

Fuzzy Systems Modeling in Environmental and Health Risk Assessment

Edited by

Boris Faybishenko • Rehan Sadiq • Ashok Deshpande



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Edited by

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Lawrence Berkeley National Laboratory

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University of British Columbia

Ashok Deshpande (Deceased)

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Foreword

Ashok Deshpande, who is one of the pioneers in the application of fuzzy set techniques in health science, along with his co-authors Rehan Sadiq and Boris Faybishenko have edited a ground-breaking volume on fuzzy systems modeling for environmental management and human health risk assessment. Zadeh's original view on the potential role of fuzzy sets was that it could be applied to enable systemic thinking and analysis that had been used so successfully in solving engineering problems to aid in the solution of human-focused problems. The editors of this volume have taken an important step toward achieving this goal. The interconnected areas of environmental management and human health are replete with the kinds of soft and subjective concepts, goals, and criteria that fuzzy set theory was developed to model. The authors contributing to this volume have provided numerous well-thought-out applications that show conclusively that the framework and mathematics of fuzzy sets and fuzzy logic have much to contribute to important problems related to human physical well-being. As the world becomes more and more enamored by the advances in artificial intelligence, it is very refreshing to see the latest technological ideas being applied to such complex, but real, problems as disease risk assessment among solid waste workers, bathing in swimming pools, and the like.

What is notable about the papers in this volume is that, while the authors are modeling processes and concepts not easily modeled by standard methodologies, the actual mathematics being used is not very difficult. This is a hallmark of fuzzy set methods. Because of their inherent simplicity and directness, the use of fuzzy methods enables engineers and environmental professionals to easily explain to the responsible manager what they have done.

I am very happy to have had the opportunity to write this foreword as it has taken me to worlds in which I don't usually travel.

*Ronald R. Yager
New York, 2022*

Preface

Boris Faybishenko and Rehan Sadiq

This special issue is dedicated to the memory of Professor Lotfi A. Zadeh, the father of fuzzy logic, and to the memory of Dr. Ashok Deshpande, who initiated this volume on using fuzzy logic for environmental problems, and solicited most of the chapters.

Since the pioneering work of Lotfi Zadeh [1], fuzzy logic (FL) analysis has been applied successfully in many scientific and real-life engineering situations, such as electrical, mechanical, civil, chemical, aerospace, agricultural, biomedical, computer, environmental, geological, industrial, as well as by mathematicians, computer software developers and researchers, natural scientists (biology, chemistry, earth science, and physics), medical researchers, social scientists (economics, management, political science, and psychology), public policy analysts, business analysts, and jurists [e.g., 2]. The methods of FL have proven to be extremely useful when dealing with environmental data, because environmental management and risk assessment activities are often based on limited, imprecise, or uncertain observations and numerical simulations. Environmental data are usually characterized by both highly aleatoric and epistemic uncertainties, which are intrinsically present in environmental problems. Aleatory uncertainty indicates that the system (or media) variables or parameters can be characterized by their probability distributions. Aleatory uncertainty is a naturally occurring phenomenon, and is not because of a *lack of information*. Therefore, aleatory uncertainty is irreducible. Examples of aleatory uncertainty are such measured variables as river discharge, precipitation, and traffic data, which can be described by probability distributions if sufficient information is available. If there is no sufficient information, these variables can be described using fuzzy numbers. Epistemic uncertainty indicates the lack of, or limited, knowledge about the real system or its models. This type of uncertainty is reducible, because if we provide more measurements or improve the models, we reduce the level of uncertainty. Moreover, a combination of human judgment, behavior, and emotions plays a central role in the management of environmental systems. FL methods can manipulate both the aleatory and epistemic types of uncertainties, and can be used to handle imprecision or uncertainty by means of using various measures of possibility. It is also important to indicate that FL and fuzzy systems modeling are among the primary components of the scientific field of soft computing, which is an emerging discipline rooted in a group of technologies that aim at exploiting the tolerance for imprecision and uncertainty in achieving solutions to complex problems [3, 4].

This volume is a collection of 16 articles representing a snapshot of the current state of the fields of the application of FL for solving water and air risk assessment, healthcare decision-making, the management of water distribution networks, and the optimization of water treatment and waste management systems. The case studies included in this book are just

the tip of the iceberg regarding the potential and usefulness of FL-based techniques and methods in environmental system modeling. We are conscious there is a great need and potential for applying fuzzy set theory and FL-based methods in other facets of environmental management systems.

This volume is expected to serve scientists, researchers, and practitioners who are interested in FL and soft computing theories and their applications in a variety of environmental sciences and engineering problems. The editors and contributors to the current volume made concerted efforts in the development of new applications of FL concepts to solve real-world problems. This volume symbolizes a milestone of transitioning from a purely scientific method to practical environmental engineering and science applications. We believe that the interested reader will get in touch with the authors to further improve the practical applications of FL-based modeling in addressing environmental challenges.

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Introduction

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Environmental pollution has been the greatest problem facing humanity for many years, and it is the leading cause of morbidity and mortality. Humankind's activities, such as urbanization, industrialization, mining, exploration, and organic and radioactive contamination, are major reasons of global environmental pollution in both developed and developing nations [e.g. 1, 2]. These problems call for immediate action on initiating pollution abatement strategies. However, predictions and environmental decision-making are often limited due to the uncertainty, vagueness, or ambiguity of observational data [e.g. 3–7]. The methods of statistical mechanics have embraced two-valued logic-based probability theory, wherein a random variable is used as the basis of probability computations. However, the standard probability theory is not designed to deal with imprecise probabilities that pervade real-world uncertainties. Fuzzy set theory is an alternative approach to modeling these uncertainties.

Since the publication of the first scientific paper on fuzzy sets by Lotfi A. Zadeh [8], fuzzy systems modeling has been applied successfully in many scientific and technological fields and has proven useful when dealing with environmental problems. The theory of fuzzy sets is based on the notion of relative graded membership, as inspired by the processes of human perception and cognition. Fuzzy logic (FL) can deal with information arising from computational perception and cognition that is uncertain, imprecise, vague, partially true, or without sharp boundaries. FL allows for the inclusion of vague human assessments in computing problems. Also, it provides an effective means for conflict resolution of multiple criteria and for the better assessment of options [4, 9, 10].

The main idea of the application of FL is the presentation of all system parameters and variables as a matter of degree or partial belief, which will allow one to produce acceptable, definitive outputs in response to incomplete, ambiguous, distorted, or imprecise inputs. Despite FL being successfully applied in various sectors, new applications are constantly being found for FL methods and fuzzy sets.

It is a deep-seated tradition in science to employ the conceptual structure of bivalent logic and probability theory as a basis for the formulation of concepts. What is widely unrecognized is that, in reality, most concepts are fuzzy in nature rather than bivalent, and thus it is generally not possible to accurately formulate most real-world problems within the conceptual structure of bivalent logic and probability theory. Thus, the techniques based on FL are more applicable for environmental system modeling wherein an expert's perception takes center stage of the modeling process.

The fuzzy set of a concept is defined by a distribution function of the degree of belief (DoB) in a qualitative parameter (the concept) over a range of variations in a quantitative or less-qualitative parameter (the scale). The concept may be determined by different scaling parameters, and each parameter on its own is not necessarily unique. So, the form of a fuzzy set depends almost entirely on the scale selected. In the environmental field, regulators, health authorities, epidemiologists, politicians, environmentalists, engineers, and the general public often define a concept, such as contamination, in different ways. The only term which is more or less unequivocally understood by all interested groups is the final risk often associated with dollar value. The proper definition and scaling of fuzzy sets can provide a common language through which experts from different disciplines can communicate during the entire process of risk assessment. Uncertainty in the input information propagates (but is neither magnified nor dampened) in a fuzzy way, so that the output remains fuzzy and can then be translated into either quantitative risk values or qualitative linguistic expressions. In this book, we examine a real risk assessment case scenario using fuzzy arithmetic.

There are several emerging and complex environmental issues wherein fuzzy sets and FL can be applied. FL-based techniques are well suited for problem-solving in a number of environmental study areas, including but not limited to climate change adaptation, water resources management, air quality management, watershed management, wildlife management, flood control and management, water quality management, environmental risk assessment, wildfire control and management, emerging pollutants control, and socio-environmental issues. The complex environmental issues in these areas can be approached, analyzed, managed, and resolved effectively using FL-based methods. The developed methods are able to measure, evaluate, and analyze complex issues characterized by uncertain, imprecise, ambiguous, and subjective features.

It is important to note that life cycle assessment (LCA) and environmental impact assessment (EIA) are commonly used for evaluating environmental impacts. LCA is used to quantify environmental impacts throughout a product's, system's, or service's entire life. It has also become a measure for evaluating the environmental performance of management strategies and industrial products. Similarly, EIA is applied to evaluate the environmental impacts of any development project before it is implemented, such as a road construction project. Both tools involve extensive modeling. Environmental modeling using imprecise or vague data may consequently lead to inaccurate or uncertain predictions. Expert knowledge is often used to address the issue of a lack of quantitative data. However, expert knowledge is intrinsically associated with uncertainties due to the vagueness and ambiguity of human thoughts. FL can be used to reduce such uncertainties. The modeling of environmental systems is primarily conducted using the principles of either Newtonian mechanics based on closed form solutions with very little uncertainty or statistical methods, such as various optimization techniques, which are based on bivalent probability theory. Moreover, quantitative environmental data can be converted to fuzzy data using fuzzy inference systems (FIS). The hybrid methodology combining FL and LCA or EIA can be used to reduce data-related uncertainty in EIA.

In today's world, data are being generated at an unprecedented speed. This will continue to increase, too. The use of data-driven methods – such as machine learning, artificial intelligence (e.g. artificial neural networks), data mining, case-based reasoning, pattern recognition – is becoming prevalent in systematic decision-making, especially in making “smart” decisions. Such decision-making systems often use automated data collection using sensors and employ the Internet of Things (IoT) for rapid decision-making. The accuracy of such data-driven methods can be improved by incorporating expert knowledge and other qualitative data, and fuzzy set theory and FL can be a powerful enhancement to the

intelligent models [11]. The complexity, vagueness, and ambiguity in data can be properly approximated using fuzzy concepts. For example, an adaptive neurofuzzy inference system (ANFIS) integrates both neural networks and the fuzzy inference concept, which can capture the benefits of both techniques. The FIS of ANFIS uses a group of *if-then rules* that have the capability to approximate highly nonlinear and complex relationships that are indiscernible by conventional mathematical techniques. FL principles enable the intelligent/smart models to conduct approximate reasoning like human brains.

The IoT assists in rapid and automated decision-making even in real time using sensor-generated data transmitted via the Internet. The biggest challenge in such a situation is data reliability. Sensors often generate faulty data, which may adversely affect the accuracy of modeling outcomes. However, the outliers flagged based on the conventional definition of an outlier can be correct data points in a highly complex and irregular system. On the other hand, the data points within a conventional data range can be faulty, too, due to instrumental error. In such situations, FL principles incorporating expert knowledge can be very useful in identifying faulty data. The fuzzy *if-then rules* are very practical and easier to comprehend and use. Moreover, the use of fuzzy concepts in neural networks reduces computational complexity, which further reduces the computational time in modeling complex systems. The FL-enhanced neural networks also require less cloud space for data storage, ultimately enhancing the efficacy of the developed models and decision-making systems. FL theory and methods can benefit the application of neural networks and data mining techniques. For example, Talpur et al. [12] provide a review of deep neural networks (DNNs) and reasoning aptitude from FIS. This study revealed that the proposed deep neural fuzzy systems' (DNFS) architectures performed better than nonfuzzy models, with an overall accuracy of 81.4%. The novel hybridization of DNN and FL was an effective way to reduce uncertainty using fuzzy *if-then rules*. The study also showed that the DNFS networks presented in the literature have integrated DNN with typical FIS, although satisfactory results can be obtained using a new generation of FIS, termed fractional FIS (FFIS), and the Mamdani complex FIS (M-CFIS). Dynamic neural networks are suggested in the replacement of static DNNs to facilitate dynamic learning for solving highly nonlinear problems. Thus, deep learning methods along with FL techniques provide better interpretability of the network, while solving complex real-world problems using fuzzy *if-then inference rules*. The introduction of fuzzy layers to the deep learning architecture can help exploit the powerful aggregation properties expressed through fuzzy methodologies, and can be used to represent fuzzified intermediate, or hidden, layers. For example, FL can be used to automatically cluster information into categories which improve performance by decreasing sensitivity to noise and outliers. For example, Prince et al. [13] propose introducing fuzzy layers into the deep learning architecture to exploit the powerful aggregation properties expressed through fuzzy methodologies, such as the Choquet and Sugeno fuzzy integrals.

The following is a summary of the individual chapters included in the current volume.

1 Theoretical Considerations

In Chapter 1, "Fuzzy Logic and Fuzzy Set Theory: Overview of Mathematical Preliminaries," Yadav provides basic definitions of FL and fuzzy set theory that are applicable to environmental management and risk assessment activities, taking into account that observations and results of numerical simulations are commonly uncertain. In particular, the author describes the general ideas of FL and fuzzy set theory, arithmetic operation rules, rules of computing with words (CW), and methods of fuzzy relational calculus: fuzzy equivalence

and fuzzy tolerance relation, similarity measures or value assignments, cosine amplitude method, max–min method, monotone measures, Dempster–Shafer theory, fuzzy C-means (FCM) clustering, and basic concepts of the Bellman–Zadeh approach.

2 Fuzzy Logic for Environmental Risk Assessment

In Chapter 2, “Fuzzy-based Integrated Risk Assessment of Methylmercury in Lake Phewa, Nepal,” Chhipi-Shrestha et al. study the distribution of mercury (Hg) entering a lake via processes of air deposition and run-off. In lake water, Hg is converted into highly neurotoxic methylmercury (MeHg), primarily by bacteria, and the MeHg is then bioaccumulated and biomagnified along the food chain. The data and models used in the risk assessment may be associated with uncertainty that can be incorporated into the analysis using a fuzzy approach. The objective of this research was to assess the integrated human health and ecological risks of MeHg in Lake Phewa, Nepal using a fuzzy approach. The measured MeHg in fish tissue was used to estimate the concentration of MeHg in the water by applying a bioaccumulation factor. A questionnaire survey was conducted to estimate fish consumption rates among different occupations: fishermen, local people, hotel owners, government staff, army/police, and others (visitors). An integrated risk assessment framework proposed by the World Health Organization (WHO) was applied to estimate the health risk to humans and the ecological risk to fishes. The results showed that fish consumption contributed approximately 90% or higher to overall human health risk and the remaining risk was attributed to rice consumption. The higher health risk was primarily due to a very high fish consumption rate. Moreover, the ecological risk to fish was within acceptable levels. The risk estimate using the fuzzy approach was used to approximate uncertainty and to build confidence in decisions for risk assessors.

In Chapter 3, “A Fuzzy Approach to Analyze Data Uncertainty in the Life Cycle Assessment of a Drinking Water System: A Case Study of the City of Penticton (CA)” Rebello et al. perform an LCA and evaluate the effect of the uncertainty in input data on the final environmental impacts of water treatment and distribution systems in the City of Penticton, Canada. Data uncertainty was evaluated using a fuzzy analysis coupled with the weighted product method (WPM) to estimate life cycle impact. Additionally, a comparison between the life cycle impact and ReCiPe endpoint single score is presented to understand how sensitive those indicators are to data uncertainties. The results indicate that the most sensible life cycle stage is water treatment and distribution use, with variations from 3 to 15%, mainly resulting from the chemical analysis in the usage phase. Additionally, the WPM methodology presented a deviation from 60 to 378% when considering the individual life cycle stages. The total LCA presented a higher robustness to the changes, with 1–8% variations in the midpoint categories; however, the WPM disparities ranged from 80 to 410% in the midpoint categories.

Ever-increasing pollution levels due to rapid urbanization and industrialization, especially in many developing countries with a minimal focus on adequate pollution abatement strategies, have resulted in widespread damage to the natural environment. It is, therefore, important to classify environmental quality. The practice en vogue for classifying air or water quality for variety of usage is by computing the air quality index (AQI) or water quality index (WQI). Why compute a numeric AQI or WQI, and then describe air/water quality linguistically? The human brain does not compute numbers. Why not describe air or water quality, for the defined usage, straightway in linguistic terms with some linguistic degree of certainty attached to each linguistic description?

Chapter 4, “Environmental Quality Assessment Using Fuzzy Logic,” by Yadav and Rijal, presents two research case studies. The first one is on the fuzzy air quality description in the Pimpri-Chinchwad Municipal Corporation (PCMC) monitoring location, and the other one relates to the linguistic classification of water quality with a degree of certainty in the PCMC area, India.

In Chapter 5, “Assessing Spatiotemporal Water Quality Variations in Polluted Rivers with Uncertain Flow Variations: An Application of Triangular Type-2 Fuzzy Sets,” Haider et al. address an important problem of dealing with high pollution loads in rivers by large cities. Rivers also experience extreme spatial and temporal flow variations due to the overexploitation of freshwater resources, poor management practices, and climate change impacts. Water quality data are usually scarce in developing countries due to the absence of planned periodic monitoring programs. Consequently, water quality parameters (i.e. biochemical oxygen demand, dissolved oxygen, unionized ammonia, and coliforms) are significantly dependent on river discharge. The morphology of rivers also influences water quality parameters because of changes in the water residence time. For a river, a WQI is a robust assessment tool that indicates the overall water quality based on the water source, such as natural freshwater, single point source loads, and cumulative loads from several outfalls along the river length. Other factors that are taken into account in the derivation of the WQI are seasonal variations in river flow, hydrodynamics, and pollution loads. Type-2 fuzzy sets, an extension of ordinary fuzzy sets, directly model the uncertainties by providing an additional degree of freedom. Type-2 fuzzy sets improve the specific kind of interface that exists due to increasing uncertainties associated with imprecision in knowledge and vagueness in information due to limited water quality data. Using the triangular type-2 fuzzy sets approach, the WQI developed in the present work effectively overcomes these uncertainties and has proved to be a more reliable water quality assessment measure for highly polluted rivers with extreme flow variations.

In Chapter 6, “Optimal Ranking of Air Quality Monitoring Stations and Thermal Power Plants in a Fuzzy Environment,” Yadav and Salla apply the Zadeh–Deshpande (ZD) FL-based formalism for linguistic description of the air quality criteria of pollutants, and the Bellman–Zadeh method for optimal ranking on the basis of risk for thermal power plants. The air quality classification obtained for 12 cities using the ZD formalism is described linguistically using the concept of degree of certainty (DC). The air quality assessment is provided for 26 thermal power plants in India.

3 Fuzzy Logic Application in Healthcare Decision-making

Environmental professionals and medical practitioners have made significant contributions using statistical methods to analyze medical data and associated air and water pollution parameters in order to determine the cause–effect relationship between air/water-borne diseases and air/water-pollution parameters. Multiple studies have been carried out and are primarily centered on exposure to exhaust pollution, and epidemiological studies associated with various respiratory diseases. Chapter 7, “Evaluation of Health Effects Due to Environmental Pollution Based on Belief and Possibility,” by Yadav and Rijal, includes two case studies that reveal a strong correlation between polluted-water and water-borne diseases, as well as polluted-air and air-borne diseases. The perceptions of experienced medical practitioners are modeled to assess the collective DoB for all possible combinations of air/water-borne diseases, and evidence theory and fuzzy relational calculus without the need of having a sizeable parametric data are also used. The objective of this chapter is,

therefore, to critically evaluate the vast armamentarium available on these facets of air- and water-pollution studies.

Chapter 8, “Respiratory Disease Risk Assessment Among Solid Waste Workers Using Fuzzy Rule Based System Approach,” by Jariwala and Christian, deals with the prediction of respiratory disease, which is considered one of the major causes of mortality. Because the symptoms of respiratory disease require a long time to manifest, an early evaluation of an individual risk prior to a medical diagnosis or a laboratory test is essential. Medical science considers the criteria of odds ratio and relative risk for the study of disease occurrence, wherein comparison is made between exposed and nonexposed groups. Reportedly, solid waste workers are at high risk of developing respiratory diseases. The present study aims at determining an individual worker’s risk of respiratory diseases under selected parameters. The factors responsible for the development of respiratory diseases were identified and measured in a group of solid waste workers from the city of Surat in India. An individual worker’s risk without any test or diagnosis is evaluated on a scale from 0 to 1 by means of applying a fuzzy rule based system (FRBS). The calculated risk value ranges from 0.08 to 0.92. The FRBS modeling results are validated based on the comparison with the pulmonary function test.

Chapter 9, “Risk Analysis for Indoor Swimming Pools: A Fuzzy-based Approach,” by Saleem et al., addresses the risk analysis in indoor swimming pools using a fuzzy-based approach to incorporate the uncertainty. The likelihood and consequences are defined using fuzzy numbers to identify the fuzzy risk as the product of both likelihood and consequence. The resultant defuzzified risk will be categorized on a linguistic scale from *very low* to *low*, *medium*, *high*, and *very high* to estimate the formation risk level of the different pool types. The model created is based on FL, which gives a risk assessor the ability to solve complex problems plagued with uncertainty and vagueness. In this chapter, formation risk is studied through the notions of likelihood and consequences, for which membership functions are established. The method adopted allows for a realistic preliminary assessment of the risk of formation in an indoor swimming pool. This method can be used by swimming pool facility managers to evaluate the risk in all pool types to ensure that safety measurements are satisfactorily based on the given data. This method can be used as a preliminary risk assessment tool, which can highlight critical situations and the need for more in-depth and complete analysis.

4 Fuzzy Logic Applied to the Management of Water Distribution Networks

In Chapter 10, “Fuzzy Parameters in the Analysis of Water Distribution Networks,” Gupta and Ormsbee present the results of a fuzzy analysis of water distribution networks (WDNs) to determine how the uncertainties in independent or basic parameters (such as nodal demands and pipe roughness coefficients) are dependent on such parameters as pipe flows, pipe velocities, and available pressure heads. The chapter shows how fuzzy analysis can be applied to identify the vulnerable zone in WDNs, as well as how to conduct a reliability-based design of WDNs under the uncertainty of various parameters. Several methodologies have been suggested for fuzzy analysis. These methodologies are categorized as: (i) optimization-based methodologies and (ii) analysis-based methodologies. The membership functions obtained by both optimization and analysis-based methodologies are compared using two types of networks. Methods for obtaining the approximate fuzzy membership functions are also discussed.

In Chapter 11, “Selection of Wastewater Treatment for Small Canadian Communities: An Integrated Fuzzy AHP and Grey Relational Analysis Approach,” Hu et al. describe an integrated fuzzy analytic hierarchy process (F-AHP) and grey relational analysis (GRA), which can be used to facilitate the selection of appropriate wastewater treatment (WWT) alternatives for small communities. Seven commonly used WWT technology alternatives were assessed for a hypothetical small community in Canada. The assessment was based on the holistic evaluation of technical, economic, social, and environmental criteria, with each criterion composed of several subindices. The weights of criteria and subindices were determined using F-AHP to address nonprobabilistic uncertainties, such as vagueness and ambiguities in human thoughts resulting from the subjective weighting process. The weighted criteria were then aggregated and, based on the aggregation results, alternatives were ranked using GRA. The results from the integrated approach show that constructed wetland, stabilized pond, and extended aeration lagoon are the top three appropriate WWT technologies for small Canadian communities. It was also found that the fuzzy-based approach and the non-fuzzy-based approach generated different rankings for the alternatives, indicating that fuzzy uncertainties could affect the decision-making process.

Vishwakarma and Sinha, in Chapter 12, “Fuzzy Logic Applications for Water Pipeline Risk Analysis,” state that civil infrastructures are considered critical systems providing economic, social, and environmental benefits for society. However, given the issue of aging water infrastructures, the cost of maintaining a sustainable level of service for a growing population is increasing. Consequently, there is an urgent need to advance the processes that drive current water pipeline renewal (repair, rehabilitation, and replacement) decision support systems. Fortunately, with the developments in computational techniques and data collection through advanced sensors, it is now possible to support prioritization of critical water pipelines with data and knowledge. This chapter explains a state-of-the-art approach to assessing the consequence of failure (CoF) built on a comprehensive list of parameters and utilizing a novel hierarchical FIS to support better criticality-based renewal decisions for water pipelines.

This chapter can also help water utilities to build data-driven decision support systems within their asset management programs. All data and models shown in this chapter are part of the PIPEiD or PIPEline Infrastructure Database. This platform is envisioned as a national database platform for advanced asset management addressing the major management levels (e.g. strategic, tactical, and operational) that will assist water utilities of all sizes in sustaining targeted levels of service with acceptable risk. It will also provide secure access to the aggregated data, models, and tools that will enable the synthesis, analysis, query, and visualization of the data for decision support.

In Chapter 13, “Fuzzy Logic Applications for Water Pipeline Performance Analysis,” Xu and Sinha present the results of studies to improve decision-making related to the problems of aging drinking water pipes. Multiple statistical models have been developed to support advanced asset management. Many models have been prepared for specific materials or conditions, and fail to be used holistically for a water distribution system. To address this issue, a comprehensive understanding of performance parameters for different pipe materials is needed. PIPEiD was created to help in understanding the critical drinking water pipeline infrastructure. It is envisioned as a national database platform for advanced asset management addressing the major management levels, including strategic, tactical, and operational, that will assist water utilities of all sizes in sustaining targeted levels of service with acceptable risk. It will also provide secure access to aggregated data, models, and tools that will enable the synthesis, analysis, querying, and visualization of the data for decision support. With the help of PIPEiD, it becomes possible to incorporate the many previous

models and develop a systematic and comprehensive approach to the statistical modeling of drinking water pipeline performance prediction. The research provides knowledge and insights about water pipe condition and performance. The research questions are related to the core tasks (i.e. assessing the pipe performance index/rating and developing pipe performance curves). This chapter explains the background knowledge needed for the development of the FL-based performance index for water pipelines.

5 Using Fuzzy Logic for the Optimization of Water Treatment and Waste Management

In Chapter 14, “Developing a Fuzzy-based Model for Regional Waste Management,” Karunathilake et al. describe a decision-making method for an integrated waste management plan that becomes complicated due to inherent variabilities and uncertainties associated with the waste inputs, processes, and the external environment, as well as the lack of data and high human involvement. It is shown that fuzzy multicriteria decision-making techniques can be used to develop a robust waste management planning model to customize regional needs and conditions. Different waste treatment modes, such as landfilling, composting, material recovery and recycling, and waste-to-energy conversion can be used to process municipal solid waste in a regional waste management strategy. This chapter uses the fuzzy technique for order of preference by similarity to ideal solution (TOPSIS) method to rank and identify the best-performing technology in a particular mode of treatment, and a fuzzy optimization model is developed to identify the best combination of technologies for a region.

In Chapter 15, “Development of a Fuzzy-based Risk Assessment Model for Process Engineering,” Ouache et al. state that ample evidence is available on the impacts of engineered systems on ecological and social risks, and there is an urgent need to assess the risks involved in operational management. The risk matrix has been commonly used to prioritize the risks associated with the prevention and remediation of environmental damage. Despite the popularity of using the risk matrix, data uncertainty is the main challenge associated with the risk matrix. The published literature identifies imprecision of a risk level and absence of data as added challenges. A FL-based risk matrix model (RMM) has been developed to overcome these challenges. The proposed RMM adopts a unique approach, integrating frequency of the risk consequence with the impact of the corresponding consequence. The frequency of risk consequence is based on four factors: (i) the frequency of risk events, (ii) exposure to risk events, (iii) the probability of failure on demand of the safeguards, and (iv) the vulnerability of safeguards. The consequence impacts involve the impact on humans, the environment, properties, and the reputation of the industry. A Simulink-MATLAB model was developed to facilitate the RMM computation. A case study is used to demonstrate the application of this model by using a case study of a reboiler oven in the petroleum industry. The study revealed that the results of the new RMM can be more reliable than traditional risk matrices.

In Chapter 16, “Application of Fuzzy Theory to Investigate the Effect of Innovation Power in the Emergence of an Advanced Reusable Packaging System,” Böröcz et al. present a novel technique to analyze the role of subjective factors, such as innovation in the economy, which influence the design of reusable packaging systems in a given industrial region. In modern supply chains, companies and packaging engineers have to make decisions on determining adequate packaging with optimal waste. The decision-making process is usually based on available data and information, taking into account the need to minimize the environmental impact. Fuzzy systems analysis is used to show that a willingness to innovate is an

indispensable requirement of the appearance of advanced packaging, but most of the time it depends on the synergic effect of local production factors and regional peculiarities.

The case studies presented in this volume may serve as models for the application of soft computer modeling of various types of pollution – air, water, soil, noise, radioactive, light, and thermal – which are the primary causes that affect our environment. All these types of pollution are interlinked and influence each other. However, discussing each of these issues in depth is beyond the scope of this volume.

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