Chapter

Introductory Chapter: Uncertainty Management to Support Pollution Prevention and Control Decisions

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1. Introduction

The progressive growth in industrialization and population caused severe environmental problems worldwide, these problems need to be analyzed, monitored, controlled and mitigated when appropriate to ensure the quality and sustainability of life [1]. Currently, there is growing international recognition for these problems and in particular environmental pollution is receiving considerable attention either on the international, regional, national and individual scales. To help controlling the existing pollution sources and preventing new pollution sources/areas, strengthen regulations have been issued and human and natural resources have been allocated all over the world [1]. The results of these efforts will be very helpful in supporting various sustainable development goals that were identified in the United Nation 2030 agenda [2]. Among these goals, the achievement of good health and well-being (Goal 2), clean water and sanitation (Goal 4), affordable and clean energy (Goal 5), industry, innovation and infrastructure (Goal 9), sustainable cities and communities (Goal 11), responsible consumption and production (Goal 12), climate action (Goal 13), life below the water and on land (Goals 14 and 15, respectively) are affected by the efforts to prevent and control the environmental pollution.

To ensure effective pollution prevention and control, there is a need to prove that each planned/operated human activity will not impose negative impacts on the human society and the environment. This situation is stressful for the decision makers, e.g. policy makers, designers, regulators, where the decisions must balance the benefits from this activity to the society and its potential negative impacts on the environment, their probabilities, and their consequences. Different assessment methodologies were ratified more than 5 decades ago and are used as tools to support the decision making process. These assessments aim to provide systematic procedures to study the impacts/risks of the human activities on their societies and on the environment. These assessments include life cycle assessment (LCA), life cycle sustainability assessments (LCSA), environmental impact assessment (EIA), strategic environmental assessments (SEA), and risk assessments (RA) [3, 4]. LCA is used to assess the environmental impacts associated with the life cycle stages of a product or service supply chain, e.g. raw material extraction processes, manufacturing and processing, transportation, usage and disposal. It includes goal definition and scoping, inventory assessment, impact assessment, and interpretation. LCSA aims to evaluate the impacts of a product or service on the environment (LCA), social life (social life cycle assessment S-LCA) and society's economic (life cycle costing, LCC) towards more sustainable products throughout their life cycle [5, 6]. EIAs are widely used for regulating human activities worldwide. EIAs focus on the evaluation of the impacts of specified project over its different life phases, i.e. construction, operation, and closure, on the ecological components of the environment. EIA performed by identifying the baseline project, assessing and mitigating the impacts, and monitoring planning. SEA aims to evaluate the environmental impacts of alternative visions and development intentions incorporated in policy, planning or program initiative [7, 8]. Finally, RA used to assess health risk assessment (HRA), hazard risk assessment (HZRA), and environmental (ecological) risk assessment (ERA).

To build confidence in these assessment's results and subsequently in the decisions to be taken based on them, there is a need to identify, present, and describe the uncertainties associated with data collection and analysis, scenario developments, and expert judgment. In this chapter, uncertainty management to support regulatory decision making process to prevent and control pollution will be presented. In this respect, it should be noted that basic elements for regulatory decision making process include clear identification of the applied laws, regulations and acceptance criteria, assessment of the safety significance, verification of collected data and information, assigning priorities, and clarification of the analysis/assessment to be performed [3]. Based on the safety significance of the activity, it might require a simple qualitative assessment, i.e. for activities of low safety significance, or it might need in-depth quantitative assessment, i.e. for activities of high safety significance. Depending on the existing regulations, this assessment can cover impacts (e.g. EIA) and/or risks (e.g. RA) to human, property, or/and the environment, and the results of the assessment are used to manage these impacts and/or risks, i.e. prioritize the efforts to minimize or mitigate the impacts and/or risk. The rest of this chapter is devoted to introduce the uncertainty management. This will be achieved by introducing the applications of risk assessment to support the regulatory decision making process, then elements of the uncertainty management will be overviewed.

2. Risk assessment to support regulatory decision making process

Early RA studies were limited to HRA and comprised health problem identification, dose–response assessment, exposure assessment, and risk characterization. Then HZRA studies were used as a tool to evaluate the risks of specific system or process. **Figure 1** illustrates the steps of HZRA that is used to support the decision making process for a system in the design phase, where the system's hazards are identified, accidents probabilities and consequences are evaluated, then risks are characterized. If the risk is acceptable, then the decision will support the construction and/or operation of the system, otherwise there will be a need to modify the system. Finally, integrated risk assessment (IRA) methodology was developed to estimate the health and ecological risks. It consists of three phases [9]:

- **Problem identification**: in which the hazard is identified and the assessment context is set up by identifying the goals, objectives, scope, and assessment activities.

- **Risk analysis**: aims to identify the exposures and their effects on human and the environment. In this step, assessment models are developed; required data are collected; and modeling results are analyzed to characterize the exposures and their effects. Detailed information about the development of assessment models are found elsewhere [1].

- **Risk characterization**: aims to estimate the risks based on the information of exposures and their effects.

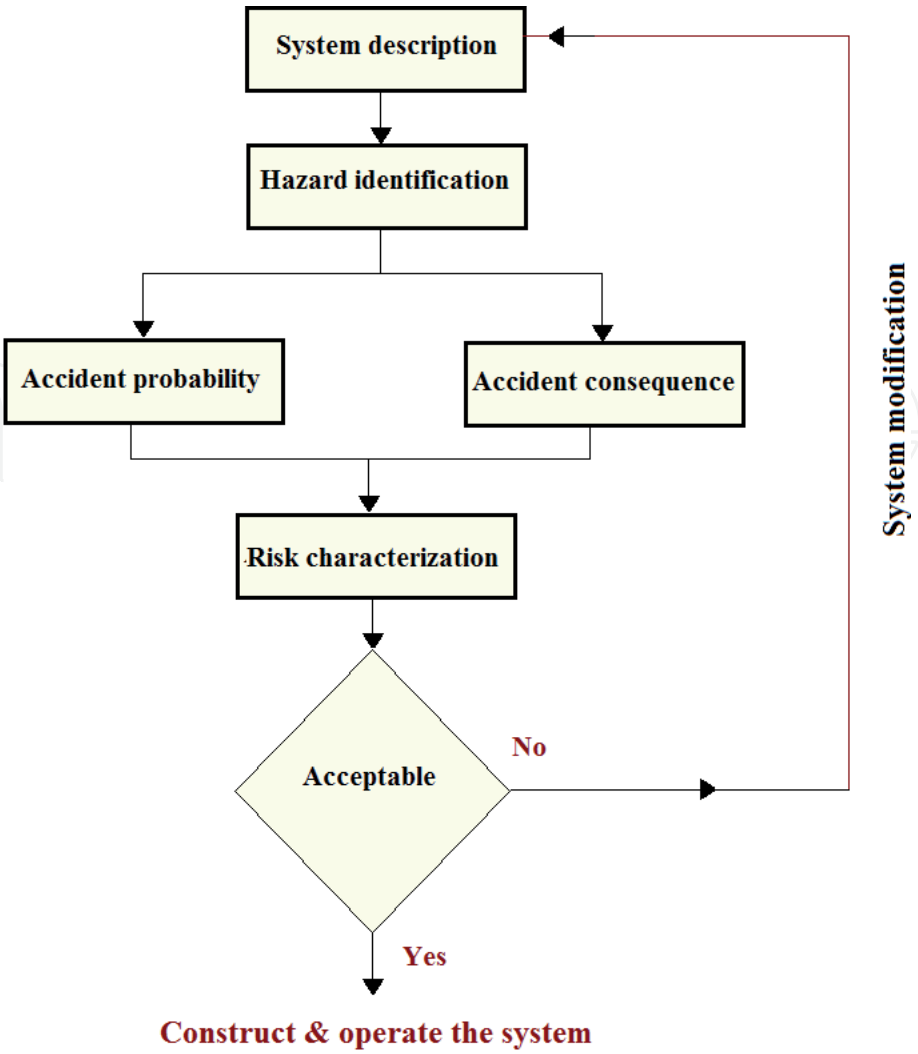

Figure 1.
Environmental risk assessment scheme for project during the design phase.

Each step in the risk assessment is associated with uncertainties that need to be identified, presented and described, and their effects needs to be quantified.

Risk assessment studies are applied to support the decision making process for policy and regulatory decision makers and for project decision makers, **Table 1** lists some of these applications and their examples [10]. Decision making process that relies on the risk assessments are classified as risk-based and risk-informed decision making processes [11]. On one hand, the first relies totally on the risk assessment results, thus allowing efficient risk management and ensure a defensible basis for the decision. On the other hand, the risk-informed decision making process consider other factors with the risk assessment results, (e.g. existing expert judgment, stakeholder involvement, and other engineering insights). The guidance for conducting the risk assessment is differed from country to another, where the level of acceptable risks, nature of the uncertainty analysis, and risk communication programs may be defined or not [12].

Risk assessments are classified based on the adopted technique to assess the risk into qualitative, semi-quantitative, and quantitative assessments. Qualitative assessments are widely used in chemical process industries to analyze potential equipment failure and human errors that can initiate incidents. They are applied throughout the facility life cycle to identify critical safety equipments for special maintenance, testing, or inspection, as a part of the facility management of change program, and to investigate possible causes of incidents [13]. Examples of qualitative hazard evaluation techniques include what if analysis, checklist analysis, and

Field	Applications	Example
Policy & regulatory	Design regulations	Determine acceptable risk level
	Prioritization of environmental risks	Identify regulated chemicals and products
	Provide basis for site-specific decision	Planning or sitting for certain installation
	Comparison of risk	Support substitution decision
Project	License application	Show compliance with legislation
	During design phase	Show the safe operation and product safety
	During sitting	Support Site selection study
	Prioritization and evaluation of risk reduction measures	

Table 1.
Application of risk assessment studies to support the decision making process.

Point of comparison	Deterministic approach	Probabilistic approach
Assumptions	Relies on conservative/bounding assumptions to address the uncertainties	Relies on best estimate, yet it uses conservative assumptions in determining the success criteria
Initiating events and hazards	Limited events are considered	Comprehensive set of events are selected including both DBA* & behind DBA
	Events frequencies & failure probabilities are treated approximately	Explicitly treatment of the initiating events frequency and failure probability
Consideration of accidents	Addressed separately	Integrate all the initiating events
Uncertainty management	Use of conservative assumptions, or best estimate codes and models with uncertainty analysis	Explicit uncertainty treatment in the models
Prioritization	Give rough indication on the relative importance of the system	Included in modern probabilistic safety assessment models

**DBA design basis accident.*

Table 2.
Features of the deterministic and probabilistic risk assessment [16].

HAZOP. Examples of risk analysis tools include failure modes, effect and criticality analysis (FMECA), and layer of protection analysis (LOPA) [14]. Quantitative risk assessments originated in nuclear, aerospace, and electronic industries, they are further sub-classified into deterministic, probabilistic or combination of them. Traditionally, deterministic approaches were adopted by relying on the defense in depth strategy and appropriate safety margin, and following conservative requirements in the design, manufacturing and operation of the project. In this approach, design basis accident is identified during the problem identification phase, its consequences are determined within the risk analysis phase, finally safety barriers are designed to mitigate or prevent the accident consequence [3, 15, 16]. On the other hand, the probabilistic approach is used to analyze all feasible scenarios; where a broad spectrum of initiating events and their event frequency are addressed in the problem identification phase. Then the consequences of those events and weights are analyzed. **Table 2** summarizes the main features of both approaches [16]. An example of the risk-informed regulatory process in the nuclear industry is the USNRC risk-informed processes that consider compliance with regulations, consistency with defense in depth strategy, risk informed analysis, and performance monitoring. USNRC indicated that the application of risk-informed decision making process enhances the deterministic approach [15].

3. Uncertainty management in risk assessments

Uncertainty management is used to build confidence in the outcome of the RA results. Subsequently, the adaptation of well-developed uncertainty identification, classification, inventory, quantification and assessment, and combination schemes are essential for reliable decision making process. In the first step, identification of inherent uncertainty sources in the studied system is achieved. In the uncertainty combination step, the total uncertainty is obtained by aggregating all the quantified uncertainties, where different forms of uncertainties with different mathematical presentations are aggregated to produce a confidence sentence in the system performance. In this section, approaches to classify, inventory and quantify uncertainties will be introduced.

3.1 Uncertainty classification

In general, different sources of uncertainty associate the problem identification and risk analysis phases in the risk assessment methodology. These uncertainties might be related to the system variability and randomness, the presence of errors, either in the measurements, or modeling and analysis, scenarios or data insignificance, and lack of knowledge, indeterminacy, judgment, and linguistic imprecision in decision making [17–25]. Some of these uncertainties could be reduced and others are irreducible.

Two uncertainty classification systems are used; the first is based on the ability to reduce these uncertainties and the second is based on their sources [18–24]. The first consists of two classes, i.e. Epistemic & Aleatory, and this system is effectively used in building confidence in the uncertainty management outcomes, where:

- **Irreducible uncertainties (Type I)** are aleatory, i.e. related to the randomness/stochastic nature of the system, and cannot be reduced but they could be better characterized. Examples include uncertainties associated with natural hazard identification, and those associated with the system heterogeneity [18, 22].

- **Reducible uncertainties (type II)** are epistemic, i.e. arose due to the lack of knowledge, and could be reduced by gaining additional information or data. Epistemic uncertainties are associated with the nature of some mechanisms at specified conditions, e.g. radiological health effects at low doses [23].

It should be noted that during uncertainty management it is important to differentiate between these types and justify the consideration of certain type that associates the features, events, or processes (FEP) of the studied system towards reliable uncertainty quantification.

Uncertainty classification based on the uncertainty sources includes the following classes, where each class includes both epistemic and aleatory uncertainties [23, 24]:

- **Natural variation in the system properties/features**: the spatial and temporal heterogeneity of the system properties or features is associated with uncertainty. This heterogeneity is inherent in the system and needs to be identified during the problem definition phase. In modeling the fate and transport of pollutants in the environment or within the engineered systems that prevent and control the migration of these pollutants, this variability act as a source for two types of uncertainties. The first is aleatory due to the randomness of the system properties/ features, e.g. the spatial distribution of permeability of the geological formation. The second is epistemic due to the lack of knowledge about the temporal evolution of this randomness, e.g. how the permeability will be changed with time.

- **Measurement errors:** these errors associate the data collection process and include random and systematic errors. The first is relatively easy to be detected and quantified, where they associate the reduced tool/device sensitivity, presence of noise, and imprecise definition. Uncertainties due to random errors are addressed using probabilistic methods [23, 24]. The systematic errors are harder to be quantified, they resulted from a bias in the sampling and they need a perfect calibration procedure to account for them.

- **Conceptual model development**. Models are abstractions of the real system; during conceptual model development there is a need to optimize the studied system. In this step, the less important FEPs are excluded [1]. This is a source of epistemic uncertainty that is reduced by performing a sensitivity analysis to optimize the selected FEPs. This source of uncertainty is more prominent in deterministic approaches.

- **Computational model errors**: there are several types of errors that associate the computational modeling of the data. Regardless the type of the used mathematical models, e.g., empirical, mechanistic, or black box, its application is associated with errors that arise from the validity of the model to represent the studied system and the accuracy and stability of the numerical model [25–27]. Uncertainties associated with model validity might be aleatory or epistemic, whereas those due to the accuracy and stability of the numerical model are epistemic and are reduced by adopting a systematic verification procedures.

- **Subjective judgment:** during the analysis of the data, expert judgment is required especially in the following cases; lack of data, and lack of knowledge; this will lead to subjective uncertainty. Examples of these cases are the need for extrapolation or interpolation of the data, and assignment of parameter distribution [28, 29].

It should be noted that both types of uncertainty classifications are used to quantify, assess and minimize the uncertainty in the decision making process. Skinner et al. developed a classification system based on the ability of the uncertainty to be reduced and their location, in the system, data, model and the subjective uncertainty in the form or language, extrapolation and decision, and their associated sub-location as illustrated in **Figure 2** [19].

3.2 Uncertainty inventory

Uncertainty inventory includes all the information and questions relating to the identified and classified uncertainty. It is developed to obtain traceable, updatable and defensible record of uncertainty assessment and quantification, where

- It includes multiple quantities of interest and permits their categorization at different levels of information, e.g. system vs. component level,
- It supports the determination of the nature of the total uncertainty and prioritizes the efforts towards efficient uncertainty reduction,
- It focuses on the information necessary for decision making, and risk/reliability estimation,

3.3 Uncertainty quantification

Both linguistic and numerical uncertainty quantifications approaches are used to analyze and assess the uncertainty in a given system. The quantification methods depend on the propagation of uncertainties in the system model and then assess the model output response due to this uncertainty propagation. The mathematical representations of the uncertainty are based on the use of probability, imprecise probability and possibility theories. For deterministic risk assessment, the uncertainty might be quantified either using a one factor at a time (OFAT) or multi- variant techniques. OFAT allows the change of one uncertain factor or parameter within a specified range with keeping the rest of the factors or parameters fixed [27]. This allows the examination of the effect of the factor variability/randomness/presence on a single process output or multi outputs. **Figure 3** illustrates the application of OFAT in assessing the risk of a system, where a single valued specified factor is propagated through the system, and the model outputs are quantified (**Figure 3a** and **b**). To quantify the uncertainty in the risk estimate of that system, discrete values or probabilistic uncertainty information of the uncertain parameter are propagated through the system which generates statistical information in the risk values for the uncertain parameter (**Figure 3a** and **c**). Different sampling methods could be used to represent the probabilistic information in that parameter, i.e. Latin hypercube sampling. OFAT does not allow the investigation of the interaction between uncertain parameters and their effect on the system output (s), nor allowing the determination of the outputs dependence [24, 26]. To overcome the latter, the parameters are often selected based on their ability to produce a conservative decision.

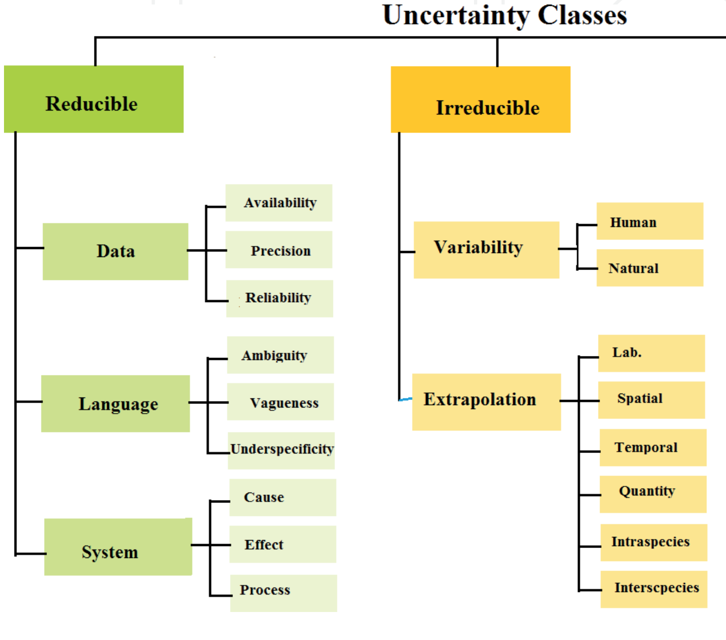

Figure 2.
Uncertainty classification according to Skinner et al. [19].

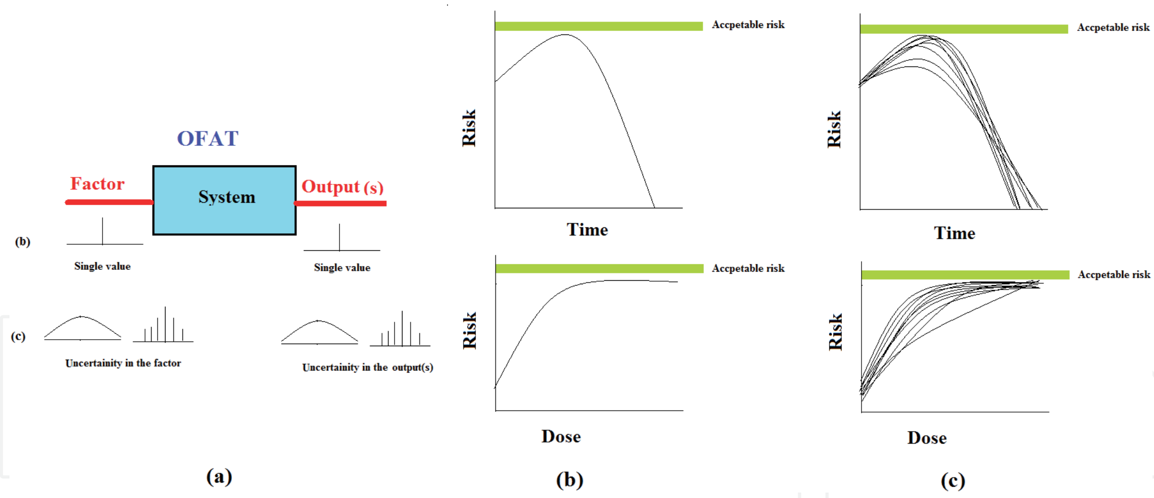

Figure 3.
Application of the OFAT approach in uncertainty quantification, (A) uncertainty propagation in the model, (b, c) modeling outputs for single parameter value (b) and uncertain parameter (c).

The use of the multi-variant approach is adopted by varying the factors or parameters simultaneously and investigating their individual and combined effects on the process output. This approach is applied using statistical experimental design, (e.g. response surface methodology, Taguchi) which allows the development of regression models that correlate between the multi variant inputs and the process outcomes either for multi-variant – single objective or multi-variant – multi objective problem based [25, 27, 30–33]. Integrated tools were developed to quantify and assess the uncertainty in RA, an example of these tools is the Quantifying Margin and Uncertainty, which used to support the certification of the reliability and safety for a physical system and quantify the performance thresholds and their margins and the associated uncertainty in their evaluation. This tool widely used to quantify uncertainties that are dominated by lack of knowledge in risk-informed decision analysis [34].

3.4 Sensitivity analysis to support the uncertainty management

Sensitivity analyses are used as tools to reduce the uncertainty, where it is used to prioritize the research efforts to reduce uncertainty associated with the scenario, conceptual model, input data, modeling process, and the designed system [35]. Differential and probabilistic sensitivity analyses are used to support the uncertainty quantification and reduction. Differential sensitivity analysis is used when exact risk formula exists, this technique is computationally efficient; however, it is only valid in vicinity of the base case and might require intensive efforts to drive the sensitivity coefficients [35]. Probabilistic sensitivity analyses are conducted by assign probability density functions to each input parameter, generate an input matrix using suitable sampling method, calculate the outputs, and assess the influences and relative importance of each input/output relationship [36]. In probabilistic risk analysis, the marginal distributions of the studied parameters and the dependence between them need to be specified [36]. In this case, interval probability, Dempster-Shafe structure, and probability boxes are widely used approaches.

4. Conclusion

In this chapter the approaches to manage uncertainty within the risk assessment framework to support the decision making process for pollution prevention and control systems are introduced. In this respect, the risk assessment, its need, and approaches were introduced and discussed. The classification of sources and reducibility of uncertainty is presented. The approaches to quantify the uncertainty were overviewed with special reference to the role of the sensitivity analysis in uncertainty management.

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