Contribuições às Ciências da Terra

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PROGRAMA DE PÓS-GRADUAÇÃO EM
EVOLUÇÃO CRUSTAL E RECURSOS NATURAIS

USING FUZZY LOGIC TO ASSIST IN PERFORMANCE ASSESSMENT OF A NUCLEAR WASTE REPOSITORY

(O Uso da Lógica Difusa na Análise de Segurança de Repositórios de Rejeitos Nucleares)

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CHAPTER 1

BACKGROUND

1.1 INTRODUCTION

Radioactive waste are generated as a result of nuclear applications in several areas of human activities such as medicine, industry and engineering. The type and amount of waste generated will depend on type of activity.

Brazil has many radioactive waste generators, such as research institutes, universities, industries, as well as Nuclear Power Plants Angra I and Angra II. For many years, low and intermediate level radioactive waste has been generated and placed in intermediate storage awaiting final disposal.

The Comissão Nacional de Energia Nuclear (The Brazilian National Nuclear Energy Commission), CNEN, has the responsibility of a safe management of radioactive wastes in Brazil. This has been achieved through the issuing of regulations, inspections, collecting and storage of the low and intermediate level waste-LILW (except those ones originating from the fuel cycle). There are interim storage facilities at CNEN institutes, containing approximately 3000 m^3 of radioactive low and intermediate level waste that stems from several nuclear applications, not including the volume of waste from the fuel cycle. It is estimated a growth rate of 50% for each ten years and consequently it can be predicted a quick diminishing of the capacity available for this interim storage system.

The CNEN has been investing money, through a Multi-Annual Development Plan of the Federal Government, on many projects related to radioactive waste disposal such as:

Development of a Decision Support System for LILW Repositories Safety Assessment.

Uncertainty Analysis on Radionuclides Migration in Soils.

Characterization, Treatment and Disposal of Radioactive Wastes.

Development of a Simplified Model for Simulation of Radionuclides release from Repository.

Management of Spent Sealed Sources.

The Law 10308, recently approved (November 20, 2001) by the Presidency of Brazil, addresses site selection, construction and licensing, operation and enforcement of radioactive waste interim storage and final disposal in Brazil. Some points are of special interest, such as Article 37 that demands that "CNEN must begin studies for site selection, project, construction and licensing, to start operation within a period of time as short as technically possible, of a final disposal facility within national territory".

1.2 SAFETY ASSESSMENT

This section provides an overview of the procedure of safety assessment of a disposal facility or repository. The principles of waste management, including waste disposal options, will be discussed in more detail in the next chapter.

Safety assessment of a radioactive waste disposal facility is a procedure for evaluating the performance of the disposal system and, as a major objective, its potential radiological impact on human health and the environment (IAEA 1999b). It requires the interaction of a large number of disciplines in order to model environmental phenomena necessary to evaluate the safety of disposal. The physical systems involved can often be very complex. The initial purpose of the safety analysis is to better understand the system under study. Eventually, as the system behavior becomes understood more fully, the assessment is used to support regulatory decisions. Corresponding to the specific goals of the project the objectives for uncertainty and sensitivity analysis will also vary, depending on the stage of the analysis.

The technical acceptability of the repository will greatly depend on the waste inventory, the engineered features of the repository and the suitability of the site. It should be judged on the basis of the results of the safety assessments, which should provide a *reasonable assurance* that the repository will meet the design objectives, performance standards and regulatory criteria (IAEA 1999b).

Typically, the safety analyst has to simplify the physical system into a conceptual model that can be modeled mathematically. Due to the complexity of the system, it has to be divided into several models. These models are simulations of the various processes (e.g., thermodynamic reactions, ground water flow, colloids transport, redox fronts movement, etc), will eventually be integrated into the same framework for support of decisions.

The first step in this process of safety assessment involves the definition of exposure scenarios and this is often a significant source of uncertainty (future climate assumptions or individual habits).

Simplification of the physical system to a mathematical model is another source of uncertainty, commonly called model uncertainty. Other sources of uncertainties include parameter estimation and random variability in parameters measurements.

Expert judgement may be required for definition of ranges of values due to lack of data, lack of knowledge concerning future conditions and parameter values (and distributions), or any aspects of the system under study that are not well understood by current science. This generates another kind of uncertainty, "subjective uncertainty".

A key issue in safety assessments for repository is to develop confidence in the results of modeling. A conceptual model of a disposal facility system is a description in terms of the general features present and their detailed characteristics. Among the most important features are those that identify the relative significance of possible radionuclide transfer routes, known as pathways (IAEA 1999b).

The results of the safety assessment, including identification of uncertainties, should be compared with the design goals and regulatory criteria, with account taken of other lines of reasoning and considerations contributing to the acceptability of the repository (IAEA 1999b).

The ability to identify and correctly quantify the uncertainties as well as the most important parameters in the safety assessment is of vital importance for good decision making. It is impossible to guarantee with absolute certainty that one has made the correct decision, but we can improve the possibility of choosing the right decision by improving the means of quantification and identification of the uncertainties in the calculations.

This work proposes a methodology for uncertainty analysis through the use of fuzzy logic principles. This process is iterative and, as refinements in data or scenario descriptions or other factors are obtained, the assessment can be improved by providing defensible technical support for decision makers regarding site selection and construction of a final disposal facility for radioactive wastes with a corresponding increase in confidence on the results.

1.2.1 Uncertainty Analysis and Decision Making in Safety Assessment

Uncertainty is inherent in any safety assessment. Sensitivity and uncertainty analyses have the important goal of extending understanding and reducing, where possible, the uncertainty in some of the results of the safety assessment by directing attention to a better definition of those parameters that most affect the results and their uncertainty (IAEA 1999b).

According to (IAEA 1989) uncertainties in safety assessment, can be classified into a) subjective, Type A uncertainty and b) objective, Type B uncertainty.

Type A uncertainty is generally those uncertainties that arise from randomness in data.

Type B uncertainty comes from fuzziness, vagueness and ambiguousness in information. Most of these types of uncertainties in safety assessment come from lack of data, ignorance regarding natural processes and complexity in parameters interaction.

The multi and inter disciplinary nature of radioactive waste disposal facilities safety assessment requires a very clear and comprehensive analysis of all the parameters and intermediate decisions interactions in order that decision makers and the public do not become confused as to how these decisions will affect the final results of the safety analysis.

These difficulties are in part due to the fact that, traditionally, the methods of uncertainty analysis are either deterministic or probabilistic, which suppose stochastic processes, while most of the uncertainties in radioactive disposal facilities system are non-probabilistic (Kozak 1997, Lemos *et al.* 1999), and therefore require the use of non-probabilistic methods of analysis.

Non-probabilistic uncertainties can be found in every aspect of a safety assessment process. Very often, due to lack of data or high complexity, experts have to use linguistic expressions to describe site conditions. This can be seen in Table 1, page 12. Expressions such as "strongly fractured rock" and "low U content" can have different meanings depending on the context of research, and therefore, a mathematical representation would be an important tool for the analyst to take advantage of its real meaning which will also contribute to a more realistic analysis of uncertainty propagation throughout the safety assessment calculation.

1.3 ISSUES IN ADDRESSING UNCERTAINTIES FROM REAL CASES OF DISPOSAL FACILITIES SAFETY ASSESSMENT.

Some examples of discussions regarding difficulties in addressing uncertainty in safety assessment are presented in this section. These examples are excerpts from studies related to licensing of two very important high level waste disposal sites, i.e., the Yucca Mountain Project and the Finnish disposal site at Olkiluoto. The documents of these two sites were analyzed by their respective countries authorities and stake holders (Hellmuth 1999, Yucca Mountain Project 2002).

In both cases, above mentioned, suggestions were made in order to bring more transparency to the calculations, so degrees of support and confidence on decisions can be shown with objectiveness and as much realism as possible.

1.3.1 Effect of simplifications on modeling

The ultimate goal of the development of conceptual model is to provide framework that will permit judgement to be made about the behavior of the total disposal system. The model should be as simple as possible but should include enough detail to represent the system's behavior adequately for the purpose of ensuring compliance with safety requirements (IAEA 1999 b).

Due to simplifications in computer models, several natural processes are lumped together in one representative parameter. However, the uncertainties associated to each of these processes may not be properly accounted for and therefore generating further uncertainties and ambiguousness.

The need for an innovative methodology of uncertainty analysis that helps improve confidence in the results of the safety assessment can be seen in the following citation that was extracted from Yucca Mountain Project 2002b:

"The primary means for demonstrating compliance with the standards is the use of computer modeling to project the performance of the disposal system under the range of expected conditions...Simplifications and assumptions are involved in these modeling effort out of necessity because of the complexity and time frames involved, and the choices made will determine the extent to which the modeling simulations realistically simulate the disposal system's performance. If choices are made that make the simulations very unrealistic, the confidence that can be placed on modeling results is very limited.

Inappropriate simplifications can mask the effects of processes that will in reality determine disposal system performance, if the uncertainties involved with these simplifications are not recognized."

Processes involved in performance assessment are *not always linear* nor stochastic. A probabilistic approach assumes *independent processes* and therefore may not be the best tool for uncertainty analysis in certain cases. The following citations illustrate this fact:

1- The Committee notes that there may be issues in finding a consistent definition of the term "conservative" and in understanding its implications to performance:

"The stated DOE practice is to choose parameter distributions that are "deliberately conservative" where uncertainty "cannot be adequately justified based on available information." To suggest that the distributions are conservative implies some knowledge about the underlying processes, and how the results are affected by parameter values. While this approach may be suitable under some circumstances, when modeling involves linear systems and independent processes, the application of this approach to the high-level waste (HLW) repository at Yucca Mountain may be flawed. This is because the underlying processes in the near field of the repository, for example, are not entirely linear or independent. To the contrary, significant coupling is expected among nonlinear hydrological, chemical, and thermal processes. Determining what is conservative and what is not under these conditions is neither intuitive nor straightforward."

Additional cautions are provided regarding the use of bounding analyses:

"There are other cautions that should be observed in the application of bounding analyses. For a complex, non-linear system, it is not always readily apparent how conditions that bound performance should be defined. This makes it difficult to judge whether, and the degree to which, the generated results are conservative. Because of the difficulties inherent in developing fully-coupled models for analyzing the flow and transport in the unsaturated zone, it may prove advantageous to begin with a simpler set of models, and then to evaluate the more complex issues through either sensitivity studies or bounding evaluations.

If these efforts demonstrate that certain aspects of the complex coupled phenomena can be ignored or treated one-dimensionally, the overall analysis will be vastly simplified. More effort, however, needs to be directed to defending this approach and ensuring that coupled effects, that are potentially detrimental to repository performance, are addressed in this manner."

Another example on how probabilistic approach may not be the best tool for uncertainty analysis on safety assessment is given through the study of the following paragraph extracted from Kozak *et al.* (1991).

"...... Currently there is no guidance concerning how to compare a distribution of possible doses with the deterministic low-level waste regulations; therefore, the minimum that can be assumed is that the regulations can not be exceeded. Consequently, the low probability doses are required to meet the low-level waste regulations. In other words, we must use the upper bound of the dose distribution results in focusing on low-probability events and processes, and the facility results in being designed for unlikely conditions, rather than probable conditions. Viewed in the language of probability theory, to what extent do we want to include the tails of the probability distribution of doses when comparing to the deterministic regulation?"

While probabilistic analysis has a strong mathematical basis, and although the probability distributions are provided, the analyst still has to deal with conditions where a combination of low probability parameter values, (which may be highly unrealistic), leads to projections on safety that are either unacceptable or nearly so. Often, the low probability parameter values have to be used as reference for the repository design. On the other hand, in the possibility approach that same value, say the 95% limit used on probability, is now a member of a set and will be taken as part or of a concept. As it will be seen later on, fuzzy sets are definitions of concepts or language expressions such as "high temperature", "safe repository", "hazardous material", etc. This means that no one single value will be used as a reference but rather a whole set which members are interdependent.

1.3.2 Quantification of uncertainties

An important component of the "package" of information that Nuclear Waste Technology Review Board describes as important for decision-making is a quantification of uncertainties. The need to quantify uncertainties, rather than just to describe them or bound them in the total system performance assessment (TSPA), is described in several correspondences by the Board (YMP 2001).

1- "The Board believes that meaningful quantification of the uncertainties associated with performance, clearly and understandably presented, is an essential element of performance characterization. The complexity of the repository system and the length of time over which performance must be estimated make uncertainty both large and unavoidable (although perhaps reducible). Especially important in such a situation is that policy-makers and other interested parties understand the uncertainty associated with key decisions (Yucca Mountain Project 2002)."

2- "The next step, important for the fast-approaching site recommendation by the Secretary of Energy, is to analyze and explain quantitatively the size and significance of those uncertainties for performance and how they vary with repository temperature...Similarly, quantifying uncertainties in variables and processes that pertain to fluid flow and transport in the repository rock over the temperature range from ambient to the maximum predicted temperature in the rock is very important (Yucca Mountain Project 2002)."

3- "The Board believes that the quantification, analysis, integration, and communication of uncertainty need to be addressed in a more rigorous manner than shown in the presentations at the Board meeting [in August, 2000]. Any projections of repository performance will be incomplete unless the DOE also provides a description and a meaningful quantification of the level of uncertainty associated with its predictions" (Yucca Mountain Project 2002).

"...the Board has recommended that DOE focus significant attention on four priority areas dealing with managing uncertainty and coupled processes, which, in the Board's view, are essential elements of any DOE site recommendation. Meaningful quantification of conservatism and uncertainties in DOE's performance assessments..." (NWTRB 2001).

4- "The Board is concerned that the PA approach now envisioned by the DOE could deprive policy-makers of critical information on possible tradeoffs between projected performance and the uncertainty in those projections. For example, one policy-maker might be willing to accept development of a repository that would release half of the permitted dose, with only a 1 in 1,000 chance of exceeding that permitted dose. However, that same policy-maker might decline to develop a repository that is expected to release only a tenth of the permitted dose, but has a 1 in 4 chance of exceeding that permitted dose. Another policy-maker's preferences might be the opposite. Because the uncertainties about repository system performance may be substantial, estimates of uncertainty about doses are at least as important as estimates of performance" (Yucca Mountain Project 2002).

5- "The Board believes that meaningful quantification of the uncertainties associated with performance, clearly and understandably presented, is essential to provide policy-makers who are deciding on a site recommendation with critical information on tradeoffs between projected performance and uncertainty in those projections...Eliminating all the uncertainties will never be possible (although they can be reduced). In fact, the Board has noted that a decision on whether to recommend the site can be made at any time, depending in part on how much uncertainty policy-makers are prepared to accept" (Yucca Mountain Project 2002).

6- "At the time a decision is made on site recommendation, the Board and scientific community are likely to be asked at least two questions: (1) Is the underlying science broadly regarded as technically sound? and (2) Are the uncertainties in estimates of performance displayed clearly and openly, especially about the major factors that may lead to a potential radioactive release? A major question for policy-makers at that point may be whether the site is suitable, given the level of uncertainty associated with the DOE's site-suitability determination. The Board believes it is critical that the DOE not only offer estimates of performance but also clarify the extent and significance of the technical and scientific uncertainties. Understanding uncertainties is vital for sound decision-making" (Knopman 2000)

1.4 IMPROVEMENT IN DECISION MAKERS CONFIDENCE

In order to improve *decision makers and stake holders confidence*, the safety assessment calculation should be clear with a systematic process for identifying, documenting, categorizing, evaluating, and quantifying uncertainties (Yucca Mountain Project 2002a).

1- The literature also contains references to "aversion to ambiguity" exhibited by decision makers (Yucca Mountain Project 2002a). These authors discuss evidence that when faced with two alternatives with equal expected consequences (both calculated over the epistemic uncertainties in the process), decision makers often prefer the alternative with the narrower epistemic uncertainty distribution. These choices need to be made in light of true, unbiased assessments of uncertainty.

2- The use of performance assessment for decision-making requires that uncertainties be reasonably quantified or appropriately bounded with adequate justification. Such quantification will provide information that decision-makers can use in making tradeoffs, assessing the credibility of DOE's positions, and developing confidence. NRC's concept of "risk-informed" decision-making includes both the expected risk and a quantitative description of the uncertainty associated with the expected risk.

3- There is a need to communicate uncertainties and risk information in a clear, meaningful manner to decision-makers and stakeholders.

4- "Expert judgment and careful interpretation of data will be needed to accurately characterize and quantify the uncertainties associated with data and their use in predicting repository performance" (Yucca Mountain Project 2002).

5- Further, methods for communicating the significance of uncertainties in ways that are understandable for decision-makers should be developed. These can include quantitative and qualitative evaluations of confidence.

6- ."...The combination of these three pieces of information should allow the decision maker to understand how much uncertainty exists in the results, how much confidence they can place in those results, and how much it matters if the results are incorrect. In a broad context, this provides a forum for DOE to summarize their level of confidence, and importantly, to show where the largest gaps remain in understanding. Communication of both of these areas is critical for technical and policymakers level audiences to be able to gain sufficient confidence in the results."

1.4.1 Understanding the impact of uncertainties

Communication of the uncertainties and their impacts is crucial to all the other components of the strategy for handling uncertainties; and understanding and communicating the impact of uncertainties will allow DOE to assess the importance of those uncertainties and to select an appropriate uncertainty management approach

. The Science and Engineering Report (Yucca Mountain Project 2002b), shows that "...several oversight groups have difficulties understanding implications of uncertainties to total system results when the inputs are a mix of conservative and realistic inputs."

The same necessity for understanding implications of uncertainties was expressed by board of reviewers for the Finnish waste repository safety assessment calculations (Apted *et al.* 1999).

According to Yucca Mountain Project (2002b), "The EPA recently issued its Public Health and Environmental Radiation Protection Standards for Yucca Mountain, Nevada (40 CFR 197 2001). The regulation provides a definition of the individual protection standard that DOE must meet and a description of "reasonable expectation," which is the context for understanding the standard and its implementation."

Due to difficulty in representing ambiguous data and the connection between intermediate decisions, experts opinions is frequently used for determination of probabilistic distribution of data as well as uncertainty and confidence representation.

Fuzzy logic tools can be useful as a contribution to the solution of these issues, i.e., understanding of ambiguous data, uncertainty propagation and quantification of confidence.

It is important to point out the concept of "reasonable expectation" used by EPA regarding performance assessment of Yucca Mountain Repository, a measure of compliance with regulation, rather than comparing results of extreme values. With this concept regulators acknowledge the existence of inherent uncertainties and the impossibility of making deterministic calculations in an ambiguous environment.

This work is intended to contribute to the solution of some of the main issues mentioned above concerning uncertainty treatment and help give a meaningful connection between the various input data and the results of the performance assessment.

1.5 THE METHODOLOGY

The whole process of performance assessment is comprised of a series of decisions. If it is possible to report the weaknesses and strength along this chain, then it will be possible to determine the degree of support for the final results. As can be seen from the above discussions, the complexity of the safety assessment calculations and the many types of sources of uncertainties, there is a need for a decision support system capable of integrating the different types of uncertainties. This means that, a comprehensive model will have to be able to handle stochastic and non-probabilistic information in the same analysis methodology.

These two approaches can be correlated through the theory of evidence (Klir .& Folger 1992). As it will be seen in Chapter 4, this theory, also called Dempster-Shafer theory, provides the tools for combining probability and possibility information in the same frame of decision support system.

This thesis is concerned with the treatment of ambiguous and vague information through fuzzy sets and fuzzy logic. Fuzzy logic is designed to deal with ambiguous information by representing scientific knowledge in terms of human language, or concepts, while keeping the original level of information.

These ambiguous data can be translated into fuzzy numbers, or fuzzy sets, that are represented in terms of membership distribution functions. The approach is intended to make the analysis easier to understand by the decision-makers and public by clearly showing the correlation between intermediate decisions and final results.

One interesting example of how scientists use linguistic expressions can be seen in Table 1. This table contains geochemical information gathered from the drillcore F1, for the Poços de Caldas project. As can be seen in that table (Mackenzie *et. al.* 1991), there are many ambiguous expressions such as "low pH", "very oxidizing conditions ", etc. Even in the case of a well-studied site such as this one, this kind of linguistic information can not easily be quantified, nor can the support and confidence one can place for the conclusions based on them.

Table 1.1: Example of geochemical descriptions for samples from the drillcore F1 which were analyzed for natural decay series radionuclides (Mackenzie *et. al.* 1991).

Sample code	Depth (m)	Rock description
6-1 A	6.00	Porous, strongly fractured, oxidized phonolite
10-1 A	9.84	Porous, fined grained porphyritic, oxidized phonolite.
16-1 A	15.07	Oxidized phonolite, average sample, low U content.
26-1 A	25.22	Oxidized phonolite, average sample, low U content.
33-1 A	32.89	Redox front, oxidized side, low U content.
34-1 B-A	33.40	Redox front, oxidized side, low U content.
34-1 B-D	33.51	Redox front, reduced side, low U content.
34-1 B-F	33.65	Redox front, reduced side, low U content.

In any long-term forecasting model, for each parameter in the model, there is a range of possible values. For a more defensible analysis, decision-makers should be aware of the different degrees of certainties for the different parameter values. For example, one of the conclusions on the Poços de Caldas Project, is that the redox front has been moving with a rate between 2 and 20 m in 10^6 years. The report by Chapman *et al.*(1991), provides different levels of support for each of these limits. This can have implications on the performance assessment. Instead of treating the values as if they had the same weight, by using the fuzzy logic methodology, the degree of support for each of these values can be estimated. This example is further developed in chapter 5.

1.6 SYMBOLS AND DEFINITIONS

Following is a list of the main symbols and definitions used in this thesis.

- CDTN: Centro de Desenvolvimento da Tecnologia Nuclear (Nuclear Technology Development Center).
- Ci: (Curie) A unit of radioactivity equal to 37 billion disintegrations per second, abbreviated .
- Dose: The amount of radioactive energy taken into (absorbed by) living tissues.
- Eh: A measure of the state of oxidation of a system. Also known as redox potential or oxidation-reduction potential.
- IAEA: International Atomic Energy Agency.
- IPEN: Instituto de Pesquisas Energéticas (Energy Research Institute).
- IEN: Instituto de Engehnaria Nuclear (Nuclear Engineering Institute).
- Kd: distribution coefficient (ratio of contaminant concentration associated with the solid to the contaminant concentration in the surrounding aqueous solution, when the system is at equilibrium).
- NWTRB: Nuclear Waste Technical Review Board.
- Near Field: The area and conditions within the repository including the drifts and waste packages and the rock immediately surrounding the drifts. The region around the repository where the natural hydrogeologic system has been significantly impacted by the excavation of the repository and the emplacement of waste.
- NCRP: Nuclear Council on Radiation Protection and Measurement.
- NRC: U.S. Nuclear Regulatory Commission

- TBq: 1 TBq=27Ci.

- TSPA: Total System Performance Analysis.

- US NRC: The U.S. Nuclear Regulatory Commission's.

- US DOE: The U. S. Department of Energy.

- Waste form: A generic term that refers to the different types of radioactive wastes.

- $\wedge$ is an operator of minimum and, $\vee$ is an operator of maximum.

1.7 THESIS OUTLINE

This work is organized as follows:

Chapter 2: *Radioactive waste and waste management*. This chapter contains explanations regarding general principles of waste management, waste classification according to guidance provided by the IAEA _ International Atomic Energy Agency. In this chapter it is also presented an overview of the waste generation in Brazil, principles of waste management, and disposal options.

Chapter 3: *Safety assessment and sources of uncertainty*. It contains information regarding waste disposal facilities safety assessment and sources of uncertainty. There are also explanations regarding approaches for treatment of types A and B uncertainties (advantages and limitations) and sensitivity analysis.

Chapter 4: This chapter presents an introduction to fuzzy sets and fuzzy logic principles and how they can be useful on safety assessment uncertainty analysis. The fundamentals of possibility theory and the theory of evidence are also presented.

Chapter 5: This chapter is dedicated to the presentation of six case studies of applications of fuzzy logic to uncertainty analysis in various aspects of radioactive waste management as follows:

Case one: The first case example is the determination of distribution coefficient, *Kd*, for the Cs137 radionuclide using fuzzy logic approaches. This parameter is of great importance on the study of release mechanisms from waste packages and migration of contaminants through the environment. It can have a large variability in space and values can vary for more than two orders of magnitude within a short distance.

Case Two: In this case example, fuzzy logic approaches for estimating release mechanisms from waste packages, based on the ambiguously defined inventory information are developed.

Case Three: This is an application of fuzzy logic for the integration of information of different nature on a safety assessment for a repository, in this case, the Abadiá de Goiás. This repository contains waste generated as a consequence of the cleaning up operation after an accident with a Cs137 sealed source in 1987, Brazil.

Case example Four "Application of Fuzzy Expert System on LILW Performance Assessment" is an extension of the previous studies and introduces new approaches regarding the relationship between concepts of safety and regulatory standard limits.

Cases five and six , "Translating Natural Concentrations and Fluxes Into Safety Indicators for Radioactive Waste Repositories" and "Evaluating Contaminant Migration Around Redox Fronts at The Poços de Caldas Uranium Mining Site (Minas Gerais, Brazil) Using Fuzzy Logic" deal with quantification of linguistic information in order to take advantage of important information which otherwise could have been lost.

Chapter 6: Discussions, conclusions and suggestions for further developments.

CHAPTER 2

RADIOACTIVE WASTES

2.1 - INTRODUCTION

Radioactive waste is generated as a result of a number of activities such as research, medicine, industry and generation of electricity by nuclear power plants. Radioactive waste may have potential negative impacts on human health and on the environment if managed improperly.

The main objective of radioactive waste management is to manage the waste safely in order to protect human health and the environment from these potential negative impacts (IAEA 1999a). Waste management should be based on some fundamental safety principles which are internationally accepted, as follows (IAEA 1999a):

- Principle 1: Protection of human health. It should secure an acceptable level of protection for human health.

- Principle 2: protection of environment. It should provide an acceptable level of protection for the environment.

- Principle 3: Protection beyond national borders. It should be managed in such a way as to assure that possible effects on human health and environment beyond national borders will be taken into account.

- Principle 4: Protection of future generations. The waste should be managed in such a way that predicted impacts on health of future generations will not be greater than relevant levels of impact that are acceptable today.

- Principle 5: Burdens on future generation. The management should not impose undue burdens on future generations.

- Principle 6: National legal framework. It should be managed within an appropriate national legal framework including clear allocation of responsibilities and provision for independent regulatory functions.

- Principle 7: Control of radioactive waste generation. Waste generation should be kept to the minimum practicable.

- Principle 8: Radioactive waste generation and management interdependencies. Interdependencies among all steps in radioactive waste generation and management shall be appropriately taken into account.

- Principle 9: Safety of facilities. The safety of facilities for radioactive waste management shall be appropriately assured during their lifetime.

The waste may range in concentration from very low levels of radioactivity (from a medical diagnosis procedure) to very high concentrations of radioactivity (spent nuclear fuel). Even though there are large differences, in origin and properties of radioactive waste, (e.g., concentration, volume, half-life and radiotoxicity), basic principles have been developed that are applicable to the management of radioactive waste.

Radioactive waste as a source of ionizing radiation, has long been recognized as hazardous to human health. Therefore, national regulations and international standards and guidelines dealing with radiation protection have been developed, based on a substantial body of scientific knowledge. These wastes may also contain chemically or biologically hazardous non-radioactive materials and it is important that these hazards are adequately considered in waste management.

2.2 OBJECTIVE OF WASTE MANAGEMENT

The objective if waste management is to handle, pre treat, treat, condition, transport, store and dispose of radioactive waste in a manner that protects human health and the environment without imposing undue burdens on future generations and that seeks to limit the generation of radioactive waste.

2.2.1 Protection of the Environment

When radionuclides are released into the environment, species other than humans can potentially be exposed to ionizing radiation, and the impacts of such exposures must be taken into consideration. Since humans are among the most radiation-sensitive organisms, measures taken to protect individual humans from radiation hazards are in general considered adequate to protect other species. Therefore, the presence of humans should be assumed when assessing impacts on the environment, particularly when assessing impacts of radioactive waste disposal.

2.3 TYPES OF WASTE

Radioactive wastes are classified according to level of radioactivity, chemical composition and origin. According to the (IAEA 2000), the following definitions apply:

1- Heat generating waste (HGW): radioactive waste which is sufficiently radioactive that the decay heat significantly increases its temperature and the temperature of its surroundings.

2- High level waste (HLW): the radioactive liquid containing most of the fission products and actinides present in spent fuel _ which forms the residue from the first solvent extraction cycle in reprocessing_ and some of the associated waste streams; this material following solidification; spent fuel (if it is declared a waste); or any other waste with similar radiological characteristics. Typical characteristics of high level waste are thermal power above about $2kW/m^3$ and long lived radionuclide concentrations exceeding limitations for short lived waste.

3- Long lived waste: radioactive waste that contains significant levels of radionuclides with half-life greater than 30 years.

4- Low and intermediate level waste (LILW): radioactive waste with radiological characteristics between those of exempt waste and high level waste. These may be long lived waste (LILW-LL) or short lived waste (LILW-SL). Typical characteristics of LILW are activity levels above clearance levels and thermal power below about $2kW/m^3$.

5- Short lived waste: radioactive waste that does not contain significant levels of radionuclides with half-life greater than 30 years. Typical characteristics are restricted long lived radionuclides concentrations (limitations of long lived radionuclides to 4000 Bq/g in individual waste packages and to an overall average of 400 Bq/g per waste package).

6- Very low level waste (VLLW): Radioactive waste considered suitable by the regulatory body for authorized disposal, subject to specified conditions, with ordinary waste in facilities not specifically designed for radioactive waste disposal.

2.4 DISPOSAL OF THE WASTE

Depending on its classification, the waste will eventually have to be disposed of in a facility especially designed for this purpose. The primarily objectives of a disposal facility is isolation of the waste from the environment and public, and protect the waste from inadvertent intrusions by humans, animals and plants.

It is important that radioactive waste repository concepts are in accordance to basic rules of radiological protection, i.e., appropriate methods for packaging, handling and disposal of the wastes.

The main disposal options are (IAEA 1999a):

1- Near surface disposal

- Shallow ground disposal.
- Disposal in cavities at intermediate depth.

2- Geological disposal

The choice of a particular disposal system will depend on the waste type and the conditions, including considerations of socio-political acceptance.

Some important features of disposal facilities are listed below.

2.4.1- Near Surface Disposal

The basic objective of the near surface disposal is to isolate the waste from water and the human environment under controlled conditions and for a period of time long enough to allow radioactivity to either decay naturally or slowly disperse to an acceptable level. This option implies that waste to be disposed of contains mainly short-lived radionuclides of low or medium specific activity with only low amounts of long-lived radionuclides and that a maximum authorized activity has to be fixed (IAEA 1999a)

Typically, this kind of repository is lined with concrete, bitumen or other material to improve isolation of waste. The space between packages is filled with soil, clay, or concrete grout. Low permeability covers are put above the disposal unit to minimize the percolation of surface water to the waste. Water diversion and drainage systems are used to direct water away from the disposal units. The system can further be protected from erosion by planting vegetation or covering surface with rock rubble.

Figure 2.1 shows a representation of a shallow ground repository. This type of repository is appropriate for low and intermediate level wastes. A disposal facility typically contains a cover to divert water away form the waste containing region. An engineered barrier to further isolate the wastes. Waste forms are placed in containers within the disposal unit (Sullivan 1993).

The basic processes that influence release from a disposal unit can be divided into four processes: (Sullivan 1993).

1- Water infiltration, which is a function of the disposal unit design and local environment (amount of rainfall, evapotranspiration, etc.).

2- Container degradation, which is a function of the container material and design, and local environment (corrosivity of the soil water, etc.).

3- Waste form leaching, which is a function of the waste form and the solute contacting the waste form ; and

4- Transport to the environment, which is a function of the contacting medium, infiltration velocity, and local chemistry.

The combination of all these factors comprise the disposal system.

2.4.2 - Deep Geological Formation Repositories

High level waste disposal is a much more complicated process than for low and intermediate waste.

Some characteristics required for a geological disposal are:

- Be deep enough so as to protect the waste against involuntary or accidental intrusions, and in very unusual cases, voluntary intrusions (usually several hundreds of meters below the earth surface);

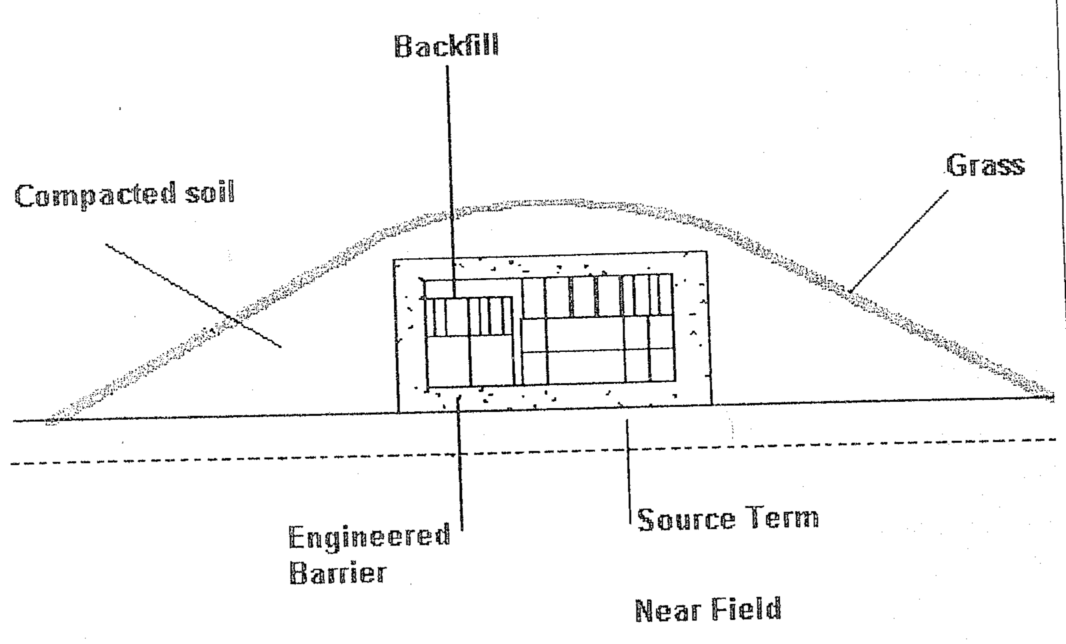


Figure 2.1:Schematic diagram of a shallow ground repository.

- Be located in a host rock which is either dry or has a very slow groundwater flow;
- Be compatible with the physical and chemical properties of the waste packages;
- Be located in seismically and geologically stable area;
- Offer a geological barrier system against mobilization and migration of radionuclides, thus avoiding the need for engineered barriers or sophisticated waste immobilization;
- Be such that waste will remain compatible with the properties of the host rock;
- Offer, at least for the foreseeable future, no or very little economic value.

The length of time during which no release or acceptable releases of radionuclides from the waste in the repository can be assured, when considering periods well beyond 10,000 years, is the subject of a very difficult analysis, and results may have a high degree of uncertainty. However, it should also be recognized that the longer the period under consideration, the lower will be the residual amount of radioactivity.

Some features of the near field must be considered for the safety assessment calculations such as redox front movements, tectonic stability and bedrock movement related to glaciation.

Finland, for example, has just finished its site selection program for spent fuel disposal. According to (Mcewen & Äikäs 2000), the factors of interest for this program, amongst others, were topography, bedrock stability, homogeneity, rock type (most of the potential areas consisted of granite rock types), faulting and fracturing (types and frequency of fractures in the bedrock), diapiric structures (geological evidence indicate that the granite domes are stable features).

2.5 WASTE GENERATORS

Radioactive waste is generated in activities that involve the use of radioactive material. These activities ca be applications of nuclear techniques in medicine, research and industry to production of electricity from nuclear energy. For more information, please refer to the Comissão Nacional de Energia Nuclear – National Nuclear Energy Commission (CNEN) official web site at www.cnen.gov.org.

The main waste generators in Brazil are presented as follows.

2.5.1 - CNEN Research Institutes

The CNEN (Comissão Nacional de Energia Nuclear – National Nuclear Energy Commission) research institutes are: Instituto de Pesquisas Energéticas -IPEN (Energy Researches Institute); Instituto de Engenharia Nuclear-IEN (Nuclear Energy Institute); Instituto de Radioproteção e Dosimetria-IRD (Radioprotection and Dosimetry Institute); and Centro de Desenvolvimento da Tecnologia Nuclear-CDTN (Nuclear Technology Development Center).

IPEN - Instituto de Pesquisas Energéticas

Most of the waste generation is due to the production of radioisotopes. The main sources of contamination are Te^{127}, Il^{31}, Br^{82}, S^{35}, and P^{32}. Most of them have short half life. The organic matter, resultant from quality control during production of radioisotopes, contaminated with I^{131} or Tc^{99} corresponds roughly to 120 Kg/month. IPEN also receives waste from industry, hospitals, universities and research institutes. Most of this waste is in solid form and includes small amounts of scintillation liquid which are contaminated with H^3 and C^{14}.

Co^{60} spent sealed sources, Ra^{226} needles (average activity 0.2 Ci –7 Gbq) and In^{192} spent sources are stored for decaying.

Currently there are stored 1200 drums with a total volume of 250 m^3 and activity of 220 TBq.

IEN *- Instituto de Engenharia Nuclear* and ***IRD****- Instituto de Radioproteção e Dosimetria*

Usually send small amounts of waste to IPEN for treatment, packaging and storage. There are approximately 35 drums and a total volume of 7 m^3.

CDTN *- Centro de Desenvolvimento da Tecnologia Nuclear (Nuclear Technology Development Center).*

Also receives waste from different origins for treatment and storage. At CDTN there are approximately 150 drums with a total volume of 30 m^3 and an estimated activity of 100 TBq.

2.5.3 - Nuclear Power Plants

Three types of waste are generated as a result of the NPP, Angra I and Angra II, operation:

Sludge, ionic exchange resins, and evaporation concentrates. Solid radioactive material (compressible and non-compressible). Organic liquids, including lubricants and solvents.

According to CNEN official web site, there are approximately 5000 drums (200 l) with a total weight of 3000 ton and an estimated total activity of 4.5 TBq.

2.5.4- Industrial complex of Poços de Caldas

At this site there are waste generated due to purification of Uranium and Thorium concentrates. A total of 12700 ton (7250 m^3) and activity of 120 TBq.

Table I- Expected waste volume for Angra I

WASTE	TREATMENT	VOLUME WITHOUT TREATMENT(m^3 /year)	VOLUME AFTER TREATMENT(m^3 /year)	WASTE VOLUME PER DRUM (m^3)	Nº OF DRUMS (200 l/year)	ACTIVITY PER DRUM
ASHES	VOLUME REDUCTION (3:1)	354	118	0.20	594	0.06 Ci
BOTTOM OF EVAPORATOR	CEMENT + VERMICULITA	154	308	0.10	1540	4.5 Ci
RESINS	CEMENT + VERMICULITA	16	64	0.05	320	85 Ci
FILTERS	——	7	7	0.20	36	23 Ci
TOTAL	——	531	497	——	2490	——

CHAPTER 3

SAFETY ASSESSMENT and SOURCES OF UNCERTAINTIES

3.1 INTRODUCTION

Safety assessment involves long-term estimates of engineered barriers performance and how it controls infiltration and the chemical environment, containers performance, waste form performance, contaminant transport through the geosphere and biosphere. These processes require the study of a variety of sciences like hydrogeology, meteorology, geochemistry, etc.

Repositories are expected to have a very long useful life, of the order of hundreds to thousands of years. It is impossible to have a method of predicting the performance of the system for such a long time frame. Therefore computer simulation through mathematical modeling has an important rule on waste repositories safety assessment.

An extensive analysis have to be done in order to demonstrate that the repository will perform according to regulatory standards. This includes features events and processes (FEP) that will affect contaminants release from the repository and migrate to the environment.

Figure 3.1 shows the components of a safety assessment. It starts with assessment of the context and with a description of the system. The quality of the subsequent steps will depend on how well the system is described. In other words, the quality of the model to be developed will depend on how well researchers can understand and represent the natural phenomena being analyzed.

Computer models are an attempt to mimic natural processes. However, due to long time frame it is not possible to validate the models through real time comparison between model results and field data. Therefore, confidence on results of computer models will depend on other methodologies such as codes benchmarking and uncertainty treatment.

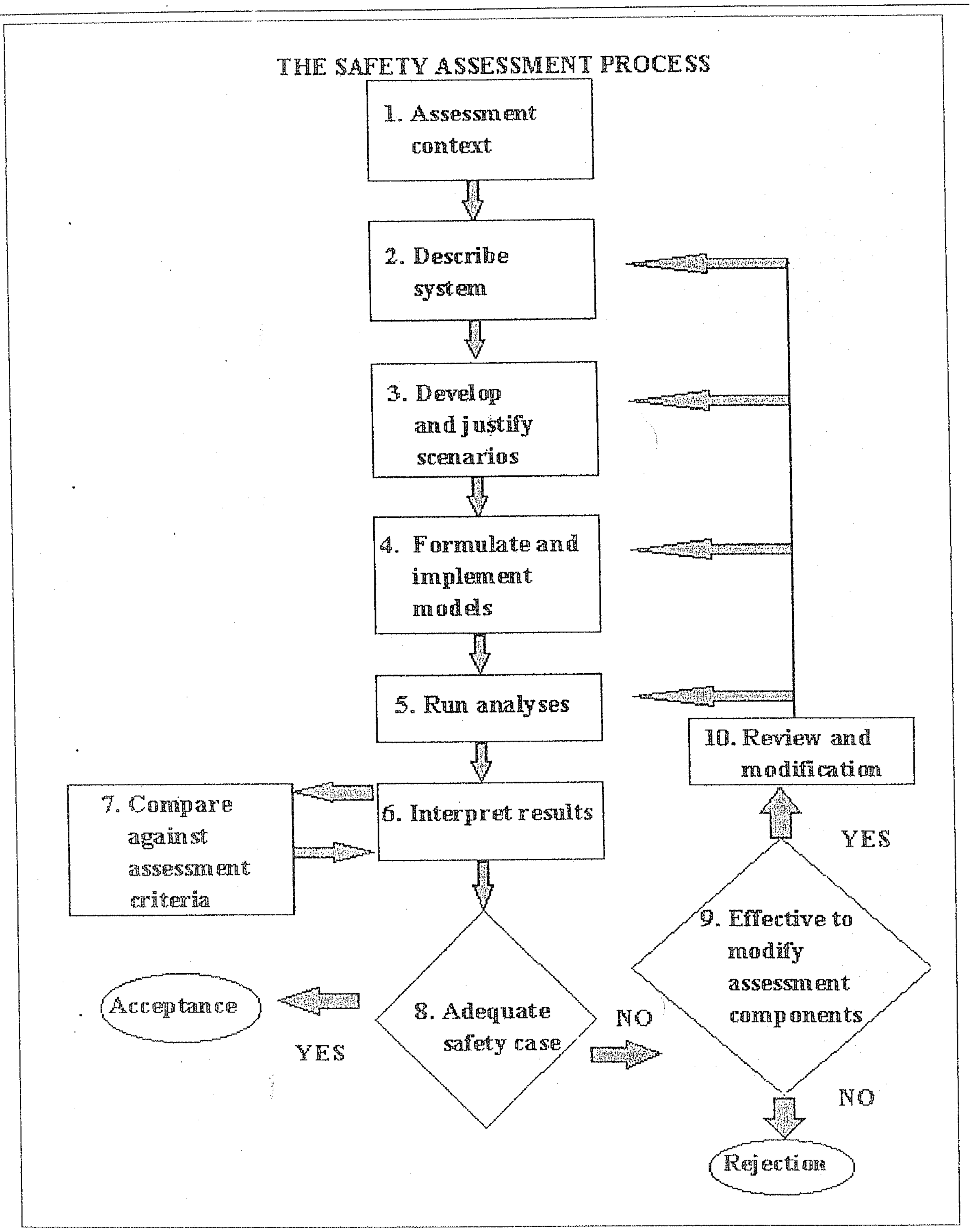


Figure 3.1: Components of a waste repository safety assessment (Lemos 1999).

3.2 TYPES OF UNCERTAINTY

According to the cause of uncertainty it can be divided into subjective, stochastic or ambiguous (lack of knowledge). International Atomic Energy Agency (1989b) classifies two types of uncertainties, type A and type B.

Type A uncertainty is due to random variability. For example, if the distribution coefficient, *Kd* is measured by laboratory experiments for the same type of soil with the same properties, one can find several different values. If the number of measurements tends to infinity, the mean value for *Kd* will be a constant number.

Type B uncertainty is due to lack of knowledge and includes conceptual model uncertainty and parameter uncertainty due to non-stochastic effects. An example for this type of uncertainty could be the actual *Kd* values under field conditions. Heterogeneity's in soil compositions can result in *Kd's* and other soil hydraulic parameters which to vary by an order of magnitude or more from one place to another within a small distance (Meyer *et al.* 1997). Therefore this variability could not be treated as random or measurement variability.

These two types of uncertainties require different approaches in order to improve the quality of the safety assessment.

We can find both kinds of uncertainties A and B in safety assessment. During the entire process the analyst constantly has to make decisions as to the best set of parameter values or probability distribution of values to represent a system, and the best conceptual models of the system, e. g.; the most likely scenario for future conditions. Those decisions are based on the analyst expertise and not on sample evidence, i.e., the decisions are subjective. So, type B uncertainty has a major role in safety assessment (Kozak 1997).

An example of combined Type A and B uncertainty in safety assessment is the determination of maximum annual committed dose equivalent per individual of the most exposed population group due to a release of radioactivity to groundwater (IAEA 1989b). In this case, the dose per individual is treated as a random variable, type A, since it is impractical to model each individual. However, additional type B uncertainty is introduced due to the lack of knowledge about the appropriate mathematical models and parameters values to use for hydrologic dispersion in groundwater as well as many other parameters to represent all processes involved in reaching the final result (IAEA 1989b).

3.2.1 Parameters Uncertainty

Parameters are variables used to represent physical processes in the models used to assess the performance of a disposal system. A complete safety assessment requires the collection of a large amount of data (IAEA 1984). A partial list of data which are used to define the parameters follows.

Waste characteristics: Radionuclides composition as a function of time; total inventory; physical and chemical form.

Containers characteristics: Mechanical and chemical performance; waste form composition in each container.

Repository characteristics: Dimensions; backfill material; concrete characteristics.

Site characteristics: Hydrogeology; geochemical properties.

Biosphere characteristics: Weather conditions; land use; population distribution.

Frequently there are large temporal and spatial variations in some of these parameters. For example the parameter known as dispersivity, which is a measure of how much spreading occurs in the contaminant plume during transport from the disposal site to the receptor, is uncertain. In this case, the impossibility of having complete understanding of parameter variability is a result of lack of knowledge. Professional judgment is then necessary to find the best values for parameters in the case of deterministic calculation and the probability distribution function (pdf's) in case of probabilistic approach.

Two examples showing the sensitivity of a specific parameter value on a dose estimate are given in Figures 3.2a and 3.2b. Figure 3.2a shows the effect on total dose from a set of 500 simulations where the *Kd* was randomly selected from a predetermined "realistic" range. From this figure it can be seen that the plutonium dose exhibited the greatest sensitivity based on the 500 trial simulation and on the realistic range.

Figure 3.2b shows the effect of varying the *Kd* in the aquifer and source backfill for a specific contaminant. In this case the data is plotted as pairs (one pair for each *Kd* value of backfill and aquifer) as this representation clearly indicates it is the *Kd* in the backfill source area which has the more significant impact.

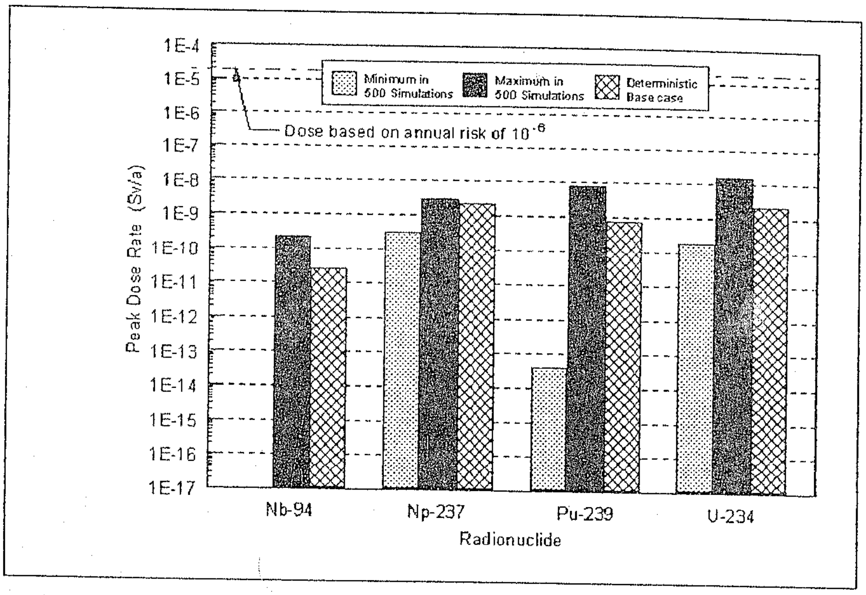


Figure 3.2 a: Effect on a total dose from a set of 500 Kd's randomly selected (Lemos *et al.* 1999).

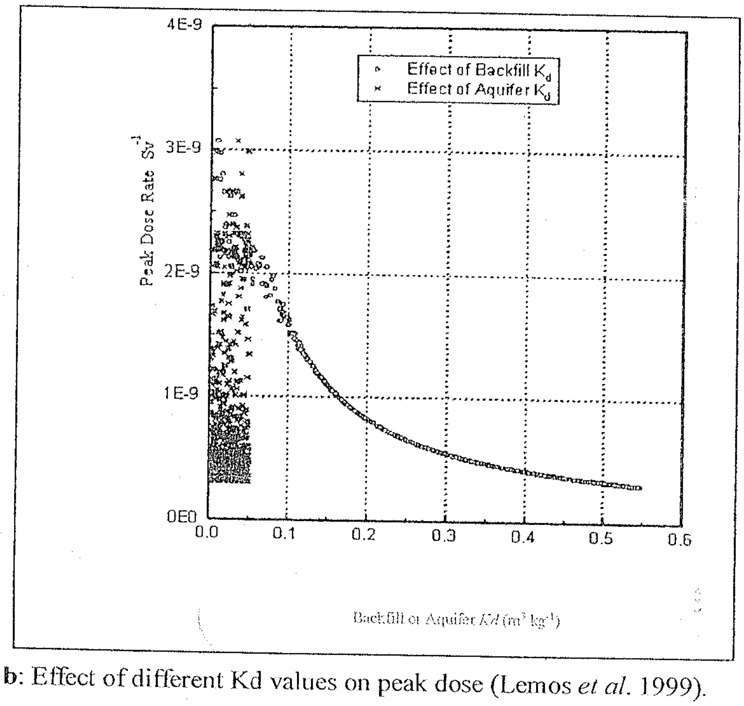


Figure 3.2 b: Effect of different Kd values on peak dose (Lemos *et al.* 1999).

Sensitivity analysis of this type can be used to help guide the assessment team in focusing effort on parameters which have the greatest impact on the results. It should be kept in mind that different models may have sensitivity to different parameters.

3.2.2 Data Uncertainty and Variability

Uncertainty and variability in data can be viewed as two separate phenomena (Murphy 1998). Both lead to uncertainty in decision making. Variability is the representation of the heterogeneity in sample population and uncertainty is the representation of the lack of perfect knowledge.

3.2.3 Models / Conceptual

A conceptual model is a description of the system based on a set of simplifying assumptions about the actual physical system. The conceptual model is used as the basis for a mathematical model, which in turn can be solved to estimate the variables of interest for a safety assessment.

In a safety assessment it is not always necessary nor ever desirable, to incorporate a detailed model into the analysis. Simplification is necessary to represent the real system for the purpose of making judgement on the safety of disposal. The simplifying assumptions are derived from site specific information and expert opinion, and include assumptions about the geometry of the system, spatial and temporal variability of parameters, isotropy of the system, and initial and boundary conditions.

In many cases, model uncertainty is the dominant type of uncertainty in a safety assessment. If an inadequate model is being used, uncertainty associated with the model input parameters becomes irrelevant (IAEA 1995).

The best method for assessing model uncertainties is through "model validation" (Freeze & Cherry 1979). Model validation is a process in which model projections are compared to data sets that are independent of the data used to develop the model.

In safety assessment the long time frame for the estimates of release makes it impossible for complete validation based on experimental data . Under these conditions, the model should be compared to other well known models and the differences in results should be explained based on differences in the conceptual model and parameter choices.

The most appropriate method to representing the physical and chemical processes in the mathematical models is not always clear. Model intercomparison studies provide some insight into the effect of choosing different conceptual models or different mathematical representations of a conceptual model. An example of an intercomparison of this nature was published by IAEA (1995), and it demonstrates the different results obtained when different models (and modelers) were applied on a relatively simple test case. Also for reasons of control and economy, the experiments on which models are calibrated are often carried out on a small scale in laboratories, rather than over longer repositories sites scales. Uncertainties arise because it is not clear that if a model that describes transport on a small scales, it will be appropriate for transport predictions over larger length-scales (Freeze & Cherry 1979).

Other causes of model uncertainties are ignorance of the actual relationships between processes that occur, and simplifications on very complex processes.

3.2.4 Scenario Uncertainty

This is related to the long term future of the disposal facility. It includes human use of the land, geophysical processes, intrusion, and other long-term processes.

There is no way to make an exact description of the future, however, one can represent what would be the most probable evolution of the system over the years to come based on past experiences and data. Expert judgment is very important in this approach. Another widely used approach to approximating future conditions is to select them based on current conditions (e.g., set climate conditions based on current conditions). In this case, these reference conditions may serve as a baseline for comparison between different scenarios and parameter sets. An important part of this approach is to choose conditions which permit a defensible, scientifically robust decision to be made.

3.3 EXAMPLES OF SOURCES OF UNCERTAINTIES

There are numerous situations in safety assessment that require expert subjective decisions.

Here are a few examples:

1- Future scenarios: Estimation for future conditions are made based on present or past conditions. Assumptions about the population nutrition habits for the next 500 years can not be unambiguously projected. Also, projections for the future climatological conditions must be made based on the average of past data and does not guarantee that in the future it will be the same. The same difficulties apply for intrusion scenarios and many others.

2- Engineered barriers: It is impossible to calculate exactly when the engineered barrier will fail. Factors such as the severity of chemical attacks from the near field environment and the quality of the concrete mixtures are very hard to quantify.

3- Waste forms: It is not always possible to know the exact content of each package. And even with well characterized waste forms, the parameters are calculated for average contents of the packages and, therefore, there is the possibility that these parameters will not properly represent the waste. Also, the effects of the waste chemicals and organic material content on the cement used to fix them is not well defined.

4- Site characterization: Dispersivity can hardly be measured with accuracy, and there is a great difference between laboratory and field scale values (Ross 1995). Typically expert judgment is used in order to choose the most appropriate values.

3.4 APPROACHES FOR UNCERTAINTY ANALYSIS

There are several approaches for uncertainty analysis. Each one is best fitted for specific situations. In this section some of these methodologies are presented.

3.4.1 Deterministic

In this approach the model and the representative sets of input parameters are selected and the analysis is performed providing a single outcome. To address uncertainties a single parameter sensitivity analysis is performed. In this approach a single parameter is altered and the effect on the projected outcome is measured. The procedure is repeated for all parameters that are expected to have a major impact on the outcome.

This approach does not permit a rigorous mathematical estimate of uncertainties. To overcome this difficulty often parameters are chosen which will over predict the dose. Thus, the confidence needed to make the decision on the safety assessment of the disposal depends on the confidence with which the selected parameters lead to conservative outcomes.

3.4.2 Probabilistic

This approach is based on the assumption that the data are random and independent, i. e., type A uncertainty. One very commonly used method is the Monte Carlo. Monte Carlo can be performed using one of two random sampling processes (Freeze & Cherry 1979): Simple Random Sampling (SRS) or Latin Hypercube Sampling (LHS).

In both approaches uncertain variables are assumed to be described by statistical parameters which define the probability of the variable having a given value.

In SRS, a random value is taken from the probability distribution specified for each uncertain model parameter, and a single estimate of the desired endpoint is calculated. This process is repeated for a specific number of samples or interactions. The result is an empirical approximation to the probability distribution of the model output or assessment endpoint.

In Latin Hypercube sampling, the range of each variable is divided into *n* intervals of equal probability . A single variable value is randomly selected from each interval. The *n* values for x_1 are randomly paired without replacement with the *n* values for x_2 to produce *n* pairs of variable values. These pairs are randomly combined without replacement with the *n* values for x_3 to produce *n* triples of variable values. This process is then continued until all *n* variables have been incorporated into the sample.

In this case parameter variability, type A uncertainty, is addressed through a rigorous mathematical procedure. Combinations of parameters leading to the highest projected outcome are calculated through the sampling procedure.

3.4.3 Subjective probability

It is recognized that in the safety assessment there are many subjective uncertainties, type B. To address these, some authors recommend the use of subjective probability. This approach uses the probability approach discussed above, however experts judgement is used to generate the probability distribution functions (pdf) representing the resulting state of knowledge for the assessment endpoint (Freeze & Cherry 1979). The most common probability framework for informational uncertainties is Bayesian probability theory in which the assessments are seen to be quantification of degrees of belief.

3.4.4 Possibilistic - Fuzzy Sets

An alternative approach for treating subjective uncertainties is the use of fuzzy sets theory. This approach provides a conceptual framework for the solution of imprecisely formulated problems. This is one of the reasons why it has been applied in a wide variety of fields of science, from medicine to industrial process control and credibility analysis (Kozak 1997).

The theory of fuzzy sets was developed to treat uncertainties that are non-stochastic in nature (Zadeh 1965), i.e., subjective variations. This kind of uncertainty appears due to the extreme complexity of a problem. Also in problems where subjective opinions are part of the decision making criteria, this subjective component can be represented as a fuzzy number. For example, social concerns will be part of the decision making for a waste disposal site.

In the possibilistic approach a degree of membership is assigned for each input parameter which is a member of a fuzzy set. This allows the data to have ambiguous characteristics belonging to two or more different sets in different degrees.

For example: If we have two sets A-plums and B- peaches, what will be the classification of the nectarine, which is a hybrid of peaches and plums, within these groups? In a traditional approach crisp sets classification we should assign degree one or zero for the nectarine in one or another group, i. e., it is either a plum or a peach. In the fuzzy sets approach however, one can assign degree of membership 0.3 to the peach set and 0.6 to the plum set. This means that fuzzy sets theory is much more flexible allowing quantifying ambiguity in information like in human speech (Kandel 1986).

Fuzzy sets could be used in safety assessment in many different ways. For example, due to the variability in soil properties *Kd* is expected to vary over the transport path. Expert judgement could be used to classify the values as members of the fuzzy sets High, Medium and Low *Kd*'s. By this procedure the *Kd* values are transformed into fuzzy numbers. The fuzzy set Low could correspond to $10 <= Kd <= 30$; Medium for $25 <= Kd <= 80$ and High for $70 <= Kd <= 100$. This could be very helpful for site characterization when making experiments for determination of *Kd* would be expensive, but at the same time a certain level of accuracy is wanted.

In this example, the fuzzy sets for *Kd* correspond to ranges of values and the assigned degree of membership represent the degree of belief that a particular value belongs to a certain range. For certain portion of the soil *Kd* could have degree of membership 0.8 to the fuzzy set High, for example. Using a similar approach structure as for Monte Carlo analysis, all of the possibilistic variables are sampled and the result is a range of possible outcomes quantified by the degree of membership. This permits the analyst to judge the most likely outcome as well as the likelihood of other outcomes.

For waste characterization the whole repository is divided into groups of wastes according to certain characteristics like release process, waste form, inventory, package material, origin and others that could be of importance for that particular facility (Murphy 1998). As it is difficult to say exactly what is inside of each package, or even if it were known, it would be difficult to find a set of parameters that fit the hundreds of packages at the same time, the analyst would than use the appropriate techniques to assign degrees of membership for each packages into a certain group or class of set of parameters.

Further these degree of membership are combined using specific techniques to find the more likely waste release from that facility.

It is very important not to confuse probability distribution function and membership function.

Probability deals with objective variability that is a result of chance or randomness. For example, problems like picking colored balls out of an urn (Ross 1995).

Fuzzy sets deals with ambiguousness in information due to lack of knowledge, complexity and vagueness.

3.5 LIMITATIONS OF SOME APPROACHES FOR UNCERTAINTY ANALYSIS

3.5.1 Deterministic

It is difficult to define the best parameters for making a decision, e.g., conservative or best estimate. Further it is often difficult to define parameters that are conservative. For example high aquifer flow rates typically lead to increased dilution and therefore lower concentrations. However, it leads to reduced travel time also, therefore for short live radionuclides it may overpredict the environmental concentrations.

Due to large uncertainties there is a tendency to choose the worst case which could lead to unrealistic values.

During the single parameter sensitivity analysis a combination of parameters is not addressed. Therefore maximums due to combinations may not be determined.

3.5.2 Probability

The basic assumption for probability to be applied is that the data are independent and randomly distributed. However in geophysical studies the main source of uncertainty is lack of knowledge as to how to represent the system rather than frequency of measurement.

Lack of data, the difficulty to understand the geological processes and the simplifications made in order to represent the enormous variety of different phenomena lead to uncertainties and so the use of experts judgment to quantify uncertainty is unavoidable. These uncertainties do not result from random variations and should be treated with other non-probabilistic methods like the fuzzy sets theory.

Other important limitations are that regulations are generally written in terms of a deterministic standard and the methods to use the probabilistic results in making a decision are not clear and the analysis are more difficult to interpret and explain to the general public.

3.5.3 Subjective Probability

In the case of Type B uncertainty, i e, when there is a lack of data or there is not much knowledge about certain process, subjective probability is some times applied. In this case definition of the subjective problem to be addressed is of critical importance in order to make a logically complete and understandable description of an issue to be addressed by an expert. Formulating correct and clearly worded questions regarding each selected issue or parameter requires a precise definition of the issue. If possible, complex issues and questions should be broken down into simpler parts for the elicitation process (Meyer *et al* 1997). As this is not always possible, the use of subjective probability is very difficult.

In this approach also there is the problem that the regulations are in general written in deterministic terms and the probabilistic results are difficult to incorporate into the decision making. In addition, the results are difficult to explained to the general public.

3.5.4 Possibility

Although fuzzy sets theory has been applied with success in almost all fields of science (Kozak 1997), it is relatively new. It was first formulated by Zadeh (1965), in the 60's while probability has been studied for more than 100 years. So this makes it even more difficult in terms of explaining the results to the general public and showing compliance with the regulatory limits.

Also it is a difficult task to represent subjective uncertainties in terms of a membership distribution function in a consistent way.

3.6 SENSITIVITY / IMPORTANCE ANALYSIS

Importance analysis is used in order to determine the relative importance or significance of the model parameters. Therefore, specific parameters or assumptions can be identified, for which additional data collection or design modification would likely provide the most benefit in terms of building confidence in the decisions regarding compliance (Kozak 1997).

Uncertainty analysis is recognized as a key factor in the decision process for safety assessment. The identification of sources of uncertainties as well as the types of uncertainties are necessary in order for the analyst to find the best way to quantify and consequently improve the degree of confidence he or she can have in the safety analysis.

Understanding uncertainty will also be a major factor in the acceptance of the safety assessment case by the public and the regulatory authorities.

CHAPTER 4

FUZZY LOGIC TOOLS

4.1 INTRODUCTION

Fuzzy logic was designed to deal with non-probabilistic uncertainties and is based on the concept of fuzzy sets theory. It was developed to deal with complex and ambiguous data. Several references can be found in the literature as for successful applications of fuzzy logic to engineering problems. Among the applications it can be pointed out industrial control systems, robotics, medical diagnostic , image processing equipment, risk assessment, and others. Please refer to Ross (1995), Zadeh (1965) for more information.

At the present there are several international groups and organizations dedicated to the support of developments in fuzzy logic applications to new technologies.

Berkeley Initiative in Soft Computing (BISC), is a program of the Department of Electrical Engineering and Computer Sciences of the University of California at Berkeley. This group was founded by Professor Zadeh and other collaborators in 1991.

It comprises studies of applications of soft computing in many areas. According to professor Zadeh, "soft computing differs from conventional (hard) computing in that, unlike hard computing, it is tolerant of imprecision, uncertainty and partial truth. In effect, the role model for soft computing is the human mind. The guiding principle of soft computing is: Exploit the tolerance for imprecision, uncertainty and partial truth to achieve tractability, robustness and low solution cost. The basic ideas underlying soft computing in its current incarnation have links to many earlier influences, among them my 1965 paper on fuzzy sets; the 1973 paper on the analysis of complex systems and decision processes; and the 1979 report (1981 paper) on possibility theory and soft data analysis. The inclusion of neural network theory in soft computing came at a later point. At this juncture, the principal constituents of soft computing (SC) are fuzzy logic (FL), neural network theory (NN) and probabilistic reasoning (PR), with the latter subsuming belief networks, genetic algorithms, chaos theory and parts of learning theory".

More information can be found in: http://www-bisc.cs.berkeley.edu/BISCProgram

Other organizations are:

- International Fuzzy Systems Association: http://www.abo.fi
- Japan Society for Fuzzy Theory and intelligent informatics: http://wwwsoc.nii.ac.jp/soft
- North American Fuzzy Information Processing Society: http://morden.csee.usf.edu
- Spanish Association of Fuzzy Logic and Technologies: http://decsai.ugr.es/flat/eflat.html
- European Society for Fuzzy Logic and Technology (EUSFLAT): http://www.eusflat.org/index.htm

This chapter presents some of the principles of fuzzy logic and artificial intelligence techniques that are used in the case examples presented in chapter 5. As it will be seen, fuzzy sets can be thought of as possibillistic distribution functions which will set the stage for a more complete assessment of evidence, i.e., theory of evidence or Dempster-Shafer theory (Ross 1995).

Through this theory it is possible to combine probability and possibility in the same framework. This will form the basis for the development of a robust decision support system for the safety assessment of radioactive waste disposal facilities. Such a decision support system will enable the decision makers to visualize the interactions of uncertainties, degrees of confidence, degrees of conservatism, and at the same time facilitate public communication. This can contribute to confidence building and public acceptance.

Some of the principles used on the developments of this work are presented below.

4.2 FUZZY SETS

A fuzzy set is a subset A of the universe of discourse X, where the transition between full membership and no membership is gradual rather than crisp (Kandel 1986).

Membership Function

The degree of ambiguity or vagueness of the data is expressed using the membership function which has the form:

$$\mu_A: X \to [0,1], \qquad \text{(Eq. 4.1)}$$

where X denotes a universal set.

In the fuzzy set theory, the membership function represents the degree of vagueness of each value and varies from 0 to 1. Zero (0) means that the value does not belongs to the fuzzy set, whereas one (1) means that there is no uncertainty that this value belongs to that set .

For instance, for the fuzzy set "high ambient temperature", we can say that 70° F has a degree of membership 0.6, and 100° F has degree of membership of 1.0. Also, the definition of degree of membership will depend on the context, i. e., if we talk about "high furnace temperature", 100° F will have a degree of membership much lower than 1.0.

It should be emphasized that degree of membership is not probability of occurrence, i.e., degree of membership 1.0 does not mean that this value has 100 % chance of occurrence, rather it quantifies the degree of ambiguity associated to a value through the membership function. The membership function can be assessed subjectively by expert opinion or by using a combination of probability and fuzzy sets (IAEA 1995).

The fuzzy set has no well defined boundaries. Traditionally, in the interval between 1 and 0, a grade 1 is assigned to a full member and 0 to a non member.

Therefore a fuzzy set A in X is a set of ordered pairs

$$A = \{x, \mu_A(x)\}, \qquad x \in X, \qquad \text{(Eq. 4.2)}$$

Where $\mu_A(x)$ is the degree of membership of x to A and is a number in the interval [0,1].

$\mu_A(x)$ can also be interpreted as the degree of possibility that x is .

4.3 OPERATIONS WITH FUZZY SETS

The study of fuzzy relations is the study of the mapping of elements of one set, A, to those of another set, R. The theory of fuzzy relations and the extension principle, which enables the extension of a deterministic function on fuzzy sets, can be found elsewhere (Ross 1995,Terano *et al.* 1992). In this thesis it is studied the mapping of elements of two sets, A removal and B deposition, to a third set R, rate of movement.

According to Ross (1995), a fuzzy relation, between two sets A on Universe X and B on universe Y, is defined as the fuzzy set R which is contained within the full Cartesian product space, or

$$A \times B = R \subset X \times Y \qquad \text{(Eq. 4.3)}$$

Where the fuzzy relation R has membership function

$$\mu_R(x, y) = \mu_{AXB}(x, y) = \min(\mu_A(x), \mu_B(y)) \qquad \text{(Eq. 4.4)}$$

4.4 POSSIBILITY DISTRIBUTIONS AS FUZZY SETS

Belief structures that are nested are called consonants. A fundamental property of consonant belief structure is that plausibility measures are possibility measures. As suggested by DuBois &Prade (1980), possibility measures can be seen to be formally equivalence, the membership grade of an element x corresponds to the plausibility of the singleton consisting of that x, that is, a consonant belief structure is equivalent to a fuzzy set F of X where $F(x) = pl(\{x\})$.

One interpretation of a possibility distribution as a fuzzy set was proposed by Zadeh (1978). He defined a possibility distribution as a fuzzy restriction that acts as an elastic constraint on the values that may be assigned to a variable. In this case the possibility distribution represents the degrees of membership for some linguistic variable, but the membership values are strictly monotonic as they are for an ordered possibility distribution. For example, let A be a fuzzy set on a universe X, and let the membership

value, μ, be a variable on X that assigns a " possibility" that an element of x is in A. So we get

$$\Pi(x) = T(x) \qquad \text{(Eq. 4.5)}$$

where:

Π(x) is the induced possibility distribution over the set X.

T (x) is the grade of membership x in the fuzzy subset A.

Or,

$$\pi(x)=\mu_A(x) \qquad \text{(Eq. 4.6)}$$

Zadeh points out that the possibility distribution is non probabilistic and is used primarily in natural language applications. There is a loose relationship, however, between the two through a possibility / probability consistency principle (Zadeh 1978). In sum, what is possible may not be probable, but what is impossible is inevitably improbable.

4.5 FUZZY MEASURES – DEGREE OF BELIEF

A fuzzy measure describes the vagueness or imprecision in the assignment of an element a to two or more crisp sets. This notion is not random.; the crisp sets have no uncertainty about them. The uncertainty is about the assignment. The uncertainty is usually associated with evidence to establish an assignment. The evidence can be completely lacking- the case of total ignorance- or the evidence can be complete- the case of probability assignment.

4.5.1 Parameter Relations

A mapping of a variable x of a universe X into universe Y can be expressed by a relation R, on the Cartesian space X x Y. A crisp relation can be described symbolically as

$$R=\{(x,y)|y=f(x)\}, \qquad \text{(Eq. 4.7)}$$

with the characteristic function describing membership of specific x, y pairs to the relation R as

$$\chi_R(x,y)=\begin{cases}1, & y=f(x)\\ 0, & y\neq f(x)\end{cases} \qquad \text{(Eq. 4.8).}$$

For a crisp set A defined in the universe X, its image, crisp set B on the universe Y, is found from the mapping, $B=f(A)=\{y|for\ all\ x\in A, y=f(x)\}$, where B will be defined by its characteristic value.

$$\chi_B(y)=\chi_{f(A)}(y)=\bigvee_{y=f(x)}\chi_A(x) \qquad \text{(Eq. 4.9)}$$

4.6 FUZZY EXTENSION PRINCIPLE

Fuzzy extension principle is an extension of crisp relation to determination of a fuzzy output from fuzzy inputs, having universes of discourse X and Y and a functional transform of the form y= f(x).

Suppose there is a collection of elements in universe X, x, that form the set A. The image of fuzzy set A in universe Y can be determined by B= f(A).

The membership functions describing A and B will now be defined on the universe of a unit interval [0,1], and for this case Eq.4.9 becomes:

$$\mu_B(y)= \bigvee_{f(x)=y} \mu_A(x) \qquad \text{(Eq. 4.10)}$$

Suppose the fuzzy set A is defined on n elements in X, for instance on $x_1,x_2, ...x_n$, and fuzzy set B is defined on m elements in Y, say on $y_1,y_2,.....y_m$. The array of membership functions for each set A and B can then be reduced to fuzzy vectors by the following substitutions:

$$a=\{a_1, a_2, ...a_n\} = \{\mu A(x_1), ... \mu_A(x_n)\}=\{ \mu_A(x_i)\}, \text{ for } i=1.....n \qquad \text{(Eq. 4.11)}$$

$$b=\{b_1,.b_2,.......b_m\} = \{\mu_B(y_1),............ \mu_B(y_m)\}=\{ \mu_B(x_j)\}, \text{ for } j=1.....m \qquad \text{(Eq. 4.12)}$$

the image of fuzzy set A can be determined through the use of the composition operation:

$B=A \circ R$ or using vector form, $b=a \circ R$. Where R is a m X n relation matrix.

For fuzzy sets $A_1, A_2, ...A_n$ defined on the universe $X_1, X_2,.......X_n$, the mapping for these input sets can be defined as $B = f(A_1,A_2, ..A_n)$, where the membership for the image B is:

$$\mu_B(y)= \max_{y=f(x_1,x_2,.....x_n)} \{\min[\mu_A(x_1),\mu_A(x_1)......\mu_A(x_n)]\} \qquad \text{(Eq. 4.13)}$$

4.7 FUZZY RELATIONS

Fuzzy relations are calculated through logic compositions. The mapping of elements of one universe Y to other universe X is made through a Cartesian product of the two universes. The strength of the relation is measured with a membership function. Methods to accomplish this are described in Ross (1995) and Klir & Folger (1988). One of these methods is the max-min. It can be imagined as the links of a chain. The strength of a chain is equal to the strength of the weakest link. In case of two parallel chains, the strongest one will determine the strength of the two of them. This can be shown by the equations:

$T = R \circ S$, where: R is a fuzzy relation on the Cartesian space X × Y and S is a fuzzy relation on the Cartesian Y × Z space, and T is a fuzzy relation on the X × Z space. Then:

$$\chi_T(x,z) = \bigvee_{y \in Y} (\chi_R(x,y) \wedge \chi_S(y,z)) \qquad \text{(Eq. 4.14)}$$

Where χT is the characteristic function of T in the interval [0,1]. This function measures the strength of the relation, i. e., a value of 1means full relation and 0 no relation (Ross 1995).

4.8 FUZZY PATTERN RECOGNITION

Site parameters can be defined as fuzzy sets. In fuzzy sets, the known patterns typically are represented as class structures, where each class structure is described by a number of features. A typical problem in pattern recognition is to collect data from a physical process and classify them into known patterns or rank them according to a pre-determined criteria (Ross 1995).

Suppose we have patterns represented as fuzzy sets A_i on X(i =1,2....m) and a new piece of data, perhaps consisting of a group of observations, is represented by a fuzzy set B on X. The task now is to find which A_i the sample B most closely matches.

According to (Ross 1995), if we define two fuzzy vectors, say **A** and **B**, then if the vectors are identical (same length and same elements) their inner product $A \bullet B^T$ reaches a maximum value as their outer product, $A \oplus B^T$ reaches a minimum value. These two norms can be used simultaneously in pattern recognition studies because they measure closeness or similarity.

$$(A,B)_1 = (A \bullet B) \wedge (\overline{A \oplus B}) \qquad \text{(Eq. 4.15)}$$

$$(A,B)_2 = \frac{1}{2}\left[(A \bullet B) + (\overline{A \oplus B})\right] \qquad \text{(Eq. 4.16)}$$

In particular, when either of the values of (A,B) above approaches 1, then the two fuzzy sets **A** and **B** are more closely similar. When either of the values are close to zero they are more far apart or dissimilar. As some of the features may be more important than others, weights can be introduced, ω_j, where:

$$\sum_{j=1}^{m} \omega_j = 1. \qquad \text{(Eq. 4.17)}$$

Therefore, equations 4.15 and 4.16 are then modified for each known pattern (i=1,2.......c):

$$(B, A_i) = \sum_{j=1}^{m} \omega_j (B_j, A_{ij}) \qquad \text{(Eq. 4.18)}$$

Sample **B** is closest to pattern A_j when,

$$(B, A_j) = \max_{1 \le i \le c} \{(B, A_i)\} \qquad \text{(Eq. 4.19)}$$

Where **B** is a collection of fuzzy sets, **B**={B_1, B_2,.........B_n}, and when **B** is a collection of crisp singletons, i. e., **B**={x_1, x_2,. ...x_n} then equation 4.19 reduces to

$$\mu_{Ai}(x) = \sum_{j=1}^{m} \omega_j \cdot \mu_{Aij}(x_j) \qquad \text{(Eq. 4.20)}$$

in the maximum approach degree, sample x is closest to pattern A_j when equation (4.20) reduces to

$$\mu_{Ai}(x) = \max_{1 \le i \le c} \{\mu_{A_i}(\mathbf{x}j)\} \qquad \text{(Eq. 4.21)}$$

Where:

$\mu_{Ai}(x_j)$ = degree of membership of x_j to A_i

A_i is a fuzzy pattern described by j = m features:

$A_i = \{A_{i1}, A_{i2}, ...A_{im}\}$

$j = 1, 2, ...m$

i represents classes or patterns:

$1 \leq i \leq c$

Fuzzy pattern recognition will be used here to give objectivity and a strong mathematical basis to data interpretation as complementary information. The approach determines at what level a certain set of data match a specific natural process or pattern (Ross 1995, Lemos *et. al.* 1998).

4.10 EVIDENCE THEORY

Probability theory and possibility theory are under the same frame and this is one of the key principle for integration of information in radioactive waste disposal facilities safety assessment.

In this context information from several different sources have to be gathered and integrated into the same models in order to give decision makers and public a single model where it can be shown the uncertainties, degrees of confidence and support for intermediate decisions and their effect on each other (through uncertainty propagation)and on the results of the analysis.

The ability to represent all the available information, including the one expressed linguistically, in the same frame will help improve confidence decision makers and public can pose on the safety assessment process.

This integration of information can be accomplished with the use of the evidence theory. The following text was extracted from Ross (1995) and Klir & Folger (1988). In this theory it is demonstrated that probability measure is a special case of fuzzy measure.

Evidence theory, or Dempster-Shafer theory, defines the belief and plausibility principles which are based on the basic probability assignment $m(A_i)$. Where A_i is a subset of A. then:

$m(A_i)(i= 1,2,3...)$ takes a [0,1] value and satisfies the following condition:

$$\begin{cases} m(\phi) = 0 \qquad (\phi : emptyset) \\ \sum_{Ai \subseteq Ao} m(A_i) = 1 \end{cases} \qquad \text{(Eq. 4.25)}$$

Belief or low probability is defined as:

$$bel(A) = \sum_{B|B\subseteq A} m(B) \quad \text{(Eq. 4.26)}$$

and upper probability or plausibility is:

$$Pl = 1 - bel(\overline{A}) \quad \text{(Eq. 4.27)}$$

$$Pl(A) = \sum_{B|A\cap B\neq\phi} m(B) \quad \text{(Eq. 4.28)}$$

If for a singleton x a basic probability assignment *m(x)=bel (x)* and *m(A)=0* for all the power set, P(X), that are not singletons, then *m(x)* is a probability measure.

Probability measure can be defined as some function *p(x)*, to the unit interval, i.e.,

$$p: x \to [0,1] \text{ or } m(x) = p(x) \quad \text{(Eq. 4.29)}$$

p(x) maps evidence only on singletons to the unit interval. According to the definition of probability measures follows:

$$bel(A) = pl(A) = p(A) = \sum_{x\in A} p(x) \text{ for all } A \in P(X) \quad \text{(Eq. 4.30)}$$

this equation also reveals the excluded middle law:

$$pl(A) = p(A) = bel(A) \to p(A) + p(\overline{A}) = 1 \quad \text{(Eq. 4.31)}$$

4.11 POSSIBILITY MEASURE

This section is an excerpt from Ross (1995).

Having a collection of all of the subsets on the power of a universe, they are nested if:

$$A_1 \subset A_2 \subset A_3 \subset \ldots\ldots \subset A_n \quad \text{(Eq.4.32)}$$

In this case the belief measures, $bel(A_i)$ and the plausibility measure, $pl(A_i)$ represent a consonant body of evidence.

The following relationships are valid for two different sets on the power set of a universe and for a consonant body of evidence:

$$bel(A \cap B) = \min[bel(A), bel(B)] \qquad \text{(Eq. 4.33)}$$

$$pl(A \cup B) = mx[pl(A), pl(B)] \qquad \text{(Eq. 4.34)}$$

This means that belief in the intersection of two sets is the smaller of the belief of the two sets and the plausibility of the union of the two sets is the larger of the plausibility measures of the two sets.

Belief and plausibility are also referred to as necessity (η) and possibility (π) measures respectively.

Possibility distribution function is defined as:

$$r : X \to [0,1] \qquad \text{(Eq. 4.35)}$$

this mapping will be related to the possibility measure, $\pi(A)$, by the relationship:

$$\pi(A) = \max_{x \in A} r(x) \qquad \text{(Eq. 4.36)}$$

A possibility distribution is defined as:

$$r = (\rho_1, \rho_2, \rho_3 \ldots \rho_n) \qquad \text{(Eq. 4.37)}$$

It can be shown that:

$$\rho_i = \sum_{k=i}^{n} \mu_k = \sum_{k=i}^{n} m(A_k) \qquad \text{(Eq. 4.38)}$$

According to Zadeh (1978), a possibility distribution can be interpreted as a fuzzy set. He defines a possibility distribution as a fuzzy restriction that acts as an elastic constraint on the values that may be assigned to a variable. Therefore, a possibility distribution represents the degrees of membership for some linguistic variable, but the membership values are strictly monotonic as they are for an ordered possibility distribution.

For a fuzzy set A in the universe X, and let the membership value, μ, be a variable on X that assigns a "possibility" that an element of x is in A:

$$\pi(A)=\mu_A(x) \qquad \text{(Eq. 4.39)}$$

Evidence theory offers a perspective within which probability and possibility theories are considered as special branches. The proof for this statement can be found in the literature (Ross 1995, Klir & Folger 1988). According to Zadeh (1978) and Ross (1995), there is a loose relationship between probability and possibility measures through a probability/possibility consistency principle. What is possible may not be probable, but what is impossible is inevitably improbable.

This consistency can be expressed formally,

$$Pro(A) \le Pos(A) \qquad \text{(Eq. 4.40)}$$

and $Pro(A)\rangle 0 \Rightarrow Pos(A)=1$ (Eq. 4.41)

for all $A \in P(X)$

the degree of consistency, c, between *Pro* and *Pos* can be measured in terms of the associated probability distribution function **p** and possibility distribution function **r** by the formula:

$$c(p,r)=\sum_{x\in X} p(x)\cdot r(x) \qquad \text{(Eq. 4.42)}$$

These relations are essential for a probability-possibility transformation. The study of this transformation is important for applications in models and expert systems where the two types of uncertainties are combined. This study is beyond the scope of this work and is left to the reader to find more on the literature (Klir & Folger 1988).

In this work some examples of uncertainty treatment with fuzzy logic and possibility theory are presented. This is the first step toward the building of an expert system for waste disposal facilities safety assessment.

4.12 AN EXAMPLE OF DIFFERENCE IN APPLICATIONS OF PROBABILITY AND FUZZY SETS APPROACHES

This section presents a typical applications of probability and possibility approaches to data analysis.

4.12.1 Probability approach

Suppose one is interested in describing the distribution of the weight of adult males in the city of Belo Horizonte.

In order to have a fair representation of the population it will be necessary thousands of samples. After that, it could be decided that the weight can be represented by a range between 50 Kg and 150 Kg and the distribution is as shown in Figure 4.1.

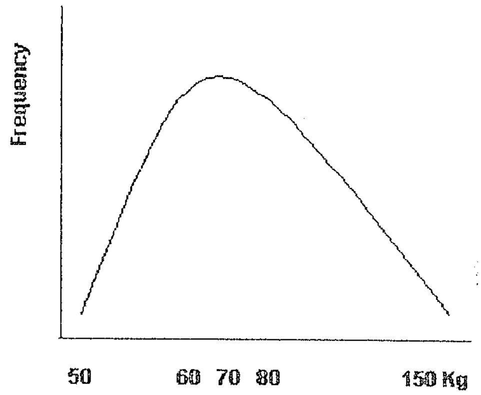


Figure 4.1: Probability Distribution Function for adult male weights.

According to Figure 4.1, weights between 60 and 80 Kg have higher frequency, or in other words, there is more chance, or probability, of finding a person within that range of weights. It should be pointed out though that all of the other weights, from 50 t o150 Kg, belong to this set, or range of weights, with the same membership. Each observation is independent from the other and figure 1 represents a distribution only of the observations within a population.

4.12.2 Fuzzy logic approach

Suppose one wants to define a person with an "average weight" in the city of Belo Horizonte.

Fuzzy logic would be more adequate for this case. A person with 150 Kg would certainly not to belong to the set "average person", neither would a person with 50 Kg.

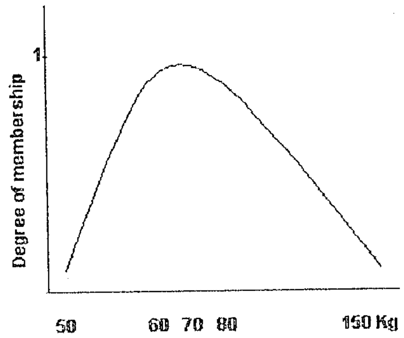


Figure 4.2: Membership function for adult males weight.

The meaning of the distribution in Fig. 4.2 is completely different from the frequency distribution (stochastic) in Figure 4.1. Figure 4.2 is a representation for the ambiguous expression "average weight" as a fuzzy set, which is non-stochastic. In this case, a person with 50 Kg has a very low degree of membership as well as a person with 150 Kg.

The same reasoning can be extended to a case of environmental data analysis. In Table 4.1, it can be seen that even for well characterized sites, such as Poços de Caldas, it is very common to find linguistic expressions to define site conditions.

Some parameter values will be defined, indirectly, based on the description of these condition. For example, if a region has a "Low Uranium Content", it may mean a "low pH" for that particular site.

Table 4.1: Example of geochemical descriptions for samples from the drillcore F1 which were analyzed for natural decay series radionuclides (Mackenzie *et. al.*, 1991).

Sample code	Depth (m)	Rock description
6-1 A	6.00	Porous, strongly fractured, oxidized phonolite
10-1 A	9.84	Porous, fined grained porphyritic, oxidized phonolite.
16-1 A	15.07	Oxidized phonolite, average sample, low U content.
26-1 A	25.22	Oxidized phonolite, average sample, low U content.
33-1 A	32.89	Redox front, oxidized side, low U content.
34-1 B-A	33.40	Redox front, oxidized side, low U content.
34-1 B-D	33.51	Redox front, reduced side, low U content.
34-1 B-F	33.65	Redox front, reduced side, low U content.
34-1 C	34.00	Very porous, fine-grained porphyritic, reduced phonolite.
35-1 A	34.31	Porous, fine-grained porphyritic, reduced phonolite, fractured.

"Low pH" is an ambiguous expression that can be represented as a fuzzy set, which is different from simply defining pH by a range of values, say from 5 to 9.

This will reflect on the uncertainty propagation too. Fuzzy logic will aggregate values according to each set definition and using fuzzy inference (*if... then* rules), please see sections on fuzzy logic tools, that will combine fuzzy sets, for example, *Low pH – High Radionuclide Concentration – Medium Oxidation Conditions, etc.*.

It is also possible to use fuzzy probabilities by using linguistic terms such as *likely, unlikely, around 0.8, etc.* which can be manipulated as fuzzy numbers or fuzzy sets.

CHAPTER 5

CASE STUDIES

5.1 INTRODUCTION

Six case studies are presented in this chapter in order to provide the reader with a wide range of applications of fuzzy logic to radioactive waste disposal facilities safety assessment. These examples represent different aspects of non-probabilistic uncertainties in safety assessment. For example, case study 1, section 5.2, Kd Determination Using Fuzzy Set Theory, is related to lack of data, natural variability and ignorance regarding natural processes. Kd, or distribution coefficient, is a very important parameter for the determination of transport patterns of radionuclides from the waste packages to and through the engineered barriers and to the environment.

Case study 2, section 5.3, Preliminary Source Term Assessment of the Abadia de Goiás Repository Using Fuzzy Sets, is related to complexity in the real world and need for simplification of data for modeling purposes. This case is the study of determination of release mechanism from waste forms. The variety of different types of wastes forms and lack of quantitative data on release rates from different waste forms makes it necessary to group wastes into categories that can be modeled as having similar release mechanisms using fuzzy logic tools.

Case study 3, section 5.4, Safety Analysis of The Abadia de Goiás Repository, a total safety assessment calculation, is related to aggregation of different types of information and propagation of uncertainties. This study demonstrates the development of a safety assessment case with the aggregation of information from case studies 1 and 2, and data from Abadia de Goiás repository. The aggregation is done by means of fuzzy logic tools; This case example is further developed in case study 4, section 5.5, "Application of Fuzzy Expert System on LILW Performance Assessment".

Cases 5 and 6, "Translating Natural Concentrations and Fluxes Into Safety Indicators for Radioactive Waste Repositories" and "Evaluating Contaminant Migration Around Redox Fronts at The Poços de Caldas Uranium Mining Site (Minas Gerais, Brazil) Using Fuzzy Logic" deal with quantification of linguistic information in order to take advantage of important information which otherwise could have been lost.

Case study 5 involves translating natural concentrations and fluxes into Safety Indicators for radioactive waste repositories. This case is a study of natural deposits of radioactive elements which can provide important and very useful information for safety evaluation of high level waste radioactive waste repositories. It has been suggested (Miller 2000, Hellmuth 1999, Lemos *et al.* 2002), that by comparing natural concentrations and fluxes against those calculated for the facility could help demonstrate how a this facility will affect the environment.

Case study 6, "Evaluating contaminant migration around redox fronts at the Poços De Caldas Uranium Mining Site (Minas Gerais, Brazil) using fuzzy logic" is the fifth case study. This subject is an important aspect of high level waste disposal safety assessment. This case is a study of the contaminants ability to migrate from a repository through the environment based on a number of factors including the site hydro-geochemical conditions. The uncertainties and ambiguousness that rise from lack of data, time frame for the useful life of the repository, subjective decisions, and other factors, are represented through fuzzy sets aiming at helping decision makers to form a "good " picture of the whole situation while dealing with the technical complexities of the problem.

These uncertainties will have an impact on the degree of belief for the results of the data analysis and interpretation and, consequently, on the results of the performance assessment of the facility.

5.2 CASE STUDY 1: KD DETERMINATION USING FUZZY SET THEORY

5.2.1 Introduction

A major problem in low and intermediate-level nuclear waste repositories safety assessment is site characterization. The site characteristics are needed as part of the decision process for site selection. During the site characterization process a series of simplifying assumptions are made in order to easily represent the complex geological system. Based on the simplification used to develop the conceptual model of the site, a preliminary analysis is performed. to evaluate the site for disposal. The preliminary analysis is often based on generic data. These data include the interaction between the contaminants (to be disposed of) and the environment, and are used for the estimation of the future repository features. The determination of transport parameters like Kd is important for the study of radionuclides migration in the geosphere and consequently for the assessment of environmental impact and human dose exposure due to a possible release of contaminants from the repository. In general, Kd can not easily be determined theoretically. Therefore, the best approach is to obtain laboratory and field measurements. However, this procedure is expensive, time consuming and does not avoid the uncertainties due to the natural variability of the local geology.

To address the variability in data in estimating transport parameters (Kd), statistical methods such as probabilistic regression or geometric averaging are used in order to predict a value for Kd. The large variability in Kd as a function of soil characteristics can lead to unrealistic results when using standard approaches. Probabilistic methods assume that the uncertainties are due to randomness and independence in data. Consequently they are inappropriate because the uncertainties related to Kd determination are due to lack of knowledge about the site characteristics rather than to random distribution of values. However, in practice, to overcome limitations of these approaches analyst's opinion is used to find the most reasonable Kd values, i. e., subjective decisions are made.

Fuzzy sets theory is specially developed for the analysis of uncertainties that come from simplification of complex systems and data which are ambiguous in nature.

This thesis describes a method using fuzzy sets to build a possible distribution of values for Cs-137 Kd accounting for the uncertainties due to lack of knowledge about the soil characteristics. Data from the literature will be used, and will be divided into a number of fuzzy sets according to soil characteristics. The results are promising and show that even though this method does not replace the need for laboratory or field measurements, a reasonable distribution function can be obtained using general data and fuzzy sets theory.

Although Cs 137 is essentially immobile in most soil systems, the analysis of its behavior can be important as for example in the Abadia De Goiás Repository, Brazil, where it is the only contaminant.

This method can be extended to other radionuclides and as such forms a basis for obtaining improved estimates of Kd and other site-specific transport parameters needed in the preliminary stages of site selection.

5.2.2 Soil Classification

In general, soils are categorized according to the amount of sand, clay, loam and organic matter. If the soil contains more than 70% of sand sized particles, it is classified as sand; those containing more than 35% of clay sized particles are classified as clay; Loam soils have a relatively even distribution of sand, clay and silt-sized particles, or containing more than 80 % of silt–sized particles. Organic soils are those containing more than 30 % of organic matter (Thibault *et al.* 1990).

In the past Kd is associated with soil types that are classified according to different soil composition. A drawback of this method of classification is its crisp limitation. If a soil sample has 31% of clay it is automatically classified as clay type soil. However if it has 29% of clay, its classification would be in a different group and consequently the Kd values obtained from this classification are not likely to be realistic.

A fuzzy classification method, on the other hand, could lead to more realistic results because the samples are clustered into classes according to the amount of their components. In addition, fuzzy set classification accounts for the transition between different classes through the concept of a membership function. This means that more similar soil samples are categorized together and the boundaries for the classes or sets are flexible rather than rigid. After the classification is made, a multiple-regression analysis is performed within each class. The equation is then used as a tool for the prediction of Kd for new samples given their amount of sand, clay, silt and organic matter.

5.2.3 Methodology

As a first step, 30 samples were chosen from the literature. Twenty five of these points have been taken as learning points and are used to determine the regression equations. The other five points have been used as for validation of the regression equations.

It was very difficult to find good quality data in the literature because the data are scarce, and are from a number of different sites. Therefore, they have very different chemistry. As our intent here is to find a way to help the specialist on the task of site selection, we suppose that the sample we will analyze are from the same region.

For the classification we used the amount of soil components, the pH and cation exchange capacity (CEC) as features. Initial studies indicated that the pH and CEC were not important in this process for the case of Cs137. This is not expected to be the case for other radionuclides Table 5.1 shows the data, measured Kd values range over two orders of magnitude and inspection does not reveal any clear relationship between soil parameters and Kd.

The classification method used was natural clustering, i. e., the points were divided into a number of classes and the more similar data naturally stayed in the same class.

5.2.4 IF-THEN Rule Formulation

The soil samples can be thought of as being the If part of an IF-THEN rule, i. e., IF the soil composition is "y, x, w, z" THEN Kd should be high (Takagi & Hayashi 1991).

It would be easy to build a relationship between a certain soil type with only one feature and its Kd value for a certain radionuclide. However as there are at least four features that have to be analyzed, (a multidimensional space), the fuzzy clustering technique is of great help. The Fuzzy-c Means method was used to obtain the classes in this work (Takagi & Hayashi 1991).

The following classes were found after the classification:

Class 1: samples number 1,2,3,14,15 and 18

Class 2: samples number 0, 4, 5, 6, 11, and 13

Class 3: samples number 20, 21, 22, and 23

Class 4: samples number 16, 17, 19, 24, and 25

Class 5: samples number 7, 8, 9, 10, and 12

5.2.5 Results

Five points were chosen for verification. First they were classified in order to determine in which of the five original classes they would fit best. Then their features were used in the regression equations determined from the other twenty six data points. The value predicted by the regression equation was compared to the measured value.

Table 5.1: Samples used for building the regression equations.

Sample (n)	Sand (%)	Silt (%)	Clay (%)	Organic (%)	Kd (ml/g)
0	74	3	23	0	405
1	29.7	40.2	17.5	.17	3529
2	32.5	34.2	14.6	.2	1557
3	37.5	35.8	11.9	.21	591
4	100	0	0	.03	119
5	93	5	2	.05	1370
6	96	4	0	.51	74
7	52	45	3	.08	11000
8	59	24	17	.4	1100
9	62	31	7	.38	11000
10	52	39	9	.33	150
11	95	2	2	.3	510
12	60	22	18	2.05	110
13	87	9	4	.1	1510
14	36	35	29	.43	17810
15	34	35	31	.4	18400
16	28	41	31	1.27	1810
17	12	55	33	.35	21000
18	34	34	32	.85	11000
19	45	44	11	.14	13500
20	31	69	0	0	5320
21	7	92	1	0	9550
22	18	71	11	0	10400
23	3	96	1	0	11400
24	44	50	6	.23	7300
25	31	34	35	.81	6200

Figure 5.1 shows the results of the regression amongst each fuzzy set, the geometric average and the measured Kd values. The geometric mean curve is a method of comparison between the results of the different methods of calculation. As can be seen, due to the nature of the data, a big interval between the higher and lower values for each point in a class exists. This makes it more difficult to use the geometric mean as a representative of the set. On the other hand, the regression curve built with the help of fuzzy sets techniques gives results closer to the measurements. The last five data are the prediction based on the regression and geometric average for each class.

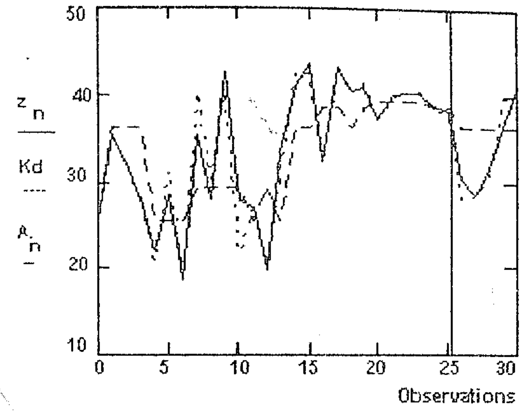


Figure 5.1: Prediction of Kd values (z_n) in comparison to the measured values (Kd_n) and the geometric average (A_n). Where: n = observation number; z_n = regression equation; A_n = geometric average.

5.2.6 Conclusions

In this thesis a new method was shown that could assist the analyst during estimation of transport parameters prior to site characterization. This information could then be used to screen sites and prioritize data collection.

Fuzzy logic is a very powerful tool for analyzing data with uncertainties similar to those required in environmental studies. This thesis has shown that the fuzzy set approach can obtain more realistic values for Kd in comparison to other traditional methods, such as the geometric mean of the data.

Future work could include a more detailed study on the range of possible values for each sample, application of other fuzzy set methods for obtaining the regression equation, and extending these principles to other radionuclides.

5.3 CASE STUDY 2: PRELIMINARY SOURCE TERM ASSESSMENT OF THE ABADIA DE GOIÁS REPOSITORY USING FUZZY SETS

5.3.1 Introduction

Safety assessments are used to provide quantitative support for decision makers that regulatory limits on release from the disposal facility will not be exceeded. A common approach to perform a safety assessment is to collect the data and perform a deterministic calculation to demonstrate reasonable assurance. Efforts are made to select data that are conservative with respect to expected outcomes and generally many deterministic calculations are performed to identify parameters that have the largest influence on the analysis.

Many, if not all, site data used as input for the safety assessment are imprecise and this limits the confidence one can place in a deterministic calculation. Further, due to the number of variables needed to assess safety, it is not always possible to identify which choice of parameters provide the most conservative outcome in a deterministic calculation. To overcome these limitations, probabilistic analysis has been suggested. This places the analyst on a more rigorous mathematical basis as far as evaluating a wider range of combinations of parameters and events that can impact the results. However, a probabilistic approach has drawbacks to this type of problem, it does not take into account subjective choices, and data for a probabilistic analysis are lacking and therefore, also highly imprecise.

Probability deals with the concept of randomness. However, characterization of the release mechanism of a waste form, is fuzzy or ill defined, for the contents of each package which control release of contamination to the environment are poorly known and ambiguous. The fuzzy set theory deals with uncertainty that comes from fuzziness or vagueness in phenomena, and has been applied in a vast variety of scientific fields with success (Ross 1995). In this thesis, the fuzzy sets approach is used to handle the uncertainty that is inherent to waste form characterization .

As an illustration of the use of fuzzy set theory, this thesis will deal only with source term analysis.

To mathematically represent the repository, it is divided into several sections or cells. Each cell represents a control volume which may contain many waste forms with different release characteristics. For each control volume our objective is to homogenize the wastes to a representative waste, with one set of release characteristics This thesis presents two approaches in order to deal with such a vast number of data. Case A is using fuzzy set theory, and Case B is a deterministic calculation.

In Case A, fuzzy set theory is used to simplify the problem to an acceptable level, while retaining the information obtained in the data (Ross 1995). First we will determine the general behavior of each particular cell or control volume, i. e., homogenize the several waste form release processes data into one general behavior per cell using fuzzy average calculation (Klir & Folger 1992). Weights will be assigned to each waste form according to its relative importance (inventory or mass) in relation to that particular cell, and according to other factors that could be of major importance. Later on, the already homogenized cells will be classified or clustered into types for representing waste forms (Ross 1995). This calculation is done for each radionuclide, independently. Further, the outcome of the analysis will provide data which can be handled by the existing deterministic computer codes, e. g., DUST code (Sullivan 1993).

In Case B, a deterministic calculation is performed. In this case both homogenization and classification are done arbitrarily. Values are chosen with the goal of being conservative, however, without knowledge of how conservative the outcome will be.

The application of fuzzy sets approach to the complete safety assessment will be studied in future works. In addition the fuzzy sets approach will be used on decontamination problems.

5.3.2 Waste Forms Classification

The waste forms can be classified according to their release mechanisms which are: Solubility-limited, Surface rinse, Surface rinse with partitioning, Diffusion and Uniform dissolution. These processes are modeled through the release parameters that are: Solubility limits, Partition coefficient, Diffusion coefficient, and Uniform dissolution rate respectively (Sullivan 1993).

As the waste form parameters are ill defined or vague, the use of fuzzy set theory is appropriate in this case. The fuzzy classification approach allows a data to be classified into a cluster even if the data does not have complete similarity to the other points of that cluster, that is, its membership to that cluster can be ambiguous or fuzzy.

In a crisp classification, however, two choices are available to classify the data, either it belongs to a set or does not. So the chances for an incorrect classification are higher than in a fuzzy sets approach, which is more flexible. This flexibility allows a better representation of the real world where the phenomena are ambiguous (Bezdek 1981).

5.3.3 Example Calculation

Several hundreds of waste forms have been disposed at Abadia de Goiás Repository. The principal forms of waste: Paper, plastic, fabric, soil, scrap, debris, animals, fruits, wood, and the remainder of the Cs-137 source (Miaw 1995).

To approximate the waste containing region of the repository, we divide the repository into ten cells of equal volume. First, for each cell, a fuzzy weighted average will be made in order to determine its general behavior or the properties that best represent its components, i. e., homogenization. After that, a fuzzy classification will be conducted in order to group the cells into a certain number of waste types.

The wastes has been grouped and packaged as follows (Miaw 1995).:

Waste form group I - Cs-137 source

Waste form group II - Paper, plastic, and fabric

Waste form group III - Soil, scrap and metallic debris

Waste form group IV - Animals, fruits and wood.

According to the above types of waste, diffusion controlled release is not appropriate and will not be modeled. The remainder of the Cs-137 source is in the form of a salt, Cesium chloride, and so instant release upon contact with infiltering water is assumed, i. e., 100 % rinse release is considered for waste form group I. For plastic, fabric and scrap wastes, the contamination is expected to be on surface, and so rinse or instant release is considered for these wastes. Also, fruits will biodegrade very fast, which can be modeled as instant release or rinse. Paper, wood and animals biodegrade less quickly than fruits, so uniform dissolution is assumed. For paper the rate of dissolution is about 20 %/yr., while for wood and animals the rate is 10 %/yr. The metallic debris is assumed to undergo corrosion, and is modeled as uniform dissolution at a rate of 5%/yr. In soil waste, adsorption and other geochemical retardation factors could be expected, and so rinse with partitioning is considered for this waste. Table 5.2 shows the approximate proportion of each release process for each group. The numbers in table 5.2 are in the form of a uncertainty distribution corresponding to degree of membership [0.2, 1.0, 0.2], and given according to expert opinion.

Table 5.2. Approximate proportion of release mechanism within each waste form groups (*)

Release	Waste form group I	Waste form group II	Waste form group III	Waste form group IV
Rinse	[100%]	[85, 90, 95%] plastic, fabric	[30, 35, 40%] scrap	[50, 55, 65%] fruits
Rinse with partitioning			[30, 35, 40%]-soil {300, 400, 1000}²	
Uniform release		[5, 10, 15%] paper biodegradation (12, 20, 30)¹	[25, 30, 35%] Metallic debris corrosion (1, 5, 10)¹	[40, 45, 55%] animals biodegradation (5, 10, 20)¹

(*) Numbers in square brackets are the relative percentage of the group that contributes to that release mechanism.
(1) Numbers in parenthesis refer to uniform diffusion rate. (2) Distribution coefficient.

Based on data in Miaw (1995), the approximate contribution in terms of % of the total volume and % of total inventory of the waste form groups are listed in table 5.3.

Table 5.3-Waste form groups approximate contribution to the repository total volume and total inventory

Waste form group	Waste form group I	Waste form group II	Waste form group III	Waste form group IV
% total volume	0.15 - 0.20	5 - 8	90 - 97	2 - 4
% total inventory	9 - 10	3 - 5	80 – 90	1 - 3

Two approaches will be applied to solve the problem of determination of waste form release characteristics. Case A using fuzzy sets, and Case B using a deterministic method. Comparison of the results will be made.

Case A. Fuzzy sets approach

In order to calculate the fuzzy weighted average, weights will be given to each waste form group according to its approximate activity per unit volume and its approximate relative volume in each cell, and consequently, the weight will also, be a fuzzy number. The existing approximate activities of waste form groups have been classified into 5 categories shown in table 5.4.

Table 5.4. Classification of the existing activities per unit volume (*)

Concentration (TBq/m^3)	[0.9, 1.0, 1.2]	[0.4, 0.5, 0.6]	[0.08, 0.1, 0.2]	[2E-2,3E-2,4E-2]	[1E-4,1E-2,1E-1]
Classification	A	B	C	D	E

(*) Values correspond to degree of membership of 0.2, 1.0, and 0.2 respectively.

Within each waste form group, there are different activities per unit volume, which will correspond to the above classification. Table 5.5 shows the % of respective cells volume according to the waste form group and the corresponding class of activity per unit volume (Miaw 1995). For example, cell 1 is occupied with 100 % of group III waste form, and its activity corresponds to letter E, i. e., from 1E-4 to 1E-1 TBq/m^3.

As the volume of waste type is also a fuzzy number, the values in the above table have respectively membership degree 0.2, 1.0, and 0.2. The membership degree were given according to expert opinion.

The fuzzy weights for each waste form group are calculated taking into account the approximate relative volume occupied in each cell (V), the approximate activity per unit volume for each group (A) and the percentage of the particular release process being analyzed (P).

$$W = f(V, A, P) \qquad \text{(Eq. 5.1)}$$

Table 5.5. Percentage of cell volume occupied by each waste form group and corresponding activity per unit volume classification as seen in table 5.4.

Cell	Group I	Group II	Group III	Group IV
1			E-[100]	
2			E-[50, 55, 65] C-[3, 5, 7] D-[35, 40, 45]	
3		E-[3, 5, 10]	D-[90, 95, 100]	
4			B-[40, 45, 55] E-[30, 35, 40]	E-[15, 20, 25]
5		E-[8, 10, 20]	E[70, 80, 90]	E-[8, 10, 20]
6		E-[15, 20, 25]	B-[40, 50, 60]	B-[25, 30, 35]
7		B-[8, 10, 20]	D-[60, 70, 80]	D-[15, 20, 30]
8		D-[15, 20, 25]	B-[75, 80, 85]	
9	A-[45, 50, 55]	E-[20, 25, 30]	D-[20, 25, 30]	
10	A-[45, 50, 55]	E-[2, 3, 5]	B-[40, 45, 50]	E-[1, 2, 5]

Taking the information from tables 5.1 to 5.5, we obtain the fuzzy average release mechanism per cell as shown in table 5.6.

Table 5.6. Calculated fuzzy average release mechanisms and dissolution rate values for each cell.(*)

Cell Number	Average percentage of rinse	Average percentage of rinse with partitioning	Average percentage of dissolution	Fuzzy average dissolution rate (%/yr)
1	[30, 35, 40]	[30, 35, 40]	[20, 30, 35]	[1.0, 5.0, 10.0]
2	[30, 35, 40]	[30, 35, 40]	[20, 30, 35]	[1.0, 5.0, 10.0]
3	[31.5, 40.6, 49.5]	[27, 33, 40]	[20, 26.4, 30]	[1.0, 5.4, 11.6]
4	[29.3, 42.0, 56.3]	[21, 25, 36]	[25, 33, 40]	[1.0, 5.1, 10.6]
5	[35.5, 50.8, 68.0]	[21, 25, 36]	[20, 25.2, 30]	[2.0, 6.7, 13.5]
6	[36.5, 53.9, 68.8]	[12, 15, 24]	[25, 31.1, 35]	[2.8, 7.2, 14.4]
7	[41.0, 56.8, 74.5]	[18, 22, 32]	[15, 21.2, 25]	[6.5, 12.6, 20.0]
8	[35.5, 46.4, 57.8]	[22, 30, 32]	[15, 23.6, 25]	[1.1, 5.2, 10.4]
9	[69.0, 82.0, 95.0]	[6, 9, 12]	[5, 8, 10]	[1.1, 6.5, 19.1]
10	[60.0, 78.0, 84.0]	[12, 16, 20]	[1.0, 6, 10]	[1.0, 5.0, 10.3]

The values correspond to degree of membership 0.2, 1.0 and 0.2 respectively.

Cells Classification

Based in information in table 5.2 – 5.6, we proceed to the cells classification by the process of fuzzy clustering (Ross 1995). In this process, the chosen parameters are used for comparison between each cell. A fuzzy set or class is obtained from the data in order to group the more similar ones in the same set based on the Euclidean distances from each point to an average center. Table 5.7.

Table 5.7- Cells classification through fuzzy clustering method.

Cell	1	2	3	4	5	6	7	8	9	10
Class	1	1	1	4	4	2	2	1	3	3

The aim of this work is the simplification of data to be used as input in deterministic codes. In this example the more than hundreds waste forms are categorized as one of four classes according to table 5.7. The cells in the same class will be represented by just one set of values as will be demonstrated below for class 1.

To this point, the data have been presented as a distribution, or membership function. To be used in a deterministic code, those data have to be defuzzified, i. e., we have to choose only one value, instead of an interval. Recalling that the waste containing region of the repository has been divided into ten cells, class I cells have been determined to exist for cells 1, 2, 3 and 8; Table 5.7. Examining the percentage of rinse release in each of these four cells, Table 5.6 shows that cell 8 has the highest percentage. It is assumed that the highest rinse percentage will lead to a conservative estimate of release. Therefore the chosen set of values to represent class 1 are those from cell 8.

As these values will be employed in a deterministic calculation, we need a method to convert fuzzy data into a single value. Some methods for defuzzification are available in the literature (Ross 1995). The choice of the method depends on the context of the problem being analyzed, and a discussion is beyond the scope of this thesis.

Expert opinion has been used to decide to use the values that have degree of membership 0.5. Assuming a triangular distribution membership function we obtain an interval of parameter values with degree of membership greater than or equal to 0.5. The intervals that correspond to degree of membership 0.5 are in table 5.8.

Table 5.8. Chosen values interval to represent class 1 according to the degree of membership

Degree of membership	% Rinse	% Rinse with partitioning	% Uniform Dissolution	Average dissolution rate
0.2	[33.5, 46.4, 57.8]	[22, 30, 32]	[15, 23.5, 25]	[1.1, 5.2, 10.4]
0.5	[42.3, 53.2]	[27, 31.3]	[20.4, 24.5]	[3.7, 8.5]

One value is chosen from table 5.8 for use in a deterministic code. The most conservative values with a degree of membership of 0.5 are: Rinse = 53.2 %, Rinse with Partitioning =31.3 %, Uniform dissolution = 24.5 %. The same approach is applied to the other three classes of waste form. The results are in table 5.9.

Table 5.9. Final crisp parameter values for the existing classes.

Class	Rinse (%)	Rinse with partitioning (%)	Uniform dissolution (%)	Dissolution rate (% / yr.)
1	53.2	31.3	24.5	8.5
2	67.9	28.3	23.6	17.2
3	90.1	10.9	9.3	14.4
4	61.6	31.9	28.2	11.0

Notice that the summation of columns Rinse, Rinse with partitioning and Uniform dissolution is greater than 100 % for all classes. This is due to the fact that these values were taken from the highest ones in each case. This adds to the conservatism of the approach.

Case B. Deterministic approach

In a deterministic approach, attempts are made to select the most conservative parameters, however the selection of values is arbitrary. For example, one could chose the 100% rinse release mechanism to represent all cells. However this value would be unrealistic. Another criteria could be based on the amount of waste form group III in each control volume. So the cells that are composed of more than 50 % of waste form group III are in class 1, and have the characteristics of that group. The cells in this case are 1 to 8 according to Miaw (1995). The other cells are in class 2, with release characteristics of waste form group I, or instant release. The results are in table 5.10.

Table 5.10. Arbitrary classification of cells.

Class	Rinse (%)	Rinse with partitioning (%)	Uniform Dissolution (%/ yr)	Dissolution rate (% / yr)
Class 1 (cells 1 to 8)	35	35	30	15
Class 2 (cells 9 and 10)	100			

In this approach there is no way to know the degree of uncertainty, and decisions are arbitrary.

5.3.4 Comparison of Results

The results in Case A have a known degree of uncertainty, which has been calculated with a well established mathematical basis. The degree of conservatism can be changed, by changing the degree of membership of the values used in the calculation. In this example, the lower the degree of membership, the higher will be the degree of conservatism and the wider will be the range of possible values. Table 5.9 shows the values corresponding to degrees of membership 0.2 and 0.5. The lower degree of membership corresponds to a wider range of values. This property allows the researcher to vary the degree of uncertainty in the calculations.

Also, other factors that influence the results are well known, as the weights assigned to the parameters in the fuzzy weighted average calculation. (Table 5.6).

In Case B, the conservatism is obtained by choosing the worst case, or some other arbitrary criteria. However, one does not have a way to quantify the degree of conservatism. In addition, arbitrary criteria which can not be shown to be the worst case, may not be easily defensible.

5.3.5 Conclusions

Usually the selected codes for safety assessment employ finite differences, or finite elements methods. In these methods the repository is divided into several cells or control volumes which contain only one set of characteristic data that represent all the waste forms in that region. However, in the repository the waste forms are dissimilar and release processes are ill defined, choosing the right data to represent waste form releases can lead to extreme conservatism, or values that are selected arbitrarily.

In the above example, we used two approaches to represent the several hundred different waste forms found in the Abadia de Goiás Repository into a few groups, in order to simplify the task of determination of the release mechanism for the waste forms.

The first approach was based on the fuzzy set theory. The repository was divided into a number of cells. For each cell the general release mechanism pattern was calculated using a fuzzy average method. The cells were than grouped into classes, according to their similarities. And finally values were chosen to represent the classes with a known degree of uncertainty. Fuzzy sets approach provides a well established mathematical basis for the decision makers that quantifies the uncertainties due to vagueness in data, through the membership function, and so the results will be given with a known degree of uncertainty.

The second approach was deterministic. In order to be conservative, one tends to choose the worst case that can lead to unrealistic values. Other options are to make arbitrary grouping with the attempt of being conservative, however this approach has a lack of rationale and therefore may be difficult to defend.

5.4 CASE STUDY 3: SAFETY ANALYSIS OF THE ABADIA DE GOIÁS REPOSITORY

5.4.1 Introduction

In this section it is presented a case study of application of fuzzy logic to radioactive waste disposal facilities safety assessment. The Low Level waste repository in the Town of Abadia de Goiás, Brazil, was chosen for demonstration purposes only. Data from the previous two case examples are used (Lemos *et al.* 2003)

The DUST code (Sullivan 1993), is used for the system modeling. This code uses finite differences for calculating transport of radionuclides from the packages to the bottom of the repository and to the near field, i.e., the source term. Source term can then be represented as a function of input data (e.g., inventory, materials properties, radionuclides characteristics, etc.) in other words, it can be represented as a relation of the form:

$$\underset{(source term)}{B} = \underset{(DUST)}{f}\ \underset{(input\ data)}{(A_1, A_2, \ldots A_n)} \qquad \text{(Eq. 5.2)}$$

The Disposal Unit Source Term (DUST) code is used in this work because of its capability to handle some important parameters as a screening tool. It is a one dimensional code that models the transport of contaminants from the waste containers to the boundary of the repository by applying either finite difference (FD) or multi-cell mixing cascade (MCMC) models. FD is a numerical solution while MCMC is an analytical one. The FD model was used for our purposes.

This code was used to analyze two different waste form release models, namely diffusion and dissolution, representing the two major possibilities of matrix for the waste immobilization.

Diffusion is usually assumed to control the release of contaminant from the porous materials such as cement and polymers.

Dissolution is assumed as the release mechanism for non-porous media such as glasses and metals.

There is a number of input data to be considered. For simplification purposes some data will be considered as deterministic and the following data will be considered as a range for the development of a case example:

Concrete degradation rate.

Containers degradation rate, inventory, and waste releasing processes.

Radionuclides transport, represented by distribution coefficient – Kd.

Each of these parameters can be thought of as a fuzzy set as will be seen in the next sections.

5.4.2 Inventory Characterization

The inventory in the Abadia de Goiás, near Goiania, Brazil repository is a result of material gathered as part of the decontamination work following an accidental breakage of a Cs-137radiotherapy source, in September 1987, which generated 40.1 TBq of waste (Lemos & Sullivan 1997).The waste occupies 2650 m^3 and is stored as follows (Lemos & Sullivan 1997).

One package containing the remaining source; 90 concrete containers; 16 cylindrical carbon steel containers with a volume of 5.7 m^3; and 987 rectangular carbon steel boxes with a volume of 1.7 m^3.

Both types of carbon steel container have a wall thickness of 6.35 mm.

The waste is 90% soil, rubbish and scrap, 8% paper, plastic and clothes, and 2% organic material. The distribution of waste within the containers is such that 62% of the activity is contained in 1.7% (45 m^3) of the volume. Also, 92% of the inventory is contained in 20% of total volume (503 m^3).

The proposed repository is above grade with a soil cover. It is 60m in length, 20 m wide, and 5 m deep, (Lemos & Sullivan 1997), see Figure 5.2. The bottom of the repository is 4 m above an aquifer.

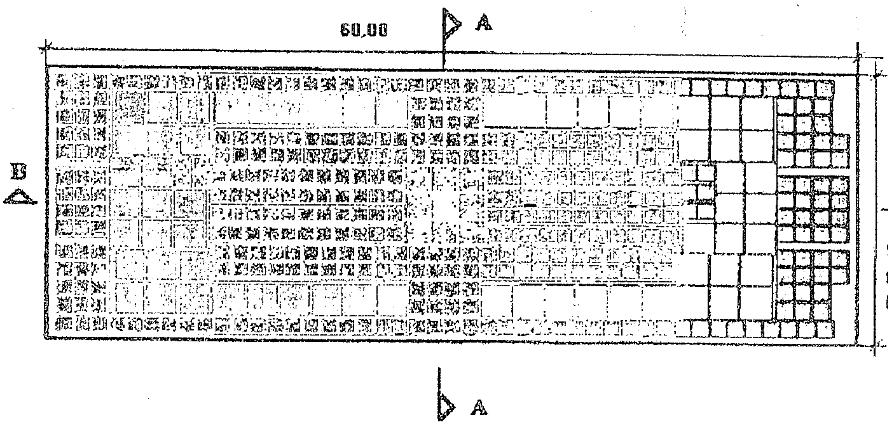


Figure 5.2-a: Plan view of containers arrangement of the proposed repository

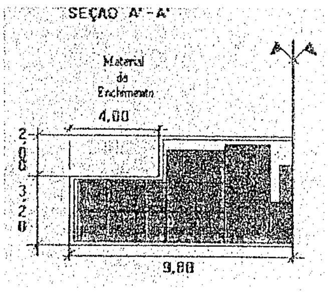


Figure 5.2-b: Cross section A-A

5.4.3 Waste Forms and release mechanisms.

In DUST code, the repository is divided into a number of cells, in this case, 10 cells. Each cell should have characteristic parameters that represent the actual repository. One of these parameters is the release mechanism to be modeled. Because of the diversity of the existing waste forms, it is very difficult to find a single parameter value for that purpose. Case example 2 proposes that, instead of using a deterministic value or a range of values, the release mechanism is represented by a fuzzy number or a fuzzy set.

The fuzzy sets for release mechanisms were chosen according to experts opinion and are as follows:

a) $$rinse = \left\{ \frac{29.3}{0.2}, \frac{46.4}{1}, \frac{56.8}{1}, \frac{95.0}{0.2} \right\} \quad \text{(Eq. 5.3)}$$

See figure 5.3 for the membership distribution function of this fuzzy set.

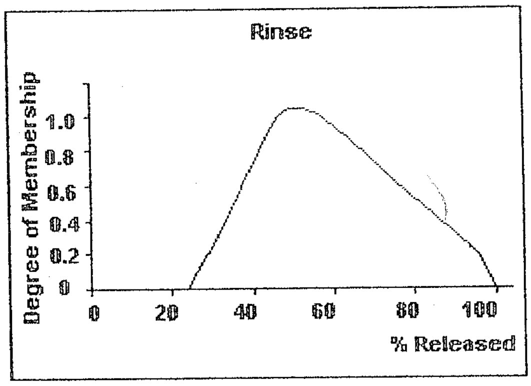


Figure 5.3: Membership distribution function of the fuzzy set of the mechanism "rinse".

b) $$dissolution = \left\{ \frac{1.0}{0.2}, \frac{12.6}{1}, \frac{20.0}{0.2} \right\} \quad \text{(Eq. 5.4)}$$

The membership distribution function of this fuzzy set can be seen in figure 5.4.

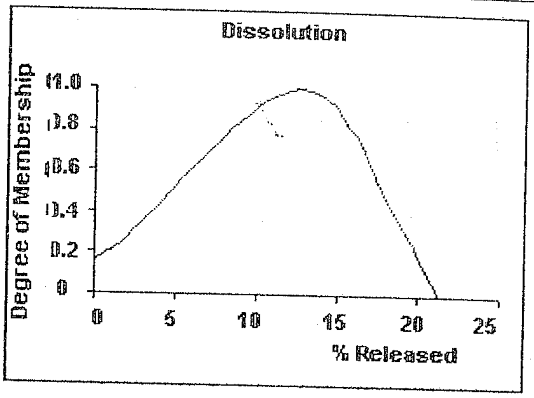


Figure 5.4: Membership distribution function of the fuzzy set of the mechanism "Dissolution".

c) $diffusion = \left\{ \frac{18}{0.2}, \frac{25}{1}, \frac{35}{1}, \frac{40}{0.2} \right\}$ (Eq. 5.5)

The membership distribution function of this fuzzy set can be seen in figure 5.5.

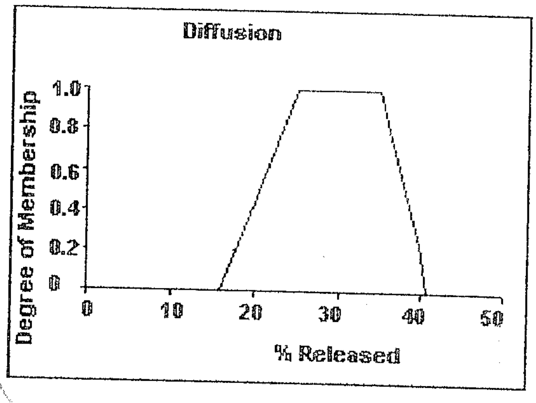


Figure 5.5: Membership distribution function of the fuzzy set of the mechanism "Diffusion".

5.4.4 *Kd* Determination

The distribution coefficient, Kd [$cm^3.g^{-1}$] is an important parameter for determination of radionuclides migration patterns. This empirical parameter accounts for all reactions between the solid and aqueous phase. This parameter depends on radionuclide and soil characteristics. This parameter has a high spatial variability and it can vary by orders of magnitude within a very small distance. Therefore, as seen in case example 5.2, the selection of a value for this parameter is ambiguous and the use of fuzzy sets approach is appropriate in this case.

According to Lemos & Sullivan (1997), the Kd value for Goiania should be around 430 $cm^3.g^{-1}$. Using this value and the method discussed in case example 5.2, the distribution coefficient can be seen as belonging to class 2 in that case example.

Therefore the fuzzy Kd is as follows:

$$Kd = \left\{ \frac{0.0154}{74}, \frac{0.96}{119}, \frac{0.89}{405}, \frac{0.023}{510} \right\} \qquad \text{(Eq. 5.6)}$$

and the membership distribution function is represented as in figure 5.6.

It should be pointed out that these results are preliminary and are meant to be used as an example to show how the calculation works. The quality of the results will depend on the quality and quantity of data available.

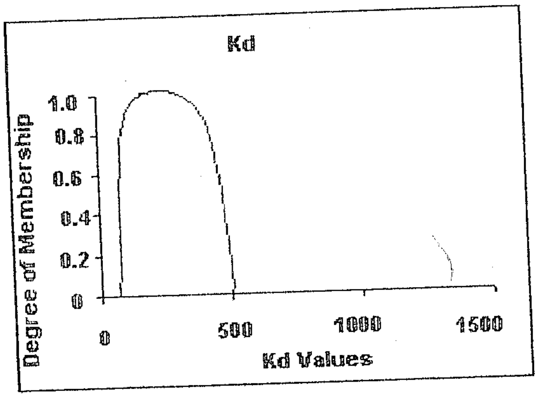


Figure 5.6: Membership distribution function of Kd as a fuzzy set.

5.4.5 Concrete Degradation Rate

Determination of expected useful life for concrete is based on a series of laboratory tests where some features or characteristics are studied and according to data interpretation a period of time is assigned as a service life.

Concrete Degradation Processes

With the state-of-the-art technological developments it is possible to have a high degree of confidence that the concrete will last for a long period of time. Some experts say it is possible to expect the concrete barriers will last for more than 500 years (Dolinar *et al.* 1996).

However, even with these advances in materials sciences it is not possible to be 100% sure on how the disposal facility will perform during its useful life. Degradation mechanisms impose limitations to the repository components and the knowledge of these mechanisms is of great importance for the safety assessment (Plansky .& Seitz 1994).

Some of the most important degradation mechanisms are: Sulfate, Chloride and Magnesium attack; Rebar corrosion ; Leaching ; Carbonation; and Cracking.

Other important factors for quality of concrete are water to cement ratio (WCR), construction methods, surrounding environment, cement quality, aggregates. Some empirical models for the degradation mechanisms have been developed and can be found elsewhere (Plansky & Seitz 1994).

For example, this can be represented by a mathematical expression as a fuzzy set "Concrete useful life" in years:

$$\textit{concrete useful life} = \left\{ \frac{1}{0}, \frac{0.99}{50}, \frac{0.8}{300}, \frac{0.4}{1000}, \frac{0}{1500} \right\} \qquad \text{(Eq. 5.7)}$$

Figure 5.7 shows the membership distribution function of this fuzzy set.

For each period of time there is a corespondent degree of belief. In this example, there is a degree of confidence of $\mu = 0.99$ that this barrier will last for a time of 50 years, $\mu = 0.8$ for the period of time of 300 years and $\mu = 0.4$ for 1000 years. As can be seen, the degrees of membership decrease considerably for times over 300 years. The longer the period, the fuzzier is the support or confidence that the engineered barrier will last for that long.

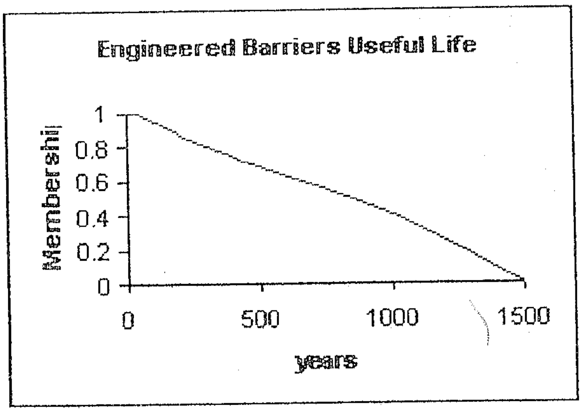


Figure 5.7: Membership distribution function of the fuzzy set "Engineered Barriers Useful Life".

Containers Degradation

In this thesis, the carbon steel drums will be considered for waste packages. Other types of containers are available and widely used. For more information please refer to the literature (Dolinar 1996). The degradation model for metallic container used in this thesis is the one available in DUST code. This model is empiric and rely on the existing corrosion in soil data base (Dolinar 1996).

Two types of failure are modeled through uses-specified time of failure. This time to failure could be estimated as averaged corrosion rate.

Corrosion rates should be obtained from site specific data, or other sources.

Based on that, a fuzzy set representing the possibility distribution for the useful life time is built as follows:

$$\text{Container useful lifetime} = \left\{ \frac{0.9}{50}, \frac{0.7}{100}, \frac{0.2}{500} \right\} \qquad \text{(Eq. 5.8)}$$

Assumptions

The assumptions for the screening calculations are:

The waste is evenly distributed within the waste form.

There is a concrete barrier at the bottom of the repository and another one as a cover.

The parameter values are as follows:

Solubility: 10 mg/cm^3, default in the DUST code. This value is high enough to ensure that solubility limits do not influence release. Diffusion coefficient: A conservative value of 10^{-6} cm^2/s. This value is equivalent to a Leach Index of 6, the minimum allowed by the waste form technical position.

The facility dimensions for this calculation are 20m high and an unsaturated zone of 15m.

Infiltration:

1e-8 cm/sec before barrier failure

1e-6 cm/sec after failure

Soil density = 1.6 gm/cm^3

Concrete density = 2.0 gm/cm^3

Moisture content (of backfill) = 0.36

The input, as fuzzy sets, are shown in Table 5.11.

Table 5.11: Input, as fuzzy sets, for DUST calculation.

Membership	Kd	Rinse (%)	Diffusion (%)	Dissol. (%)	Eng. Barrier (Years)
0	70	20	20	2	1500
0	600	70	27	60	1500
0.33	70	35	22	8	1200
0.33	450	70	26	48	1200
05	80	40	23	10	800
0.5	450	65	26	40	800
1	400	60	25	20	50
1	100	60	25	20	0

5.4.6 Results

After using the DUST code and using the extension principle, the result, mass flux, is in the form of a fuzzy set as follows:

$$mass\ flux\left(\times e^{-1}\right)=\left\{\frac{0}{4.9},\frac{0.33}{4.99},\frac{0.5}{4.99},\frac{1}{5.04},\frac{0.5}{5.13},\frac{0.33}{5.22},\frac{0}{5.34}\right\} \quad \text{(Eq. 5.9)}$$

and the membership distribution function is:

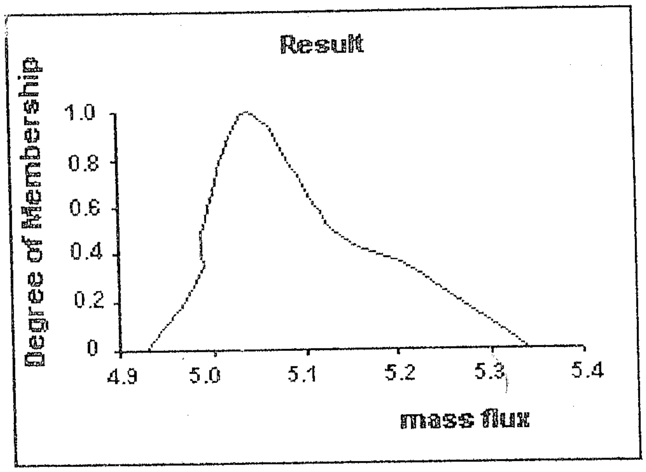


Figure 5.8: Membership distribution function for the fuzzy set " around 5.0E-1".

Discussion and Interpretation of Results

The result of this safety assessment (mass flux at the bottom of the repository) is presented as a fuzzy set, see figure 5.8. Therefore this result should be interpreted as a concept, for example, "around 5e-1", or "low flux", etc.

It should be pointed out that a degree of membership $\mu=1$ does not mean that this event is the more probable. For example, there is almost 100% certainty that engineered barriers will last for at least 50 years and there is no certainty that it will last for 1500 years. These values can be changed as more knowledge, or information, is made available to experts.

5.4.7 Conclusions

In this case example, a methodology was shown to assisting the analyst on the evaluation of input data and uncertainty representation for waste disposal facilities safety assessment. The improvements in this type of calculations is that it allows the use of more realistic scenarios, i.e., ambiguous input data can be translated into mathematical expressions.

Fuzzy logic is a very powerful tool for analyzing data with uncertainties similar to those required in environmental studies. This thesis has shown that the fuzzy set approach can help on more realistic evaluation of natural processes in comparison to other traditional methods.

It was considered only four parameters as fuzzy sets: concrete degradation rate, containers degradation rate, waste form release mechanism and radionuclide distribution coefficient. Even for a simplified case it was possible to show that the possibility distribution function for the result would not be trivial.

In a real case, a more complex analysis would have to be done and the methodology can be of a great help on the quantification of the model uncertainty.

5.5 CASE STUDY 4:APPLICATION OF FUZZY EXPERT SYSTEM ON LILW PERFORMANCE ASSESSMENT

5.5.1 Introduction

The case example 3 can be further developed by considering the degree of confidence to the choices of fuzzy sets. The following example is a study about the application of fuzzy relations as a basis for building an expert system (Lemos & Sullivan 2002).

The objective of a performance assessment is to show that a repository is safe and for this purpose it is not necessary to have an accurate predictive mathematical model of the performance of this repository for the period of its useful life time (Kozak 1997). Instead, what is needed is a model that can be relied upon to provide defensible estimates of future behavior without necessarily predicting that behavior. For example, future weather conditions can not be accurately determined for the next 1000 years. The model must account for the range of weather conditions that could occur but will not necessarily occur. While this analysis needs a strong mathematical basis, many times, traditional methodologies have the drawback that they are not fit for analysis of ambiguous data as is the case for environmental processes.

In order to gain public confidence in the modeling results, a methodology of decision making should be able to integrate expertise of different fields of science, interaction with the public and decision makers. Due to the large number of natural processes and diversity of interactions, ambiguity is expected and communication of major issues between all the stake holders needs to be part of the decision process.

An expert system can simulate the problem-solving behavior of an expert in his particular discipline. This thesis presents the use of one aspect of an expert system, which is fuzzy relations, where from known relations between fuzzy (ambiguous) data, the relation one is seeking can be deduced.

5.5.2 Expert systems

An expert system is normally composed of a knowledge base (information, heuristics, etc.), inference engine (analyzes the knowledge base), and the end user interface (Kandel 1986). These systems can address imprecise and incomplete data through the assignment of membership functions to parameter values. Due to the ability to incorporate expert reasoning into a codified software structure, expert systems can enhance confidence in the results.

The quantification of imprecise data by degree of membership in a fuzzy set can be seen as degrees of certainty to the available information. This can make the system a powerful tool to deal with incomplete data and integrate knowledge of experts in many fields of science.

The fact that this is done upon agreement between all the stakeholders, makes this methodology very suitable to provide explanation for how the results were derived and consequently will gain higher confidence on the results.

5.5.3 Case Study

For this case study data from the Abadia de Goiás repository will be considered. This repository was constructed due to an accident that happened some 10 years ago with a Cs137 source (Lemos & Sullivan 1997). The waste was classified according to its concentration.

Table 5.12. Classification of the existing activities per unit volume (*)

Concentration (TBq/m^3)	[0.9, 1.0, 1.2]	[0.4, 0.5, 0.6]	[0.08, 0.1, 0.2]	[2E-2, 3E-2,4E-2]	[1E-4,1E-2,1E-1]
Classification	A	B	C	D	E

(*) Values correspond to degree of membership of 0.2, 1.0, and 0.2 respectively.

It is the intent of this exercise to find a relation between the many different inventory types, according to Table 5.1, to their contribution to the source term. This can be done by examining the relation of waste type to waste forms, then waste forms to type of release mechanism and finally the relation between waste type and release mechanism can be deduced. With this information it is possible to determine what would be the most likely contribution of the type E waste to the source term, for example.

The waste has been grouped and packaged as shown in Table 5.13.

Table 5.13: classification of waste forms in groups (Miaw 1995).

Waste form group	Description
I	Cs-137 source
II	Paper, plastic, and fabric
III	Soil, scrap and metallic debris
IV	Animals, fruits and wood

Due to the diversity of the waste, it is not possible to exactly associate each waste package to waste form and consequently to its release mechanism (Lemos & Sullivan 1997). In a traditional methodology, this would be resolved, for example, through the selection of a representative parameter, taken conservatively. However, performance assessment is not meant to provide an exact model of all the physical chemical processes, but rather provide enough information to support decisions on a reasonable assurance regarding the repository safety (Kozak 1997). The fuzzy set methodology can fulfill this need in many manners:

- dealing with ambiguous data and information,
- providing an estimate of the degree of confidence of the results,

- treating uncertainty in a more understandable way. Sources of uncertainty include: complexity, lack of information and ignorance. Other methods treat uncertainty either through considering the worst case or by probability.

Some drawbacks to these other methods are:

- it is difficult to know the degree of conservatism in the results, and

- probabilistic methods are difficult to understand to non-technical audiences (e.g. public and decision makers) and relies on data that is ambiguous and uncertain. This makes interpretation difficult.

As an example of the fuzzy relations approach, according to equation 4.14, the following vectors are built:

Waste forms, according to Table 5.13:

$$WF = \left\{ \frac{0.1}{I}, \frac{0.3}{II}, \frac{0.9}{III}, \frac{0.1}{IV} \right\} \qquad \text{(Eq. 5.12)}$$

Release mechanism: $$RM = \left\{ \frac{0.7}{R}, \frac{0.3}{R \,\&\, P}, \frac{0.3}{D} \right\} \qquad \text{(Eq. 5.14)}$$

Where: R= rinse; R&P= rinse with partitioning; D= uniform dissolution.

Waste type, $$WT = \left\{ \frac{0.1}{A}, \frac{0.5}{B}, \frac{0.1}{C}, \frac{0.6}{D} \right\} \qquad \text{(Eq. 5.15)}$$

These vectors were built based on expert opinion to select the degree of memberships (u) and the weights, A full description of this example can be found in Lemos & Sullivan (1997). Due to lack of space, only the final matrix will be built as an example. After making the combinations as WT × WF and WF × RM, the following combination WT × RM was found:

$$\begin{array}{c|ccc|} & R & R\&P & D \\ A & 0.1 & 0.1 & 0.1 \\ B & 0.3 & 0.9 & 0.3 \\ C & 0.1 & 0.1 & 0.1 \\ D & 0.6 & 0.1 & 0.1 \end{array} \qquad \text{(Eq. 5.16)}$$

By inspection of the above matrix one can see that type B waste, around 0.5 TBq/m^3, would be the most likely, degree of 0.9, from the coordinate (B, R&P), to contribute to the source term as Rinse with partitioning. This information can be used to focus resources on gaining a better understanding of the performance characteristics of type B wastes.

5.5.6 Conclusions

The above calculations show that it is possible to assign degrees of confidence to the assumptions and to the results, with agreement between stakeholders. This facilitates communication, not only between experts from different expertise, but also between experts and decision makers and public. This will enhance confidence and defensibility of the performance assessment.

5.6 CASE STUDY 5: TRANSLATING NATURAL CONCENTRATIONS AND FLUXES INTO SAFETY INDICATORS FOR RADIOACTIVE WASTE REPOSITORIES

5.6.1 Introduction

There are many sources of uncertainties in the traditional dose and risk calculations used in Performance Assessment (PA). A main source of uncertainties is the need for making assumptions regarding human future habits, and the repository performance during its useful life (Lemos *et al.* 2002).

In an attempt to improve confidence and public acceptance of the results of the performance assessment calculations, the use of complementary safety indicators has been suggested (IAEA 1999). One of these complementary methodologies would be to compare predictions of repository releases with natural fluxes and concentrations of chemical species. This methodology would have an additional advantage which is the use of a natural context for safety demonstration making it easier for the public to understand.

However, the use of natural fluxes and concentrations requires the use of a huge amount of data that may not be readily available. The lack of data together with spatial variations, are important sources of uncertainties and ambiguousness in data analysis.

Some solutions to this problem, such as a global average flux value (for example, the global average activity flux due to groundwater discharge) masks considerable variation in the fluxes which occur at different sites, and in different geological and climatic environments.

This shows that the use of these complementary safety indicators will not reduce uncertainties, rather they have the advantage of placing the calculations in a framework that can be compared to natural processes. While these safety indicators do enhance confidence, there still exist ambiguousness in the results due to the uncertainties.

It is within this context that this work suggests the use of a methodology, based on fuzzy logic tools, which is designed to handle ambiguous data and allows the use of natural language terms for the comparisons between repository system and natural environments.

5.6.2 The Use of Elemental Flux as a Natural Safety Indicator

Calculated fluxes of naturally occurring materials are result of a series of processes (or features) in the surface and subsurface environments (Miller 2000). In order to keep this example simple, a few of the most important features will be considered in the analysis. This list can be changed upon experts agreement. Typically, it is very difficult to obtain a consistent database of natural geochemical and process rate data, and therefore accurate determinations of average values. A number of assumptions have to be made when quantifying natural concentrations and fluxes to be compared against the repository source term.

Processes driving natural fluxes have considerable variation in their rates. However, these variations are not always due to differences in the inherent properties of the geological materials (such as hydraulic conductivity). Elemental fluxes may be calculated for specific processes and so a range of mass fluxes corresponding to different processes can be generated for the same element (e.g. flux due to groundwater discharge, erosion, river flow, etc.). In this manner the most significant mass transport mechanism can be readily identified. In terms of providing direct comparisons with repository releases, it is anticipated that fluxes associated with processes which drive the transfer of materials from the groundwater discharge (solute transfer) and erosion (solid transfer) will dominate.

5.6.3 Repository system

The calculated fluxes inside a repository will depend on a number of parameters and processes. For example, intrinsic factors of the waste: the radionuclide waste stream, waste form, and container control release from the waste (Sullivan 1993). These factors together with radionuclide specific parameters such as half life, solubility limits, transport parameters (Kd), water flow and moisture contents, initial conditions and boundary conditions will fully describe the problem.

However, due to the large number of different container types and waste forms, it is not always possible to have precise values for all the parameters in order to model the release processes. Rather, analysts professional experience is used to find a model representative of the system.

Let's say containers fall into 3 types, A, B, and C. Type A has an expected lifetime of 1 – 150 years. Type B from 30 – 500 years, and Type C from 300 – 1000 years. A deterministic, conservative (early failure or worst case) model would assign lifetimes of 1, 30 and 300 years to each categories. A probabilistic approach would sample along the ranges and values combined randomly. However, as can been seen, the categories blend in each others intervals, therefore it would not be clear during calculations how a container which expected life time of 100 years would be classified in the category A or B.

A fuzzy set approach would address the problem by using language terms to define the containers conditions such as category A (short life), B (medium) and C (long life). Now a container with life time of 100 years would be placed in both categories A and B, however with different degrees of memberships. The same rationale would be used for determining the release mechanisms in order to describe classes of waste forms.

Upon analysts agreement, it is possible to determine a group of features or parameters (fuzzy sets), to compose vectors for comparison between the repository and the sites features. An example of this approach will be given in the next section.

5.6.4 Example calculations

Suppose one wishes to demonstrate how differently a disposal unit would affect candidate sites' environments. The pattern recognition technique can be used in two ways. First, according to the degree of similarity, the approach can be used to provide a measure of the similarity between each site and the repository. Second, it can determine an ordering of similarity between each site and the repository features. In other words, what site would the repository most closely match.

In a traditional procedure a list of 20 or more sites would be screened for use as a repository site. Simple screening criteria would be evaluated to narrow the list to 5 potential repository sites. These five sites would be presented to decision makers for further consideration. For these sites, it is required to know the effect repository construction and performance would have on each of the near field environment of these sites. Assuming that the sites which are least impacted by the repository should receive further consideration, two sites can be selected.

At the point where there is a list of 5 sites, it would be necessary to conduct a more detailed analysis, with a more detailed data collection and more complex performance analysis. However, making a complete site characterization for 5 sites would be extremely expensive. Even for well studied sites, such as Poços de Caldas in Brazil, the lack of data, force analysts to use natural language (ambiguous) to describe site conditions.

A question remains on how to enhance confidence that one meets the objectives of the site selection, i.e., a list of 5 sites with acceptable degrees of safety and how the repository will affect the selected site.

In this example, a list of 5 candidate sites will be studied and two that have the closest match to the repository will be selected for further characterization, just for demonstration purposes. Then the influence of the repository on the sites will be assessed.

Upon experts agreement the features to be used as comparison factors in this example are:

Inventory concentration, Redox fronts, Sorption, Dispersion/diffusion, Water flow rate, pH, Speciation, and Colloid concentrations.

Table 5.14 shows a set of features, for each site and repository, after a study of their respective characteristic functions. Some of these features may be typically very different inside the repository and in the environment or between two different sites and this does not necessarily mean that one site has better performance features. How can we then compare the features at both sites? For example, how can one make a comparison between the repository and the site if pH inside the repository is between 9 and 11, and in the environment it is between 6-8. If either range of pH has very little influence on the calculated fluxes for their respective context how should they be compared? Conversely, if pH has a large impact on predicted flux what is the basis for comparison?

An answer would be the characteristic function χ which is defined in the interval [0,1]. This function measures the strength of the link on a relation. In this example, the link is a measure of the impact of a parameter on contaminant flux to the environment. For the first parameter, pH, if Repository pH (between 9-11 due to cementitious materials used to construct the repository) has a very weak link to flux (where $T = pH \circ Flux$) then χ(pH) will be "low", the same is valid for site pH 6-8. If this range of pH, for any reason, has a weak link to flux it will also generate a "low" characteristic function. Now the characteristic functions can be compared and in this example they would be similarly "low".

This reasoning can be applied to other features such as colloid concentrations, dissolution limits and others. Cs 137, for example, has a high sorption capacity and therefore a high water flow rate may not have a high impact on the calculated flux. However, the transport can be facilitated by the presence of colloids from package corrosion. So, instead of simply comparing water flow rate, it would be more effective to compare between the characteristic function of its link to the flux, depending on each context.

Figure 5.9 shows a representation of fuzzy sets low and medium χ(pH) for repository and site 1 respectively. Applying equation 4.14 to find the degree of compatibility between site 1 and repository for the comparison factor pH gives:

$$\mu(\text{Repository } \chi \text{ (pH)} \bullet \text{ site 1 } \chi \text{ (pH)}) = \max([(0 \wedge 1),(0 \wedge 0.75), (0.4 \wedge 0.4), 0.25 \wedge 0.75), (1 \wedge 0)] = 0.4$$

In the above expression, the values for the membership function are evaluated over the domain of the characteristic function at several points. At each point, the degree of compatibility between the two fuzzy sets (pH characteristics in the repository and site 1) is taken as the minimum at each point. The maximum value from this set of minima is the degree of compatibility, Equation 4.14.

The final degree of compatibility will be the sum of each of the features degrees of approaching along with respective weights, Equation 4.19. For site 1 the analysis found the following:

(Repository, site 1) = 0.4 *0.05+0.3*0.1+ 0.5*0.1+ 0.3*0.3 +0.8*0.05 +0.1*0.2 + 0.5*0.2 = 0.02+0.03+0.05+0.09+0.24+0.02+0.1= 0.55

Table 5.14: Example of characteristic functions for each site and repository to be compared

Mode (process)	χ(pH) ω_1=0.05	χ(Redox) ω_2=0.1	χ(Gwt flow rate) ω_3=0.1	χ(Inventory com.) ω_4=0.3	χ(sorption) ω_5=0.05	χ(colloid conc.) ω_6=0.2	χ(dispersion/diff.) ω_7=0.2
Site 1	Medium	Medium	High	Low	High	Medium	High
Site 2	Low	High	Very high	Very low	High	High	Low
Site 3	Medium	Low	Medium	High	Medium	Very high	Low
Site 4	Very low	Low	Medium	Low	Medium	Medium	High
Site 5	Low	Medium	Low	High	High	Low	Medium
Repository	Low	Medium	Medium	Medium	High	Low	Medium

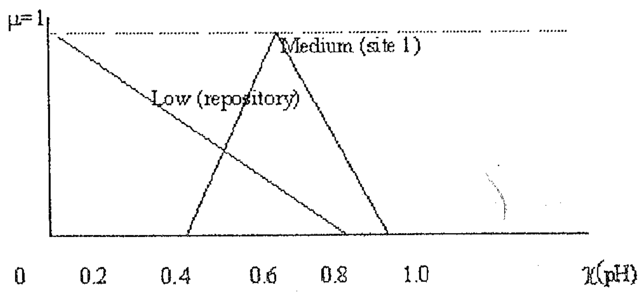


Figure 5.9. Example of a comparison between fuzzy sets describing influence of pH on flux, χ(pH), between repository and site 1.

This same calculation is repeated for all pairs (site, repository), and the following results were obtained, Table 5.15.

Table 5.15: Comparison of compatibility of the repository with each site.

Repository/site	Degree of compatibility or approaching
Site 1	0.55
Site 2	0.50
Site 3	0.3
Site 4	0.6
Site 5	0.2

This analysis indicates that the proposed repository will be more closely similar to sites 4 and 1 regarding the selected features. After a more detailed analysis, the values of 0.6 or 0.55 could also lead to the conclusion that, as it is close to 1, it would not have a strong impact on the site's environment, while a value of 1 would suggest no impact. It is important to recognize that the fuzzy set approach has taken the ambiguous data in Table 5.14 and permitted a ranking among the sites. This clearly could not be done by inspection of Table 5.14.

5.6.5 - Conclusions

A fuzzy logic based approach has been developed to examine site information which are usually given in ambiguous expressions, so they can be treated in a mathematical basis and yet keep its natural language characteristics.

The major advantages of the approach are:

It translates language expressions into mathematical values, or fuzzy sets.

The use of natural language makes it easier for the public and decision maker to be more familiar with the meaning of the results.

A simple example that examined the compatibility of five hypothetical repository sites with the proposed repository conditions was performed and it was found that the approach successfully met its objective to give support for a site selection decision that would best match natural conditions with those envisaged for the repository.

This calculation has another advantage of being easier to communicate to the public as it uses natural language expressions which are familiar to public and decision makers. In addition, the approach is flexible and readily permits incorporation of new information into the analysis as it becomes available.

5.7 CASE STUDY 6: EVALUATING CONTAMINANT MIGRATION AROUND REDOX FRONTS AT THE POÇOS DE CALDAS URANIUM MINING SITE (MINAS GERAIS, BRAZIL) USING FUZZY LOGIC

5.7.1 Introduction

Performance assessment for a nuclear waste facility is a very complex task. The analyst has to understand many processes, including geochemical processes, that will affect the migration of the contaminants from the repository to the environment. A typical performance assessment uses numerical or computer models that simulate the environmental conditions. The analysis requires a number of parameters that the analyst chooses in order to represent the interactions and processes involved.

To model all the processes and events that may occur for the hundreds and thousands of years over the spatial scale of the analysis is not possible. Simplifications are used to reduce the size and complexity of the computational model with the goal of retaining the most important processes and parameters that affect performance. These modeling simplifications lead to uncertainty in the validity of the predicted performance.

There are other sources of uncertainties such as ignorance concerning actual environmental conditions, which comes from the lack of data and extreme complexity of interactions. Besides, there is the uncertainty in the future behavior of the system (repository plus environment) which can not be predicted based only on laboratory experiments.

Uncertainties are often addressed through performing Monte Carlo analysis or other statistical evaluations. These analyses assign parameters a range of values and repeatedly sample through the range of all values to obtain a distribution of potential outcomes. While this is a mathematically defensible framework, it relies on having accurate data to support the range of parameter values. In contrast, site characterization reports often have terms such as: "very aggressive" soil conditions; "moderate reducing conditions"; etc, which are ambiguous and uncertain linguistic terms which do not readily lend themselves to a Monte Carlo analysis. This work proposes the use of a fuzzy logic approach to data analysis to help translate ambiguous site characterization data into a form useful for performance analysis.

This thesis presents a case study with data interpretation using the fuzzy logic methodology to determine the behavior of radionuclides in the vicinity of a redox front. The data were taken from technical reports of the Poços de Caldas Project (Mackenzie *et. al* 1991).

Five intermediate to deep boreholes (F1-F5) and three shallow holes were drilled in the mine area (Mackenzie *et. Al.* 1991). This thesis uses data from the drillcore F1, which crosses 3 redox fronts, and in this example the redox front, at the depth of 33.4 m is studied. According to the technical report by Chapman *et. al.* (1991) this redox front has moved between 2-20 m within the last 10^6 years. However, there are different degrees of support or evidence for each of theses numbers and consequently the results of safety assessment calculations, using these values as input, will also have different degrees of support or belief.

5.7.2 Pattern recognition

Very often the complexity of environmental interactions, along with lack of data, make it difficult for the analyst to correctly interpret the data, leading to ambiguity. In order to cope with this ambiguity and be more realistic, the analyst uses language expressions, which are still vague, that complement information provided by the data. For example, Figure 5.10 shows a plot of $^{234}U/^{238}U$ activity ratio versus $^{230}Th/^{238}U$ activity ratio. According to Mackenzie *et. al.* (1991), depending on the coordinates of a point, there will be different conclusions as for the natural processes Uranium has undergone, as will be seen later.

It is assumed that rock initially exists with natural decay series radionuclides in a state of secular equilibrium, which is at some time disturbed by the addition of uranium from groundwater, or removal of uranium to the groundwater, either in a single rapid event or in a continuous process. The $^{234}U/^{238}U$ versus $^{230}Th/^{238}U$ plot can be divided into various sectors representing the effects of different processes. Each of the regions in Figure 5.10 can be considered as a pattern or class of natural processes. However, it will not always be possible to distinguish, without ambiguity, to what pattern a certain point belongs. This will lead to ambiguity on the further conclusions and calculations.

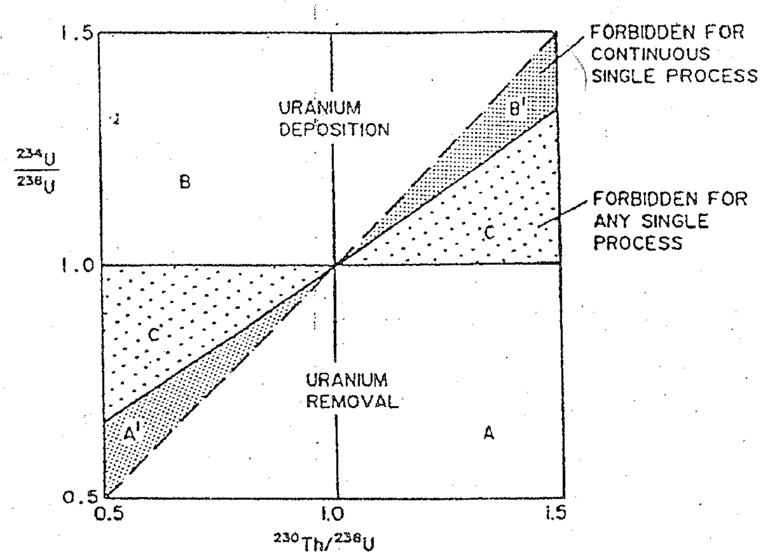


Figure 5.10: $^{234}U/^{238}U$ activity ratio versus $^{230}Th/^{238}U$ activity ratio diagram and corresponding sectors of Uranium deposition and removal (Mackenzie et al. 1991).

5.7.3 Natural decay series analytical data

In this work the $^{234}U/^{238}U$ and $^{230}Th/^{238}U$ activity ratios are used to provide important information as for the redox front behavior. Figures 5.10 and 5.11 present the natural decay series in the form of a graph plotting $^{234}U/^{238}U$ against $^{230}Th/^{238}U$ (Chapman *et. al.* 1991). This form of presentation is of great help in that, according to the sectors of the graph, the data can be interpreted as follows:

A – Uranium removal: Either continuous or sudden removal of Uranium.

A' – Forbidden for continuous single process: Samples which have undergone removal of uranium in a single rapid event and can not be attained by samples subject to continuous removal of uranium

B - Uranium deposition sector: Involving either continuos or sudden deposition of uranium.

B' - Forbidden for continuous single process: Samples which have undergone deposition of uranium in a single rapid event and can not be attained by samples subject to continuous removal of uranium.

C – Complex sector: combinations of $^{234}U/^{238}U$ and $^{230}Th/^{238}U$ activity ratios which can not be produced in the rock by any single uranium addition or removal process, whether continuous or a single rapid event.

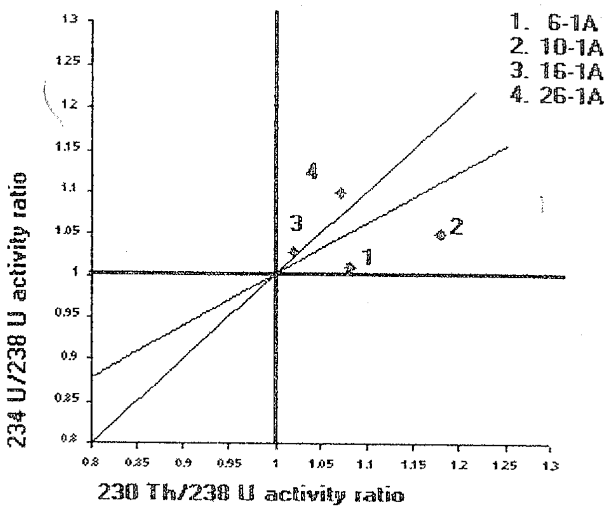


Figure 5.11: $^{234}U/^{238}U$ activity ratio versus $^{230}Th/^{238}Th$ activity ratio diagram for samples from the oxidized rock in the F1 drillcore above the 33.4 m redox front (Mackenzie *et al.*1991).

5.7.4 Case Study

The correct interpretation of data is of major importance, especially when interpretation is used as a basis for performance assessment of a repository. Although the approach in Figure 5.10 is very helpful to this end, there is the problem of ambiguous interpretation when data are close to the limits or boundaries of the sectors. For example, some data used as support for the calculation of the rate of movement of the 33.4 m redox front (Table 5.16) are very close to the limits between removal and deposition sectors, see Figures 5.11 and 5.12 (Chapman *et. al.* 1991). Fuzzy logic will be used to improve the assignment of degree of confidence for estimates of the rate of movement for this redox front.

Table 5.16: $^{230}Th/^{234}U$ activity ratio and uranium concentrations for the F1 drill core

Sample code	Depth (m)	$^{230}Th/^{238}U$	U (mg/kg)
6-1 A	6	1.06 ± 0.04	96
10-1 A	9.84	1.09 ± 0.04	28
16-1 A	15.07	0.99 ± 0.04	20
26-1 A	25.22	0.31 ± 0.04	16
33-1 A	32.89	0.96 ± 0.03	89
34-1B-A	33.4	0.26 ± 0.04	19
34-1B-D	33.51	0.21± 0.05	17
34-1B-F	33.65	0.46 ± 0.04	48
34-1C	34	0.13 ± 0.09	20
35-1 A	34.31	1.9 ± 0.06	41

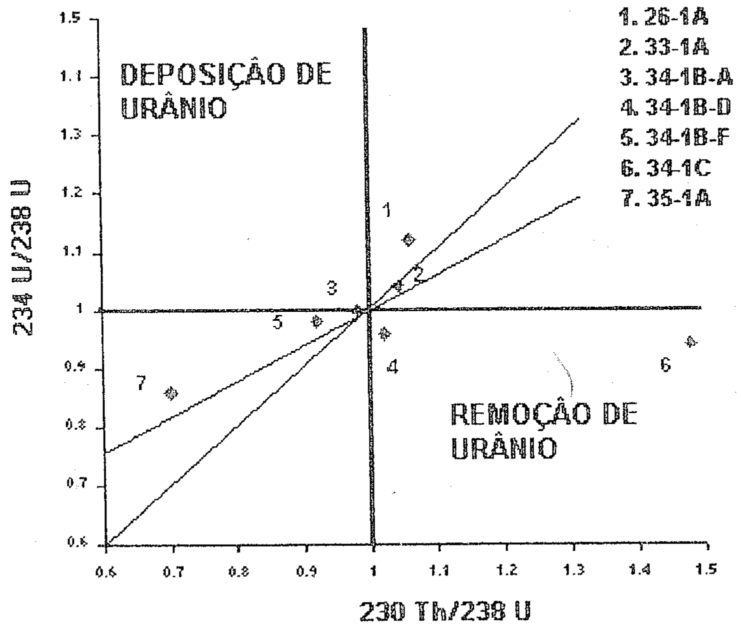


Figure 5.12: $^{234}U/^{238}U$ activity ratio versus $^{230}Th/^{238}U$ activity ratio diagram for samples from the vicinity of the 33.4 m redox front in the F1 drillcore (Mackenzie *et al.* 1991).

However, recognizing that there is uncertainty around the crisp or rigid boundaries, the approach can be generalized into more flexible or "fuzzy" boundaries, which are the basis for having fuzzy sets. Now the degrees of membership of a pair of data to the different sectors (or fuzzy sets) can be assigned.

The methods of assignment of degrees of membership can be based on some logical operations as for example geometry of the fuzzy sets (Ross 1995). One approach, which is used in this study, could be assigning degrees of membership according to the data points relative positions to the centers of gravity of each area using polar coordinates.

In this case study a fuzzy set with a core region is defined with full membership to that set, see Figures 5.13 a and 5.13 b. Away from the core region, the degree of membership linearly decreases to 0. The definition of the limits for the core and boundaries are determined by expert opinion and may change depending on further studies. In this example, the core represents 70% of the total area of each sector. All of the information contained in a fuzzy set A is described by its membership function (Ross 1995). Figures 5.13 a and 5.13 b show a representation of a fuzzy sector or set, in this case Uranium Removal, and its membership function along with its features, i.e., core, boundaries and support.

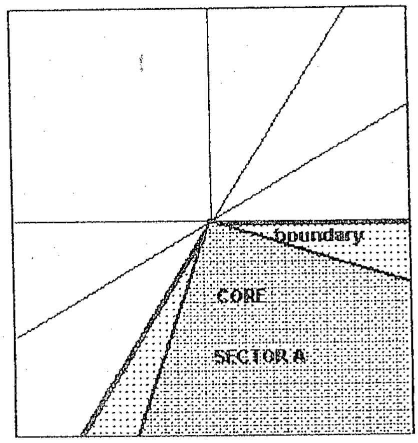
The boundaries are comprised of those elements with degree of membership between 0 and 1, i.e.,

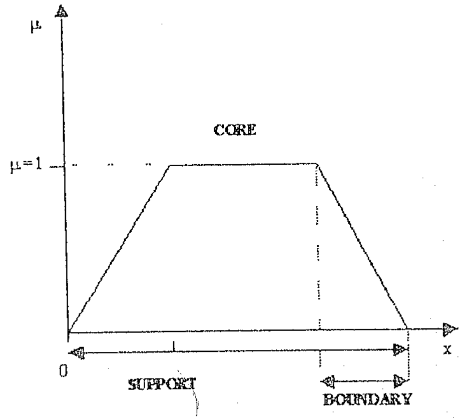
$$0 < \mu_A < 1$$

The core is defined as the region of the universe containing elements of degree of membership one, i.e., $\mu_A(x) = 1$.

Support is the region of the universe of elements with non-zero membership in set A.

To determine the degree of membership for a data point, the angle from each data point to the nearest cores is calculated. The smallest angle between each point and a core will determine to what sector that point belongs to the " most". These degrees of membership can be used to represent the level of support to a certain result.





(a) (b)

Figure 5.13 (a) and 5.13 (b): Representation of a fuzzy set (a) and its correspondent membership function (b).

5.7.5 Discussion

Data Interpretation

As already mentioned, fuzzy logic tools will be used here to translate the information contained in the site characterization report (Mackenzie *et. al.* 1991), which are ambiguous, into objective and more transparent information. The above mentioned report concludes, for example, that the redox front at 33.4m of F1 drillcore has a downward movement rate between 2 and 20 m per 10^6 years. This statement was based on a series of sample tests, and inferences. Some of the reasoning follows:

"...the deviation from equilibrium in the section of F1 drillcore, between 70 and 30m, in the $^{230}Th/^{238}U$ imply dissolution, transport and deposition processes affecting Uranium have been operating within the last $3X10^5$ years" (Mackenzie *et al.* 1991).

" The results for samples 6-1A, 10-1A, 16-1 A and 26-1 A from the oxidized phonolite are plotted on a $^{234}U/^{238}U$ X $^{234}Th/^{238}Th$ diagram, Figure 5.11, from which it can be seen that 16-1 A and 26-1 A lie on the Uranium deposition sector of the graph while 6-1 A and 10-1 A lie in the complex process zone. If the redox is assumed to have moved downwards through this section of rock in response to groundwater movement and erosion of the land surface" ...... "then the influence of the redox front processes would have affected sample 26-1 A more recently then sample 16-1 A, and the position of these two samples on the activity ratio plot is consistent with this, with 16-1 A lying closer to equilibrium then 26-1 A" (Mackenzie *et. al.* 1991).

" If the simplest possible approach is taken then it could be assumed that this decrease in $^{234}U/^{238}U$ represents the return to equilibrium of the $^{234}U/^{238}U$ system via decay of excess ^{234}U which had been deposited as a consequence of the movement of the redox front through the rock" (Mackenzie *et. al.* 1991).

"Thus, if it is assumed that the excess ^{234}U would have decayed to non-detectable levels in the course of four half-lives (approximately 1 million years), the observed decrease in $^{234}U/^{238}U$ activity ratio would suggest a rate of downward movement of the redox front of the order of 20 m in 10^6 years" (Mackenzie *et. al.* 1991).

An interesting remark concerning the confidence in this result is:

"Considerable caution must be employed in assessing the confidence which can be placed in this conclusion since it is evident from the U concentration versus depth, Table IV, and from Figure 5.11, that subsequent to the passage of the redox front, further process have started to act upon samples 6-1 A and 10-1 A" (Mackenzie *et. al.* 1991).

As stated above and according to Figure 5.11, sample 6-1A is located in the complex zone. The calculation of the movement rate is based on the assumption of removal from one point and deposition on another. However, in this case, only sample 26-1 A is clearly located in the deposition zone, while sample 6-1 A has some degree of membership to the removal zone. This will be analyzed in the next section.

Considering the arguments for the 2 m per 10^6 years, the report has the following information:

" The $^{230}Th/^{238}U$ activity ratio, Figure 5.12, for samples from 25.22 m (26-1 A) down to 33.65 m (34-1 B-F) on the oxidized side of the 33.4 m redox front all lie within the limits of analytical uncertainty of equilibrium. Thus if the maximum in the Uranium concentration at the 32.89 m (sample 33-1A) is taken to represent a location of Uranium deposition, then the Uranium was deposited here at least $3*10^5$ years ago, an estimated maximum rate of downward movement of the redox of the order of 2m in 10^6 years can be derived" (Mackenzie *et. al.* 1991).

An explanation of which two samples were used to derive this result was not provided. However, if the other sample is the 34-1B-A, which is 0.51 m apart from 33-1A, gives the result of approximately 2m in 10 ^{6} years. For this case, the two samples have similar pattern to the former ones. In other words, sample 33-1A is located in the complex zone, with some degree of membership to the removal zone, while sample 34-1B-A is located in the deposition zone.

Finally there is the conclusion that results from two independent analysis of the uranium deposition pattern from drill core F1 are consistent with a downward movement of the front at the 33.4 m redox front at a rate between 2 and 20 m per 10^6 years.

This work is concerned with the interpretation of existing data only, therefore, the justification for selecting certain data to estimate the movement of the redox front nor the methodology for gathering data will no be reviewed. The reported data will be used directly to examine the fuzzy set concepts and their applications.

Applying Fuzzy Logic tools to interpret information

The first step begins with defining the fuzzy sets to be used as patterns against which the data will be compared. This definition criteria will depend on agreement between experts and decision makers and can be changed at any time as more knowledge become available.

As already stated, for this case study, the fuzzy sets are considered as having a core whose elements have degrees of membership equal to 1, $\mu_A(x) = 1$ with a region extending from the core in which the degree of membership ranges from 0 to 1. Based on that, Table 5.17 shows the degrees of membership of points in Figures 5.11 and 5.12.

Applying equation 4.14 to calculate the degrees of membership or support for each of these rate limits to the fuzzy set R ("rate of movement" in this case example) it follows:

For rate of 20 m in 10^6 Years:

Two points, sample 6-1A and 26-1 A were used to estimate the maximum rate of movement of the redox front. The transition from removal to deposition of Uranium provides a measure of the movement of the redox front. Sample 6-1 A (6m) has degree of membership, to sector Removal, of 0.2, $\mu_A=0.2$. Sample 26-1A (25.22m) has a degree of membership, to the sector Deposition, of 0.80, $\mu_B=0.80$.

Table 5.17: Degrees of membership for the points from the F1 drill core and shown in Figure 5.11.

Sample #	Sample code (depth)	Degree of membership	Fuzzy sector
1	6-1 A – (6.0 m)	μ_A=0.2	Removal
2	26-1 A - (25.22m)	μ_B=0.8	Deposition
3	33-1 A - (32.89m)	μ_A=0.44	Removal
4	34-1B-A -(33.40m)	μ_B=0.59	Deposition
5	34-1B-D -(3.51m).	μ_A=0.73	Removal
6	34-1B-F- (33.65m)	μ_B=0.44	Removal
7	34-1C - (34.00m)	μ_A=0.93	Removal
8	35- 1 A - (34.31m)	μ_C=0.61	Complex

To determine the degree of membership of the rate of movement, fuzzy set R, based on the degree of membership of the information in the deposition and removal data requires a mathematical operation to combine this information. In this case, the appropriate operation is the intersection between two fuzzy sets A and B. The intersection provides the minimum degree of membership, between the two fuzzy sets, to the fuzzy set R, which provides the maximum degree of confidence in the results.

Mathematically, the intersection is represented as (Ross 1995):

$$\mu_{A \times B}(x) = \mu_R(x) = \mu_A(x) \wedge \mu_B(x) = \min(\mu_A=0.2, \mu_B=0.8)$$

where: min = minimum value

Therefore, the rate of 20m in 10^6 years has a degree of membership 0.2 to the fuzzy set R (rate of movement) which is a result of the relation between Deposition (B) and Removal (A). In other words, μ_R (20) = 0.2

b) The same reasoning is used for the rate of 2 m in 10^6 years:

Considering points 33-1 A and 34-1B-A it follows from Table 5.17:

Degree of membership of sample 33-1 A, to the fuzzy set removal of Uranium, μ_A=0.44.

Degree of membership of sample 34-1B-A, to the fuzzy set deposition of Uranium, μ_B=0.59.

Taking the minimum of both values, i.e., $\mu_A(x) \wedge \mu_B(x) = \min(\mu_A=0.44, \mu_B=0.59)$, the degree of membership to the fuzzy set R is $\mu_R(2) = 0.44$. Then the degree of confidence of this rate of movement is 0.44.

Now there is additional information in relation to the results found in the Poços de Caldas technical report by Mackenzie *et al.* (1991). According to this fuzzy set methodology, the rates of movement are accompanied by a number that gives its degree of confidence, making it easier to the decision makers and public to understand the data and calculations. The degrees of membership are in agreement with the information, in other words, for the limit of 20 meters in 10^6 years, the authors advised the reader to be cautious as for the degree of confidence one should place on this result. This statement, translated into numbers would be consistent with a degree of membership of 0.2, while an absolute confidence would have a value of 1.0.

For the other limit, 2 m in 10^6 years, the degree of membership was higher, although still low. Based on the fuzzy set analysis, this value is the most appropriate for use in other calculations based on the rate of movement of the redox front.

The fuzzy set approach also helpful in that, as more knowledge becomes available, the values of degree of support can be easily reviewed and updated if appropriate.

5.7.6 Conclusion

It was shown that it is possible to keep important information, regarding environmental data interpretation, linked to the results of a performance analysis. In this example, movement of the redox front from drillcore F-1at the Poços de Caldas site was previously estimated to range between 2 and 20 m in 10^6 years. Using the fuzzy sets approach to analyze the data it was determined that the estimate of 2 m in 10^6 years is more likely to occur than the other. This conclusion is supported by a mathematical basis. This could impact subsequent performance assessment calculations.

The fuzzy set approach, which often relies on information, provided in ambiguous language expressions, will help the decision makers and public to understand the calculations more objectively, while making the performance assessment calculations more transparent and flexible, by showing the weaknesses and strengths at each step of the process. Another advantage of the fuzzy set approach is that it makes it easier for the performance assessment analyst and the decision makers to revise calculations at any time when more knowledge becomes available.

CHAPTER 6

CONCLUSIONS

6.1CONCLUSIONS AND RECOMMENDATIONS

Uncertainties are inherent to environmental data analysis and natural processes modeling. This is specially true for radioactive waste disposal facilities safety assessment in which experts have to mathematically model complex processes and interactions that are not completely known (lack of data) nor can they be precisely known.

The analysis of the performance of the system formed by the repository and the surroundings involves the interaction of experts from several disciplines. Each one of these disciplines (for example, geochemistry, geology, hydrology, etc.) has several sources of uncertainties in their segment of the analysis. These uncertainties are of two types: probabilistic, which suppose stochastic phenomena; and non-probabilistic, which suppose ambiguous and vague phenomena. The latter one comprises most of the uncertainties in safety assessment.

As a result of the ambiguousness and vagueness in information, experts very often have to use professional and linguistic expressions to describe site conditions. This was exemplified in chapter 1, Table 1.1.

Due to difficulties in quantifying this kind of information through, its meaning may be lost and not used in the safety assessment calculations. This fact may create gaps in the uncertainties propagation sequence and consequent confusion as for the interactions between intermediate decisions and their impact on the final result. Possibilistic approaches, based on fuzzy set theory, removes these limitations and permits the use of qualitative linguistic expressions, e.g. “high pH”, “low redox conditions”, etc., to build the safety assessment case.

Failure to properly treat the uncertainties can lead to confusion as the quantitative evaluation of the degrees of confidence and conservatism, and consequently, confidence in results can be lowered. All of these problems can be a strong obstacle to the development of a decision support system that would integrate results of the several disciplines that comprise the safety assessment. In other words, the development of an robust safety assessment case will require the integration of all parameters involved in the safety assessment.

This thesis provided 6 case examples of non-stochastic uncertainties which come from different sources related to waste disposal as follows:

Case 1 is about the lack of data, natural variability and ignorance regarding natural processes. The distribution coefficient is a very good example of simplification of complex natural processes into one single parameter. The spatial variability of this parameter makes it difficult for the analyst to predict with a reasonable confidence the values it will assume along the radionuclide migration path.

As a result conservative values are chosen, often based on experts professional opinion. As it is difficult to evaluate the degree of conservatism analysts tend to use worst case values. However, by choosing extreme values it is not possible to take advantage of the full range of values. This can be made possible by using of the fuzzy sets approach. Lemos et al. (1998).

Instead of using a value, or an average value, the expression "low Kd" can be translated into a fuzzy set, which can be used in its full meaning, as a representation of the current knowledge. As a result more realistic analysis is performed.

In case 2 uncertainty regarding to the inventory characterization and respective release mechanisms was studied. These uncertainties are related to complexity and simplification in the real world data for modeling purposes.

Computer models, in this case the DUST code, assume an homogenous distribution of packages and waste forms for each section or cell. As this does not always correspond to the real situation, experts need to chose values, e.g. release mechanism, that represent that entire section of the repository.

Choosing of worst case may lead to unrealistic solution. Also, this is not a random variable, rather it is ambiguous and therefore more suited for a non-probabilistic approach.

Case 3 is a development of a safety assessment where data from cases 1 and 2 are used as input for a deterministic code, DUST. By using the extension principle, for uncertainty propagation, it was possible to calculate a mass flux as a fuzzy set.

This example showed that by treating ambiguous information as fuzzy sets, the result will also be a fuzzy set. This allows a more realistic analysis compared to stochastic approach, since a probabilistic approach assumes knowledge of what is not known by the observer. This is the principle of excluded middle law. In other words, if P(A) is the probability of an event A, then it is assumed that P (1-A) is also known. As the information is ambiguous, this may not be true. The possibility theory does not requires the application of the excluded middle law, which makes this approach more flexible.

Case 4, is an example of how an expert system based on possibilistic and probabilistic approaches can be applied to safety assessment. Through this example it can be seen that all the information used in a safety assessment case can be gathered into the same framework, which will enable a more complete representation of the whole system, and therefore, a more robust decision support system.

Case 5 and 6 are related to high level radioactive waste disposal. They deal with quantification of linguistic information regarding site conditions. For example, table 1.1 shows linguistic expressions been used for site characterization. Other examples of such an expressions are "low pH", "slightly reducing conditions".

Usually, these expressions would not have been taken into account due to its ambiguity. Rather, experts would have used average values or a probabilistic distribution function based on subjective opinion. Both options would not take full advantage of the information because they can not quantify the degrees of conservatism or confidence and consequently the propagation of uncertainty on to the final result will be unknown or confusing. A methodology of quantification of linguistic, and/or ambiguous, information could help to use it in its entirety and therefore, more realistic calculations will be made possible.

As can be seen from the case examples, uncertainties are not always raised by stochastic phenomena, and therefore, can not be treated using a probabilistic methodology. They show that complexity, lack of data and ignorance, generate the ambiguity in information. This ambiguity (and vagueness) force the experts to use their professional judgement to the determination of probability distribution functions for range of values of parameters and, even very often, to use linguistic expressions for description of site conditions which, on the other hand, if not properly quantified, this kind of information may be lost.

Possibilistic approach was shown to be useful on the task of uncertainty quantification, bringing transparency and helping simplify the complex safety assessment process. Through this methodology, it can be easier to demonstrate the correlation between intermediate decisions and the final result, which is an important aspect to support decision makers, and improve public communication.

The application of non-probabilistic approaches to safety assessment would require some change in regulation standards. For example, concepts such as dose limits, would have to be modified to another perspective such as "around dose", or the repository is "reasonably safe", or "similarly safe to site". This would also require education of regulatory authorities regarding the theories here studied.

Currently, in the USA, the US-EPA (American Environment Protection Agency) adopts the concept of reasonable assurance that a certain limit will not be exceeded. However, there is still a strict dose limit. Stated differently, there must be a 'reasonable assurance" that the dose is less than, for example, 25 mrem/yr.

Possibilistic approaches could still be used to support findings of reasonable assurance, for example, by defining the expression "reasonable assurance". In this case, there is a degree of belief that the dose will be 25 mrem/yr. This mathematical representation of reasonable assurance could then help make the calculation more transparent for public communication.

6.2 FUTURE WORK

This thesis demonstrated the application of fuzzy sets, or possibility, for treatment of ambiguous information in radioactive waste management problems. Possibility theory sets a step towards a more robust decision support system in which both forms of uncertainties, i. e., probabilistic and non-probabilistic, would be integrated into the same framework. The evidence theory, also called Dempster – Shafer theory, provides the necessary principles that will enable the aggregation of probabilistic and possibilistic approaches into the same framework. This will bring more transparency to the safety analysis and consequently will enhance public acceptance and confidence while enabling more realistic assumptions.

The author suggests as a further step to this work, the development of an expert system in which the uncertainty propagation can be calculated with more transparency by using the correlation between possibility and probability theories. Therefore, more realistic calculations will be possible.

An expert system is a computational tool that emulates a human expertise in a well defined problem domain. Through the use of *If-Then* rules, it is possible to model very complex systems by correlating abstract , ambiguous and even contradictory information.

Some applications could be: waste acceptance criteria, repository siting, public communication, integration of natural analogues and other natural safety indicators to the calculation, comparison and ranking between sites, selection of technologies for site decontamination.

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