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# Water Resources Research Report

## A Decision Support System for Integrated Risk Management

By:
Ibrahim El-Baroudy
and
Slobodan P. Simonovic

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# A DECISION SUPPORT SYSTEM FOR INTEGRATED RISK MANAGEMENT

**By**


Ibrahim El-Baroudy, Ph.D. Candidate

Department of Civil and Environmental Engineering

University of Western Ontario, London, Ontario

**and**

Slobodan S. Simonovic, Professor and Research Chair

Department of Civil and Environmental Engineering

Institute for Catastrophic Loss Reduction

University of Western Ontario, London, Ontario


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**TABLE OF CONTENT**

## LIST OF FIGURES

## LIST OF TABLES

# 1 INTRODUCTION

## 1.1 Objectives and Organization of the Report

This report provides a detailed description of the Risk Assessment Support System (RASS) for use in municipal water supply. The report explores the utility of the developed support system for evaluating the performance of a complex water supply system. A regional water supply system for the city of London is used as the case study. The theoretical foundations and computational requirements for the implementation of the RASS are provided in the report.

This chapter introduces fuzzy and probabilistic approaches that are used to handle different aspects of uncertainty. Calculation of different risk measures, simulation, optimization and multi-objective analysis using both approaches are explained in details focusing on their application to water supply infrastructure systems.

Chapter 2 provides a detailed description of RASS and its tool boxes. Chapter 3 explores the utility of the quantitative risk assessment component (QNRA) of RASS for evaluating the performance of a complex water supply system. In this chapter, the sensitivity of fuzzy risk measures to the different shapes of fuzzy membership functions is explored first. The utility of the fuzzy simulation, optimization, and multi-objective analysis toolboxes is demonstrated afterwards. Finally, the conclusions of the analysis performed in Chapter 3 are presented in Chapter 4.

## 1.2 Introduction

The improvement in performance and service quality of engineering systems are widely recognized targets for meeting, both public needs and expectations. Special attention is given to systems providing essential services that directly affect the health and wellbeing of the human population. Organizational and management procedures are the core of the targeted performance improvement so, (Alegre, 2004).

Most of the engineering systems that provide essential services, such as water supply, have been growing in size and complexity due to the rapid population growth. As a result, those large and complex engineering systems will be exposed to wide range of possible future conditions. Risks of systems failure are often unavoidable, (Ang and Tang, 1984). Uncertainties associated with the quantification of potential failure conditions are imposing a great challenge to systems' design, planning and management. Therefore, the assurance of satisfactory and reliable system performance cannot be simply achieved. Quantification of risk due to these uncertainties is a pivotal step in the engineering risk and reliability analysis.

Uncertainty is measured using different system performance measures and figures of merit to evaluate its consequences for the safety of engineering systems. Performance measures are the main components of many standardized performance assessment procedures (Alegre, 2004).

The probabilistic (stochastic) reliability analysis has been extensively used to deal with the problem of uncertainty in many engineering systems (Modarres et al., 1999). In the probabilistic approach, the analysis involves describing systems' resistance and load as belonging to respective possible probability distributions. Probabilistic approach depends on non-deterministic models that incorporate a measure of randomness as a way to express uncertainty, (Klir and Yuan, 1995). Therefore, system reliability may be realistically measured in terms of probability. The principle objective of the probabilistic reliability analysis is to insure that the load does not exceed the resistance throughout a specified time horizon in terms of probability. Prior knowledge of the probability density functions of both, resistance and load, and/or their joint probability distribution function is a prerequisite. However, the characteristics of resistance and/or load cannot always be measured precisely or formulated using a proper probabilistic conceptualization, especially in the absence of necessary data. Therefore, the probabilistic approach fails to address the problems of human error, subjectivity, and the lack of system performance history and records.

The concept of fuzzy sets is a conceptual and mathematical framework within which imprecise and vague phenomena can be studied, (Zimmermann, 1996). Fuzzy set theory and fuzzy logic are used to overcome ambiguity or lack of knowledge in human conception of real life phenomena as a source of uncertainty. The basic definition of a fuzzy set is that it is characterized by a membership function mapping the elements of a domain, space, or universe of discourse G to the unit interval [0,1], (Pedrycz and Gomide, 1998) that is

$A : G \rightarrow [0,1]$ **……….(1)**

where:

A is the fuzzy set in universe of discourse G; and

G is the domain, or the universe of discourse.

The characteristics of resistance and/or load in engineering systems cannot always be measured precisely or treated as random variables. Moreover, application of probabilistic reliability analysis is invariably related to the availability of data that can be used to determine probability distribution functions to be used, objectively or subjectively. Data insufficiency is a well-known problem in almost all engineering problems and is dealt within the probabilistic approach by using the Bayesian approach or the subjective probability estimation.

Bayesian method is one of the rigorous ways of dealing with uncertainty, especially when combined with multi-attribute utility theory to incorporate the variability in system performance and uncertainty in system parameters. The difficulty in the development of the utility function and its ability to capture the priorities of all interest groups in decision-making process are the main drawbacks of this method, (Hashimoto et al, 1982).

Subjective probability, on the other hand, is a description of state of information (or state of uncertainty) where the degree of information is interpreted as a degree of belief, related to the personal state of information, (Spizzichino, 2001). To be valid, the subjective probability approach (i) should reflect the belief of the assessor of the uncertainty, and (ii) should be consistent with the basic probability axioms.

Decision-making processes involve multi-disciplinary teams from all fields and decision-makers might not be able to match these requirements. People's judgment and believes are rarely expressed using mathematical tools. They prefer to use what is known as heuristic, or simple mental strategies, to express uncertainty. These heuristic strategies are usually successful tools for dealing with the uncertainty. However, they may introduce bias or inconsistencies with the mathematical probability principles, (Vick, 2002).

Fuzzy set theory was intentionally developed to try to capture people judgmental believes, or as mentioned before, the uncertainty that is caused by the lack of knowledge. Relative to the probability theory, it has some degree of freedom with respect to aggregation operators, types of fuzzy sets (membership functions), etc, which enables the adaptability to different contexts. During the last twenty years, fuzzy set theory and fuzzy logic contributed successfully to the technological development in different application areas such as mathematics, algorithms, standard models, and real-world problems of different kinds, (Zimmermann, 1996).

Probabilistic and fuzzy set approaches provide complementary conceptual and computational frameworks for representing and addressing the uncertainties in the real-world engineering systems, (Pedrycz and Gomide, 1998). The developed risk assessment support system incorporates both approaches for engineering risk and reliability analysis. It also provides support for engineering systems simulation, optimization and multi-objective analysis. Therefore, the decision support system can be used for integrated risk management.

## 1.3 RASS Purpose and Architecture

The complexity of water supply systems due to a large number of interdependent physical constituents and subsystems, together with multi-level decision making process, present a great challenge to the efforts in disaster risk management. The present work aims at the development of a decision support system for (a) qualitative framing of the disaster risk to water supply systems; (b) quantitative disaster risk assessment; and (c) integrated disaster risk management. The main objective of RASS is to identify potential hazards, estimate the impacts of each hazard and propose possible improvements and management actions which will significantly reduce the risk. The support system consists of two main components; (i) qualitative risk assessment component (QLRA), and (ii) quantitative risk assessment component (QNRA).

### 1.3.1 Qualitative Risk Assessment Component (QLRA)

The QLRA component examines and evaluates the user's information on the risks associated with the water supply system under consideration. It, also, assists the user in experimenting with the available management toolboxes within QNRA component (such as simulation, optimization, and multi-criteria analysis) to decide on the appropriate action scenarios. The user is presented with ten questions for which a combination of

Yes/No and numerical answers is required to initiate the QNRA component and perform the quantitative risk analysis. Appendix I contains a list of the ten questions together with comments and directions to guide the user of RASS.

The QLRA consists of two main steps; (i) evaluation of risk knowledge, and (ii) development of action scenario. The first step explores the user's knowledge of risk, it cause and possible impact. The result of this step is a list of causes and impacts together with estimations of contribution of each cause to overall risk hazard. The second step uses the results of the previous step to investigate the effects of possible action scenarios on risk mitigation using the QNRA toolbox. The result of this step is a list of suggested system improvements which can guide future management decisions, as shown in Figure 1.

### 1.3.2 Quantitative Risk Assessment Component (QNRA)

The QNRA incorporates a set of tools for system performance evolution, simulation of system behavior and single and multi-objective optimization of system performance. Both, probabilistic and fuzzy approaches are incorporated in the QNRA as illustrated in Figure 1. The QNRA consists of two toolboxes; (i) Probabilistic Toolbox, and (ii) Fuzzy Toolbox. The probabilistic toolbox provides access to (a) Performance evaluation tool that calculates reliability, resiliency and vulnerability measures; (b) Simulation tool; and (c) Optimization tool. The fuzzy toolbox contains: (a) Performance evaluation tool that calculates combined fuzzy reliability-vulnerability, fuzzy robustness and fuzzy resiliency measures; (b) Fuzzy Simulation tool; (c) Fuzzy Optimization tool; and (d) Fuzzy Multi-

Objective Analysis tool.  A detailed description of RASS and its management toolboxes follows in Chapter 2.

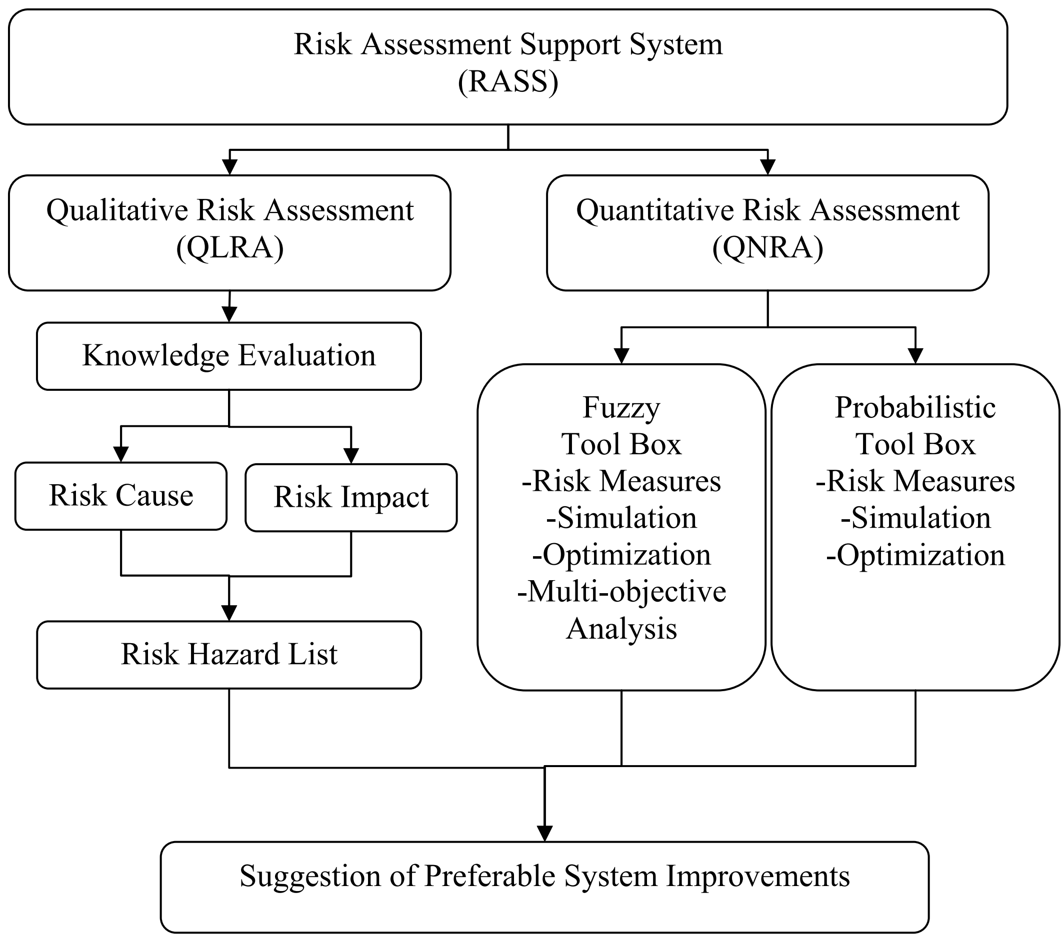



**Figure 1. Interaction between the two main components of the risk assessment support system (RASS).**

### 1.4 Basics of the Fuzzy Reliability Analysis

Engineering system risk and reliability analysis uses load and resistance as the fundamental concepts to define the risk of system failure, (Simonovic, 1997). Load and resistance are used in structural engineering to reflect the characteristic behavior of an engineering system under external loading conditions. System load is defined as the variable that reflects different loading conditions that may be imposed over the useful life of the system, (Ang and Tang, 1984). System resistance, on the other hand, is defined as the system characteristic variable which describes the capacity of the system to resist potential loading conditions.

The fuzzy reliability analysis uses membership function concept (MF) to express uncertainty in both - load and resistance - variables. The general representation of a membership function is:

$$\tilde{X} = \{(x, \mu_{\tilde{X}}(x)) : x \in R; \mu_{\tilde{X}}(x) \in [0,1]\} \qquad \textbf{.........(2)}$$

where:

$\tilde{X}$ is the fuzzy membership function;

$\mu_{\tilde{X}}(x)$ is the membership value of an element *x* to $\tilde{X}$; and

R is the set of real numbers.

Membership functions are usually defined by their $\alpha$ -cuts. The $\alpha$ -cut is the ordinary set of all the elements belonging to the fuzzy set whose value of membership is α or higher (see Figure 2):

$$X(\alpha) = \{x : \mu_{\tilde{X}}(x) \geq \alpha;\ x \in R;\ \alpha \in [0,1]\} \qquad \textbf{.........(3)}$$

where

$X(\alpha)$ is the ordinary set at the α-cut; and

$\alpha$ is the membership value.

Another characteristic property of the fuzzy membership function is its support. The support of the fuzzy membership function can be defined as the ordinary set (see Figure 2):

$$S(\tilde{X}) = \tilde{X}(0) = \{x : \mu_{\tilde{X}}(x) > 0\} \qquad \textbf{.........( 4)}$$

where

$S(\tilde{X})$ is the ordinary set at the α-cut=0.

The fuzzy membership function support is the 0-cut set and includes all the elements with the membership value higher than 0, as shown in Figure 2. Construction of a membership function is based on the system design data and choice of the suitable shape. There are many shapes of membership functions. However, the application context dictates the choice of the suitable shape. Triangular and trapezoidal shapes are the simplest MF shapes that are widely used in the literature.

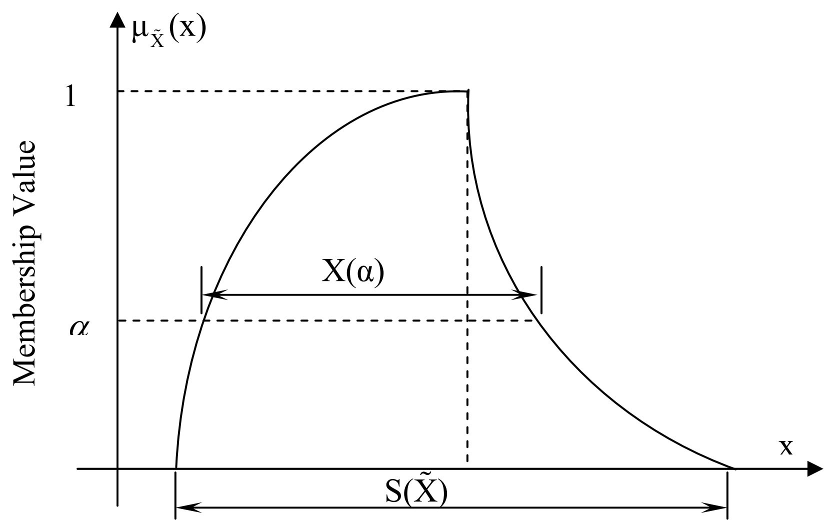



**Figure 2. Support and α-cut of the fuzzy membership function (after Ganoulis, 1994).**

### 1.4.1 Fuzzy Performance Measures for Engineering Systems

Risk identification is the first step in the engineering risk analysis, where all sources of uncertainty causing risk of failure are clearly detailed. Quantification of risk is the second step through which uncertainties are measured using different system performance measures and figures of merit.

El-Baroudy and Simonovic (2004) proposed three fuzzy measures for system performance evaluation: (i) combined reliability-vulnerability measure, (ii) robustness measure, and (iii) resiliency measure. The proposed fuzzy measures quantify the reliability, vulnerability, robustness and resiliency of multi-component engineering systems reflecting different systems' configurations. These measures provide a tool to assess system performance through the introduction of a wide variety of uncertain conditions.

Fuzzy performance measures use membership functions to represent both uncertain load and resistance of various system components. The load-resistance problems are usually formulated in terms of the safety margin or the factor of safety. Therefore, the load and resistance membership functions, for each system component, are aggregated into one membership function representing the component-state membership function, defined as follows

$$\tilde{S}(m) = \tilde{X} - \tilde{Y}$$

and **……….(5)**

$$\tilde{S}(\theta) = \frac{\tilde{X}}{\tilde{Y}}$$

where:

$\tilde{X}$ is the fuzzy supply;

$\tilde{Y}$ is the fuzzy demand;

$\tilde{S}(m)$ is the component-state membership function of the margin of safety; and

$\tilde{S}(\theta)$ is the component-state membership function of the factor of safety.

The calculation of fuzzy performance measures depends on the definition of unsatisfactory system performance. For most engineering systems it is challenging to arrive at a precise definition of failure because of the uncertainties in determining system resistance, load, and the acceptable unsatisfactory performance threshold. Therefore, a fuzzy membership is used to represent the acceptable level of system performance:

$$\tilde{M}(m) = \begin{cases} 0, & \text{if } m \le m_1 \\ \varphi(m), & \text{if } m \in [m_1, m_2] \\ 1, & \text{if } m \ge m_2 \end{cases}$$

or **……….(6)**

$$\tilde{\Theta}(\theta) = \begin{cases} 0, & \text{if } \theta \le \theta_1 \\ \varphi(\theta), & \text{if } \theta \in [\theta_1, \theta_2] \\ 1, & \text{if } \theta \ge \theta_2 \end{cases}$$

where:

$\tilde{M}$ is the fuzzy membership function of margin of safety;

$\varphi(m)$ and $\varphi(\theta)$ are functional relationships representing the subjective view of the acceptable risk;

$m_1, m_2$ are the lower and upper margin of safety bounds of the acceptable failure region respectively;

$\tilde{\Theta}$ is the fuzzy membership function of factor of safety; and

$\theta_1, \theta_2$ are the lower and upper safety factor bounds of the acceptable failure region, respectively.

Figure 3 is a graphical representation of the definition presented in Equation 6. The lower and upper bounds of the acceptable failure region are given in Equation 6 as $m_1$ (or $\theta_1$) and $m_2$ (or $\theta_2$). The value of the margin of safety (or factor of safety) below $m_1$ (or $\theta_1$) is definitely unacceptable. Therefore, the membership function value is zero. The value of the margin of safety (or factor of safety) above $m_2$ (or $\theta_2$) is definitely acceptable and therefore belongs to the acceptable failure region. Consequently, the membership value is one. The membership of the in-between values varies with the subjective assessment of a decision maker. Different functional forms may be used for $\varphi(m)$ (or $\varphi(\theta)$) to reflect the subjectivity of different decision makers' assessments. The freedom given by this definition of failure, through the choice of the lower bound, upper bound, and the function $\varphi(m)$ (or $\varphi(\theta)$) facilitates the introduction of the ambiguity of risk acceptance exhibited by different decision-makers. This approach, also, provides an easy and comprehensive tool for risk communication. That has been acknowledged as the major problem in the application of probabilistic approach.

High system reliability is reflected through the use of high values of margin of safety (or factor of safety), i.e. high values for both $m_1$ and $m_2$ (or $\theta_1$ and $\theta_2$). The difference between $m_1$ and $m_2$ (or $\theta_1$ and $\theta_2$) inversely affects the system reliability, i.e. the higher the difference, the lower the reliability.

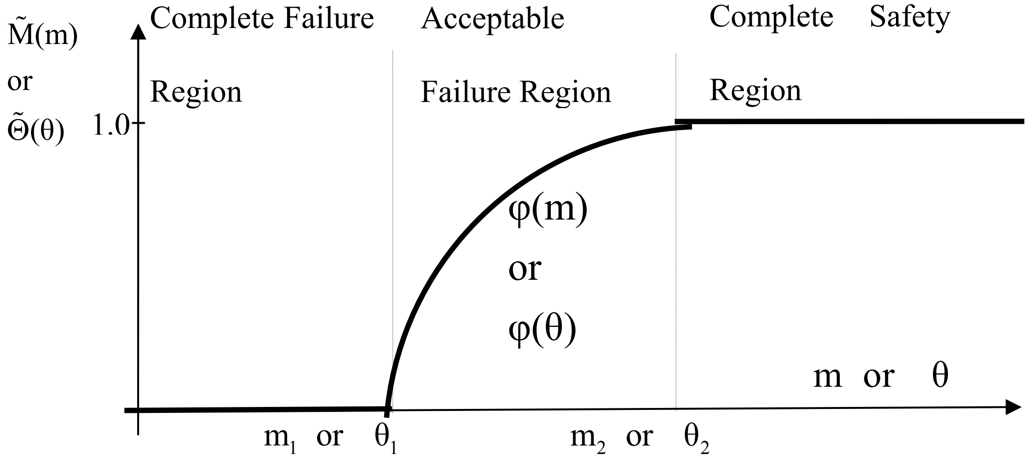



**Figure 3. Fuzzy representation of an acceptable failure region.**

Therefore, the reliability reflected by the definition of an acceptable level of performance can be quantified in the following way:

$$LR = \frac{m_1 \times m_2}{m_2 - m_1}$$

or **……….(7)**

$$LR = \frac{\theta_1 \times \theta_2}{\theta_2 - \theta_1}$$

where:

LR is the reliability measure of the acceptable level of performance.

**Combined fuzzy reliability-vulnerability performance measure**

The compatibility between the system-state and the acceptable level of performance membership functions is the basis for the calculation of the combined fuzzy reliability-vulnerability performance measure. It is illustrated in Figure 4 and calculated as follows:

$$\text{Compatibility Measure (CM)} = \frac{\text{Weighted overlap area}}{\text{Weighted area of system - state function}} \qquad \textbf{……….(8)}$$

Therefore, the fuzzy combined reliability-vulnerability performance measure can be expressed as follows:

$$RE_f = \frac{\max\limits_{i \in K}\{CM_1, CM_2, \ldots\ldots\ldots CM_i\} \times LR_{max}}{\max\limits_{i \in K}\{LR_1, LR_2, \ldots\ldots\ldots LR_i\}} \qquad \textbf{……….(9)}$$

where:

$RE_f$ is the combined fuzzy reliability-vulnerability measure;

$LR_{max}$ is the reliability measure of the acceptable level of performance with which the system-state has the maximum compatibility value(*CM*);

$LR_i$ is the reliability measure of the i-th acceptable level of performance;

$CM_i$ is the compatibility measure for system-state with the i-th acceptable level of performance; and

K is the total number of defined acceptable levels of performance.

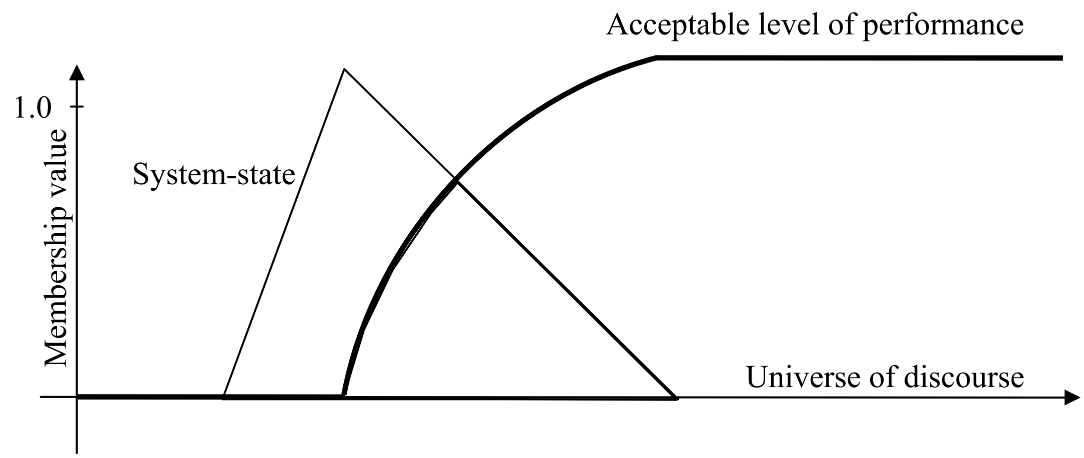



**Figure 4. Fuzzy combined reliability-vulnerability measure based on the compatibility measure.**

**Fuzzy robustness performance measure**

The fuzzy robustness performance measure describes the system's ability to adapt to a wide range of possible future load conditions (El-Baroudy and Simonovic, 2004). The fuzzy form of change in future conditions is obtained through the definition of different acceptable levels of performance, as shown in Figure 5. Therefore, the system's fuzzy robustness index is defined as the change in the compatibility measure:

$$RO_f = \frac{1}{CM_1 - CM_2} \qquad \textbf{.........(10)}$$

where:

$RO_f$ is the fuzzy robustness index;

$CM_1$ is the compatibility measure before the change in conditions; and

$CM_2$ is the compatibility measure after the change in conditions.

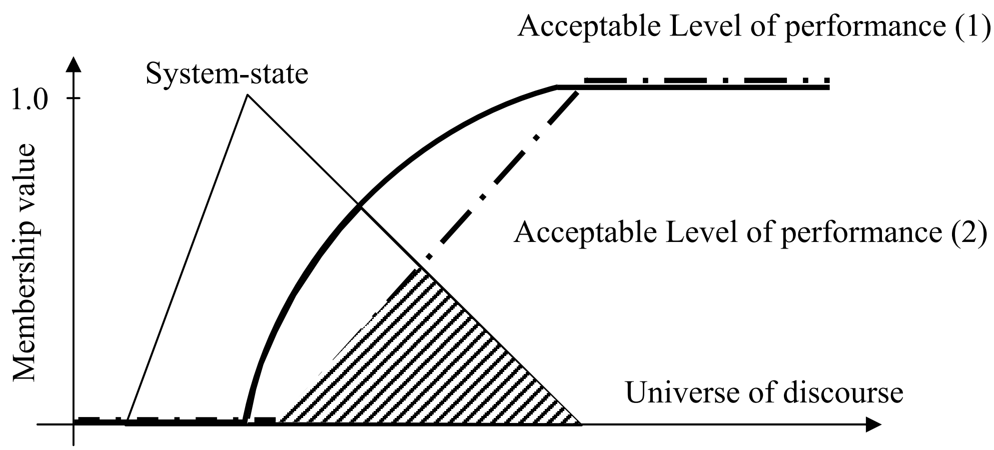



**Figure 5. Fuzzy robustness measure based on the compatibility measure with different acceptable levels of performance.**

**Fuzzy resiliency performance measure**

The time required to recover from the failure state can be represented as a fuzzy set. The reasons for failure may differ; therefore, the system recovery time will vary with the type of failure. A series of fuzzy membership functions can be developed to allow for various types of failure. The maximum recovery time is used to represent the system-failure recovery time (Kaufmann and Gupta, 1985):

$$\tilde{T}(\alpha) = \left( \max_{j \in J}[t_{1_1}(\alpha), t_{1_2}(\alpha), \ldots\ldots., t_{1_J}(\alpha)], \max_{j \in J}[t_{2_1}(\alpha), t_{2_2}(\alpha), \ldots\ldots., t_{2_J}(\alpha)] \right) \qquad \textbf{.........(11)}$$

where:

$\alpha$ is the membership value or $\alpha$-level;

$\tilde{T}(\alpha)$ is the system fuzzy maximum recovery time at $\alpha$ -level;

$t_{1_J}(\alpha)$ is the lower bound of the j-th recovery time at $\alpha$ -level;

$t_{2_J}(\alpha)$ is the upper bound of the j-th recovery time at $\alpha$ -level; and

J is total number of failure events.

The system-failure membership function is used to calculate the fuzzy resiliency performance measure, as follows

$$RS_f = \left[ \frac{\int_{t_1}^{t_2} t\, \tilde{T}(t)\, dt}{\int_{t_1}^{t_2} \tilde{T}(t)\, dt} \right]^{-1} \qquad \textbf{..........(12)}$$

where;

$RS_f$ is the fuzzy resiliency measure;

$\tilde{T}(t)$ is the membership function of system maximum recovery time;

$t_1$ is the lower bound of the support of the system recovery time ; and

$t_2$ is the upper bound of the support of the system recovery time.

### 1.4.2 Multi-Component Systems

Engineering systems are made up of a variety of interconnected subsystems. Each subsystem has multiple components where the configuration of interconnections affects the overall system performance. Multi-component systems have several system-state membership functions representing the system-state of each component. Aggregation of these membership functions results in a system-state membership function for the whole-system.

**Aggregation of System-State Membership Functions**

The main configurations of multi-component systems are; (i) serial, (ii) parallel, and (iii) combined. For each component, a fuzzy membership function, representing the component's state, can be determined based on the component's load and resistance. The overall system-state is then determined using the system configuration.

Let us assume that a serial system is composed of I components, as shown in Figure 6a. The *i*-th component has a state membership function $\tilde{S}_i(m)$, defined on the universe of discourse M. The weakest component, in terms of system-state, controls the whole system-state. Therefore, the system-state can be calculated as follows:

$$\tilde{S}(m) = \min_{I}\left(\tilde{S}_1, \tilde{S}_2, ........., \tilde{S}_I\right) \qquad \textbf{.........(13)}$$

where:

$\tilde{S}(m)$ is the system-state; and

$\left(\tilde{S}_1, \tilde{S}_2, \ldots\ldots\ldots, \tilde{S}_I\right)$ are component system-states.

An example of a parallel system configuration composed of J components is shown in Figure 6b. The j-th component has a state membership function $\tilde{S}_j(m)$, defined on the universe of discourse M. All states of the components contribute to the system-state. A system failure occurs if all the components fail. Hence, the system-state can be calculated as follows:

$$\tilde{S}(m) = \sum_{1}^{J} \tilde{S}_j(m) \qquad \textbf{..........(14)}$$

where:

$\tilde{S}_j(m)$ is the m-th component system-state; and

J is the total number of parallel components.

Combined systems are systems with parallel and serial subsystems. The system-state in this case can be arrived at by calculating subsystems-states according to Equations 11 and 12.

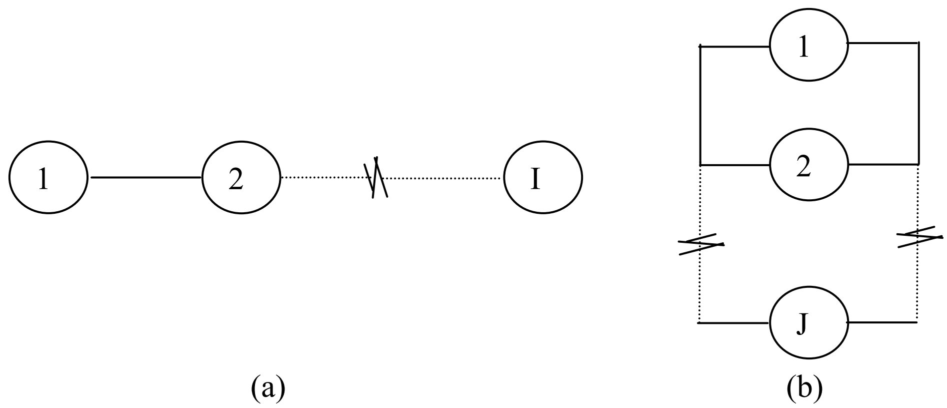



**Figure 6. A serial (a) and a parallel (b) system configurations**

**Aggregation of recovery time membership functions**

The aggregation of recovery time membership functions (required for calculation of fuzzy resiliency) is achieved in a different way from the aggregation of system-state membership functions. System-state membership function determines the performance (or state) of the system that can be satisfactory or unsatisfactory. Therefore, aggregation is based on the contribution of each component to the system state. Recovery time function, on the other hand, is the characteristic of the system in failure state.

For a serial system configuration of I components, the i-th component has a maximum recovery time membership function $\tilde{T}_i(t)$, defined on the universe of discourse T. The component having the longest recovery time controls the system recovery time. Therefore, the system recovery time can be calculated as follows:

$$\tilde{T}(t) = \tilde{T}_c(t) \qquad \textbf{.........(15)}$$

given

$$S(\tilde{T}_c) = \max_I \left(S(\tilde{T}_1), S(\tilde{T}_2), ........., S(\tilde{T}_I)\right)$$

and ……….(16)

$$\tilde{T}_c(1) = \max_I \left(\tilde{T}_1(1), \tilde{T}_2(1), ........., \tilde{T}_I(1)\right)$$

where:

$\tilde{T}(t)$ is the system recovery time;

$\tilde{T}_c(t)$ is the controlling recovery time;

$S(\tilde{T}_c)$ is the support of the controlling recovery time fuzzy membership functions;

$\left(S(\tilde{T}_1), S(\tilde{T}_2), ........., S(\tilde{T}_I)\right)$ are the support sets of N components;

$\tilde{T}_c(1)$ is the controlling recovery time set at the $\alpha$-cut level=1; and

$\left(\tilde{T}_1(1), \tilde{T}_2(1), ........., \tilde{T}_I(1)\right)$ are the recovery time sets at credibility level=1 of the I components.

In a parallel system of J components, the j-th component has a maximum recovery time membership function $\tilde{T}_j(t)$, defined on the universe of discourse T. The total failure event equals the failure of every component in the system. As a result, the membership function of system recovery time can be calculated as follows:

$$\tilde{T}(t) = \max_{J}\left(\tilde{T}_1, \tilde{T}_2, \ldots\ldots\ldots, \tilde{T}_J\right) \qquad \textbf{.........(17)}$$

where:

$\tilde{T}(t)$ is the system recovery time; and

$\left(\tilde{T}_1, \tilde{T}_2, \ldots\ldots\ldots, \tilde{T}_J\right)$ are component recovery times.

The combined system recovery time membership function can be determined by calculating subsystems recovery time membership functions according to either Equation 15 or 17.

### 1.4.3 Fuzzy Simulation

Engineering risk and reliability analysis is a general methodology for quantification of uncertainty and evaluation of its consequences for the safety of engineering systems (Ganoulis, 1994). Simulation and optimization techniques are the core of the risk assessment and management process. They provide vital tools for system performance analysis which guide decision-making process (Haimes, 2004). Computer simulation model is a formal attempt to construct a computer model of a complex real engineering system to make adequate predictions of its behavior under different initial and boundary conditions, (Pedrycz and Gomide, 1998). Deterministic and stochastic simulation models are commonly used to simulate performance of the engineering systems. Fuzzy simulation can be an appropriate approach to include various inherent uncertainties of engineering systems into the simulation process. Several commonly used classes of fuzzy simulation models are; (i) fuzzy-relational equations, (ii) fuzzy neural networks, and (iii) fuzzy regression models.

The fuzzy simulation toolbox of the developed QNRA uses the fuzzy regression to simulate the dependency of system output on its inputs. Fuzzy regression models are simple tools capable of capturing system uncertainties using fuzzy system parameters. The dependency of an output variable on input variables (Klir and Yuan, 1995) is expressed as follows:

$$\tilde{\mathrm{F}} = \sum_{i=1}^{n} \tilde{\mathrm{C}}_{\mathrm{i}} z_{\mathrm{i}} \qquad \textbf{……….(18)}$$

where:

$\tilde{\mathrm{F}}$ is the system fuzzy output variable,

$\tilde{\mathrm{C}}_{\mathrm{i}}$ are fuzzy coefficients; and

$z_{\mathrm{i}}$ are the system real-valued input variables.

For example, for given m-set of crisp data observations of system input and output, i.e. $(a_1,b_1)$, $(a_2,b_2)$,…. $(a_m,b_m)$, the fuzzy regression toolbox calculates the fuzzy parameters of the assumed model that represent the best fit of these observations.

Using a symmetric triangular fuzzy membership function to represent the fuzzy coefficients in the form (Klir and Yuan, 1995),

$$\tilde{C}_i(c) = \begin{cases} 1 - \dfrac{|c - c_i|}{v_i}, & \text{if } c_i - v_i \le c \le c_i + v_i \\ 0, & \text{elsewhere} \end{cases} \qquad \textbf{……….(19)}$$

where:

$c_i$ is the value at which the parameter $\tilde{C}_i(c)$ membership value=1; and

$v_i$ is half of the support of $\tilde{C}_i(c)$.

The output variable is also a symmetric triangular fuzzy membership number in the following form (Klir and Yuan, 1995),

$$\tilde{F}(f) = \begin{cases} 1 - \dfrac{|f - Z^T c|}{v^T |Z|}, & \text{if } z \ne 0 \\ 1, & \text{if } z = 0, f \ne 0 \\ 0, & \text{if } z = 0, f = 0 \end{cases} \qquad \textbf{……….(20)}$$

for all $f \in R$

where:

$$Z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix}, \qquad c = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{bmatrix}, \qquad v = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix}, \qquad |Z| = \begin{bmatrix} |z_1| \\ |z_2| \\ \vdots \\ |z_n| \end{bmatrix}; \text{ and}$$

T denotes the transposition operation.

Therefore, the problem is converted into finding the c and s vectors such that $\tilde{F}(f)$ fits the observations as good as possible. The two criteria of goodness of fit are: (i) for each given input observation $z_j$, the output observation, $f_j$, should belong to the corresponding fuzzy number $\tilde{F}_j$ with a grade greater or equal than given h value, as shown in Figure 7, where $h \in [0,1]$; i.e. $\tilde{F}_j(f_j) \geq h$ for each $j \in m$; and (ii) The total non-specificity of the fuzzy parameters must be minimized. Non-specificity of parameter $C_i$ is expressed by the value $v_i$.

Therefore, the problem of regression parameter selection can be formulated as simple linear programming optimization problem:

$$\begin{aligned} &\text{minimize} \quad \sum_{i=1}^{n} v_i \\ &\text{subject to} \quad (1-h)v^T |z_j| - |f_j - z_j^T c| \geq 0, j \in m \\ &\qquad\qquad\quad v_i \geq 0, i \in n \end{aligned} \qquad \textbf{……….(21)}$$

Chapter 2 explains in details the procedure of fuzzy simulation using the fuzzy simulation toolbox of the QNRA. Chapter 3 provides an example of numerical application to clarify this procedure.

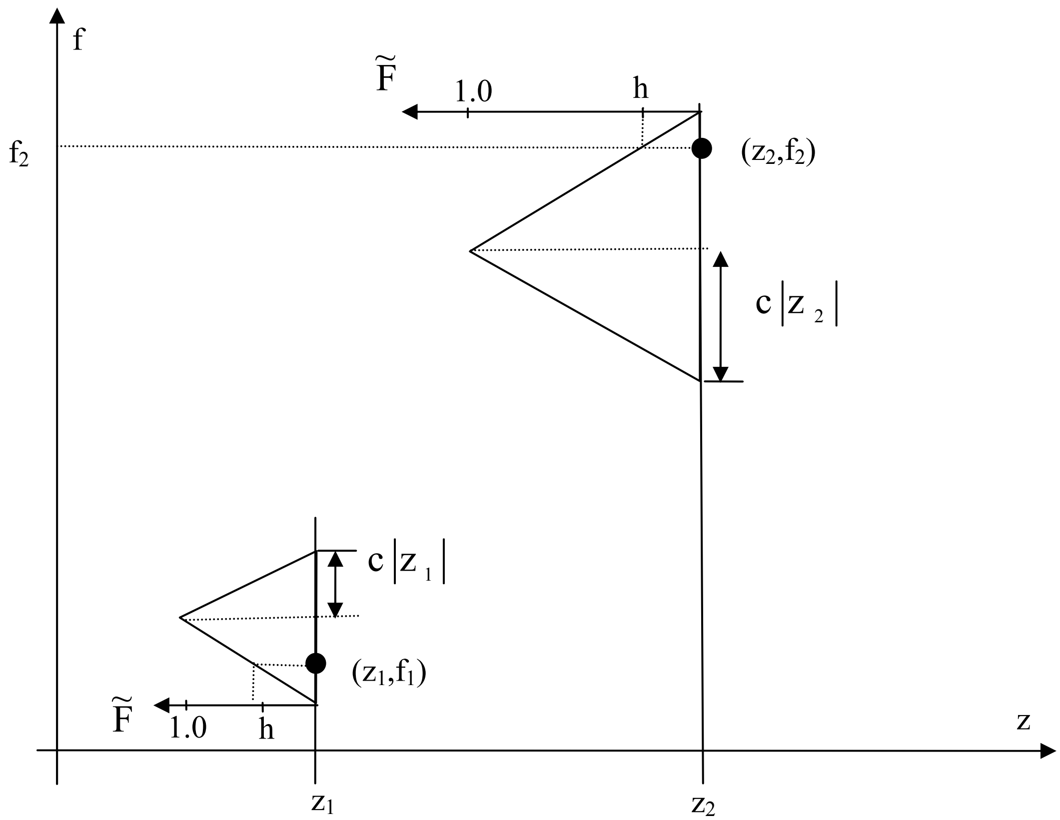



**Figure 7. Typical example of fuzzy regression model:** $\tilde{F} = \tilde{C}z$ **(after Terano et al, 1991)**

### 1.4.4 Fuzzy Optimization

Optimization is a mathematical process through which the optimum (maximum or minimum) value of a given objective function is achieved that satisfies a set of constraints (Onwubiko, 2000). In 1970 Bellman and Zadeh suggested an optimization model for decision making in a fuzzy environment when the objective function and the constraints are characterized by their fuzzy membership functions. Based on the analogy to a non-fuzzy decision making, they suggested the use of the intersection of the fuzzy objective function and fuzzy constraints to obtain the optimum fuzzy decision (elaborated by Zimmermann, 1996). Figure 8 depicts the fuzzy optimization process, which can be formulated as follows:

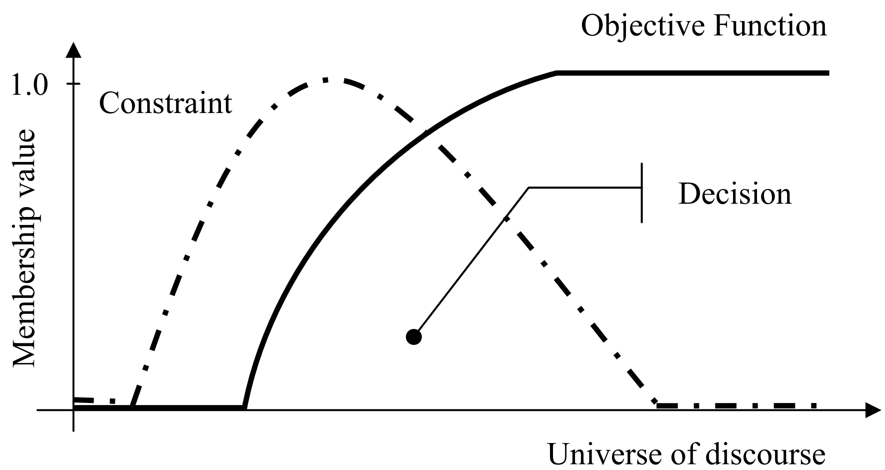



**Figure 8. A fuzzy decision by optimization.**

$\tilde{D}(d) = \tilde{O}(o) \wedge \tilde{C}(c)$ **……….(22)**

where

$\tilde{D}(d)$ is the fuzzy membership function of the decision,

$\tilde{O}(o)$ is the fuzzy membership function of the objective function,

$\tilde{C}(c)$ is the fuzzy membership function of the constraint(s); and

$\wedge$ is the fuzzy intersection operator.

Replacing the fuzzy intersection operator by the minimum operator for N constraints, the previous equation can be rewritten in the following form:

$$\tilde{D}(d) = \min_{j \in N}\{\tilde{O}, \tilde{C}_1(c), \tilde{C}_2(c), ..., \tilde{C}_j(c)\} \quad \textbf{.........(23)}$$

where

$\tilde{C}_j(c)$ is the fuzzy membership function of the j-th constraint; and

N is the total number of constraints.

Zimmermann (1996) states that minimum operator is not the appropriate operator to be used in modeling the aggregation of fuzzy membership functions representing managerial decisions , i.e. as in optimization. The fuzzy optimization toolbox of the QNRA uses the fuzzy linear programming to model the optimization problem in a fuzzy environment.

The classical linear programming problem defines the decision probelm by a set of constraints and objective function. This problem can be formulated as follows:

$$\begin{array}{ll} \text{maximize} & f(x) = c^T x \\ \text{subject to} & Ax \leq b \\ & x \geq 0 \end{array} \quad \textbf{........(24)}$$

where

$c^T$ is the coefficient vector;

x is the decision variable vector;

A is the constraints' coefficient matrix; and

b is the constraint limiting value vector.

Vagueness can be introduced to the classical Linear Programming (LP) problem in different ways. For example, the objective function can be used to represent goals (objectives) that can not be defined by a crisp value. All the coefficients in Equation 24 can, also, be represented by a fuzzy set to express vague perception. Fuzzy representation of Equation 24 allows marginal valuation of the constraints which can not be achieved using the classical LP problem, where any violation of constraints discards the solution. In addition, different degrees of violation can be introduced thought the use of the fuzzy formulation of the LP problem. It has to be noted that there is not a unique fuzzy LP model that fits all optimization problems. A variety of models exist depending on the context of the problem and the accompanying assumptions. The maximization problem, expressed by Equation 24 can be converted into the fuzzy format, where the decision maker can not precisely define both, the objective function and the constraints, as follows (Zimmermann, 1996):

$$\begin{aligned} &\text{maximize} && c^T x \tilde{\geq} z \\ &\text{subject to} && Ax \tilde{\leq} b \quad \textbf{........(25)} \\ & && x \geq 0 \end{aligned}$$

where $\tilde{\geq}$ and $\tilde{\leq}$ are the fuzzy forms of $\geq$ and $\leq$, respectively. The desired level z is introduced in the Equation 25 to express decision-makers' uncertainty in the optimization problem. The previous equation can be re-written as follows, (Zimmermann, 1996):

$$\text{find x such that} \quad \begin{aligned} Bx &\tilde{\leq} b \\ x &\geq 0 \end{aligned} \quad \textbf{........(26)}$$

$$\text{where} \quad B = \begin{pmatrix} -c \\ A \end{pmatrix} \text{ and } d = \begin{pmatrix} -z \\ b \end{pmatrix}$$

The model represented by Equation 26 includes m +1 rows, where m is the number of the constraints and 1 refers to the addition of the objective function. Each row of Equation 26 is a fuzzy set represented by a fuzzy membership function $\mu_i(x)$, that represents the degree to which x fulfils the fuzzy inequality $B_i x \tilde{\leq} d_i$ (Zimmermann, 1996). Using the triangular shape of the membership function to represent $\mu_i(x)$ as follows:

$$\mu_i(x) = \begin{cases} 1 & \text{if} \quad B_i x \leq d_i \\ 1 - \dfrac{B_i x - d_i}{p_i} & \text{if} \quad d_i < B_i x \leq d_i + p_i \\ 0 & \text{if} \quad B_i x > d_i + p_i \end{cases} \quad \textbf{........(27)}$$

where $p_i$ is the subjective tolerance which is used to express admissible violations of the objective function and the constraints.

The resultant of the optimization problem in Equation 26 is an optimal fuzzy set. The decision makers sometimes prefer the use of crisp optimal solution rather than optimal fuzzy set. Therefore, the maximum of the Equation 26 gives the required crisp optimal solution (Zimmermann, 1996)

$$\max_{x\geq 0} \mu_{\tilde{D}}(x) = \max_{x\geq 0} \min_{j\in(m+1)} \{\mu_i(x)\} \text{ ........(28)}$$

### 1.4.5 Fuzzy Multi-Objective Analysis

Water resources planning, designing and management problems are characterized by multiple and conflicting objectives (Haimes, 1998). Therefore, an optimal solution for a real problem under multiple objectives can not be attained. Solutions to those problems are often reached through the analysis of trade-offs between multiple objectives (Akter and Simonovic, 2002).

Decisions in water resources problems have to be made under conflicting objectives, uncertain, imprecise and incomplete knowledge. To face those problems, the vagueness and incompleteness of the available information has to be represented properly (Perny and Roubens, 1998). The use of the fuzzy set theory in multi-objective analysis provides a way for capturing and incorporating vagueness uncertainty into decision making.

A classical multi-objective problem consists of a vector $Z(x)$ of n-objective functions to be optimized (maximized or minimized) as follows:

$$Z(x) = [Z_1(x), Z_2(x), \ldots Z_n(x)] \text{ ........(29)}$$

where:

$x \in X$ and;

$x$ is the solution space.

Different x values result in different values for each objective function of the vector $Z(x)$. Optimization of the vector of objective functions can not be achieved. The decision maker preferences are required to obtain an optimal solution. Akter and Simonovic (2002) state that without the decision maker preferences the objectives are "incommensurable and incomparable".

A variety of multi-objective analysis techniques exists that are used to identify the trade-off solutions of a multi-objective problem. The compromise programming technique is one of multi-objective techniques commonly used in water resources management, (Akter and Simonovic, 2002). Therefore, the fuzzy version of this technique is used in the RASS. The compromise programming uses a distance metric, i.e. a measure of distance from the ideal solution, to identify the compromise subset (Prodanovic and Simonovic, 2003). Figure 9 shows an example of a two-objective problem. The distance metric $L_i$ exists for each alternative $A_i$ that determines its closeness to the ideal solution. The distance metric is calculated as follows, (Prodanovic and Simonovic, 2003):

$$L_i = \left[ \sum_{z=1}^{j} \left\{ w_z^p \left( \frac{f_z^* - f_z}{f_z^* - f_z^-} \right)^p \right\} \right]^{\frac{1}{p}} \quad \textbf{........(30)}$$

Where:

z represents objectives 1,2,3…..j;

i represents alternatives 1,2,…..n;

$L_i$ is the distance metric of alternative i;

$w_z$ is the subjective weight of objective z;

p is a parameter p=(1,2,∞);

$f_z^*$ and $f_z^-$ are the best and worst value of objective z; and

$f_z$ is the actual value of objective z.

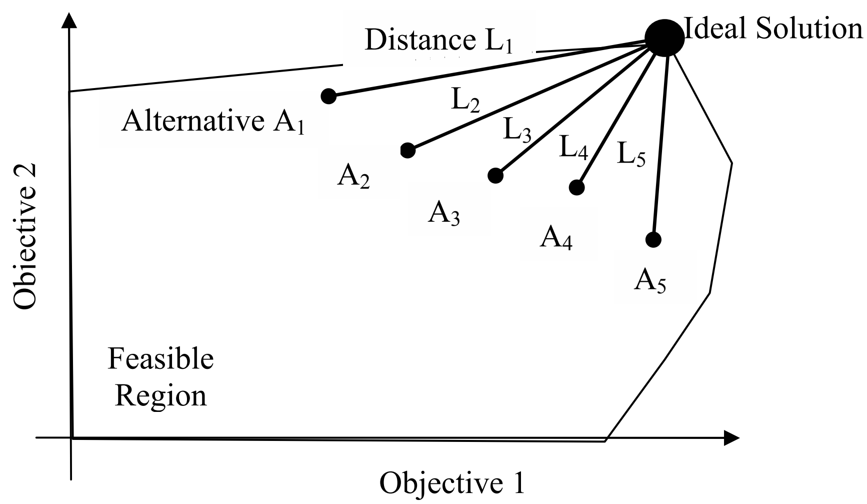



**Figure 9 Compromise programming method for a two-objective problem, (after Akter and Somonovic, 2002)**

Prodanovic and Simonovic (2003) state that “The parameter p corresponds to the weight (importance) given to the maximal deviation from the ideal solution”. This parameter assumes positive values ranging from 1 to ∞. As mentioned earlier, the decision-maker preferences are important in order to obtain the best compromised solution. They are introduced as the weights $w_z$ in Equation 30. Subjective nature of water resources problems requires proper tool for addressing subjective uncertainties. Fuzzy set theory is a better tool for addressing subjective uncertainties than the set theory. This is generally true, especially when dealing with criteria weights, deviation parameter and positive and negative ideals.

Fuzzy Compromise Programming is introduced by transforming all the crisp (single) inputs of Equation 30 into fuzzy inputs using the extension principle. Therefore, the distance between the ideal solution and any alternative can not assume crisp value as several other distances have relative belonging (membership) (Bender and Simonovic, 2000). Therefore, fuzzy sets ranking methods have to be used to select the smallest fuzzy distance metric. Several fuzzy sets ranking methods exist in the literature. Prodanovic and Simonovic (2002) conducted a comparison of those methods and suggested the method of Chang and Lee (1994). This report adopts the suggested method to be used in the fuzzy multi-objective analysis in the QNRA fuzzy toolbox.

Change and Lee use an Overall Existence Ranking Index (OERI) Prodanovic and Simonovic (2003):

$$\mathrm{OERI}(j) = \int_0^1 w(\alpha)\left[\chi_1 \mu_{jL}^{-1}(\alpha) + \chi_2 \mu_{jR}^{-1}(\alpha)\right] d\alpha \quad \textbf{........(31)}$$

Where:

$j$ is a subscript for the j-th alternative,

$\chi_1$ and $\chi_2$ are the subjective type weighting indicating neutral, optimistic or pessimistic preferences of the decision maker, given that $\chi_1 + \chi_2 = 1$;

$w(\alpha)$ is the parameter used to specify weights corresponding to certain degrees of membership $\alpha$ (if any); and

$\mu_{jL}^{-1}(\alpha)$ and $\mu_{jR}^{-1}(\alpha)$ are the inverse of the left and right parts of the membership function, respectively.

OERI is defined as "a sum of the weighted areas between the membership axis and the left and right inverses of a fuzzy number." (Prodanovic and Simonovic, 2003).

## 1.5 Probabilistic Approach

Probabilistic analysis examines the reliability of the engineering system from different perspective of potential improvements by taking into consideration risk and uncertainty (Haimes, 1998). Several system performance measures can be used to quantify the associated risks and consequently identify potential areas for system performance improvement.

### 1.5.1 Probabilistic Performance Measures

**Probabilistic reliability measure**

Reliability index is used to provide a description of the system performance in case of failure. It depends on the number of failures during the life time of the system (Smith, 2005):

$$\alpha = \frac{1}{NT}\frac{1}{ND}\sum_{t=1}^{NT}\sum_{d=1}^{ND} Z_{t,d} \text{ ........}\mathbf{(32)}$$

where,

$Z_{t,d}$ is the failure or non-failure state that takes 0 or 1 value, respectively,

NT is the number of time periods; and

ND is the number of dimensions of failure, (i.e.3= quantity, quality, and pressure).

Failure or non-failure states are defined as the indicators of system state outside or inside the bounds of a given criteria, respectively. It has to be noted that there can be maximum and minimum criteria values. The system dimension, ND, refers to each step within the system where failure can occur. For example, the treatment process can fail in several locations (such as in Chlorination, filtration,…etc) that might result in an overall system failure.

The NT value (number of time periods) refers to the length of the overall data record. It is required that each dimension have a data record of identical length in order to facilitate calculations.

**Probabilistic resiliency measure**

The resiliency is a measure of how quickly a system recovers from a failure state. Failures can last for a single time step or can last for several consecutive time steps. Failures that last for several consecutive time steps are considered to be part of the same failure event. A new failure event is identified by a failure state following a non-failure state. Resiliency is calculated as follows, (Smith, 2005)

$$\gamma = \frac{1}{\left(\frac{MD}{NT}\right)NF} \text{..........}\mathbf{(33)}$$

where

MD is the maximum duration of effective failure events; and

NF is the number of failure events.

An effective failure is the failure that affects the system output. The maximum duration of an effective failure is the length of the longest recorded failure event. That is, the longer the failure event the longer it takes to recover, therefore, the system is less resilient. The number of failure events is the count of the number of time steps within which the system is in the failure state. Failure events that occur in separate system locations are counted as distinct failures.

**Probabilistic vulnerability measure**

Vulnerability measures the consequences of the failure event. It is calculated as follows, (Smith, 2005)

$$\nu = \underset{k}{\text{Minimum}} \prod_{d=1}^{ND} \left(1 - P_{k,d}\right) \text{..........}\mathbf{(34)}$$

where,

$P_{k,d}$ is a standardized measure of the failure consequences (i.e. a complete failure (maximum consequences)=1 and no failure=0); and

K is the failure event; and

The standardized measure of failure takes the highest value, 1, in case of complete failure to indicate that the bad consequences are as great as possible. It takes the lowest value in case of non-failure state where there are no bad consequences. In between values are calculated based on the ratio between the system output and given criteria. For example, if the system discharges 3 $m^3$/sec and the failure criterion is set to be less than 5 $m^3$/sec, then the standardized measure takes the value of 0.67.

Measurements (system output) are examined across each dimension for each time step. The composite measure for each failure event is then the product of the $P_{k,d}$ values for each dimension. The overall vulnerability, $\nu$ , is the smallest of the calculated k-product.

### 1.5.2 Probabilistic Simulation

The probabilistic simulation toolbox of the QNRA adopts the Markov model, as a probabilistic (stochastic) model that incorporates uncertainty due to randomness. This model provides the basis for Monte Carlo simulation used to create new data sets using the historical mean, standard deviation, and correlation, in addition to the type of distribution that the original data fit. The QNRA simulation toolbox accommodates different distribution types; (i) normal, (ii) lognormal, (iii) Gamma, and (iv) Gumbel distribution.

It is important to initially characterize the historical data based on distribution type prior to the synthesis of a new series of similar distribution characteristics. The data is fitted to a given cumulative distribution function. Its parameters, such as mean, standard deviation, and correlation are estimated using method of moments or least square estimator technique. Once the historical data are characterized, new data sets of varying record lengths are synthesized using stochastic Markov chain Monte Carlo method:

$$Q_i = \bar{Q} + r(Q_{i-1} - \bar{Q}) + tS_Q\sqrt{1-r^2} \quad \textbf{.........(35)}$$

where

$Q_i$ is the new data point,

$\bar{Q}$ is the mean of the historical data set,

$Q_{i-1}$ is the previous data point,

r is the correlation of the historical data set,

t is a normal random deviation; and

$S_Q$ is the standard deviation of the historical data set.

It is also possible to simulate data sets that vary seasonally and have seasonally distinct means, standard deviation, and correlation by using the appropriate seasonal statistical parameters. Markov chain simulation uses normally distributed random variables. Therefore, it is possible that negative values are generated. Whenever a negative value is generated, it is corrected and assumed to be zero.

### 1.5.3 Probabilistic Multi-Objective Analysis

The objective of the probabilistic multi-criteria analysis is to minimize the distance to an ideal solution (which is always not feasible). The ideal for each probability measure will be the point that provides maximum value of reliability, resiliency, and vulnerability. The distance from the ideal point is calculated (Smith, 2005) as follows:

$$\text{Minimum}\left[ L_s = \beta_1^s \left( \frac{z_1^* - z_1}{z_1^* - z_1^{**}} \right)^s + \beta_2^s \left( \frac{z_2^* - z_2}{z_2^* - z_2^{**}} \right)^s + \beta_3^s \left( \frac{z_3^* - z_3}{z_3^* - z_3^{**}} \right)^s \right] \textbf{....(36)}$$

Where,

$z_1$, $z_2$ and $z_3$ are reliability, resiliency, and vulnerability, respectively;

$z_i^*$ is the optimal solution for i criterion;

$z_i^{**}$ is the worst solution for i criterion; and

$\beta_1$, $\beta_2$, and $\beta_3$ are the weights and reflect the decision makers preferences for each risk measure; and

s is the exponent that weights the deviation from the ideal solution.

The minimum distance from an ideal point is measured by $L_s$ metric. The best and the worst solution for each field are determined as the maximum and minimum value of the reliability, resiliency, and vulnerability measures. Typical values for s are 1, 2, 3, and infinity. The QNRA Probabilistic toolbox requires specification of s value to solve Equation 36 and identify the best compromise set of solutions.

# 2 RASS DESCRIPTION

## 2.1 Introduction

The Treasury Board of Canada Secretariat (2001) emphasizes the that " the challenge for the public service of Canada is to approach risk management in a more integrated and systematic way that includes greater emphasis on consultation and communication with stakeholders and the public at large". This emphasis on "organization-wide" risk management supports the call for new risk assessment and management.

It is difficult to precisely define Decision Support Systems (DSS), as they do not refer to specific area of specialty. However, DSS(s) can be defined as interactive computer programs that help decision makers to make use of data and the advanced computer technology to effectively manage large and complex engineering systems, (Ejeta and Mays, 2004). Therefore, it can be concluded that the main goal of all Decision Support Systems (DSS) is the improvement of the decision making process in terms of "problem identification and problem solving at all decision making levels" (Simonovic, 1996). Using new theoretical approach, capable of capturing qualitative knowledge, such as fuzzy set theory, together with other quantitative approaches provides the basis for new generation of intelligent DSS(s). Simonovic (1996) refers to the intelligent decision support concept as the suitable link between engineering expertise and decision- and policy-makers.

## 2.2 RASS Components

RASS consists of two main components; (i) quantitative risk assessment component (QNRA), and (ii) qualitative risk assessment component (QLRA). The QNRA incorporates a set of components for the assessment of system performance, simulation of system behavior and optimization of system performance. As shown in Figure 10, the QNRA component of RASS consists of two toolboxes; (i) probabilistic toolbox, and (ii) fuzzy toolbox. The probabilistic toolbox provides access to (a) performance evaluation tool that calculates reliability, resiliency and vulnerability measures; (b) simulation tool; and (c) multi-objective analysis tool. The fuzzy toolbox contains: (a) performance evaluation tool that calculates combined fuzzy reliability-vulnerability, fuzzy robustness and fuzzy resiliency measures; (b) fuzzy simulation tool; (c) fuzzy optimization tool; and (d) fuzzy multi-objective analysis tool.

**RASS Interface**

Haimes (1998) defines the risk assessment process as "a set of logical, systematic, and well-defined activities that provide the decision maker with a sound identification, measurement, quantification, and evaluation of the risk associated with certain natural phenomena or man-made activities". The previous definition emphasizes the importance of "sound identification" of the risk, as the first step of the risk assessment process. Therefore, RASS starts with an introductory screen providing two options for starting the risk assessment process, as shown in Figure 11. If the user is starting a new risk assessment process he/she is guided to start the QLRA and identify different risks associated with the system under consideration. This step assists the user to quantify different qualitative elements of risk (which uses vague and ambiguous linguistic terms).

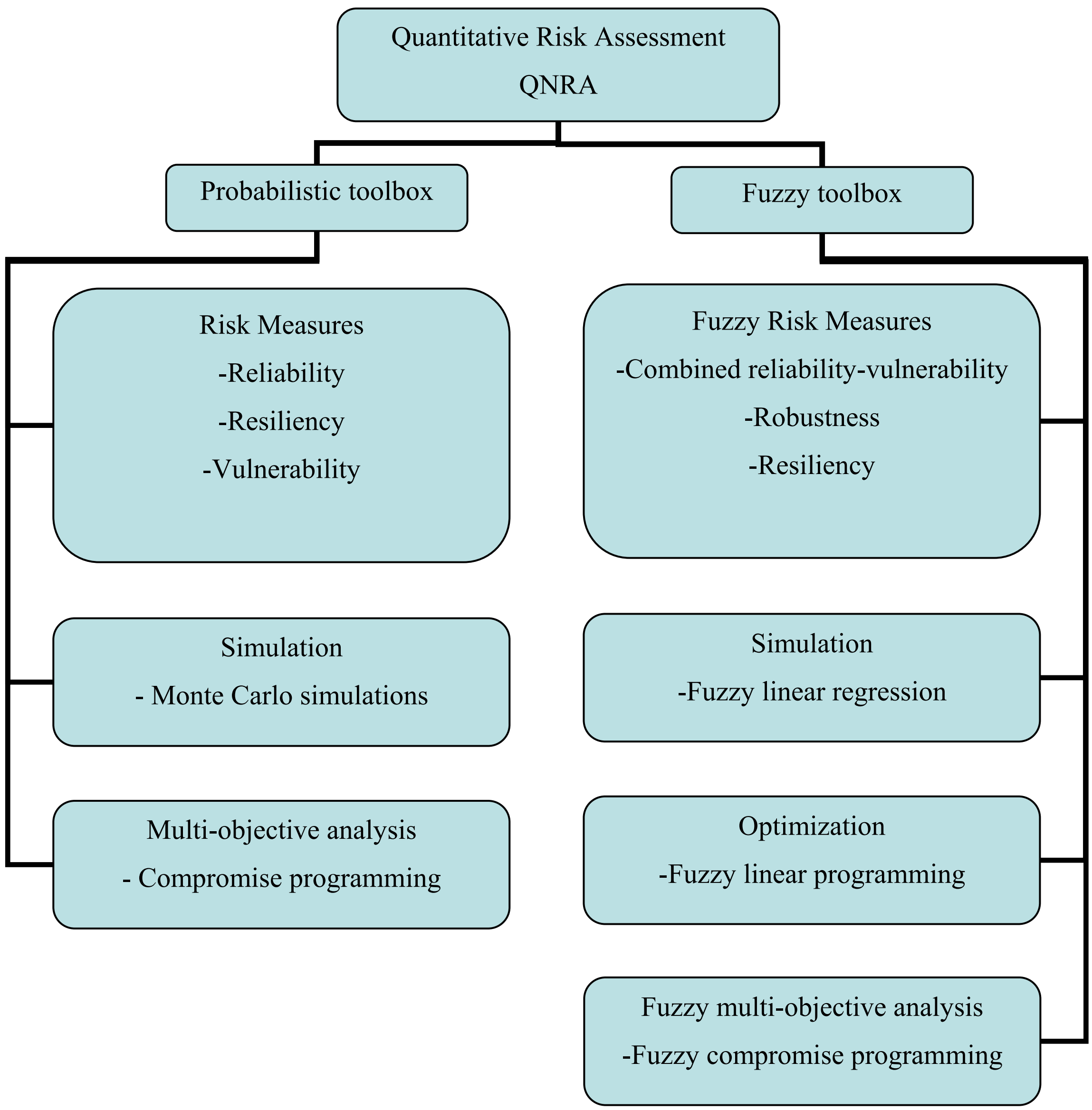



**Figure 10 Quantitative risk assessment component (QNRA) of RASS.**

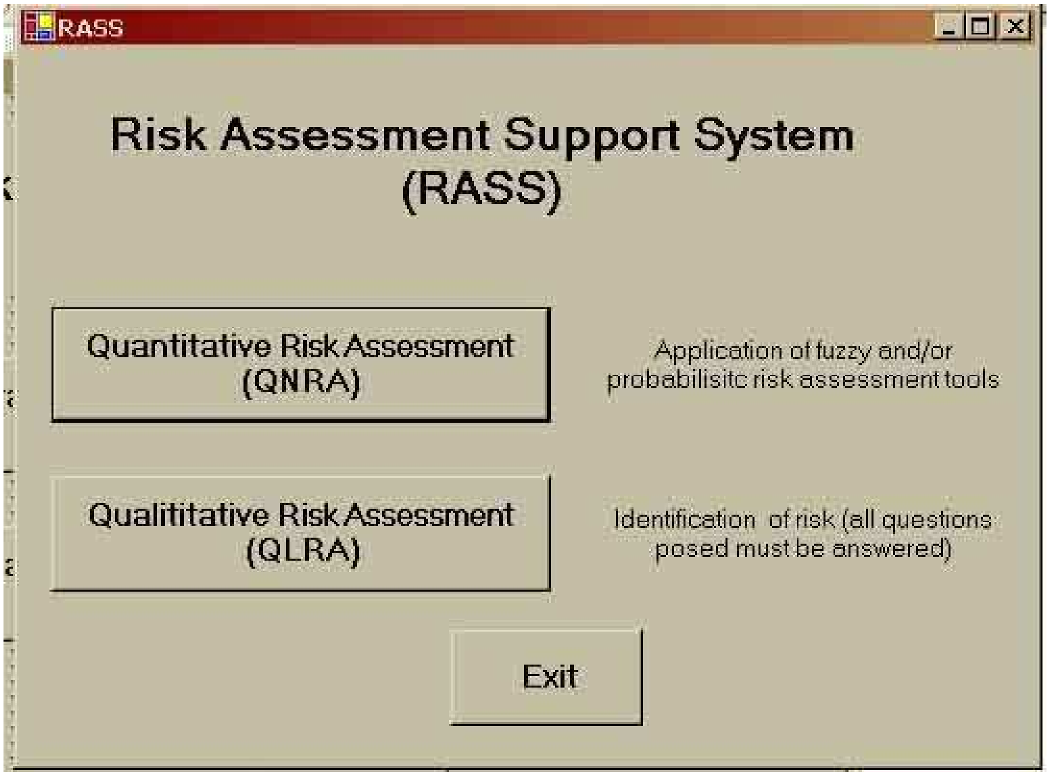



**Figure 11. RASS introductory screen.**

### 2.2.1 Qualitative Risk Assessment (QLRA)

Qualitative assessment starts with the exploration of user's risk knowledge, risk causes and potential impacts. The result of this analysis is a list of causes and impacts together with estimations of contribution of each cause to risk hazards. The user is introduced to 10 questions. A combination of Yes/No answers and numerical inputs is requested for each question. Detailed presentation of all questions is provided in Appendix I. Both, answers and numerical inputs, are used to clearly identify different risks and provide input for quantitative risk analysis using QNRA. As shown in Figure 12 the questions introduced to the user are clarified with a guiding comment to help the user. The numerical inputs are requested after each "Yes" answer given by the user. If the user answers "No" the QLRA moves to the next question.

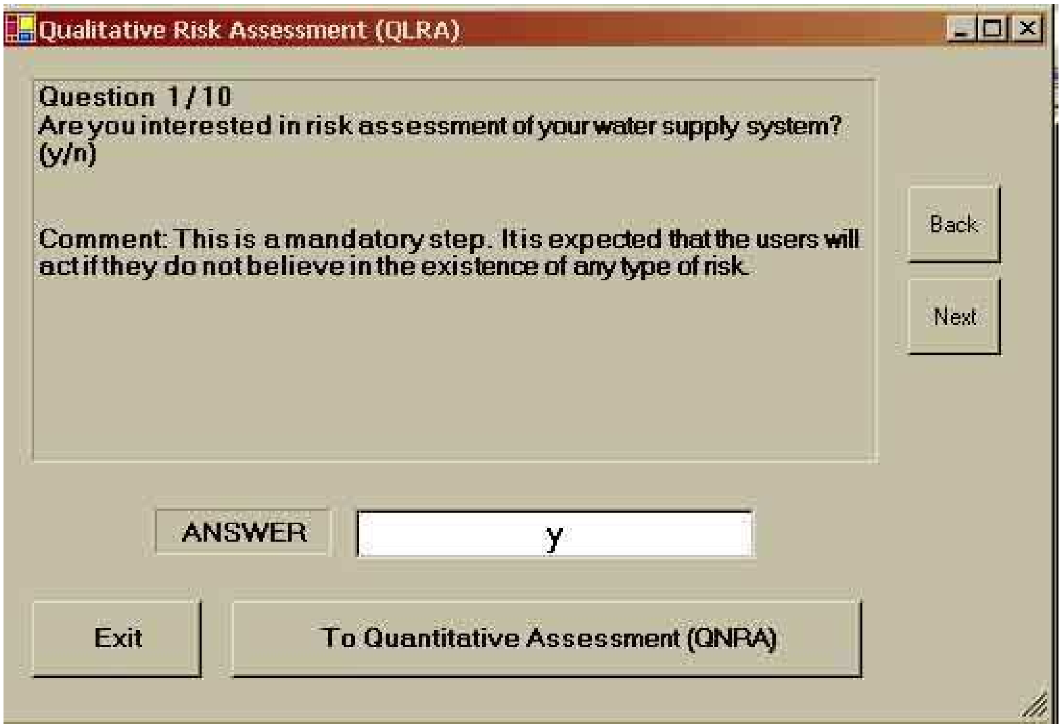



**Figure 12. A typical QLRA screen.**

The calculation of fuzzy performance measures depends on the definition of unsatisfactory system performance. Answering all the questions provided in the QLRA provides a means for evaluation of the fuzzy membership function(s) representing the acceptable level of system performance.

Generally, the evaluation of fuzzy membership function requires subjective judgment of an expert decision maker. Despic and Simonovic (1997) provides a review of different methods used to estimate fuzzy membership functions. This study uses the piecewise linear method to construct the acceptable level of performance using the information supplied by the user to the QLRA. This method is chosen because the filter function F with two parameters can be applied directly to evaluate membership function of the acceptable level(s) of performance. This function is mathematically expressed as follows:

$$\tilde{F}(x) = \begin{cases} 0, & \text{for } x \in \left[-\infty, b - \frac{w}{2}\right] \\ \frac{1}{w}\left(x - b + \frac{w}{2}\right), & \text{for } x \in \left[b - \frac{w}{2}, b + \frac{w}{2}\right] \\ 1, & \text{for } x \in \left[b + \frac{w}{2}, \infty\right] \end{cases} \quad \textbf{..........(37)}$$

where:

b is the crossover point, $b = \inf\{x\text{: } x \in \tilde{F}(\alpha), \alpha = 0.5\}$, and

w is the width of fuzziness (the smallest distance between zero membership and unity membership).

The values of w and b are determined based on the values supplied by the user to the QLRA. High significance values of risk concerns imply fewer acceptances to system failure, as shown in Figure 13. For example, if the average significance value of risk concerns (the total significance scores over their number) is 0.9, crossover point, b, will be 0.9 (in margin of safety units) or 1.9 (in safety factor units). Crisp value (0) for margin of safety and (1) for safety factor are considered the basic values above which average significance value is added to estimate crossover point, b. The width, w, is considered to reflect the number of risk concerns. Fewer risk concerns reflects higher confidence in the system and consequently smaller w value. The user can identify different acceptable levels of performance by supplying different significance values in each run of the QLRA.

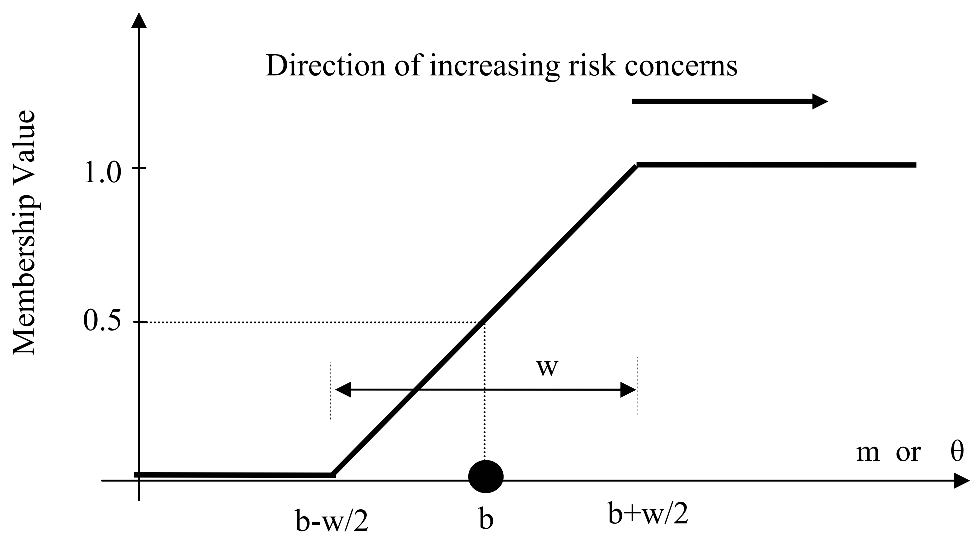



**Figure 13. Filter function (after despic and Simonovic, 1997).**

If the user used the QLRA before starting the fuzzy toolbox, the user can skip this step as the acceptable levels of performance have already been identified by the data of the QLRA.

### 2.2.2 Quantitative Risk Assessment (QNRA)

The QNRA incorporates a set of toolboxes for system performance evaluation, simulation of system behavior and single and multi-objective optimization of system performance. Both, probabilistic and fuzzy approaches are incorporated in the QNRA. QNRA starts with an introductory screen providing the user with two optional toolboxes as shown in Figure 14.

**The Fuzzy Toolbox**

Choosing the fuzzy toolbox button provides access to fuzzy tools. Figure 15 shows the opening screen of the fuzzy toolbox. The screen is arranged into two main parts, the first part (left side of the screen) is concerned with the data input. The numbers adjacent to the buttons refer to the sequence of data entry.

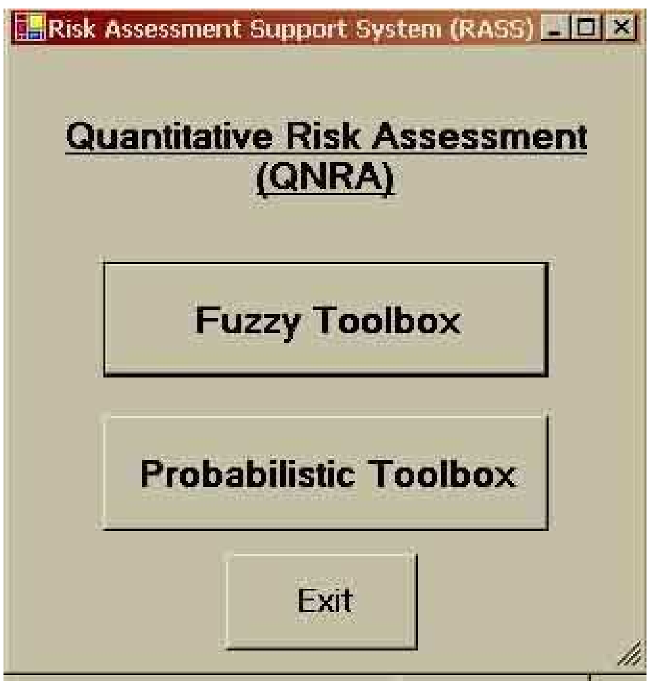



**Figure 14 QNRA opening screen.**

First, the user has to identify the system under consideration, then the type of the capacity-requirement relation to be used in the analysis. Second, the acceptable levels of performance have to be specified by pressing the second button. Completing these two main input steps is mandatory to enable the tool to use different analysis tools, i.e. calculation of risk measures, simulation or optimization. It has to be noted that the selection of a certain capacity-requirement relation will require expressing all acceptable levels of performance in the same manner, i.e. in terms of margin of safety or safety factor.

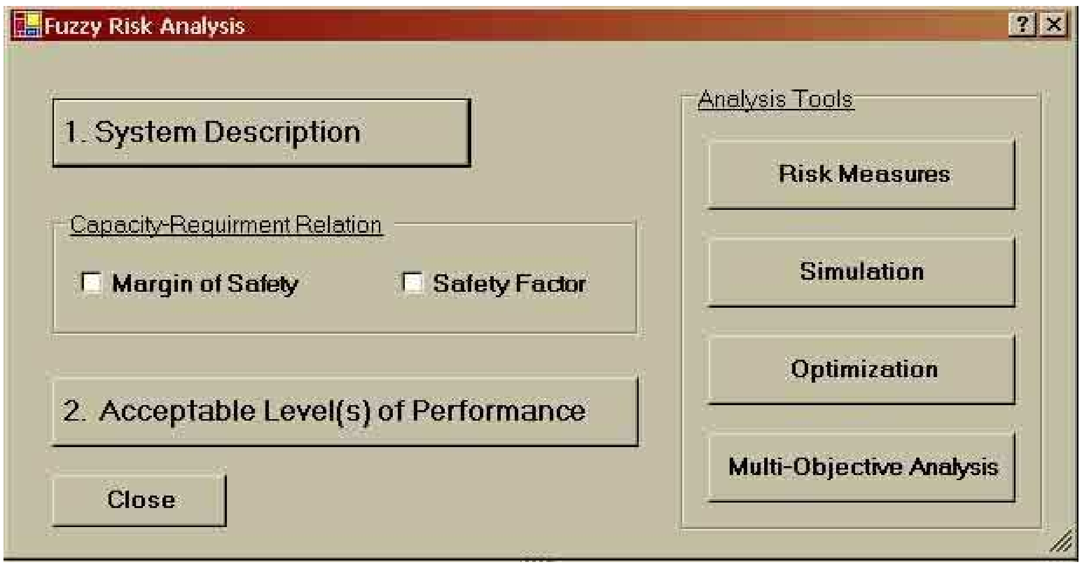



**Figure 15. Fuzzy toolbox screen.**

Selection of the "System Description" button will prompt the user to specify the name of the parameter(s) list file, as shown in Figure 16. The parameter list file contains a list of all the parameters used in the analysis of the system (i.e. as an example for water supply system this list can include discharge, pressure and different water quality parameter). The toolbox will check the number of input data against the number of parameters and prompt the user if there is any inconsistency between the two files.

It has to be noted that all the data files used by the RASS are in the comma separated file format (.CSV format). This format is selected because files in this format can be created easily with the help of any text editor. Appendices II and III contains detailed steps of different toolboxes and samples of all the data files required by the QNRA.

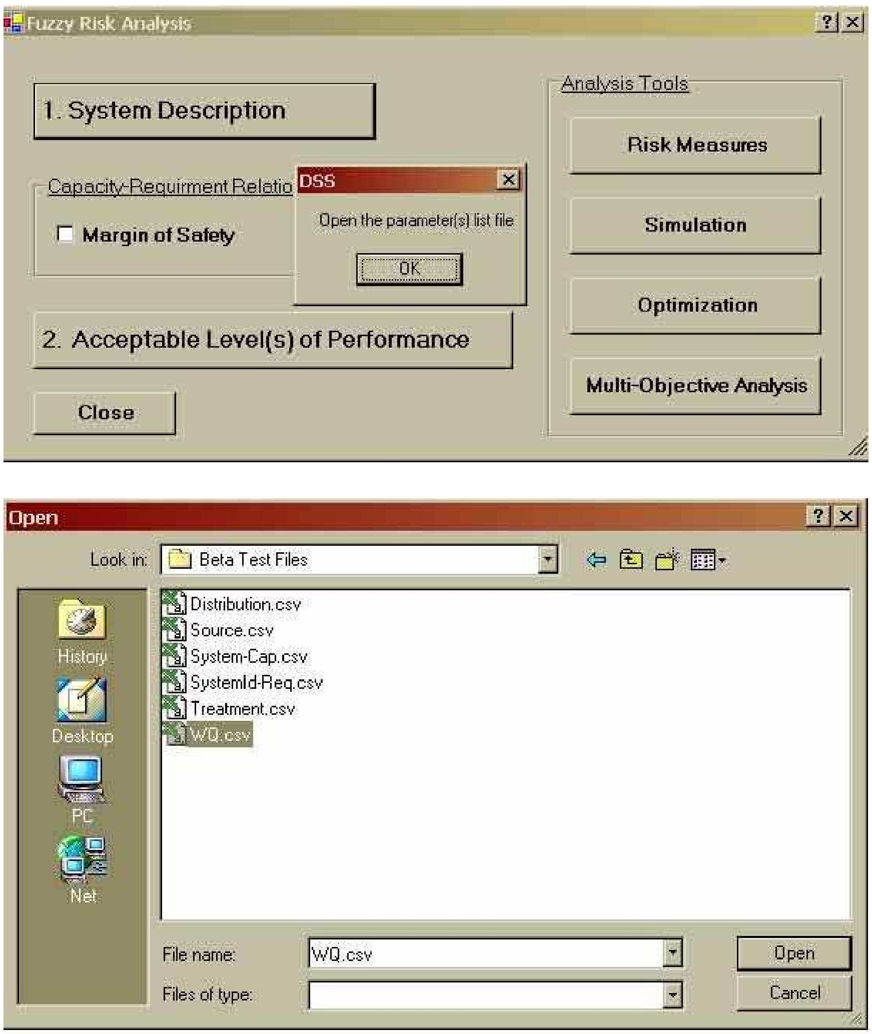



**Figure 16 Water quality parameter list selection.**

The user, then, has to specify the type of membership function to be used in the analysis. Fuzzy reliability analysis requires membership functions to describe the uncertainty in both, resistance (supply capacity) and load (water requirement), for each system component. Construction of the membership function is based on the system design data and choice of a suitable function shape. There are many possible shapes of membership functions. However, the QNRA considers only the choice between the triangular and the trapezoidal shapes. These are the simplest and most commonly used membership function shapes. The RASS prompts the user for one of these two shapes. Selected shape of the membership function requires the following input files to be consistent with that choice. For example, choosing the trapezoidal shape requires four values in the input file, while the triangular shape requires only three points, as shown in Figure 17.

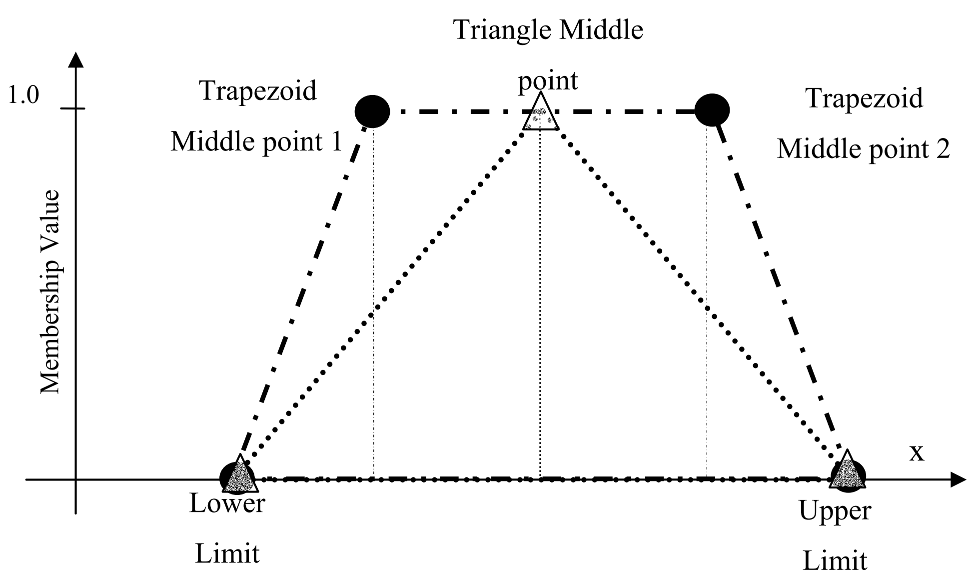
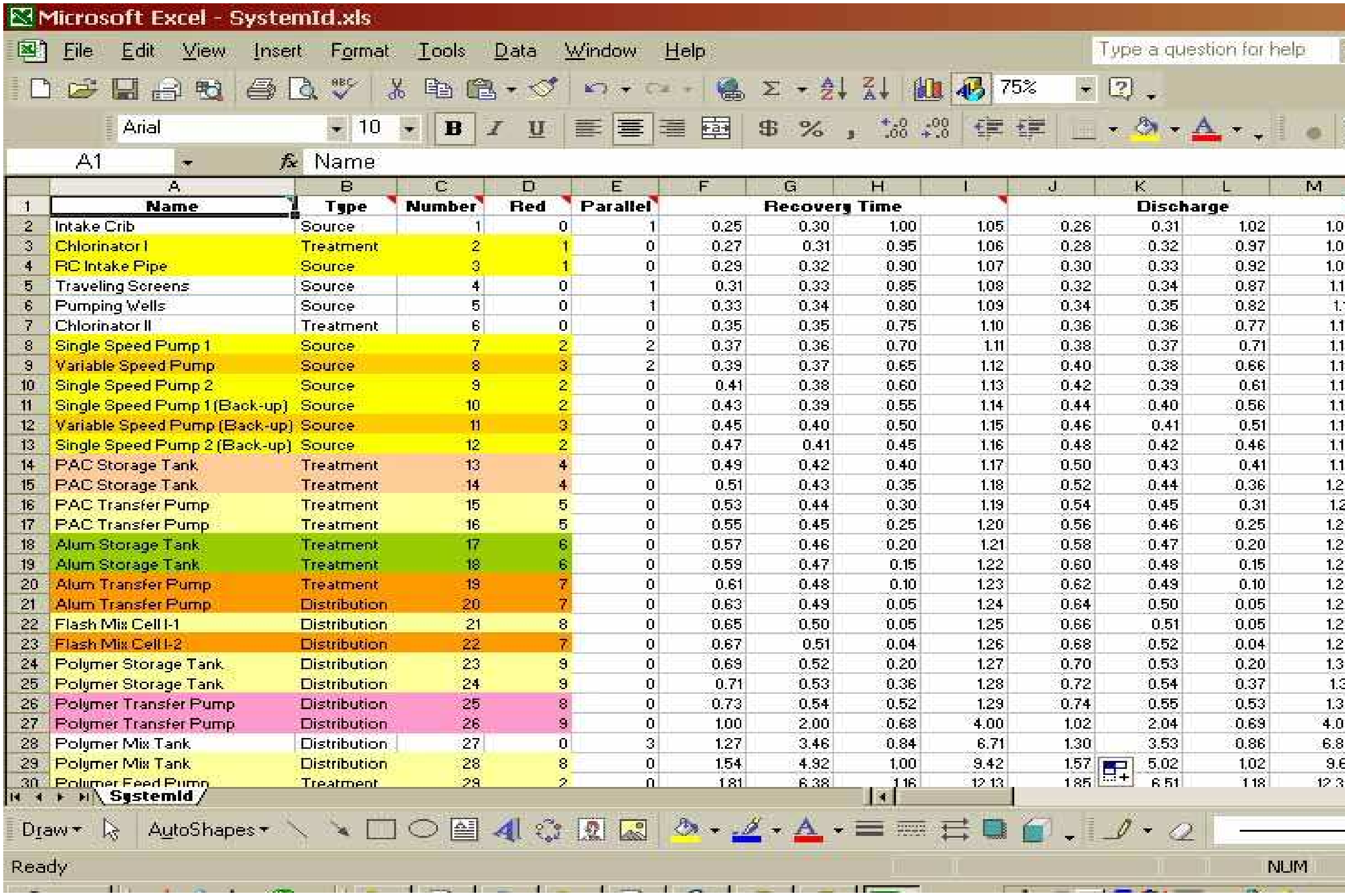



**Figure 17. Typical triangular and trapezoidal membership functions.**

The QNRA, then, prompts the user for the location of the supply capacity input file. This file contains supply capacity data for all system components. Figure 18 shows a part of the resistance (supply capacity) Excel input file for a trapezoidal membership function. Heading row is included in Figure 18 only for illustrative purposes. The listing of system components supply capacity data starts from the first row. The sequence of columns (fields) for each component is:

- Component Name: in this field the user inputs the name of a system component;
- Component Type: this field is for the use with the probabilistic toolbox. In the probabilistic toolbox, the water supply system is divided into three main subsystems; (i) source, (ii) treatment; or (iii) distribution. Different components are fitted into those three subsystems. The fuzzy toolbox uses different system components without any classification.
- Component Number: order number of the system components.
- Component Redundancy Group: redundancy group number. Redundant components are the components which have a stand by component(s) to account for the failure of working components. Redundant group numbers are set by the user without any specific considerations.
- Component Parallel Group: parallel group number. Parallel components are the components which work simultaneously. Parallel group numbers are set by the user without any specific considerations.
- Component Recovery Time: The time required to recover from the failure state can be represented as a fuzzy set, as in Equation 11. A recovery time membership function is specified by three or four values according to the selected membership function shape.




| | Name | Type | Number | Red | Parallel | Recovery Time | | | | Discharge | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | A | B | C | D | E | F | G | H | I | J | K | L | M |
| 2 | Intake Crib | Source | 1 | 0 | 1 | 0.25 | 0.30 | 1.00 | 1.05 | 0.26 | 0.31 | 1.02 | 1.0 |
| 3 | Chlorinator I | Treatment | 2 | 1 | 0 | 0.27 | 0.31 | 0.95 | 1.06 | 0.28 | 0.32 | 0.97 | 1.0 |
| 4 | RC Intake Pipe | Source | 3 | 1 | 0 | 0.29 | 0.32 | 0.90 | 1.07 | 0.30 | 0.33 | 0.92 | 1.0 |
| 5 | Traveling Screens | Source | 4 | 0 | 1 | 0.31 | 0.33 | 0.85 | 1.08 | 0.32 | 0.34 | 0.87 | 1.1 |
| 6 | Pumping Wells | Source | 5 | 0 | 1 | 0.33 | 0.34 | 0.80 | 1.09 | 0.34 | 0.35 | 0.82 | 1.1 |
| 7 | Chlorinator II | Treatment | 6 | 0 | 0 | 0.35 | 0.35 | 0.75 | 1.10 | 0.36 | 0.36 | 0.77 | 1.1 |
| 8 | Single Speed Pump 1 | Source | 7 | 2 | 2 | 0.37 | 0.36 | 0.70 | 1.11 | 0.38 | 0.37 | 0.71 | 1.1 |
| 9 | Variable Speed Pump | Source | 8 | 3 | 2 | 0.39 | 0.37 | 0.65 | 1.12 | 0.40 | 0.38 | 0.66 | 1.1 |
| 10 | Single Speed Pump 2 | Source | 9 | 2 | 0 | 0.41 | 0.38 | 0.60 | 1.13 | 0.42 | 0.39 | 0.61 | 1.1 |
| 11 | Single Speed Pump 1 (Back-up) | Source | 10 | 2 | 0 | 0.43 | 0.39 | 0.55 | 1.14 | 0.44 | 0.40 | 0.56 | 1.1 |
| 12 | Variable Speed Pump (Back-up) | Source | 11 | 3 | 0 | 0.45 | 0.40 | 0.50 | 1.15 | 0.46 | 0.41 | 0.51 | 1.1 |
| 13 | Single Speed Pump 2 (Back-up) | Source | 12 | 2 | 0 | 0.47 | 0.41 | 0.45 | 1.16 | 0.48 | 0.42 | 0.46 | 1.1 |
| 14 | PAC Storage Tank | Treatment | 13 | 4 | 0 | 0.49 | 0.42 | 0.40 | 1.17 | 0.50 | 0.43 | 0.41 | 1.1 |
| 15 | PAC Storage Tank | Treatment | 14 | 4 | 0 | 0.51 | 0.43 | 0.35 | 1.18 | 0.52 | 0.44 | 0.36 | 1.2 |
| 16 | PAC Transfer Pump | Treatment | 15 | 5 | 0 | 0.53 | 0.44 | 0.30 | 1.19 | 0.54 | 0.45 | 0.31 | 1.2 |
| 17 | PAC Transfer Pump | Treatment | 16 | 5 | 0 | 0.55 | 0.45 | 0.25 | 1.20 | 0.56 | 0.46 | 0.25 | 1.2 |
| 18 | Alum Storage Tank | Treatment | 17 | 6 | 0 | 0.57 | 0.46 | 0.20 | 1.21 | 0.58 | 0.47 | 0.20 | 1.2 |
| 19 | Alum Storage Tank | Treatment | 18 | 6 | 0 | 0.59 | 0.47 | 0.15 | 1.22 | 0.60 | 0.48 | 0.15 | 1.2 |
| 20 | Alum Transfer Pump | Treatment | 19 | 7 | 0 | 0.61 | 0.48 | 0.10 | 1.23 | 0.62 | 0.49 | 0.10 | 1.2 |
| 21 | Alum Transfer Pump | Distribution | 20 | 7 | 0 | 0.63 | 0.49 | 0.05 | 1.24 | 0.64 | 0.50 | 0.05 | 1.2 |
| 22 | Flash Mix Cell I-1 | Distribution | 21 | 8 | 0 | 0.65 | 0.50 | 0.05 | 1.25 | 0.66 | 0.51 | 0.05 | 1.2 |
| 23 | Flash Mix Cell I-2 | Distribution | 22 | 7 | 0 | 0.67 | 0.51 | 0.04 | 1.26 | 0.68 | 0.52 | 0.04 | 1.2 |
| 24 | Polymer Storage Tank | Distribution | 23 | 9 | 0 | 0.69 | 0.52 | 0.20 | 1.27 | 0.70 | 0.53 | 0.20 | 1.3 |
| 25 | Polymer Storage Tank | Distribution | 24 | 9 | 0 | 0.71 | 0.53 | 0.36 | 1.28 | 0.72 | 0.54 | 0.37 | 1.3 |
| 26 | Polymer Transfer Pump | Distribution | 25 | 8 | 0 | 0.73 | 0.54 | 0.52 | 1.29 | 0.74 | 0.55 | 0.53 | 1.3 |
| 27 | Polymer Transfer Pump | Distribution | 26 | 9 | 0 | 1.00 | 2.00 | 0.68 | 4.00 | 1.02 | 2.04 | 0.69 | 4.0 |
| 28 | Polymer Mix Tank | Distribution | 27 | 0 | 3 | 1.27 | 3.46 | 0.84 | 6.71 | 1.30 | 3.53 | 0.86 | 6.8 |
| 29 | Polymer Mix Tank | Distribution | 28 | 8 | 0 | 1.54 | 4.92 | 1.00 | 9.42 | 1.57 | 5.02 | 1.02 | 9.6 |
| 30 | Polymer Feed Pump | Treatment | 29 | 2 | 0 | 1.81 | 6.38 | 1.16 | 12.13 | 1.85 | 6.51 | 1.18 | 12.3 |

**Figure 18 Typical example of the (resistance) capacity input data file in Excel.**

- Component Discharge: discharge capacity of each component in the water supply system membership function values (three or four points according to the selected type, as shown in Figure 17).
- Component Pressure: Pressure capacity of each component in the water supply system membership function values (three or four points according to the selected type, as shown in Figure 17).
- Component Water Quality: water quality capacity of each component in the water supply system membership function values (three or four points according to the selected type, as shown in Figure 17). The number of water quality parameters in this file should correspond to the number of water quality parameters used in the list file selected in the first step.

The use of QNRA continues with the specification of a water requirements input file. This file contains all the fields as the supply capacity input file, except the component type, number, redundancy group, parallel group and recovery time. Both files must have the same number of components; otherwise the RASS will alert the user of this mistake.

The final step in system description is the required solution accuracy (alpha in Equation 3). Specifying a small value for alpha results in high solution accuracy and longer processing time. Required value is a positive number between 0 and 1, Equation 3.

The system description is completed with this step. The user is left to select one of the two available relations (margin of safety or safety factor) between the supply capacity and the water requirement by checking one of the check boxes on the screen. Both relations are equally useful. The choice between either one is the sole preference of the decision maker.

**Acceptable level of performance**

The calculation of fuzzy risk measures depends on the specification of the acceptable level of performance by the decision maker. Therefore, the following step in the use of fuzzy toolbox requires identification of the acceptable levels of performance for discharge, pressure and each water quality parameter. The QNRA prompts the user for manual input of those data or the use of an already prepared file. An example of the file content is shown in Figure 19, and is also in CSV format.

The first column, column B in Figure 19, specifies the belonging of the level of performance to one of the three domains used in RASS: discharge, pressure, or water quality. The second column, column C, is a title (name) given by the user to the level of performance. Column E specifies the number order of the specified levels. It has to be noted that the numbering, given in column E, is independent for discharge, pressure and each water quality parameter. The total number of levels for discharge, pressure, and water quality parameters is given in column G. The last two columns, columns I and J, are the required input values of the two points to numerically identify the level. As shown in Figure 20, each level of performance requires two points for complete identification. It has to be noted that the connection from point 1 to point 2 can assume different forms. A linear relation is assumed in the QNRA.

| Item | Title | LevelNo | | | TotalNo | | Pt1 | Pt2 |
|---|---|---|---|---|---|---|---|---|
| DISCHARGE | Safe | Level NO: | 1 | out of | 3 | Levels | 0.00 | 4.00 |
| DISCHARGE | Risky | Level NO: | 2 | out of | 3 | Levels | 0.20 | 2.00 |
| DISCHARGE | Neutral | Level NO: | 3 | out of | 3 | Levels | 0.60 | 1.00 |
| PRESSURE | High | Level NO: | 1 | out of | 2 | Levels | 1.00 | 2.00 |
| PRESSURE | Low | Level NO: | 2 | out of | 2 | Levels | 2.00 | 3.00 |
| WATER QUALITY - Ph | Acid | Level NO: | 1 | out of | 2 | Levels | 1.00 | 2.00 |
| WATER QUALITY - Ph | Alkaline | Level NO: | 2 | out of | 2 | Levels | 1.00 | 2.00 |
| WATER QUALITY - Temperature | High | Level NO: | 1 | out of | 1 | Levels | 12.00 | 17.00 |
| WATER QUALITY - Turbidity | Good | Level NO: | 1 | out of | 2 | Levels | 4.00 | 5.00 |
| WATER QUALITY - Turbidity | Bad | Level NO: | 2 | out of | 2 | Levels | 2.00 | 3.00 |

**Figure 19 An example of the acceptable level of performance file.**

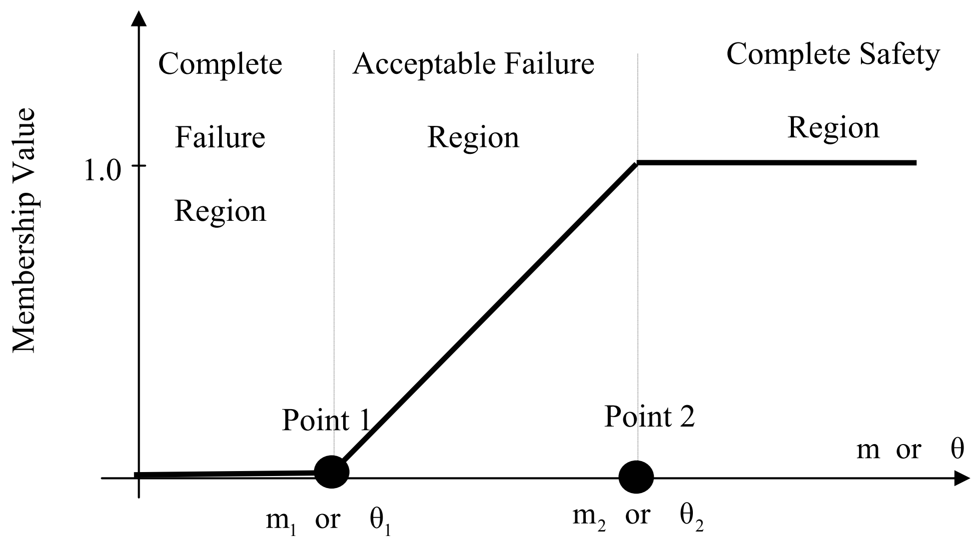



**Figure 20. Fuzzy membership function of the acceptable level of performance.**

If the user chooses to manually enter the levels file, the QNRA will start a Level Editor to assist the user in the preparation of input data. Figure 21 shows the Level Editor where the user enters the level title and two numeric values for each level. It has to be noted that the numeric values supplied are expressed in terms of margin of safety or safety factor (according to the choice made previously). As shown in Figure 21, the user has only to specify the title of the acceptable level of performance together with the two identification points. Once the user has finished entering the data for all acceptable levels of performance belonging to a certain domain, the interface automatically changes the domain title and prompts the user to start entering its levels of performance.

The values of the acceptable levels of performance membership functions are expressed in terms of safety factor or margin of safety, as in Equation 5. For example, if the first point value is set to be 0.5 (expressed in terms of factor of safety), this indicates that the complete failure region is identified when the resistance (supply capacity) is less than half of the load (water requirement). These input values are specified by the user based on his/her preferences which reflect personal perception of risk. At the end of this step the QNRA has all the data required by the fuzzy tools to calculate the fuzzy performance measures.

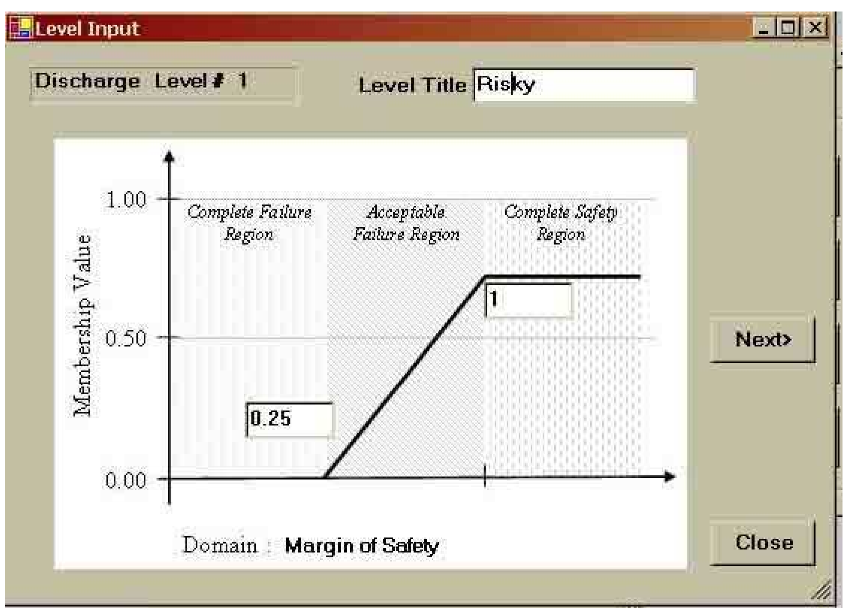



**Figure 21 Acceptable level of performance editor.**

**Fuzzy performance measures toolbox**

The three fuzzy performance measures suggested by El-Baroudy and Simonovic (2004) are used to quantitatively evaluate the performance of the system. These measures are: (i) combined reliability-vulnerability measure, (ii) robustness measure, and (iii) resiliency measure. Figure 22 presents the flowchart of the calculation process for water supply system domains, i.e. discharge, pressure and water quality parameters. Equations 9, 10 and 12 are used to perform the calculation of these measures. Two fuzzy performance measures, reliability-vulnerability and robustness, are calculated for each domain. Therefore, the overall system fuzzy reliability-vulnerability measure is calculated to be the average of the fuzzy reliability-vulnerability index for each domain as follows:

$$RE_{f-S} = \frac{1}{N}\sum_{N}^{i=1} RE_{f-i} \quad \textbf{……….(38)}$$

Where:

$RE_{f-S}$ is the system overall combined fuzzy reliability-vulnerability measure;

N is the total number of domains, i.e. discharge, pressure, all water quality parameters; and

$RE_{f-i}$ the combined fuzzy reliability-vulnerability measure of the i-th domain.

The same applies to the fuzzy robustness index:

$$RO_{f-S} = \frac{1}{N}\sum_{N}^{i=1} RO_{f-i} \quad \textbf{..........(39)}$$

Where:

$RO_{f-S}$ is the system overall fuzzy robustness measure;

N is the total number of domains, i.e. discharge, pressure, all water quality parameters; and

$RO_{f-i}$ the fuzzy robustness measure of the i-th domain.

As shown in Figure 22, the calculation of the fuzzy risk performance measures starts by collecting system and level(s) input data. Load and resistance fuzzy membership functions are created and the corresponding alpha cuts are calculated for each function.

For each system component, load and resistance membership functions are combined in a single membership function in terms of load-resistance relationship specified by the user (i.e. margin of safety or safety factor). Membership functions of redundant and parallel components are augmented to produce single membership function for each redundant/parallel group. All membership functions are augmented with membership functions of other serial components to produce a single membership function for the whole system (i.e. system-state fuzzy membership function).

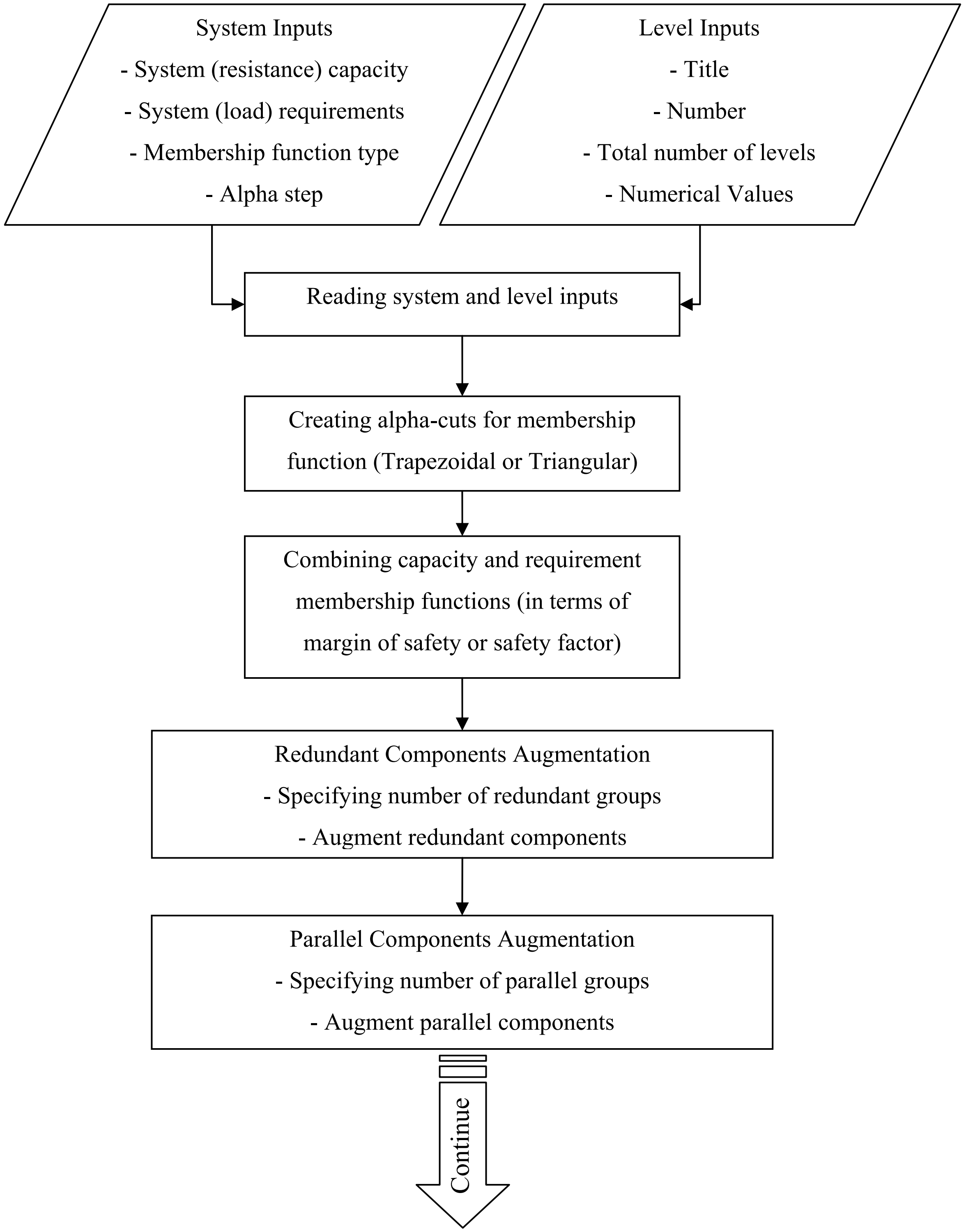



**Figure 22 Flowchart of the fuzzy risk measures calculation for each domain.**

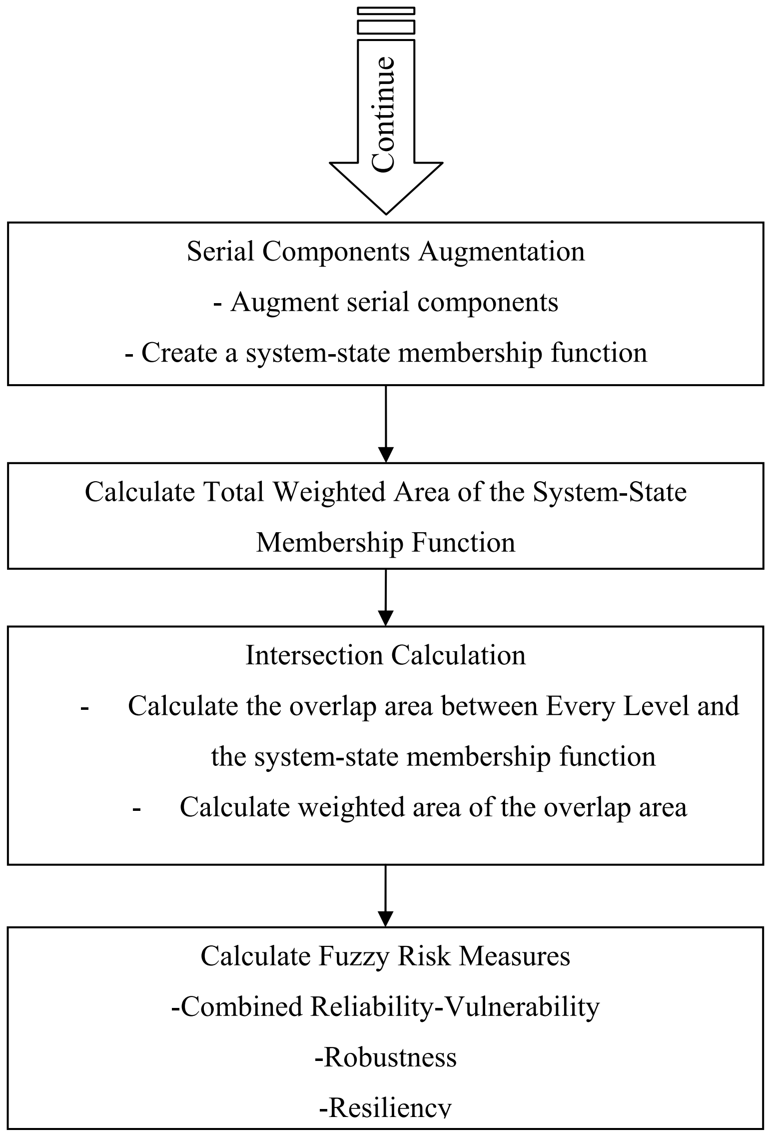



**Figure 22 (continued). Flowchart of the fuzzy risk measures calculation for each domain.**

Then, the overlap areas of the system-state membership function with different acceptable levels of performance are determined. Equations 9, 10, 12 are used to calculate the three fuzzy performance measures. These calculations are repeated for each system parameter (i.e. discharge, pressure, and water quality parameters).

**Fuzzy simulation toolbox**

The QNRA fuzzy toolbox uses the fuzzy regression to simulate the dependency of the different system outputs to its inputs. For example, the system discharge at certain time step t, depends on the system discharge of the previous time step, t-1, as follows

$$\tilde{Q}_t = \tilde{C}_Q . Q_{t-1} \quad \text{..........(40)}$$

where:

$\tilde{Q}_t$ is the system fuzzy discharge at time step t,

$\tilde{C}_Q$ is the discharge fuzzy simulation coefficient; and

$Q_{t-1}$ is the crisp discharge at time step, t-1.

Assuming that a set of crisp data observations of system discharge at different consecutive time steps, i.e. ($Q_{t1-1}$, $Q_{t1}$), ($Q_{t2-1}$, $Q_{t2}$),($Q_{t3-1}$, $Q_{t3}$),….is given. The fuzzy regression involves the calculation of the fuzzy parameter of the assumed model that represents the best fit of these observations. Using a symmetric triangular fuzzy membership function to represent the fuzzy coefficient:

$$\tilde{C}_Q(c) = \begin{cases} 1 - \dfrac{|c - c_q|}{s_q}, & \text{if } c_q - s_q \le c \le c_q + s_q \\ 0, & \text{elsewhere} \end{cases} \quad \text{..........(41)}$$

where:

$c_q$ is the value at which the parameter $\tilde{C}_Q(c)$ membership value=1; and

$s_q$ is half of the support of $\tilde{C}_Q(c)$.

It has to be noted that the output discharge at time step t will be a symmetric triangular fuzzy membership number in the following form

$$\tilde{Q}_t(q) = \begin{cases} 1 - \dfrac{|q - Q_{t-1}c_q|}{s_q |Q_{t-1}|}, & \text{if } Q_{t-1} \neq 0 \\ 1, & \text{if } Q_{t-1} = 0, Q_t \neq 0 \\ 0, & \text{if } Q_{t-1} = 0, Q_t = 0 \end{cases} \qquad \textbf{.........(42)}$$

Therefore, the problem is converted into finding the $c_q$ and $s_q$ vectors such that $\tilde{Q}_t(q)$ fits the observations as well as possible. The two criteria of goodness of fit are:

(i) For each given input observed discharge $Q_{t1-1}$, the output observed discharge, $Q_{t1}$, should belong to the corresponding fuzzy number $\tilde{Q}_t$ with a grade greater or equal than given h value, where h $\in [0,1]$; i.e. $\tilde{Q}_t(Q_t) \geq h$ for each t and. The value of both h and the total number of simulation years is supplied by the user as shown in Figure 23.

(ii) The total non-specificity of the fuzzy parameters is minimized. Non-specificity of parameter $c_q$ is expressed by the value $s_q$.

Therefore, the problem is formulated as a linear programming problem:

$$
\begin{aligned}
&\text{minimize} \quad s_q \\
&\text{subject to} \quad (1-h)s_q\left|Q_{t-1}\right| - \left|Q_t - Q_{t-1}c_q\right| \geq 0 \\
&\qquad\qquad\quad s_q \geq 0
\end{aligned}
\qquad \textbf{..........(43)}
$$

The QNRA fuzzy simulation toolbox solves this linear programming problem using the input observations and simulates discharge. The simulated fuzzy output discharge is given in the form of a text file for each time step (i.e. three values for each time step since the resultant membership function is a symmetric triangular fuzzy membership function). The same process is performed for each domain, i.e. pressure and water quality parameters, where the user has to supply the tool with output membership grade h and simulation period for each domain.

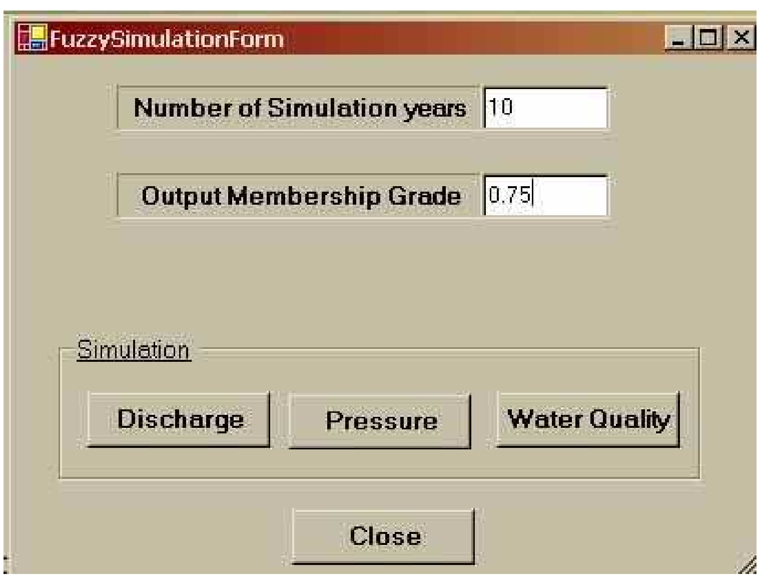



**Figure 23 Fuzzy simulation toolbox.**

**Fuzzy optimization toolbox**

The fuzzy combined reliability-vulnerability and robustness indices are directly proportional to the compatibility measure, as in Equations 9 and 10. That is, the bigger the overlap area between the system-state membership function and the acceptable level of performance the higher the value of both measures. Therefore, the QNRA fuzzy optimization toolbox uses this direct relation to perform fuzzy optimization. Maximizing summation of independent components' state membership functions increases the overlap area, i.e. the compatibility with the corresponding acceptable level of performance. If it is required to maximize the fuzzy resiliency index, the fuzzy optimization toolbox minimizes the summation of the recovery-time membership functions, as shown in Figure 24. The minimization problem is transformed into a maximization problem by multiplying the objective function by (-1).

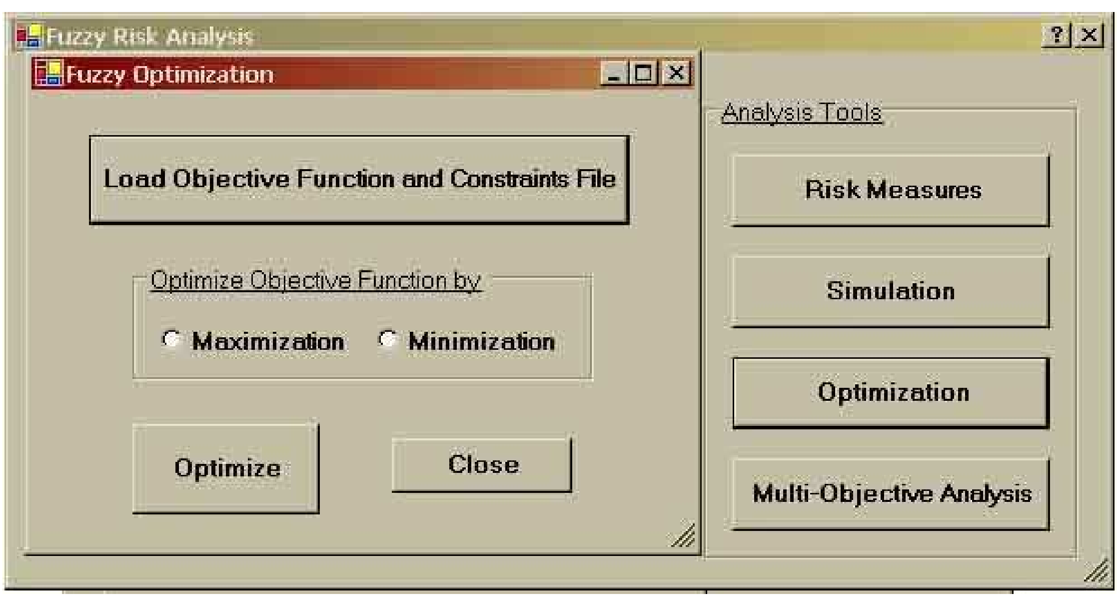



**Figure 24 Fuzzy optimization toolbox.**

This means that the QNRA optimization toolbox solves only maximization problems in the following form:

$$\begin{aligned} &\max\text{imize} \quad X_1 + X_2 + \ldots X_m \\ &\text{subject to} \quad [A][X] \tilde{\leq} [b] \\ &\qquad\qquad\quad X_1, X_2, \ldots X_m \geq 0 \end{aligned} \quad \textbf{........(44)}$$

where:

$X_m$ is the m-th decision variable,

$[A]$ is the constraints coefficients matrix,

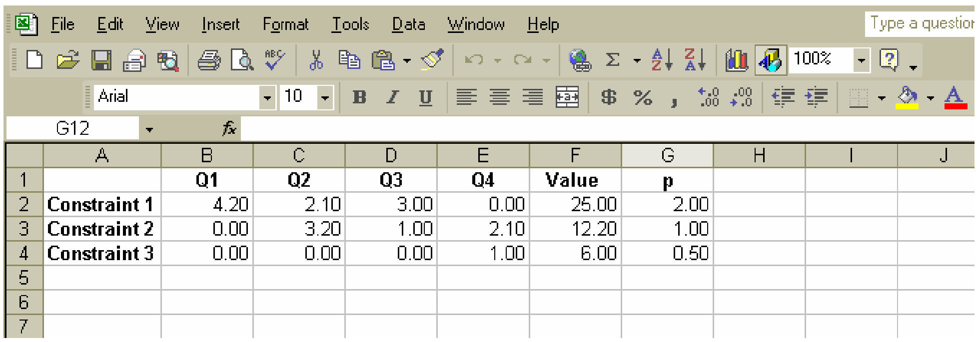
$[X]$ is the decision variable matrix,

$[b]$ is the left hand side constraint limit vector; and

$\tilde{\leq}$ is the fuzzy form of the "smaller than".

If it is required to maximize water supply system discharge reliability. The QNRA user has to specify system components that are to be maximized. It is also required to specify different constraints on components discharge capacities. The fuzzy optimization toolbox uses this information to maximize the summation of the discharge.

Figure 25 shows a typical example of the input file that is to be used by the optimization toolbox. The toolbox uses crisp decision variables and objective function. Fuzziness is introduced to the optimization problem using the fuzzy inequality $\tilde{\leq}$. This provides flexibility to the decision maker to express the constraints in less restrict approach. As it can be seen from Equation 44, all components are assumed to be of equivalent weight, i.e. the coefficients in the objective function are all set to be unity.  The solution of this fuzzy linear programming problem gives the optimal crisp values of the decision variables.



| | Q1 | Q2 | Q3 | Q4 | Value | p |
|---|---|---|---|---|---|---|
| Constraint 1 | 4.20 | 2.10 | 3.00 | 0.00 | 25.00 | 2.00 |
| Constraint 2 | 0.00 | 3.20 | 1.00 | 2.10 | 12.20 | 1.00 |
| Constraint 3 | 0.00 | 0.00 | 0.00 | 1.00 | 6.00 | 0.50 |

**Figure 25. Fuzzy optimization input file.**

**Fuzzy multi-objective toolbox**

The fuzzy multi-objective analysis toolbox uses two CSV format input data files(without headings), as shown in Figure 26.  The first input file is the ideal and weights file.  In this file, positive (best), negative (worst) ideal values together with weights, for each criterion, are defined as fuzzy membership functions, as shown in Figure 27.  The second input file is another CSV format file with different alternatives to be analyzed by the toolbox, as shown in Figure 28.

Then, the user has to specify the type of the fuzzy membership function to be used by the toolbox to start ranking alternatives.  The toolbox produces a summery report file containing the ranking of the alternatives for each decision-maker preferences (i.e. 9

values starting from 0.1-0.9, $x_1$ and $x_2$ values in Equation 31). Appendix II includes detailed steps to use the toolbox together with examples of the output text file.

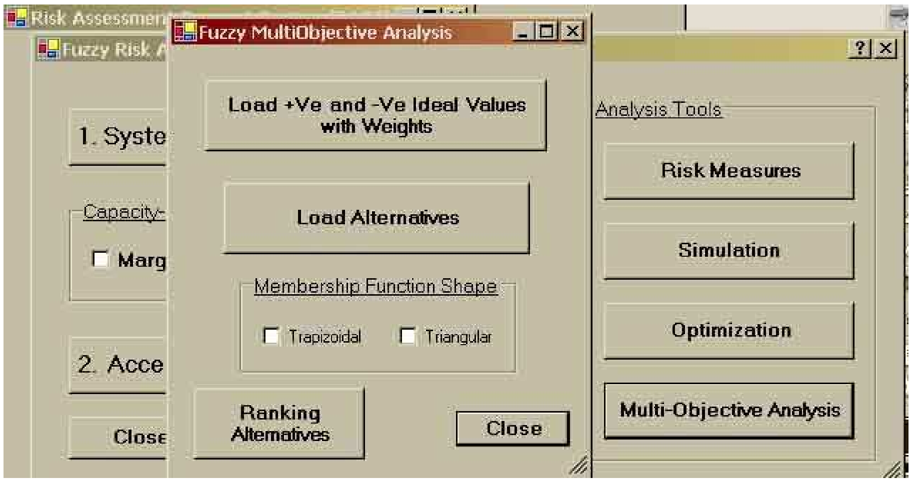
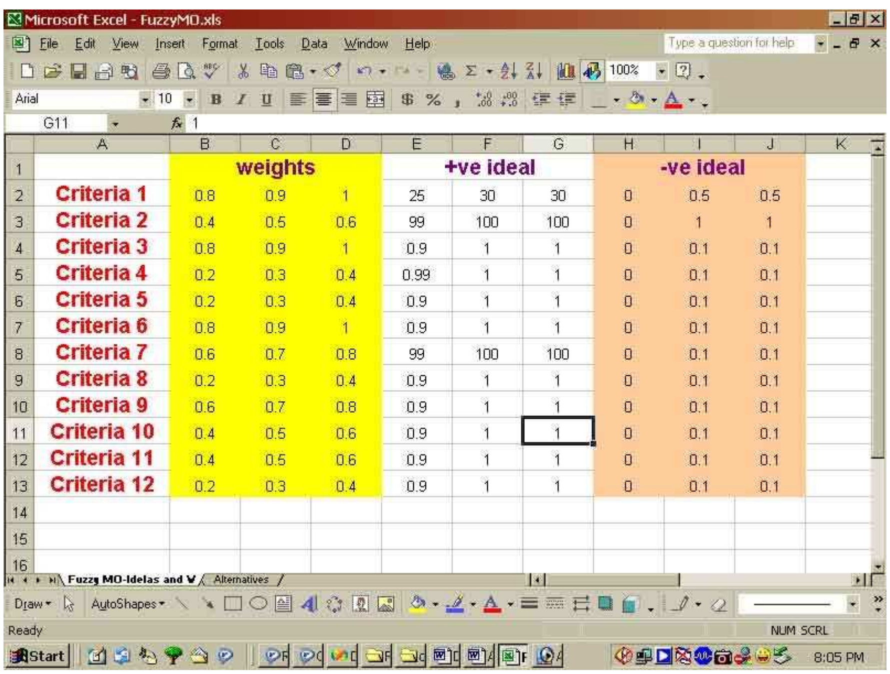
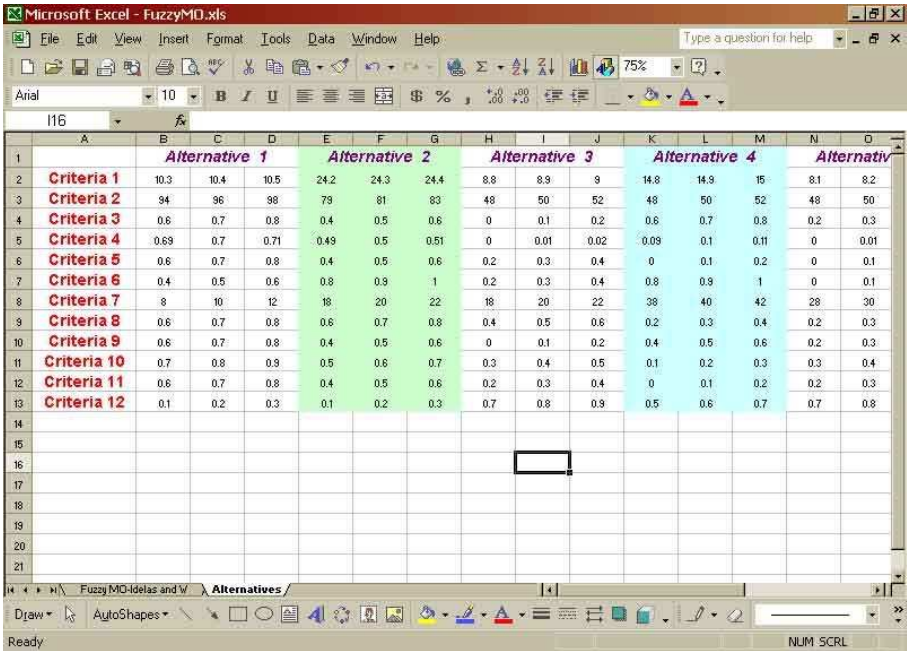



**Figure 26. Fuzzy multi-objective toolbox.**




| | weights | | | +ve ideal | | | -ve ideal | | |
|---|---|---|---|---|---|---|---|---|---|
| Criteria 1 | 0.8 | 0.9 | 1 | 25 | 30 | 30 | 0 | 0.5 | 0.5 |
| Criteria 2 | 0.4 | 0.5 | 0.6 | 99 | 100 | 100 | 0 | 1 | 1 |
| Criteria 3 | 0.8 | 0.9 | 1 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 4 | 0.2 | 0.3 | 0.4 | 0.99 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 5 | 0.2 | 0.3 | 0.4 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 6 | 0.8 | 0.9 | 1 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 7 | 0.6 | 0.7 | 0.8 | 99 | 100 | 100 | 0 | 0.1 | 0.1 |
| Criteria 8 | 0.2 | 0.3 | 0.4 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 9 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 10 | 0.4 | 0.5 | 0.6 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 11 | 0.4 | 0.5 | 0.6 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 12 | 0.2 | 0.3 | 0.4 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |

**Figure 27. Fuzzy multi-objective analysis first input data file (ideal values and weights).**




| | Alternative 1 | | | Alternative 2 | | | Alternative 3 | | | Alternative 4 | | | Alternativ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Criteria 1 | 10.3 | 10.4 | 10.5 | 24.2 | 24.3 | 24.4 | 8.8 | 8.9 | 9 | 14.8 | 14.9 | 15 | 8.1 | 8.2 |
| Criteria 2 | 94 | 96 | 98 | 79 | 81 | 83 | 48 | 50 | 52 | 48 | 50 | 52 | 48 | 50 |
| Criteria 3 | 0.6 | 0.7 | 0.8 | 0.4 | 0.5 | 0.6 | 0 | 0.1 | 0.2 | 0.6 | 0.7 | 0.8 | 0.2 | 0.3 |
| Criteria 4 | 0.69 | 0.7 | 0.71 | 0.49 | 0.5 | 0.51 | 0 | 0.01 | 0.02 | 0.09 | 0.1 | 0.11 | 0 | 0.01 |
| Criteria 5 | 0.6 | 0.7 | 0.8 | 0.4 | 0.5 | 0.6 | 0.2 | 0.3 | 0.4 | 0 | 0.1 | 0.2 | 0 | 0.1 |
| Criteria 6 | 0.4 | 0.5 | 0.6 | 0.8 | 0.9 | 1 | 0.2 | 0.3 | 0.4 | 0.8 | 0.9 | 1 | 0 | 0.1 |
| Criteria 7 | 8 | 10 | 12 | 18 | 20 | 22 | 18 | 20 | 22 | 38 | 40 | 42 | 28 | 30 |
| Criteria 8 | 0.6 | 0.7 | 0.8 | 0.6 | 0.7 | 0.8 | 0.4 | 0.5 | 0.6 | 0.2 | 0.3 | 0.4 | 0.2 | 0.3 |
| Criteria 9 | 0.6 | 0.7 | 0.8 | 0.4 | 0.5 | 0.6 | 0 | 0.1 | 0.2 | 0.4 | 0.5 | 0.6 | 0.2 | 0.3 |
| Criteria 10 | 0.7 | 0.8 | 0.9 | 0.5 | 0.6 | 0.7 | 0.3 | 0.4 | 0.5 | 0.1 | 0.2 | 0.3 | 0.3 | 0.4 |
| Criteria 11 | 0.6 | 0.7 | 0.8 | 0.4 | 0.5 | 0.6 | 0.2 | 0.3 | 0.4 | 0 | 0.1 | 0.2 | 0.2 | 0.3 |
| Criteria 12 | 0.1 | 0.2 | 0.3 | 0.1 | 0.2 | 0.3 | 0.7 | 0.8 | 0.9 | 0.5 | 0.6 | 0.7 | 0.7 | 0.8 |

**Figure 28. Fuzzy multi-objective analysis second input data file (alternatives).**

### 2.2.3 Probabilistic Toolbox

The probabilistic toolbox requires system description using input files in CSV format. In the probabilistic approach the system is broken down into three main components, i.e. source, treatment and distribution, following the main categories of a typical water supply system. Figure 29 shows the introductory screen of the probabilistic toolbox.

System identification button, as shown in Figure 29, prompts the user to specify the location of the input files. The user is required to specify number of input fields (i.e. variables) in every input file which corresponds to the number of data columns. As the system is broken down into three main components, the user is required to specify the number of the input columns in all three components' files.

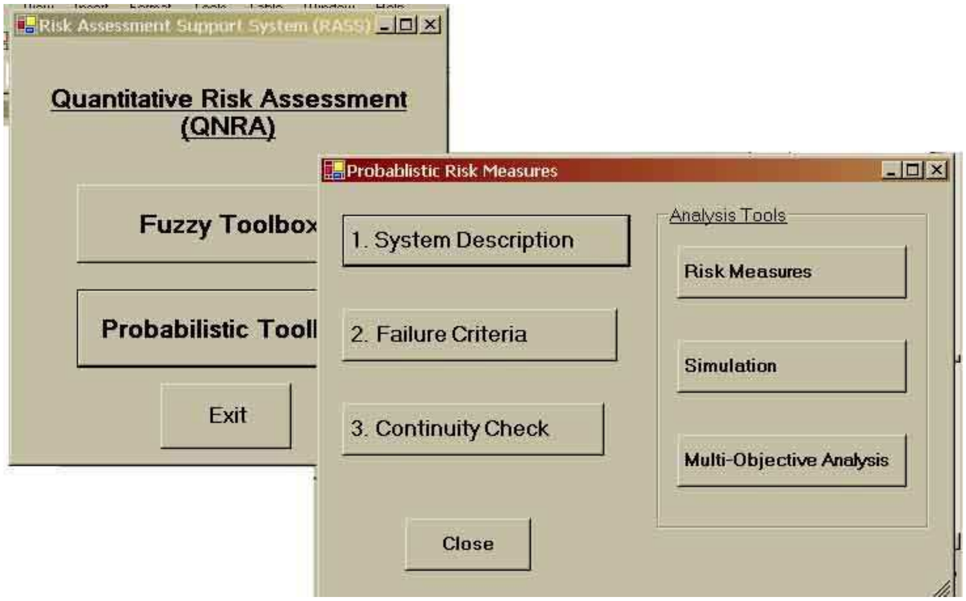



**Figure 29 Probabilistic toolbox.**

As shown in Figure 29, the second step is to identify the failure criterion for each input field. The failure criterion is the threshold beyond which system is considered in failure mode. It has to be noted that this threshold may vary from one component to another and each component can have two different thresholds (i.e. maximum and minimum values). The user can enter a maximum, minimum or both, maximum and minimum, for each system component.

If the time periods across each input field are not the same and not continuous then the program will abort the run. If there is an entire date missing from one of the files such that the duration of the data's time period is not equal to the number of time increments, then the program will display an error message: correction of input data file is required. Therefore, it is very important to perform the continuity check using the corresponding button on the main screen. If the time periods are complete but there are gaps in the data, the program will infill any missing data.

**Probabilistic risk indices**

The tool is now ready to use any of the analysis toolboxes, i.e. probabilistic risk indices calculation, simulation or optimization. Figure 30 shows the flowchart for the calculation of the probabilistic risk indices. The toolbox requires the user to name of the summary report. Appendix III includes an example of a summary report file, where the calculated risk indices are provided together with other detailed information about the corresponding system and the data provided by the user.

**Probabilistic simulation toolbox**

The probabilistic simulation is designed to generate a synthetic data set using a Monte Carlo style discrete Markov model based on Equation 36. The tool synthesizes new data records using the probabilistic distribution of the original data set. In order to do this, the program requires the user input indicating the historical mean, standard deviation, and correlation, in addition to the type of probabilistic distribution that fits the original data, as shown in Figure 31. It may also require additional parameters, such as skew in case of Gamma distribution.

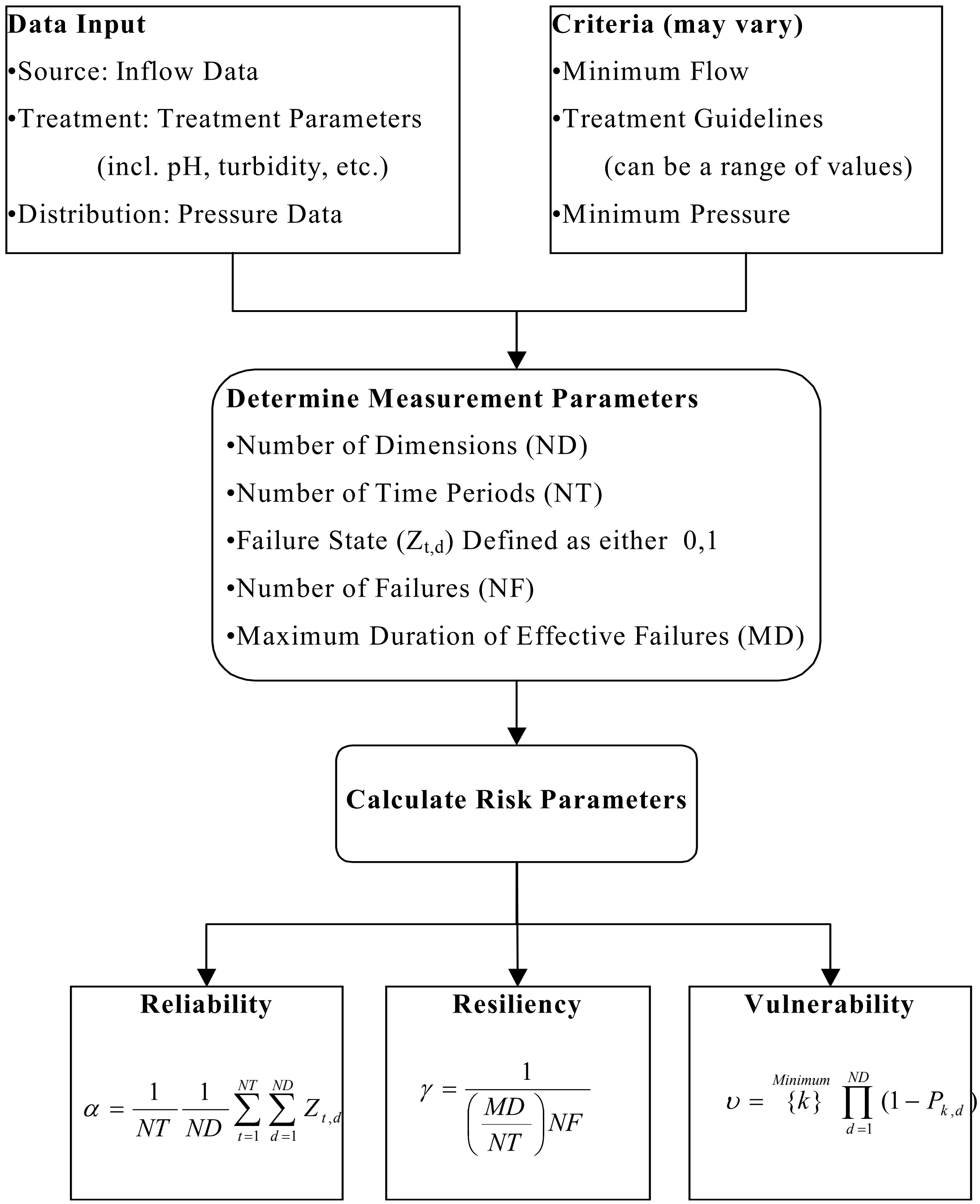



**Figure 30 Risk measures calculation flowchart (after Smith, 2005).**

New data records are generated for the given number of simulation years. Statistical parameters for the synthetic data set are also calculated for comparison purposes. Those parameters are calculated annually and then averaged over all years. The tool is equipped to run with Normal, Lognormal, Gamma, and Gumbel distributions, as shown in Figure 31. Furthermore, the tool can generate new data set taking into consideration seasonal variations within the historical data for the source and distribution components. For the water supply inflow, the tool can consider the seasonal variation in statistical parameters (i.e. winter, spring, summer, and fall have different inflow mean, standard deviation, and correlation). It is assumed that the water treatment parameters (i.e. treatment guidelines) are constant throughout the year, regardless the change in the water quality.

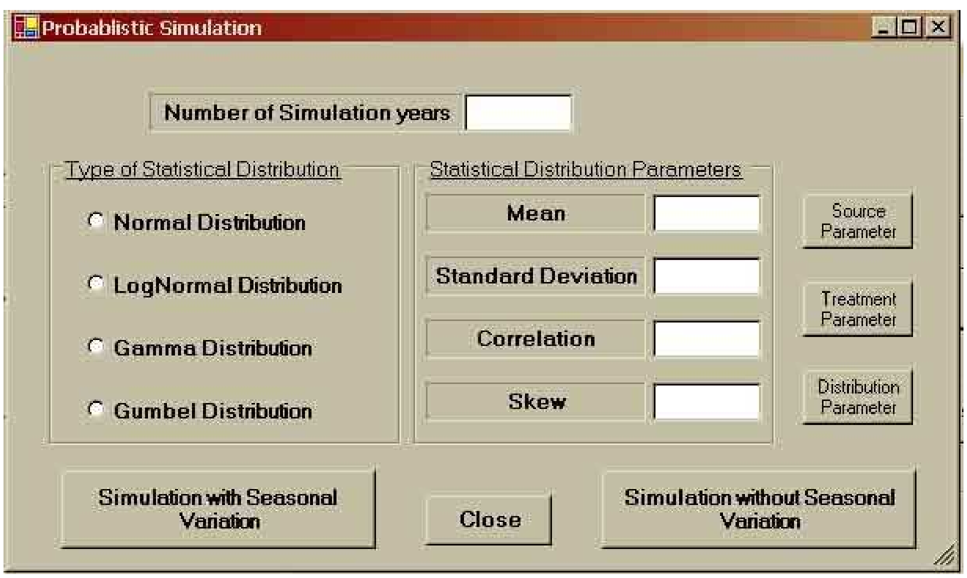



**Figure 31 Probabilistic simulation toolbox.**

The program runs using normally distributed random numbers for the Markov simulations. Thus, it is possible that negative values are generated. Whenever this occurs, negative inflows assumed to be zero.

**Probabilistic multi-objective analysis toolbox**

The multi-objective analysis toolbox uses linear compromise programming to optimize (minimize) the distance to the ideal solution (i.e. the best calculated reliability, resiliency and vulnerability indices) (Smith, 2005). The overall minimum distance ($L_s$ metrics) is calculated using Equation 36. The optimization is conducted using the compromise programming. It maximizes the overall system reliability and resiliency, and minimizes the system vulnerability.

The user starts by loading input data files for each system component, i.e. source, treatment, and distribution. Those files contain different alternatives for source, treatment and distribution inputs. The user has to specify how many alternatives (in each component) the tool should use (total number column in the probabilistic optimization screen). In addition, the user is asked to supply 3 different values for weights and deviation exponent in order to compare various alternatives, as shown in Figure 32.

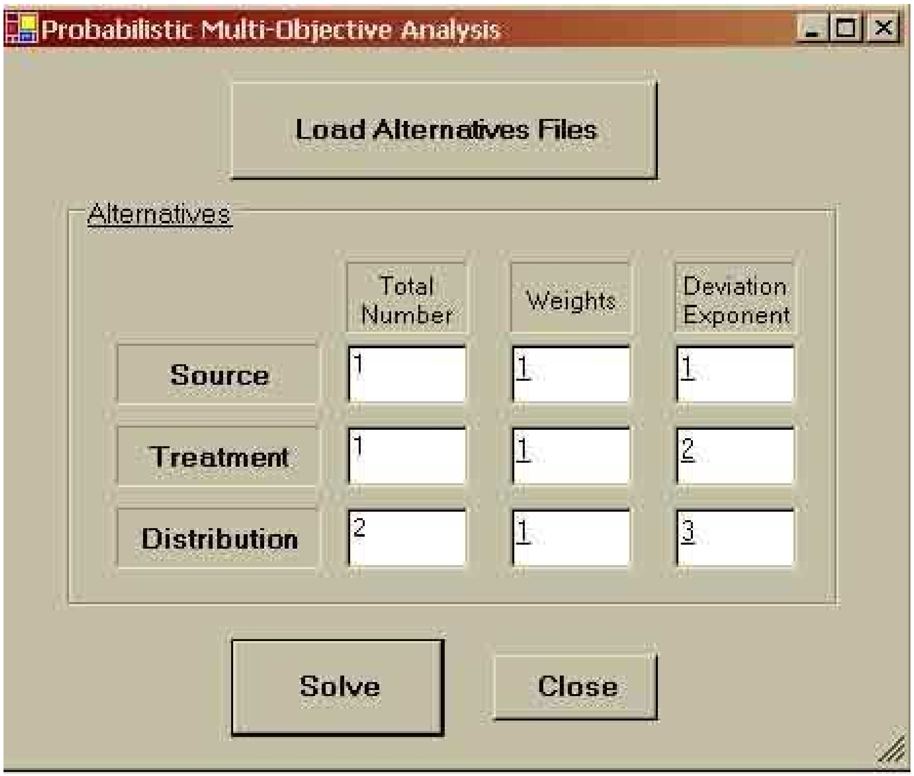



**Figure 32 Probabilistic multi-objective analysis toolbox.**

# 3 QNRA APPLICATION

This chapter explores the utility of some of the fuzzy toolboxes of the developed RASS for evaluating the performance of a complex water supply system. Regional water supply system for the City of London is used as the case study. The two main components being investigated in this case study are; (i) the Lake Huron Primary Water Supply System (LHPWSS), and (ii) the Elgin Area Primary Water Supply system (EAPWSS).

## 3.1 System Description

The City of London regional water supply system consists of two main components; (i) the Lake Huron Primary Water Supply System (LHPWSS), and (ii) the Elgin Area Primary Water Supply system (EAPWSS). The LHPWSS system obtains raw water from the Lake Huron. Water is treated and pumped from the lake to the terminal reservoir in Arva, as shown in Figure 33. Water from the Arva reservoir is pumped to the north of the City of London where it enters the municipal distribution system. The system provides water for the City of London as well as a number of smaller neighboring municipalities (through a secondary system).

The EAPWSS system treats raw water from the Lake Erie and pumps the treated water to the terminal reservoir located in St. Thomas. Water from the reservoir is pumped to the south of the City of London where it enters the municipal distribution system, as shown in Figure 33. In the case of emergency, the City of London can obtain additional water from a number of wells located inside the City and in the surrounding areas.

### 3.1.1 Lake Huron Primary Water Supply System (LHPWSS)

The Lake Huron treatment facility has a treatment capacity of about 336 million liters per day (336,400 m3/day). The plant's individual components are designed with a 35% overload capacity resulting in the maximum capacity of 454,600 m3/day. The current daily production, based on the annual average, is 157,000 m3/day with a maximum production value of 64,000 m3/day in 2001. The water treatment system employs conventional and chemically assisted flocculation and sedimentation systems, dual-media filtration, and chlorination as the primary disinfection. Both, the treatment system and the water quality are continuously monitored using computerized Supervisor Control and Data Acquisition (SCADA) system.

### 3.1.2 Elgin Area Primary Water Supply System (EAPWSS)

The Elgin water treatment facility was constructed in 1969 to supply water from the Lake Erie to the City of London, St. Thomas and a number of smaller municipalities. In 1994, the facility has been expanded to double its throughput to its current 91,000$m^3$/day capacity. A series of upgrades took place from 1994 to 2003 to add surge protection and introduce fluoridation treatment. The design capacity of the treatment facility is 91,000 $m^3$/day, with an average daily flow of 52,350 $m^3$/day, which serves about 94,400 persons.

The water treatment in EAPWSS employs almost the same conventional treatment methods used in LHPWSS. The only exception is that the facility uses the fluoridation treatment system to provide dental cavity control to the users. As in LHPWSS, the treatment system and water quality are continuously monitored using computerized

Supervisor Control and Data Acquisition (SCADA) system. The finished treated water is pumped to the terminal reservoir located in St. Thomas.

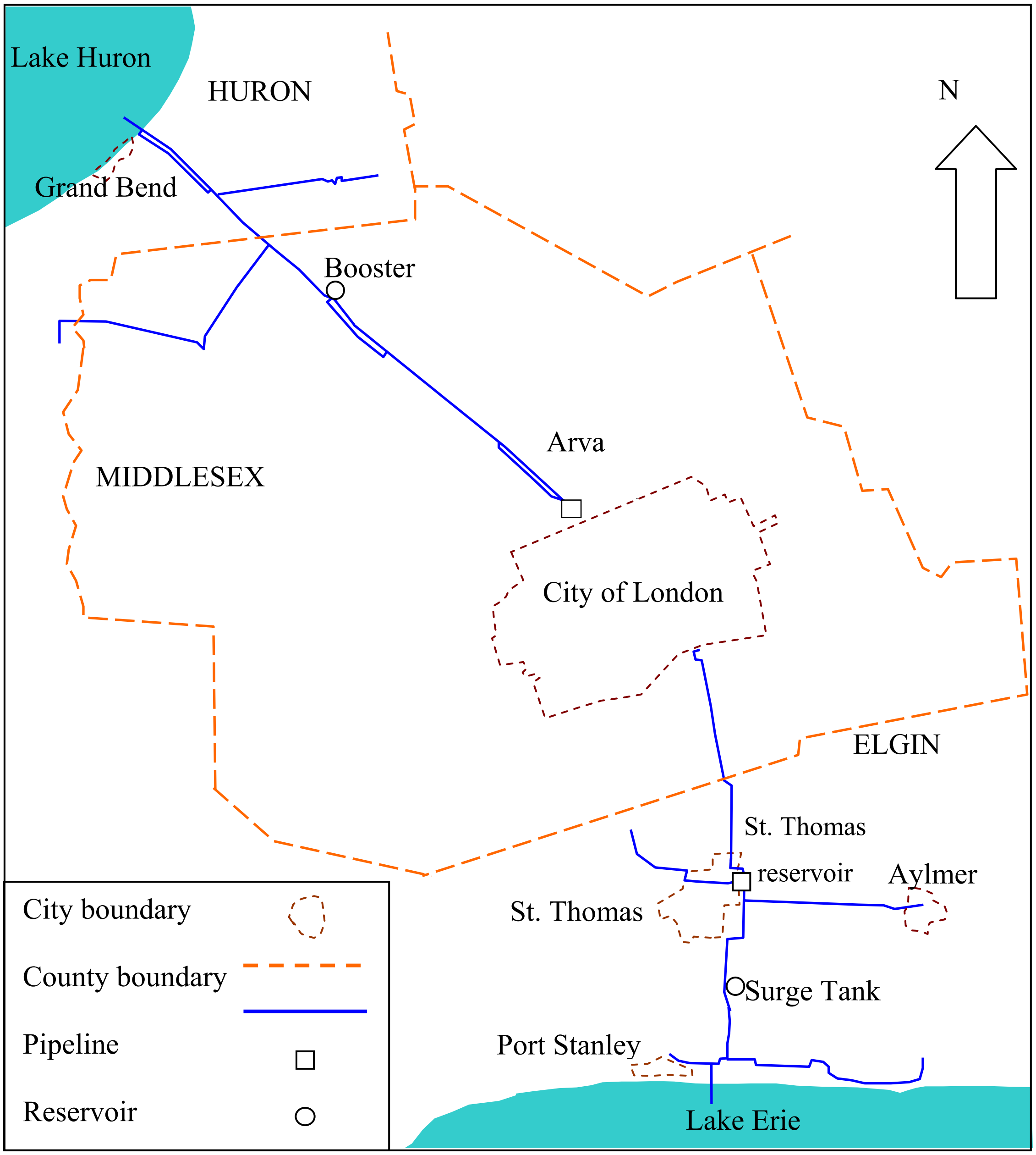



**Figure 33 The City of London regional water supply system.**

El-Baroudy and Simonovic (2005) give detailed description of different processes involved in both LHPWSS and EAPWSS. A schematic of main processes used in both systems is shown in Figure 34.

### 3.2 Case Study Application

Input CSV files for both systems' components, LHPWSS and EAPWSS, are prepared based on the data from (Earth Tech Canada Inc.,2000), (Earth Tech Canada Inc.,2001), (American Water Services Canada-AWSC, 2003a), (American Water Services Canada-AWSC, 2003b), and (DeSousa and Simonovic, 2003).

Three acceptable levels of performance are arbitrary defined on the universe of the safety factor; as (0.75,1.25), (0.50,1.00), and (0.25,1.25). They are selected to reflect three different views of decision-makers as shown by the reliability measure in Equation 6. Their reliability measures are 1.88, 1.00 and 0.31, respectively. Further, they are referred to as reliable level (level 1), neutral level (level 2), and unreliable level (level 3), as shown in Figure 35.

The DSS tool can accommodate an unlimited number of water quality parameters. Temperature, turbidity, pH, and residual Chlorine are selected as representatives of water quality parameters for both LHPWSS and EAPWSS. The three fuzzy measures are calculated for both shapes of membership functions, i.e. triangular and trapezoidal.

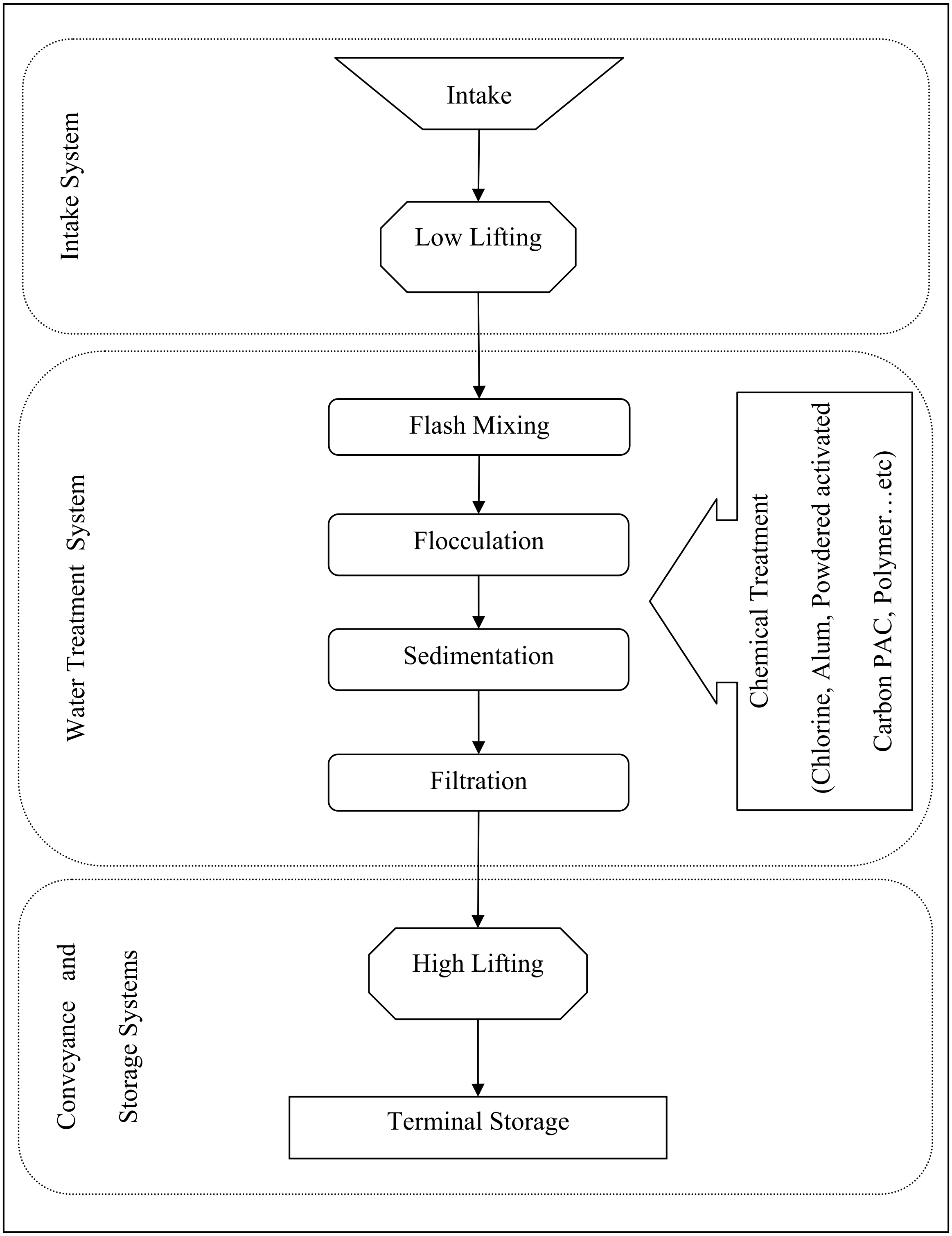



**Figure 34 Schematic representation of the main process in LHPWSS and EAPWSS.**

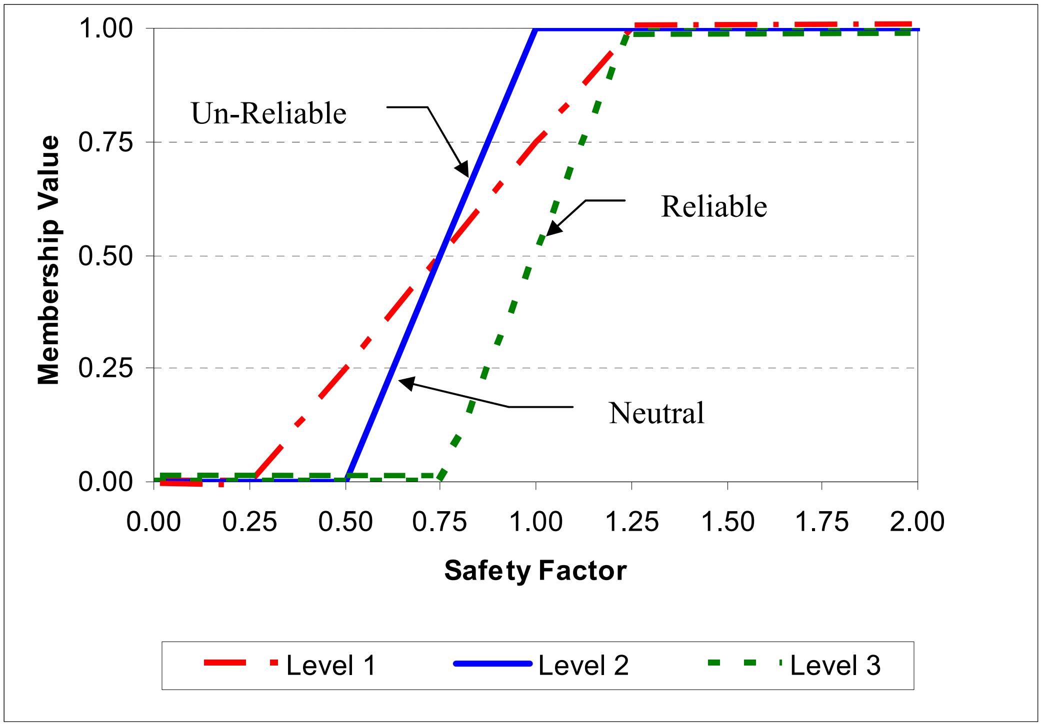



**Figure 35 Acceptable levels of performance.**

### 3.2.1 Fuzzy Performance Measures

The same acceptable levels of performance are used to calculate the fuzzy combined reliability-vulnerability and robustness measures for the four water quality parameters and discharge.

The results in Table 1, show that the discharge fuzzy combined reliability-vulnerability measure for LHPWSS is 0.427. This value reflects the compatibility of the system with one of the three predefined levels of performance, as defined in Equation 17; in this case it is the neutral level (level 2). This measure increases to 0.451 in case of using the triangular membership function shape. The same effect on the fuzzy robustness is evident for all water quality parameters. For example, the discharge fuzzy robustness measure for the LHPWSS ranges from 45-160 in case of using the trapezoidal shape and 51-170 in case of the triangular shape.

**Table 1 The LHPWSS system fuzzy performance measures for different membership function shapes.**

| | Fuzzy Performance Measure | Triangular MF | Trapezoidal MF |
|---|---|---|---|
| **Discharge** | **Combined Reliability-Vulnerability** | 0.451 | 0.427 |
| | **Robustness (level 2 – level 1)** | 170 | 160 |
| | **Robustness (level 3 – level 1)** | 51 | 45 |
| | **Robustness (level 3 – level 2)** | 72 | 64 |
| **Temperature** | **Combined Reliability-Vulnerability** | 0.517 | 0.516 |
| | **Robustness (level 2 – level 1)** | NA | 160 |
| | **Robustness (level 3 – level 1)** | 8421 | 8000 |
| | **Robustness (level 3 – level 2)** | 8421 | 8000 |
| **Turbidity** | **Combined Reliability-Vulnerability** | 1.000 | 1.000 |
| **pH** | **Combined Reliability-Vulnerability** | 1.000 | 1.000 |
| **Residual Chlorine** | **Combined Reliability-Vulnerability** | 1.000 | 1.000 |
| **Resiliency** | | 0.020 | 0.020 |

NA* Not-available value as there is no change in overlap area.

The fuzzy combined reliability-vulnerability measure for the remaining water quality parameters, reaches its maximum as the system-state membership functions of these parameters are completely overlapped by the reliable accepted level of performance (level 1), as shown in Figure 36.

The complete overlap indicates that the fuzzy robustness index reaches infinity, as defined by Equation 9. This measure is extremely high for all water quality parameters. For example, the range is from 160-8000 for temperature. Therefore, LHPWSS is considered to be highly robust.

The fuzzy resiliency measure value for the LHPWSS is 0.020, which means that it takes the system more than 49 days after failure to return to the full operation mode, as defined by Equation 10. This value is high as it means the system service can be disrupted for about 2 months and large portion of the population served by this system (estimated to be about 325 000 person) can be affected by this disruption.

Similar conclusions are read for EAPWSS from the results shown in Table 2. Although EAPWSS is much less reliable than LHPWSS as its discharge fuzzy reliability-vulnerability index ranges from 0.035 in the case of trapezoidal membership function shape to 0.05 in the case of triangular shape. As concluded for LHPWSS, the use of a triangular fuzzy membership function positively affects the system reliability, as shown in Figure 37.

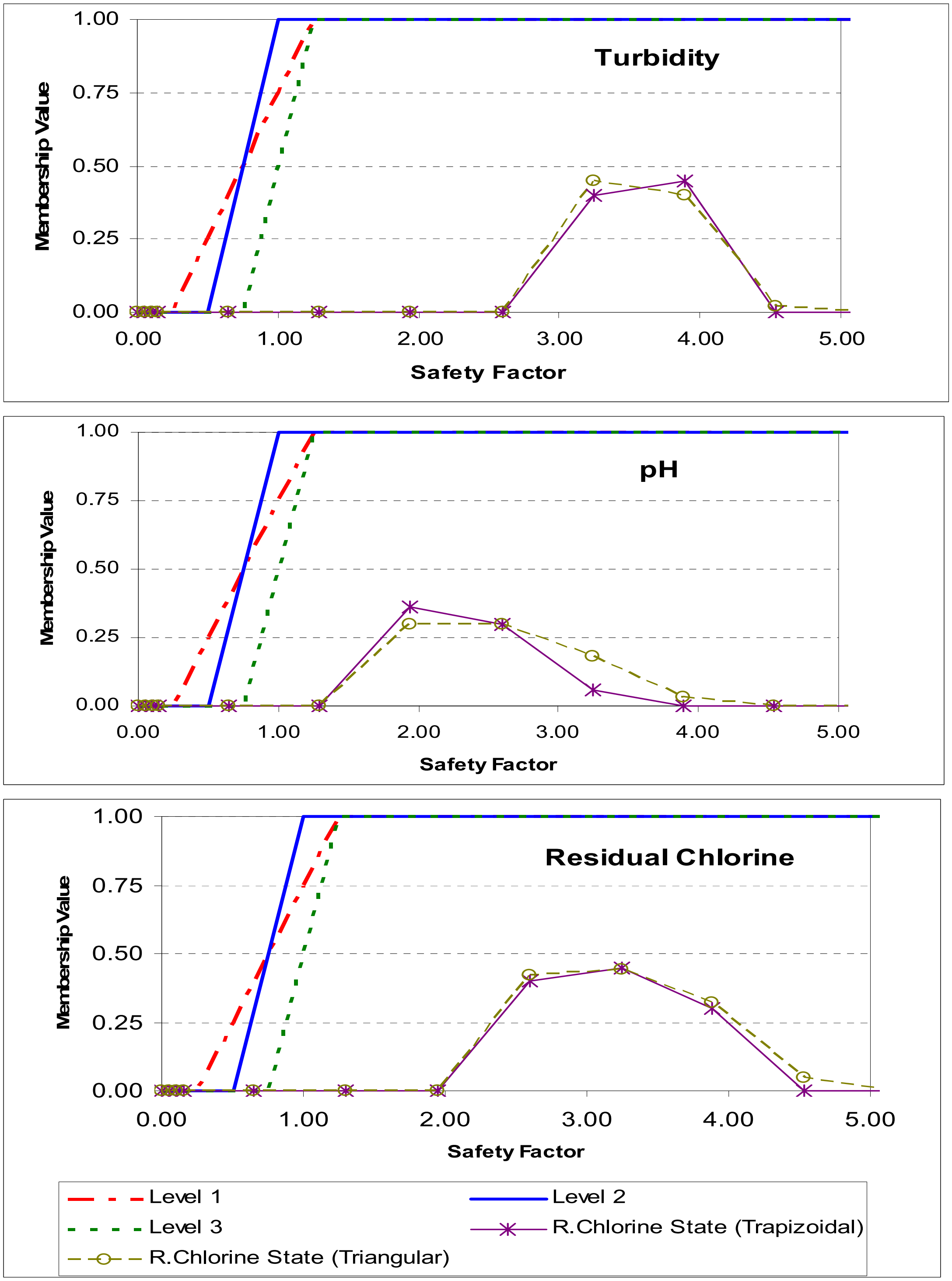



**Figure 36 LHPWSS water quality parameters states.**

**Table 2 The EAPWSS system fuzzy performance measures for different membership function shapes.**

| | Fuzzy Performance Measure | Triangular MF | Trapezoidal MF |
|---|---|---|---|
| **Discharge** | **Combined Reliability-Vulnerability** | 0.050 | 0.035 |
| | **Robustness (level 2 – level 1)** | 6 | 3 |
| | **Robustness (level 3 – level 1)** | 4 | 2 |
| | **Robustness (level 3 – level 2)** | 5 | 4 |
| **Temperature** | **Combined Reliability-Vulnerability** | 0.188 | 0.165 |
| | **Robustness (level 2 – level 1)** | 898 | 1128 |
| | **Robustness (level 3 – level 1)** | 299 | 564 |
| | **Robustness (level 3 – level 2)** | 3592 | 4699 |
| **Turbidity** | **Combined Reliability-Vulnerability** | 1.000 | 1.000 |
| **pH** | **Combined Reliability-Vulnerability** | 1.000 | 1.000 |
| **Residual Chlorine** | **Combined Reliability-Vulnerability** | 1.000 | 1.000 |
| **Resiliency** | | 0.045 | 0.045 |

NA* Not-available value as there is no change in overlap area.

The fuzzy resiliency measure value for the EAPWSS is 0.045, which means that it is more resilient than LHPWSS as it takes the system 21 days after failure to return to the full operation mode. These conclusions agree with the previous work reported by El-Baroudy and Simonovic (2005). Appendix II includes example output files produced by the QNRA component.

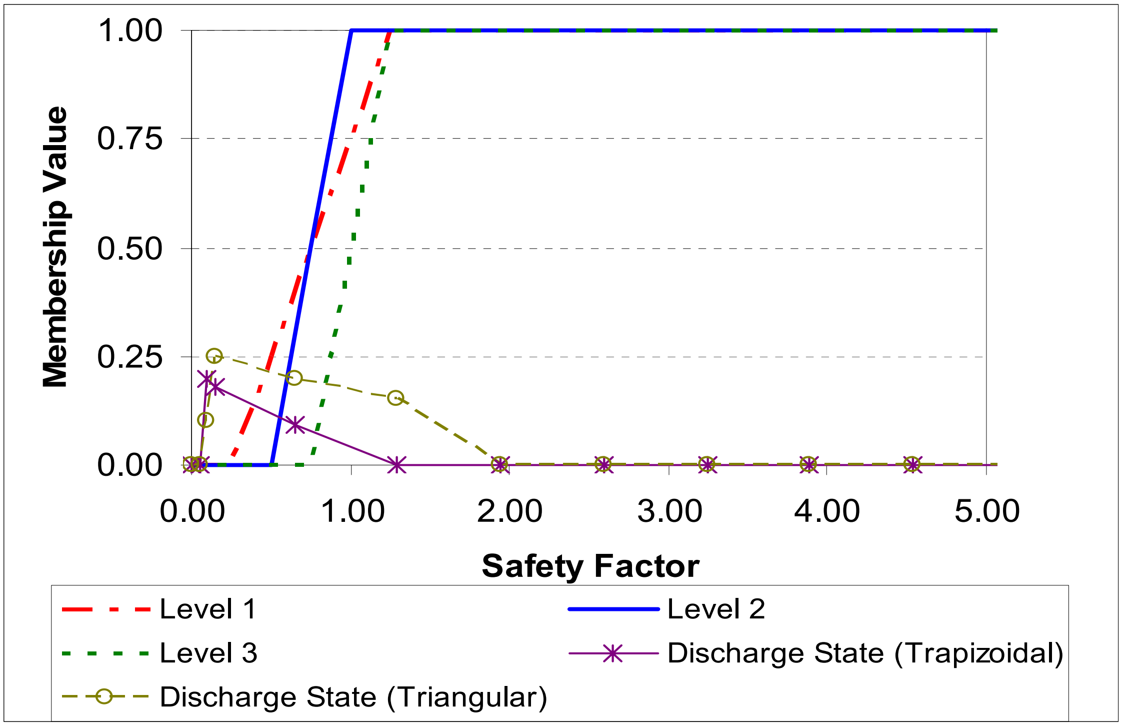



**Figure 37 EAPWSS discharge-state for triangular and trapezoidal membership functions.**

### 3.2.2 Fuzzy Simulation

RASS Tool is used to simulate discharge data of LHPWSS using 2003 monthly data, (American Water Services Canada-AWSC, 2003b). A 0.75 is used as an output threshold membership grade (h in Equation 43), i.e. the simulated discharge belongs to the discharge output membership function with a grade that is larger or equal to 0.75, as in Equation 21. Figure 38 shows one year output using both classical least-square method and the output discharge fuzzy membership functions. Appendix II includes example output file produced by the QNRA.

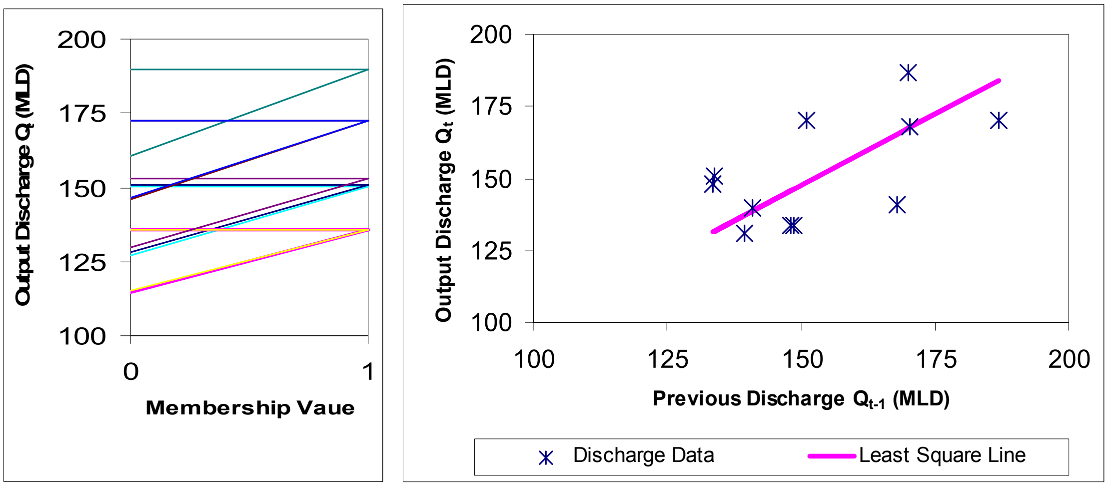



**Figure 38 Fuzzy and the least-square simulation of LHPWSS discharges.**

### 3.2.3 Fuzzy Optimization

The discharges values for six high lift pumps used in LHPWSS are optimized. The objective function of the optimization process is the summation of those discharge values. The objective function and the constraints of the fuzzy optimization problem are as follows:

$$\begin{aligned} &\max\text{imize} \quad Q_1 + Q_2 + Q_3 + Q_4 + Q_5 + Q_6 \\ &\text{subject to} \qquad Q_1 + Q_2 + Q_3 \le 1.75, \quad p_1 = 0.5 \\ &\qquad\qquad\qquad 1.15 Q_1 \le Q_2 \\ &\qquad\qquad\qquad Q_1, Q_2, Q_3, Q_4, Q_5, Q_6 \ge 0 \end{aligned} \qquad \textbf{.....(45)}$$

where

$Q_i$ is the i-th pump discharge;

i is the subscript for pump, where i=1,2,…; and

$p_1$ is the tolerance to the violation of the first constraint.

The first constraint in Equation 45 is set for the three active pumps, where the other three pumps are used as back-ups. The left hand side (LHS) of this constraint is set to be equal to the discharge requirement of the plant. Fuzziness is introduced to this constraint using the tolerance $p_1$. This value indicates the tolerance permitted to this constraint, i.e. the optimum solution can violate the constraint LHS value not more than 0.5 $m^3$/sec. The second constraint requires that the discharge of the variable speed pump, $Q_2$, be 15% higher than the discharge of the single speed pump. This constraint has tolerance value of zero, i.e. no tolerance to constraint violation.

The QNRA optimization toolbox uses this objective function, the constraints and the tolerance of the first constraint to solve the fuzzy linear programming problem and the results are shown in Figure 39. The summery result report, shown in Figure 39, starts by listing the optimum values of the decision variables (i.e. pumps' discharge). The optimum value of the objective function is provided after the decision variable list. The user has to update the capacity file (using optimum discharge values for the corresponding pumps) and re-run the risk measures toolbox to re-calculate the new fuzzy risk measures.

In this case, with optimal discharge of the high lifting pumps, the resultant fuzzy reliability-vulnerability and robustness measure do not change, i.e. their values are 0.451 and 72, respectively. It can be concluded that the system discharge reliability and robustness do not depend on the high lift pumps, therefore, it is recommended to use the tool to identify the weak link in the system that has a direct effect on its reliability and robustness.

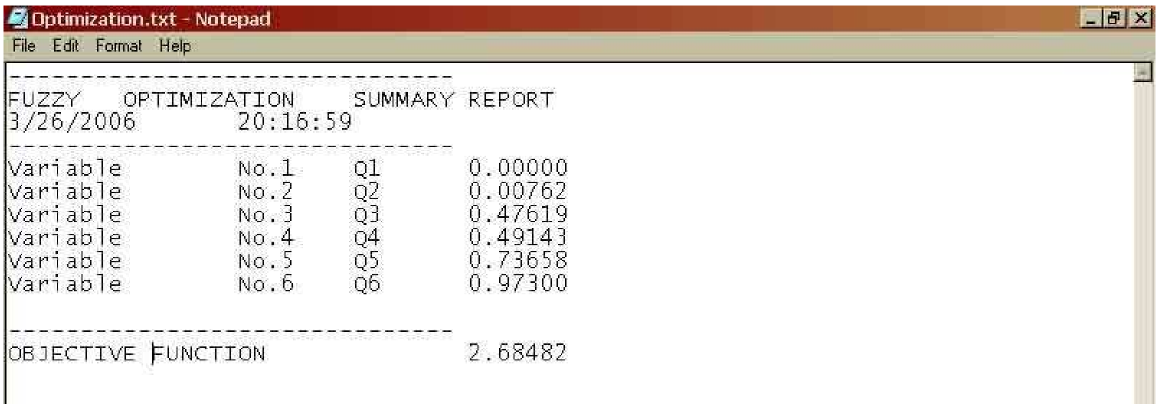


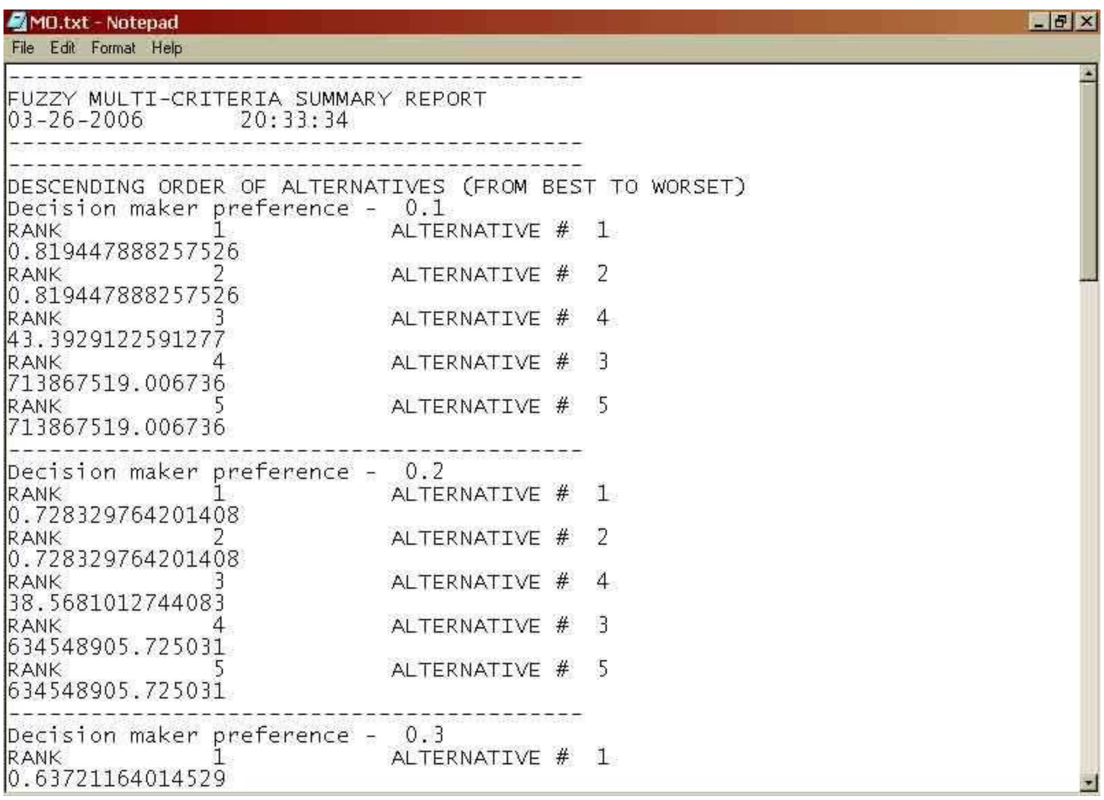

**Figure 39 DSS fuzzy optimization output.**

### 3.2.4 Fuzzy Multi-Objective Analysis

The utility of the fuzzy multi-objective analysis toolbox is demonstrated using hypothetical input data. LHPWSS and EAPWSS technical reports do not contain enough information to build real case study application. It is assumed that the two single speed pumps of the low lifting system in LHPWSS are to be replaced. Five pump brands (alternative 1- alternative 5) are considered based on five criteria as shown in Table 3. These criteria are; (1) prices in dollars, (2) size in square meters, (3) maximum discharge capacity in $m^3$/sec., (4) installation time in days, and (5) brand quality. It has to be noted that triangular membership function is used to express uncertain and qualitative criteria. Using the fuzzy multi-objective toolbox the ranking of the five alternatives revealed that alternative 1 is the best alternative and alternative 5 is the worst for every decision making preference, as shown in

**Table 3. Criteria ideal values and weights of LHPWSS multi-objective case study.**

| Criterion | Weight | | | Best ideal | | | Worst ideal | | |
|---|---|---|---|---|---|---|---|---|---|
| price ($) | 0.8 | 0.9 | 1 | 25 | 30 | 35 | 40 | 50 | 60 |
| size (Square m) | 0.4 | 0.5 | 0.6 | 1 | 2 | 3 | 2 | 4 | 6 |
| capacity ($m^3$/s) | 0.8 | 0.9 | 1 | 0.5 | 0.8 | 1 | 0.2 | 0.4 | 0.6 |
| installation time (day) | 0.2 | 0.3 | 0.4 | 4 | 6 | 8 | 10 | 12 | 14 |
| Brand quality | 0.2 | 0.3 | 0.4 | 0.5 | 0.8 | 1 | 0 | 0.1 | 0.2 |



```
MO.txt - Notepad
File  Edit  Format  Help
------------------------------------------
FUZZY MULTI-CRITERIA SUMMARY REPORT
03-26-2006        20:33:34
------------------------------------------
------------------------------------------
DESCENDING ORDER OF ALTERNATIVES (FROM BEST TO WORSET)
Decision maker preference -   0.1
RANK          1           ALTERNATIVE #  1
0.819447888257526
RANK          2           ALTERNATIVE #  2
0.819447888257526
RANK          3           ALTERNATIVE #  4
43.3929122591277
RANK          4           ALTERNATIVE #  3
713867519.006736
RANK          5           ALTERNATIVE #  5
713867519.006736
------------------------------------------
Decision maker preference -   0.2
RANK          1           ALTERNATIVE #  1
0.728329764201408
RANK          2           ALTERNATIVE #  2
0.728329764201408
RANK          3           ALTERNATIVE #  4
38.5681012744083
RANK          4           ALTERNATIVE #  3
634548905.725031
RANK          5           ALTERNATIVE #  5
634548905.725031
------------------------------------------
Decision maker preference -   0.3
RANK          1           ALTERNATIVE #  1
0.63721164014529
```

**Figure 40. Summary results of LHPWSS Fuzzy multi-objective problem.**

# 4 CONCLUSION

The developed RASS is used as a risk assessment and management tool that accommodates two different approaches; (i) fuzzy approach, and (ii) probabilistic approach. The tool can be used as an integrated risk management framework to strengthen the risk management practice within the public service. This can be achieved through the use of the capabilities of the two approaches to handle different aspects of uncertainty in real world problems. The RASS is designed to provide a simple, comprehensive and user-friendly tool that accommodates different levels of decision-making and promotes public interest in risk management.

The RASS is used to asses the performance of the Lake Huron Primary Water Supply System (LHPWSS) and the Elgin Area Primary Water Supply system (EAPWSS) as a case study. It is concluded that LHPWSS system is more reliable and less vulnerable than EAPWSS system. It is, concluded, that the robustness of LHPWSS outweighs that robustness of EAPWSS for all parameters, i.e. discharge and water quality parameters. The findings of the case study support the results reported by El-Baroudy and Simonovic (2005). The case study is also used to perform simulation and optimization and demonstrate the utility of the RASS in risk assessment and management in water supply system, as a typical example of complex engineering systems. The tool can be used to identify weak points in the system and the potential for performance improvement.

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(accessed August, 2005)

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003_Compliance_Report.pdf)
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# APPENDICES

# APPENDX I

# QNRA QUESTIONS AND COMMENTS

### (i) Evaluation of knowledge of Risk

**a. Are you interested in risk assessment of your water supply system?**

**Expected User Input:** YES/NO

**User Action:** If the answer is YES, proceed to the next step.

If the answer is NO, quit the RASS.

*Comment:* This step is mandatory. It is expected that the users will not act if they do not believe in the existence of any type of risk.

**b. (CAUSES)**

**1. Role of engineering in risk assessment**

**"Is the current water supply system capacity sufficient to meet the demand?"**

**Expected User Input:** YES/NO

**"Using a scale from 0 to 1, indicate how significant the system capacity is for system performance."**

**Expected User Input:** Value (0 → 1)

**User Action:** If the answer is YES, give numeric value (from 0 to 1) representing the significance of this cause and proceed to the next step. If the answer is NO, proceed to the next step.

*Comment:* The input value provided by the user in case of YES answer can be fine tuned by using the performance tool of the QNRA component. The estimated values are compared to the calculated values that are obtained by changing capacity of system components.

**2. Role of regulations and planning in risk assessment:**

**<u>"Are sufficient water supply system regulation and planning documentation available? "</u>**

**Expected User Input:** <u>YES/NO</u>

**<u>"Using a scale from 0 to 1, indicate how significant the availability of regulation and planning documentation is for the mitigation of system risks."</u>**

**Expected User Input:** Value (0 → 1)

**User Action:** If the answer is YES, give numeric value (from 0 to 1) representing the significance of this cause. If the answer is NO, proceed to the next step.

*Comment:* some planning practices have a direct effect on the risk of contamination to water supplies, such as zoning laws which play a significant role in water supply protection. This is in addition to the requirement to meet the needs of the heavily populated areas which impose a great load on the municipalities. Therefore, increasing system requirements, accepting less restrict quality standards and accommodating high risk polluting activities (such as industrial activities) reflect those effects.

**3. Role of human activities in risk assessment:**

**<u>"Is there a possible conflict between human activities and the protection of the water supply source?"</u>**

**Expected User Input:** YES/NO

**<u>"Using a scale from 0 to 1, indicate how significant the impact of human activities is on the protection of the water supply source."</u>**

**Expected User Input:** Value (0 → 1)

**User Action:** If the answer is YES, give numeric value (from 0 to 1) representing the significance of this cause and then proceed to the next step. If the answer is NO, proceed to the next step.

*Comment:* Human activities contribute to multiple point- and non-point source pollution of water supply.

**4. Role of natural hazards in risk assessment:**

**<u>"Are there natural hazards that may affect the water supply system? "</u>**

**Expected User Input:** YES/NO

**<u>"Using a scale from 0 to 1, indicate how significant the impact of natural hazards is on the system performance."</u>**

**Expected User Input:** Value (0 → 1)

**User Action:** If the answer is YES, give numeric value (from 0 to 1) representing the significance of this cause and then proceed to the next step. If the answer is NO, proceed to the next step.

*Comment:* Naturally occurring extreme events can significantly affect the availability of water supply or the quality of the water supply.

**5. Role of terrorism in risk assessment:**

**<u>"Is the water supply system vulnerable to possible terrorist attack? "</u>**

**Expected User Input:** YES/NO

**<u>"Using a scale from 0 to 1, indicate the significance of possible terrorist attacks on the system performance."</u>**

**Expected User Input:** Value (0 → 1)

**User Action:** If the answer is YES, give numeric value (from 0 to 1) representing the significance of this cause and then proceed to the next step. If the answer is NO, proceed to the next step.

*Comment:* Terrorist attacks can have similar affects to the worst naturally occurring events on the availability of water supply. They can also cause a deterioration of the quality of the water supply.

**c. IMPACTS**

**1. Health Impacts:**

**<u>"Is a water-born disease outbreak possible?"</u>**

**Expected User Input:** YES/NO

**<u>"Using a scale from 0 to 1, indicate how significant the impact of water-born disease outbreak is?"</u>**

**Expected User Input:** Value (0 → 1)

**User Action:** If the answer is YES, give numeric value (from 0 to 1) representing the significance of this impact and then proceed to the next step. If the answer is NO, proceed to the next step.

*Comment:* Health impact of water supply quality deterioration is one of the main concerns. That should be avoided by all means (Walkerton incident of May 2000 can be used as an example).

**2. Environmental Impacts :**

**<u>"Is a water-born disease outbreak possible? "</u>**

**Expected User Input:** YES/NO

**<u>"Using a scale from 0 to 1, indicate the significance of the conflict between the human use of water and the ecosystem well-being."</u>**

**Expected User Input:** Value (0 → 1)

**User Action:** If the answer is YES, give numeric value (from 0 to 1) representing the significance of this impact and then proceed to the next step. If the answer is NO, proceed to the next step.

*Comment:* The dependence of other life forms on the availability of water resources that are also used by humans is usually neglected when there is a pressing social need for water.

**3. Social Impacts :**

**<u>"Is there a link between water availability and the life style of the community?"</u>**

**Expected User Input:** YES/NO

**<u>"Using a scale from 0 to 1, indicate how significant the impact of water availability is on the life style of the community."</u>**

**Expected User Input:** Value (0 → 1)

**User Action:** If the answer is YES, give numeric value (from 0 to 1) representing the significance of this impact and then proceed to the next step. If the answer is NO, proceed to the next step.

*Comment:* The daily availability of water makes people overlook its importance as a source of life. However, water contamination from non-point sources (created from everyday activities such as lawn watering, parking lot run-off…etc) can significantly affect water supply quality.

**4. Economic Impacts :**

**<u>"Is there a link between the water supply and the economic activity of the community?"</u>**

**Expected User Input:** <u>YES/NO</u>

**<u>"On a scale from 0 to 1, indicate how significant the impact of water supply is on the economic activities of the community?"</u>**

**Expected User Input:** Value (0 → 1)

**User Action:** If the answer is YES, give numeric value (from 0 to 1) representing the significance of this impact and then proceed to the next step. If the answer is NO, proceed to the next step.

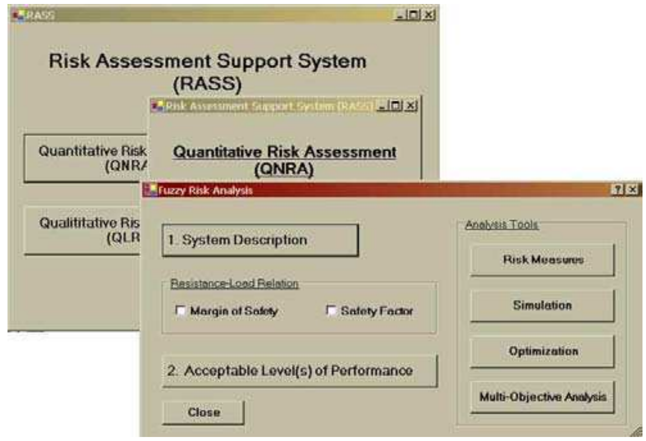
*Comment:* Every aspect of human life depends solely on the daily availability of water supply. Water supply shortage and poor water quality pose a major threat to human health and consequently threaten economic well-being. For example, using bottled water as an alternative to drinking directly from the water supply can significantly affect the economic well-being of low-income families.

# APPENDIX II

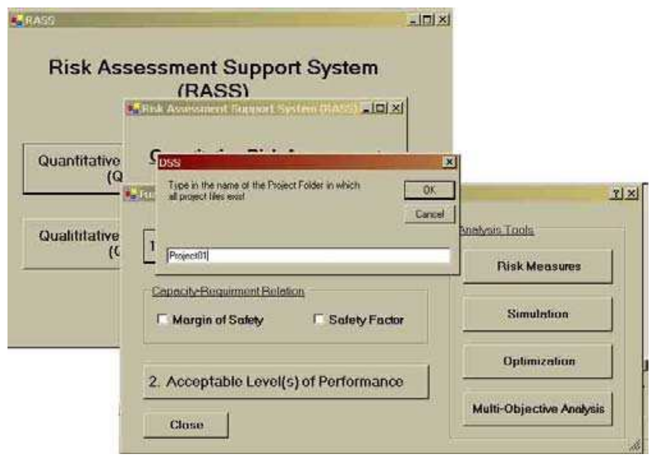
# RASS TOOLBOXES GUIDE

## II.1 Fuzzy performance measures toolbox

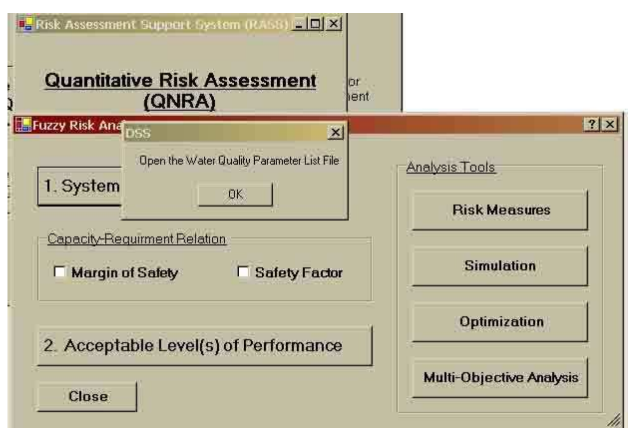
Step 1 Select the fuzzy toolbox by pressing the corresponding button.



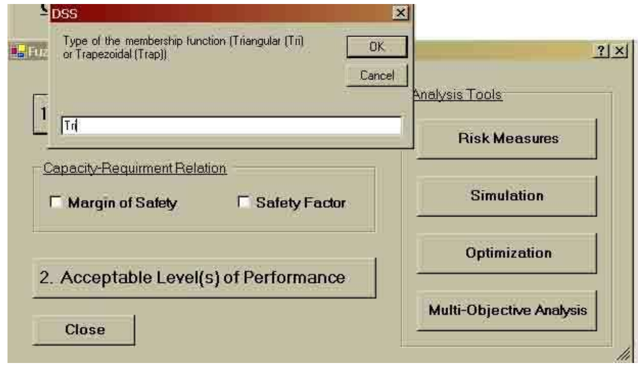

Step 2 Specify the project folder, where all the output data files are stored.



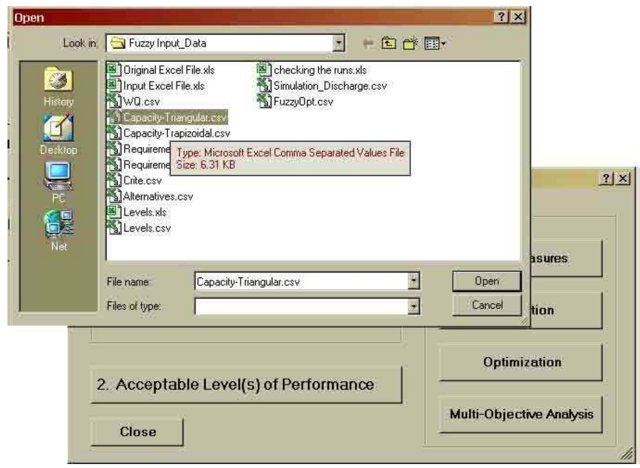

Step 3 Specify the location of the water quality parameter list file. It is a CSV format file containing all water quality parameters included in the input data files.



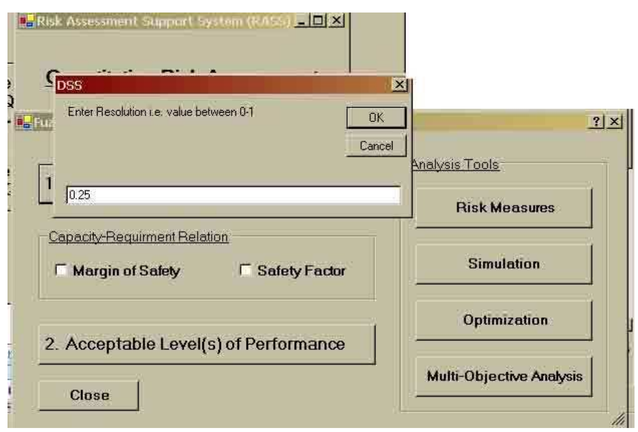
Step 4 Select the shape of the fuzzy membership function (Triangular or Trapezoidal)



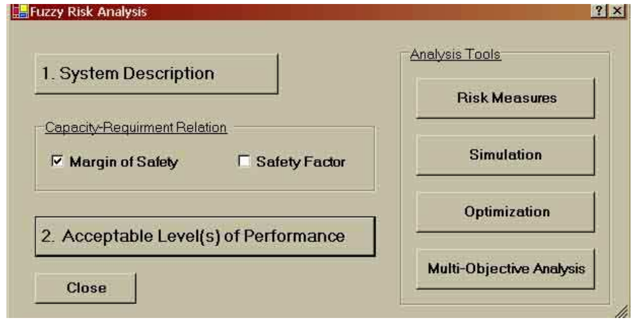

Step 5 Specify the location of the system resistance (supply capacity) and the load (requirement). Both files have to be in CSV format (without headings).



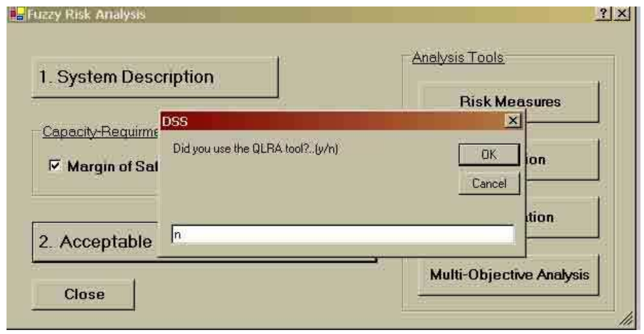

Step 6 Type in the resolution of the alpha step (a value between 0-1).

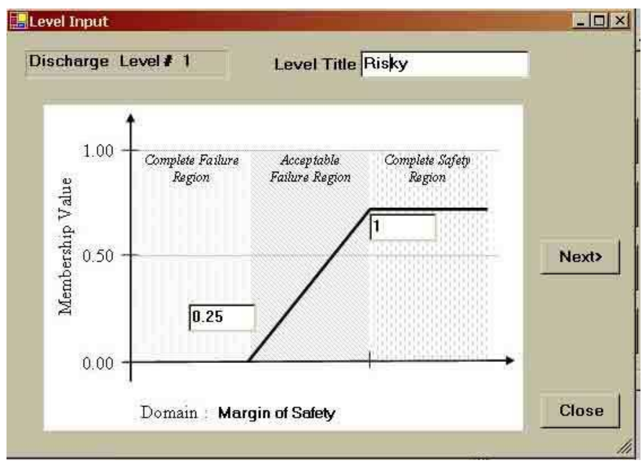


Step 7 Select the type of load-resistance (Capacity-demand) relationship.



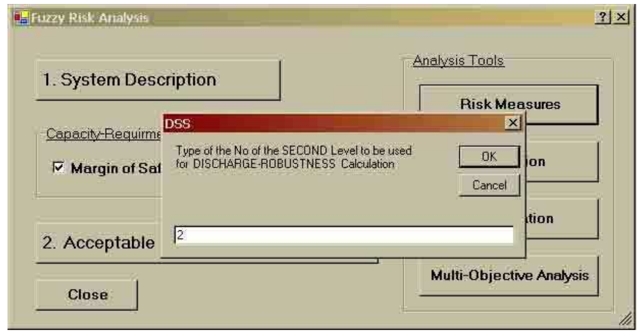

Step 8 Define the acceptable levels of performance. The user has to specify level(s) of performance for each domain of the input fields (i.e. discharge, pressure, and water quality parameters). The Level Editor can be used to enter manually those levels, or he/she can prepare a CSV input file. The tool asks the user to select the way he/she prefers to enter the levels with.



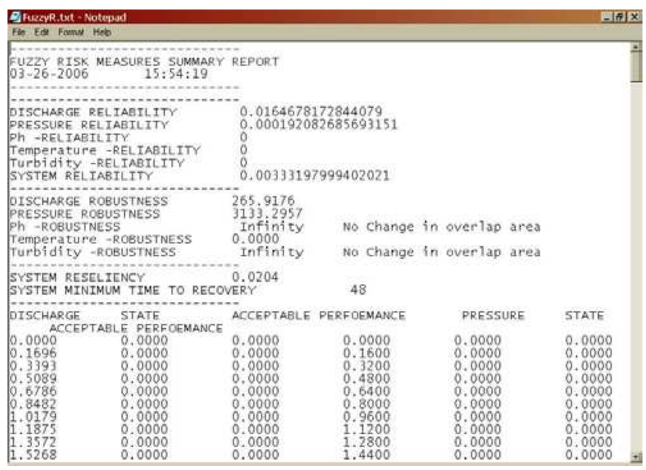



Step 9 Calculate fuzzy risk measures by pressing the risk measures button in the analysis toolbox.

Identify the levels to be used for calculating the robustness index (it requires two different levels of performance).



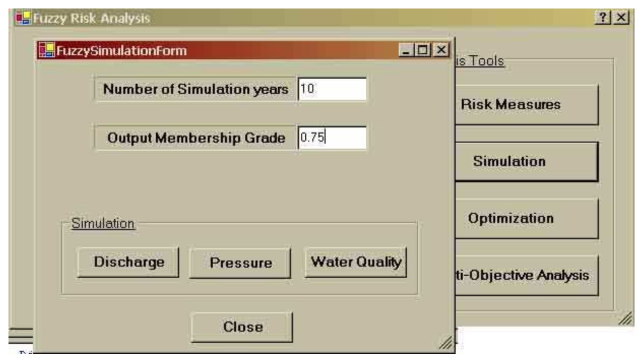

Step 10 Save the summary report. The tool produces a space separated output text file. Any text editor can open this output file.



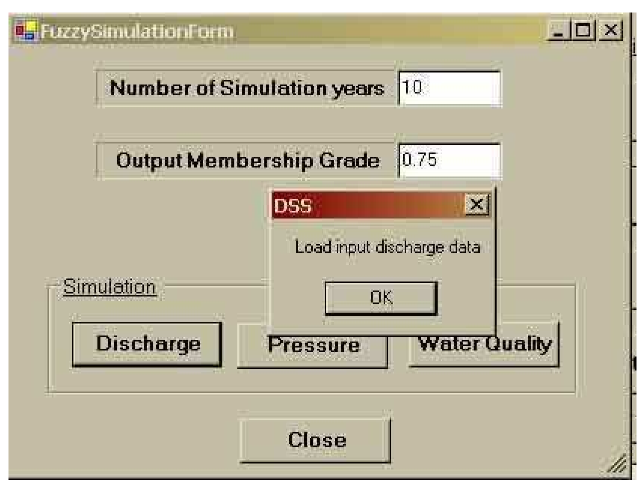
## II.2 Fuzzy simulation toolbox

Step 1 Select the fuzzy toolbox by pressing the corresponding button. Start simulation by pressing the simulation button in the analysis toolbox.

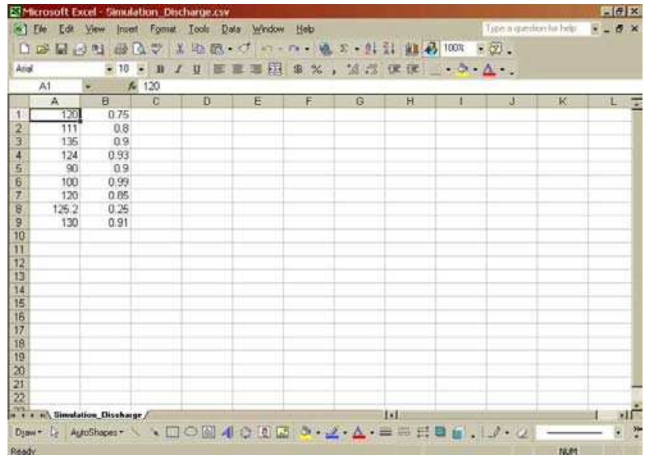

Step 2 Specify the number of simulation years and the output membership (belonging) grade. The value of the grade ranges between 0 and 1.



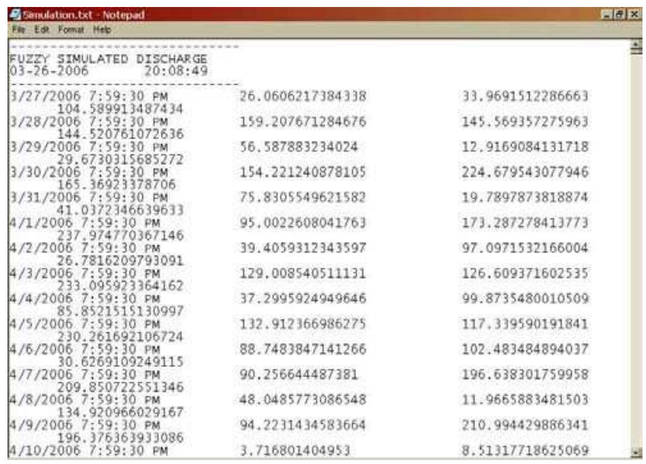

Step 3 Select the domain of simulation (i.e. discharge, pressure, or water quality parameter) to be simulated.



Step 4 Load the input data file. It is a CSV file format (without headings) containing historical domain data records and the corresponding membership value for each record.

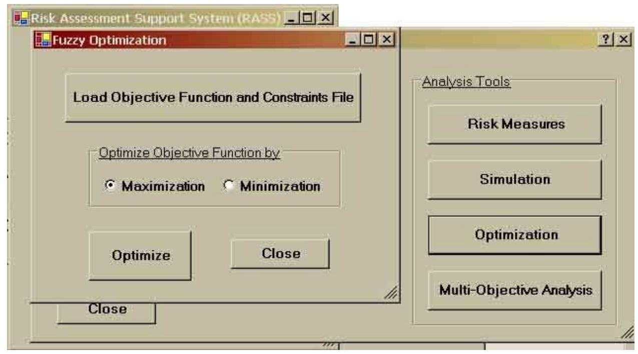



Step 5 Save the summary report. The tool produces a space separated output text file. Any text editor can open this output file.

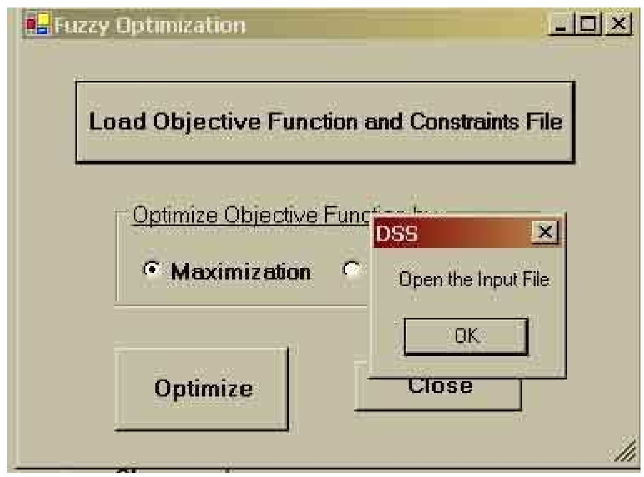


## II.3 Fuzzy optimization toolbox

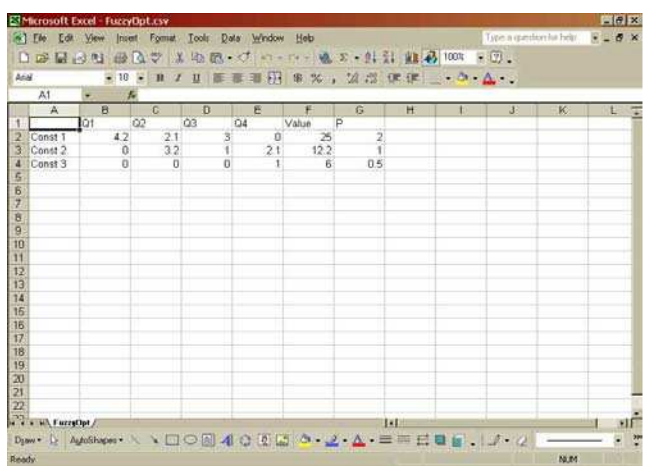
Step 1 Select the fuzzy toolbox by pressing the corresponding button. Start optimization by pressing the optimization button in the analysis toolbox.



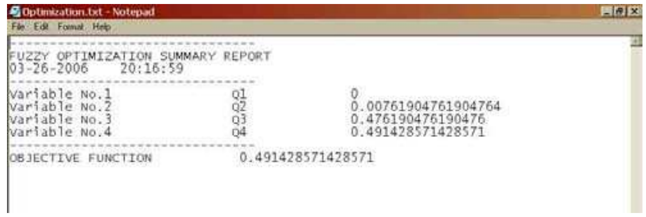

Step 2 Specify optimization type (i.e. maximization or minimization).




Step 3 Load the input data file. It is a CSV file format (with headings) containing constraints coefficients, right hand side values, and tolerance values.

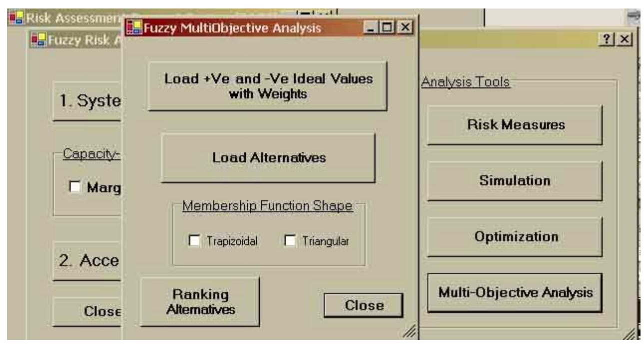


Step 4 Save the summary report. The tool produces a space separated output text file. Any text editor can open this output file.




## II.4 Fuzzy multi-objective analysis toolbox

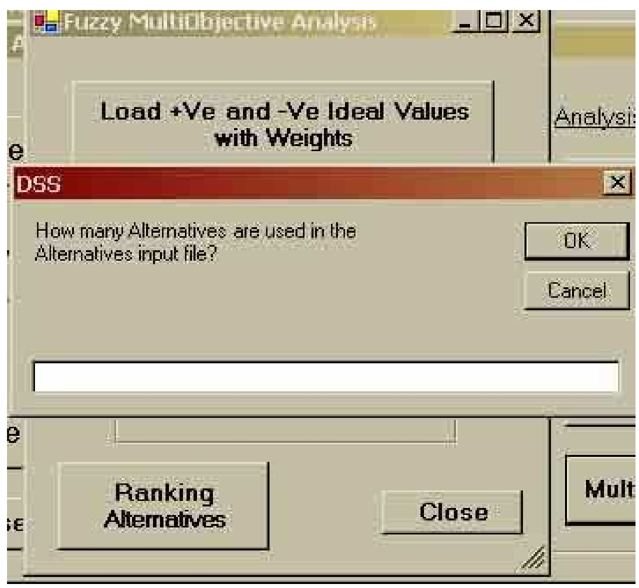
Step 1 Select the fuzzy toolbox by pressing the corresponding button. Start multi-objective analysis by pressing the multi-objective analysis button in the analysis toolbox.



Step 2 Specify the shape of the membership function to be used by the tool (i.e. Triangular or Trapezoidal)


Step 3 Load the input data files. The first file contains the positive and negative values for each criterion and the corresponding weights. The second file contains different alternative. Both files are in CSV file format (without headings).

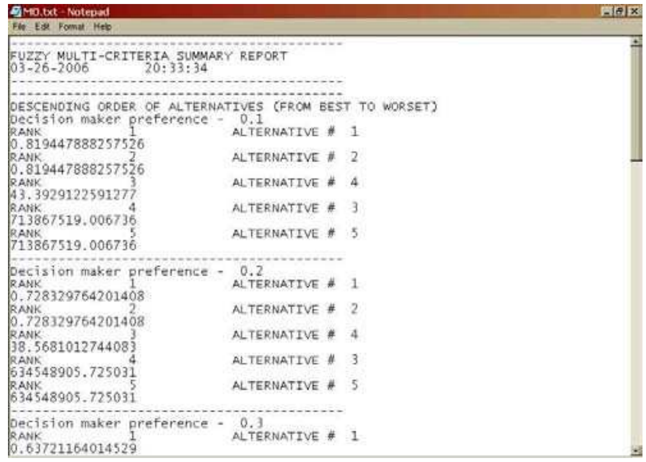
The user has to specify the number of alternatives used in the alternatives'



input data file.

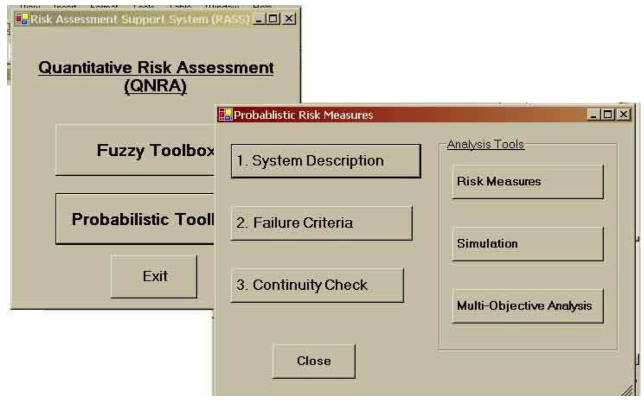
Step 4 Start ranking different alternatives by pressing the ranking button.

Save the summary report. The tool produces a space separated output text file. Any text editor can open this output file.

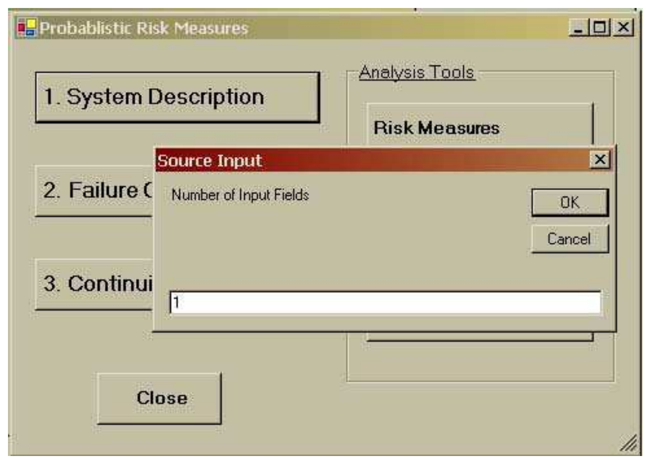


## II.5 Probabilistic performance measures toolbox

Step 1 Select the probabilistic toolbox by pressing the corresponding button.

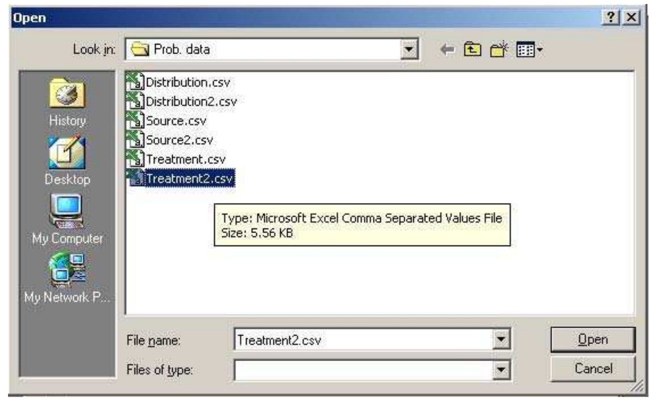



Step 2 Specify number of input fields (i.e. discharge fields) in the source input file which will be read by the tool.



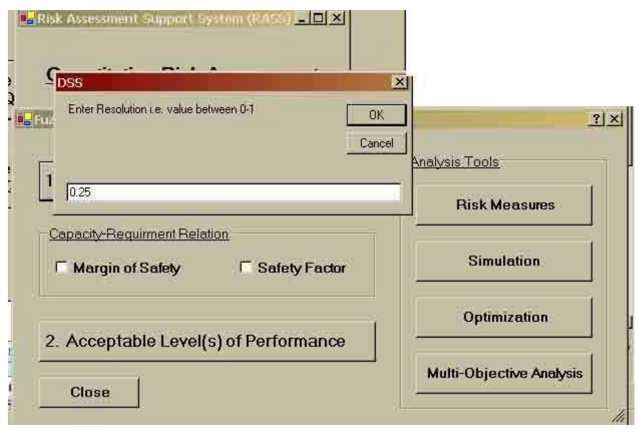

Step 3 Type in the name you would like to be used for the previously input fields (i.e. "Discharge").

Step 4 Specify the location of the source input file.

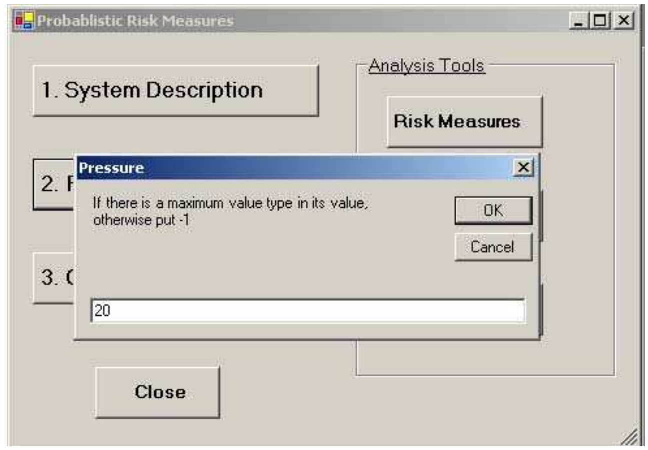



Step 5 Repeat steps 2-4 for treatment input(s) and distribution input(s)

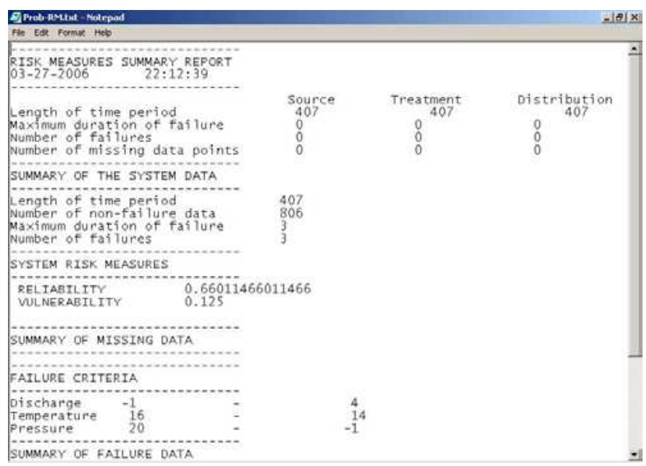
Step 6 Check records continuity by pressing the corresponding button. Discontinuity in any file of the three input data files is reported to the user.



Step 7 Specify failure criteria (threshold) for each input. Each input field can have a maximum and/or minimum or both, maximum and minimum failure criteria). If there are no maximum or minimum thresholds a value of -1 is entered.

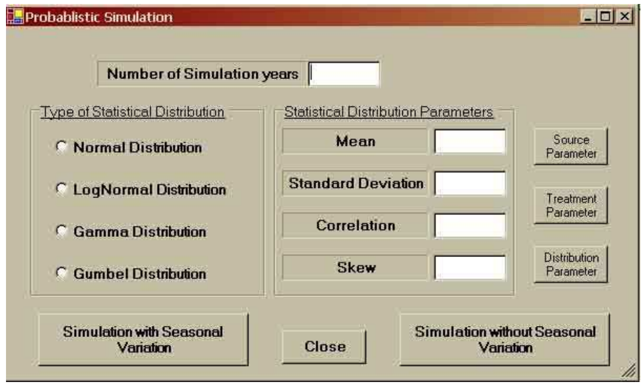



Step 8 Save the summary report. The tool produces a space separated output text file. Any text editor can open this output file.

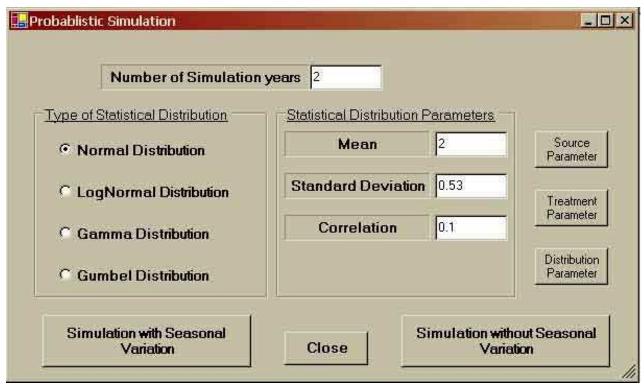


## II.6 Probabilistic simulation toolbox

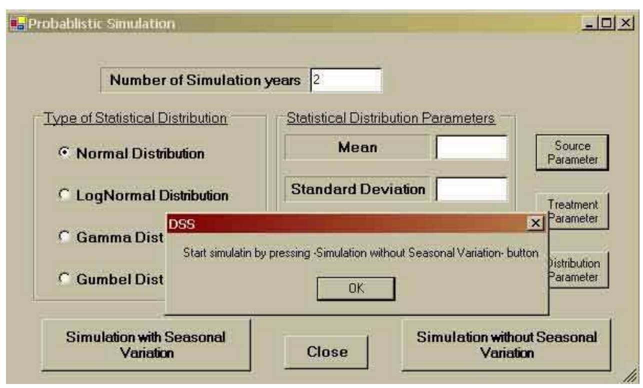
Step 1 Select the probabilistic toolbox by pressing the corresponding button. The select the "simulation" button.



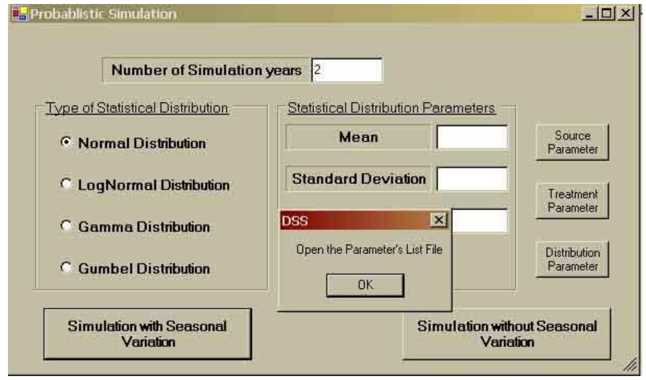

Step 2 Specify number of simulation years. Simulation can be performed for each domain independently.



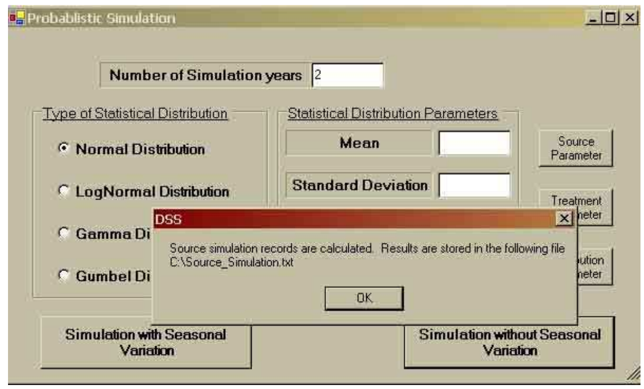

Step 3 Choose the preferred simulation option (i.e. with or without seasonal variation), In the former case, the user has to select the preferred distribution and specify its parameters in the corresponding text boxes. In the later case,

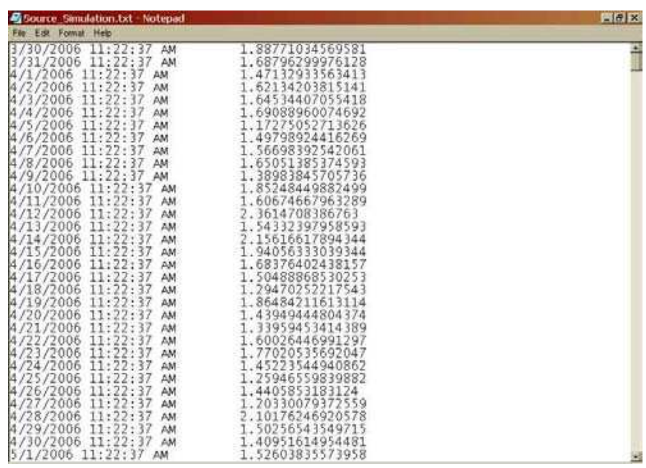


the user has to specify an input data file with three distributions (one for each domain) and the corresponding parameters.



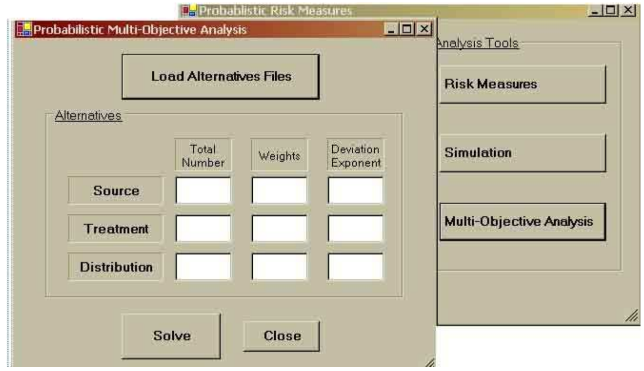

Step 4 The tool notifies the user of the location of the simulated records for each domain.



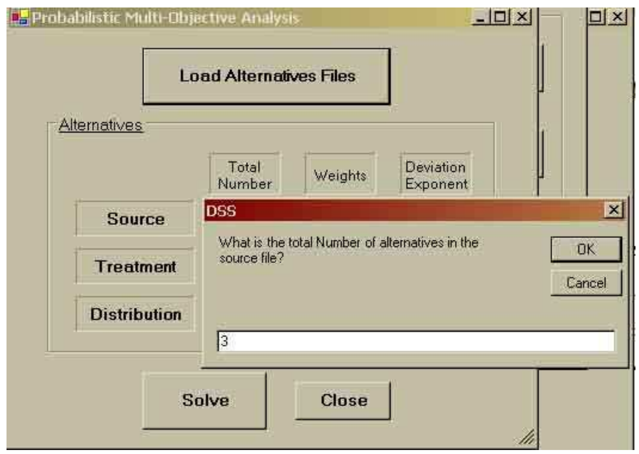



## II.7 Probabilistic multi-objective analysis toolbox

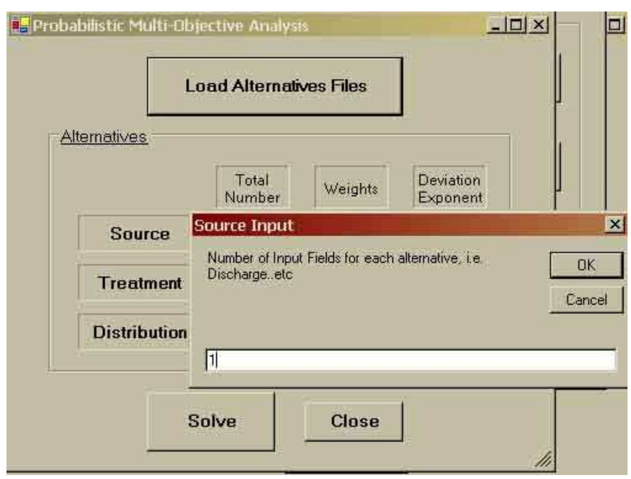
Step 1 Select the probabilistic toolbox by pressing the corresponding button. The select the "multi-objective analysis" button.



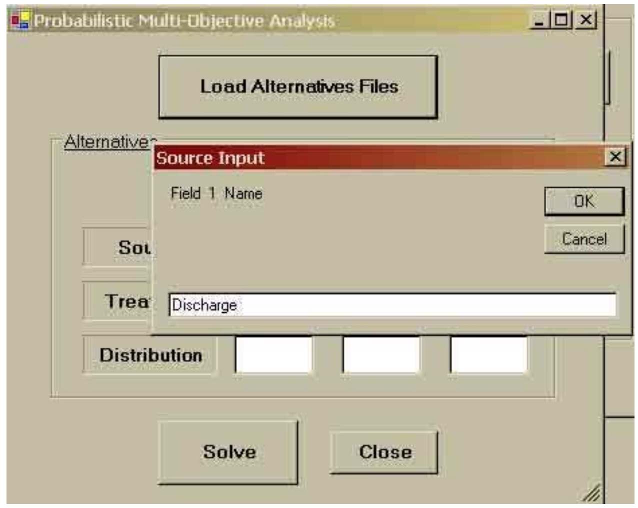

Step 2 Load alternatives input file by pressing the corresponding button. Specify the total number of source alternatives (i.e. 3 discharge alternatives).




Step 3 Specify the number of input fields in each alternative (i.e. 3 different fields for each alternative). As an example, there can be temperature, ph under each treatment alternative.

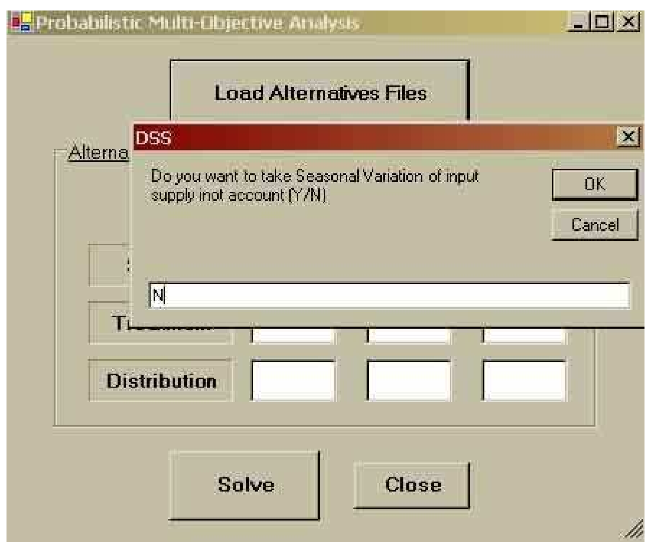


Step 4 Give a title name for each input field (i.e. discharge, temperature…etc)

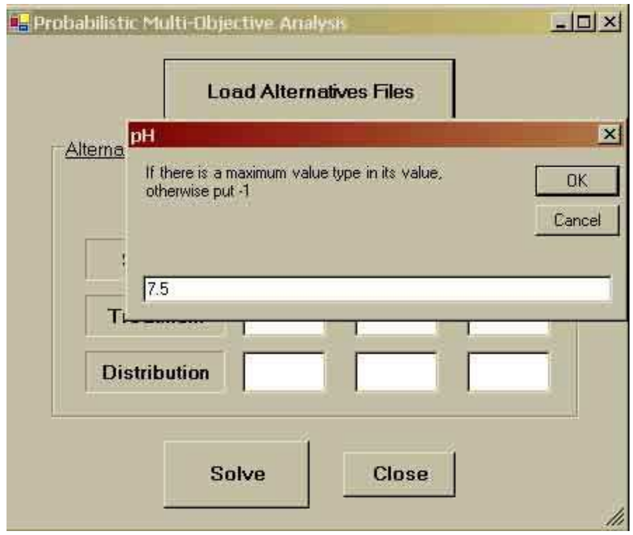



Step 5 Repeat steps 2-4 for each domain, i.e. treatment and distribution.

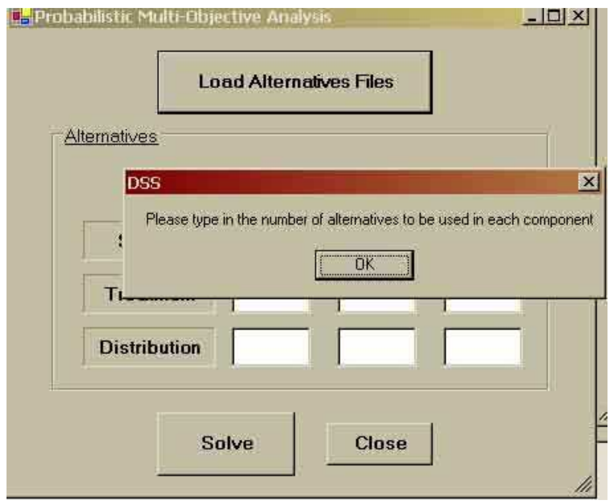
Step 6 The tool notifies the user if he/she wants to consider seasonal variation of input inputs. The user has to answer with (y) in case of approval to account for seasonal variation or (n) in the other case.

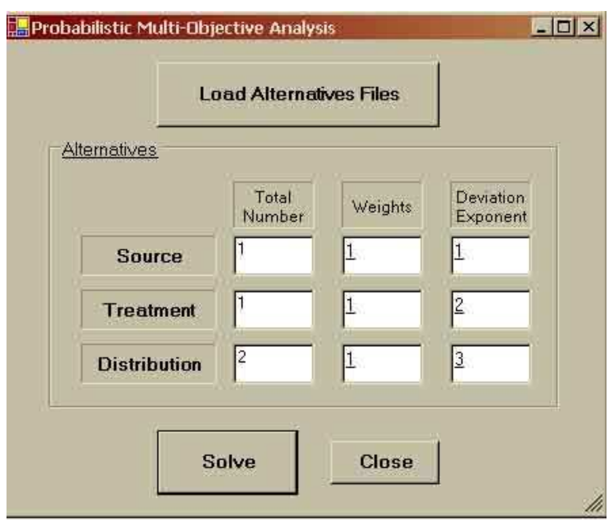


Step 7 Specify the maximum and minimum failure criteria (threshold). It is optional to specify both values or one value and assign (-1) for the other value to indicate the use of single failure criteria.

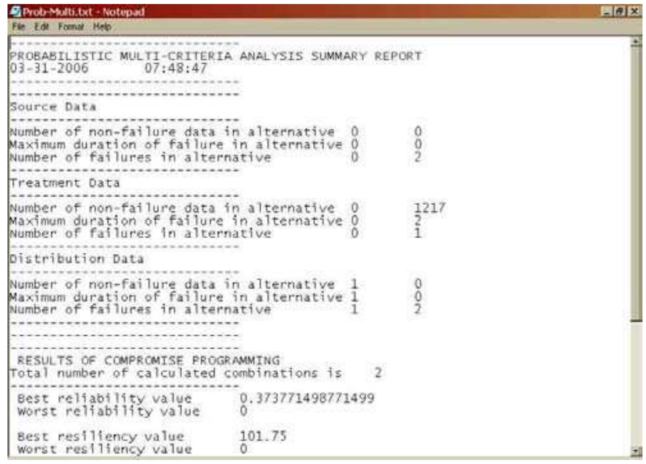



Step 8 Fill in the number of alternatives to be used, weights for each domain and deviation exponent.



Step 9 The tool notifies the user of the location of the summery results file.



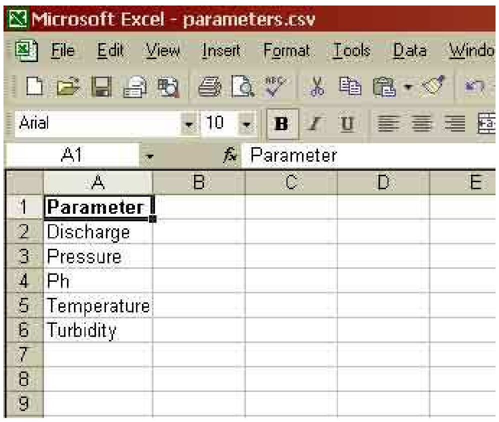
# APPENDIX III

# SAMPLE OF INPUT FILES

**III.1 Fuzzy performance measures toolbox**

**1. Parameter list file**

It lists all the parameters included in the resistance (capacity) and load (requirement) input data files. It is in CSV format (without headings).

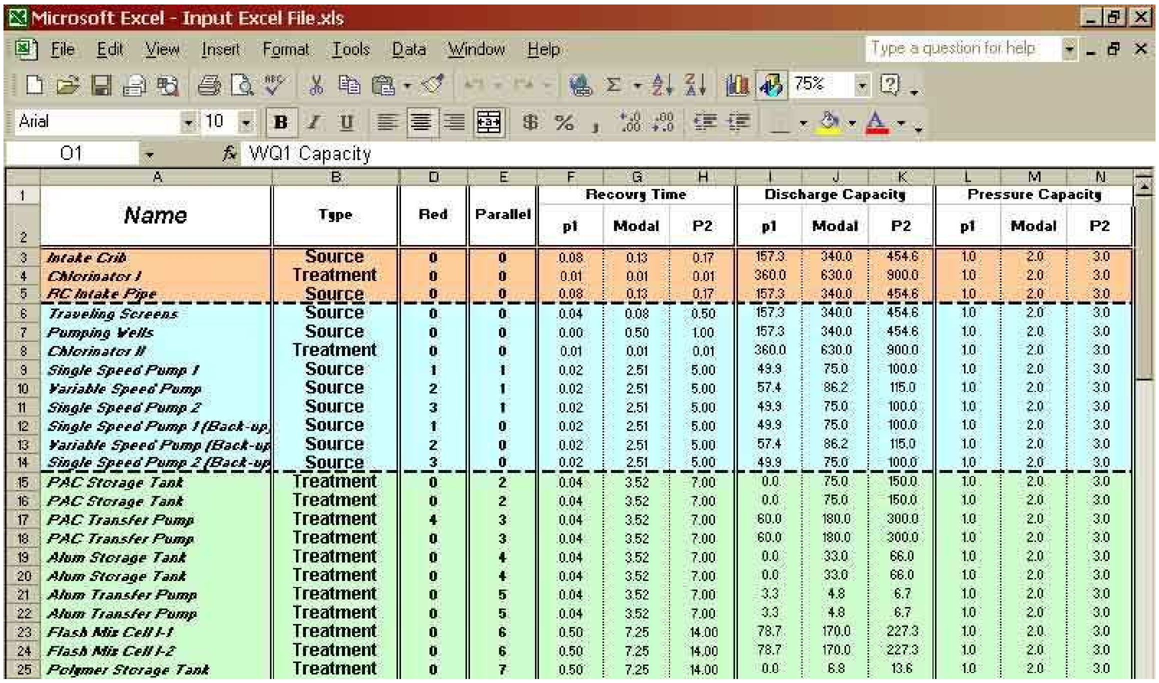



**2. Resistance (capacity) file**

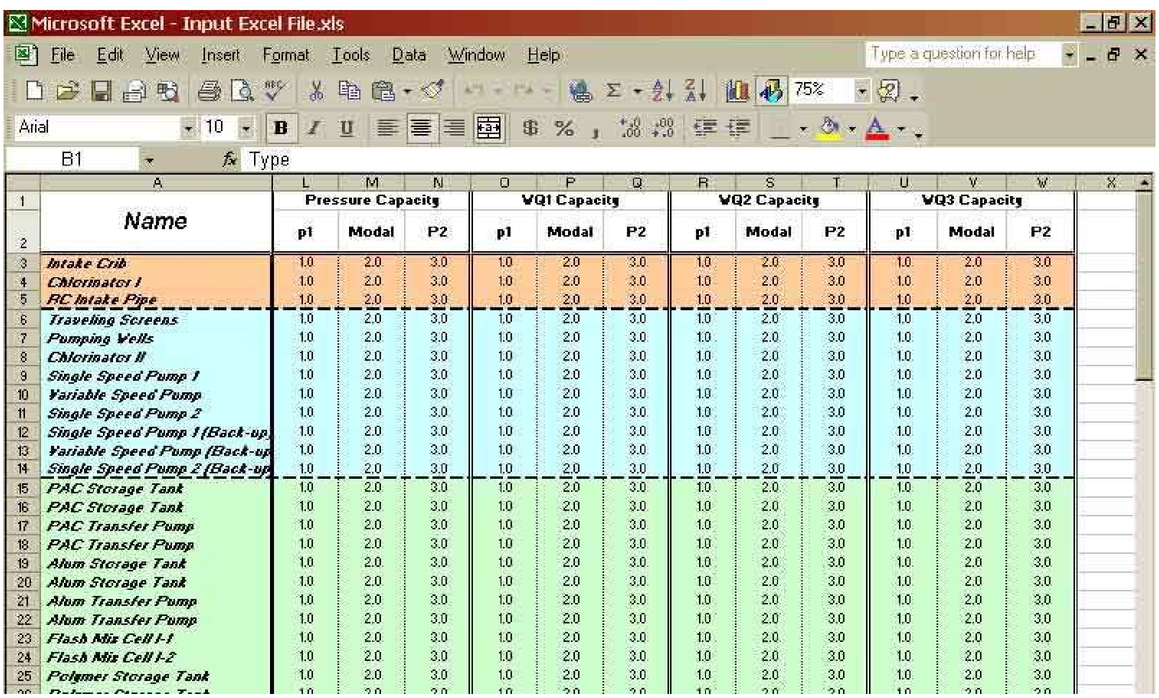
It contains all the required resistance (capacity) data for each system component. It is in CSV format (without headings). For each component the following data fields are required:

- Component Name
- Component type: this field is required to help in constructing the data file for the probabilistic toolbox. The system in the probabilistic toolbox is divided into three main components, i.e. source, treatment, and distribution.
- Component affiliation in parallel and/or redundant groups: it specifies the number of the parallel and/or redundant group to which the component belongs.

- Recovery time: three or four values (depending on the shape of the used fuzzy membership function, i.e. triangular, or trapezoidal) specifying the membership function values of the time required to recover from failure.



| Name | Type | Red | Parallel | Recovry Time | | | Discharge Capacity | | | Pressure Capacity | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | p1 | Modal | P2 | p1 | Modal | P2 | p1 | Modal | P2 |
| Intake Crib | Source | 0 | 0 | 0.08 | 0.13 | 0.17 | 157.3 | 340.0 | 454.6 | 1.0 | 2.0 | 3.0 |
| Chlorinator I | Treatment | 0 | 0 | 0.01 | 0.01 | 0.01 | 360.0 | 630.0 | 900.0 | 1.0 | 2.0 | 3.0 |
| RC Intake Pipe | Source | 0 | 0 | 0.08 | 0.13 | 0.17 | 157.3 | 340.0 | 454.6 | 1.0 | 2.0 | 3.0 |
| Traveling Screens | Source | 0 | 0 | 0.04 | 0.08 | 0.50 | 157.3 | 340.0 | 454.6 | 1.0 | 2.0 | 3.0 |
| Pumping Wells | Source | 0 | 0 | 0.00 | 0.50 | 1.00 | 157.3 | 340.0 | 454.6 | 1.0 | 2.0 | 3.0 |
| Chlorinator II | Treatment | 0 | 0 | 0.01 | 0.01 | 0.01 | 360.0 | 630.0 | 900.0 | 1.0 | 2.0 | 3.0 |
| Single Speed Pump 1 | Source | 1 | 1 | 0.02 | 2.51 | 5.00 | 49.9 | 75.0 | 100.0 | 1.0 | 2.0 | 3.0 |
| Variable Speed Pump | Source | 2 | 1 | 0.02 | 2.51 | 5.00 | 57.4 | 86.2 | 115.0 | 1.0 | 2.0 | 3.0 |
| Single Speed Pump 2 | Source | 3 | 1 | 0.02 | 2.51 | 5.00 | 49.9 | 75.0 | 100.0 | 1.0 | 2.0 | 3.0 |
| Single Speed Pump 1 (Back-up) | Source | 1 | 0 | 0.02 | 2.51 | 5.00 | 49.9 | 75.0 | 100.0 | 1.0 | 2.0 | 3.0 |
| Variable Speed Pump (Back-up | Source | 2 | 0 | 0.02 | 2.51 | 5.00 | 57.4 | 86.2 | 115.0 | 1.0 | 2.0 | 3.0 |
| Single Speed Pump 2 (Back-up | Source | 3 | 0 | 0.02 | 2.51 | 5.00 | 49.9 | 75.0 | 100.0 | 1.0 | 2.0 | 3.0 |
| PAC Storage Tank | Treatment | 0 | 2 | 0.04 | 3.52 | 7.00 | 0.0 | 75.0 | 150.0 | 1.0 | 2.0 | 3.0 |
| PAC Storage Tank | Treatment | 0 | 2 | 0.04 | 3.52 | 7.00 | 0.0 | 75.0 | 150.0 | 1.0 | 2.0 | 3.0 |
| PAC Transfer Pump | Treatment | 4 | 3 | 0.04 | 3.52 | 7.00 | 60.0 | 180.0 | 300.0 | 1.0 | 2.0 | 3.0 |
| PAC Transfer Pump | Treatment | 0 | 3 | 0.04 | 3.52 | 7.00 | 60.0 | 180.0 | 300.0 | 1.0 | 2.0 | 3.0 |
| Alum Storage Tank | Treatment | 0 | 4 | 0.04 | 3.52 | 7.00 | 0.0 | 33.0 | 66.0 | 1.0 | 2.0 | 3.0 |
| Alum Storage Tank | Treatment | 0 | 4 | 0.04 | 3.52 | 7.00 | 0.0 | 33.0 | 66.0 | 1.0 | 2.0 | 3.0 |
| Alum Transfer Pump | Treatment | 0 | 5 | 0.04 | 3.52 | 7.00 | 3.3 | 4.8 | 6.7 | 1.0 | 2.0 | 3.0 |
| Alum Transfer Pump | Treatment | 0 | 5 | 0.04 | 3.52 | 7.00 | 3.3 | 4.8 | 6.7 | 1.0 | 2.0 | 3.0 |
| Flash Mix Cell I-1 | Treatment | 0 | 6 | 0.50 | 7.25 | 14.00 | 78.7 | 170.0 | 227.3 | 1.0 | 2.0 | 3.0 |
| Flash Mix Cell I-2 | Treatment | 0 | 6 | 0.50 | 7.25 | 14.00 | 78.7 | 170.0 | 227.3 | 1.0 | 2.0 | 3.0 |
| Polymer Storage Tank | Treatment | 0 | 7 | 0.50 | 7.25 | 14.00 | 0.0 | 6.8 | 13.6 | 1.0 | 2.0 | 3.0 |



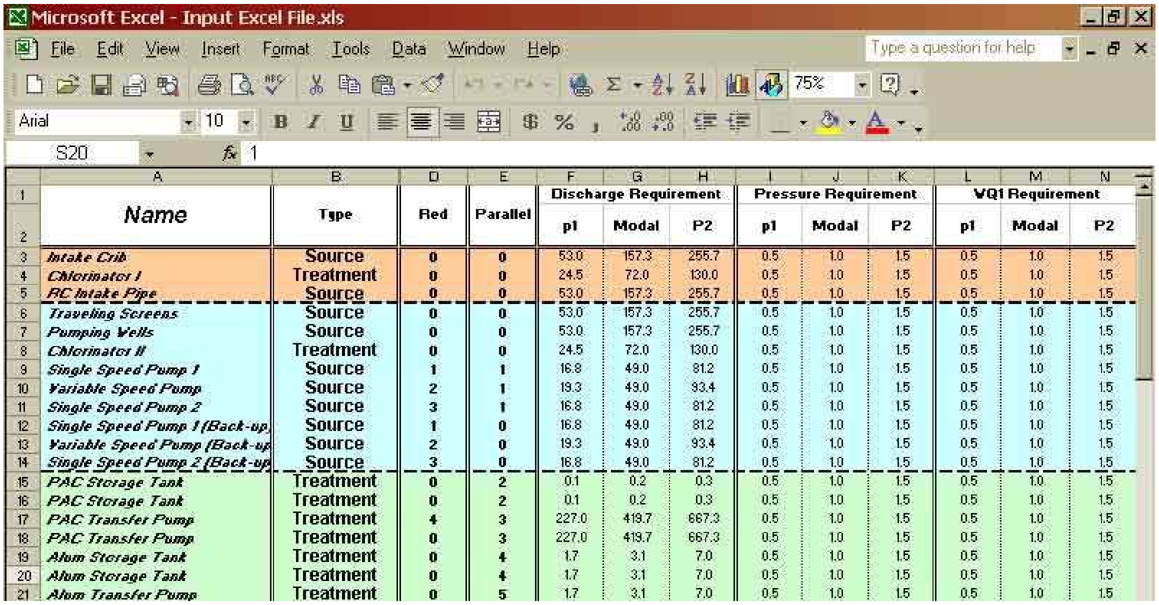
| Name | Pressure Capacity | | | WQ1 Capacity | | | WQ2 Capacity | | | WQ3 Capacity | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | p1 | Modal | P2 | p1 | Modal | P2 | p1 | Modal | P2 | p1 | Modal | P2 |
| Intake Crib | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Chlorinator I | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| RC Intake Pipe | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Traveling Screens | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Pumping Wells | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Chlorinator II | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Single Speed Pump 1 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Variable Speed Pump | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Single Speed Pump 2 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Single Speed Pump 1 (Back-up | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Variable Speed Pump (Back-up | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Single Speed Pump 2 (Back-up | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| PAC Storage Tank | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| PAC Storage Tank | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| PAC Transfer Pump | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| PAC Transfer Pump | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Alum Storage Tank | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Alum Storage Tank | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Alum Transfer Pump | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Alum Transfer Pump | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Flash Mix Cell I-1 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Flash Mix Cell I-2 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |
| Polymer Storage Tank | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 | 1.0 | 2.0 | 3.0 |

- Parameters: groups of three or four values (depending on the shape of the used fuzzy membership function, i.e. triangular, or trapezoidal) specifying the membership function values of the parameters used. The number of the parameter has to be consistent with the number in the list and the load (requirement) file.

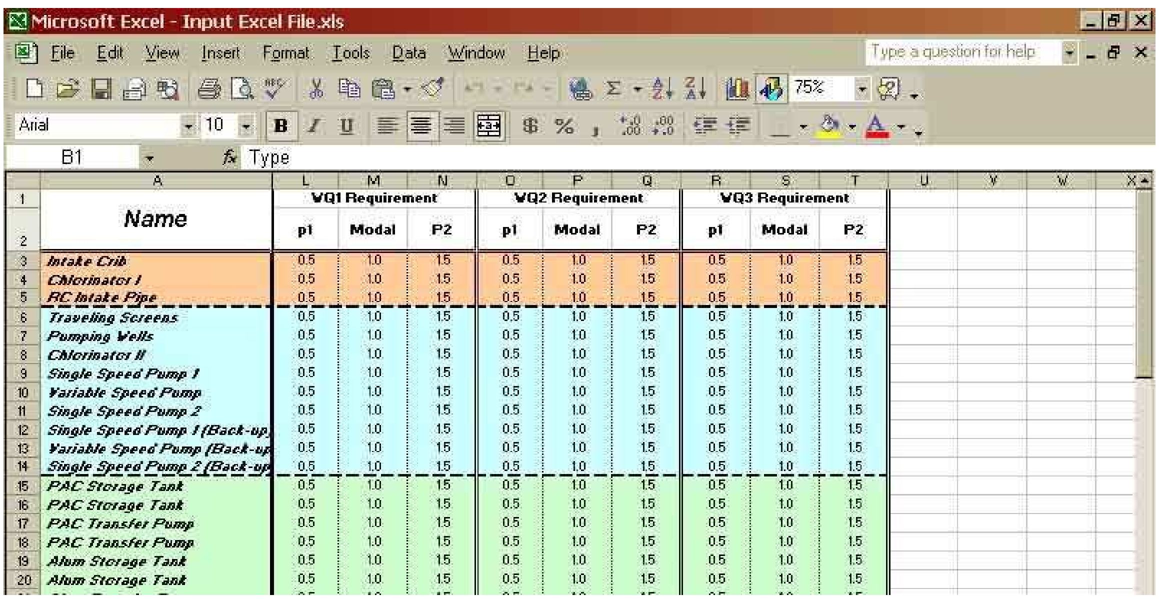
**3. Load (requirement) file**

It contains all the required load (requirement) data for each system component. It is in CSV format (without headings). For each component the following data fields are required:

- Component Name
- Component type: this field is required to help in constructing the data file for the probabilistic toolbox. The system in the probabilistic toolbox is divided into three main components, i.e. source, treatment, and distribution.
- Component affiliation in parallel and/or redundant groups: it specifies the number of the parallel and/or redundant group to which the component belongs.
- Parameters: groups of three or four values (depending on the shape of the used fuzzy membership function, i.e. triangular, or trapezoidal) specifying the membership function values of the parameters used. The number of the parameter has to be consistent with the number in the list and the resistance (capacity) file.



| Name | Type | Red | Parallel | Discharge Requirement p1 | Discharge Requirement Modal | Discharge Requirement P2 | Pressure Requirement p1 | Pressure Requirement Modal | Pressure Requirement P2 | VQ1 Requirement p1 | VQ1 Requirement Modal | VQ1 Requirement P2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intake Crib | Source | 0 | 0 | 53.0 | 157.3 | 255.7 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Chlorinator I | Treatment | 0 | 0 | 24.5 | 72.0 | 130.0 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| RC Intake Pipe | Source | 0 | 0 | 53.0 | 157.3 | 255.7 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Traveling Screens | Source | 0 | 0 | 53.0 | 157.3 | 255.7 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Pumping Wells | Source | 0 | 0 | 53.0 | 157.3 | 255.7 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Chlorinator II | Treatment | 0 | 0 | 24.5 | 72.0 | 130.0 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Single Speed Pump 1 | Source | 1 | 1 | 16.8 | 49.0 | 81.2 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Variable Speed Pump | Source | 2 | 1 | 19.3 | 49.0 | 93.4 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Single Speed Pump 2 | Source | 3 | 1 | 16.8 | 49.0 | 81.2 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Single Speed Pump 1 (Back-up) | Source | 1 | 0 | 16.8 | 49.0 | 81.2 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Variable Speed Pump (Back-up | Source | 2 | 0 | 19.3 | 49.0 | 93.4 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Single Speed Pump 2 (Back-up | Source | 3 | 0 | 16.8 | 49.0 | 81.2 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| PAC Storage Tank | Treatment | 0 | 2 | 0.1 | 0.2 | 0.3 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| PAC Storage Tank | Treatment | 0 | 2 | 0.1 | 0.2 | 0.3 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| PAC Transfer Pump | Treatment | 4 | 3 | 227.0 | 419.7 | 667.3 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| PAC Transfer Pump | Treatment | 0 | 3 | 227.0 | 419.7 | 667.3 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Alum Storage Tank | Treatment | 0 | 4 | 1.7 | 3.1 | 7.0 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Alum Storage Tank | Treatment | 0 | 4 | 1.7 | 3.1 | 7.0 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Alum Transfer Pump | Treatment | 0 | 5 | 1.7 | 3.1 | 7.0 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |



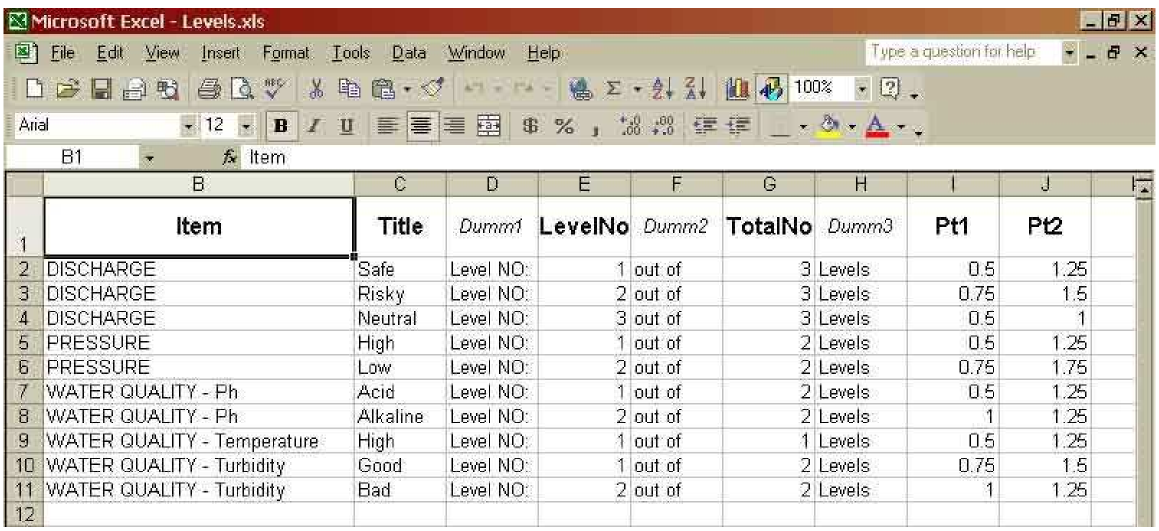
| Name | VQ1 Requirement p1 | VQ1 Requirement Modal | VQ1 Requirement P2 | VQ2 Requirement p1 | VQ2 Requirement Modal | VQ2 Requirement P2 | VQ3 Requirement p1 | VQ3 Requirement Modal | VQ3 Requirement P2 |
|---|---|---|---|---|---|---|---|---|---|
| Intake Crib | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Chlorinator I | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| RC Intake Pipe | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Traveling Screens | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Pumping Wells | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Chlorinator II | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Single Speed Pump 1 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Variable Speed Pump | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Single Speed Pump 2 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Single Speed Pump 1 (Back-up) | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Variable Speed Pump (Back-up | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Single Speed Pump 2 (Back-up | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| PAC Storage Tank | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| PAC Storage Tank | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| PAC Transfer Pump | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| PAC Transfer Pump | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Alum Storage Tank | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |
| Alum Storage Tank | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 | 0.5 | 1.0 | 1.5 |

### 3. Levels file

It contains all the required data for different acceptable levels of performance. It is in CSV format (without headings). The following data fields are required:

- Level affiliation with different parameters. For example, if the level is defined for discharge, the item filed will be "Discharge".

- o Level’s Title: the title name of the level.
- o Level number: it indicates the number of levels for each domain (i.e. 3 for discharge domain…etc)
- o Total number of levels in each domain.
- o Point1 and point 2 values expressed in terms of margin of safety or safety factor units.
- o Other in-between dummy text fields are required but are not important as they will not be used. These filed are required so as to clarify the file for other users.

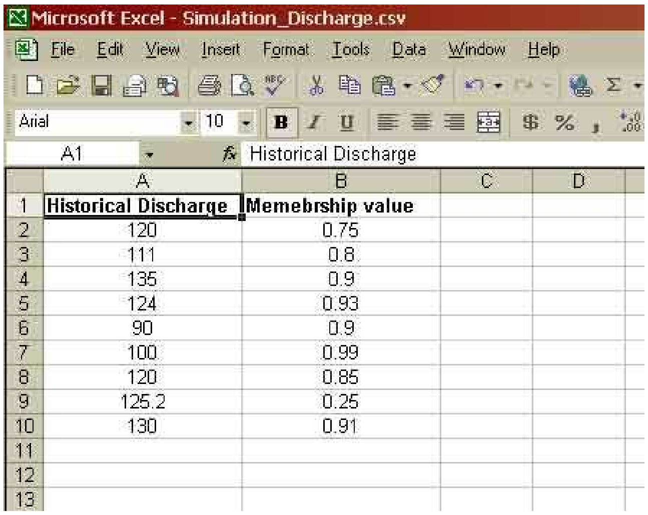



| | B | C | D | E | F | G | H | I | J |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Item | Title | Dumm1 | LevelNo | Dumm2 | TotalNo | Dumm3 | Pt1 | Pt2 |
| 2 | DISCHARGE | Safe | Level NO: | 1 | out of | 3 | Levels | 0.5 | 1.25 |
| 3 | DISCHARGE | Risky | Level NO: | 2 | out of | 3 | Levels | 0.75 | 1.5 |
| 4 | DISCHARGE | Neutral | Level NO: | 3 | out of | 3 | Levels | 0.5 | 1 |
| 5 | PRESSURE | High | Level NO: | 1 | out of | 2 | Levels | 0.5 | 1.25 |
| 6 | PRESSURE | Low | Level NO: | 2 | out of | 2 | Levels | 0.75 | 1.75 |
| 7 | WATER QUALITY - Ph | Acid | Level NO: | 1 | out of | 2 | Levels | 0.5 | 1.25 |
| 8 | WATER QUALITY - Ph | Alkaline | Level NO: | 2 | out of | 2 | Levels | 1 | 1.25 |
| 9 | WATER QUALITY - Temperature | High | Level NO: | 1 | out of | 1 | Levels | 0.5 | 1.25 |
| 10 | WATER QUALITY - Turbidity | Good | Level NO: | 1 | out of | 2 | Levels | 0.75 | 1.5 |
| 11 | WATER QUALITY - Turbidity | Bad | Level NO: | 2 | out of | 2 | Levels | 1 | 1.25 |
| 12 | | | | | | | | | |

## III.2 Fuzzy simulation toolbox

### Historical data file

It contains historical records to be simulated together with membership value( belonging) of each record.. It is in CSV format (without headings).

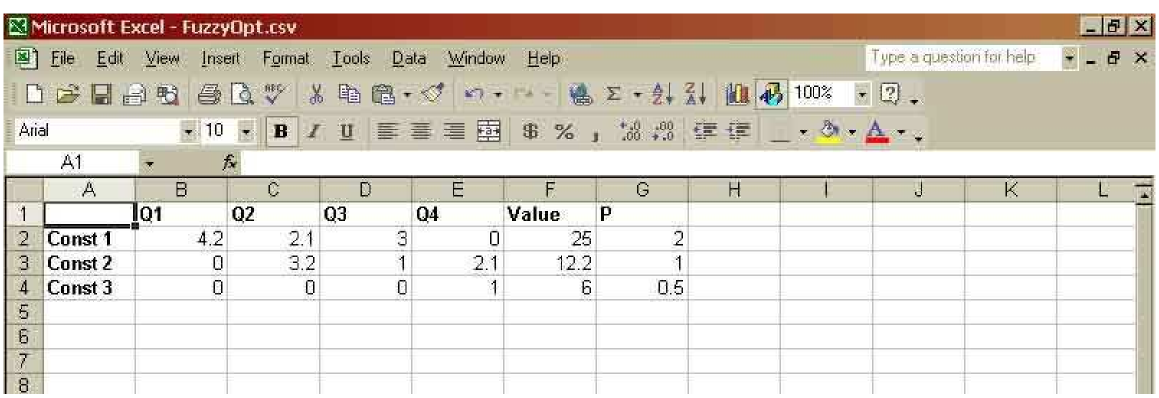



| Historical Discharge | Memebrship value |
|---|---|
| 120 | 0.75 |
| 111 | 0.8 |
| 135 | 0.9 |
| 124 | 0.93 |
| 90 | 0.9 |
| 100 | 0.99 |
| 120 | 0.85 |
| 125.2 | 0.25 |
| 130 | 0.91 |

## III.3 Fuzzy optimization toolbox

### Historical data file

It contains constraints' coefficients, right hand side (RHS) values and tolerance values for each constraint. It is in CSV format (with headings).

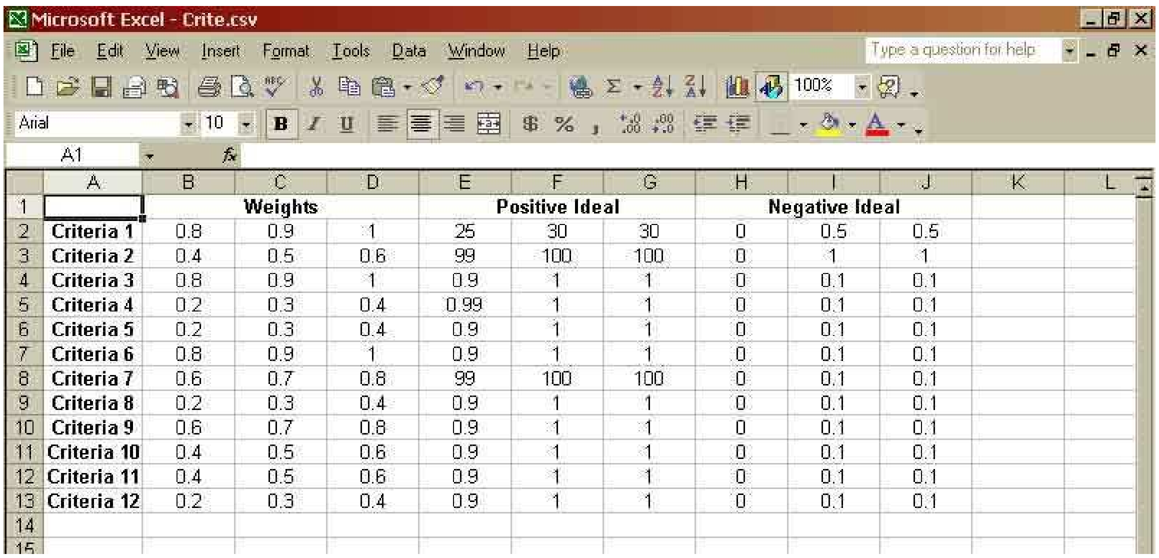



| | Q1 | Q2 | Q3 | Q4 | Value | P |
|---|---|---|---|---|---|---|
| Const 1 | 4.2 | 2.1 | 3 | 0 | 25 | 2 |
| Const 2 | 0 | 3.2 | 1 | 2.1 | 12.2 | 1 |
| Const 3 | 0 | 0 | 0 | 1 | 6 | 0.5 |

## III.4 Fuzzy multi-objective toolbox

### 1. Weights and ideal values data file

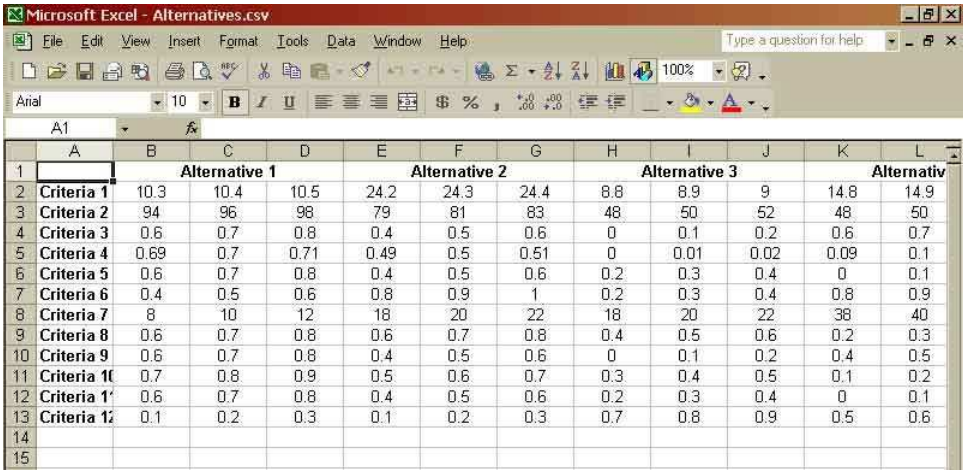
It contains criteria's weights, positive (best) ideal values, and negative (worst) ideal values. These values are given in groups of three or four values (depending on the shape of the used fuzzy membership function, i.e. triangular, or trapezoidal). It is in CSV format (without headings).




| | Weights | | | Positive Ideal | | | Negative Ideal | | |
|---|---|---|---|---|---|---|---|---|---|
| Criteria 1 | 0.8 | 0.9 | 1 | 25 | 30 | 30 | 0 | 0.5 | 0.5 |
| Criteria 2 | 0.4 | 0.5 | 0.6 | 99 | 100 | 100 | 0 | 1 | 1 |
| Criteria 3 | 0.8 | 0.9 | 1 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 4 | 0.2 | 0.3 | 0.4 | 0.99 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 5 | 0.2 | 0.3 | 0.4 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 6 | 0.8 | 0.9 | 1 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 7 | 0.6 | 0.7 | 0.8 | 99 | 100 | 100 | 0 | 0.1 | 0.1 |
| Criteria 8 | 0.2 | 0.3 | 0.4 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 9 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 10 | 0.4 | 0.5 | 0.6 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 11 | 0.4 | 0.5 | 0.6 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |
| Criteria 12 | 0.2 | 0.3 | 0.4 | 0.9 | 1 | 1 | 0 | 0.1 | 0.1 |

### 2. Alternatives data file

It contains different alternatives values. These values are given in groups of three or four values (depending on the shape of the used fuzzy membership function, i.e. triangular, or trapezoidal). It is in CSV format (without headings).

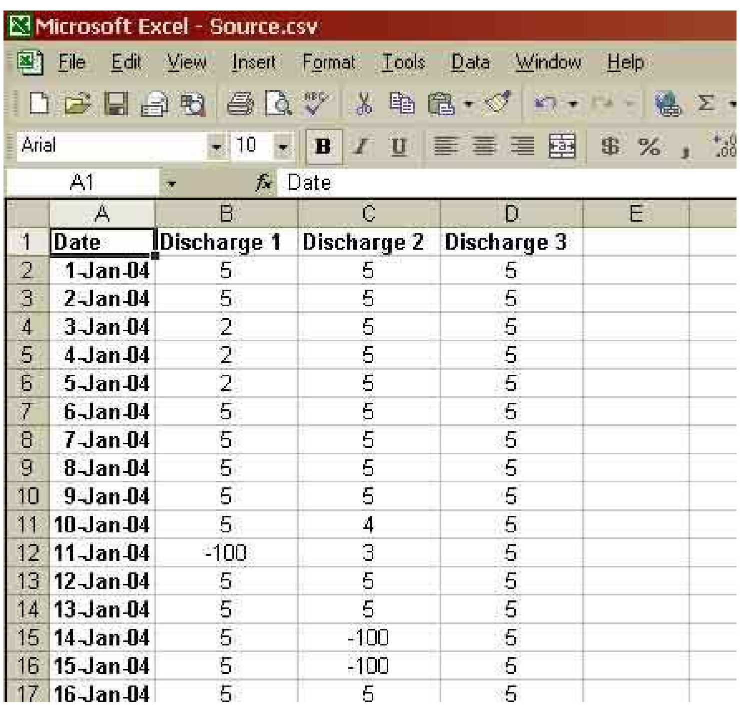



| | A | B | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | Alternative 1 | | | Alternative 2 | | | Alternative 3 | | | Alternativ | |
| 2 | Criteria 1 | 10.3 | 10.4 | 10.5 | 24.2 | 24.3 | 24.4 | 8.8 | 8.9 | 9 | 14.8 | 14.9 |
| 3 | Criteria 2 | 94 | 96 | 98 | 79 | 81 | 83 | 48 | 50 | 52 | 48 | 50 |
| 4 | Criteria 3 | 0.6 | 0.7 | 0.8 | 0.4 | 0.5 | 0.6 | 0 | 0.1 | 0.2 | 0.6 | 0.7 |
| 5 | Criteria 4 | 0.69 | 0.7 | 0.71 | 0.49 | 0.5 | 0.51 | 0 | 0.01 | 0.02 | 0.09 | 0.1 |
| 6 | Criteria 5 | 0.6 | 0.7 | 0.8 | 0.4 | 0.5 | 0.6 | 0.2 | 0.3 | 0.4 | 0 | 0.1 |
| 7 | Criteria 6 | 0.4 | 0.5 | 0.6 | 0.8 | 0.9 | 1 | 0.2 | 0.3 | 0.4 | 0.8 | 0.9 |
| 8 | Criteria 7 | 8 | 10 | 12 | 18 | 20 | 22 | 18 | 20 | 22 | 38 | 40 |
| 9 | Criteria 8 | 0.6 | 0.7 | 0.8 | 0.6 | 0.7 | 0.8 | 0.4 | 0.5 | 0.6 | 0.2 | 0.3 |
| 10 | Criteria 9 | 0.6 | 0.7 | 0.8 | 0.4 | 0.5 | 0.6 | 0 | 0.1 | 0.2 | 0.4 | 0.5 |
| 11 | Criteria 1( | 0.7 | 0.8 | 0.9 | 0.5 | 0.6 | 0.7 | 0.3 | 0.4 | 0.5 | 0.1 | 0.2 |
| 12 | Criteria 1' | 0.6 | 0.7 | 0.8 | 0.4 | 0.5 | 0.6 | 0.2 | 0.3 | 0.4 | 0 | 0.1 |
| 13 | Criteria 1: | 0.1 | 0.2 | 0.3 | 0.1 | 0.2 | 0.3 | 0.7 | 0.8 | 0.9 | 0.5 | 0.6 |
| 14 | | | | | | | | | | | | |
| 15 | | | | | | | | | | | | |

## III.5 Probabilistic performance measures toolbox

### Source, treatment, and distribution files

They contain record dates and values. Each domain should be in one file. Missing data points must have (-100) values and should not be left empty. It is in CSV format (without headings).




| | A | B | C | D | E |
|---|---|---|---|---|---|
| 1 | Date | Discharge 1 | Discharge 2 | Discharge 3 | |
| 2 | 1-Jan-04 | 5 | 5 | 5 | |
| 3 | 2-Jan-04 | 5 | 5 | 5 | |
| 4 | 3-Jan-04 | 2 | 5 | 5 | |
| 5 | 4-Jan-04 | 2 | 5 | 5 | |
| 6 | 5-Jan-04 | 2 | 5 | 5 | |
| 7 | 6-Jan-04 | 5 | 5 | 5 | |
| 8 | 7-Jan-04 | 5 | 5 | 5 | |
| 9 | 8-Jan-04 | 5 | 5 | 5 | |
| 10 | 9-Jan-04 | 5 | 5 | 5 | |
| 11 | 10-Jan-04 | 5 | 4 | 5 | |
| 12 | 11-Jan-04 | -100 | 3 | 5 | |
| 13 | 12-Jan-04 | 5 | 5 | 5 | |
| 14 | 13-Jan-04 | 5 | 5 | 5 | |
| 15 | 14-Jan-04 | 5 | -100 | 5 | |
| 16 | 15-Jan-04 | 5 | -100 | 5 | |
| 17 | 16-Jan-04 | 5 | 5 | 5 | |

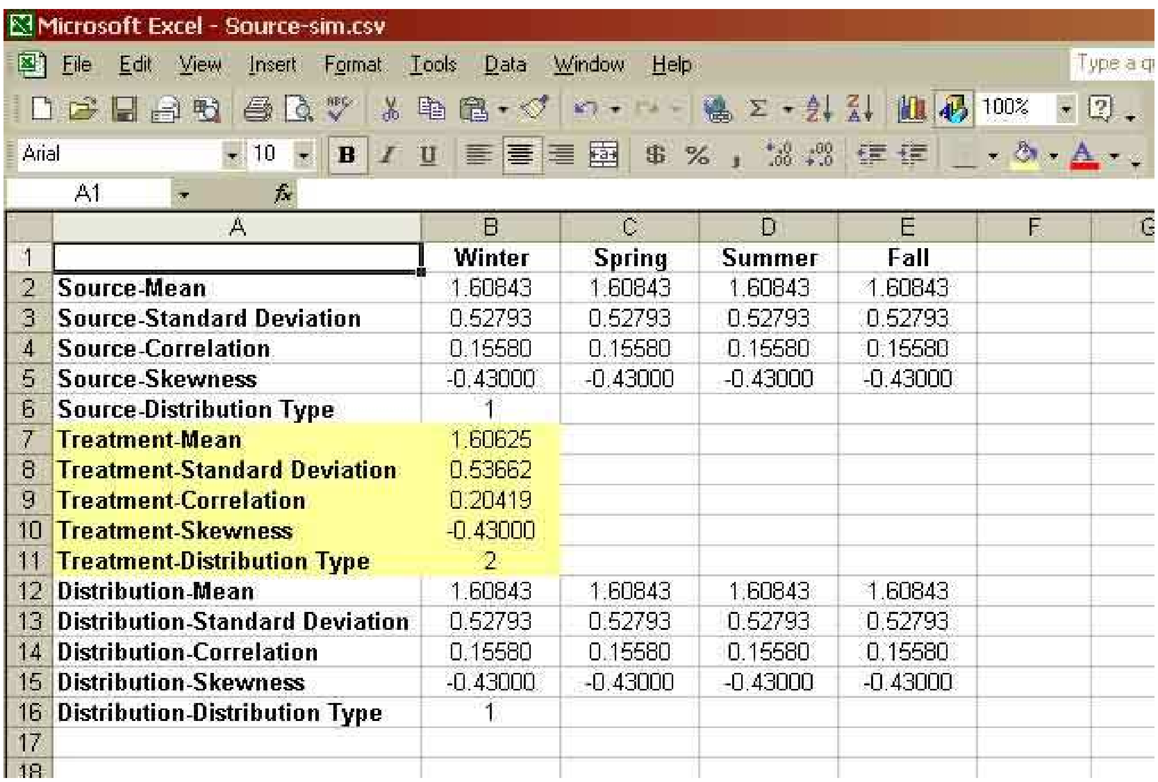
## III.6 Probabilistic simulation toolbox

### Historical records' statistics files

It contains all statistics of the three domains. It is in CSV format (without headings).

These statistics are:

- Mean
- Standard Deviation
- Correlation
- Skewness
- Distribution type: 1 for normal distribution, 2 for log normal distribution, 3 for Gamma distribution, and 4 for Gumbel distribution.

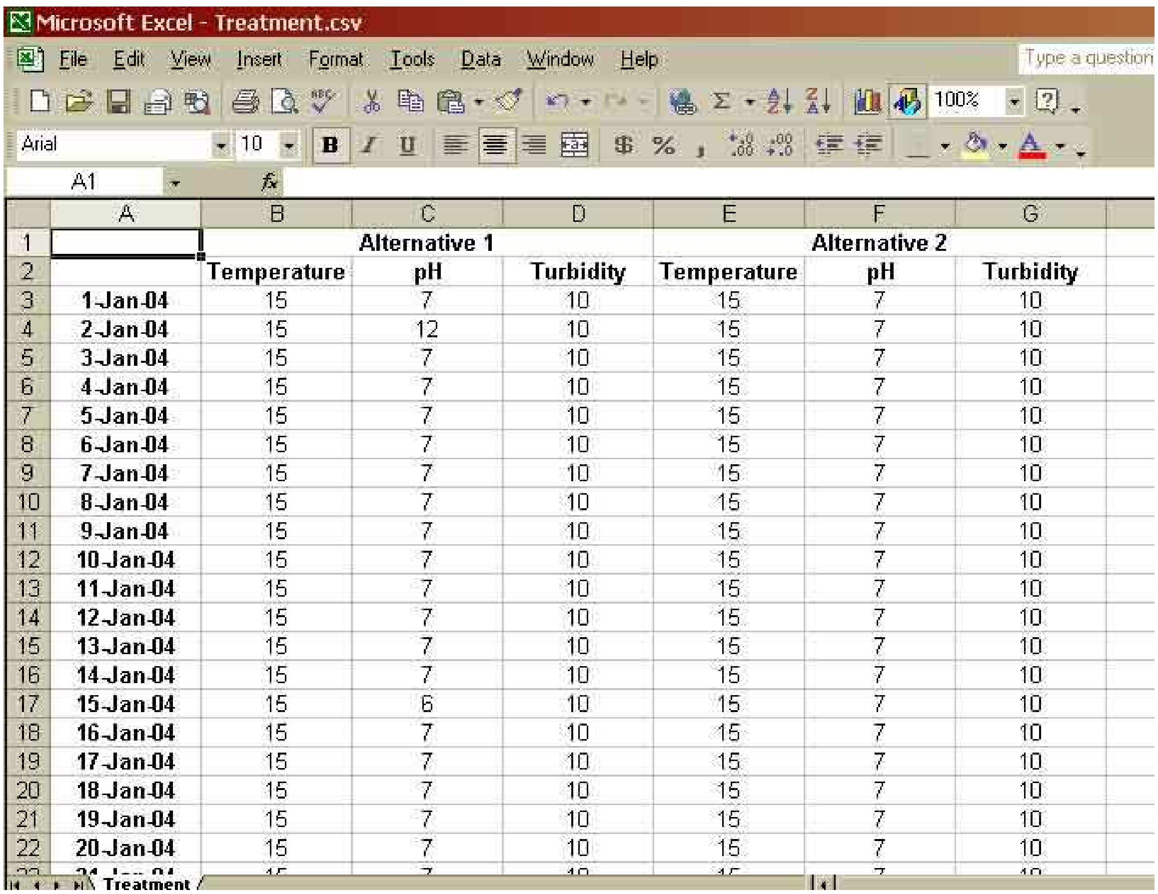



| | A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|---|
| 1 | | Winter | Spring | Summer | Fall | | |
| 2 | Source-Mean | 1.60843 | 1.60843 | 1.60843 | 1.60843 | | |
| 3 | Source-Standard Deviation | 0.52793 | 0.52793 | 0.52793 | 0.52793 | | |
| 4 | Source-Correlation | 0.15580 | 0.15580 | 0.15580 | 0.15580 | | |
| 5 | Source-Skewness | -0.43000 | -0.43000 | -0.43000 | -0.43000 | | |
| 6 | Source-Distribution Type | 1 | | | | | |
| 7 | Treatment-Mean | 1.60625 | | | | | |
| 8 | Treatment-Standard Deviation | 0.53662 | | | | | |
| 9 | Treatment-Correlation | 0.20419 | | | | | |
| 10 | Treatment-Skewness | -0.43000 | | | | | |
| 11 | Treatment-Distribution Type | 2 | | | | | |
| 12 | Distribution-Mean | 1.60843 | 1.60843 | 1.60843 | 1.60843 | | |
| 13 | Distribution-Standard Deviation | 0.52793 | 0.52793 | 0.52793 | 0.52793 | | |
| 14 | Distribution-Correlation | 0.15580 | 0.15580 | 0.15580 | 0.15580 | | |
| 15 | Distribution-Skewness | -0.43000 | -0.43000 | -0.43000 | -0.43000 | | |
| 16 | Distribution-Distribution Type | 1 | | | | | |
| 17 | | | | | | | |
| 18 | | | | | | | |

## III.7 Probabilistic multi-objective toolbox

### Source, treatment, and distribution files

They contain records dates and values for each alternative. Each domain should be in one file. Missing data points must have (-100) values and should not be left empty. It is in CSV format (without headings).




| | A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|---|
| 1 | | | Alternative 1 | | | Alternative 2 | |
| 2 | | Temperature | pH | Turbidity | Temperature | pH | Turbidity |
| 3 | 1-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 4 | 2-Jan-04 | 15 | 12 | 10 | 15 | 7 | 10 |
| 5 | 3-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 6 | 4-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 7 | 5-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 8 | 6-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 9 | 7-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 10 | 8-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 11 | 9-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 12 | 10-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 13 | 11-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 14 | 12-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 15 | 13-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 16 | 14-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 17 | 15-Jan-04 | 15 | 6 | 10 | 15 | 7 | 10 |
| 18 | 16-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 19 | 17-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 20 | 18-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 21 | 19-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |
| 22 | 20-Jan-04 | 15 | 7 | 10 | 15 | 7 | 10 |