €500 000
1	8,8	1,1	12,3	32 057	713 524	True
2	4,9	0,1	4,8	30 139	295 607	False
3	8,8	3,3	2,1	33 825	479 112	False
4	17,0	2,9	3,5	35 253	825 770	True
5	9,1	0,8	10,2	31 878	640 316	True
6	10,2	2,3	12,1	25 657	629 381	True
7	8,4	2,6	10,2	30 691	653 318	True
8	11,7	2,1	9,8	23 148	546 694	True
9	6,8	5,3	7,1	39 145	752 843	True
10	16,4	3,2	4,8	29 551	723 021	True
…	…	…	…	…	…	…
9995	14,3	1,5	12,4	39 051	1 101 146	True
9996	9,6	0,6	3,6	27 749	383 956	False
9997	9,4	1,4	10,1	23 574	493 253	False
9998	10,0	4,5	13,1	28 939	799 440	True
9999	13,0	0,6	6,5	36 812	741 727	True
10000	5,7	1,0	6,5	32 388	428 883	False

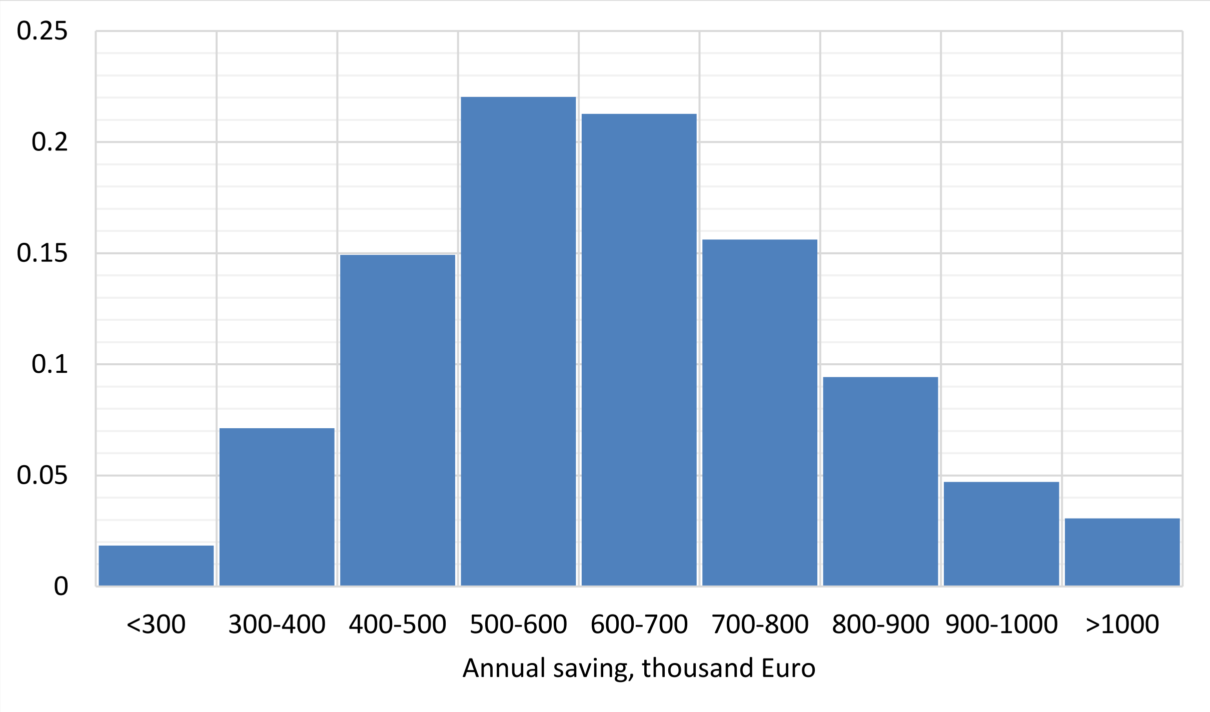

Figure 2. Distribution of annual savings by value ranges.

Of all the resulting annual savings, about 25% will be less than 500 thousand euros. This means that the probability of damage is 25%. This number represents a meaningful risk assessment.

The choice of which affine approximation to use depends on the problem to be solved. In some applications it is important to compute interval bounds which contain only positive numbers, e.g. computation of the square root. In such cases, the min-range approximation should be chosen. The range optimality is also needed in computer graphics (de Figueiredo, Stolfi, 1997) or when the denominator of an expression is an affine form. In the latter case, the narrower interval is less likely to contain zero.

When uncertainty is described using fuzzy numbers, a decision-maker can give arbitrary values of possibility degrees according to own feelings. Fuzzy approach does not impose the form of expression of subjective opinions as much as probabilistic approach does Kuchta (2001). Mohammed and McCowan (2001) argue that for most practitioners triangular and trapezoidal fuzzy numbers are much easier to understand and to apply than probability distributions. People hardly think in probabilistic terms, fuzzy sets notation or linguistic description of uncertainty seems to be more natural and much closer to human thinking. The construction of a triangular fuzzy number based on the best, the worst and average values is closer to the possibility theory than to the probability theory (Mohammed, McCowan, 2001). Moreover, many authors question the legitimacy of modeling the absolute lack of knowledge about selected parameter using uniform probability distribution (Baudrit et al., 2006; Shafer, 1976).

The consideration of knowledge elements in mining organization activity is relevant to the operating process for the development of a company and is accompanied by defining its priorities. Focusing on the key activities of an organization will allow firm to transform available information about a risk into specific knowledge. This knowledge includes the distinctive features of a project potential consequences and gives a manager the basic idea of making decision on project applying. It is necessary to do this based on knowledge management cycle (see Table 4) (Polyanska, Malynka, 2014).

Table 4.
Knowledge elements which should be considered in the context of mining company project realization

Knowledge management cycle	General characteristics	Knowledge management implication on project activity in mining company
Review	Result estimate Comparison of old and new results	State of new possibilities of equipment usage that are given as result of it exploration
Conceptualize	Check (review) of knowledge and organizational context. Analysis of strengths and weaknesses	Justification of the idea of total saving of resources in the project and its advantages Determination of the impact of the environment on the implementation of the project, as well as the consequences of the implementation of the project
Reflect	Identification and necessary improvements. Improvement planning	Working out of production programs, achieving the appropriate level of product brake even point, working out the training program for people, raw material resources saving program
Act	Knowledge synthesis. Knowledge combination, information technologies.	Human resources management in conditions of changes. Knowledge about risks of project realization. Knowledge allocation among spheres of project activity

So, getting results of uncertainty analysis that indicating the risk on a project, create preconditions for working out appropriate measures of potential risk limitation or mitigation that, in turn could transform in knowledge and be used in management of organization. On the example of the mining company, it can be said that the obtained indicators gave an opportunity annual savings, about 25 % will be less than 500 thousand euros that is quite risky for project implementation.

It should be noted that the next step to the application and dissemination of methods, investigating the uncertainness impact on the enterprise's activities proposed in the article, will be the integration of the acquired knowledge into the decision support system at the enterprise. Today, research in this direction covers the issue of using the acquired knowledge through decision support systems (DSS). Moreover, today these systems are expanding their functions to support knowledge work using the so-called "knowledge work support systems" (Burstein, Carlsson, 2008).

6. Discussions

To examine the possibilities of knowledge management for getting necessary for company information on it activity results, the methods of uncertainness analysis were discussed. A study is based on the interval regression and affine arithmetic and could successfully be used to model dependencies between uncertain parameters. In the literature there is a lack of research that exploits these two approaches. Continuous effort~~s~~ will be required to rely on using besides probability and possibility distributions also interval numbers~~,~~ to represent uncertainty. This combination of uncertainty descriptions has been not yet used to solve decision problems in a company. Whereas preliminary research show that it can be successfully applied to more accurate LCA models. Another study will be conducted on simultaneous processing of different descriptions of uncertainty, without the need for transformation between them. Finally, it must be emphasized that the research conducted in this study focuses on hybrid LCA. The resulting models and methods can be successfully used in the analyses in other areas, e.g., in financial analysis or economic problems. Considerations about relations between economic and environmental parameters are crucial for hybrid data processing. Economic and environmental problems often involve parameters that are mutually correlated. For example, there is a correlation between enterprise product prices and raw material prices or between volumes of sales of different assortments, as well as the number of shares of pollutions of the environment. The omission of these dependencies leads to systematic errors in calculations. Proposition of methods for processing hybrid data allows simultaneous consideration and processing of different types of uncertainty in LCA model. Moreover, based on this, future LCA work would benefit from the results for the evaluation of the effectiveness and risks of LCA projects.

So, results of uncertainness analysis provide new or additional knowledge for its further exploitation in organization management.

7. Conclusions and recommendations

This study focuses on the management of knowledge that is acquires by analyzing the uncertainties in the LCA models based on the hybrid approach combining MC simulation and fuzzy logic, as applied to fuzzy set theory, being an alternative way of modeling of uncertainty.

The methods for hybrid data processing have two main weaknesses which limit their practical usage. First, they do not account for interdependencies between parameters described by different representation of uncertainty, which causes systematic errors in the results. The second weakness is the lack of easy-to-interpret measures synthetically expressing uncertainty of the result of an LCA.

The proposed approaches to uncertainness assessment methods combination with hybrid LCA method were considered on the example of industrial company dealing with mining equipment. The obtained results allow summing up the next conclusions:

- this method combines several tools and mathematical mechanisms and is quite effective in evaluating investment projects;
- it makes the possibility to assess the riskiness of investments with a high reliability and to reduce them;
- by considering knowledge management cycle the potential of Knowledge management implication on project activity in mining company was considering.

It is hoped that the presented study will substantially increase the knowledge on processing of hybrid descriptions of uncertainty. This subject is still relatively new and the scope of applications of hybrid models is not, yet, well recognized. Presented study move the hybrid LCA one step forward. In the future, it is planned to carry out research on the implementation of knowledge management in the decision support system, which makes it easier for managers to make decisions in conditions of uncertainty with help of discussed methods.

As a result of the mentioned above, the main direction of our further research is to consider the ways of knowledge management implementation in the organizational decision support system, especially in mining enterprises. This requires a more detailed study of the organizational system of the enterprise and the level of its digitalization and the potential for continuous improvement as well as justification of possible methods of accumulation, storage and flexible use of data obtained from experience in decision support systems with the analysis and evaluation of the performance of these systems.

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