INTEGRATED RISK ASSESSMENT OF AMBIENT AIR QUALITY BY STOCHASTIC AND FUZZY APPROACHES

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Integrated Risk Assessment of Ambient Air Quality by Stochastic and Fuzzy Approaches

By

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ABSTRACT

The risk associated with a power generation system often refers to the contaminants emission from combustion facilities, which could violate environmental standards and affect human health through various exposure pathways. In this research, an integrated risk assessment by stochastic and fuzzy approaches was applied to systematically examine both probabilistic and possibility uncertainties existing in environmental conditions and evaluation criteria within an ambient air quality management system.

The contaminant concentrations in ambient air predicted from a numerical simulation model usually contain probabilistic uncertainties due to the variations in modeling input parameters; while the temporal and spatial variations of environment make the consequences of contaminant concentrations violating relevant guidelines and health evaluation criteria to be linked with possibilistic uncertainties due to the vagueness of expert's judgments. This leads to difficulties in direct implementation of the deterministic environmental guidelines because of the existence of uncertain factors. To help resolve the problem, this study aims at developing a integrated risk assessment system for the management of ambient air quality by stochastic and fuzzy approaches. The objective entails the following tasks: (a) Monte Carlo simulation of sulfur dioxide (SO_2) dispersion in the ambient air through a regulatory steady-state plume numerical modeling system

AERMOD, to generate cumulative distribution functions for stochastic uncertainties; (b) fuzzy environment and health risk assessment based on stochastic simulation: quantification of environmental guidelines and health criteria using fuzzy membership functions acquired from a questionnaire survey; determination of risk levels by developing a fuzzy rule-based assessment system. The contaminant of interest in this study is SO_2. The environmental quality guideline was divided into three categories: loose, medium and strict. The environmental-guideline-based risk (ER) and health risk (HR) due to SO_2 inhalation were evaluated to obtain the general risk levels through a fuzzy rule base. The ER and HR levels were divided into five categories of low, low-to-medium, medium, medium-to-high and high, respectively. The general risk levels included six categories ranging from low to high. The fuzzy membership functions and the fuzzy rule base were established through a questionnaire survey. Thus the developed approach was able to integrate fuzzy logic, expert experience, and stochastic simulation within a general framework. The robustness of the evaluation results can be enhanced through the effective reflection of the two types of uncertainties as compared with the conventional risk assessment approaches. In order to test the feasibility and effectiveness, the developed model was applied to a thermal power station in Atlantic Canada. The results were analyzed under three scenarios with different environmental quality guidelines, leading to the variations of risk levels (based on different degrees of guideline strictness acquired from questionnaire survey). It is indicated that, the integrated risk assessment can more effectively elucidate the relevant environmental and health risks resulting from SO_2 emission. The developed approach can offer a unique tool for quantifying uncertainties in air quality modeling and risk assessment, and also provide realistic support for related decision-making processes.

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CHAPTER 1 INTRODUCTION

1.1 BACKGROUND

Clean air is essential to our own health and that of the environment. Research has shown that since the industrial revolution, the quality of the air we breathe has deteriorated considerably, mainly as a result of human activities (Ross, 1972). The rising industrial and energy production and the burning of fossil fuels all contribute to air pollution in our towns and cities which, in turn, can lead to serious environmental and health problems. In the 1960s, scientists began to realize that the effects of air pollution were global, not just local (Yousif, 2006). Emissions from industries, automobiles, and other sources could have negative effects thousands of miles away. Electricity production, as one of the main sources of air pollution (Bigano, 2000), has been of much concern in recent years since the emissions from the power plants are known to contribute to acid rain, haze, smog, and climate change, etc. This is why power plants have become one of the biggest single causes of unhealthy air. They can result in massive health damage only by the emission of air pollutants: respiratory diseases, heart attacks, and premature deaths – all of these are among the serious public health problems caused by air pollution from the electric power sector. In June 2004, the American Abt Associates (2004) reviewed the contribution of power plants to particulate pollution and compared the relative benefits of the proposals policies to reduce power plant fine particle emission. The key findings included the following: pollution from power plants cuts short the lives of nearly 24,000 Americans nationwide every year; those 24,000 Americans die an average of 14 years early because of exposure to power plant pollution; 2,800 of those deaths are from lung cancer; power plant pollution is responsible for 38,200 non-fatal heart attacks per year; the elderly, children, and those with respiratory disease are most severely affected by fine particle pollution from power plants; and people who live in metropolitan areas near coal-fired plants feel their impacts most acutely and their attributable death rates are much higher than areas with few or no coal-fired plants.

The global work in controlling air pollutants emission from power generation is one of the major issues under environment and health. The related communities are reacting at many levels to reduce exposure to air pollution through environmental institutions (e.g., United States Environmental Protection Agency (US EPA) and European legislation), through cooperation at the wider international level in order to reduce trans-boundary pollution, through working with sectors responsible for air pollution and with national and regional authorities, and through research and development of advanced pollution prevention, control and remediation technologies. One of the major focuses for the next decades will be advancement of air quality standards and coherency of all air legislation and related policy initiatives. For instance, the Institution of Electrical Engineers (IEE) (2000) published the Environment & Energy Fact File to describe the environmental effects of all forms of electricity generation currently in use or propose. Another interesting research by the United States Public Interest Research Group Education Fund (US IRGFF) reported a comprehensive review on America's dirtiest power plants. This report documented the 2002 emissions of smog-forming nitrogen oxides (NO_X), soot-forming sulfur dioxide (SO_2), and carbon dioxide (CO_2) from the 548 power plants in the nation and quantified the emissions that would continue unabated. Each of the plants examined in this report emitted at least 20 tons of "excess" NO_X or SO_2 emissions that could be eliminated if the plant was to install appropriate pollution control equipment (US IRGFF, 2003). The United States EPA announced on July 2, 2007, that East Kentucky Power Cooperative, a coal-fired electric based in Winchester, KY, was required to spend approximately $650 million on pollution control and pay a $750,000 penalty to resolve alleged violations of the Clean Air Act at its three plants. The U.S. Department of Justice (DOJ) claimed that scientists, environmental engineers, legislation agencies and government authorities would continue to work on the air quality management to protect the environment from any adverse effects caused by generating electricity and industries.

In Canada, the power sector has registered remarkable growth since the first hydroelectric generating station was constructed at Chaudière Falls in 1886 (Canadian Electricity Association, 2006).The significant scale of new generation required to meet growing demand was made apparent in a 2003 National Energy Board (NEB) report (NEB, 2003), which claimed that Canada's electricity supply would need to reach 814 TWh in 2020 to meet requirements. In other words, the combination of an increasing population, growing economic and greater use of electrical equipment means that electricity demand will continue to grow at an annual average rate of 1.5 to 2% (Canadian Electricity Association, 2006). By now, Canada possesses a diverse generation portfolio, covering a range of mature and emerging electricity-producing technologies. For example, power generation from hydro, fossil fuels (coal, natural gas and oil), nuclear sources and wind, bio-energy and other sources in 2005 was 60%, 28%, 12%, and 2% respectively, while coal, natural gas, and oil are contributing 61%, 14%, and 25% of thermal power generation, respectively (Canadian Electricity Association, 2006). In 2005, the Commission for Environmental Cooperation (CEC) released the first comparability report 'North American Power Plant Air Emissions' on emissions data from over 1000 individual fossil-fuel power plants in North America (Canada, Mexico and the United States) (Miller, et al., 2005), which found that only a small percentage of facilities release much of the electricity sector's sulfur dioxide, nitrogen oxides, mercury and carbon dioxide emissions in North America. Therefore, as demand for power generation increases, so dose the need to ensure acceptable environmental quality. Canadians expect that their increasing electricity needs will be met in an environmentally-friendly fashion. One of the key components in a prosperous economy is low-cost, reliable electricity that does not unduly burden the environment. Governments are implementing a growing number of environmental demands on the sector, through legislative regimes and international commitments (e.g., the Kyoto Protocol). In response to these trends, the industry's environmental performance continues to improve: electricity intensity is descending, air emissions from fossil generation (coal, oil and gas) are declining; waste and hazardous materials are being reduced or more effectively managed; and species and habitat management gets growing concerns during decision-making on existing and new projects. In general, environmental issues need to be integrated into the planning, development, and operational processes of power plants in order to maximize socio-economic benefits and minimize adverse environmental impacts. Also, appropriate environmental guidelines play an important role in establishing the base for sustainable development by facilitating developer ad to adopt environmentally sound technology and better management practices. For all the issues discussed above, risk assessment will offer a means for decision support by carefully assessing and ranking severity of site contamination, and thus allowing identification of critical issues for mitigation actions. As a result, from both electrical section and the government aspects, it is vital to assess the related risks and liabilities, not only insight into pollutant-migration mechanisms, natural conditions and environmental impacts, but also a comprehensive view for providing support for decisions related to prevention, detection and correction of the contamination problems. Therefore, risk assessment is a significant component for power plant air emission management.

The assessment of risks at an electrical section is mainly based on the modeling of the air dispersion in forecasting whether its evolution is under risk. Mathematical models, recognized as effective tools for facilitating examine contaminant transport and transform behaviors in the atmosphere, are applied widely in power plant management. Finardi and his group (2001) used the three-dimensional modeling system, composed of a mass-consistent wind field model and a Lagrangian particle model, which was applied to a Mediterranean complex coastal site to describe the atmospheric dispersion of pollutants emitted by thermal power plants. In Egan's study (Egan, et al., 2002), the air quality implications of sources affected by sea breeze flows were simulated by coupling of a fine grid version of MM5 (short for Fifth-Generation NCAR/Penn State Mesoscale Model) and meteorological model, to drive dispersion models capable of accommodating spatial and time-varying meteorological fields. The application of the CALMET (a diagnostic 3-dimensional meteorological model) and CALPUFF (an air quality dispersion model) to the Yatagan district was described by Ulas Im and Yenigun (2005), to study the impact of Yatagan Power Plant emissions on the SO_2 levels. Davis and Jesse (2006) concluded that the air dispersion modeling (ADM) used as an alternative or in conjunction with monitoring, was a valuable tool, since it was not limited by physical locations, and could simulate any specified meteorological conditions, making it ideal for theoretical analysis and forecasting. However, extensive applications of the developed models to practical problems were limited due to the ineffectiveness in quantification of the uncertainties, the management of the input parameters, and, in particular, the extension to risk assessment.

The risk associated with pollutants generated from a power plant often refers to the chance of damaging the environment or human health through various exposure pathways. This was indicated in previous studies of human health risk assessment for power plants. For instance, a methodology for performing exposure and risk assessments for airborne trace element emissions from an oil fired power plant was presented in Saperstein' s (1986) study, in which an assessment of potential cancer risks from arsenic emissions from an oil fired power plant located in a densely populated urban area was conducted. It is obvious that the risk assessment plays such a significant role in the pollution prevention system and follows are more examples: In Amaral's (1983) research, methods were presented for the incorporation of uncertainty into quantitative analysis of the problem of estimating health risks from coal-fired power plants. Bailey (1985) developed a "site-specific" health risk assessment methodology for application at coal-fired power plants. Another study by Munshi (1986), the risk assessment was used as one of sub models to provide information for the integrated pollution control (IPC) methodology, which is viewed as an approach which seeks the most cost-effective way of reducing the overall risk to human health and the environment from all pollutants in all environmental media. This model was applied to a case-study involving a hypothetical coal-fired power plant situated in a realistic physical setting. Based on the previous research, in 2004, Kazuo Asakura and his group in Japan developed an inhalation risk assessment method for trace elements emitted from coal-fired power plants and assessed the inhalation risks of much more trace elements for domestic coal-fired power plants. Most recently, Chandler and his associates in Cantox Environmental Inc. (2006) provided a summary of the final report of the update of the human health risk assessment of the Holyrood Thermal Generating Station, which was provided to Newfoundland and Labrador Hydro.

These previous risk assessment studies were mostly based on stochastic approaches that were effective in reflecting probabilistic uncertainties in source and media conditions. However, further study is needed to address the possibilistic uncertainties that exist in the evaluation criteria and subjective judgment (Chen, et al., 2003). Many of these uncertain factors cannot be expressed, however, as probability distributions, such that methods of stochastic risk assessment are inapplicable. In general, manipulations of the uncertain modeling inputs would result in considerable under-or over-estimation in the simulation and risk assessment results. The underestimated predictions may introduce risk to human health, while the overestimated ones may lead to economic loss due to over-conservative mitigation designs. More efforts should then be made to incorporate possibilistic uncertainties within the modeling system. Thus, in order to more accurately simulate the ambient air dispersion and the following risk analysis under the complexity of uncertainties, an integrated approach is desired. On the other hand, fuzzy-set theory has been used widely for handling uncertainties with discrete and/or imprecise characteristics (Hu, et al.,2003). For the site risk assessment, fuzzy membership functions can be employed to quantify uncertainties associated with the evaluation criteria.

1.2 OBJECTIVES

To conduct the research, it should be noticed from the beginning that the randomness of the events and the role that human judgment plays in determining the risk level classify the uncertainties associated with risk in two broad categories: (1) stochastic (due to the randomness); and, (2) cognitive (due to the vagueness of expert's judgments). The proper management of these uncertainties has become a major concern in environmental risk assessment studies. Traditionally, the probabilistic approach has been the most used in risk assessment and considered appropriate to deal with the uncertainties of risk (Ma, 2000; Schumacher et al., 2001; Passarella et al., 2002; etc.). But, when some experts realized that probabilistic models could fail to provide satisfactory descriptions of cognitive uncertainties, applications of fuzzy logic started to be more common (Uricchio et al., 2004; Deshpande, 2005; Darbra et al., 2007; etc.). Recently, some researchers have explored the possibility of carrying out environmental risk assessment by combining two different modes of representation of uncertainty (i.e. probabilistic and possibilistic theories) in a single computational procedure, known as the "hybrid approach" (Guyonnet et al., 2003; Vemula et al., 2004; Li et al., 2007; etc.). However, the involved cases and uncertainties were limited (e.g., subsurface environment), which is calling for much more further study, such as focusing on the ambient air environment.

Therefore, the main objective of this research is to develop an integrated fuzzy-stochastic risk assessment system for the management of air-contaminated sites. This effort will help accurately in predicting the contaminant transport and fate in the ambient air and effectively assessing the associated environmental and health risks. The results obtained from the improved risk assessment will provide realistic decision support and bring enormous environmental and economic benefits. The objective entails the following tasks: (a) Monte Carlo simulation of SO_2 dispersion in the ambient air through a regulatory steady-state plume numerical modeling system AERMOD, to generate cumulative distribution functions for stochastic uncertainties; (b) fuzzy environment and health risk assessment based on stochastic simulation: quantification of environmental guidelines and health criteria using fuzzy membership functions acquired from a questionnaire survey; (c) determination of risk levels by developing a fuzzy rule-based assessment system.

1.3 ORGANIZATION

The structure of this dissertation consists of the following chapters:

Chapter 2 reviews previous studies on air dispersion modeling, uncertainty analysis and risk assessment, particularly the existing techniques tackling uncertainties in emission simulation and risk assessment, such as fuzzy and stochastic analysis methods, are examined to identify their advantages and disadvantages. The recent development in mathematical modeling, uncertainty analysis and risk assessment approaches is also discussed in this chapter.

Chapter 3 describes a case study for modeling the air pollutant dispersion from a thermal power station in order to set the stochastic base by simulation results for the risk assessment.

Chapter 4 proposes an integrated risk assessment approach for examining uncertainties associated with atmospheric conditions, underlying surface influence, environmental quality guidelines and health impact criteria in an ambient air quality management system based on stochastic simulation, fuzzy logic, and expert involvement. The developed approach is applied to the air quality management of a thermal power plant within the eastern Canadian context.

Chapter 5 presents the conclusions of the dissertation research. Future directions of integrated risk assessment studies and their applications within the North American context are put forward.

CHAPTER 2 REVIEW OF LITERATURE

The significance of the air dispersion modeling and risk assessment is growing, and the past few years have seen increased awareness of the complexity and difficulty of air contamination problems which need advanced air dispersion modeling and innovative risk assessment approaches. This chapter will review the previous research on air dispersion modeling and risk assessment, and critical issues, that deserve further exploration, will be identified.

2.1 AIR DISPERSION MODELING

One of the main goals of the dispersion modeling is to provide a tool for supporting the stakeholders whose decisions are often based on emission measurements. Models are linking the emissions to air pollution concentrations and exposure via meteorological data. The models can normally be as reliable as the emission inventories they use. For impact assessment, there will always be a need for both measurements and models. In some cases, a model is actually more applicable than a measurement. Measurements are usually not representative for a large area, and their quality is sometimes questionable (Brock and Richardson, 2001). A model can provide estimates of concentrations in the areas where one does not have measurements, at least allowing for certain refinements. For health impact assessment including exposure evaluations the use of models of some kind is essential. Models are also necessary for forecasting and planning purposes. Models are presently being developed to combine meteorological forecast models with air pollution dispersion models to enable air quality forecasts in urban areas across the world (Brandt, 2001; Pasken and Pietrowicz, 2005). With high-speed computers and more advanced information technologies they may represent some of the future public information services. In practical applications, modeling results should be compared with officially established criteria to draw certain conclusions about the safety of human beings and the environment.

2.1.1 Overview of air quality modeling

Air quality modeling is used for determining and visualizing the significance and impact of emissions on the atmosphere. An overview is given here of the history and the current status of atmospheric transport and dispersion models applied to chemical, biological, and nuclear (C/B/N) agents' releases. The discussion includes questions being asked of models, history and types of models, links to meteorological inputs, and evaluation with field data, uncertainties, future systems and research needs. Models are being applied in real time, in historical mode, and in planning mode to address the following types of concerns: In real-time, for a known C/B/N release, what areas should be evacuated or other precautions taken? Alternatively, for an unknown C/B/N release but with observed concentrations, what was the dose for past C/B/N releases (e.g., Chernobyl in World War I)? For planning analysis, what are the typical impacts of expected C/B/N release scenarios? Experience shows that transport and dispersion research is driven by major events or step-changes rather than long-term planning. Examples of major events are the use of CB agents in World Wars I and II, the nuclear tests of the 1950s, the 1968 Clean Air Act and its 1990 amendments passed by the U.S. Congress, the discovery of acid lakes in the 1970s, the discovery of the ozone hole in the 1980s, the Bhopal chemical accident, the Chernobyl nuclear plant accident, the Gulf war, and the Japanese subway chemical agent release.

The fundamental problem in any transport and dispersion exercise is that, no matter what model is used, the turbulence must somehow be parameterized. This has been a central theme of research over the past 80 years, beginning with Taylor (1922) and Richardson's (1926) and fundamental studies. Transport and dispersion model research was funded by C/B/N concerns for several decades (e.g., the Pasquill and Calder studies in the 1940s, 1950s, and 1960s, and the Porton Down and Prairie Grass field experiments in the 1950s). There were extensive classified studies in the United States, since there was a C/B/N offensive problem during the Vietnam War. Large field experiments were conducted in many types of geographic locations, such as urban areas (Fort Wayne) and coastal zones (Cape Canaveral and Vandenburgh Air Force Base). At the Department of Energy national labs and National Oceanic and Atmospheric Administration (NOAA), research was carried out in the 1950s and 1960s on models for nuclear releases, fallout, and source estimation.

Over the past 20-30 years, as a result of the Clean Air Act, the research emphasis switched to EPA pollutants (e.g., SO_2) and concerns (e.g., industrial point sources, mobile sources, acid rain, regional ozone precursors, particles and toxics). Many large EPA field experiments (e.g., the St. Louis Regional Air Pollution Study and the Complex Terrain Tracer Studies) took place, and model development efforts were conducted, leading to, for example, the Models-3 regional modeling system and the AMS/EPA Regulatory

Model (AERMOD). Many urban- to regional-scale field experiments have addressed the ozone issue and, more recently, fine particles and potentially toxic chemicals. The past five years have seen a switch back to Department of Defense (DOD) and Department of Energy (DOE), with most of the new model development and the new field experiments being supported with C/B/N concerns in mind.

The types of transport and dispersion models have evolved over the past 50-60 years, beginning with the analytical models (Gaussian, similarity, K) or nomograms used through the 1960s. In the 1970s, the focus switched to computer solutions of Gaussian plumes or of three-dimensional grid models involving the eddy diffusivity, K. In1980s, the Lagrangian puff models and one-dimensional Eulerian models were developed (but with few grid nodes). Gaussian models were adapted to account for Monin-Obukhov and convective similarity, and there were great advances in three-dimensional Eulerian models linked with numerical weather prediction models (e.g., the EPA's Models-3 system), and algorithms were improved in Gaussian-Lagrangian-puff models. So far in the 2000s, we have seen an increase in studies with computational fluid dynamics (CFD) models, in linked emissions-meteorology-dispersion-exposure-risk systems, and in improved algorithm in Gaussian-plume models for building downwash and for concentration fluctuations.

There always have been strong links between meteorology and transport/dispersion models. Early models used a single meteorological monitor for input (e.g., NWS airport site or on-site tower). In 1970s and 1980s, the meteorological models were reported, which interpolated among several observing sites and added a mass conservation constraint (e.g., Lawrence Livermore National Laboratory [LLNL] MATTHEW, EPA CALMET). In the 1990s, some methods were devised to accommodate numerical weather prediction (NWP) model outputs (although the grid was coarse and the NWP model could not be run in real time). In 2000s, the grid resolution of NWP models and computer speed has been improved, which have allowed real-time linked with NWP and dispersion models (e.g., RAMS or Eeta with HYSPLIT, MM5 with CMAQ as part of Models-3, Coupled Ocean/Atmosphere Mesoscale Prediction System (COAMPS) with National Atmospheric Release Advisory Capability (NARAC).

2.1.2 Dispersion models of air pollutant concentration

The atmospheric dispersion models are also known as atmospheric diffusion models, air dispersion models, air quality models, and air pollution dispersion models. Atmospheric dispersion modeling is the mathematical simulation of how air pollutants disperse in the ambient atmosphere. It is performed with computer programs that solve the mathematical equations and algorithms which simulate the pollutant dispersion. The dispersion models are used to estimate or to predict the downwind concentration of air pollutants emitted from sources such as industrial plants and vehicular traffic. Such models are important to governmental agencies tasked with protecting and managing the ambient air quality. The models are typically employed to determine whether existing or proposed new industrial facilities are, or will be, in compliance with the National Ambient Air Quality Standards (NAAQS) in the United States and other nations. The models also serve to assist in the design of effective control strategies to reduce emissions of harmful air pollutants.

The dispersion models require the input of data, which includes:

(1) Meteorological conditions such as wind speed and direction, the amount of atmospheric turbulence (as characterized by what is called the "stability class"), the ambient air temperature and the height to the bottom of any inversion aloft that may be present.

(2) Emissions parameters such as source location and height, source vent stack diameter and exit velocity, exit temperature and mass flow rate.

(3) Terrain elevations at the source location and at the receptor location.

(4) The location, height and width of any obstructions (such as buildings or other structures) in the path of the emitted gaseous plume.

Many of the modern, advanced dispersion modeling programs include a pre-processor module (e.g., AERMET, AERMAP) for the input of meteorological and other data, and many also include a post-processor module for graphing the output data and/or plotting the area impacted by the air pollutants on maps.

The technical literature on air pollution dispersion is quite extensive and dates back to the 1930's and earlier. One of the early air pollutant plume dispersion equations was derived by Bosanquet and Pearson (1936). These equations did not assume Gaussian distribution, nor did include the effect of ground reflection of the pollutant plume.

Sutton (1947) derived an air pollutant plume dispersion equation, which did include the assumption of Gaussian distribution for the vertical and crosswind dispersion of the plume, and also included the effect of ground reflection of the plume.

Under the stimulus provided by the advent of stringent environmental control regulations, there was an immense growth in the use of air pollutant plume dispersion calculations between the late 1960s and today. A great number of computer programs for calculating the dispersion of air pollutant emissions were developed during that period of time and they were called "air dispersion models" (US EPA, 2000). Various methods have been devised for the prediction of atmospheric pollution, which led to over 100 types of model for different applications (Cooper, 2001). The Gaussian air dispersion model, or its various segmented plume and puff advection progeny, is the most popular and widely adopted model in the world.

Gaussian distribution models can be use under many conditions, but when it is used in areas in different landform and meteorological conditions, its diffusion factors σ_y and σ_z are different. Therefore when the original type of Gaussian model is used in different area, its actual form is changed. But because of its applicability, it is widely used, and many models are base on this diffusion model.

The first-generation air quality model

In the first generation air quality models, it was assumed that the air pollutants in the atmosphere followed the Gaussian distribution. For example, an overhead continuous point source with an effective height of H_e (Figure 2.1), and the discharge load of pollutant in unit time is Q, in normal conditions the concentration of pollutant C (x, y, z) in a discretional point of the space (x, y, z) can be calculated by the following formula (Beychok, 2005):

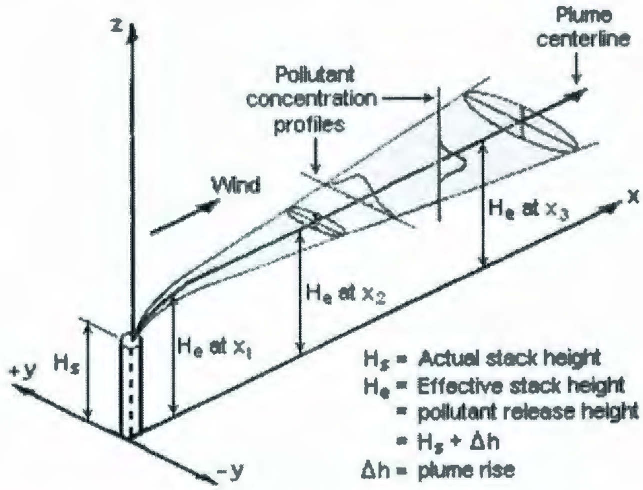


Figure 2.1 The diffusion of air pollution (Mbeychok, 2007)

$$C(x,y,z) = \frac{Q}{2\pi u \sigma_y \sigma_z} \exp\left[-\frac{y^2}{2\sigma_y^2}\right]\left\{\exp\left[-\frac{(z-H_e)^2}{2\sigma_z^2}\right] + \exp\left[-\frac{(z+H_e)^2}{2\sigma_z^2}\right]\right\} \tag{2.1}$$

Where, σ_y and σ_z are the diffusion parameters for the cross wind and vertical direction, in m, and u is the wind speed, m/s.

If the ground and the mixed top layer are considered as impermeable layer, the formula is changed by setting a virtual source:

$$C(x,y,z) = \frac{Q}{2\pi u \sigma_y \sigma_z} \exp\left[-\frac{y^2}{2\sigma_y^2}\right] \sum_{x \to +\infty}^{x \to -\infty} \left\{\exp\left[-\frac{(z-H_e+2nH_z)^2}{2\sigma_z^2}\right] + \exp\left[-\frac{(z+H_e+2nH_z)^2}{2\sigma_z^2}\right]\right\} \tag{2.2}$$

Where, H_z is the thickness of the mix top layer, and *n is* the refractive index.

Assume the origin of the coordinate is at the center of the stack, the positive direction of x axes is the downwind direction, y axes is crosswind, and the z axes vertically goes up.

Equation (2.2) is the basic arithmetic for the CRETER model developed by the US EPA. The diffusion parameters σ_y and σ_z are determined by the condition of the turbulent boundary layer. To confirm σ_y and σ_z, the stability can be divided into 6 types based on the wind speed and sunlight or cloud account according to the Pasquill's method, which are A to F degrees (Pasquill, 1961). Afterward, Turner (1964) presented a method for determining 1-7, or A-G stability categories from data that are routinely collected at National Weather Service (NWS) stations. The method estimates the effects of net radiation on stability from solar altitude (a function of time of day and time of year), total cloud cover, and ceiling height. From the end of the 70s and the beginning of the 80s, almost all environmental protection agencies in the world used this air quality model system.

The first-generation air quality model, no matter the point source model, or the line source, area source and cubic source which are based on the point source, all have the following two characters: 1) The calculation of concentration in horizontal and vertical direction are both used the Gaussian distribution assumption. 2) The classification of turbulent flow and diffusion parameter were based on the discretely experiential method. This is not only theoretically disobeying the turbulent character of the atmosphere boundary layer, but also disagrees with the research result of the turbulent diffusion in the end of 70s and the beginning of 80s, especially in the convective condition (US EPA, 2008).

Therefore, from the beginning of 1980s, many atmospheric diffusion scientists conducted many experiments, trying to develop models that were more agreeable to the monitoring result (Venkatram 1980, 1983; Misra 1982; Briggs 1985,1988; Hanna and Paine 1989; and Perry et al., 1994). From the beginning of the 1990s, many countries' environmental protection agencies started to support research institutions in developing a new generation of air quality model.

The second generation air quality model

From the middle of 1980s, researchers started to develop a new generation of air quality models to make the predictive result more agreeable to the distribution of pollutant under the convective condition.

These models had many new characteristics and the two most important ones which distinguished them with the first-generation air quality models are: 1) totally abandoned the traditional discrete Pasquill - Turner stability classification and Pasquill – Gifford diffusion parameter system; 2) Under the convective condition, the diffusion model did not use Gaussian arithmetic in calculating the pollutant concentration in the cross distribution. According to these rules, the Hybrid Plume Dispersion Model (HPDM) (Hanna and Paine, 1989) which was developed by the American Sigma company for the American electric power graduate school, and the Advanced Dispersion Modeling System (ADMS) (Carruthers et al 1995, CERC 1998), which was developed by the British Cambridge environmental consultative company, and the AMS/EPA Regulatory Model (AERMOD) (Cimorelli et al., 1998), which was developed by the AMS/EPA Regulatory Model Improvement Committee, are belonging to the second generation air quality model system. The OML system (Operationelle Meteorologiske Luftkvalitetsmodeller) (Berkowicz et al., 1993) which was developed by the Denmark National Environmental Laboratory, and the ISC model (EPA, 1995) which was developed by the US EPA, although they concluded many new achievements in the turbulent diffusion research of the atmospheric boundary layer, but they are only regarded as the transitional system from the first generation to the second generation. The OML system used the Gaussian model system under all the stability condition, which disagreed with the result of the turbulent diffusion for the convective mix layer in 80s, and the ISC model not only used Gaussian system, but also used the traditional Pasquill – Turner method in the stability classification (Willis and Deardorff, 1981).

After the 1990s, some European countries were very active in developing a new generation of air quality model. They had held many pro-seminars for the air quality model used for guideline. For example, in 1992, a pro-seminar was held in Denmark with the goal of developing a new generation used for short distance air diffusion. A number of American researchers cooperated to develop a model system AERMOD, which belongs to the second-generation and shows its greatest overall success in reproducing the concentration distributions for buoyant, tall-stack releases in moderate to complex topography (Perry et al., 2005).

Normally, the second generation air quality models have the following common characteristics:

1) The meteorological modules are all based on the conventional meteorological data, which includes wind speed at the height of 10 meters, temperature at the height of 1.5 or 2 meters, and cloud cover, etc. The characteristic parameters for the calculation of plume rise and diffusion, such frictional velocity u, Monin – Obukhov length L, mix layer thickness H_z, and turbulent parameter, can be calculated based on the conventional meteorological data (Poreh and Cermak, 1984).

2) New generation air quality models totally abandon the Pasquill – Gifford diffusion parameter system, therefore, it is unnecessary to classify the stability of the atmosphere boundary layer which only needs to be divided into stable and unstable, according to the positive of negative of the heat flux. Some model systems add a neutral condition to limit the instability between the superposition of the last two stabilities, but it is not necessary.

Normally, the diffusion parameters in the new system are calculated by uniform formulas:

$$\sigma_y = \frac{\sigma_v}{u} x f_y \left(\frac{x}{2uT_y} \right) \tag{2.3}$$

$$\sigma_z = \frac{\sigma_w}{u} x f_z \left(\frac{x}{2uT_z} \right) \tag{2.4}$$

Where, σ_v and σ_w refer to the standard deviation of the wind speed in the cross wind direction and vertical direction, which can be calculated based on the conventional meteorological data when there is a lack of monitoring data; u is the average wind speed in the boundary layer; T_y and T_z are the time integral measure in the cross wind direction and the vertical direction.

For the overhead plume of the thermal plant, normally the additional diffusion caused by the plume buoyancy should be considered.

3) New types of air quality models did not use the Gaussian distribution function when calculating the vertical concentration under the convective condition, instead of which, probability distribution function (PDF) is used (Li and Briggs, 1988). The normally used functions are the double Gaussian stack and the error function. For example, the HPDM model, the AERMOD model and the AQMS model in the convective condition use the double Gaussian stack for the contribution of direct source and indirect source: besides considering the contribution from the direct source and the indirect source, AERMOD and AQMS also consider the contribution from the penetration inversion layer, and the HPDM only considers the contribution from the direct source and the indirect source; another important difference is that the HPDM uses constants as the distributive and rise

coefficients in the double Gaussian part, and the AERMOD and AQMS use parameters (Yao, 1999).

Recently, new generation air quality models still use Gaussian distribution under the stable condition, but are different from the first generation models in dealing with the diffusion parameters, plume rise, and the penetration of the inversion layer.

Furthermore, most of the second generation air quality models include particular modules which are used in diffusion calculating under some special conditions, such as the inshore fumigator model, building shadow model, and complex landform model, etc. For example, in Stunder and SethuRaman's research (1986), the Misra or van Dop model was claimed to be the best model for the onshore fumigator model; Weil (2005) introduced a building shadow model based on the idea of PDF; Perry et al. (2005) developed a complex landform model CTMPLUS based on the Venkatram' theory, but this model has a complex calculating process, which made it not fit for being used as a guideline model. Therefore, AERMOD model system uses its basic idea, but more simple arithmetic. In recent decades, much advanced research has been done in the turbulent construction and diffusion character fields, so it is mature and advanced in the diffusion model under the convective condition, and is more agreeable with the monitoring data.

2.2 ENVIRONMENTAL RISK ASSESSMENT UNDER UNCERTAINTY

Environmental risk assessment is an essential element in decision-making process in order to minimize the effects of human activities on the environment. Unfortunately, environmental data often tends to be vague and imprecise, so uncertainty is associated with any study related with these kinds of data. Essentially, uncertainty in risk assessment may have two origins – randomness and vagueness. There are two main ways to deal with these uncertainties – probability theory and fuzzy logic. Probability theory is based on a stochastic approach, using probability functions to describe random variability in environmental parameters. Fuzzy logic uses membership functions and linguistic parameters to express vagueness in environmental issues. Reviews on the previous studies on these two approaches are presented below.

2.2.1 Overview of Environmental Risk Assessment and Existing Uncertainty

"Risk" is generally defined as the combination of hazard and vulnerability; hazard represents the probability that a potentially detrimental event of given characteristics occurs in a given area, for a time period; vulnerability is the degree of intrinsic weakness of the system (Varnes, 1984). "Risk assessment" is defined as the process of estimating the possibility that a particular event may occur under a given set of circumstances (Finizio and Villa, 2002). "Risk management" is the process whereby decisions are made about whether an assessed risk needs to be managed, and the means for accomplishing that management, for the protection of public health and environmental resources (Linthurst et al., 1995).

With the growing concern about the environment and the potential risks associated with many human activities and new technologies, there is increasing interest in environmental risk assessment, which is a critical, essential and the most important step of any decision making process. It provides a scientific, sound basis for assessing and ranking potential pollution of the environment, so the environmental risk due to anthropogenic activities is evaluated for the following mitigation of their impact on natural resources and in recreating the co-evolutionary process between human and natural components of the environment. Decision makers of ecological policy and management require sound scientific information on the environmental risk associated with many different activities in order to arrive at and to justify their decisions (Finizio and Villa, 2002), so there is a need to evaluate all potential risks that can cause environmental damage. The results of this environmental risk assessment should be effectively communicated to the decision makers and regulators to allow them to take the most appropriate decisions.

Uncertainty can be described as a lack of knowledge regarding the true value of a parameter (Schumacher et al., 2001). This concept often appears in modeling environmental systems, particularly in uncertainty concerning the data and the relations between the system components (Borri et al., 1998). As risk assessments have become important aids in the decision-making process for the management of sources of contamination, uncertainty with respect to the values of model parameters is of primary importance (Guyonnet et al., 2003). Generally, there are two sources of uncertainty affecting parameters in risk assessments: (1) randomness due to variability of phenomena, or because all factors affecting the system being studied cannot be modeled or fully understood; and, (2) incompleteness when there is simply a lack of information regarding parameter values. Insight about risks is limited by the randomness inherent in nature and the lack of sufficient information about the chances of a risk occurring and the potential consequences of such an occurrence. In some cases, extensive statistical data may be available and can contribute to an understanding of the frequency and the severity of the hazard. However, it is very common that environmental data is qualitative, vague or imprecise. As stated by Uricchio et al. (2004), incomplete information is notoriously common in environmental issues. The ideal way to address uncertainty due to randomness is to collect data and perform a statistical analysis. When information is incomplete or statistical data are not available, human experts can supply information on parameter values (Guyonnet et al., 2003). However, it is important to remember that the final decision of how to manage risk generally human relies on nature. This means that, apart from the results gathered in the risk assessment, social and cultural values, economic realities and political factors are borne in mind. Therefore, the randomness of the events and the role that human judgment plays in determining the risk and communicating its significance classify the uncertainties associated with risk in two broad categories (Destouni, 1992; Blair et al, 2001): stochastic (due to the randomness) and cognitive (due to the vagueness of expert's judgments). The proper management of these uncertainties has become a major concern in studies of environmental risk assessment (Kentel, 2007). In response, research is under way to explore techniques that can incorporate uncertainty and imprecision into the assessment process (Lein, 1992). It has been found from the literature review that, to accommodate these kinds of uncertainty, probability theory (i.e. Monte Carlo simuloation) for stochastic uncertainties and possibilistic theory (i.e. fuzzy logic) for cognitive uncertainties have been commonly used to accommodate uncertainties associated with risk-modeling inputs and outputs. In the probabilistic approach, probability distributions are used to describe random variability in parameters, while in the possibilistic or fuzzy-set approach, membership functions are used to characterize vagueness in human thought. The rationales behind these two approaches for dealing with uncertainty are different (Chen, 2000). The probabilistic approach is widely used when sufficient information is available for estimating the probability distributions of uncertain parameters, while the fuzzy-set method is well suited to dealing with uncertainties when little information is known (e.g., imprecise knowledge associated with human-language descriptions) (Li, 2007).

Although risk assessment has been a very common subject of discussion for many years, applications to the environmental field are quite recent. Traditionally, the probabilistic approach was the most used in risk assessment and considered appropriate to deal with the uncertainties of risk. But, when some experts realized that probabilistic models could fail to provide satisfactory descriptions of phenomena, applications of fuzzy logic started to be more common (Lein, 1992). Recently, some researchers have explored the possibility of carrying out environmental risk assessment by combining two different modes of representation of uncertainty (i.e. probabilistic and possibilistic theories) in a single computational procedure, known as the ''hybrid approach''. Follows are examples of these three approaches to the field of environmental risk assessment, especially for water resources and hazardous waste management.

2.2.2 Stochastic Risk Assessment

In groundwater risk assessment, a methodology to predict health risks to individuals from contaminated groundwater using probabilistic techniques was developed by Maxwell et al. (1999). This approach incorporated the elements of uncertainty and variability in geological heterogeneity, physiological exposure parameters, and cancer potency. A two-dimensional distribution (or surface) of human-health risk was generated as a result of the simulations. Passarella et al. (2002) developed an approach to assess the risk of groundwater quality degradation with regard to fixed standards, based on a probabilistic methodology, Disjunctive Kriging (DK), which allows one to evaluate the Conditional Probability (CP) of overriding a given threshold of concentration of a pollutant at a given time, and at a generic point in a considered groundwater system. The result of such investigation over the considered area was plotted in form of maps of spatial risk. By repeating this analysis at different times, several spatial risk maps were produced, one for each considered time. By means of non-parametric statistics, the temporal trend of the CPs was evaluated at every point of the considered area. The trend index, assessed by means of a sort of classification of the trend values obtained as described above, were superimposed on the most recent values of the spatial risk (i.e., the most recent values of probability). Consequently a classification of the risk of groundwater quality degradation results with which to weigh both the spatial distribution and the temporal behaviour of the probability to exceed a given standard threshold. The methodology was applied to values of nitrate concentration sampled in the monitoring well network of the Modena plain, northern Italy. This area was characterised by intensive agricultural exploitation and hog breeding along with industrial and civil developments. The influence of agriculture on groundwater resulted in a high nitrate pollution that limits its use for potable purposes.

In hazardous waste risk assessment, Batchelor et al. (1998) developed a stochastic risk-assessment model for a site contaminated with polychlorinated biphenyls (PCBs) by representing the modeling parameters as PDFs rather than single values. The PDF for total risk calculated by the model was approximately lognormal, although the PDF of parameters took on a variety of forms. A first-order approximation to the model provides good estimates for the high end of the distribution, which is of concern when conservative risk assessments are desirable. The first-order approximation provides good estimates even when the level of variation of the parameters is increased well above levels that are normally expected. A procedure was developed to apply the stochastic risk assessment model in a series of calculations to determine preliminary remediation goals for the site. In addition, a simplified technique was developed to calculate preliminary remediation goals using only results from simulating risk with initial site conditions. Draper et al. (1999) applied probability theory in risk assessments related to the underground disposal of nuclear waste. Six variables were required for such risk assessment (i.e. past data, future observables, scenario, and structural, parametric and predictive uncertainties). The developed model was applied to nuclear waste disposal using a computer simulation environment – GTMCHEM – which "deterministically" modeled the one-dimensional migration of radionuclide through the geosphere up to the biosphere. The incremental lifetime risks due to polychlorinated dibenzo-p-dioxins and dibenzofurans (PCDD/Fs) for the residents living in the surroundings of a municipal solid waste incinerator (MSWI) have been assessed by Schumacher et al. (2001) using Monte-Carlo simulation techniques. Two different pathways of exposure to PCDD/Fs, ingestion through the diet and exposure from MSWI emissions were compared. Monte-Carlo simulations were carried out to obtain variability and uncertainty propagation. The joint analysis of uncertainty and variability included a sensitivity analysis that identified the contribution to variance by different inputs. In general terms, PCDD/F ingestion through the diet contributed with more than 99% of the total risk, whereas direct exposition to PCDD/F emissions from the MSWI was less than 1%. The results show that the median (50% percentile) of non-carcinogenic risk due to PCDD/Fs in the population living in the surroundings of the MSWI was 0.72 and the ratio of the 95th percentile and fifth percentile was about 2. With respect to the total carcinogenic risk, the median increment in individual lifetime was 7.90×10^{-5}, while the ratio between the 95th percentile and the fifth percentile was about 1.5. In this analysis, a sequential structural decomposition of the relationships between the input variables has been used to partition the variance in the output (risk) in order to identify the most influential contributors to overall variance among them.

In the case of polluted sites, Labieniec et al. (1997) used PDFs to address uncertainty in estimating the risk of human exposure due to the presence of contaminated land. They performed an evaluation of the uncertainty in predicted carcinogenic risk resulting from uncertainty in site properties and fate and transport predictions for a simple contaminated soil site. SoilRisk, a risk model for organic contaminants in soil, was applied to a case-study and a thin, near surface, unconfined aquifer. The site-related parameters found to affect predicted risk most significantly were the soil-water volumetric flux rate (J_w) in the unsaturated zone, the longitudinal dispersivity (α_L) and the Darcy velocity (V_d) in the saturated zone, and the soil organic carbon fraction in both zones (foc, foc_{sat}). Model runs using PDFs for these input parameters yielded cumulative distribution functions (CDFs) for the total risk estimates, the shape and location of which depended on the chemical and exposure scenario. In general, uncertainty in risk at the case-study site was found to be greater for the more mobile and less degradable of the chemicals (e.g., trichloroethylene (TCE) and chlordane) than for benzene, which is highly degradable, and benzo[α]pyrene(BaP), which is very immobile in the subsurface. Ma (2000) presented a methodology for incorporating uncertainty and variability into a multi-medium, multipathway, multi-contaminant risk assessment, and for placing this assessment into an optimization framework to identify optimal management strategies. The framework was applied to a case study of a sludge-management system proposed for North Carolina and the impact of stochasticity on selection of an optimal strategy was considered. Different sets of decision criteria reflecting different ways of treating stochasticity are shown to lead to different selections of optimal management strategies.

Such probabilistic methods are really effective when the information and the environmental data are available. However, in some cases, they can fail to model the environmental parameters, especially when these do not have really defined boundaries. In this situation, assigning PDFs to the parameters of the risk equation may not be the best option and using fuzzy logic may be better.

2.2.3 Fuzzy Risk Assessment

In groundwater risk assessment, Dahab et al. (1994) introduced a rule-based fuzzy-set approach to risk analysis of nitrate-contaminated groundwater. The developed method was used to assist decision makers in estimating human health risks corresponding to a particular nitrate dose to humans and in determining whether regulatory action must be taken to reduce the health risks. A case in a community with a nitrate water quality problem was employed to illustrate the method. The uncertainty associated with assessing health risks of nitrate and its impact on results are represented by using a fuzzy-set approach and incorporated into the nitrate risk assessment. Therefore, a nitrate risk assessment can be made that is more realistic and appropriate than the one made without taking uncertainty into account. Uricchio et al. (2004) proposed a decision support system, based on fuzzy logic, for groundwater pollution risk evaluation. It provided information on the environmental impact of anthropogenic activities by examining their effects on groundwater quality. The combined value of both intrinsic vulnerability of a specific local aquifer were used, which were obtained by implementing a parametric managerial model (SINTACS), and a degree of hazard value, which takes into account specific human activities. Incomplete information is notoriously common in environmental planning. To overcome this deficiency the researchers applied a qualitative approach based on expert judgment incorporated into the system's knowledge base. The decision support system took into account the uncertainty of the environmental domain by using fuzzy logic and evaluates the reliability of the results according to information availability. This tool was conceived as a useful planning tool for decision makers involved in the management of sustainable use of natural resources.

In contaminated site risk assessment, the evaluation of the risk of polluted sites through fuzzy logic was studied by Lehn and Temme (1996). A model to assess the risk of a contaminated site for the environment, in particular human health, was developed. As claimed by the researchers, the unsuitability of formal risk analysis methods and various sources of incompleteness, uncertainty and vagueness of the whole research field motivated the use of fuzzy methods, and in particular the use of fuzzy classification providing a rough ranking method. Feature generation, the other main part of the approach, allowed selecting, valuating and tuning the properties of the sites in such a way to ensure an optimal classification. For maximizing the expressive power of the system's results, it would be able to compromise between a detailed survey of a site and an easy to survey representation of a site with resulting loss of information caused by a certain a priori aggregation of properties. This estimation of the risk served as a basis for a decision-making tool (i.e. whether further steps with respect to that site needed to be taken). The information obtained from the sites suspected of being contaminated was incomplete, uncertain or vague. For this reason, the use of fuzzy logic was approved appropriate in this study. Mohamed and Cote (1999) reported another study on risk assessment of contaminated sites. A decision analysis based model (DAPS 1.0, Decision Analysis of Polluted Sites) was developed to evaluate risks that polluted sites might pose to human health. In the developed model, exposure pathways were simulated via transport models (i.e. groundwater transport model, runoff-erosion model, air diffusion model, and sediment diffusion and resuspension model). Quantitative estimates of health risks arised from ingestion of and dermal contact with polluted water and soil, as well as through inhalation of polluted air were evaluated for both carcinogenic and non-carcinogenic pollutants. Being very heterogeneous, soil and sediment systems were characterized by uncertain parameters. Concepts of fuzzy set theory were adopted to account for uncertainty in the input parameters which are represented by fuzzy numbers. An inference model using fuzzy logic was also constructed for reasoning in the decision analysis.

Fuzzy risk assessment approaches were also applied to other areas such as river quality, soil/agriculture management, etc. For example, the risk of brominated flame retardants (BFRs) on aquatic organisms was studied by Darbra et al. (2007), where a preliminary risk-assessment model was developed to support decision making for the management of releases of these lipophilic substances in rivers. In water quality management, McKone and Deshpande (2005) considered how fuzzy logic and fuzzy arithmetic could be applied to risk assessment and environmental policy and presented a case study in the Ganges River in India. Mays et al. (1995) presented a methodology to demonstrate how fuzzy soil interpretations provided a realistic approach to decision-making for risk-based soil interpretations. Fuzzy logic was used to characterize uncertainty in soil information so that a risk-based method of soil interpretations could be implied. For agriculture, Van der Werf and Zimmer (1998) proposed a fuzzy expert system to calculate an agro-ecological indicator "IPEST" which could reflect an expert perception of the potential environmental impact of the application of a pesticide in a field crop. The practical implementation of the expert system and its validation are discussed. The system is flexible and can be tuned to expert perception, it can be used as a decision aid tool to rank or choose between alternative pesticide application options with respect to their potential environmental impact. Results of a sensitivity analysis of module and this impact was calculated through the analysis of the risk of three major compartments (i.e. groundwater, surface water and air) scores for some pesticide application cases are presented. Lein (1992) calculated the environmental risk from a hazardous waste facility using fuzzy logic to assess the risk and performance of high-level radioactive waste repositories. The aim of the study was to produce a geographic expression of the concept ''safe distance'' using fuzzy reasoning when applied to the problem of sitting a hazardous facility. For releases of ecotoxic substances in chemical plants, Darbra et al. (2008) presented a fuzzy-logic methodology to assess the risk of such releases. This method was based on the assessment of three macrovariables (i.e. the hazardousness of the substance, the vulnerability of the site and the level of preventive and protective measures). With this information, it was possible to obtain a final assessment of the risk of ecotoxic substances released from the chemical plants in the Piedmont Region of Italy.

The flexibility of fuzzy logic to express results in a natural language, in line with human reasoning, together with the possibility of dealing with uncertainties makes it highly recommended as a tool for use in communicating risk. However, the subjectivity involved due to human judgment can make one think that probabilistic methods, based on calculations, are more reliable. A combined approach may therefore be the best solution to deal with the uncertainties.

2.2.4 Hybrid Risk Assessment

There are also some hybrid applications to groundwater risk assessment. Chen et al. (2003) developed a hybrid fuzzy-stochastic risk assessment (FUSRA) approach for examining uncertainties associated with both source/media conditions and evaluation criteria in a groundwater quality management system. In this study, a number of tasks were undertaken, including Monte Carlo simulation for the fate of contaminants in subsurface, examination of contamination levels based on the simulation results, quantification of evaluation criteria using fuzzy membership functions, and risk assessment based on the combined fuzzy/stochastic inputs. The developed FUSRA was applied to a petroleum-contaminated groundwater system in western Canada, indicating that, with the expanded evaluation dimensions; the FUSRA can more effectively elucidate the relevant health risks and provide support for related remediation decisions. Guyonnet et al. (2003) proposed an approach combining Monte-Carlo random sampling of PDFs with fuzzy calculus. The approach was applied to a real case of estimating human exposure, via vegetable consumption, to cadmium present in the surface soils of an industrial site located in the north of France. Kentel and Aral (2004 and 2005), combined the fuzzy-set theory together with probability theory to incorporate uncertainties into the health-risk analysis due to exposure to contaminated waters. Based on the form of available information, a combination of fuzzy sets and probability functions were generated to incorporate parameter uncertainty and variability into mechanistic risk-assessment models. Vemula et al. (2004) presented a methodology for evaluation of risk for a river water quality management problem. A fuzzy waste load allocation model was solved with a simulation–optimization approach for obtaining optimum fractional removal levels for the dischargers to the Tunga–Bhadra River in southern India. Monte-Carlo and fuzzy-logic approaches were used to treat the variables. With the help of fuzzy membership functions defined for the fuzzy risk of low water quality and frequency distributions of key random variables using Monte Carle simulation, fuzzy risk levels are computed at the key checkpoints (identified by sensitivity analysis and first-order reliability analysis under optimal fractional removal levels). Recently, Li et al. (2007) developed an integrated fuzzy-stochastic risk-assessment (IFSRA) approach to assess the risk associated with groundwater contamination by xylene. This model systematically quantified both probabilistic and fuzzy uncertainties associated with site conditions, environmental guidelines, and healthimpact criteria. The contaminant concentrations in groundwater predicted from a numerical model were associated with probabilistic uncertainties due to the randomness in modeling-input parameters, whereas the consequences of contaminant concentrations violating relevant environmental quality guidelines and health evaluation criteria were linked with fuzzy uncertainties. However, for the development of this integrated approach, the involved cases and uncertainties were limited (e.g., subsurface environment), which is calling for much more further study.

2.3 SUMMARY

The recent development in air dispersion modeling, uncertainty issues and risk assessment approaches, are presented and discussed in this chapter.

It was found that in the past decades, many research efforts have been made in numerical simulation, uncertainty analysis, and risk assessment for problems associated with environmental contamination. When talking about environmental risk assessment, uncertainty cannot be left out as a parameter. It is inherent to any environmental system and it has two main origins: randomness of the system and lack of environmental data. Bearing this in mind, environmental parameters involved in risk assessment should be defined. However, they do not all have the same behavior and uncertainties associated. There exist two main ways to deal with such uncertainties: probability theory and fuzzy logic. Applications of both approaches can be found in the literature, and even a combination of the two techniques is starting to attract further interest. The hybrid approach is based on the nature of the parameters, because some of the parameters are best suited to involve PDFs, while others, based on linguistic expressions, are better expressed with fuzzy numbers. The most important output from risk assessment is the capacity to provide the basis of a decision-making process. The results of such decisions should be presented to the environmental managers and public in plain language and in line with the way humans think, rather than as difficult numbers or calculations. As a result, the inherent complexities in problems provide an adequate reason for a focused effort to more in-depth and effective uncertainty analysis and risk assessment. However, for the development of this integrated approach, the involved cases and uncertainties were limited (as far as I know, e.g., limited to subsurface environment), which is calling for much more further study on other uncertainties and environmental systems. The ambient air quality management system, which is essential to our daily life and plays significant role in the sustainable development, need to be considered for applying the in-depth risk assessment approach (i.e., hybrid risk assessment). In this research, the integrated fuzzy-stochastic method will be developed and applied in a real case study of the risk assessment of ambient air quality. This effort will help in accurately predicting the contaminant transport and fate in the ambient air and effectively assess the associated environmental and health risks. The results obtained from the improved simulation, uncertainty analysis and risk assessment will provide more realistic decision support and bring enormous environmental and economic benefits.

CHAPTER 3 MODELING OF AMBIENT AIR QUALITY

3.1 METHODOLOGY

In this study, air dispersion modeling of air pollutant emission from stacks will be conducted using AMS/EPA Regulatory Model (AERMOD), ISC-AERMOD View (Version 5.1), provided by Lakes Environmental Software. AERMOD is one of the most up-to-date and widely recognized software utilized for air dispersion modeling of short-range dispersion from stationary sources. It includes a wide range of options for air quality modeling, applicable to rural and urban areas, flat and complex terrain, surface and elevated releases, and multiple sources (including, point, area and volume sources), making it a popular choice among the modeling community for a variety of applications.

AERMOD was developed by the AMS/EPA Regulatory Model Improvement Committee (AERMIC), a collaborative working group of scientists from the AMS and the EPA (Cimorelli, 1998) and specially designed to support the EPA's regulatory modeling programs. It is a regulatory steady-state plume modeling system with three separate components: AERMOD (Dispersion Model), AERMAP (Terrain Preprocessor), and AERMET (Meteorological Preprocessor). Following provides a general overview of this model.

3.1.1 Model Overview

In the stable boundary layer (SBL), the concentration distribution is assumed to be Gaussian in both the vertical and horizontal. In the convective boundary layer (CBL), the horizontal distribution is assumed to be Gaussian, but the vertical distribution is described with a bi-Gaussian probability density function (PDF). This behavior of the concentration distributions in the CBL was demonstrated by Willis and Deardorff (1980) and Briggs (1993). Additionally, in the CBL, AERMOD treats "plume lofting," whereby a portion of plume mass, released from a buoyant source, rises to and remains near the top of the boundary layer before becoming mixed into the CBL. AERMOD also tracks any plume mass that penetrates into elevated stable layer, and then allows it to re-enter the boundary layer when and if appropriate (USEPA, 2004).

AERMOD incorporates, with a new simple approach, current concepts about flow and dispersion in complex terrain, where appropriate the plume is modeled as either impacting and/or following the terrain. This approach has been designed to be physically realistic and simple to implement while avoiding the need to distinguish among simple, intermediate and complex terrain, as is required by present regulatory models. As a result, AERMOD removes the need for defining complex terrain regimes; all terrain is handled in a consistent and continuous manner that is simple while still considering the dividing streamline concept in stably-stratified conditions (Snyder, 1985).

One of the major improvements that AERMOD brings to applied dispersion modeling is its ability to characterize the planetary boundary layer (PBL) through both surface and mixed layer scaling. It constructs vertical profiles of required meteorological variables based on measurements and extrapolations of those measurements using similarity (scaling) relationships. Vertical profiles of wind speed, wind direction, turbulence, temperature, and temperature gradient are estimated using all available meteorological observations. AERMOD can be run with a minimum of observed meteorological parameters. As a replacement for the ISC3 model AERMOD can operate using data of a type that is readily available from a National Weather Service (NWS) stations. It requires only a single surface (generally, 10 m) measurement of wind speed (between 7 z_0 (surface roughness length) and 100 m), direction and ambient temperature. Like ISC3, It also needs observed cloud cover. However, if cloud cover is not available (e.g. from an on-site monitoring program) two vertical measurements of temperature (typically at 2 and 10 m), and a measurement of solar radiation can be substituted. It also requires the full morning upper air sounding to calculate the convective mixing height throughout the day. In addition, it needs surface characteristics (surface roughness, Bowen ratio, and Albedo) in order to construct its PBL profiles. Unlike existing regulatory models, AERMOD accounts for the vertical inhomogeneity of the PBL. This is accomplished by "averaging "the parameters of the actual PBL into "effective" parameters of an equivalent homogenous PBL. Figure 3.1 shows the flow and processing of information in AERMOD.

The modeling system consists of one main program (AERMOD) and two pre-processors (AERMET and AERMAP). AERMET uses meteorological data and surface characteristics to calculate boundary layer parameters (e.g. mixing height, friction velocity, etc.) needed by AERMOD. The data is representative of the meteorology in the modeling domain. The meteorological INTERFACE, internal to AERMOD, uses these parameters to generate profiles of the needed meteorological variables. In addition,

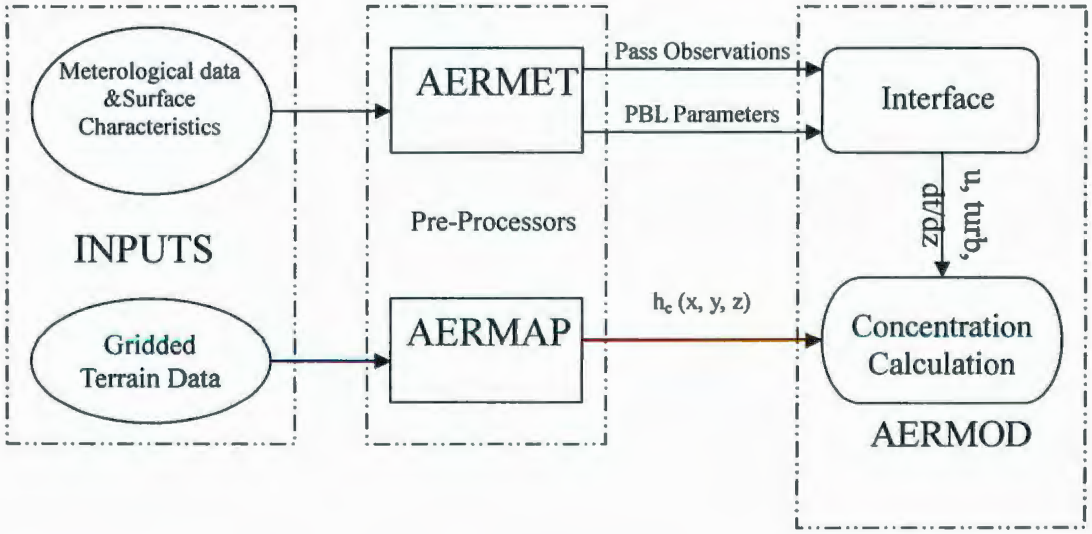


Figure 3.1 Data Flow in the AERMOD Modeling System
(adapted from USEPA, 2004)

AERMET passes all meteorological observations to AERMOD. Surface characteristics in the form of Albedo, surface roughness and Bowen ratio, plus standard meteorological observations (wind speed, wind direction, temperature, and cloud cover), are input to AERMET. AERMET then calculates the PBL parameters: friction velocity (u_*), Monin-Obukhov length (L), convective velocity scale (w_*), temperature scale (t_*), mixing height (z_i), and surface heat flux (H). These parameters are then passed to the INTERFACE (which is within AERMOD) where similarity expressions (in conjunction with measurements) are used to calculate vertical profiles of wind speed (u), lateral and vertical turbulent fluctuations (σ_v, σ_w), potential temperature gradient (dt/dz), potential temperature (t), and the horizontal Lagrangian time scale (T_{Ly}).

AERMAP uses gridded terrain data for the modeling area to calculate a representative terrain-influence height (h_c) associated with each receptor location, which is also referred to as the terrain height scale. The terrain height scale, which is uniquely defined for each receptor location, is used to calculate the c dividing streamline height. The gridded data is supplied to AERMAP in the format of the Digital Elevation Model (DEM) data from the United States Geological Survey (USGS). The terrain preprocessor can also be used to compute elevations for both discrete receptors and receptor grids. The elevation for each specified receptor is automatically assigned through AERMAP. For each receptor, AERMAP passes the following information to AERMOD: the receptor's location (x_r, y_r), its height above mean sea level (z_r), and the receptor specific terrain height scale (h_c).

There are comprehensive description of the basic formulation of the AERMOD dispersion model including the INTERFACE, AERMET, and AERMAP (U.S.EPA, 2004; Prater and Midgley, 2006; Brode, 2006).

3.1.2 AERMOD vs ISC3

With the exception of applications involving wet and dry deposition, AERMOD serves as a replacement for Industrial Source Complex Model Version 3 (ISC3) (Paine et al., 1998). Although performance evaluations have shown models such as ISC3 to be relatively unbiased, these evaluations have not included all situations in which ISC3 is used. For those situations where the model has not been evaluated, confidence in its predictive abilities is related to how well its underlying scientific assumptions are satisfied. For example, ISC3's reliance on the Pasquill-Gifford (PG) dispersion curves limits our confidence in applying the model to elevated releases. AERMOD's improved theoretical basis will greatly increase the confidence in its application, particularly in situations where the models have yet to be evaluated (Durham, 2006).

Industrial Source Complex Model Version 3 (ISC3):

ISC3 (EPA, 1995) is recommended in EPA's Guideline on Air Quality Modeling for applications to refinery-like sources and other industrial sources in simple terrain. It is a straight line trajectory, Gaussian-based model that has evolved for over two decades. It is typically used with a minimum of requirements for meteorological input data (e.g., nearest NWS airport wind speeds and directions, ceiling heights, cloud cover, and Pasquill-Gifford stability class for each hour). ISC3 is generally run with a sequence of hourly meteorological conditions to predict concentrations at receptors for averaging times of one hour up to a year. In some applications, many years of hourly data are used as inputs to develop a better understanding of the statistics of calculated short-term hourly peaks or of longer time averages. ISC3 contains detailed sets of algorithms to handle building downwash, deposition of particles, and area and line source releases. The major advantages of ISC3 over AERMOD are its relative simplicity of use and its robust predictions (i.e., the same results are obtained by different users for the same scenario). The amount of meteorological input data required by ISC3 is relatively small, and the model can be run sequentially with routinely collected NWS airport data. For a single meteorological condition for a passive pollutant, the meteorological data needed are a single wind speed, a wind direction, a stability class determination, and an assumed mixing depth. Terrain elevations at receptor points, building dimensions in addition to emissions and stack parameters are also needed. The disadvantages of ISC3 are largely associated with the fact that an improved knowledge of the structure of the atmospheric boundary layer and resulting estimations of turbulent dispersion processes cannot be accommodated in the model.

AMS/EPA Regulatory Model (AERMOD):

AERMOD is being proposed as a replacement for ISC3 for many applications, and has been built on the framework of ISC3 (Cimorelli et al., 1998). It retains the single straight line trajectory limitation of ISC3 but contains advanced algorithms to describe turbulent mixing processes in the planetary boundary layer for both convective and stably stratified layers. It also includes a detailed treatment of the dynamics of plumes that rise to interact with elevated inversions at the top of the convective mixed layer. AERMOD also offers new and potentially improved algorithms for plume rise and buoyancy, and the computation of vertical profiles of wind, turbulence and temperature. It is able to address complex terrain above stack release heights and incorporate improved algorithms (over ISC3) for building downwash and deposition processes.

Comparisons of Technical Components:

The scientific review of the technical documents AERMOD (Cimorelli et al., 1998) suggests that many of its components are based on similar sets of state-of-the-art algorithms (e.g., it assumes the bimodal distribution of turbulent vertical velocities for convective conditions). On the other hand, ISC3 represents the typical Gaussian "workhorse" model that has been in wide use for 30 years (EPA, 1995). The downwash algorithm in AERMOD is unchanged from that in ISC3. Because several of the components of AERMOD are relatively new, it would appear to be wise to carry out a series of sensitivity tests with a wide range of source and meteorological and terrain conditions, in order to be sure that the solutions are robust. ISC3 requires a determination of whether the area surrounding a facility is either rural or urban, thus establishing the set of horizontal and vertical dispersion curves (Pasquill-Gifford for rural or McElroy-Pooler for urban). There are no intermediate or other dispersion rates used. AERMOD can include surface conditions such as soil moisture (via Bowen Ratio), surface Albedo (for net radiation estimations), and the surface roughness length. Surface roughness affects the vertical profiles of wind and temperature and the dispersion rates in the surface layer, and is an important variable in assessing dispersion in the vicinity of refineries and other industrial sites. ISC3 uses routine meteorological data to calculate the height of the well-mixed layer. For plume rises less than the mixing-height, the plume is "trapped" and continues to mix within the layer by the use of reflection concepts. For plume rises above the mixing-height, the plume can no longer diffuse to the ground. AERMOD include algorithms which quantify partial penetration of an elevated plume. The amount that is left to diffuse to the ground depends upon the strength of the inversion and the plume buoyancy. This parameterization is important for very buoyant plumes or for moderately buoyant plumes interacting with relatively low level inversions. To sum up, AERMOD currently contains new or improved algorithms for: 1) dispersion in both the convective and stable boundary layers; 2) plume rise and buoyancy; 3) plume penetration into elevated inversions; 4) computation of vertical profiles of wind, turbulence, and temperature; 5) the urban boundary layer; and 6) the treatment of receptors on all types of terrain from the surface up to and above the plume height.

3.2 MODELING APPLICATION

SO_2 is one of the primary components of ambient air pollution. SO_2 emissions from power plants react with other chemicals in the atmosphere to form sulfate particles, an important contributor to the fine particle mix that circulates with the air we breath. These fine particles can be inhaled more deeply into the lungs than larger particles, and are linked to a number of serious human health problems, particularly among children, the elderly, and individuals with pre-existing cardiovascular or lung diseases (e.g., asthma). These health effects include premature death, increased respiratory symptoms and disease, decreased lung function, alterations in lung tissue and structure, and changes in respiratory tract defense mechanisms; SO_2 emissions are also a major contributor to acid deposition, commonly known as "acid rain," which can result in harm to fish and other aquatic life, forests, crops, buildings, and monuments; Fine particles formed from SO_2 emissions also are significant contributors to poor visibility at scenic panoramas across North America because the particles efficiently scatter natural light, thus creating hazy views. Most of the anthropogenic sulfur inputs to the atmosphere are due to the emission of SO_2 as a consequence of burning fossil fuels. Coal and oil both contain varying concentrations of sulfur, with the result that power plants create SO_2 when burning these fuels.

In this study, AERMOD is applied for modeling SO_2 emission from the Holyrood thermal electric generating station in Newfoundland. The pollutant concentrations from the modeling result can then sustain risk assessment in the next chapter.

3.2.1 Overview of the Study Site

The Holyrood Thermal Generating Station is owned and operated by Newfoundland and Labrador Hydro. It is located on the Avalon Peninsula near the southern tip of Conception Bay approximately 48 meters south west of St. John's, Newfoundland, Canada (Figure 3.2).

The initial installation of the power plant started in 1969 included two generating units each capable of producing 150 megawatts (MW) which are propelled by steam heated by two large oil burning furnaces to provide a reserve back-up to the hydropower system.

Figure 3.2 Location of the Holyrood electrical thermal power station
(after Wikipedia, 2008; Google Earth, 2008)

The Bunker 'C' oil used in the plant to keep the furnaces going is delivered by shuttle tankers to the marine terminal constructed as part of the project. In a thermal generating station, fuel is burned in a boiler to convert water to steam. The high-pressure steam is directed into a turbine that is connected to an electrical generator that produces electricity as it turns. A seawater condenser is used for cooling the spent steam from the turbine, converting it back to water that is reused in the boiler. Holyrood uses over 250,000 liters per minute of seawater for cooling on each unit and 900,000 liters per day of freshwater for make-up purpose (NFLD Hydro, 2005). The plant generators operate at 16,000 volts and 7,000 amperes transformed up to 230,000 volts for transmission on the island grid to all parts of the system. In a single year, the Holyrood Generating Station has the capacity to generate over four billion units of power, about 30 to 40% of the island's total requirement which is equivalent to over 3 billion units of power (NFLD Hydro, 2005). There is no air pollution control on these stacks. However, recently combustion technology improvements have been made to burn fuel more efficiently (NFLD Hydro, 2005).

More than 100 people work at Holyrood. Many of the employees live in the Holyrood/Conception Bay South area. Newfoundland and Labrador Hydro's Holyrood Thermal Generating Station is an essential part of the province's generating system. The plant burns bunker "C" oil at the rate of approximately 6,000 barrels (1,000 m^3) per day, per unit at full load to produce steam at 1000 degrees Fahrenheit (540 degrees Celsius) and 13,000 kPa at a rate of over 500 megagrams per hour (NFLD Hydro, 2005). Burker "C" oil is thick, viscous, and hard to degradable by natural process. Because of its low price, it has been used as the fuel in the boiler. As the island load increased, a third unit rated at 150 MW was added in 1979 to increase the output to 450 MW and Holyrood became a major source of energy for the province. In 1988-89 the original two first stage units were each upgraded to a capacity of 175 MW. The total generating capacity for Holyrood is currently 490 MW.

The Holyrood thermal generating station is located in a rural and mostly residential area. The hilly topography around the thermal station is complex and air concentrations resulting from facility emissions can be affected by the complex terrain as well as sea breezes (Jacques Whitford Environment Limited (JWEL), 2003a; 2004a). The dominant winds have been reported to be from the south to southwest with north-easterly winds being important as well (JWEL, 2003a). The strongest winds tend to occur most often from the south and southwest (JWEL, 2004a). Additional information on the meteorological conditions in the vicinity of the HTGS can be found in JWEL (2003a; 2004a).

3.2.2 Ambient Air Dispersion Modeling

This study assessed the air quality impacts by portraying the plume dispersion pattern and estimated the ground-level concentrations of the SO_2 by applying AERMOD air dispersion model.

Gathering and combination of baseline data

Source Parameters:

There are three units in the plant, Units 1 to 3. As illustrated above, Unit 1 and Unit 2 were set up in 1969, and Unit 3 was set up in 1979. There were tests done in 2001, 2003, and 2005 for the units (NFLD Hydro., 2005). The datasets were provided by the Newfoundland & Labrador Hydro (2005). The stack gas exit velocity could be calculated by Equation 3.1:

$$v = \frac{Q}{0.25\pi D^2} \times \frac{1}{3600} \tag{3.1}$$

Where: v = Stack gas exit velocity, m/s; Q = Gas Flow, m^3/h; D = Stack diameter, m.

The emission datasets and gas exit velocity were inputs to the Source pathway in the AERMOD model (Table 3.1).

Terrain data:

U.S. Geological Survey Digital Elevation Models (USGS DEM) were used in this study, the projection for the data was Universal Transverse Mercator (UTM), the zone was 22 (54° W - 48° W – Northern Hemisphere), and the Datum was World Geodetic System 1984 (WGS84). The size of the modeling domain was 24 km by 24 km with the boundary shown in Table 3.2.

The data was processed by the AERMAP terrain data preprocessor in the model. The contour map and the location of three stacks are provided in Figure 3.3.

Meteorological data:

Two kinds of hourly meteorological data were used in the study, one was the surface data, and the other was the upper air data, and obtained from Environmental Canada (2006).

Table 3.1 Source data inputs for SO_2

Source Type:	**Source ID:**								
Point	Stack1			Stack 2			Stack 3		
Source Location									
X Coordinate(m)	341888			341911			341939		
Y Coordinate(m)	5257701			5257686			5257767		
Base Elevation(m)	0			0			0		
Release Height Above Ground(m)	91.4			91.4			109.8		
Source Release Parameters									
Emission Rate (g/s)		2005			2003			2001	
	Stack1	2	3	1	2	3	1	2	3
	312	440	297	429	426	424	393	381	296
Stack Gas Exit Temperature(k)	452			443			443		
Stack Gas Exit Velocity (m/s)	10.8			11.1			15.9		
Stack Inside Diameter at Release Point(m)	4.1			4.1			3.0		

Table 3.2 Boundary of the modeling domain

in longitude and latitude (^{o})	E		W	
S	47.3152084	53.9305038	47.3093948	53.2491931
N	47.5319366	53.9384460	47.5260811	53.2584038
in Coordinates (m)	E		W	
S	354100.006	5242000.00	330000.000	5242000.00
N	354100.006	5266100.10	330000.000	5266100.10

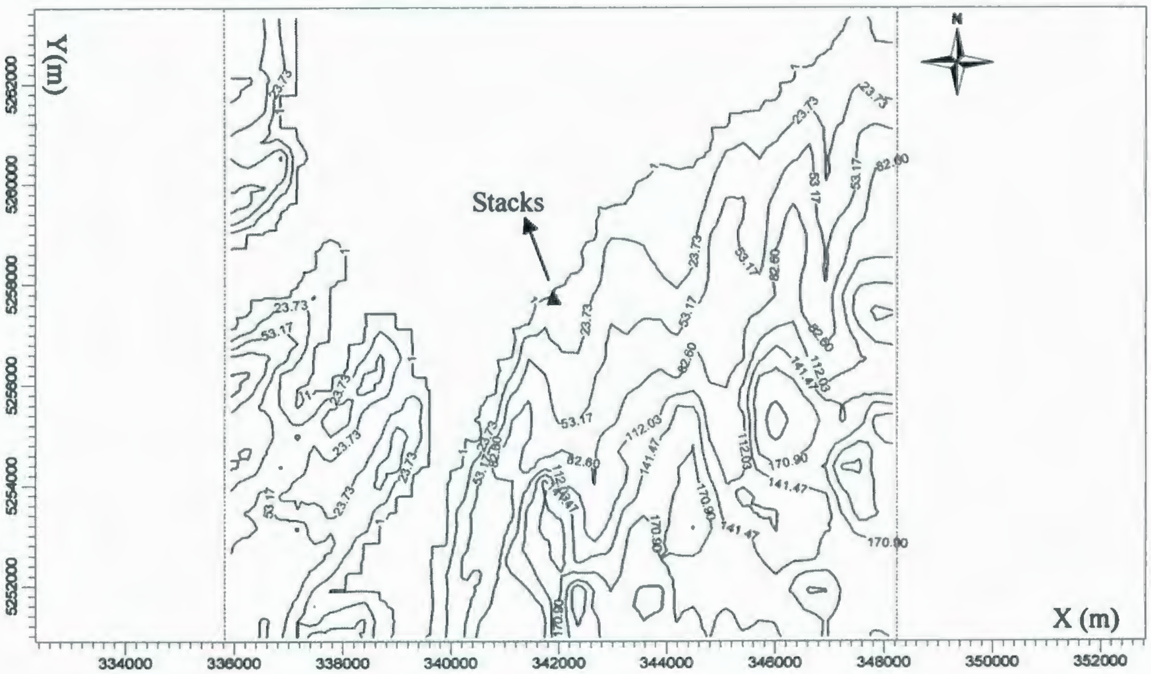


Figure 3.3 The contour map of the modeling domain and stacks location
(in coordinaters)

The weather station is located in St John's airport in Newfoundland (Climate ID: 8403506 for surface data and 14531 for upper air data; location: Latitude 47.62 N and Longitude 53.74 W; Elevation: 140.5 m.)

The meteorological data used for the analysis period ranged from 2000 to 2006.

AERMET is the meteorological data pre-processor used for AERMOD model. The surface data needed for the modeling are summarized in Table 3.3.

Besides, AERMET uses the surface data and the mixing height estimator to figure out the mixing height. The upper air data was in FSL format. Part of the data for both the surface information and upper air meteorological information from 2000 to 2006 obtained from Environmental Canada could be found in Appendices I and II .

There are two output documents from AERMET which are needed by AERMOD, the pre-processed surface met data file and the profile met data file (Table 3.4).

Receptor:

Uniform Cartesian grids were used for covering the 441 receptors set in the project. The spacing of each grid was 1,140 m by 1,140 m.. The receptor setting is shown in Figure 3.4.

3.2.3 Result and discussion

Based on the meteorological data, terrain data, and the source data, AERMOD was processed. Since the buildings around the stacks are most residential houses, which are much lower than the stacks, there was no need to apply the ISC-PRIME (Plume Rise

Table 3.3 Input surface meteorological data
(USEPA, 2002)

Parameter	Unit
Year	Not applicable
Month	Not applicable
Day	Not applicable
Hour	Not applicable
Opaque Cloud cover	Tenths
Dry bulb temperature	deg C
Relative humidity	%
Station pressure	mb
Wind direction	deg
Wind speed	m/s
Ceiling height	m
Hourly precipitation amount	Hundredths of inches
Global horizontal radiation	wh/m^2

Table 3.4 AERMET output meteorological data (USEPA, 2002)

Parameter	Unit
Year	Not applicable
Month	Not applicable
Day	Not applicable
Hour	Not applicable
Sensible heat flux	W/m^2
Surface friction velocity	m/s
Convective velocity scale	m/s
Vertical potential temperature gradient above PBL	Not applicable
Height of convectively-generated boundary layer – CBL	Not applicable
Height of mechanically-generated boundary layer - SBL	m
Monin-Obukhov length	m
Surface roughness length	m
Bowen ratio	m
Albedo	Not applicable
Wind speed-Ws	m/s
Wind direction-Wd	degrees
Reference height for Ws and Wd	m
Temperature-Temp	K
Reference height for Temp	m
Precipitation rate	mm/hr
Relative humidity	%
Cloud cover	tenths
Measurement height	degrees
If this is the last (highest) level for this hour	1 or 0
Wind speed for the current level	m/s
Temperature at the current level	degree C
Standard deviation of the vertical wind speed fluctuations	m/s

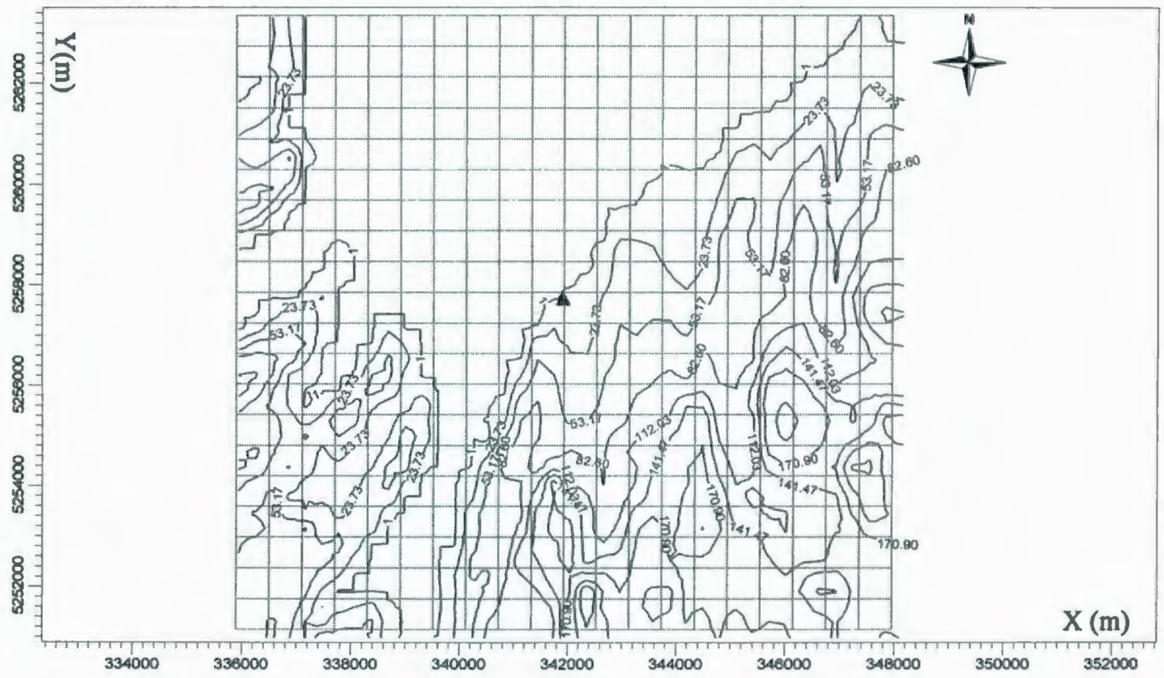


Figure 3.4 Receptor setting for the case study

Model Enhancements) for building downwash in this study.A typical air pollutant, SO_2, was targeted for air dispersion modeling in 2001, 2003, and 2005. A seasonally analysis were also conducted.

<u>Annually concentration distribution</u>

Wind rose and wind class frequency distribution:

Base on the meteorological data, the wind roses and wind class frequency distributions for 2001, 2003, and 2005 were given out by WRPLOT tool in AERMOD model.

As shown in the wind rose plots (Figures 3.5 to 3.10), the direction vector 90 deg had appeared 35% in 2001, the direction vector 72 deg had appeared 43% in 2003, the direction vector 91 deg had appeared 27% in 2005. Therefore, the main wind direction was most significant in 2003 and least significant in 2005 among the three years.

The wind class frequency distribution of the three years combined with the former corresponding wind rose plots showed that during the three years, the very high wind frequency appeared from the west to the east, and a low frequency appeared from the east to the west, and wind was relatively strong in 2003 and weak in 2005.

Concentration distribution:

Figures 3.11 to 3.13 showed the SO_2 average ground concentration distribution in 2001, 2003, and 2005. The AERMOD yearly highest average concentration and location for three years are summarized in Table 3.5.

It was found that the concentration and distribution were mainly affected by the wind

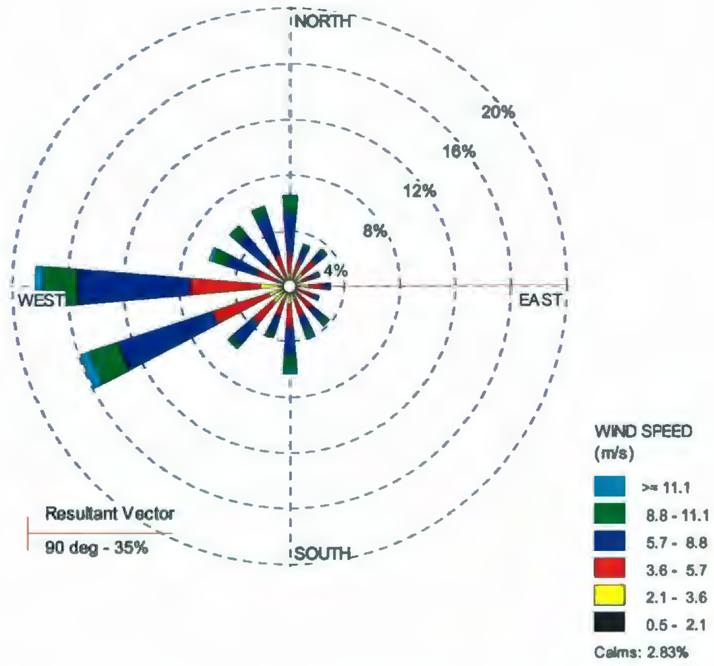


Figure 3.5 Wind rose plot for 2001

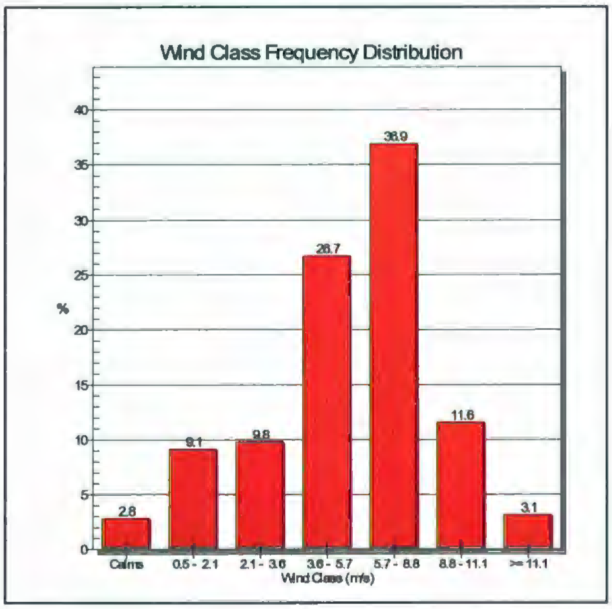


Figure 3.6 Wind class frequency distribution in 2001

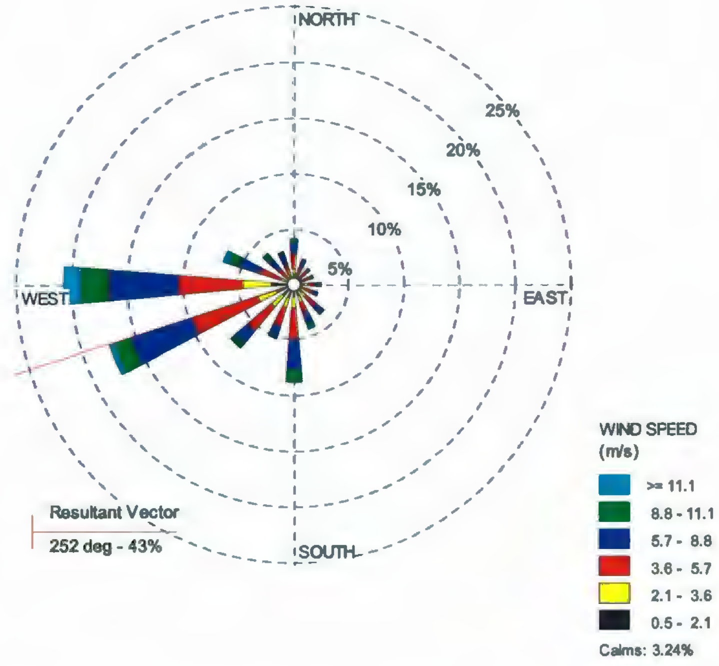


Figure 3.7 Wind rose plot for 2003

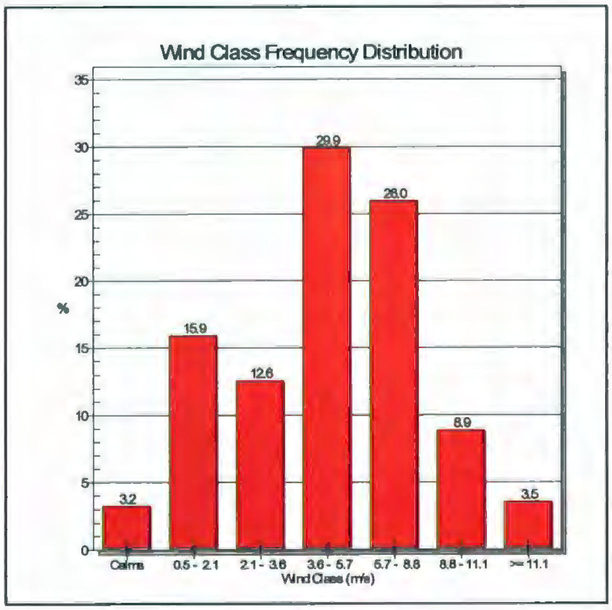


Figure 3.8 Wind class frequency distribution in 2003

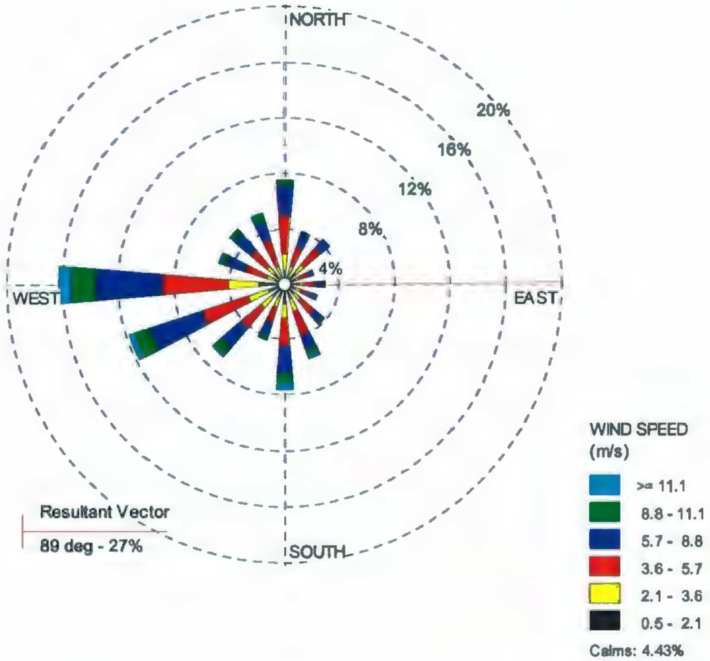


Figure 3.9 Wind rose plot for 2005

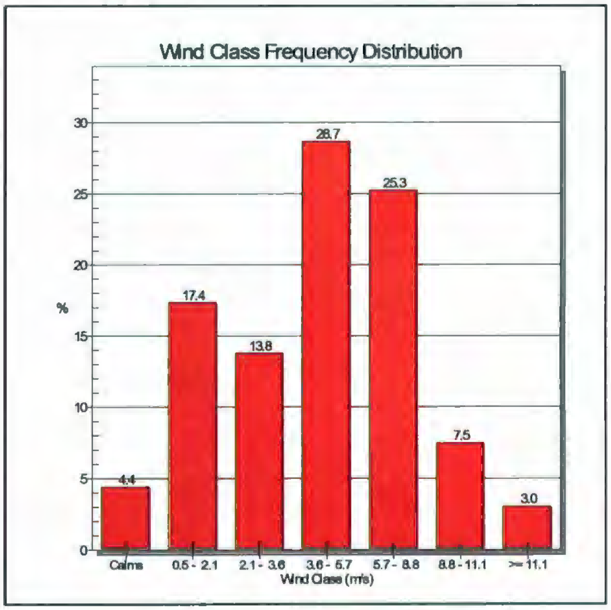


Figure 3.10 Wind class frequency distribution in 2005

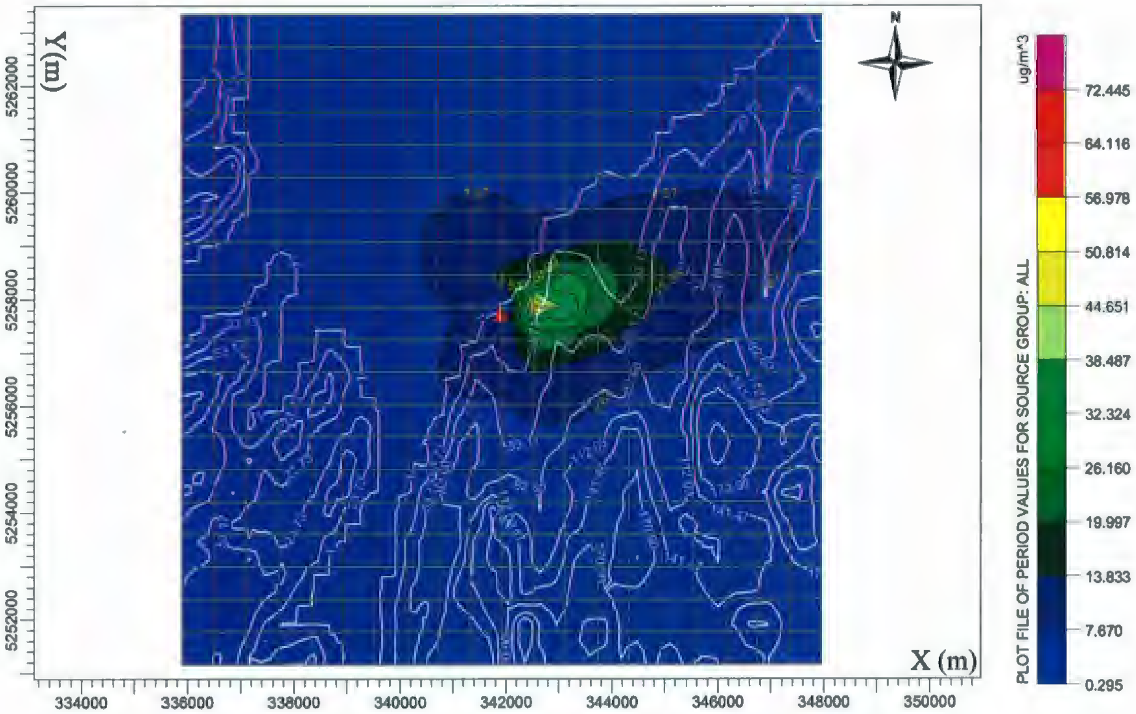


Figure 3.11 Modeling result for SO_2 annual ground concentration in 2001 by AERMOD

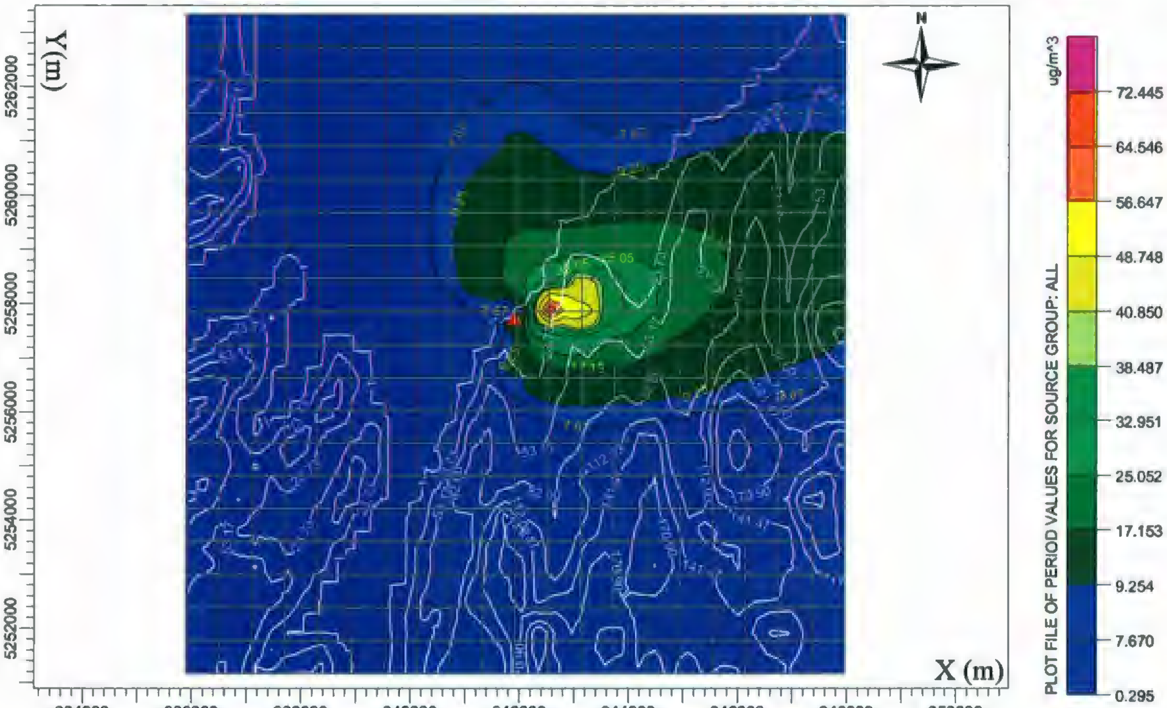


Figure 3.12 Modeling result for SO_2 annual ground concentration in 2003 by AERMOD

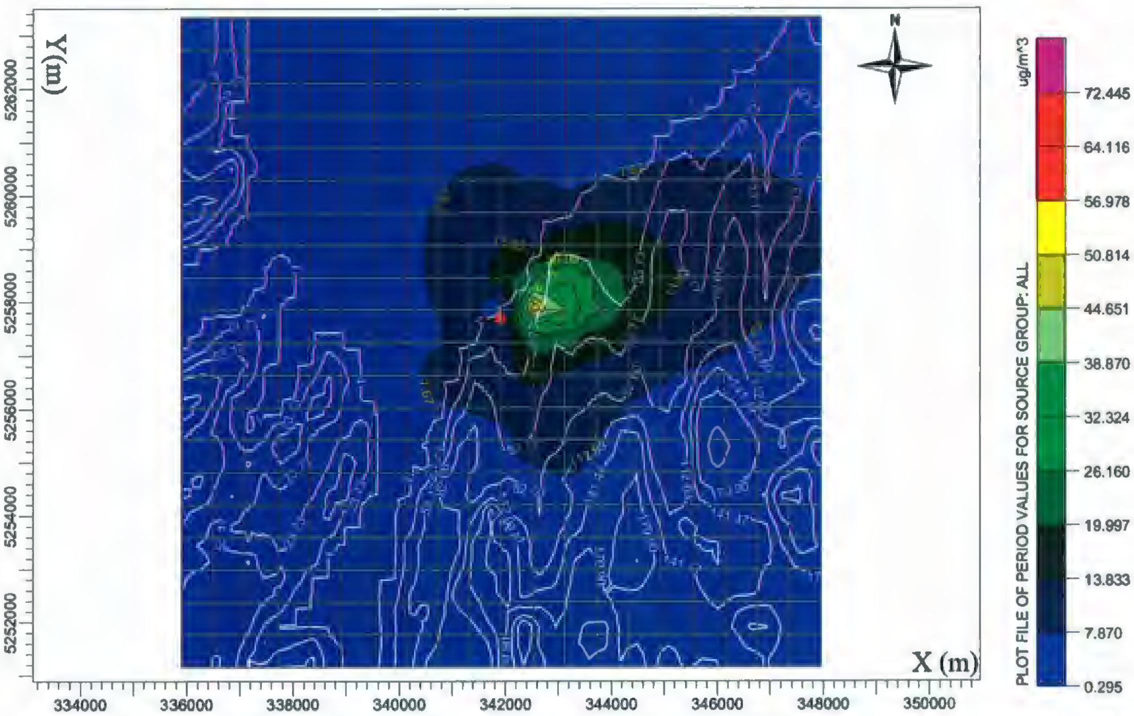


Figure 3.13 Modeling result for SO_2 annual ground concentration in 2005 by AERMOD

Table 3.5 AERMOD yearly highest average concentration and location for three years

Year	($\mu g/m^3$)	X	Y
2001	53. 9236	342535.19	5257854.50
2003	72. 445	342535.19	5257854.50
2005	56.97885	342535.19	5257854.50

direction, wind strength and terrain. Almost all the concentration appeared in the eastern high concentration distribution was observed in the direction of the high strong wind frequency. The maximum values of ground concentration in each year were in line with the wind direction vector of the year. The concentration distribution area is relative wide than that in 2001 and 2005. This indicated the significant influence of wind direction and strength. Terrain also affected the ground concentration distribution of SO_2, since there was high elevation (e.g. 112.08m) in the pathway where highest wind direction frequency occurred in the three years, the dispersion of the pollutant was limited in a relative small area.

<u>Seasonally concentration distribution in 2005</u>

Wind rose and wind class frequency distribution:

Figures 3.14 to 3.21 show the wind rose plots and the wind class frequency distribution for the four seasons in 2005. The 1st season (January-March) had a direction vector 129 ° appearing in 26% of the time in the season, the 2nd season (April-June) had a direction vector 123° appearing in 16% of the time in the season, the 3rd season (July-September) had a direction vector 68° appearing in 45% of the time in the season, and the 4th season (October-December) had a direction vector 79° appearing in 34% of the time in the season. Strongest wind happened in the 1st season, and the winds blow from North or West much of the time. Three main wind directions appeared in the 2nd season. The 3rd season had relative small wind strength, but a relative concentrated wind direction from east. Main wind direction appeared at North and East in the 4th season.

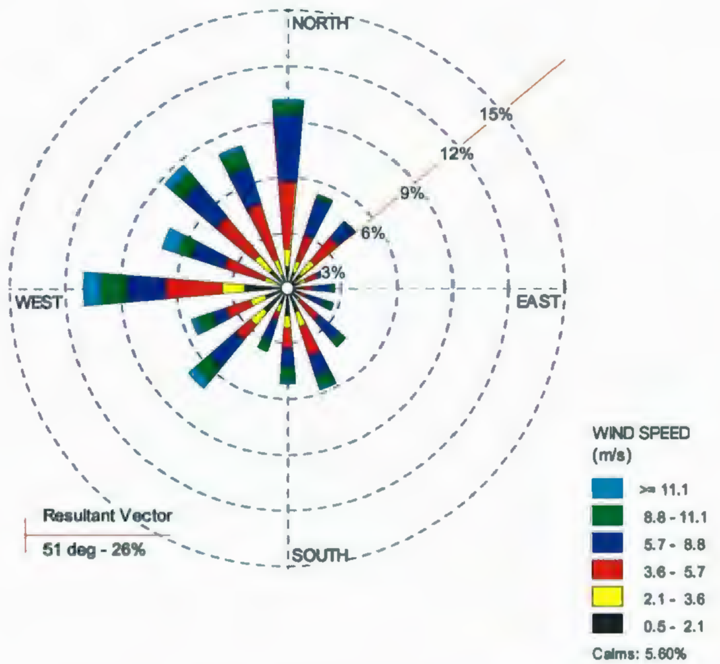


Figure 3.14 Wind rose for the first season in 2005 (January – March)

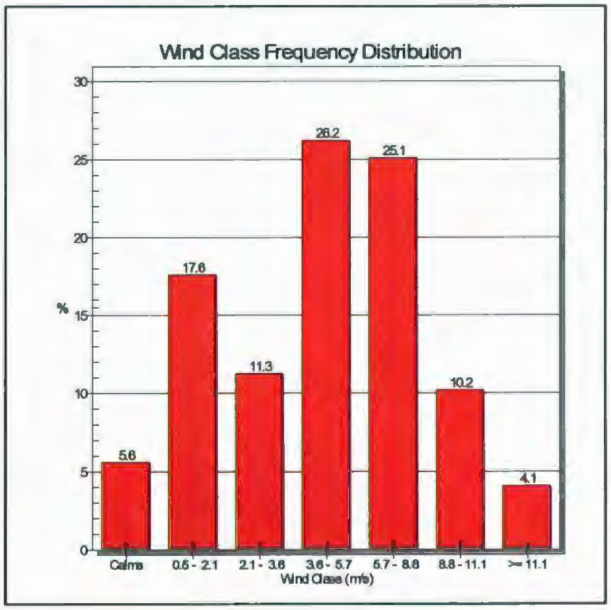


Figure 3.15 Wind class frequency distribution for the first season in 2005 (January – March)

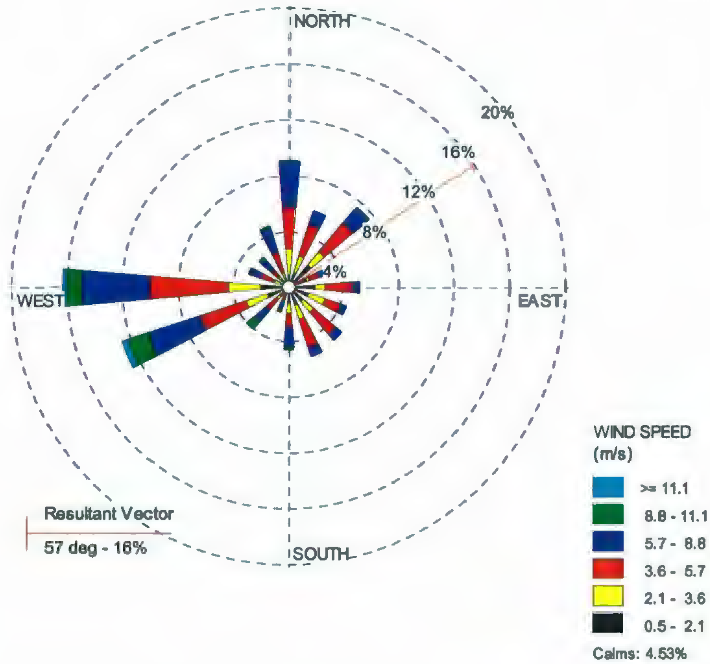


Figure 3.16 Wind rose for the second season in 2005 (April – June)

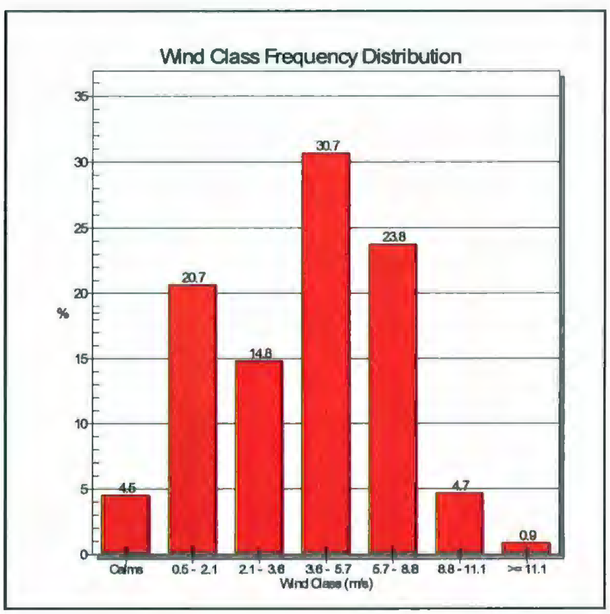


Figure 3.17 Wind class frequency distribution for the second season in 2005 (April – June)

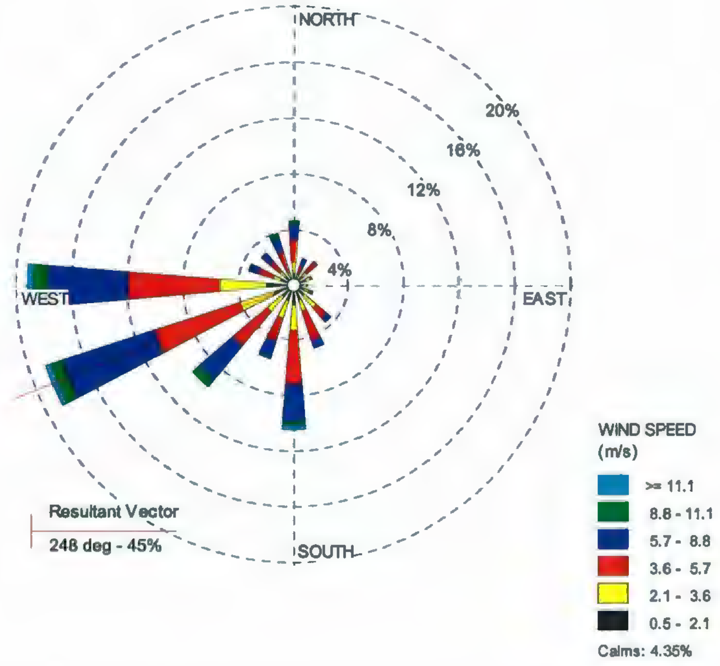


Figure 3.18 Wind rose for the third season in 2005 (July – September)

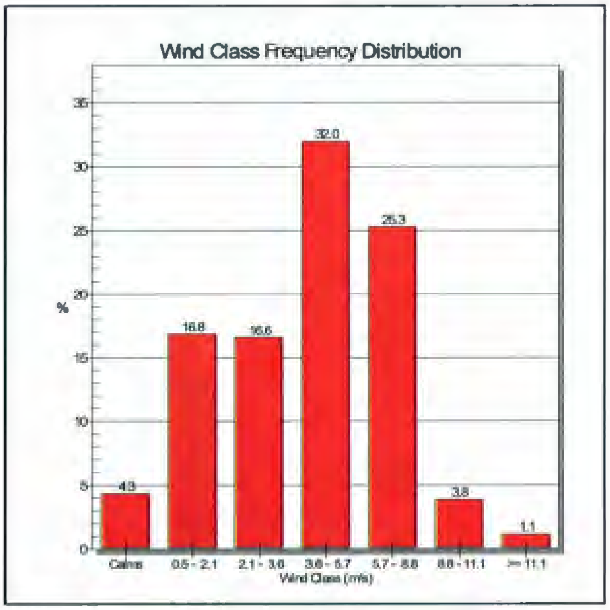


Figure 3.19 Wind class frequency distribution for the third season in 2005 (June – September)

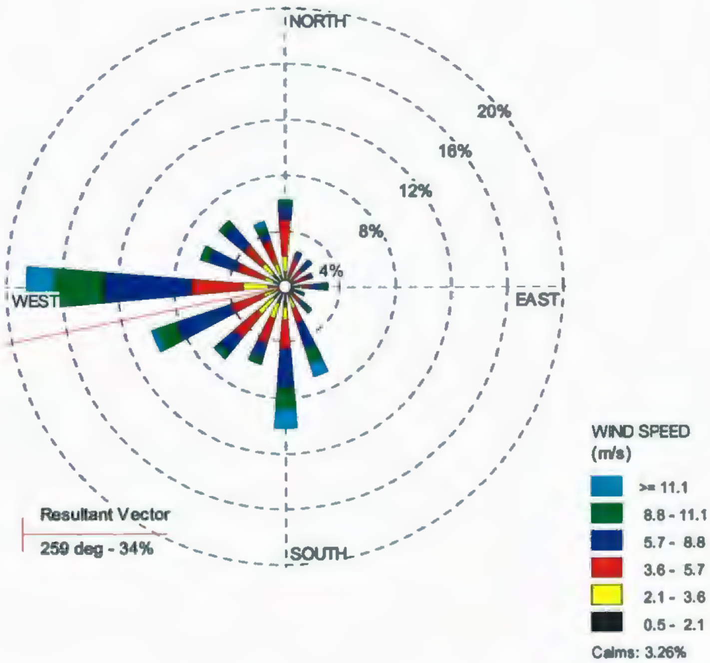


Figure 3.20 Wind rose for the fourth season in 2005 (October – December)

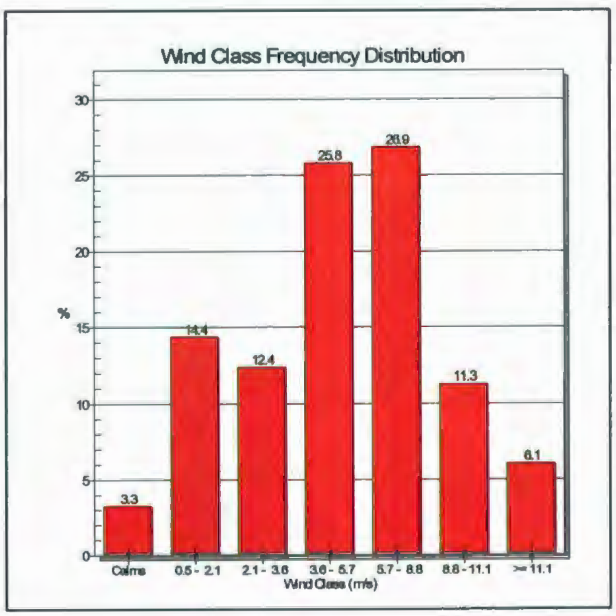


Figure 3.21 Wind class frequency distribution for the fourth season in 2005 (October – December)

Concentration distribution:

Figures 3.22 to 3.25 showed the SO_2 seasonal ground concentration distribution in 2005 (the most recent year). The yearly highest average concentrations and locations for 4 seasons in 2005 are summarized in Table 3.6. The modeling result indicated that the concentration distribution in four seasons of the year was closely correlated to the wind frequency in the season. For the first and the fourth season, high percentages of the concentration distribution were observed in the eastern part of the study area. The first season had the strongest wind in the year, but the max value of concentration was not far from the source (the stacks), probably due to the relative high elevation in the main dispersion pathway. The fourth season had the second largest wind strength among the four seasons, leading to relative smaller concentration distribution area than that in the first season. The second season had a relative even concentration distribution area, which could be related to the distribution of wind frequency in three directions. The third season had the most concentrated main wind direction in the year, which could also be related to the distribution of wind frequency. Temperature and wind speed may also contribute to the pollutant dispersion, e.g. from the unit operation schedule (Table 3.7), the main downtime concentrated in the second and third season, however they still keep highest concentration compared with the other two seasons and this could be the reason that the concentrated main wind direction in the year, which could also be related to temperature in Summer and August is highest in the year, while the wind speed is lowest among the year, the combined temperature inversion conditions and low wind speeds cause a long residency of the SO_2 over the industry area (EPA,2005), in other words, results in

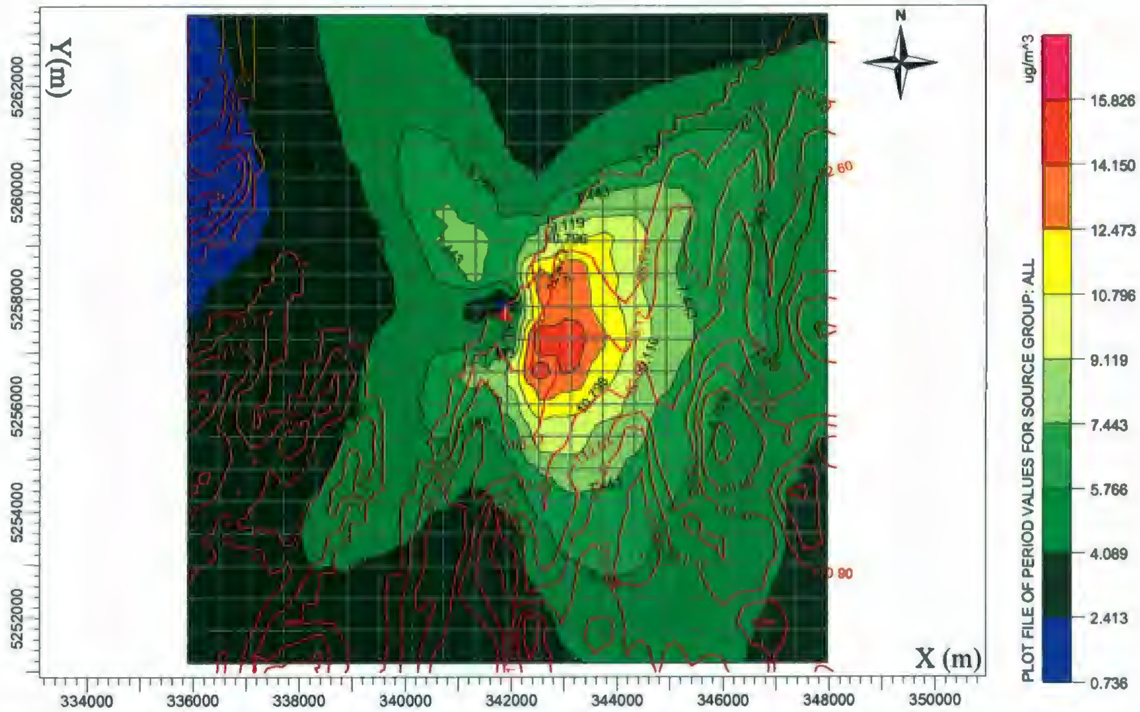


Figure 3.22 SO_2 seasonally ground concentration distribution in the first season in 2005

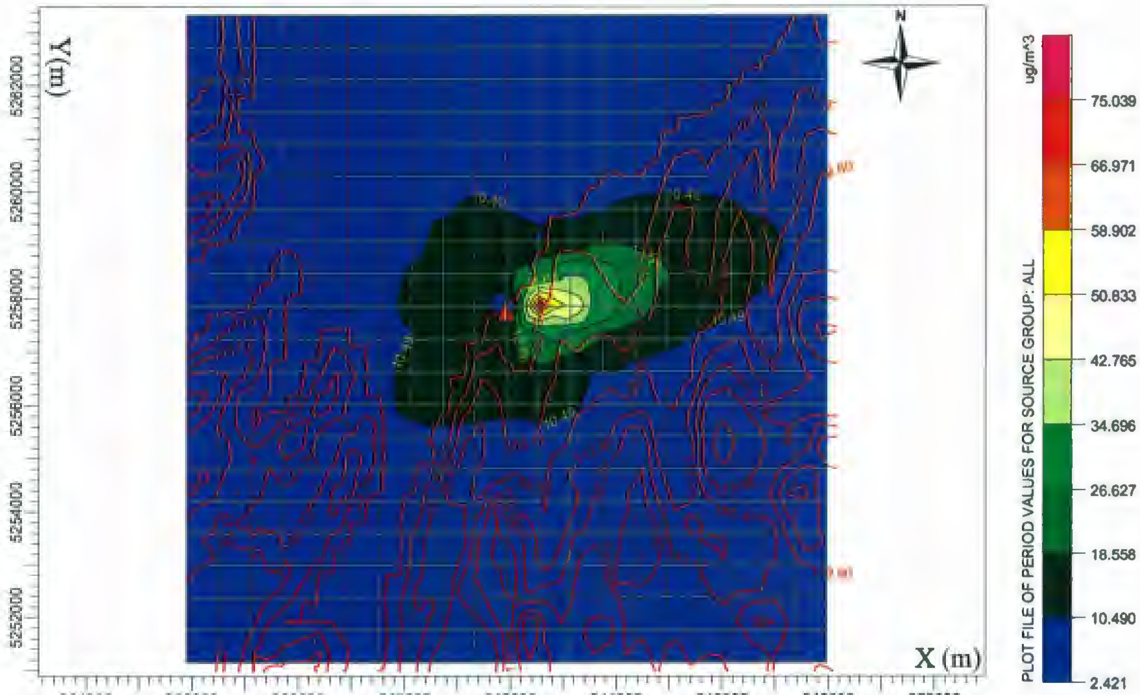


Figure 3.23 SO_2 seasonally ground concentration distribution in the second season in 2005

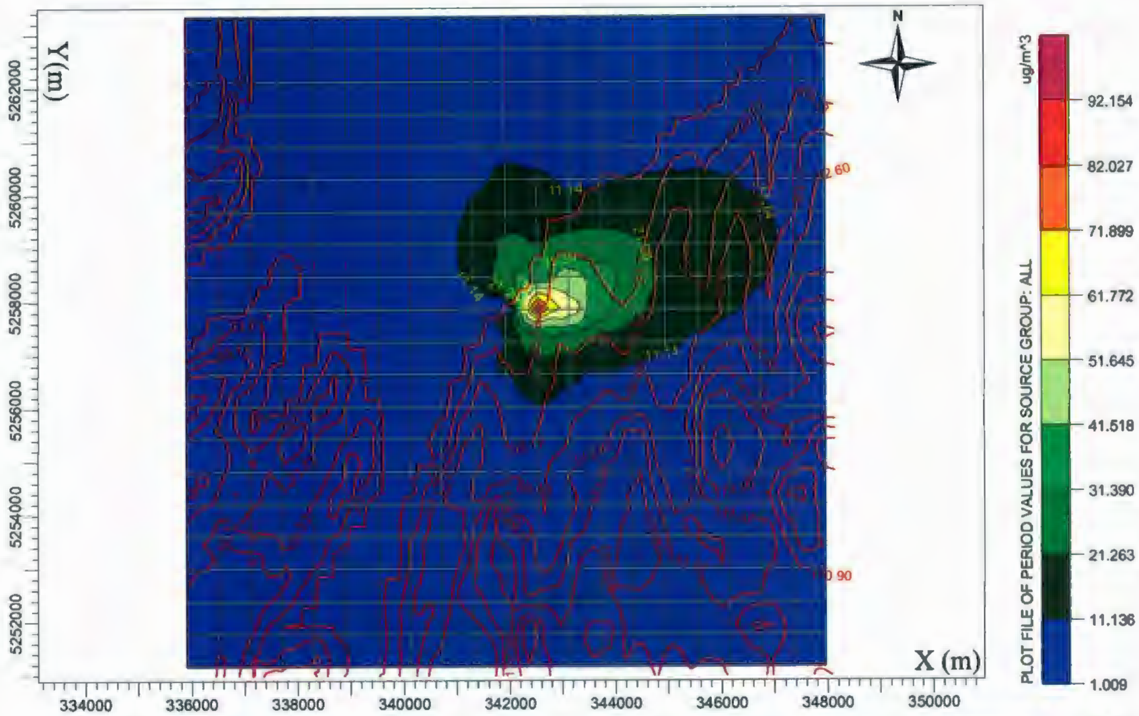


Figure 3.24 SO_2 seasonally ground concentration distribution in the third season in 2005

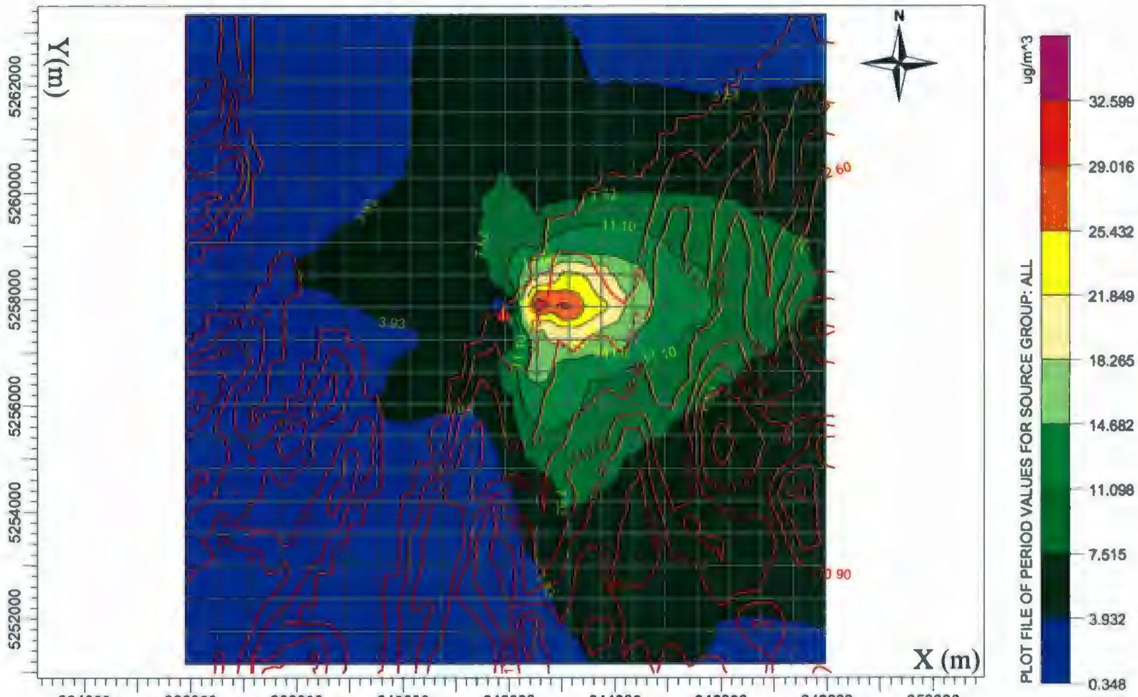


Figure 3.25 SO_2 seasonally ground concentration distribution in the fourth season in 2005

Table 3.6 AERMOD yearly highest average concentrations and locations for 4 seasons in 2005

Season	Concentration ($\mu g/m^3$)	X (m)	Y (m)
1st January-March	15.83	342535.19	5257245.00
2nd April-June	75.04	342535.19	5257854.50
3rd July-September	92.15	342535.19	5257854.50
4th October-December	32.60	342535.19	5257854.50

Table 3.7 Unit Operation schedule (days)

	Boiler 1			Boiler 2			Boiler 3		
	2001	2003	2005	2001	2003	2005	2001	2003	2005
January	31	31	31	31	31	31	31	31	31
February	28	28	28	28	26	23	25	28	28
March	30	31	30	31	31	31	30	30	31
April	30	30	19	30	30	**13**	**0**	**0**	27
May	31	19	**0**	31	28	21	**0**	**11**	**2**
June	30	**0**	**0**	**11**	27	**0**	**0**	**0**	**4**
July	19	**0**	**0**	**3**	**0**	**0**	**7**	**0**	31
August	**0**	**0**	**0**	**6**	**0**	**0**	23	17	17
September	**1**	**10**	**0**	30	**2**	**2**	30	30	29
October	26	22	16	29	31	30	29	29	**4**
November	28	**14**	30	30	25	30	31	26	**0**
December	28	31	21	31	31	31	31	25	22
Work Days	282	216	175	290	262	212	226	227	226

localized (not far away) air pollutant concentration by preventing the rise and dispersal of pollutant from the lower layers of the atmosphere， which made the pollutant hardly to be transported in the atmosphere.

Surface characteristics Analysis

Besides the meteorological and terrain input variables (e.g. wind speed, wind direction frequency, and site elevation) that affect the pollutant concentration distribution, efforts have also to be made to avoid model formulation discontinuities wherein large changes in calculated concentrations result from small variations in input parameters. As illustrated at the beginning of this chapter, in this step, AERMOD needs surface characteristics (surface roughness, Bowen ratio, and Albedo) in order to construct its Planetary Boundary Layer (PBL) profiles, which are the overwhelmingly dominant environmental parameters that the must be entered into the AERMOD model and can not directly measured. This part is supposed to analyze the effects of such parameters on the AERMOD modeling. The three factors considered are Albedo Ratio (A), Bowen Ratio (B), and Surface Roughness length (C).

Figure 3.26 shows that the ground-level concentration of SO_2 increased as the Surface Roughness or Bowen Ratio change from low level (-1) representing 0.0001/0.1 to high level (+1) representing 1.3/6 (the range of all possible surface roughness is 0.0001-1.3 from USEPA), while the ground-level concentration of SO_2 decreased as the Albedo changes from low level (-1) representing 0.1 to high level (+1) representing 0.6 (the range of all possible Albedo value is 0.1-0.6 from USEPA. All factors are run at two levels, and the response variable is the concentration generated from AERMOD modeling without

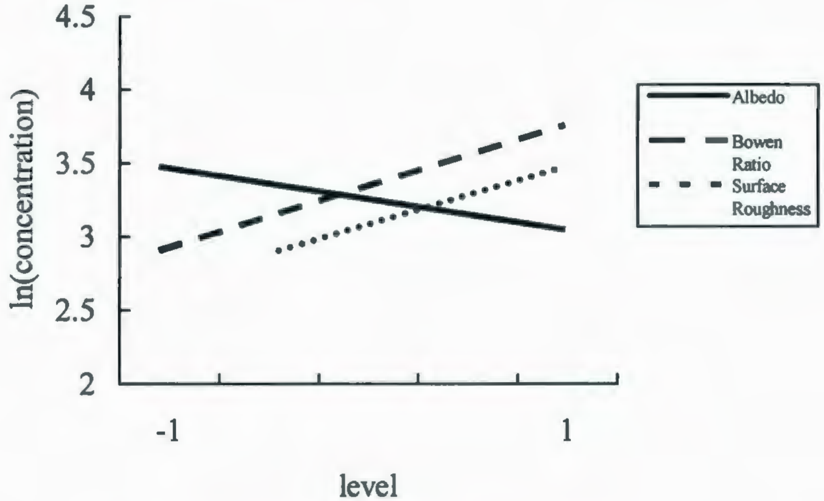


Figure 3.26 Factors Vs Concentration

changing other parameters during modeling. The 2^3 factorial experiment was conducted by only one replication and no blocking through Design Expert 7© (Tables 3.8).

Tables 3.9 show the analysis input and output, respectively. And the results indicated that the greatest and the most significant factor is C (i.e., surface roughness length) with 51.13% contribution. Other interactions make relative small contribution to the model. So, surface roughness length is chosen for Monte Carlo simulation and later risk assessment. Detailed illustration will be provided in the next chapter.

3.3 SUMMARY

The SO_2 concentration was significantly affected by the wind speed and direction frequency. Large percentage of SO_2 concentrations were observed in the south-east part to the plant and low concentrations distributed in the western part of the study area.

Terrain also affected the concentration distribution of the pollutant. If high elevation (e.g. hills) was in the pathway where highest wind direction frequency happened, the dispersion of the air pollutant would be limited.

Temperature combined with wind speed could be another contribution to the pollutant dispersion. As illustrated above, the combined temperature inversion conditions and low wind speeds cause a long residency of the SO_2 over the industry area. This is quite agreeable with the modeling results that the concentration distribution varied with the season. In the spring and winter season (with relative low temperature and high wind speed), relatively low concentration and large distribution area would be identified, along with the long distance between the stacks and the location with maximum SO_2

Table 3.8 2^3 factorial experimental design data

Std	Run	Factor A: Albedo	Factor B: Bowen Ratio	Factor C: Surface Roughness Length	Response: Concentration ($\mu g/m^3$)
1	2	-1	-1	-1	13.8738
2	3	1	-1	-1	11.4472
3	8	-1	1	-1	33.3836
4	6	1	1	-1	18.3225
5	1	-1	-1	1	30.6561
6	5	1	-1	1	24.6054
7	4	-1	1	1	63.3039
8	7	1	1	1	41.8316

Table 3.9 Statistic analysis results

Term	Standardized effects	Sum of Squares	% Contribution
A (Albedo)	-0.35	0.24	10.55
B (Bowen Ratio)	0.64	0.82	36.25
C (Surface Roughness)	0.76	0.15	51.13
AB	-0.14	0.039	1.71
AC	0.036	3.576E-003	0.11
BC	-0.020	7.635E-004	0.034
ABC	0.050	4.938E-003	0.22
ME		0.28	
SME		0.67	

ground-level concentration; in the summer and autumn season (with relative high temperature and low wind speed), relatively high concentration and small dispersion area could be identified, along with the short distance between the stacks and the location with maximum SO_2 ground-level concentration.

CHAPTER 4 STOCHASTIC – BASED FUZZY RISK ASSESSMENT OF AMBIENT AIR QUALITY

4.1 METHODOLOGY

4.1.1 Monte Carlo Simulation of Contaminant Transport

The stochastic modeling technique is intended to represent the uncertainties associated with the physical system and the model parameters as functions of the mathematical randomness or as typically selected or mathematically produced sample data set. The normal distribution function is commonly used to represent the various input parametric distributions, as shown below:

$$P_N(x) = \exp[-\frac{(n-\mu_x)^2}{2\sigma_x^2}]/[(2\pi)^{0.5}\sigma_x] \tag{4.1}$$

Where x is random variable, $P_N(.)$ is the probability density function, σ_x is the standard deviation of x, and μ_x is the mean value of x.

One of the most straightforward and popular solution forms used with stochastic modeling is Monte Carlo simulation. Monte Carlo simulation is a computational method for generating probability distributions of variables that depend on other variables or parameters represented as probability distributions (Rubinstein and Kroese, 2007). It is an analytical process to assess uncertainty when input variables are too complex to be represented by single, deterministic values. Due to the increasing dissatisfaction with the deterministic or point estimate calculations typically used in quantitative contaminant concentration (Mosegaard et al., 1995), Monte Carlo simulation has become increasingly common in simulating the contaminant transport in environmental field. The procedure consists of the generation of random numbers from known probability distribution. The generated numbers are used as inputs to governing equations, and all the corresponding outputs are computed. Theoretically, this method is based on an entirely random process and proves statistically that with enough sampling iterations one can accurately generate output realization distributions, which are then analyzed to define the output statistics. Compared with other modeling methods, it has the following advantages: (1) Adaptation of the algorithms for computer programming along with existing simulators is straightforward; (2) No additional difficulties arise in solving problems with discontinuous boundary functions and non-smooth boundaries; (3) Problems associated with random parameters and their correlation can be solved easily.

In specific, input variables are assigned probability distributions rather than single values and the required calculations are repeated many times with the input variables changing for each iteration. The results of the simulations are presented as probability distributions. The specific values of the input variables are taken from and determined by the assumed probability distributions. For example, if a normal probability distribution is assumed for an input variable, values around the average will be used most frequently in the calculations, and values greater than and less than the average will be used with equal frequency. In order to adequately represent the range of all possible input variables in a Monte Carlo analysis, several hundred iterations of the calculations are required.

Modeling of pollutant transport in the ambient air requires of various physical, chemical and biological parameters. For example, the AERMOD dispersion model has a meteorological pre-processor (AERMET) that requires the input of site-specific land use parameters corresponding to land-use categories, including Albedo, Bowen ratio, and Surface roughness, however, such fundamental parameters are generally difficult to acquire with accurate and deterministic values, and a number of uncertainties are associated with them temporally and spatially. (Lahkim and Garcia, 1999; Sax and Isakov, 2003; Manomaiphiboon, and Russell, 2004; Hanna, 2007). In this study, the Monte Carlo simulation algorithm was developed and incorporated within the AERMOD modeling system for reflecting uncertainties with surface roughness, which has been found to be the most important factor in reflecting surface characteristics and affecting model results (Lahkim and Garcia, 1999). The major procedures of the Monte Carlo simulation are shown in Figure 4.1.

4.1.2 Probabilistic risk assessment

In a given system, risk can be expressed as P_F (R < S), where R denotes e.g. SO_2 concentration (random variable), S is environmental loading capacity (random variable); and P_F denotes probability. More specifically, environmental risk could be expressed as the probability of SO_2's concentrations or loading (denoted as random number L) exceeding a prescribed safety level or capacity (denoted as random number C), i.e., P_F = P(L > C). Thus, the risk can be quantified as follows:

$$P_F = P(L > C) = \int_0^{\infty}\left\{\int_0^{L} f_{LC}(L,C)dC\right\}dL \tag{4.2}$$

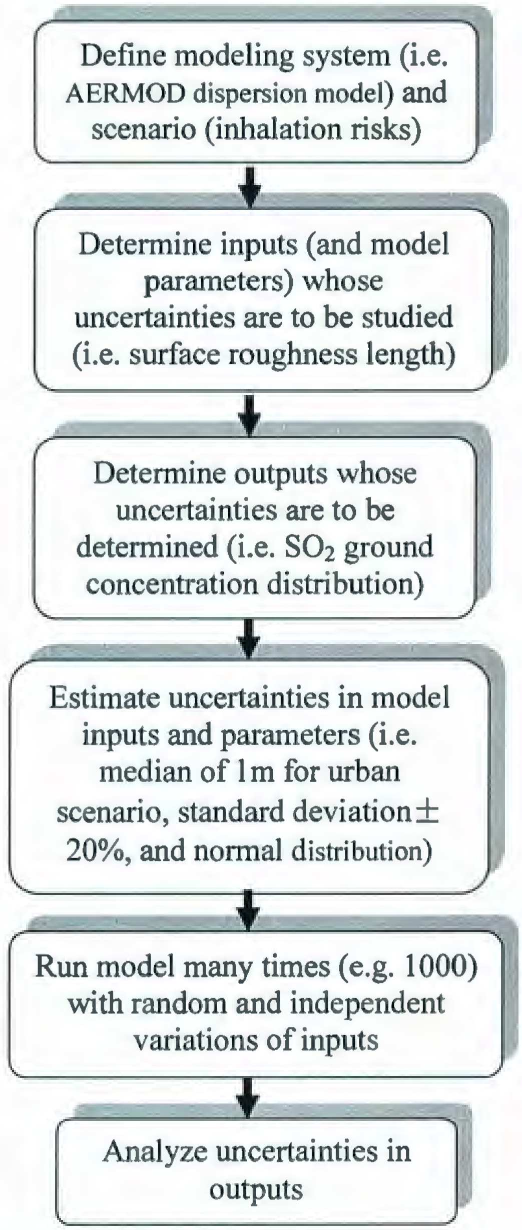


Figure 4.1 the Monte Carlo simulation algorithm

Where P_F is risk level quantified as probability of system failure, and f_{LC} is associated probability density function.

If random number C can be defined by some local environmental guidelines (i.e., if C = C_0), then the risk can be quantified as follows (Chen et al., 1998b):

$$P_F = P(L > C_0) = \int_{C_0}^{\infty} f_L(L)dL \tag{4.3}$$

Obviously, if different guidelines are adopted to describe SO_2 concentration, different risk-assessment results will be derived from implementing proposed stochastic risk assessment (Chen, Z. et al. 1998).

4.1.3 Fuzzy Sets Theory and Fuzzy Logic

Forty years have gone by since Zadeh's pioneering paper introducing fuzzy sets and fuzzy logic (Zadeh, 1965). Such kind of theory efficiently helps address deficiencies inherent in binary logic and propagates uncertainties through models. Figure 4.2 illustrate the difference between traditional crisp set theory and fuzzy set theory. The key terms and their explanations are presented below:

Fuzzy Sets

A fuzzy set is any set that allows its members to have different grades of membership (membership function) in the interval [0, 1]. In fuzzy sets, there is no crisp definition of belonging (binary), instead, uses degree of belonging or membership functions (μ). In specific, a fuzzy set is a pair (A, μ) where A is a set and for each $x \in A$, $\mu(x)$ is the grade of membership of x. The triangular membership function, one of the most popular

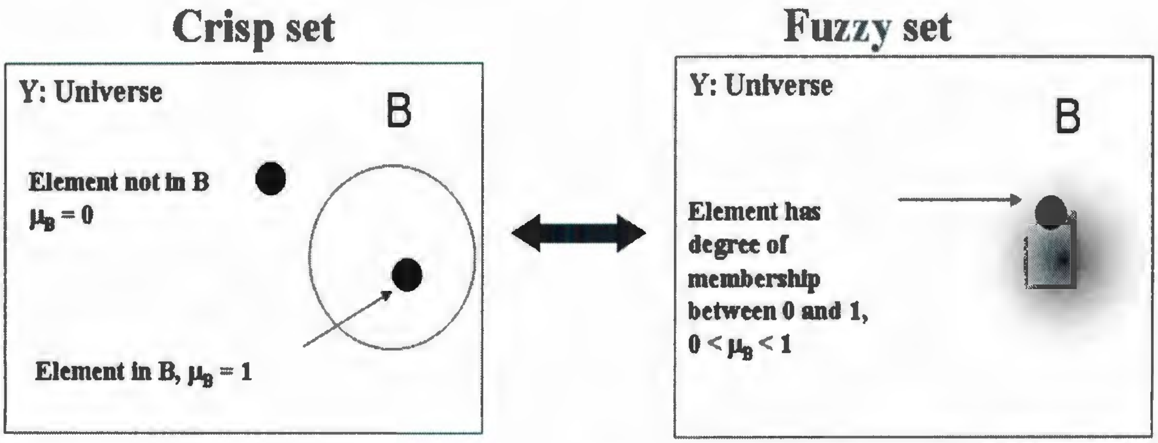


Figure 4.2 Comparison between crisp set and fuzzy set

approaches for generating membership functions is employed by many researchers due to its simplicity (Civanlar and Trussel, 1986; Dou et al., 1997; Chen et al., 2003). As illustrated in Figure 4.3, a triangular fuzzy number can be defined by specifying three numbers: the lowest possible value, the highest possible value and the most credible value. An element mapping to the value 1 describes a fully included member or the most credible value, any number that less than the lowest possible value or greater than the highest possible is not included in the fuzzy set and thus mapping to the value 0. Values strictly between 0 and 1 characterize the fuzzy members and they could be obtained by linear interpolation (Bauer, 1995). It can also be found the α-cut and support value in Figure 4.3. The fuzzy set that contains all elements with a membership of $\alpha \in [0,1]$ and above is called the α-cut of the membership function. At a resolution level of α, it will have support of $A\alpha$. The wider the support of the membership function, the higher the uncertainty; the higher the value of α, the higher the confidence in the parameter (Li and Yen, 1995).

Fuzzy Logic

Fuzzy logic is a form of multivalued logic derived from fuzzy set theory to deal with reasoning, making inferences from observed imprecise phenomena. In fuzzy logic the degree of truth of a statement can also range between 0 and 1. It is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth - truth values between "completely true" and "completely false" (Zadeh, 1965). Valuations $\mu : V_o \rightarrow W$ of propositional variables (V_0) into a set of membership degrees

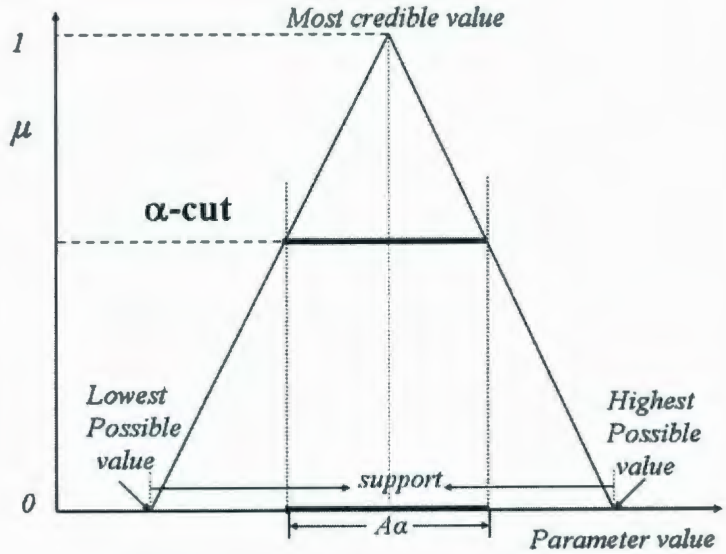


Figure 4.3 Example of a triangular fuzzy set

(W) can be thought of as membership functions mapping predicates into fuzzy sets (or more formally, into an ordered set of fuzzy pairs, called a fuzzy relation.

With these valuations, many-valued logic can be extended to allow for fuzzy premises from which graded conclusions may be drawn (Gottwald and Siegfried, 2001). The concept can be illustrated with the following example about people and "cancer risk". If the set S (the universe of discourse: the range of all possible values for an input to a fuzzy system) is defined as the set of people. A fuzzy subset “cancer risk” is also defined, which answers the question "to what degree is person x face cancer risk?" To each person in the universe of discourse, a degree of membership in the fuzzy subset “cancer risk” should be assigned. The easiest way to do this is with a membership function based on the hazards index ($HI = \frac{CDI}{SF}$). Let $\mu_{A1}(HI(x))$, $\mu_{A2}(HI(x))$ and $\mu_{A3}(HI(x))$ be the membership functions of the fuzzy sets “low-risk”, “medium-risk” and “high-risk”, respectively. Then the $\mu_{A1}(HI(x))$, $\mu_{A2}(HI(x))$ and $\mu_{A3}(HI(x))$ can be defined as follows in order to characterize such linguistic variables (note: $\phi = HI(x)$):

$$\mu_{A1}(\phi) = \begin{cases} 1 & when \quad \phi \in [0,a] \\ f_A(\phi) & when \quad \phi \in [a,b] \\ 0 & otherwise \end{cases} \tag{4.1}$$

$$\mu_{A2}(\phi)=\begin{cases}1 & when \quad \phi=b\\ g_B(\phi) & when \quad \phi\in[a,b]\\ r_B(\phi) & when \quad \phi\in[b,c]\\ 0 & otherwise\end{cases} \tag{4.2}$$

$$\mu_{A3}(\phi)=\begin{cases}h_C(\phi) & when \quad \phi\in[b,c]\\ 1 & when \quad \phi=c\\ 0 & otherwise\end{cases} \tag{4.3}$$

A graph can be used to represent the equations (Figure 4.4):

Fuzzy Set Operation

The operations on fuzzy sets are generalization of crisp set operations. There is more than one possible generalization. The most widely used standard fuzzy set operations include: fuzzy unions, fuzzy intersections, and fuzzy complements.

Standard union (Figure 4.5): The membership function of the union of two fuzzy sets A and B with membership functions μ_A and μ_B respectively is defined as the maximum of the two individual membership functions. This is called the maximum criterion. The union operation in fuzzy set theory is the equivalent of the OR operation in Boolean algebra.

$$\mu_{A\cup B}=\max(\mu_A,\nu_B) \tag{4.4}$$

Standard intersection (Figure 4.6): The membership function of the intersection of two fuzzy sets A and B with membership functions μ_A and μ_B respectively is defined as

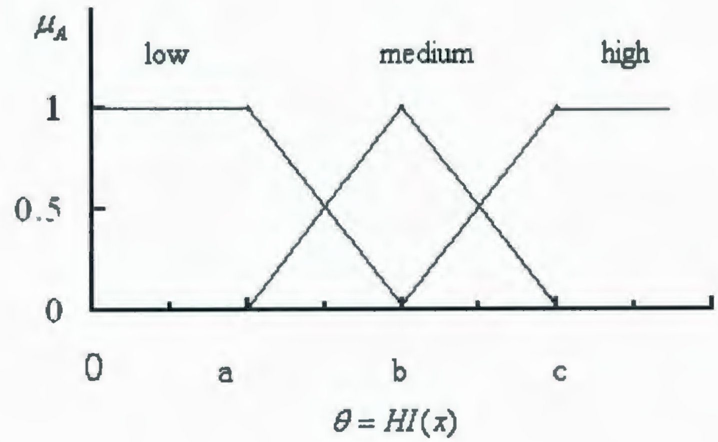


Figure 4.4 Membership functions of "low risk", "medium risk", and "high risk"

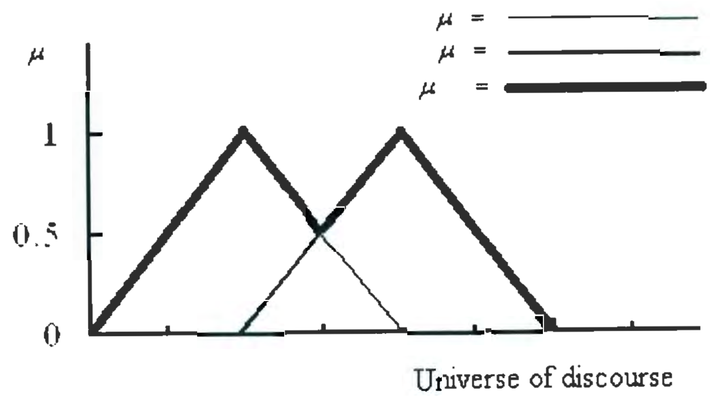


Figure 4.5 Fuzzy set operations - standard union

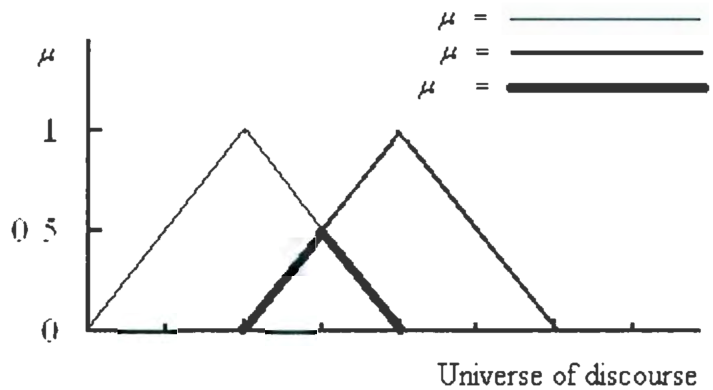


Figure 4.6 Fuzzy set operations - standard intersection

the minimum of the two individual membership functions. This is called the minimum criterion. The intersection operation in fuzzy set theory is the equivalent of the AND operation in Boolean algebra.

$$\mu_{A \cap B} = \min(\mu_A, \nu_B) \tag{4.5}$$

Standard complement (Figure 4.7): The membership function of the complement of a fuzzy set A with membership function μ_A is defined as the negation of the specified membership function. This is called the negation criterion. The complement operation in fuzzy set theory is the equivalent of the NOT operation in Boolean algebra.

$$\mu_{\bar{A}} = 1 - \mu_A \tag{4.6}$$

<u>**Fuzzy Rule-based Systems**</u>

Fuzzy control, which directly uses fuzzy rules, is the most important application in fuzzy set theory. The rule-based fuzzy system contains a rule base and a reasoning algorithm, which is used to process fuzzy input values $x_i, i = 1,\ldots,n$ to a crisp output value y (Figure 4.8).

Using a procedure originated by Mamdani (1975) in the late 1970s, three steps are taken to create a rule-based fuzzy system:

1) Fuzzification -- Using membership functions to graphically describe a situation;

2) Rule evaluation -- Application of fuzzy rules by the combination of two sub processes: inference and composition based on defined fuzzy rules; and

3) Defuzzification -- Obtaining the crisp or actual results.

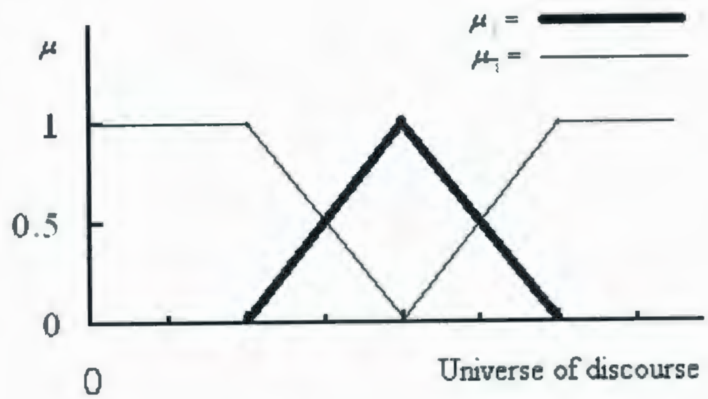


Figure 4.7 Fuzzy set operations - standard complement

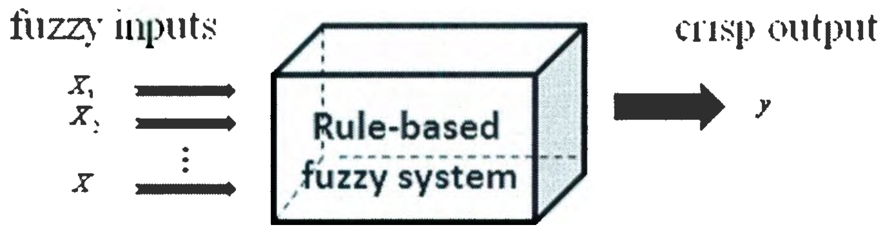


Figure 4.8 the Rule-based fuzzy system with n fuzzy inputs and one crisp output

Fuzzification:

First of all, the different levels of input are defined by specifying the membership functions for the fuzzy sets, the membership functions defined on the input variables are applied to their actual values, to determine the degree of truth for each rule premise. The degree of truth for a rule's premise is sometimes referred to as its alpha.

If a rule's premise has a nonzero degree of truth (if the rule applies at all...) then the rule is said to fire. The first step is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions.

Rule evaluation:

The next step is to define the fuzzy rules and processing inference and composition based on defined fuzzy rules. The fuzzy rules are merely a series of if-then statements. These statements are usually derived by an expert to achieve optimum results. In the inference sub-process, the truth value for the premise of each rule is computed, and applied to the conclusion part of each rule. This results in one fuzzy subset to be assigned to each output variable for each rule. In the composition sub-process, all of the fuzzy subsets assigned to each output variable are combined together to form a single fuzzy subset for each output variable. There are three built-in methods: max (maximum), prob. (probabilistic OR), and sum (simply the sum of each rule's output set, chosen for the current research).

Defuzzification:

Sometimes it is useful to just examine the fuzzy subsets that are the result of the composition process, but more often; this fuzzy value needs to be converted to a single number with a crisp value. The result of the fuzzy controller as of known is a fuzzy set. In order to choose an appropriate representative value as the final output (crisp values), defuzzification must be done. There are numerous defuzzification methods, but the most common one used is the CENTROID methods (Kosko et al., 1993) (which is also applied in the current research). In the CENTROID method, the crisp value of the output variable is computed by finding the variable value of the center of gravity of the membership function for the fuzzy value.

To summarize, Figure 4.9 shows the contents of a rule-based fuzzy system. The input signals combined to the vector $x = [x_1, x_2, ..., x_n]^T$ are crisp values, which are transformed into fuzzy sets in the fuzzification. The output comes out directly from the defuzzification block, which transforms an output fuzzy set back to a crisp value using defuzzifications. The set of membership functions responsible for the transforming part and the rule base as the relational part contain as a whole the modeling information about the system, which is processed by the inference and composition.

4.1.4 Probabilistic versus fuzzy reflection of uncertainties in environmental systems

Probability theory and fuzzy logic are powerful tools to overcome the uncertainty (Blair, 2001). Probability theory is mainly responsible for representation and processing of uncertainty (randomness) while fuzzy logic is used for representation and processing of vague data. The differences between the probability measure and membership function could be summarized in four aspects (Dubois and Prade, 1993): 1) Probability measure calculates the probability that an ill-known variable x ranging on U hits the well-known

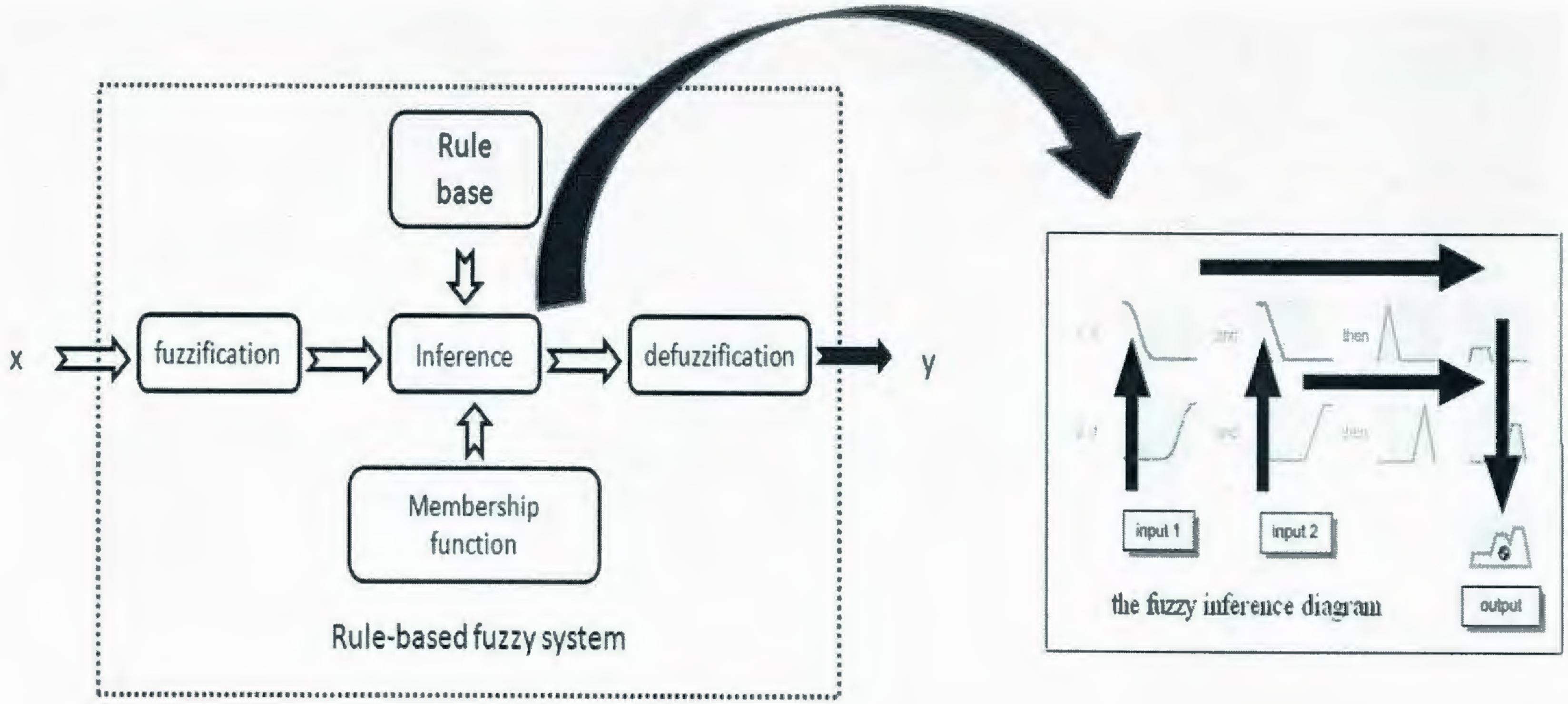


Figure 4.9 A Rule-based fuzzy system

set A, while membership function calculates the membership of a well-known variable x ranging on U hits the ill-known set A; 2) Probability measure is conducted before an event happens membership function is applied after it happened to figure out the vagueness of the fuzzy part; 3) Probability belongs to the measure theory, and membership function is a kind of set theory; 4) The domain of probability measure is following Boolean Algebra, but membership function domain cannot be a Boolean Algebra since it implements soft linguistic variables on a continuous range of truth values, thus having the power of handling the concept of "partial truth" (Chen and Pham, 2001). As described above, there have been a number of environmental applications using either probabilistic or fuzzy set approaches individually during the past years. However, uncertainty manipulation through individual approaches may not be feasible in real-world situations as it was challenged by complex uncertain inputs in modeling procedures. There were also some studies on the combination of stochastic and fuzzy methods, but the involved cases and uncertainties were limited, which is calling for further studies. In this research, an integrated fuzzy-stochastic method will be developed and applied in a real-world case study of the risk assessment of ambient air quality.

The SO_2 concentrations predicted through the Monte Carlo simulation can be regarded as stochastic events due to the randomness in the input parameters. The stochastic event can be characterized through a probability concept. According to the definition, probability is a measure of an empirical, objective and physical fact of the external world, and independent of human attitudes, opinions, models and simulations. It is never relative to evidence or opinion. As a result, the outcome of the stochastic event (e.g., SO_2

concentration exceeds the selected concentration in dose-response relationship) should be either true or false. However, the outcome may be given by a quantity other than true or false due to the uncertainties in SO_2 dose-response relationship and the Monte Carlo outputs. This means that the outcome will show fuzziness, and this kind of fuzziness may be quantified by a degree of belief (e.g., membership function) (Chen, 2000).

Thus, the occurrence of environmental risk can be treated as a fuzzy event. Randomness associated with the SO_2 concentration is linked to this fuzzy event using the concept of fuzzy logic. The concentration levels of SO_2 dose-response relationship are categorized into "low", "low-to-medium", "medium", "medium-to-high", and "high" by associating them with different magnitudes of probability of guideline violation that is obtained from Monte Carlo outputs. The construction of membership functions for these fuzzy events can be constructed through questionnaire survey. Thus, fuzzy logic, expert involvement, and stochastic simulation will be integrated within a general framework. It also links the probabilistic and possiblistic uncertainties using the concept of fuzzy logic.

4.1.5 Approaches for Environmental and Health Risk Assessment

The objective of the risk assessment is to provide an independent, scientifically-based opinion of whether the pollutants (e.g. air emissions from the power station) pose a potential risk of adverse environmental or health effects to the surrounding communities. For a specific case, the related risk characterization can be conducted through environmental-standard-based risk assessment (ERA) and health risk assessment (HRA) (Carrington and Bolger, 1998; Batcherlor et al., 1998; USEPA, 1999). The approach of environmental-standard-based risk assessment (ERA) is to compare contaminant concentration with the corresponding ambient air quality standards. In cases when the concentrations are above standards but there is no exposed population, the pollution control can then be perceived as being not a top priority issue of the ambient air quality management. This situation cannot be characterized by environmental risk assessment (ERA) alone, further health risk assessment (HRA) is needed for better risk management. The approach of health risk assessment (HRA) for non-carcinogenic contaminants (e.g. SO_2) is to compare the human chronic intake of contaminant with the corresponding reference dose.

Environmental-standard-based risk assessment (ERA)

As mentioned above, through Monte Carlo simulation, the probability under which the contaminant concentration exceeds the environment quality standard can be described as follows:

$$P_F = P(C>C_S) = 1-F\ (C_S) \qquad (4.7)$$

Where C is the contaminant concentration, C_s is the ambient air quality standard, and F (C_s) is the cumulative distribution function (CDF) of contaminant concentration which can be obtained from Monte Carlo simulation results.

Health risk assessment (HRA)

The fundamental elements of risk assessment include hazard identification, toxicity assessment, exposure assessment, and risk characterization (USEPA, 1999). Figure 4.10 shows components of the human health risk assessment process, and the detailed explanations are described below.

Hazard Identification:

The data gathered and evaluated in this stage provide information into the layout of the site, chemicals which may be of potential concern, possible exposure pathways and routes by which people living in the area may be exposed to these chemicals, the types of people within the area who have the highest potential for exposure based on their lifestyles, activities, etc., and any other specific areas or issues of concern to be addressed. The outcome of this task forms the basis of the approach taken in the risk assessment. Public input is an important part of this step to ensure information collected reflects the community being evaluated and addresses their needs and concerns.

In terms of volume and variety of contaminants emitted, no other single pollution source comes close to matching the negative impact from electric power plants. In Canada, nationally, annual power plant emissions are responsible for 22% of carbon dioxide pollution, 20% of sulfur dioxide pollution, 11% of nitrogen oxide pollution, and 25% of mercury pollution (NPRI, 2002). SO_2, as one of the key primary pollutants of concern produced by fossil fuel power plants, is selected for evaluation in the human health risk assessment of air emissions from the Holyrood Thermal Generating Station.

This section is aiming at evaluating the potential for adverse health effects to local residents exposed to current measured SO_2 concentrations; and the exposure pathways selected for case evaluation in the human health risk assessment is inhalation of outdoor/indoor air by adults/children age 2-12.

The potentially exposed populations would include:

(1) Present population in vicinity of the plant; It is identified as those living within

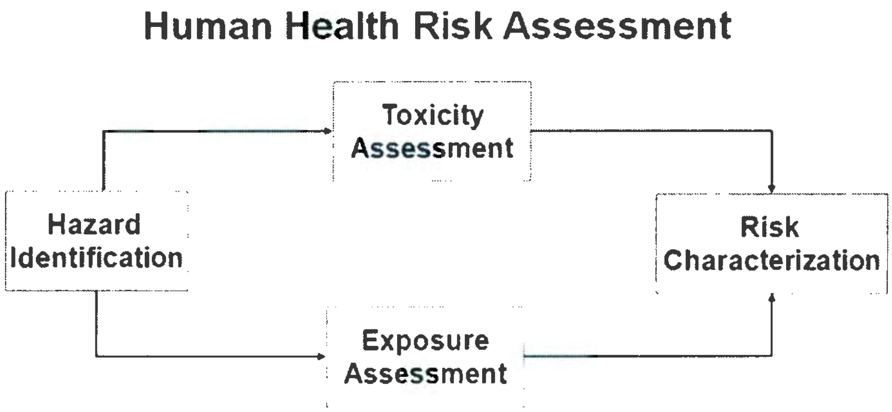


Figure 4.10 Human health risk assessment process

specified distances from site boundaries. Here, the $400 \times 400\ m^2$ of central area and the point of maximum pollutants concentrations were chose as the target area.

(2) Subpopulations of special concern, e.g., young children.

Exposure Assessment:

The amount of exposure to each of the emissions of concern that people living in the area could be receiving are estimated using computer models and environmental monitoring data.

Since the contaminant is not a recognized or suspect carcinogen, there is no need to do the exposure assessment taking them as carcinogens. Here just do the noncarcinogenic exposure assessment of the pollutant as noncarcinogens. For Inhalation:

$$I_N = \frac{C \times CR \times EF \times ED \times RR \times Abs}{BW \times AT} \tag{4.8}$$

Where I_N = intake (mg/kg of body weight/day); C = concentration at exposure point (e.g., mg/L in water or mg/m^3 in air); CR = contact rate (e.g., L/day or m^3/day); EF = exposure frequency (days/year); ED = exposure duration (years); RR = retention rate (%); Abs =Absorption rate (%); BW = body weight (kg); AT = averaging time (days)

Table 4.1 lists the assumed parameters of adults and children age 2-12 (subpopulations of special concern) for calculation of dosage and intake determined for the Holyrood Thermal Generating Station.

Chronic daily intake by adults and children age 2-12 were calculated with the results showed in Table 4.2.

Table 4.1 Parameters for calculation of dosage and intake

Parameter	Adults	Child age 2-12
Average body weight (kg)	70	22.5
Air breathed (m^3/day)	0.83	0.355
Retention rate (inhaled air)	100%	100%
Absorption rate (inhaled air)	100%	100%
Exposure frequency (days/year)	365	365
Exposure duration (years)	30	5

Table 4.2 Chronic daily intake by adults and children age 2-12

Target Groups	Chemicals	Chronic Daily Intake (μg /kg*d) at $C_{min} = 7.030 \mu g/m^3$
adults	SO_2	2.501
children	SO_2	0.555

Toxicity Assessment:

In this step, exposure limits are selected for each of the chemicals of potential concern being evaluated in the assessment. Exposure limits represent the amount of a chemical an individual can be exposed to on a daily basis without developing health effects or where the risk of developing a health effect is considered to be at an acceptable level. Exposure limits exist for many chemicals and have been established by regulatory agencies such as Health Canada, United States Environmental Protection Agency and World Health Organization. For air pollutants (e.g. sulfur dioxide), the regulatory air quality guideline is selected as the exposure limit, i.e., Ambient air SO_2 RfC is $660\mu g/m^3$.

Risk Characterization:

To determine whether or not the estimated exposures to the chemicals of potential concern would be expected to result in any adverse health problems, the estimated exposure level is compared to the exposure limit. If the estimated exposures are less than the exposure limit, no adverse health effects are predicted. If estimated exposures are greater than exposure limits, there is a possibility of adverse health effects. Prior to concluding that adverse health effects could actually be occurring, the assumptions used in the assessment (which are intentionally protective or conservative to ensure exposures and risks are not underestimated) need to be re-examined, and their impact on the exposure and risk estimates should be understood.

Since SO_2 is not a recognized or suspect carcinogen, there is no need to consider its carcinogenic toxicity. In this study, only its noncarcinogenic toxicity resulted from emission from the thermal plant was evaluated. The toxicity scores for SO_2 in the ambient air could be obtained as follows,

$$TS = C_{\max} / RfC \tag{4.9}$$

Where TS = toxicity score; C_{max} = maximum concentration, $\mu g / m^3$; RfC = chronic reference concentration, ($\mu g / m^3$).

From the results of the air dispersion modeling before (Chapter 3), all the concentrations of SO_2 emitted from the stacks are far from both the local and federal standards. In risk assessment, only the maximum annual average concentrations occurred in south-east from the plant were considered. In addition, for the purpose of comparison, the 400 meters diameter local area surrounding the plant was targeted and it can be easily tell from Table 4.3 that the concentrations of such points always demonstrated the lowest value. By this way, it is enough to generate a range of the health effects between the lowest and highest damage.

Noncarcinogenic risk is normally characterized in terms of a hazard index. The hazard index is calculated by

$$HI = I_N / RfD \tag{4.10}$$

Where HI = hazard index; I_N = chronic daily intake of noncarcinogen, $\mu g / kg$; RfD = reference dose, $\mu g / kg$.

The inhalation noncarcinogenic risk to adults and children age 2-12 in the selected location can be calculated and the outputs are shown in Table 4.4.

Table 4.3 Toxicity analysis for SO_2 emission in 2003

Chemical	C($\mu g/m^3$)		Inhalation	Toxicity Score	
SO_2	Max.	Central area	RfC ($\mu g/m^3$)* (OEHHA-CREL)	Max	Central area
	54.45819	7.030	660	0.0825	0.0107

* Only consider the major human health risks through inhalation.

Table 4.4 Noncarcinogenic Risk Output

Chemicals		Dose (ug/kg*d)		Inhalation RfD (ug/kg*d)*	Noncarcinogenic Risk	
		Max.	Central area		Max.	Central area
Adults	SO_2	19.372	2.501	NA	-	-
Children	SO_2	4.296	0.555	NA	-	-

The Inhalation RfDs of these contaminants are not available, and so, it is impossible to conduct the assessment by this method.

4.1.6 Stochastic – based Fuzzy Risk Assessment

An attempt was made to link the probabilistic and possibility uncertainties through the concepts of statistical analysis and fuzzy logic. Consequently, an integrated risk assessment approach was developed. This development will be based on (a) Monte Carlo simulation for the fate and transport of SO_2 in the study domain through an air dispersion model; (b) examination of SO_2 concentrations based on the simulation results that are expressed as cumulative distribution functions or probability density functions; (c) quantification of environmental quality guidelines and health impact criteria using fuzzy-logic techniques through a number of questionnaire surveys; (d) quantification of environmental and health risks based on fuzzy/stochastic inputs, and (e) risk assessment and decisions analysis based on fuzzy logic inference. Figure 4.11 shows the flow chart of the developed system.

The integrated risk level is derived from comprehensive consideration of environmental and health risks. The quantification of the integrated risk level can only be based on subjective opinions rather than through probabilistic analyses. Therefore, fuzzy logic is an effective tool for facilitating this kind of risk quantification. In this study, determination of the integrated risk is based on a series of fuzzy rules as acquired through questionnaire survey for inputs from experts and stakeholders. The risk levels are set to include six categories of fuzzy sets: "low", "low-to-medium", "medium", "medium-high", "high", and "very-high". The fuzzy logic operator "AND" is used to join factors in the antecedent

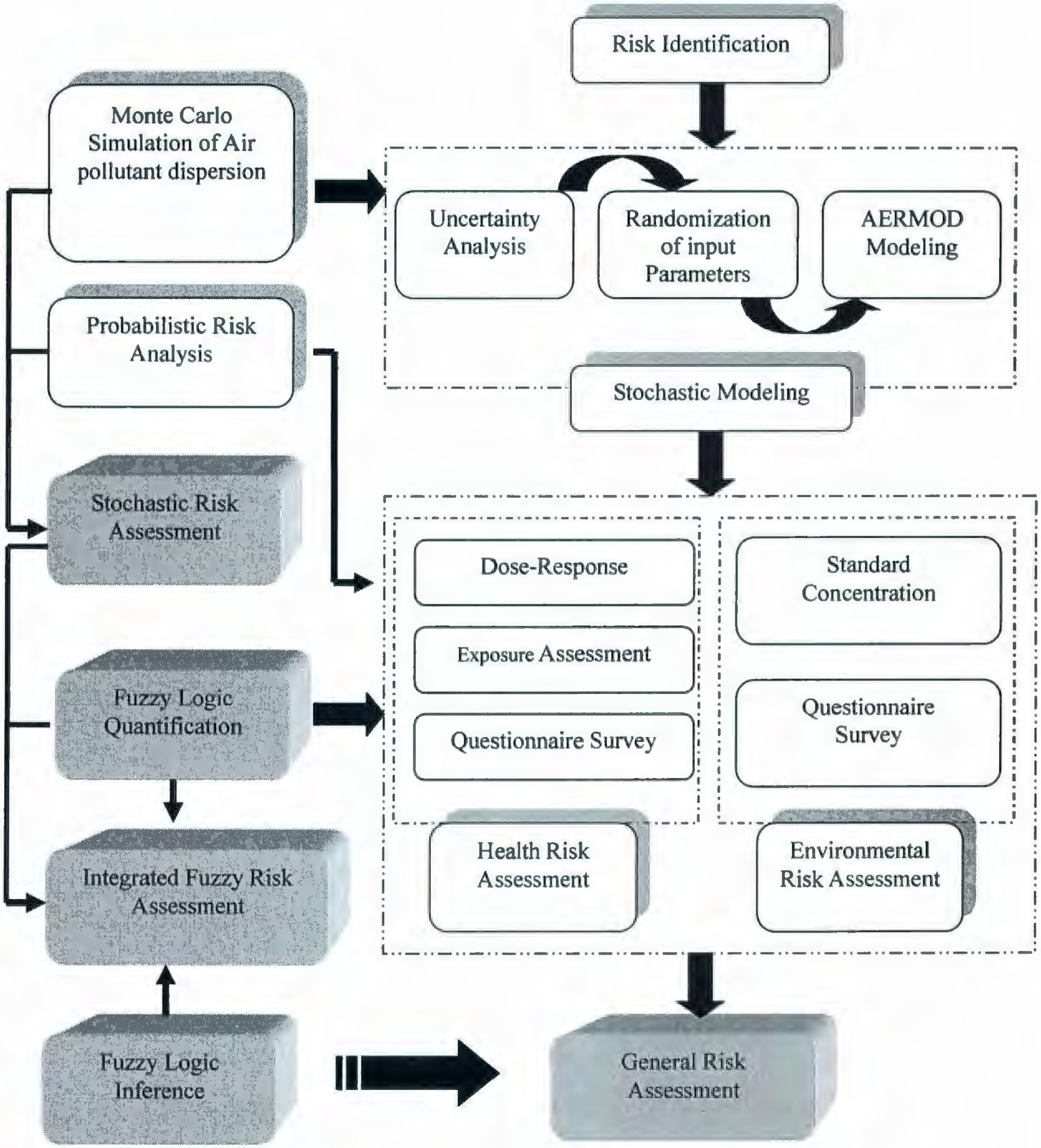


Figure 4.11 Framework of the Integrated Risk Assessment Approach for Ambient Air Quality Management

of the rules.

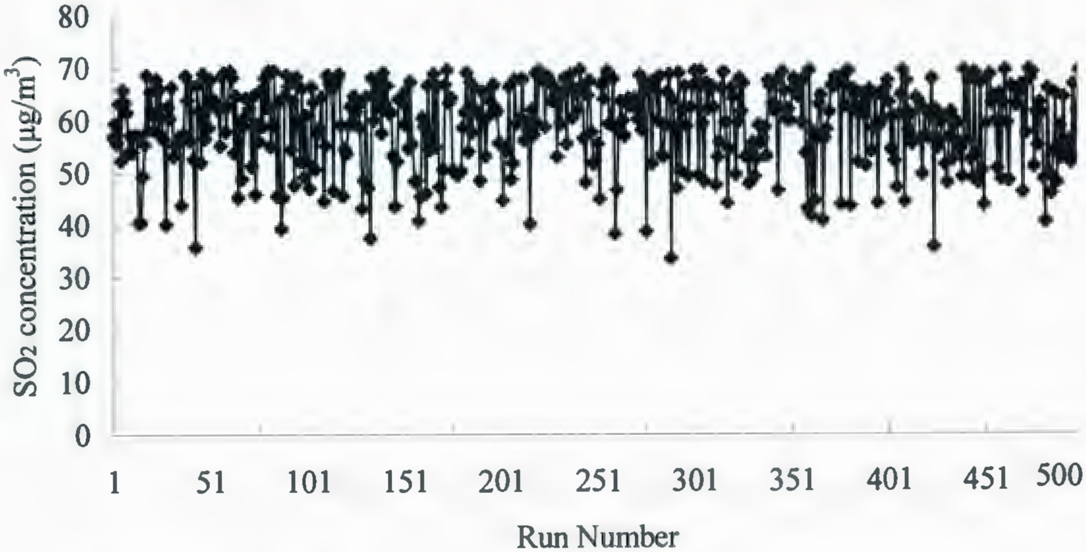
The corresponding membership functions of these risk levels can be established according to the method developed by Hwang and Chen (1999). The range of the integrated risk levels (i.e. IRL = [0, 100]) is subjectively given to the fuzzy sets in order for them to have single numerical risk scores (RS) after de-fuzzification. These numerical values have no direct relationship with the values of the input risk factors (e.g., environmental risk and health risk). However, after establishing the fuzzy sets of the integrated risk level, a numerical site score can be obtained through the fuzzy "AND" or fuzzy "OR" operations based on the environmental guideline, the probability of guideline violation, and the corresponding hazard index. The management decisions can then be made based on the calculated RS that describe the integrated risk level.

4.1.6.1 Monte Carlo Simulation of SO_2 Transport

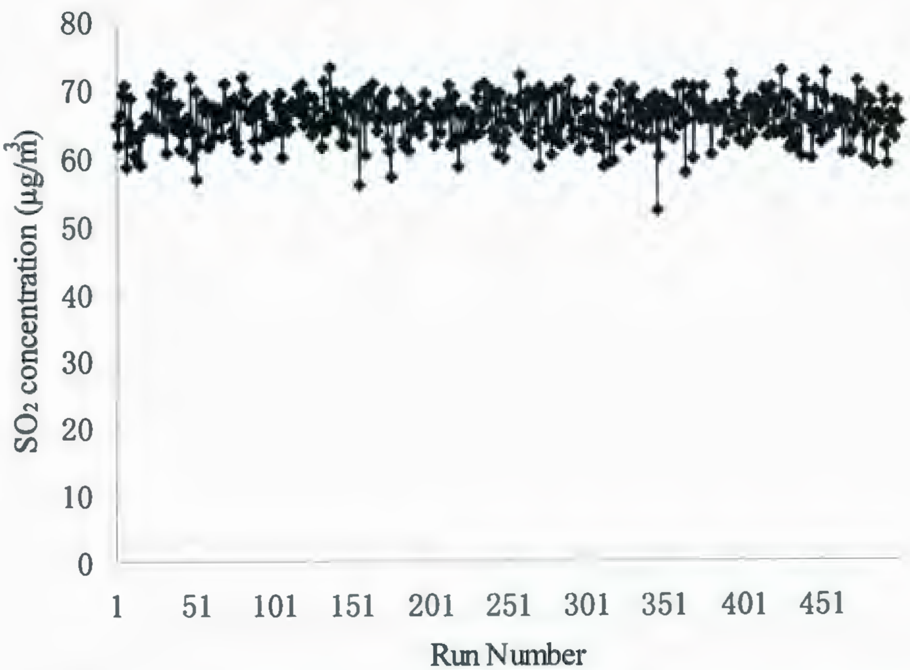
The stochastic modeling was used to simulate SO_2 transport in the ambient air in 2003 which showed the highest SO_2 concentration in the modeling results. The value of surface roughness was assumed to be normally distributed (Manomaiphiboon and Russell, 2004). The mean value and standard deviations of surface roughness length were used for Monte Carlo simulation. Due to uncertainties in this parameter, 1000 random numbers of the surface roughness value are generated, while 500 were generated from the whole possible surface roughness distribution range (0.0001-1.3m) (US EPA, 2006) of the modeling system and the other 500 random numbers were generated from the surface roughness (1.0m) chosen for the case study basing on the assumed probabilistic distribution (±20%). The reason to conduct the two sets of simulation is to see how the surface roughness performs on modeling results (i.e., SO_2 ground concentration) in both specific surface condition (urban) and all possible surface conditions (vary temporally and spatially). As a result, two 500 sets of SO_2-concentration-distribution patterns could be obtained by Monte Carlo simulation running. With a conservative consideration, only the peak concentrations of the yearly average were identified for further risk assessment, leading to the peak values as shown in Figure 4.12 (a) and (b). Figure 4.13 (a) and (b) show the corresponding cumulative distribution functions. A summary of the results from the Monte Carlo simulation is given in Table 4.5. It is obviously that the average concentration of (b) representing the ground concentration obtained from modeling by using urban yearly surface roughness is higher than that of (a) representing the ground concentration obtained from modeling by using the whole range of surface roughness varied temporally and spatially. The CDF of (b) be will used as a stochastic base for the following fuzzy risk assessment.

4.1.6.2 Fuzzy Environmental Quality Guidelines

The environmental risk assessment involves a comparison of the contaminant concentration with the corresponding environmental standard. However, the ambient air quality standards are different among countries, states or provinces. As indicated in Table 4.6, taken the annual average as an example, the guidelines for SO_2 range from 30 to $80\mu g/m^3$. As a result, for a specific case study, such kind of guidelines could be over/under-conservative or impractical for environmental risk analysis since the risk indicators such as the degrees of guideline violation are not compatible among different regions. Therefore, a number of uncertainties exist in the applicability of the guidelines.

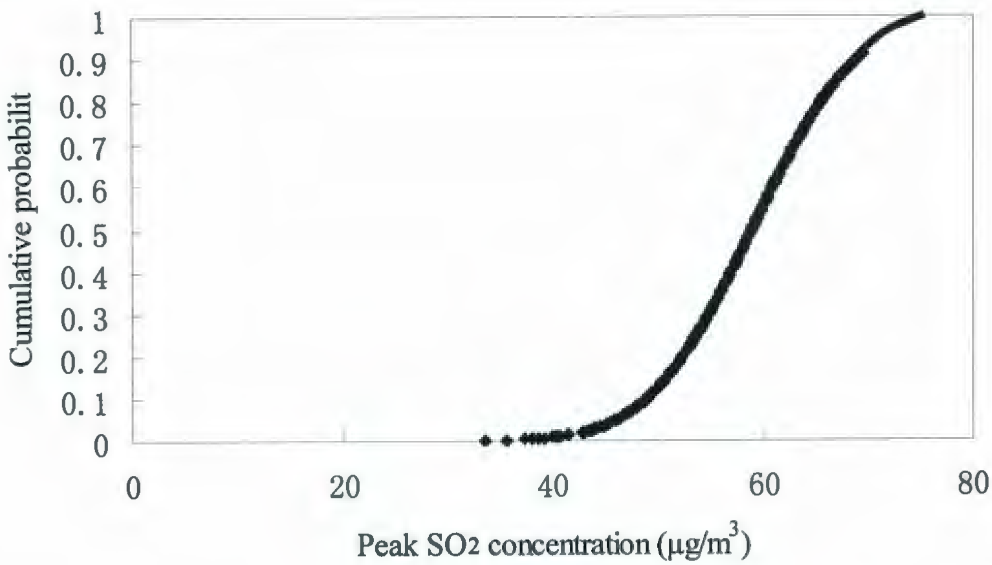


(a) Generated from the whole range of possible surface roughness value

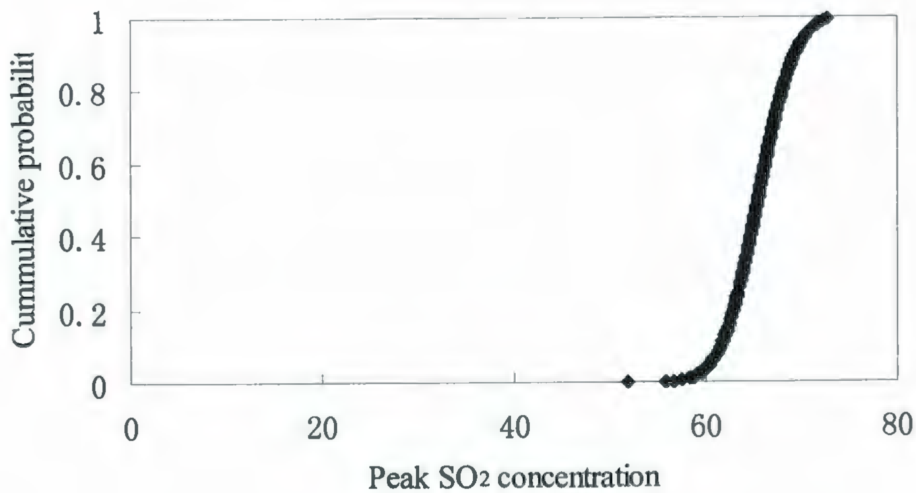


(b) Generated from the yearly average urban surface roughness value (not an exact representation of the Holyrood area)

Figure 4.12 Peak SO_2 concentrations ($\mu g/m^3$) in ambient air from Monte Carlo simulation runs



(a)



(b)

Figure 4.13 Cumulative distribution functions of peak SO_2 concentrations

Table 4.5 Summary of Monte Carlo simulation results

(a)

Contaminant concentration in ambient air	Minimal (μg/m^3)	Maximum (μg/m^3)	Average μg/m^3)	Standard deviation (ug/m^3)	Skewness (μg/m^3)
SO_2	34.474	69.574	59.04	7.82	-0.73

(b)

Contaminant concentration in ambient air	Minimal (μg/m^3)	Maximum (μg/m^3)	Average (μg/m^3)	Standard deviation (μg/m^3)	Skewness (μg/m^3)
SO_2	52.02	72.82	65.50	4.01	-0.48

Table 4.6 Ambient air quality standards for SO_2 Respiratory irritation in sensitive individuals

World Health Organization ($\mu g/m^3$)(WHO, 2000)	10min avg GV= 500 12h avg GV = 125 Annual avg GV= 50
Environment Canada/Health Canada National Ambient Air Quality (NAAQO) ($\mu g/m^3$)(CCME, 2002)	1h max desirable = 450 24h max desirable= 150 Annual max desirable= 30 1h max acceptable = 900 24h max acceptable=300 Annual max acceptable=60 24h max tolerable=800
Newfoundland and Laborador Regulation 39/04 ($\mu g/m^3$)(NL, 2004)	1h Ambient Air Quality Standard (AAQS) = 900 3h AAQS = 600 24h AAQS = 300 Annual AAQS= 60
U.S.EPA National Ambient Primary Air Quality Standards ($\mu g/m^3$) (U.S. EPA, 2005)	24 hour average= 366 Annual average = 80
National Standards for Criteria Air Pollutants in Australia (ppm) (DEH, 2005)	1hour average= 0.20 24 hour average= 0.08 Annual average = 0.02
Air Quality Standards for the Europe ($\mu g/m^3$) (EEC Directive Directive 80/779) (EEC, 2005)	24 hour average= 250 Annual average = 80

Such uncertainties can hardly be quantified by probabilistic distributions, but they can be described through linguistic variables that can be quantified through fuzzy logic. To facilitate a guideline-based environmental risk analysis, the guidelines are divided into three strictness levels, namely "strict", "medium" and "loose". Construction of membership functions for these three fuzzy sets will rely on experiences of the experts and stakeholders who have in-depth knowledge of the concerned system and can provide valuable inputs for quantifying the uncertainties. Fuzzy logic provides an effective tool for processing such subjective opinions. A questionnaire survey was conducted to collect data for establishing the membership functions (see Appendix III). The annual average guideline for SO_2 was of interest in this study. Table 4.7 lists the survey results regarding the three strictness levels of guidelines. The results indicated that 67% of the surveyed respondents preferred the "strict" guideline, which means "the annual average SO_2 concentration should be approximately 30 $\mu g/m^3$"; around 47% of the respondents selected "60 $\mu g/m^3$" as a "medium" one for the annual average SO_2 concentration; and 67% of the respondents preferred that "the annual average SO_2 concentration should be approximately 80 $\mu g/m^3$ or less" as a "loose" one. So the membership functions of these three strictness levels can then be constructed based on the survey results (Figure 4.14). For example, if the ambient air quality guideline is 60 $\mu g/m^3$, then it can be categorized as "medium" (with a membership grade of 1); if the guideline is 40 $\mu g/m^3$, then it can be categorized as partly "strict" (with a membership grade of 0.35) and partly "medium" (with a membership grade of 0.68).

4.1.6.3 Linkage between Fuzzy and Stochastic Events

Table 4.7 Survey on ambient air quality guideline

(1) Survey on Strict ambient air quality guideline

The annual average SO_2 concentration should be approximately:	No. of Respondents	Percentage (%)
$30 \mu g/m^3$ or less	20	67
$50 \mu g/m^3$ or less	9	30
$55 \mu g/m^3$ or less	0	0
$60 \mu g/m^3$ or less	0	0
$65 \mu g/m^3$ or less	1	3
$70 \mu g/m^3$ or less	0	0
$80 \mu g/m^3$ or less	0	0
Total No. of Respondents	30	100

(2) Survey on Medium ambient air quality guideline

The annual average SO_2 concentration should be approximately:	No. of Respondents	Percentage (%)
30μg/m^3 or less	3	10
50μg/m^3 or less	6	20
55μg/m^3 or less	3	10
60μg/m^3 or less	14	**47**
65μg/m^3 or less	3	10
70μg/m^3 or less	1	3
80μg/m^3 or less	0	0
Total No. of Respondents	30	100

(3) Survey on loose ambient air quality guideline

The annual average SO_2 concentration should be approximately:	No. of Respondents	Percentage (%)
$30\mu g/m^3$ or less	2	7
$50\mu g/m^3$ or less	1	3
$55\mu g/m^3$ or less	2	7
$60\mu g/m^3$ or less	2	7
$65\mu g/m^3$ or less	1	3
$70\mu g/m^3$ or less	2	7
$80\mu g/m^3$ or less	20	**67**
Total No. of Respondents	30	100

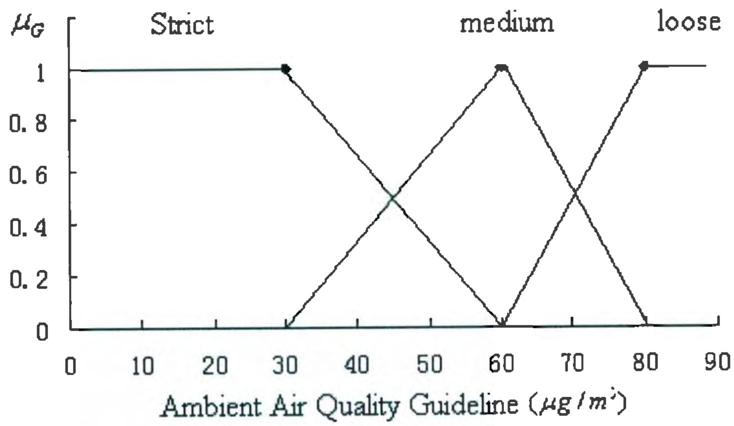


Figure 4.14 Membership functions of ambient air quality guidelines

The direct application of environmental risk analysis via Monte Carlo simulation methods may lead to two potential shortcomings. Firstly, risk analysis using the Monte Carlo outputs requires that distributions for the input parameters be precisely specified; secondly, researchers mostly assume the input parameters are independent of one another even though they are obviously not. Although methods to simulate correlations among the parameters exist, they are not detailed enough for further risk quantification, especially when the dependencies are not well known.

The SO_2 concentrations predicted through the Monte Carlo simulation can be regarded as stochastic events due to the randomness in the input parameters (e.g. surface roughness). The stochastic event can be characterized through a probability concept. According to the definition, probability is a measure of an empirical, objective and physical fact of the external world, independent of human attitudes, opinions, models and simulations. It is never relative to evidence or opinion. As a result, the outcome of the stochastic event (e.g., SO_2 concentration exceeds the guideline) should be either true or false. However, the outcome may be given by a quantity other than true or false due to the uncertainties in the environmental guidelines and the Monte Carlo outputs. In this study, the occurrence of environmental risk due to the violation of the environmental guideline is treated as a fuzzy event. Randomness associated with the SO_2 concentration is linked to this fuzzy event using the concept of fuzzy logic. The environmental risk levels can be categorized into "low", "low-to-medium", "medium", "medium-to-high", "high" by associating them with different magnitudes of probability of guideline violation that is obtained from Monte Carlo outputs. In addition, the guidelines with different strictness degrees are also incorporated within the modeling system for quantifying the environmental risk levels. The construction of membership functions for these fuzzy events still relies on questionnaire survey. Thus, this study has integrated fuzzy logic, expert involvement, and stochastic simulation within a general framework. It has also attempted to link the probabilistic and possibilistic uncertainties using the concept of fuzzy logic.

(1) Fuzzy environmental risk under the strict guideline

Table 4.8 lists the survey results of environmental risk levels under the strict environmental guideline.

It was found that 53% of the surveyed respondents selected "30% or less" as "low environmental risk" for the probability of guideline violation under the strict guideline; 57% of the respondents preferred that "the probability of guideline violation should be approximately 40%" as a "low-to-medium environmental risk" under the strict guideline; 57% of the respondents chose "the probability of guideline violation should be approximately 50%" as a "medium environmental risk"; 53% of the respondents showed "the probability of guideline violation should be approximately 60%" as a "medium-to-high environmental risk"; and 47% of the respondents selected "the probability of guideline violation should be approximately 70% or greater" as the "high environmental risk". According to Hwang and Chen (1992), the membership functions of these fuzzy sets can then be constructed based on the survey results (Figure 4.15). In this figure, "L", "L-M", "M", "M-H" and "H" represent "Low", "Low-to-Medium", "Medium", "Medium-to-High" and "High", respectively.

For example, if the probability of strict-guideline violation is 55% from the Monte Carlo

Table 4.8 Survey on environmental risk levels under the strict guideline

(1) Survey on low environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	7	23
20% or less	3	10
30% or less	16	**53**
40% or less	2	7
50% or less	2	7
60% or less	0	0
70% or less	0	0
80% or less	0	0
90% or less	0	0
Total No. of Respondents	30	100

(2) Survey on low-to-medium environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	1	3
20% or less	6	20
30% or less	4	13
40% or less	17	**57**
50% or less	0	0
60% or less	2	7
70% or less	0	0
80% or less	0	0
90% or less	0	0
Total No. of Respondents	30	100

(3) Survey on medium environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	1	3
20% or less	1	3
30% or less	5	17
40% or less	4	13
50% or less	17	**57**
60% or less	0	0
70% or less	2	7
80% or less	0	0
90% or less	0	0
Total No. of Respondents	30	100

(4) Survey on medium-to-high environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	0	0
20% or less	0	0
30% or less	1	3
40% or less	5	17
50% or less	3	10
60% or less	16	**53**
70% or less	3	10
80% or less	2	7
90% or less	0	0
Total No. of Respondents	30	100

(5) Survey on high environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	1	3
20% or less	0	0
30% or less	1	3
40% or less	0	0
50% or less	6	2
60% or less	2	7
70% or less	14	**47**
80% or less	2	7
90% or less	4	13
Total No. of Respondents	30	100

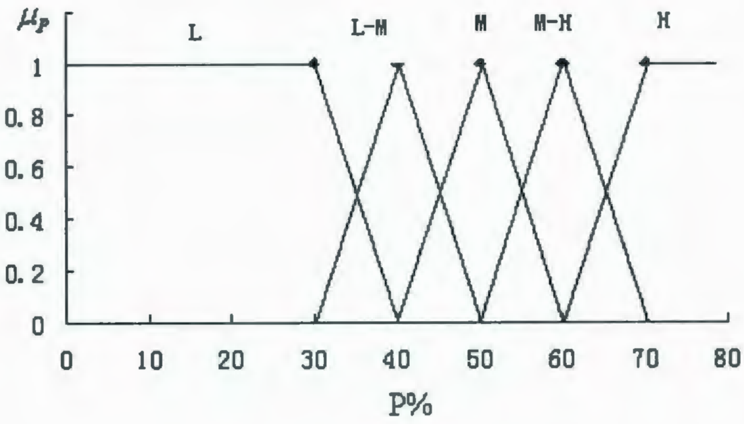


Figure 4.15 Membership function of environmental risk associated with the probability of violating the strict ambient air quality standard (note: P% = Probability of contaminant concentration exceeding its corresponding ambient air quality standard)

simulation, then the related environmental risk can be categorized as partly "medium" (with a membership grade of 0.5) and partly "medium-to-high" (with a membership grade of 0.5). If the probability is 35%, then the risk can be categorized as partly "low" (with a membership grade of 0.5) and partly "low-to-medium" (with a membership grade of 0.5).

(2) Fuzzy environmental risks when medium guideline is applied

Table 4.9 lists the survey results of environmental risk levels under the medium environmental guideline.

Similarly, the membership functions can be established according to the survey results: "the probability of guideline violation should be approximately 20% or less" corresponds to "low environmental risk" under the medium guideline; "the probability of guideline violation should be approximately 30%" is of "low-to-medium environmental risk" under the medium guideline; "the probability of guideline violation should be approximately 40%" corresponds to "medium environmental risk"; "the probability of guideline violation should be approximately 50%" is of "medium-to-high environmental risk"; and "the probability of guideline violation should be approximately 60% or greater" corresponds to "high environmental risk" under the medium guideline.

The membership functions of these fuzzy events are shown in Figure 4.16. For example, if the probability of medium-guideline violation is 42.5% from the Monte Carlo simulation, then the related environmental risk can be categorized as partly "medium" (with a membership grade of 0.75) and partly "medium-to-high" (with a membership grade of 0.25). If the probability is 22.5%, then the risk can be categorized as partly "low" (with a membership grade of 0.75) and partly "low-to-medium" (with a membership

Table 4.9 Survey on environmental risk levels under the medium guideline

(1) Survey on low environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	8	27
20% or less	17	**57**
30% or less	4	13
40% or less	0	0
50% or less	1	3
60% or less	0	0
70% or less	0	0
80% or less	0	0
90% or less	0	0
Total No. of Respondents	30	100

(2) Survey on low-to-medium environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	2	7
20% or less	7	23
30% or less	16	**53**
40% or less	4	13
50% or less	0	0
60% or less	1	3
70% or less	0	0
80% or less	0	0
90% or less	0	0
Total No. of Respondents	30	100

(3) Survey on medium environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	1	3
20% or less	1	3
30% or less	5	17
40% or less	19	**63**
50% or less	3	10
60% or less	1	3
70% or less	0	0
80% or less	0	0
90% or less	0	0
Total No. of Respondents	30	100

(4) Survey on medium-to-high environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	1	3
20% or less	1	3
30% or less	1	3
40% or less	3	10
50% or less	19	**63**
60% or less	4	13
70% or less	1	3
80% or less	0	0
90% or less	0	0
Total No. of Respondents	30	100

(5) Survey on high environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	1	3
20% or less	0	0
30% or less	1	3
40% or less	1	3
50% or less	4	13
60% or less	16	**53**
70% or less	4	13
80% or less	3	10
90% or less	0	0
Total No. of Respondents	30	100

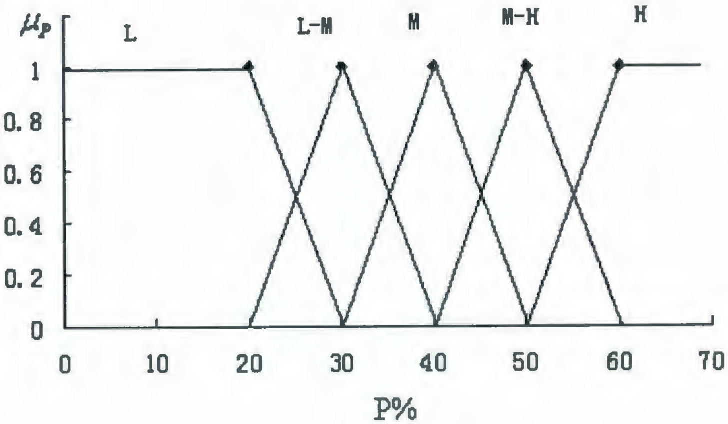


Figure 4.16 Membership function of environmental risk associated with the probability of violating the medium ambient air quality standard (note: P% = Probability of contaminant concentration exceeding its corresponding ambient air quality standard)

grade of 0.25).

(3) Fuzzy environmental risk under the loose guideline

Table 4.10 lists the survey results of environmental risk levels under the loose environmental guideline.

The membership functions of the fuzzy sets can be established according to the following investigation results: "the probability of guideline violation should be approximately 10% or less" correspond to "low environmental risk" under the strict guideline; "the probability of guideline violation should be approximately 20%" is of "low-to-medium environmental risk" under the strict guideline; "the probability of guideline violation should be approximately 30%" correspond to "medium environmental risk"; "the probability of guideline violation should be approximately 40%" is of "medium-to-high environmental risk"; and "the probability of guideline violation should be approximately 50% or greater" corresponds to "high environmental risk" under the strict guideline. The membership functions of these fuzzy events are shown in Figure 4.17. For example, if the probability of medium-guideline violation is 50% from the Monte Carlo simulation, then the related environmental risk can completely be categorized as "high" (with a membership grade of 1). If the probability is 45%, then the risk can be categorized as partly "medium-to-high" (with a membership grade of 0.5) and partly "high" (with a membership grade of 0.5).

4.1.6.4 Fuzzy Health Risk Assessment

The toxicological data used to calculate reference doses (RFD) and slope factors (SF)

Table 4.10 Survey on environmental risk levels under the loose guideline

(1) Survey on low environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	26	**87**
20% or less	0	0
30% or less	3	10
40% or less	1	3
50% or less	0	0
60% or less	0	0
70% or less	0	0
80% or less	0	0
90% or less	0	0
Total No. of Respondents	30	100

(2) Survey on low-to-medium environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	4	13
20% or less	19	**63**
30% or less	3	10
40% or less	3	10
50% or less	1	3
60% or less	0	0
70% or less	0	0
80% or less	0	0
90% or less	0	0
Total No. of Respondents	30	100

(3) Survey on medium environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	2	7
20% or less	1	3
30% or less	19	**63**
40% or less	4	13
50% or less	3	10
60% or less	1	3
70% or less	0	0
80% or less	0	0
90% or less	0	0
Total No. of Respondents	30	100

(4) Survey on medium-to-high environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	2	7
20% or less	1	3
30% or less	0	0
40% or less	17	**57**
50% or less	6	20
60% or less	2	7
70% or less	2	7
80% or less	0	0
90% or less	0	0
Total No. of Respondents	30	100

(5) Survey on high environmental risk

The probability of guideline violation should approximately be:	No. of Respondents	Percentage (%)
10% or less	1	3
20% or less	0	0
30% or less	1	3
40% or less	0	0
50% or less	20	**67**
60% or less	1	3
70% or less	5	17
80% or less	1	3
90% or less	1	3
Total No. of Respondents	30	100

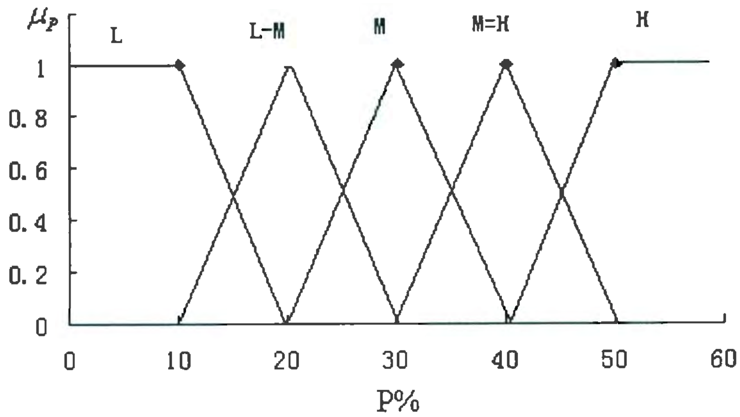


Figure 4.17 Membership function of environmental risk associated with the probability of violating the loose ambient air quality standard (note: P% = Probability of contaminant concentration exceeding its corresponding ambient air quality standard)

usually came from laboratory studies on animals. The health risk assessment often adopted reference doses and slope factors published by the US EPA. The US EPA has been updating the health risk limits to keep them current. As more and more toxicological studies have been completed, many updated data on reference doses and cancer potency slope factors have been added to the US EPA database. As a result, a number of uncertainties exist when these parameters are used to analyze health risks. These uncertainties should be incorporated within the process of risk analysis. However, the quantity of information available is not good enough for using probabilistic distributions to describe the applicability or suitability of the guidelines, resulting in consequent difficulties in quantifying the associated health risks. Such uncertainties usually show subjective features; as a result, a fuzzy logic approach was proposed in this study to account for such complexity. In this study, non-carcinogenic health risk introduced by SO_2 was investigated. The health risk levels were categorized into fuzzy sets of "low", "low-to-medium", "medium", "medium-to-high", and "high" by associating them with different magnitudes of toxicity score (TS, the ratio of contaminant concentration to the reference concentration). A questionnaire survey was conducted to obtain the associated membership functions. The investigated TS was set to vary from 0.045 (corresponding to the Canadian Ambient Air quality Guideline for SO_2 (CCME, 2002)) to 0.12 (approximately corresponding to the USEPA guideline for SO_2 (US EPA, 2005)).

Table 4.11 lists the survey results on health-risk levels. Similar to the identification of environmental risk levels, the membership functions of the related fuzzy health risk levels can be established according to the survey results: "the toxicity score is approximately

Table 4.11 Survey on health risk levels

(1) Survey on low health risk

The toxicity score should be approximately:	No. of Respondents	Percentage (%)
0.045 or less	28	**93**
0.054 or less	1	3
0.062 or less	1	3
0.070 or less	0	0
0.078 or less	0	0
0.086 or less	0	0
0.094 or less	0	0
0.100 or less	0	0
0.12 or less	0	0
Total No. of Respondents	30	100

(2) Survey on low-to-medium health risk

The toxicity score should be approximately:	No. of Respondents	Percentage (%)
0.045 or less	3	10
0.054 or less	6	20
0.062 or less	18	**60**
0.070 or less	3	10
0.078 or less	0	0
0.086 or less	0	0
0.094 or less	0	0
0.100 or less	0	0
0.12 or less	0	0
Total No. of Respondents	30	100

(3) Survey on medium health risk

The toxicity score should be approximately:	No. of Respondents	Percentage (%)
0.045 or less	1	3
0.054 or less	2	7
0.062 or less	5	17
0.070 or less	3	10
0.078 or less	19	**63**
0.086 or less	0	0
0.094 or less	0	0
0.100 or less	0	0
0.12 or less	1	3
Total No. of Respondents	30	100

(4) Survey on medium-to-high health risk

The toxicity score should be approximately:	No. of Respondents	Percentage (%)
0.045 or less	1	3
0.054 or less	1	3
0.062 or less	1	3
0.070 or less	4	13
0.078 or less	4	13
0.086 or less	1	3
0.094 or less	18	**60**
0.100 or less	0	0
0.12 or less	1	3
Total No. of Respondents	30	100

(5) Survey on high health risk

The toxicity score should be approximately:	No. of Respondents	Percentage (%)
0.045 or less	0	0
0.054 or less	0	0
0.062 or less	1	3
0.070 or less	2	7
0.078 or less	4	13
0.086 or less	0	0
0.094 or less	0	0
0.100 or less	5	17
0.12 or less	18	**60**
Total No. of Respondents	30	100

0.045or less" is corresponding to "low health risks"; "the toxicity score is approximately 0.062" is corresponding to "low-to-medium health risks"; "the toxicity score is approximately 0.078 or less" is corresponding to "medium health risks"; "the toxicity score is approximately 0.094 or less" is corresponding to "medium-to-high health risks"; and "the toxicity score is approximately 0.12 or less" is corresponding to "high health risks". Consequently, the membership functions of these fuzzy events were obtained (Figure 4.18). For example, if the calculated TS is 0.107, then the related health risk can be categorized as partly "medium-to-high" (with a membership grade of 0.5) and partly "high" (with a membership grade of 0.5). If the calculated TS is 0.07, then the related health risk can be categorized as partly "low-to-medium" (with a membership grade of 0.5) and partly "medium" (with a membership grade of 0.5).

4.1.6.5 General Risk Levels and Rules Base for Risk Management

The risk characterization can be conducted through environmental-standard-based risk and health risk levels as discussed in the previous sections. In this study, the environmental risk was defined as the risk introduced from the violation of environmental guidelines or regulations, and the health risk as the risk of health impact due to chronic intake of the contaminant (i.e., SO_2). The general risk levels were derived from an integrated consideration of environmental and health risks based on a series of fuzzy rules as acquired through questionnaire survey for inputs from experts and stakeholders. The risk levels were set to include six categories of fuzzy sets: "low", "low-to-medium", "medium", "medium-to-high", "high", and "very high". The fuzzy logic operator "AND" was used to join factors in the antecedent of the rules. Since both environmental and

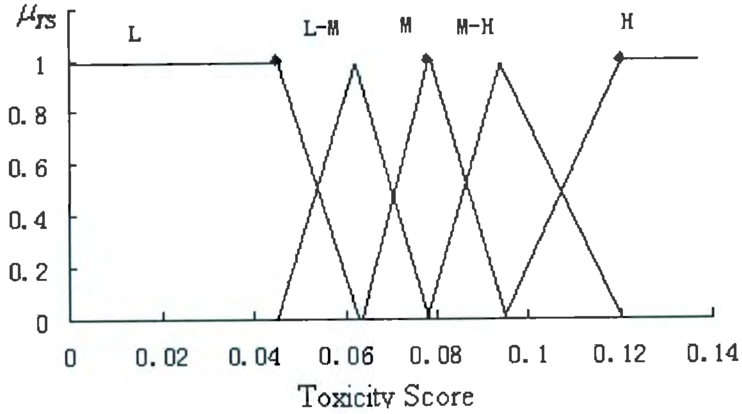


Figure 4.18 Membership function of health risk associated with toxicity score

health risks included five categories of fuzzy events, there were a total of 150 rules (5×5×6). Assume that, if a rule obtains the highest frequency in the survey, then it can be kept in the rule base for the determination of the general risk level. Table 4.12 lists the survey results for building the fuzzy rule base.

It was found that 96.7% of the surveyed respondents selected "if both environmental and health risks are low, then the general risk level will be low"; 84.3% of them selected "if the environmental risk is low and the health risk is low-to-medium, then the general risk will be low-to-medium"; 74.3% of them chose "if the environmental risk is low and the health risk is medium, then the general risk will be medium"; 70.0% of them showed "if the environmental risk is low and the health risk is medium-to-high, then the general risk will be medium-to-high", and 64.3% of them selected "if the environmental risk is low and the health risk is high, then the general risk will be high". The highest frequencies for other can be found in Table 4.12 as shown in bold font. As a result, 25 fuzzy rules were obtained (Table 4.13). Since the general risk level can be categorized into "low", "low-to-medium", "medium", "medium-to-high", "high" and "very high", the corresponding membership functions of these fuzzy events can then be established according to Hwang and Chen (1992) and Mohamed et al. (1999) (Figure 4.19). The range of the general risk levels (i.e. GRL = [0, 100]) is subjectively given to the fuzzy sets in order for them to have single numerical scores after de-fuzzification. These numerical values have no direct relationship with the values of the input risk factors (e.g., environmental risk and health risk). However, after establishing the fuzzy sets of the general risk level a numerical score can be obtained from Figure 4.19 through the fuzzy

Table 4.12 Survey on fuzzy rules

Antecedent		The general risk level is "number of respondents (percentage)"					
ER	HR	L	L-M	M	M-H	H	V-H
L	L	**29 (96.7%)**	1	0	0	0	0
L	L-M	3	**25 (84.3%)**	2	0	0	0
L	M	1	5	**22 (74.3%)**	1	1	0
L	M -H	2	0	6	**21 (70%)**	0	1
L	H	0	1	2	7	**19 (64.3%)**	1
L -M	L	5	**23 (76.7%)**	0	2	0	0
L -M	L -M	0	**28 (94.3%)**	1	1	0	0
L -M	M	0	2	**26 (86.7%)**	0	2	0
L -M	M -H	0	2	3	**21 (70%)**	3	1
L -M	H	0	1	3	3	**22 (74.3%)**	1
M	L	1	5	**23 (76.7%)**	1	0	0
M	L -M	0	5	**24 (80.0%)**	1	0	0
M	M	0	1	**24 (80.0%)**	4	1	0
M	M -H	0	0	3	**20 (66.7%)**	5	2
M	H	0	0	3	5	**13 (44.3%)**	1
M -H	L	0	2	4	**23 (76.7%)**	1	0
M -H	L -M	0	0	6	**23 (76.7%)**	1	0
M -H	M	0	0	2	**26 (86.7%)**	2	0
M -H	M -H	0	0	0	**20 (66.7%)**	9	1
M -H	H	0	0	0	5	**23 (76.7%)**	2

Table 4.12 Survey on fuzzy rules (Continue)

Antecedent	The general risk level is "number of respondents (percentage)"						
ER	HR	L	L-M	M	M-H	H	V-H
High	L	0	2	2	4	**22 (74.3%)**	0
High	L -M	0	1	5	2	**22 (74.3%)**	0
High	M	0	0	1	5	**23 (76.7%)**	1
High	M-H	0	0	0	3	**24 (80.0%)**	3
High	H	0	1	0	0	8	**21 (70.0%)**

Table 4.13 Rules for assessing the general risk level

Rule#	Antecedent		Consequence
	If environmental risk (ER) is	And health risk (HR)is	Then the general risk level (GRL) is
1	low	Low	Low
2	Low	Low-to-medium	Low-to-medium
3	Low	Medium	Medium
4	Low	Medium-to-high	Medium-to-high
5	Low	High	High
6	Low-to-medium	Low	Low-to-medium
7	Low-to-medium	Low-to-medium	Low-to-medium
8	Low-to-medium	Medium	Medium
9	Low-to-medium	Medium-to-high	Medium-to-high
10	Low-to-medium	High	High
11	Medium	Low	Medium
12	Medium	Low-to-medium	Medium
13	Medium	Medium	Medium
14	Medium	Medium-to-high	Medium-to-high
15	Medium	High	High
16	Medium-to-high	Low	Medium-to-high
17	Medium-to-high	Low-to-medium	Medium-to-high
18	Medium-to-high	Medium	Medium-to-high
19	Medium-to-high	Medium-to-high	Medium-to-high
20	Medium-to-high	High	High
21	High	Low	High
22	High	Low-to-medium	High
23	High	Medium	High
24	High	Medium-to-high	High
25	High	High	Very High

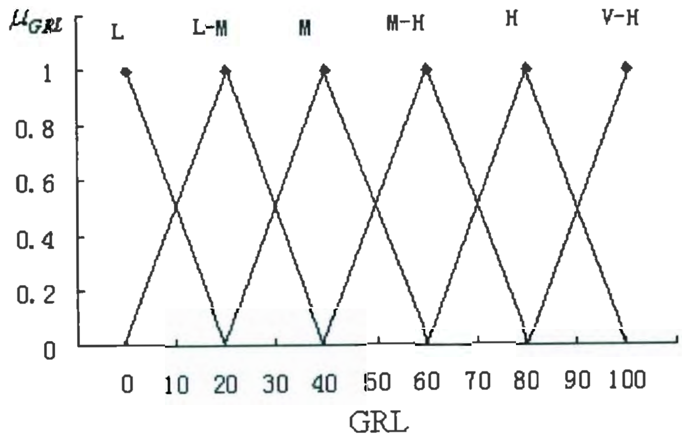


Figure 4.19 Membership functions of general risk levels

"AND" or fuzzy "OR" operations based on the environmental guideline, the probability of guideline violation, and the corresponding toxicity score. This will be illustrated in the result analysis as it applied to the SO_2 emission form the thermal station. The management decisions can then be made based on the calculated scores that describe the general risk level. Table 4.14 lists the relationship between scores and suggested management actions.

4.2 REAL CASE APPLICATION

Three scenarios were examined based on the annual average Ambient Air quality standards formulated by the Province of Newfoundland and Labrador, the Environment Canada, and the USEPA. The strictness degrees of the guidelines were analyzed, and the probabilities of guideline violation were obtained to analyze the associated environmental risks. The mean of the 500 peak SO_2 concentrations from the Monte Carlo simulation (b) was used for analyzing the hazard index through inhalation pathways. The associated health risks can be quantified. Thus, the general risk level due to the environmental and health risks would be obtained through fuzzy "AND" and "OR" operations.

4.2.1 Scenario 1: under the Environment Canada Ambient Air Quality Guideline

Environment Canada Ambient Air quality Guideline for the annual maximum desirable SO_2 is 30 $\mu g/m^{3.}$ It was indicated from Figure 4.14 that this guideline was "strict" (with a membership grade of 1). It was also found from Figure 4.13 (b) that $P(C<30) = F(30) = 0.0$; thus the probability of guideline violation was $P_F = 1\text{-}F(0.3) = 1.0$. As a result, the

Table 4.14 Risk management actions

Calculated Site Score	Risk Management Action
90-100	The SO_2 emission should be immediately controlled
70-90	Take full actions to control the SO_2 emission
50-70	restrict SO_2 emission
30-50	Take interim control measures
10-30	The air quality should be monitored
0-10	No actions are required

environment risk (ER) would be "High" with a membership grade of 1.0 according to Figure 4.15 when the probability was 1.0 and the guideline was "strict".

The associated toxicity score (TS) can be calculated as 0.099 when a reference dose (RFD) of 660 $\mu g/m^3$ was used. It could then be found from Figure 4.18 that the corresponding health risk (HR) would be partly "medium-to-high" (with a membership grade of 0.8) and partly "high" (with a membership grade of 0.2). Therefore, two combinations of the antecedents include: (a) if ER is "High" and HR is "Medium-to-high", and (b) if both ER and HR are "High". The input and output data were analyzed in the inference process as shown in Figure 4.20. The fuzzy "AND" operation was applied to the rule's antecedent to determine its consequence according to the rule base as shown in Table 4.13. In other words, the minimum degree of membership grade of the two input factors (ER and HR) was given to the output factor (GRL). In the rule number 24, μ_{GR} = min (1, 0.8) = 0.8, and in rule number 25, μ_{GR} = Min (1.0, 0.2) = 0.2. The outputs from the inference procedure, which were also the inputs for the composition process, were then two scaled down fuzzy GRL values. In the composition process, the fuzzy "OR" operation was applied to the two fuzzy GRL values. In other words, the two fuzzy GRL value were superimposed to obtain the final fuzzy GRL. The final GRL would be "High" with a membership grade of 0.8 under this scenario, and the crisp final GRL value was obtained by calculating the centroid of the fuzzy GRL value as 84. As a result, the suggested risk management action would be "take full actions to control the SO_2 emission" according to Table 4.14.

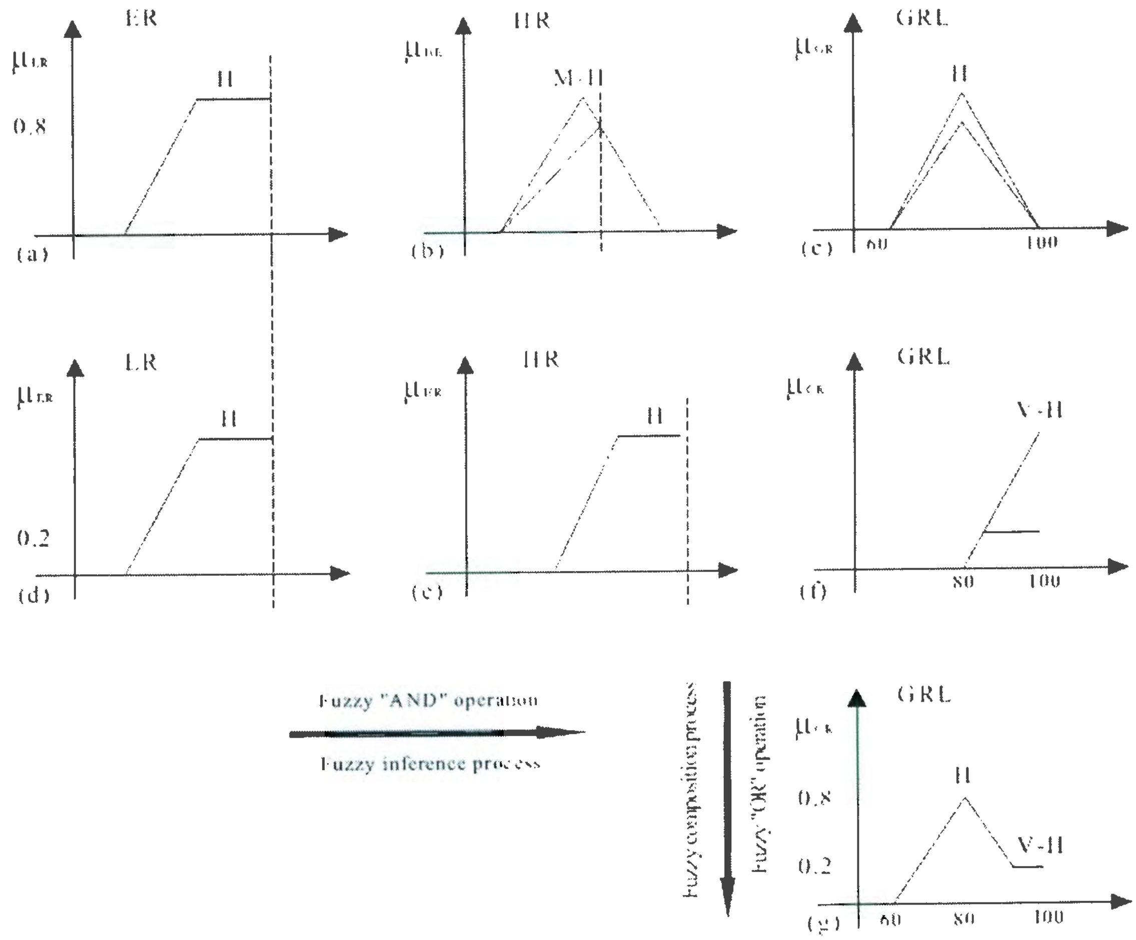


Figure 4.20 Fuzzy inference and composition process under scenario 1

4.2.2 Scenario 2: under the Newfoundland and Labrador Ambient Air quality Guideline

Newfoundland and Labrador Ambient Air quality Guideline for the annual average SO_2 is $60\mu g/m^3$. It was indicated from Figure 4.14 that this guideline was "medium" (with a membership grade of 1). It was also found from Figure 4.13 that P(C<60) = F (60) =0.05; thus the probability of guideline violation was P_F = 1-F (60) = 0.95. As a result, the environment risk (ER) would be "High" with a membership grade of 1.0 according to Figure 4.16 when the probability was 0.95 and the guideline was "medium".

The corresponding health risk (HR) would still be partly "medium-to-high" (with a membership grade of 0.8) and partly "high" (with a membership grade of 0.2). Therefore, we would have two combinations of the antecedents including: (a) if ER is "medium" and HR is "Medium-to-high" and (b) if ER is "medium" and HR is "High".

The input and output data were analyzed in the inference process as shown in Figure 4.21. The fuzzy "AND" operation was applied to the rule's antecedent to determine its consequence according to the rule base as shown in Table 4.13. In other words, the minimum degree of membership grade of the two input factors (ER and HR) was given to the output factor (GRL). In the rule number 24, μ_{GR} = Min (1, 0.8) = 0.8, and in rule number 25, μ_{GR} = Min (1.0, 0.2) = 0.2. The outputs from the inference procedure, which were also the inputs for the composition process, were then two scaled down fuzzy GRL values. In the composition process, the fuzzy "OR" operation was applied to the two fuzzy GRL values. In other words, the two fuzzy GRL value were superimposed to obtain

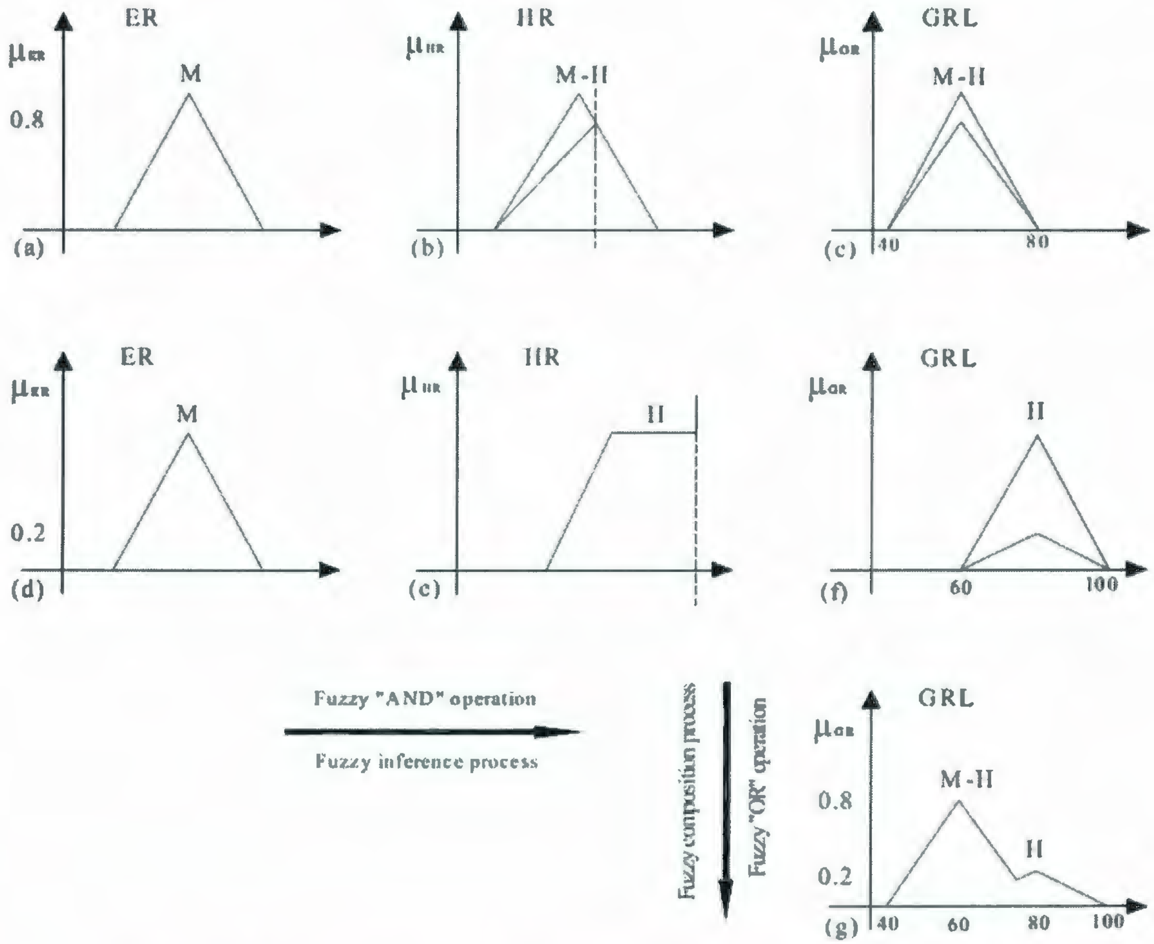


Figure 4.21 Fuzzy inference and composition process under scenario 2

the final fuzzy GRL. The final GRL would be "High" with a membership grade of 0.8 under this scenario, and the crisp final GRL value was obtained by calculating the centroid of the fuzzy GRL value as 64. As a result, the suggested risk management action would be "restrict SO_2 emission" according to Table 4.14.

4.2.3 Scenario 3: under the USEPA Ambient Air Quality Guideline

The USEPA Ambient Air quality Guideline for the annual average SO_2 is 80μg/m[4]. It was indicated from Figure 4.14 that this guideline was "loose" (with a membership grade of 1). It was also found from Figure 4.13 that $P(C<80) = F(80) = 1.0$; thus the probability of guideline violation was $P_F = 1 - F(80) = 0$. As a result, the environment risk (ER) would be "Low" with a membership grade of 1.0 according to Figure 4.17 when the probability was 0 and the guideline was "loose".

The corresponding health risk (HR) would still be partly "medium-to-high" (with a membership grade of 0.8) and partly "high" (with a membership grade of 0.2). Therefore, we would have two combinations of the antecedents including: (a) if ER is "Low" and HR is "Medium-to-high" and (b) if ER is "Low" and HR is "High".

The input and output data were analyzed in the inference process as shown in Figure 4.22. The fuzzy "AND" operation was applied to the rule's antecedent to determine its consequence according to the rule base as shown in Table 4.13. In other words, theminimum degree of membership grade of the two input factors (ER and HR) was given to the output factor (GRL). In the rule number 24, $\mu_{GR} = \text{Min}(1, 0.8) = 0.8$, and in rule number 25, $\mu_{GR} = \min(1.0, 0.2) = 0.2$.The outputs from the inference procedure,

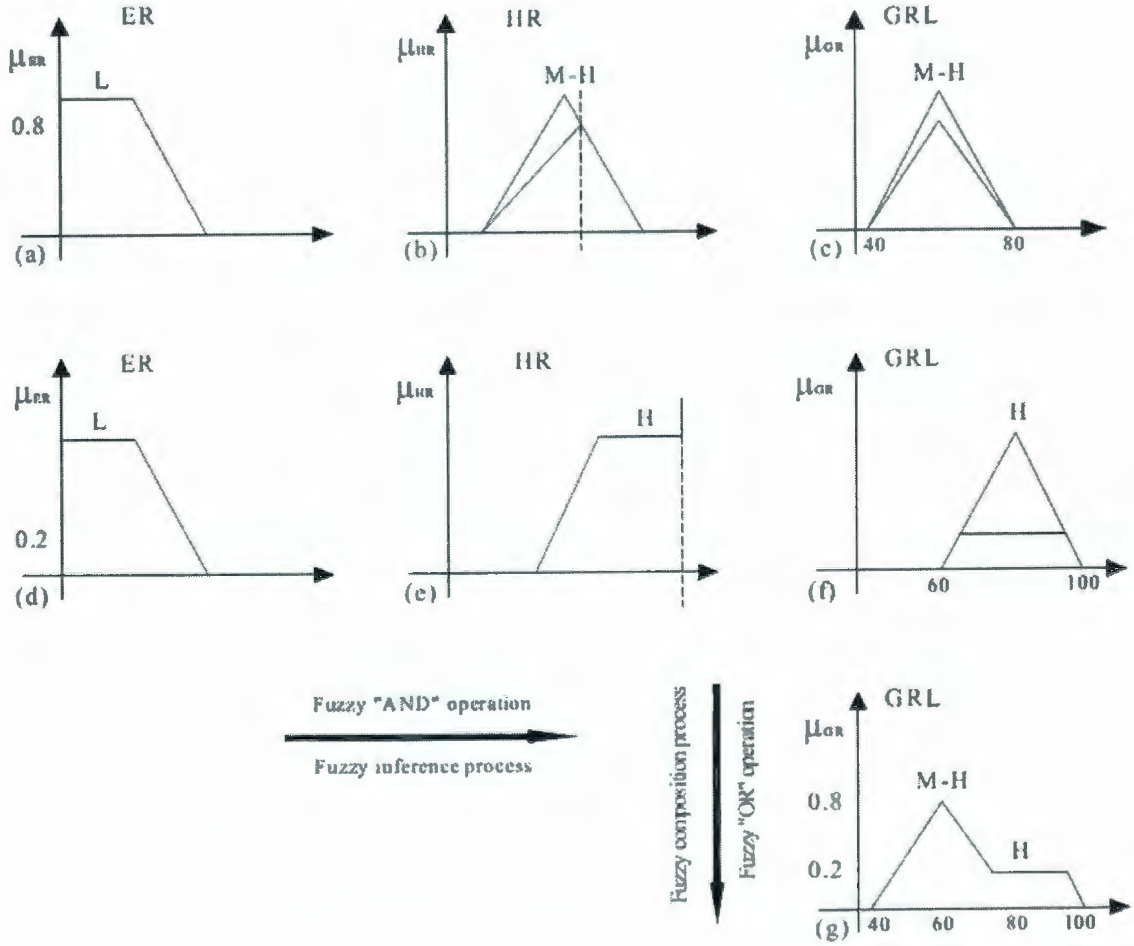


Figure 4.22 Fuzzy inference and composition process under scenario 3

which were also the inputs for the composition process, were then two scaled down fuzzy GRL values. In the composition process, the fuzzy "OR" operation was applied to the two fuzzy GRL values. In other words, the two fuzzy GRL value were superimposed to obtain the final fuzzy GRL. The final GRL would be "High" with a membership grade of 0.8 under this scenario, and the crisp final GRL value was obtained by calculating the centroid of the fuzzy GRL value as 64. As a result, the suggested risk management action would be "restrict SO_2 emission" according to Table 4.14.

4.3 MORE DISCUSSIONS

Actually, recently, the SO_2 from the Holyrood generation station is not violating the Ambient Air Quality guideline for both Canada and Newfoundland, the reason got here is just based on the peak value of Monte Carlo simulation results generated from the urban average surface roughness value which could not satisfactory describe the surface situation of the study area and make the results over-conservative, especially, for scenario one, the rule based system application is only conducted based on the desirable guideline, all of the remediation action decisions provided here are just representing the possible choice when there is more stringent guideline applied in the future.

4.3.1 Focus on North-Atlantic Region

For the northern regions in Canada like Labrador, the fragile ecosystems (e.g., reserves and parks) and remote communities are more vulnerable to environmental hazards than those in other regions. In the questionnaire survey, the respondents were supposed to show their opinion about whether or not to recommend a more stringent guideline for SO_2

in northern regions in Canada. From the 30 answers, 24 said "Yes", insisting that the risk should be based on the area specifics for better protecting the ecosystems and human being. For example, people said, "I believe all emissions guidelines should be stricter and more readily enforced", "It depends on the industry, for coal plants in this area, yes", ….,

and "Most of the contamination in the north is due to southern activities so it makes sense to put stringent guidelines all over". Only 6 people claimed "No". They concerned much on the pollution source and hold that: "stringent regulations would be needed in industrial part of each province. Therefore, even if we have more fragile ecosystem in those areas, we should have more concern of the hazard sources and their main production regions"; "All the ecosystems are fragile wherever they are. However, the natural SO_2 is different from the industrial SO_2. The background concentration of SO_2 varies with regions. However the industrial SO_2 is toxic even in tiny levels. So the objective would be to eliminate the industrial SO_2 to protect the environment in any area".

Based on their preference and understanding, the annual average guideline for SO_2 for northern regions in Canada, especially the fragile ecosystems and remote communities were further investigated in this study. Table 4.15 lists the survey results.

It was found that 80% of the surveyed respondents indicated that the opinion of "the annual average SO_2 concentration should be approximately 30 $\mu g/m^3$" is a "strict" guideline; 53% of the respondents selected ""the annual average SO_2 concentration should be approximately 50 $\mu g/m^3$" as a "medium" one; and 57% of the respondents showed "the annual average SO_2 concentration should be approximately 80 $\mu g/m^3$ or less" as a "loose" one.

The results also indicated that more stringent guideline was preferred. The membership functions of these three fuzzy sets can then be constructed based on the survey results (Figure 4.23). For example, if the ambient air quality guideline is 50μg/m3, then it can be categorized as "medium"(with a membership grade of 1); If the guideline is 40 μg/m3, then it can be categorized as partly "loose"(with a membership grade of 0.5) and partly "medium" (with a membership grade of 0.5).

Table 4.15 Survey on ambient air quality guideline for northern regions in Canada

(1) Survey on Strict ambient air quality guideline

The annual average SO_2 concentration should be approximately:	No. of Respondents	Percentage (%)
$30 \mu g/m^3$ or less	24	**80**
$50 \mu g/m^3$ or less	4	13
$55 \mu g/m^3$ or less	0	0
$60 \mu g/m^3$ or less	0	0
$65 \mu g/m^3$ or less	2	7
$70 \mu g/m^3$ or less	0	0
$80 \mu g/m^3$ or less	0	0
Total No. of Respondents	30	100

(2) Survey on Medium ambient air quality guideline

The annual average SO_2 concentration should be approximately:	No. of Respondents	Percentage (%)
30μg/m^3 or less	2	7
50μg/m^3 or less	16	**53**
55μg/m^3 or less	5	17
60μg/m^3 or less	5	17
65μg/m^3 or less	1	3
70μg/m^3 or less	1	3
80μg/m^3 or less	0	0
Total No. of Respondents	30	100

(3) Survey on loose ambient air quality guideline

The annual average SO_2 concentration should be approximately:	No. of Respondents	Percentage (%)
$30\mu g/m^3$ or less	0	0
$50\mu g/m^3$ or less	3	10
$55\mu g/m^3$ or less	4	13
$60\mu g/m^3$ or less	2	7
$65\mu g/m^3$ or less	1	3
$70\mu g/m^3$ or less	3	10
$80\mu g/m^3$ or less	17	57
Total No. of Respondents	30	100

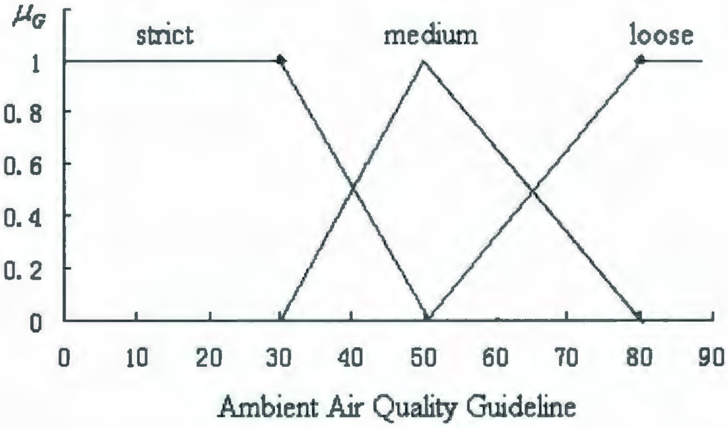


Figure 4.23 Membership functions of ambient air quality guidelines

CHAPTER 5 CONCLUSIONS

5.1 SUMMARY

The extent of air pollution problem depends greatly on the type and amount of air emission, and their dispersion into the atmosphere. How to effectively evaluate the associated risks of violating environmental standards and health criteria has become one of the major challenges for environmental engineers and managers. In this study, an integrated risk assessment model was developed for systematic and in-depth analysis of environmental and human health risks associated with SO_2 emission from power systems. The proposed risk assessment system is based on the following elements: (a) Monte Carlo simulation for the SO_2 dispersion in the ambient air through a regulatory steady-state plume numerical modeling system , AERMOD, to account for stochastic uncertainties, and statistic analysis of simulation results that were expressed as cumulative distribution functions, (b) in-depth risk assessment based on stochastic modeling results by fuzzy set theory application: quantification of environmental guidelines and health impacts using fuzzy membership functions acquired from a questionnaire survey; quantification of risk levels (environmental risk, health risk and general risk) by fuzzy set operation in a developed fuzzy rule-based system. A brief summary of their features and application are given as follows:

(1) Air dispersion modeling for SO_2 emission from a thermal power station was conducted as a case study to demonstrate applicability of the proposed modeling system. One input parameter (surface roughness length) was considered to be uncertain with

known probability distribution. Random numbers regarding the surface roughness were generated to support 1,000 Monte Carlo runs. The output was statistically examined and formed the bases of the risk assessment on the next stage. It provided a systematic manner to tackle uncertainties with probabilistic uncertainties within the modeling system.

(2) An integrated risk assessment approach was proposed in dealing with both uncertainties associated with terrain conditions and evaluation criteria in an ambient air quality management system. This development was based on the result of former Monte Carlo simulation for the ground concentration of SO_2 by the use of numerical air dispersion model, AERMOD. At first, SO_2 concentration levels obtained from the simulation results were examined and set as the inputs for the risk analysis, then a questionnaire survey was conducted for qualifying criteria and generating the corresponding fuzzy membership functions; finally, the risk assessment related to environmental, human health and general risks was conducted based on the stochastic simulation-based fuzzy inputs in a developed fuzzy rule-based system. The developed approach was applied to real-world case study in Canada. Three scenarios with application of different environmental quality guidelines were analyzed, and the results were useful for understanding environmental risk resulting from standards violation and human health risk due to SO_2 inhalation. It could directly support decision making on emission control by providing general risk corresponding to different control options.

5.2 RESEARCH ACHIEVEMENTS

As an extension of the previous studies, the proposed integrated risk assessment model is able to systematically quantify both probabilistic and possibilistic uncertainties associated with terrain conditions, environmental guidelines, and health criteria in air quality management systems. This study is based on the fact that due to the existence of many uncertain and complex factors spatially and temporally, deterministic environmental guidelines could be impractical and not suit to be implemented. Fuzzy membership functions are then employed to quantify these uncertainties and complexities. With this expanded evaluation dimensions, the FUSRA can more effectively elucidate relevant health risks. Thus, the linkage between both types of uncertainties was also effectively established by integrating stochastic simulation, expert involvement, and fuzzy logic within a general framework.

This dissertation research presents a distinguished condition over traditional methods of risk assessment by direct incorporation of related physical system simulation for getting insight into system conditions, seamless integration of air quality modeling and risk analysis process for the in-depth assessment of system risk and reliability and effective quantification of system uncertainties using statistical, stochastic, and fuzzy logic techniques. Specifically, the proposed methods can advance the existing methodologies of risk analysis for more effectively addressing critical issues in power generation systems. Thus, useful decision analysis tools based on the proposed methods can be available for resolving obstacles before any control actions become reality.

Generally, the integrated risk assessment model can be used by environmental engineers to provide insight and technical bases for supporting air quality management and pollution control decisions. For example, the real-world application indicates that not only can the probabilistic health risk level be quantified based on simulation of the dispersion of air pollutants under uncertainty in the atmosphere, but also the suitability of using a standard in the risk analysis process is given. This further addresses the possibility of having a predicted probabilistic risk level for a real-world ambient air quality management system under various layers of complex uncertainties in a short- or long-term period. Additionally, scenario and post analysis based on this approach and its outputs may produce plenty of information and extensive interpretation of risk conditions. In summary, with these expanded evaluation dimensions, the integrated risk assessment approach can more effectively elucidate the relevant risks associated with air emissions under concern. Therefore, solid decision support and more confidence can be expected in dealing with air pollution and potential environmental and health risks.

5.3 RECOMMENDATION FOR FUTURE RESEARCH

(1) Due to the complex nature of air pollution problems, the data required for the case study is extensive. Although most data sources are relatively accurate, others are less so. Therefore, increasing the accuracy and certainty of the data sets through further investigation and verification would help to increase the quality of the generated forecasting and assessment results.

(2) Technically, an integrated modeling and risk assessment system has been developed in this study which involves air dispersion modeling, Monte Carlo simulation and stochastic simulation-based fuzzy risk assessment. In this research, only one typical air pollutant (i.e., SO_2) is considered for the risk assessment. In fact, the emission from a power plant is usually containing many other pollutants such as NO_X. These pollutants can be characterized as carcinogen and non-carcinogen, resulting in two types of human

health risk impacts (e.g. excessive lifetime cancer risk for carcinogen, and hazard index for non-carcinogen). Moreover, each pollutant has its own environmental guideline and health risk evaluation criterion. To quantify the general risk level, the environmental risks from guideline violation as well as the carcinogenic and non-carcinogenic health risks from multiple pollutants should be considered. As a result, more uncertainties would exist in such complex conditions. Moreover, this study only considers uncertainties in surface roughness (due to its significant impact on the modeling results), environmental guidelines and health criteria. However, more uncertain information associated with transport simulation input parameters such as air dispersion coefficient and need to be further considered in the modeling system; meanwhile, uncertainties in human-impact parameters (e.g., daily ingestion rate, body weight, and exposure time), may also affect the risk levels, and should be examined in further studies and be incorporated within the modeling system to further improve the forecasting and assessment. With these considerations, simulation of the evolution of environmental systems would be more accurate and then the related risks could be better characterized.

(3) In risk assessment, it is essential to examine and explain the degree of uncertainty associated with the estimate. In many instances, this variability is not properly presented to decision makers who use the risk estimates. When risk numbers are reported in the public press, the uncertainty is rarely reported, much less explained. The methods used in each of the four stages of risk assessment have deficiencies that can introduce a high degree of uncertainty and thus impair the validity of the results. For example, the hazard identification stage is based on data for which detection,

identification, and quantification limits could introduce errors. Exposure assessments of future conditions depend heavily on air dispersion models, estimates of the performance of control options, and production of electricity as well as assumptions about the frequency and duration of the exposure. Each is a potential source of uncertainty. The toxicity assessment stage has a very high degree of uncertainty associated with the reference doses. Even for those chemicals where data exist, extrapolation introduces a large measure of uncertainty (e.g., extrapolation from animal tests to human exposures and particularly extrapolation to the range of a 0.0001% carcinogenesis response). Finally, the computation of risk is an exercise in applied probability of extremely rare events. It is not possible to enumerate every conceivable outcome, and credible worst-case exposure scenarios are used. This introduces an inherent conservatism that often results in assessing scenarios that will never be experienced. The above uncertainties are needed to be further studies in the future research.

REFERENCES

Abt Associates, "Dirty Air, Dirty Power: Mortality and Health Damage Due to Air Pollution from Power Plants". June 2004.

Amaral, Deborah Ann Lannen. "Estimating uncertainty in policy analysis: Health effects from inhaled sulfur oxides from coal-fired power plants". Ph. D. thesis, Carnegie Mellon University, 1983,

Bailey, Deborah Ann. "Site-specific health risk assessment: Discussion of application of methodologies at coal-fired power plants". Ph.D. thesis, University of California, 1985.

Batcherlor, B., Valdés, J., and Araganth, V. (1998) Stochastic risk assessment of site contaminated by hazardous wastes, Journal of Environmental Engineering, 124 (4): 380-388.

Bauer, P., Klement, E.P., Moser, B. and Leikermoser, A. (1995) "Modeling of control functions by fuzzy controllers", Theoretical Aspects of Fuzzy Control (Wiley, New York), Chapter 5: 91–116.

Berkowicz, R. and Olesen, H. R. (1993) Danish point source dispersion model - OML, MST Luft-A94, NERI, Roskilde, Denmark.

Beychok, Milton R. (2005) Fundamentals Of Stack Gas Dispersion, 4th Edition, author-published. ISBN 0-9644588-0-2. www.air-dispersion.com

Bigano, A,, Proost, S., and Van Rompuy J. (2000) Alternative Environmental Regulation Schemes for the Belgian Power Generation Sector Environmental and Resource Economics. 16: 121–160.

Blair, A. N., Ayyub, B. M., and Bender, W.J. (2001) Fuzzy stochastic risk-based decision analysis with the mobile offshore bases as a case study. Marine Structures, 14 (1): 69-88.

Borri, D., Concilio, G, Conte, E. Comput. (1998) A fuzzy approach for modeling knowledge in environmental systems evaluation. Computers, Environment and Urban Systems, 22 (3): 299-313.

Bosanquet, C.H. and Pearson, J.L. (1936) "The spread of smoke and gases from chimneys", Trans. Faraday Soc., 32:1249.

Brandt, J., J. H. Christensen, L. M. Frohn and Zlatev, Z. (2001) "Operational air pollution forecast modeling by using the THOR system". Physics and Chemistry of the Earth (B), 26 (2): 117-122.

Briggs, G. A. (1985) "Analytical parameterizations of diffusion: the convective boundary layer", J. Climate Applied Meteor, 24: 1167-1186.

Briggs, G. A. (1993) Plume dispersion in the convective boundary layer. Part II: Analysis of CONDORS field experiment data. J.Appl.Meteor., 32, 1388-1425.

Brock, Fred V. and Richardson, Scott J. (2001) Meteorological Measurement System Published by Oxford University Press US. ISBN 0195134516, 9780195134513, 290 pages

Brode, R.W. (2006) AERMOD Technical Forum, EPA R/S/L Modelers Workshop, San Diego, California, April 16.

Canadian Electricity Exports and Imports – An Energy Market Assessment. National Energy Board, January 2003.

Cantox Environmental Inc. (2006) Update of the Human Health Risk Assessment of Air Emissions from the Holyrood Thermal Generating Station, Holyrood, Newfoundland. Final Report. Prepared for Newfoundland and Labrador Hydro.

Carrington, C. D., and Bolger, P. M. (1998) Uncertainty and risk assessment, Human and Ecological Risk Assessment, 4(2): 253-257.

Carruthers D.J., Edmunds H.A., Ellis K.L., McHugh C.A., Davies B.M. and Thomson D.J. (1995) The Atmospheric Dispersion Modeling System (ADMS): comparisons with data from the Kincaid experiment. J. Envir. & Poll. 5:111-120.

Chen, G., and Pham T. T. (2001) Introduction to Fuzzy Sets, Fuzzy Sets, Fuzzy Logic, and Fuzzy Control Systems, CRC Press, Boca Raton, FL.

Chen, S.Q. (2000) Comparing Probabilistic and Fuzzy Set Approaches for Design in the Presence of Uncertainty, Ph.D. Dissertation, Virginia Polytechnic Institute and State University, Blacksburg, Virginia, USA.

Chen, Z., Huang, G. H., and Chakma, A. (2003) Hybrid fuzzy-stochastic modeling approach for assessing environmental risks at contaminated groundwater system. Journal of environmental engineering, 129(1): 79-88.

Cimorelli A.J., Perry S.G., Venkatram A., Weil J.C., Paine R.J., Wilson R.J., Lee R.F. and Peters W.D. (1998) AERMOD —Description of Model Formulation (Version 98314 (AERMOD and AERMET) and 98022 (AERMAP). USEPA, RTP, NC 27711, 113 pages.

Civanlar, M.R., and Trussel, H.J. (1986) Constructing membership functions using statistical data, Fuzzy Sets and Systems, 18: 1-13.

Cooper, N. S. (2001) A review of evaluation procedures for atmospheric dispersion models. International Journal of Environment and Pollution. 16 (1/2/3/4/5/6):116-128.

Dahab, M.F., Lee, Y.W., and Bogardi, I. (1994) A rule-based fuzzy-set approach to risk analysis of nitrate-contaminated groundwater. Water Sci. Technol. 30: 45.

Darbra, R.M., Demichela, M., Mure, S. (2008) Trans. Inst. Chem. Eng. Part B Process Safety Environ. Prot. 86 (2): 103.

Darbra, R.M., Eljarrat, E., Barcelo', D. (2007) Application of fuzzy logic to the preliminary risk assessment of fish pollution due to lipophilic substance releases in rivers, Riskbase, 1st Thematic Workshop, Lisbon, Portugal, pp. 119–122.

Davis GB, and Jesse DR. (2006) The need for air dispersion modeling. Proceedings of International Interdisciplinary Conference on Sustainable Technologies for Environmental Protection, ICSTEP2006.

Deardorff, J. W. (1980) Progress in Understanding Entrainment at the Top of a Mixed Layer. Preprints, Workshop on the Planetary Boundary Layer, American Meteorological Society, Boston, MA.

Destouni, G. (1992) Prediction uncertainty in solute flux through heterogeneous soil. Water Resources Research 28: 793–801.

Dou, C., Woldt, W., Bogardi, I., and Dahab, M. (1997) Numerical solute transport simulation using fuzzy sets approach, Journal of Contaminant Hydrology, 27(1-2): 107-126.

Draper, D., Pereira, A., Prado, P., Saltelli, A., Cheal, R., and Eguilior, S. (1999) Scenario and parametric uncertainty in GESAMAC: A methodological study in nuclear waste disposal risk assessment. Computer Physics Communications, 117 (1): 142.

Dubois, D. and Prade, H. (1993) Fuzzy sets and probability: Misunderstandings, bridges and gaps, Proc. of the Second IEEE Inter. Conf. on Fuzzy Systems, 2: 1059-1068.

Egan BA, Seaman NL, Yamartino R, Purdum J. (2002) Modeling pollutant dispersion from elevated and ground level sources affected by sea-breeze circulations produced by CAPE COD and its surroundings. AMS 12th Joint Conference on the Applications of Air Pollution Meteorology with A&WMA. Norfolk, VA, 20–24 May, 2pp.

Finardi S, Tinarelli G, Nanni A, Brusasca G, Carboni G. (2001) Evaluation of a 3-D flow and pollutant dispersion modeling system to estimate climatological ground level concentrations in complex coastal sites. International Journal of Environment and Pollution 16(1/2/3/4/5/6):472–482.

Finizio, A., and Villa, S. (2002) Environment risk assessment for pesticides. Environ.

Impact Assessment Rev, 22 (3): 235.

Goedkoop M. and Spriensma R. (2001) A damage oriented method for Life Cycle Impact Assessment. Annex report Eco-indicator 99.

Gottwald and Siegfried. (2001) A Treatise on Many-Valued Logics. Baldock, Hertfordshire, England: Research Studies Press Ltd., ISBN 978-0863802621

Guyonnet, D., Bourgine, B., Dobois, D., Fargier, H., Coˆme, B., Chile´s, J-P. (2003) Environ. Eng. (Resten, VA) 129 (1): 68.

Hanna R S. and Paine R J. (1989) "Hybrid Plume dispersion model (HPDM) development and evaluation", J. Applied Meteor, 28:206-224

Hanna, Steven R. (2007) A review of uncertainty and sensitivity analyses of atmospheric transport and dispersion models, Developments in Environmental Sciences, 6: 331-351.

Hu, Z.Y., Huang, G. H., Christine W.C. (2003) A fuzzy process controller for in situ groundwater bioremediation. Engineering Applications of Artificial Intelligence, 16: 131–147.

Institution of Electrical Engineers (IEE), 2000. "The Environmental Effects of Electricity Generation".

JWEL. (2003a). Air Quality Assessment of 1997 – 2001 SO_2, PM and NOx Emissions Holyrood Generating Station. Project No. ONT50264. Jacques Whitford Environment Limited.

JWEL. (2004a). Air Quality Assessment 2003 Trace Metal Emissions Holyrood Generating Station. Project No. ONT50448. Prepared for: Newfoundland and Labrador Hydro. Jacques Whitford Environment Limited.

Kazuo Asakura et al. (2004) "Inhalation risk assessment of trace elements emitted from coal-fired power plants", CRIEPI Report T03032 (in Japanese).

Kentel, E. Aral, M.M. (2004) Probabilistic Health Risk Modeling. Stochastic Environmental Research and Risk Assessment (SERRA), 18 (5): 324-338.

Kentel, E. Aral, M.M. (2005). 2D Monte Carlo versus 2D Fuzzy Monte Carlo health risk assessment. Stochastic Environmental Research and Risk Assessment (SERRA), 19 (1): 86.

Kentel, E., Aral, M.M. (2007) Risk Tolerance Measure for Decision Making in Fuzzy Health Risk Assessment. Stochastic Environmental Research and Risk Assessment (SERRA), 21: 405-417.

Labieniec, P.A., Dzombak, D.A., and Siegrist, R.L. (1997) Evaluation of uncertainty in a site-specific risk assessment. J. Environ. Eng. 123 (3): 234.

Lahkim, M.B., and Garcia, L.A. (1999) Stochastic modeling of exposure and risk in a contaminated heterogeneous aquifer, 1: Monte Carlo uncertainty analysis, Environmental Engineering Science, 16(5): 315-328.

Lehn, K., and Temme, K. (1996) Fuzzy classification of sites suspected of being contaminated. Ecol. Modell. 85 (1): 51.

Lein, J.K. (1992) Expressing environmental risk using fuzzy variables: a preliminary examination. The Environmental Professional. 14: 257 – 267.

Li Z. K. and Briggs G. A. (1988) "Simple PDF models for convectively driven vertical diffusion", Atmos. Environ, 22: 54-74.

Li, H.X. and Yen, V.C. (1995) Fuzzy Sets and Fuzzy Decision-Making. CRC Press.

Li, J., Huang, G.H., Zeng, G., Maqsood, I., and Huang, Y. (2007) J. Environ. Manage. 82 (2): 173.

Linthurst, R.A., Bourdeau, P., and Tardif, R.G. (1995) Methods to Assess the Effects on Chemical Ecosystems, SCOPE 53, Wiley, New York, USA, p. 416.

Ma, H.-W. (2000) The incorporation of stochasticity in risk analysis and management: a case study. Stochastic Environ. Res. Risk Assessment 14: 195.

Mamdani, E.H. and Assilian, S. (1975) "An experiment in linguistic synthesis with a fuzzy logic controller," International Journal of Man-Machine Studies, 7 (1) : 1-13.

Manomaiphiboon Kasemsan and Russell, Armistead G. (2004) Effects of uncertainties in parameters of a Lagrangian particle model on mean ground-level concentrations under stable conditions, Atmospheric Environment, 38:5529–5543

Maxwell, R.M., Pelmulder, S.D., Tompson, A.F.B., and Kastenberg, W.E. (1998) Water Resour. Res. 34: 833.

Mays, M.D., Holzhey, C.S., Bogardi, I., and Bardossy, A. (1995) Managing risk and variability with fuzzy soil interpretations, Site specific management for agricultural systems, Proc. Conf., Minneapolis, MN, USA, pp.187–198.

McKone, T.E., and Deshpande, A.W. (2005) Environ. Sci. Technol. Can Fuzzy Logic Bring Complex Problems into Focus? 39 (1): 42A.

Misra P K. (1982) "Dispersion of nonbuoyant particles inside a convective boundary layer", Atmos.Environ, 16:239-243.

Mohamed, A.M.O., and Cote, K. (1999) Decision analysis of polluted sites — a fuzzy set approach. Waste Manage.19: 519.

Mosegaard, Klaus, and Tarantola, Albert, (1995) Monte Carlo sampling of solutions to inverse problems. J. Geophys. Res., 100 (B7): 12431-12447.

Munshi, Usha. "An integrated approach to pollution control". Ph. D. thesis, Virginia Polytechnic Institute and State University, 1986.

National Pollutant Release Inventory (NPRI) database for 2002, accessible at http://www.ec.gc.ca/pdb/npri/npri_dat_rep_e.cfm.

Newfoundland & Labrador Hydro report, 2005.Unit 1, 2, and 3 Emission Test.

NFLD Hydro. (2005) Newfoundland and Labrador Hydro website. About Holyrood.http://www.nlh.nl.ca/Hydroweb/hydroweb.nsf/GeneralDocs/18C5A3C549162EBAA3256FD6006EF4B5?OpenDocument.

OEHHA-CREL: California EPA, Office of Environmental Health Hazard Assessment. Air Toxics Hot Spots Program Risk Assessment Guidelines, Part III: Technical Support Document "Determination of Noncancer Chronic Reference Exposure Levels". Includes all Chronic Reference Exposure Levels (CRELs) adopted by OEHHA as of August 2003.

Paine R.J., Lee R.F., Brode R., Wilson R.B., Cimorelli A.J., Perry S.G., Weil J.C., Venkatram A., and Peters W.D. (1998), Model Evaluation Results for AERMOD. USEPA, RTP. NC 27711.

Pasken, Robert and Pietrowicz, Joseph A. (2005) Using dispersion and mesoscale meteorological models to forecast pollen concentrations. Atmospheric Environment.39(40):7689-7701.

Pasquill, F. (1961) The estimation of the dispersion of windborne material, Meteorol. Mag. 90: 33-49.

Passarella, G., Vurro,M., Agostino, V.D., Giuliano, G.D', Barcelona, M.J. (2002) A Probabilistic Methodology to Assess the Risk of Groundwater Quality Degradation Environ. Monit. Assessment. 79 (1): 57.

Perry, Steven G., Cimorelli, Alan J., Paine, Robert J., Brode, Roger W., Weil, Jeffrey C., Venkatram, Akula., Wilson, Robert B., Lee, Russell F., Peters, Warren D. (2005) AERMOD: A Dispersion Model for Industrial Source Applications. Part II: Model Performance against 17 Field Study Databases. Journal of Applied Meteorology, 44 (5): 694-708.

Plant operating manual. Newfoundland and Laborador Hydro. Holyrood Generating Station. St. John's, NL.

Poreh M. and Cermak J E. (1984) "Wind tunnel diffusion in a convective boundary layer", Bound-Layer Meteor, 30: 431-455.

Power Generation in Canada: A Guide. (2006) Canadian Electricity Association.

Prater, E.T. and Midgley, C. (2006) A new air dispersion modeling system is helping create more accurate industrial source models. Environmental Protection. 17(3): 24-27.

R.D.Ross.1972. Air pollution and Industry. Van Nostrand Reinhold Company, pp, 1-6.

Ramakrishnan, D.; Zwicke, G.; Wall, D.; Remsburg, A. M. (2003) A Performance Comparison of AERMOD vs. Current Guideline Models in a Real World Scenario, #03-A-27-AWMA.

Richardson L.F. (1926) Atmospheric diffusion shown on a distance-neighbour graph. Proc. R. Soc. Lond. A 110: 709-37.

Rubinstein, R.Y. and Kroese, D. P. (2007). "Simulation and the Monte Carlo Method" (second edition). New York: John Wiley & Sons, ISBN 978-0-470-17793-8.

Saperstein, Mark David. "Risk assessment of trace element emissions from an urban oil-fired power plant". Ph.D. thesis, University of California, 1986.

Sax, Todd and Isakov, Vlad. (2003) A case study for assessing uncertainty in local-scale regulatory air quality modeling applications Atmospheric Environment, 37(25): 3481-3489.

Schumacher, M., Meneses, M., Xifro, A., and Domingo, J.L. (2001) The use of Monte-Carlo simulation techniques for risk assessment: study of a municipal waste incinerator. Chemosphere, 43: 787.

SETAC (1993) Guidelines for Life-Cycle Assessment: A "Code of Practice", Society of Environmental Toxicology and Chemistry, Brussels Belgium.

Snyder, Thompson, W. H., R. S., Eskridge, R. E., Lawson, R. E., Castro, I. P., Lee J. T., Hunt, J. C. R., and Ogawa, Y. (1985) The structure of the strongly stratified flow over hills: Dividing streamline concept. J.Fluid Mech., 152, 249-288.

Stander M. and Sethraman S. (1986) "A statistical evaluation and comparison of coastal point source dispersion models", Atmos. Environ., 20:301-315.

Sutton, O.G. (1947) "The problem of diffusion in the lower atmosphere", QJRMS, 73:257, and "The theoretical distribution of airborne pollution from factory chimneys", QJRMS, 73:426.

Taylor G.I. (1922) Diffusion by continuous movements. Proc. Lond. Math. Soc. 20: 196-212.

Turner, D.B. (1964) A diffusion model for an urban area. J. Appl. Meteor. 3: 83-91.

U.S Public Interest Research Group Education Fund (US IRGFF), 2003. Report; "American dirtiest power plants".

U.S. Enviromental Protection Agency. (2004) AERMOD: Description of model formulation. EPA-454/R-03-004, U.S. Environmental Protection Agency, Research Triangle Park, NC. U.S.

U.S. Enviromental Protection Agency. (1995). User's Guide for the Industrial Source Complex (ISC3) Dispersion Model (Revised). Volume II - Description of Model Algorithms. EPA-454/b-95-0036. Research Triangle Park, NC. U.S.

U.S. Enviromental Protection Agency. (2002) User's guide for the AMS/EPA Regulatory Model – AERMOD. Revised draft. Office of Air Quality Planning and Standards, Research Triangle Park, NC. U.S.

U.S. Environmental Protection Agency. Integrated Risk Information System (IRIS), 2002. Office of Research and Development, Washington, DC. 1999.

Ulas Im, Yenigun O. (2005) An application of a puff dispersion model on power plant emissions in Yatagan region, Turkey. International Journal of Environment and Pollution 23(3):314–324.

Uricchio, V.F., Giordano, R. and Lopez, N. (2004) A fuzzy knowledge-based decision support system for groundwater pollution risk evaluation. J. Environ. Manage. 73 (3): 189.

Van Der Werf, H.M.G., and Zimmer, C. (1998). An indicator of pesticide environmental impact based on a fuzzy expert system. Chemosphere 36(10): 2225.

Varnes, D.J. (1984) Commission on Landslides and Other Mass Movements, IAEG. Landslide Hazard Zonation: A Review of Principles and Practices, The UNESCO Press, Paris, France.

Vemula, V.R.S., Mujumdar, P.P., and Ghosh, S. (2004) J. Water Resour. Planning Manage 130 (5): 411.

Venkatram, A. (1980) "Dispersion from an elevated source in the convective boundary layer", Atmos. Environ, 14: 1-10.

Venkatram, A. (1983) "On dispersion in the convective boundary layer", Atmos. Environ, 17:529-533.

Willis G E. and Deardorff J W. (1981) "A laboratory study of dispersion from a source in the middle of the convectively mixed layer", Atmos. Environ, 15:109-117.

Yao Z. Q. (1999) "Evaluation and comparison of AERMOD and HPDM models", Seventh International Conference on Air Pollution.

Yousif, Saib A., Salemz, Abubaker A., Nassar Yasser F., and Bader. Issam F. (2006) Investigation of pollutants dispersion from power stations. International Journal of Energy Research. 30:1352–1362.

Zadeh, L. A. (1965) Fuzzy sets and systems. In: Fox J, editor. System Theory. Brooklyn, NY: Polytechnic Press, 1965: 29–39.

APPENDIX

I

Part of data for the surface meteorological information from 2000 to 2006 (from environmental Canada)

GRP118 - HOURLY WEATHER CONDITIONS 23/11/2006 11:22 AM (c) Environment Canada

Meteorological Service of Canada

**** CONTROL OPTIONS SELECTED ****

Selection used for the analysis period is YEAR between 2000 and 2006
Analysis only includes Quality Control Data
Wind direction output format is 10's of degree true
Report does not include 'SPECIALS'

ST JOHN'S A, NFLD — Climate ID: 8403506 — Lat: 47.62 — Long: -52.74
Elevation: 140.5 m — TC ID: YYT — Station Type: ATI — WMO ID: 71801

YYYY-MM-DD-HH:MM	Ceiling 30's m (71)	Vis km (72)	Wind Direction 10's deg (156/75)	Wind Speed km/hr (76)	Dry Bulb deg C (78)	Wet Bulb deg C (79)	Dew Point deg C (74)	RH % (80)	MSL Press kPa (73)	Station Press kPa (77)	Cloud Opacity tenths (81)	Cloud Amount tenths (82)	Weather (03-106 260)
2000/01/01/ 00:30	UNL	24.1	28	11	-10.6	-11.2	-14.4	74	101.71	99.95	4	4	-
2000/01/01/ 01:30	UNL	24.1	27	13	-9.4	-10.1	-13.5	72	101.69	99.91	3	0	-
2000/01/01/ 02:30	UNL	24.1	25	9	-9.7	-10.3	-13.4	74	101.77	99.98	4	0	-
2000/01/01/ 03:30	UNL	24.1	31	7	-12	-12.3	-14.9	79	101.71	99.95	3	5	-
2000/01/01/ 04:30	UNL	24.1	29	17	-12	-12.2	-14.3	83	101.7	99.91	3	5	-
2000/01/01/ 05:30	UNL	24.1	27	9	-10.5	-10.9	-13.3	80	101.74	99.98	4	0	-
2000/01/01/ 06:30	UNL	24.1	25	13	-9.2	-9.8	-12.8	75	101.8	100.01	4	0	-
2000/01/01/ 07:30	160	24.1	23	7	-10.2	-10.4	-12.3	85	101.85	100.08	6	0	-
2000/01/01/ 08:30	UNL	24.1	24	9	-10.6	-10.8	-12.8	84	101.88	100.08	4	4	-
2000/01/01/ 09:30	40	24.1	22	7	-9.1	-9.6	-12	79	101.93	100.15	7	7	SW-
2000/01/01/ 10:30	160	24.1	26	11	-7.4	-8	-10.4	79	101.98	100.18	6	6	SW-
2000/01/01/ 11:30	UNL	24.1	22	11	-5.6	-6.4	-9	77	101.85	100.08	1	1	-
2000/01/01/ 12:30	UNL	24.1	25	13	-4.8	-5.7	-8.3	76	101.82	100.05	3	3	-
2000/01/01/ 13:30	15	24.1	27	19	-4.6	-5.3	-7.5	80	101.82	100.05	9	9	-
2000/01/01/ 14:30	42	24.1	28	24	-5.2	-5.8	-7.8	82	101.86	100.08	6	6	SW-
2000/01/01/ 15:30	UNL	24.1	28	28	-5.7	-6.4	-8.9	78	101.91	100.15	2	2	-
2000/01/01/ 16:30	UNL	24.1	28	28	-6.1	-6.9	-9.7	76	101.95	100.18	1	1	-
2000/01/01/ 17:30	UNL	24.1	29	28	-6.5	-7.4	-10.4	74	102.08	100.28	2	2	-
2000/01/01/ 18:30	UNL	24.1	26	7	-6.9	-7.7	-10.8	74	102.2	100.41	1	1	-
2000/01/01/ 19:30	UNL	24.1	28	19	-7.8	-8.8	-12.6	68	102.24	100.45	1	1	-
2000/01/01/ 20:30	UNL	24.1	32	9	-8.1	-8.8	-11.6	76	102.25	100.45	2	0	-
2000/01/01/ 21:30	130	24.1	27	9	-8.6	-9.2	-12	76	102.33	100.55	8	0	-
2000/01/01/ 22:30	UNL	24.1	28	26	-7.1	-7.8	-10.6	76	102.34	100.55	4	0	-

Part of data for upper air meteorological information from 2000 to 2006 (from Environmental Canada)

254	0	1	JAN	1994		
1	14531	71801	47.67N	52.75W	140	2325
2	100	273	273	51	32767	3
3		YYT			10	ms
9	987	140	-51	-87	290	133
4	1000	37	32767	32767	32767	32767
5	976	227	-59	-119	32767	32767
6	966	304	32767	32767	290	185
5	950	437	-79	-105	32767	32767
6	929	609	32767	32767	285	205
4	925	645	-97	-112	295	200
5	902	838	-115	-120	32767	32767
6	893	914	32767	32767	300	190
5	868	1132	-117	-123	32767	32767
6	858	1219	32767	32767	300	180
4	850	1293	-129	-136	300	185
6	824	1524	32767	32767	300	175
5	805	1705	-161	-170	32767	32767
5	796	1789	-155	-201	32767	32767
6	792	1828	32767	32767	300	175
6	760	2133	32767	32767	295	169
5	746	2276	-179	-269	32767	32767
6	730	2438	32767	32767	285	195
5	716	2581	-209	-289	32767	32767
6	701	2743	32767	32767	290	205
4	700	2752	-205	-295	290	205
5	685	2912	-201	-311	32767	32767
6	619	3657	32767	32767	290	241
6	569	4267	32767	32767	290	267
5	548	4542	-271	-411	32767	32767
6	523	4876	32767	32767	295	293
4	500	5190	-307	-427	290	308
6	439	6096	32767	32767	290	339
5	420	6409	-379	-479	32767	32767
4	400	6750	-403	-503	285	365

III

Ambient Air Quality Risk Survey

ICEHR Approved

Faculty of Engineering

MEMORIAL UNIVERSITY OF NEWFOUNDLAND

ST.JOHNS, NEWFOUNDLAND & LABORADOR CANADA

February 2008

Please provide the following profile information:

Prefix:	**Mr.**	**[ ]**
	Ms.	**[ ]**
Education:	**Post-graduate**	**[ ]**
	Undergraduate	**[ ]**
	Others	**[ ]**
Age range:	**<30 (young adults)**	**[ ]**
	30-60 (adults)	**[ ]**
	>60 (senior)	**[ ]**
Company/Institution:	**Industry**	**[ ]**
	Government	**[ ]**
	Research organization	**[ ]**
	Non-governmental organization	**[ ]**
	Others	**[ ]**
Residence:	**Newfoundland**	**[ ]**
	Labrador	**[ ]**
	Other provinces in Canada	**[ ]**
	Other countries	**[ ]**

1 Survey on Ambient Air Quality Guideline for Sulfur Dioxide (SO_2)

Note: The ambient air quality standards for SO_2 are different among countries, states and provinces. For example, only considering the annual average guideline, Canadian National Ambient Air Quality Objectives for SO_2 is 30~60 $\mu g/m^3$; US EPA has established the National Ambient Air Quality Standard (NAAQS) of 80$\mu g/m^3$; WHO Air Quality Guidelines for Europe is 50 $\mu g/m^3$; National Standards for Criteria Air Pollutants in Australia is 57 $\mu g/m^3$; Air quality standards for the SILAQ countries: 50 $\mu g/m^3$ in Bulgaria, 60 $\mu g/m^3$ in Czech Rep./Slovakia, 32 $\mu g/m^3$ in Poland, and 60 $\mu g/m^3$ in Romania. This part is to survey your preferred range of guideline levels that can be defined as strict, medium and loose. (Only the annual average standards for SO_2 are discussed here)

Based on your preference and understanding, please answer the following questions:

(1) For a **strict** ambient air quality guideline, which of the following SO_2 concentrations would you like to choose?(Please choose one)
(a) approximately 30$\mu g/m^3$ or less
(b) approximately 50$\mu g/m^3$ or less
(c) approximately 55$\mu g/m^3$ or less
(d) approximately 60$\mu g/m^3$ or less
(e) approximately 65$\mu g/m^3$ or less
(f) approximately 70$\mu g/m^3$ or less
(g) approximately 80$\mu g/m^3$ or less

(2) For a **medium** ambient air quality guideline, which of the following SO_2 concentrations would you like to choose? (Please choose one)
(a) approximately 30$\mu g/m^3$ or less
(b) approximately 50$\mu g/m^3$ or less
(c) approximately 55$\mu g/m^3$ or less
(d) approximately 60$\mu g/m^3$ or less
(e) approximately 65$\mu g/m^3$ or less
(f) approximately 70$\mu g/m^3$ or less
(g) approximately 80$\mu g/m^3$ or less

(3) For a **loose** ambient air quality guideline, which of the following SO_2 concentrations would you like to choose?(Please choose one)
(a) approximately 30$\mu g/m^3$ or less
(b) approximately 50$\mu g/m^3$ or less
(c) approximately 55$\mu g/m^3$ or less
(d) approximately 60$\mu g/m^3$ or less
(e) approximately 65$\mu g/m^3$ or less
(f) approximately 70$\mu g/m^3$ or less
(g) approximately 80$\mu g/m^3$ or less

2 Survey on Environmental Risk

Note: The approach of environmental risk assessment is to compare contaminant concentration with the corresponding ambient air quality standards. The environmental risk due to violation of the environmental guideline can be categorized into **"low"**, **"low-to-medium"**, **"medium"**, **"medium-to-high"**, and **"high"** by associating them with different magnitudes of probability of guideline violation.

Environmental Risk under the strict Ambient Air Quality Guideline

Note: This part is to survey the environmental risk level under the **strict** ambient air quality guidelines. Based on your preference and understanding, please answer the following questions:

(4) To have a **low** environmental risk level, which probability of guideline violation would you think is suitable under the **strict guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

(5) To have a **low-to-medium** environmental risk level, which probability of guideline violation would you think is suitable under the **strict guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

(6) To have a **medium** environmental risk level, which probability of guideline violation would you think is suitable under the **strict guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]

(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

(7) To have a **medium-to-high** environmental risk level, which probability of guideline violation would you think is suitable under the **strict guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

(8) To have a **high** environmental risk level, which probability of guideline violation would you think is suitable under the **strict guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

Environmental Risk under the Medium Ambient Air Quality Guideline

Note: This part is to survey the environmental risk level under the **medium** ambient air quality guidelines. Based on your preference and understanding, please answer the following questions:

(9) To have a **low** environmental risk level, which probability of guideline violation would you think is suitable under the **medium guideline?** (Please choose one)

(a) Approximately 10% or less [ ]

(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

(10) To have a **low-to-medium** environmental risk level, which probability of guideline violation would you think is suitable under the **medium guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

(11) To have a **medium** environmental risk level, which probability of guideline violation would you think is suitable under the **medium guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

(12) To have a **medium-to-high** environmental risk level, which probability of guideline violation would you think is suitable under the **medium guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]

(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

(13) To have a **high** environmental risk level, which probability of guideline violation would you think is suitable under the **medium guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

Environmental Risk under the Loose Ambient Air Quality Guideline

Note: This part is to survey the environmental risk level under the **loose** ambient air quality guidelines. Based on your preference and understanding, please answer the following questions:

(14) To have a **low** environmental risk level, which probability of guideline violation would you think is suitable under the **loose guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

(15) To have a **low-to-medium** environmental risk level, which probability of guideline violation would you think is suitable under the **loose guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]

(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

(16) To have a **medium** environmental risk level, which probability of guideline violation would you think is suitable under the **loose guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

(17) To have a **medium-to-high** environmental risk level, which probability of guideline violation would you think is suitable under the **loose guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

(18) To have a **high** environmental risk level, which probability of guideline violation would you think is suitable under the **loose guideline?** (Please choose one)

(a) Approximately 10% or less [ ]
(b) Approximately 20% or less [ ]
(c) Approximately 30% or less [ ]
(d) Approximately 40% or less [ ]
(e) Approximately 50% or less [ ]
(f) Approximately 60% or less [ ]
(g) Approximately 70% or less [ ]
(h) Approximately 80% or less [ ]
(i) Approximately 90% or less [ ]

3 Survey on Health Risk

Note: The approach of health risk assessment for non-carcinogenic contaminants like SO_2 is to compare the contaminant concentration level with the corresponding reference concentration. The toxicological data used to calculate reference concentration usually come from laboratory studies on animals. California Air Pollution Control Officers Association suggests 660 $\mu g/m^3$ for the RfC of SO_2. Here, the health risk level is categorized into **"low"**, **"low-to-medium"**, **"medium"**, **"medium-to-high"**, and **"high"** by associating them with different magnitudes of toxicity score (the ratio of contaminant concentration to the reference concentration). The ratio is set to vary from 0.045 (corresponding to the Canadian Guideline) to 0.12 (approximately corresponding to the USEPA Guideline). Based on your preference and understanding, please answer the following questions:

(19) To have a **low** health risk level, which ratio of contaminant concentration to the reference concentration would you think is suitable? (Please choose one)

(a) approximately 0.045 or less
(b) approximately 0.054 or less
(c) approximately 0.062 or less
(d) approximately 0.070 or less
(e) approximately 0.078 or less
(f) approximately 0.086 or less
(g) approximately 0.094 or less
(h) approximately 0.100 or less
(i) approximately 0.12 or less

(20) To have a **low-to-medium** health risk level, which the ratio of contaminant concentration to the reference concentration would you think is suitable? (Please choose one)

(a) approximately 0.045 or less
(b) approximately 0.054 or less
(c) approximately 0.062 or less
(d) approximately 0.070 or less
(e) approximately 0.078 or less
(f) approximately 0.086 or less
(g) approximately 0.094 or less
(h) approximately 0.100 or less
(i) approximately 0.12 or less

(21) To have a **medium** health risk level, which ratio of contaminant concentration to the reference concentration would you think is suitable? (Please choose one)

(a) approximately 0.045 or less

(b) approximately 0.054 or less
(c) approximately 0.062 or less
(d) approximately 0.070 or less
(e) approximately 0.078 or less
(f) approximately 0.086 or less
(g) approximately 0.094 or less
(h) approximately 0.100 or less
(i) approximately 0.12 or less

(22) To have a **medium-to-high** health risk level, which ratio of contaminant concentration to the reference concentration would you think is suitable? (Please choose one)

(a) approximately 0.045 or less
(b) approximately 0.054 or less
(c) approximately 0.062 or less
(d) approximately 0.070 or less
(e) approximately 0.078 or less
(f) approximately 0.086 or less
(g) approximately 0.094 or less
(h) approximately 0.100 or less
(i) approximately 0.12 or less

(23) To have a **high** health risk level, which ratio of contaminant concentration to the reference concentration would you think is suitable? (Please choose one)

(a) approximately 0.045 or less
(b) approximately 0.054 or less
(c) approximately 0.062 or less
(d) approximately 0.070 or less
(e) approximately 0.078 or less
(f) approximately 0.086 or less
(g) approximately 0.094 or less
(h) approximately 0.100 or less
(i) approximately 0.12 or less

4 Survey on the General Risk Level

Note: The related risk characterization can be conducted through environmental-quality-standard-based risk assessment and health risk assessment. In this study, the environmental risk is defined as the risk introduced from the violation of environmental guidelines or regulations, and the health risk as the risk of health impact due to chronic intake of the contaminant. The general risk level can be derived from an integrated consideration of environmental and health risks. The risk levels are categorized into: **low, low-to-medium, medium, medium-to-high, high**, and **very high**. Based on your preference and understanding, please answer the following questions:

(24) If both environmental and the health risk levels are **low**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(25) If the environmental risk is **low** and the health risk is **low-to-medium**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(26) If the environmental risk is **low** and the health risk is **medium**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(27) If the environmental risk is **low** and the health risk is **medium-to-high**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(28) If the environmental risk is **low** and the health risk is **high**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(29) If the environmental risk is **low-to-medium** and the health risk is **low**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(30) If the environmental risk is **low-to-medium** and the health risk is **low-to-medium**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(31) If the environmental risk is **low-to-medium** and the health risk is **medium**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(32) If the environmental risk is **low-to-medium** and the health risk is **medium-to-high**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]

(f)) very high [ ]

(33)If the environmental risk is **low-to-medium** and the health risk is **high**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(34)If the environmental risk is **medium** and the health risk is **low**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(35) If the environmental risk is **medium** and the health risk is **low-to-medium**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(36)If the environmental risk is **medium** and the health risk is **medium**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(37)If the environmental risk is **medium** and the health risk is **medium-to-high**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(38)If the environmental risk is **medium** and the health risk is **high**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(39)If the environmental risk is **medium-to-high** and the health risk is **low**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(40)If the environmental risk is **medium-to-high** and the health risk is **low-to-medium**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(41)If the environmental risk is **medium-to-high** and the health risk is **medium**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]

(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(42) If the environmental risk is **medium-to-high** and the health risk is **medium-to-high**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(43) If the environmental risk is **medium-to-high** and the health risk is **high**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(44) If the environmental risk is **high** and the health risk is **low**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(45) If the environmental risk is **high** and the health risk is **low-to-medium**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(46) If the environmental risk is **high** and the health risk is **medium**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(47) If the environmental risk is **high** and the health risk is **medium-to-high**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

(48) If the environmental risk is **high** and the health risk is **high**, what will be the general risk level? (please choose one)

(a) low [ ]
(b) low-to-medium [ ]
(c) medium [ ]
(d) medium-to-high [ ]
(e) high [ ]
(f)) very high [ ]

5 More discussions

(1) For the northern regions in Canada like Labrador, the fragile ecosystems (e.g., reserves and parks) and remote communities are more vulnerable to environmental hazards than those in other regions. Would you recommend a more stringent guideline for SO_2 in northern regions in Canada like Labrador?

Yes [ ]
No [ ]

We appreciate your additional comments:________________________________

____

____

____

(2) For a **strict** ambient air quality guideline, which of the following SO_2 concentrations would you like to choose?(Please choose one)
(a) approximately 30μg/m^3 or less
(b) approximately 50μg/m^3 or less
(c) approximately 55μg/m^3 or less
(d) approximately 60μg/m^3 or less
(e) approximately 65μg/m^3 or less
(f) approximately 70μg/m^3 or less
(g) approximately 80μg/m^3 or less

(3) For a **medium** ambient air quality guideline, which of the following SO_2 concentrations would you like to choose? (Please choose one)
(a) approximately 30μg/m^3 or less
(b) approximately 50μg/m^3 or less
(c) approximately 55μg/m^3 or less
(d) approximately 60μg/m^3 or less
(e) approximately 65μg/m^3 or less
(f) approximately 70μg/m^3 or less
(g) approximately 80μg/m^3 or less

(4) For a **loose** ambient air quality guideline, which of the following SO_2 concentrations would you like to choose?(Please choose one)
(a) approximately 30μg/m^3 or less
(b) approximately 50μg/m^3 or less
(c) approximately 55μg/m^3 or less
(d) approximately 60μg/m^3 or less
(e) approximately 65μg/m^3 or less
(f) approximately 70μg/m^3 or less
(g) approximately 80μg/m^3 or less