The Use of Risk Analysis Techniques to Determine the Probability of Producing Non-Compliant Drinking Water: Focusing on Dual Media Rapid Gravity Filtration

by

Lawrence Brett McAllister

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

ABSTRACT

The main goal of a drinking water treatment plant is to provide safe drinking water for its consumers. Historically, this was accomplished through monitoring the influent and effluent water quality to ensure that the water quality met a set of guidelines and regulations. However, as the limitations of relying on compliance monitoring become more evident, water utilities and drinking water treatment plants are beginning to utilize risk management frameworks to help provide safe drinking water and to mitigate potential risks. Applying a risk management framework requires an evaluation of potential risks. This systematic evaluation can be performed through using risk analysis methods.

The overall goal of this research is to analyze and evaluate risk analysis methodologies that are used in a variety of engineering fields, select two risk analysis methods, and use them to evaluate the probability of producing non-compliant drinking water from a rapid gravity filtration unit with respect to turbidity.

The risk analysis methodologies that were used in this research were the consequence frequency assessment and computer modelling combined with probabilistic risk analysis. Both of the risk analysis methodologies were able to determine the probability of producing non-compliant water from a rapid gravity filtration unit with respect to turbidity. However, these methodologies were found to provide different numerical results with respect to each other. The consequence frequency assessment methodology was found to be easier to implement; however, the consequence frequency assessment was only able to be performed on one parameter at a time.

Computer modelling and probabilistic risk analysis enabled the inclusion of multiple parameters which provided a more comprehensive understanding of the filtration unit.

The primary conclusion from this research is that the risk analysis methods, as they are described in this thesis, are not sufficient to use directly on a rapid gravity filtration unit without further modification. Furthermore, although the risk analysis methods provided some guidance, these methods should only be used as a part of a complete risk management process.

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CHAPTER 1
INTRODUCTION

1.1 Background

The primary goal of any water treatment plant is to provide safe, quality drinking water to the public. To achieve this goal, water treatment plants have historically monitored the effluent water quality to ensure that the concentration of specific effluent parameters is below a regulation or guideline. This reliance on effluent monitoring as a tool of ensuring that safe drinking water is produced has some inherent problems which need to be addressed.

Monitoring effluent water quality is limited in its scope because only a limited number of the possible parameters present in treated water can be monitored on a regular basis (Sinclair & Rizak, 2004). This limitation of scope exists since there is not enough time or money to monitor every possible water treatment parameter. Consequently, indicator water quality parameters are used to monitor a set of parameters as opposed to monitoring each parameter individually. However, when using indicator water quality parameters, there can be a lack of correlation between the indicator water quality parameter and the parameter of interest. For example, although microbiological parameters are monitored by a set of indicator organisms which correlate well with the presence of bacteria, the same indicator organisms do not provide an accurate measurement of the amount of viruses and protozoa present in the water (Sinclair & Rizak, 2004).

Secondly, monitoring often is performed by sampling the effluent water quality on an intermittent basis. This intermittent sampling is then considered representative of the water quality throughout the entire time period of interest (Sinclair & Rizak, 2004). However, it is possible that a water quality parameter exceeds a guideline or regulation during the time period between sampling points.

Finally, reliance on compliance monitoring promotes a system that corrects failures after they have occurred, not a system that focuses on the elimination of these failures before they happen (Sinclair & Rizak, 2004). This can create a situation where a water treatment plant corrects a specific problem over the short term to avoid being out of compliance with a guideline or regulation without attempting to stop these situations from occurring again.

The limitations stated above concerning compliance monitoring and the effect of these limitations on treatment systems can be seen through evaluating the Walkerton outbreak in May 2000. Hrudey (2004), states that the outbreak did not occur because of an inadequacy in the level of stringent regulations and guidelines, but rather through a failure within the overall management of water quality. Therefore, to avoid the limitations of compliance monitoring, there has begun a transition in the water treatment sector to manage water quality through risk management frameworks.

Even with the shift to risk management frameworks, as recently as 1996, it has been reported that the use of risk assessment techniques is not widespread in the water treatment field (Egerton, 1996). Currently, the Australian Drinking Water Guidelines (National Health and Medical

Research Council, 2004) provide one of the most comprehensive frameworks for the management of water quality. In Canada the use of water management frameworks has also begun to develop as exemplified by Saskatchewan's 2005-06 Provincial Budget Performance Plan – Safe Drinking Water Strategy (Saskatchewan Environment, 2005).

1.2 Objectives and Significance of Research

The goal of this research is to examine the concepts of risk management, risk assessment and risk analysis as they apply to water treatment. As risk management becomes more commonly applied, water utilities will eventually begin to use risk assessment and risk analysis tools. While there are tools available for risk analysis to assess a treatment failure, there is currently no consensus on the methods to be used in such an analysis. Therefore, this research focuses on risk analysis methods and their use to evaluate risks associated with the production of safe drinking water. Specifically the objectives of this research are as follows:

- Provide a brief overview of risk analysis methods that have been used in analyzing water treatment processes for the risk of producing non-compliant water;
- Select and modify one or more of the evaluated risk analysis methods so they can be applied to water treatment for the analysis of operational risks, as opposed to mechanical risks, for producing non-compliant water;
- Determine the risk of producing non-compliant water on a properly operated water treatment plant with respect to turbidity using two risk analysis techniques;
- Comment on the information that can be ascertained from the two different operational risk analyses; and

- Discuss the ability of the two operational risk analysis methods to adequately assess the risk of producing non-compliant water from a rapid gravity filter specifically and from a water treatment plant in general.

1.3 Outline of Thesis

Risk management is a complex process composed of different parts. Therefore, to establish a frame of reference for a discussion concerning risk management, Chapter 2 begins with a review of some of the basic principles of risk management, risk assessment, and risk analysis and the relationship between these three elements. Sections 2.2 - 2.5 review some of the more common methods of performing risk analysis and discuss if they have been used to analyze the risk of producing non-compliant water in a water treatment facility. Finally, Section 2.6 provides a review of different computer software packages that are currently available to model drinking water treatment processes.

Chapter 3 focuses on providing an overview of the analysis methods that were used in completing the rest of the thesis. This discussion will include a detailed description of the selected risk analysis methods including a description of the system that was analyzed, a theoretical discussion of the chosen treatment unit (rapid gravity filtration), and a discussion of the statistical and numerical methods that were used during the risk analysis.

Chapters 4 and 5 present the results and discussion related to the individual risk analysis methods. These chapters will focus on how that particular risk analysis mechanism is able to provide an estimate of the risk of producing non-compliant water from a properly operated filtration unit.

A comparison between the two risk analysis methodologies is provided in Chapter 6. Focus is placed on how the two analysis methodologies analyze the risk or producing non-compliant water in a filter and what affect the risk analysis can have on an understanding of the filtration process. A general discussion of these two risk analysis methodologies and their use in assessing water treatment performance is also given.

Several conclusions and recommendations are made in Chapter 7 and 8 so that the operational risk analysis process can be improved to provide a more comprehensive and accurate analysis of a system in the future.

CHAPTER 2
LITERATURE REVIEW

2.1 The Terminology of Risk and Risk Based Methods

The term "risk" has multiple meanings depending on when and how it is used. This issue is emphasized by Jardine and Hrudey (1997), who identify the need for all parties involved in a discussion concerning risk to eliminate misunderstandings before they occur. Consequently, before discussing risk and the use of risk based methods to assess water treatment performance, a clear understanding of the terms used during the discussion is needed. This discussion provides a frame of reference for the rest of the thesis; however, it should be noted that there is no comprehensive agreement for some of the definitions provided. Thus the discussion is provided so the terminology and its use can be related to this thesis alone.

2.1.1 Risk

A number of definitions for risk are available within the field of risk management and risk assessment. Kaplan and Garrick (1981) provide a comprehensive definition of risk while Jardine and Hrudey (1997) provide a discussion on the many possible meanings of risk. However, for this thesis, the following definition from the U.S. Presidential/Congressional Commission on Risk Assessment and Risk Management (1997) will be used as a definition of risk.

Risk is "the probability that a substance or situation will produce harm under specified conditions. Risk is a combination of two factors: the probability that an adverse event will occur (such as a specific disease or type of injury) and the consequences of the adverse event" (U.S.

Presidential/Congressional Commission on Risk Assessment and Risk Management, 1997). This definition of risk incorporates the three components of risk that are most commonly used in a discussion of specific risks. The threat must be identifiable, it must be able to occur and it must cause harm under a specific set of situations.

2.1.2 Risk Management Frameworks

Risk management frameworks can be loosely described as organized methodologies that are designed to help understand what risks are present in a situation and to help mitigate these risks. The following definition from the U.S. Presidential/Congressional Commission on Risk Assessment and Risk Management (1997) provides a better overview of the actions and process of risk management.

Risk Management is "the process of identifying, evaluating, selecting, and implementing actions to reduce risk to human health and to ecosystems. The goal of risk management is scientifically sound, cost-effective, integrated actions that reduce or prevent risks while taking into account social, cultural, ethical, political, and legal considerations" (U.S. Presidential/Congressional Commission on Risk Assessment and Risk Management, 1997).

An example of a risk management framework is the U.S. Presidential/Congressional Commission Framework. A pictorial representation of the framework is shown in Figure 2.1. From this figure it is evident that the U.S. Presidential/Congressional Commission Framework separates the management of risks into seven integrated stages. These stages provide a methodological way of evaluating and managing the risks associated with environmental health. These stages are described in detail in U.S. Presidential/Congressional Commission on Risk

Assessment and Risk Management (1997) or in Krewski et al. (2002); however, a brief summary will be presented here.

1. Define the problems and place them in their context
2. Analyze risks using risk assessment to accurately characterize the risk
3. Estimate options for managing the risk
4. Make a decision based on the best available knowledge
5. Take action to implement the solutions
6. Evaluate the results to determine if new action should be undertaken and whether the action taken was sufficient
7. Engage the stakeholders throughout the process

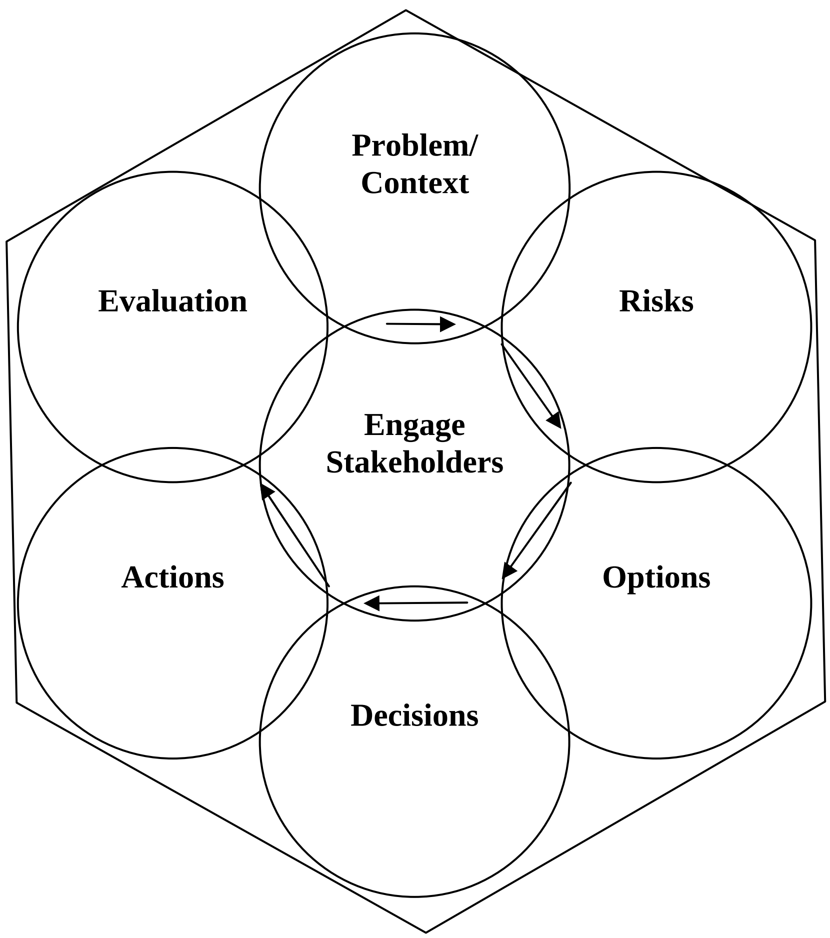

Figure 2.1: The U.S. Presidential/Congressional Commission Framework. (Source: United States, Presidential/Congressional Commission on Risk Assessment and Risk Management, 1997)

Risk management frameworks, such as the U. S. Presidential/Congressional Commission Framework, were not specifically designed for the water treatment field. Although these frameworks are useful to understand some issues in water treatment (Sinclair & Rizak, 2004), there are some principles of risk management, such as those described by Hrudey (2001, 2004), that directly relate to the water treatment field. Consequently, risk management frameworks that are directly applicable to the water treatment field have recently been developed. .

One example of a risk management framework developed for a water utility is provided by Considine (2004) who presented an outline of a risk management framework that has been implemented by Barwon Water, a water authority in the Victoria Region of Australia. A general framework is provided by the Australian Drinking Water Guidelines (ADWG) which has implemented one of the first risk management frameworks for water treatment with the Framework for Management of Drinking Water Quality. This framework was developed after a review of a number of existing risk management frameworks and it focuses specifically on issues related to the management of drinking water (Sinclair & Rizak, 2004). Although a full evaluation will not be completed here, Figure 2.2 outlines the basic principles of the Framework.

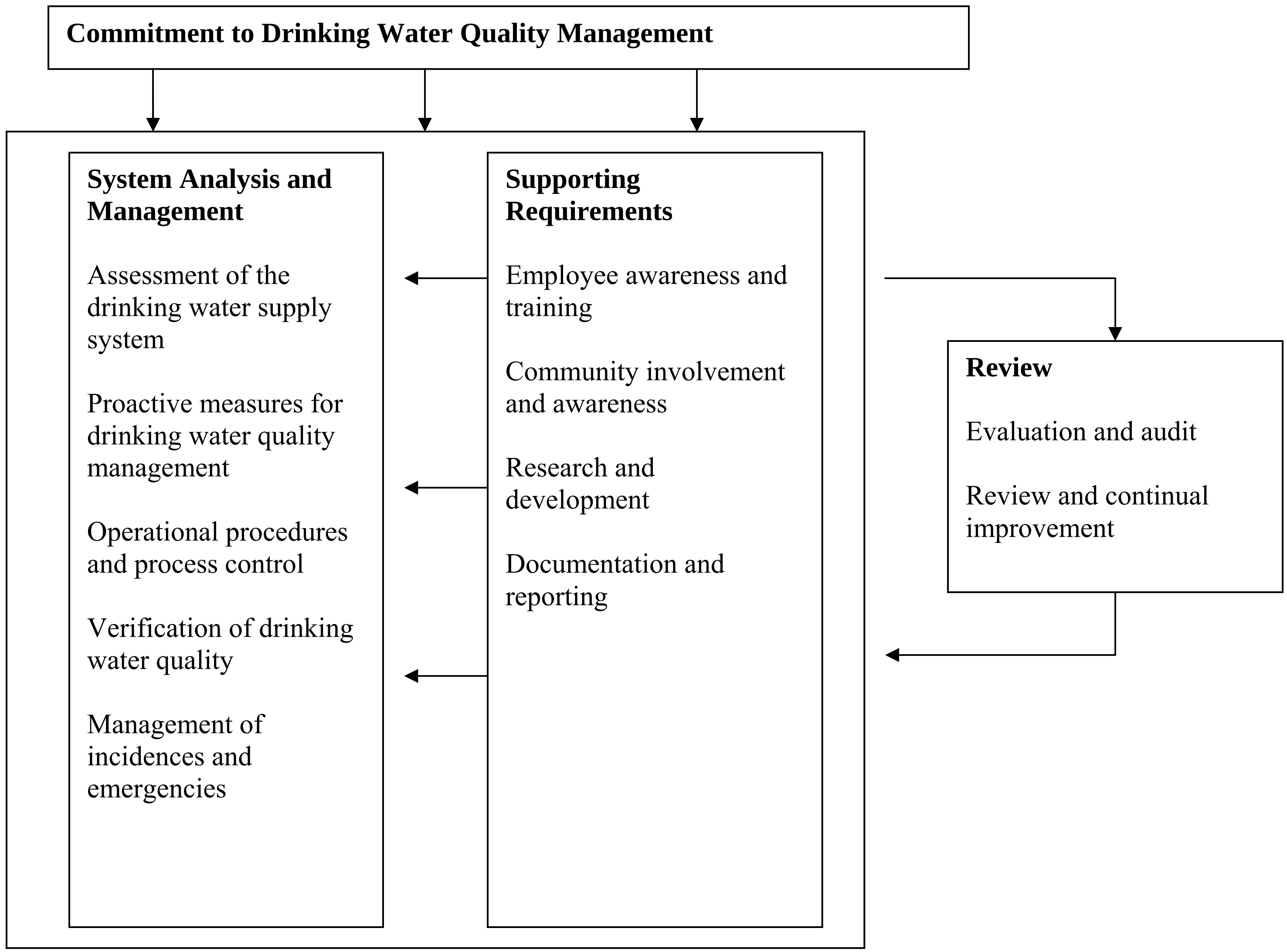

Figure 2.2: Framework for Management of Drinking Water Quality (Source: National Health and Medical Research Council, 2004)

An important aspect of the Framework for Management of Drinking Water is that it does not rely on one system of compliance, such as compliance monitoring; however, the framework incorporates all elements of providing water to consumers from water supply to the final delivery of potable water (National Health and Medical Research Council, 2004). Therefore, this framework provides a complete guide to water quality management which starts with an organizational commitment to drinking water quality management. Once this organization commitment is in place, a series of steps can be taken which include developing a system wide analysis and management plan, developing supporting requirements such as employee training and providing a regular review of how the framework is functioning (Sinclair & Rizak, 2004).

2.1.3 Risk Analysis, Risk Assessment and Risk Management

Risk management frameworks regularly incorporate a process called risk assessment as part of their overall approach. This is evident as both the more general U.S. Presidential/Congressional Commission Framework and the Australian Framework for Management of Drinking Water Quality have an element that can be described as risk assessment. Furthermore, risk assessment incorporates the process of risk analysis. The overall relationship between risk analysis, risk assessment and risk management is shown in Figure 2.3.

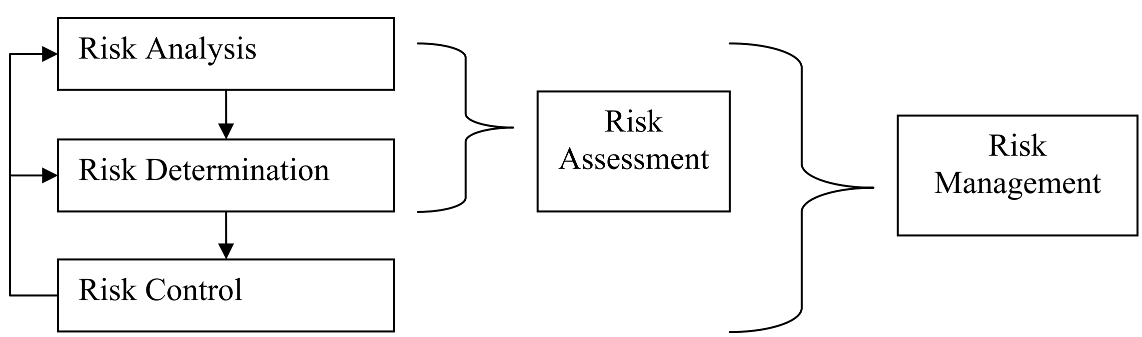

Figure 2.3: Relationship between risk analysis, risk assessment and risk management (adapted from Rak, 2003)

Specifically, risk assessment is "an organized process used to describe and estimate the likelihood of adverse health outcomes…" (U.S. Presidential/Congressional Commission on Risk Assessment and Risk Management, 1997). The use of risk assessments is common in many fields such as microbial risk assessments, human health risk assessments, or ecological risk assessments. The formal process of risk assessment can be broken down into the analysis of the three components of risk proposed by Kaplan and Garrick (1981). These components are identifying possible hazards, evaluating the probability of a specific hazard occurring and determining the consequence of the hazard if it occurs.

Risk analysis provides a mechanism to evaluate the different risks identified within a formal risk assessment (Rak, 2003). Therefore, risk analysis methodologies focus on the probability of a risk occurring and the consequences of that risk. From Figure 2.3 it can be seen that risk analysis is a unique element of both risk assessment and risk management. The rest of this thesis will focus on the topic of risk analysis and the mechanisms used to perform a risk analysis on a water treatment plant; however, the reader is encouraged to consult the above mentioned articles for more information on risk management frameworks or on risk assessment.

2.2 Risk Analysis Methodologies

After a series of risks have been identified through a risk assessment and risk management process, it is necessary to evaluate these risks. There are many different methodologies and techniques that are used to perform risk analysis. This next section briefly covers some common risk analysis methodologies. It is not the intent that the following discussion be comprehensive or sufficient for a full understanding of all the different risk analysis methodologies available, but that a broad picture of different methodologies is provided.

One aspect of risk analysis to take into account during the following discussion is that, although by definition risk analysis is concerned with the probability of an event and the consequence of that event, in many instances the methodologies evaluated focus solely on the probability of the event occurring. The implication here is that it is up to the risk evaluator to take into account the consequences of an event occurring.

2.2.1 Conservative Approach

The output from a system can be represented by the combination of the model of the system and a given set of inputs to the system. The model of the system can be represented as a mathematical performance function, $g(\mathbf{X}_1,\mathbf{X}_2..\mathbf{X}_n)$, while the set of inputs can be represented by the vectors of possible inputs to the model, $\mathbf{X}_1$, $\mathbf{X}_2..\mathbf{X}_n$. The vectors of inputs reflect the variable nature of the input. During the conservative approach, a value of $\mathbf{X}_1$, $\mathbf{X}_2..\mathbf{X}_n$ is chosen which would result in the worst possible outcome if run through the performance function that describes the system. If the system can handle this situation, then it is said to be reliable or it is able to deal with the specific risk. This concept is common in fields such as structural engineering (Ang & Tang, 1984), human health and environmental engineering (Cullen & Frey, 1992).

Although this method is common, Ang and Tang (1984) state that there is difficulty in choosing the worst case scenario for a system because determining the worst case is often based on a subjective judgment. Furthermore, both Ang and Tang (1984) as well as Cullen and Frey (1992) indicate that there is difficulty in using a single numerical value to represent an input that may not be accurately known and therefore inputs may be better represented by a distribution. Even with these difficulties, conservative estimates are still used but sometimes only as a screening tool for more complicated assessments (Cullen & Frey, 1992).

2.2.2 Algebraic Analysis

Algebraic methods of analysis were developed so that conservative values would not have to be used. The algebraic analysis uses the same model of the performance function of the system as defined before, $g(\mathbf{X}_1,\mathbf{X}_2..\mathbf{X}_n)$, and the same set of input variables, $\mathbf{X}_1$, $\mathbf{X}_2..\mathbf{X}_n$,. However, instead of choosing a conservative value of the input variables, the input values to the model are characterized as probability distributions. The performance function of the system is then analyzed to see how often the input variables will produce a situation which causes a failure within the model over the entire range of all input values.

The result of using probability distributions of input variables is that the output is also a distribution; thus the risk is defined by a distribution instead of a single value (Verdonck, 2003). There are a variety of different methods used to determine the output distribution including combining probability distributions, and approximate solutions. Although the approximate methods allow for algebraic methods to be used in a larger number of situations, even with a well-defined performance function the mathematics necessary to undertake a risk analysis using one of the methods are often difficult or impossible to perform. Furthermore, all algebraic methods, whether exact or approximate, require a situation where the mathematical performance function of the system is explicitly known. If the performance function is not known, algebraic methods are not possible.

2.2.2.1 Combining Probability Distributions

If the probability distribution of the different incoming variables is known precisely, it is possible to mathematically combine the separate distributions together within the performance function to determine the output distribution. For example, if a performance function of a system is defined as Z = X*Y and both X and Y can be described as exponential distributions with cumulative distribution functions of $F(X) = 1\text{-}e^{-X/\alpha}$ and $F(Y) = 1\text{-}e^{-Y/\beta}$, then the cumulative distribution function of Z is $F(Z) = 1\text{-}e^{-Z*(\alpha+\beta)/\alpha\beta}$ (Vose, 1996). This method is difficult to implement as the number of variables and the level of complexity of the performance function increases. Furthermore, complexities can arise from a variety of sources such as correlation. If X and Y are correlated, then the above analysis is not correct.

2.2.2.2 Approximate Methods of Combining Probability Distributions

As the complexity of the performance function increases, it becomes difficult to combine the individual probability distributions; therefore, a number of approximate methods have been developed. Some of these methods are the First-Order Second Moment Method (FOSM or MVFOSM), Advanced First-Order Second Moment Method (AFOSM) or the First-Order Reliability Method (FORM) (Pandey, 2004). These methods simplify the analysis by using approximating techniques, such as Taylor series expansion, enabling more complex performance functions to be analyzed.

2.2.3 Qualitative Methods

In some situations it is not possible or necessary to perform a numerical risk analysis of a system; under these conditions risk analyses can be performed qualitatively. This method of analyzing risk involve listing possible risks and then determining their approximate level in a qualitative manner such as “low” or “high” (Pollard, Strutt, Macgillivray, Hamilton, & Hrudey, 2004). A qualitative risk analysis can be performed using any number of criteria such as the chance of a risk occurring or the cost of a risk after it occurs. The result from a qualitative risk analysis is then an understanding of what risks should be addressed based upon the analysis criteria. The qualitative nature of this assessment allows the analysis to be performed without the presence of a mathematical performance function.

A specific qualitative method is provided by the Australian Drinking Water Guidelines (National Health and Medical Research Council, 2004). This method analyzes risks based on two criteria: the likelihood of an event occurring and the outcome of an event. The likelihood of an event is evaluated based on a scale that ranges from rare to almost certain, while the outcome of such an event is evaluated based on a scale that ranges from insignificant to catastrophic. An overall risk level is then determined, ranging from low to very high, through a combination of the two criteria. For example, if an event was almost certain to occur but the consequences of the event were low; the resulting risk level could be classified as moderate (National Health and Medical Research Council, 2004).

2.2.4 Fault Trees

A fault tree analysis can be used in either a quantitative or qualitative manner. The fault tree methodology begins with a failure, called a fault, and then identifies and describes the series of events leading up to the fault (Ang & Tang, 1984). The primary mechanism of analysis is through a pictorial tree diagram where different events are represented by symbols and the relationship between the events represented by lines.

Through a fault tree analysis, it is possible to understand what mechanism or mechanisms can cause one fault, enabling a qualitative understanding of the system. To obtain a quantitative analysis of a fault tree, a probability value is assigned to each event in the fault tree. The overall probability of the fault is then calculated through a probabilistic analysis of its related events.

2.2.5 Event Trees

The event tree methodology is similar to a fault tree, except that the methodology begins with an initiating event and identifies a series of events that occur after the initial event to see if any of the future events lead to a failure (Ang & Tang, 1984). In that respect, fault and event trees are different ways to analyze the same system. Fault trees start with a fault and see what events can lead up to it, while event trees take an event and see if they result in a fault.

Event trees are also described by pictorial diagrams with symbols representing events and lines representing the relationship between the events. Qualitatively, event tree analysis allows for an understanding of how an event will affect a system. An event tree can also be analyzed quantitatively by assigning probabilities to each of the identified events and calculating any adverse fault through probabilistic analysis.

2.2.6 Critical Component Analysis

The critical component analysis (CCA) is a method developed by the Unites States Environmental Protection Agency (EPA) in 1982 for use within the wastewater treatment industry (as cited in Eisenberg, Soller, Sakaji, & Olivieri, 1998). The method uses past maintenance and repair records to determine the reliability of each individual component in the wastewater treatment system (Eisenberg et al., 1998). The overall reliability of the system is then calculated using historical data and probability concepts to combine the individual reliability of each component into overall system reliability.

2.2.7 Simulation Methodologies

The use of simulation during a risk analysis involves performing a risk calculation a number of times with different input values to get a representation of the overall risk. Although simulations are often used when performing a probabilistic risk analysis, this is not always the case. A probabilistic risk analysis is a type of risk analysis that uses probability models to calculate and represent risk levels (EPA, 2001). Using these definitions, it is possible for some of the above discussed methods such as FORM to fall into the category of probabilistic risk analysis methods but not use simulation to perform the analysis.

Simulations are useful when a model of the system is available but the algebraic analysis required for methodologies such as FORM and AFOSM is not possible due to the complexity of the system. Furthermore, because mathematical manipulation is not needed, a model of the system which is not a mathematical performance function, such as a computer model, can be used to represent the system in a simulation risk analysis.

For a simulation risk analysis, a model of a system is developed such as $g(\mathbf{X})$, where $g(\mathbf{X})$ can be a mathematical equation or some other model of the system in question. A system of variables, $\mathbf{X}_1$, $\mathbf{X}_2..\mathbf{X}_n$, represent the inputs to the model. Similar to the algebraic analysis, the input values are characterized as probability distributions which represent the variability of the inputs. Input values are randomly selected from the input distributions and inputted into the model to produce an output. Performing this simulation many times creates a series of outputs from the model that represent possible outcomes for the system under different situations. This procedure is shown in Figure 2.4 where the distributions are represented as probability distribution functions (PDFs). Although simulation is mathematically easier to perform than algebraic analysis, the method is data intensive and numerous trials are necessary to accurately characterize the possible output from the system.

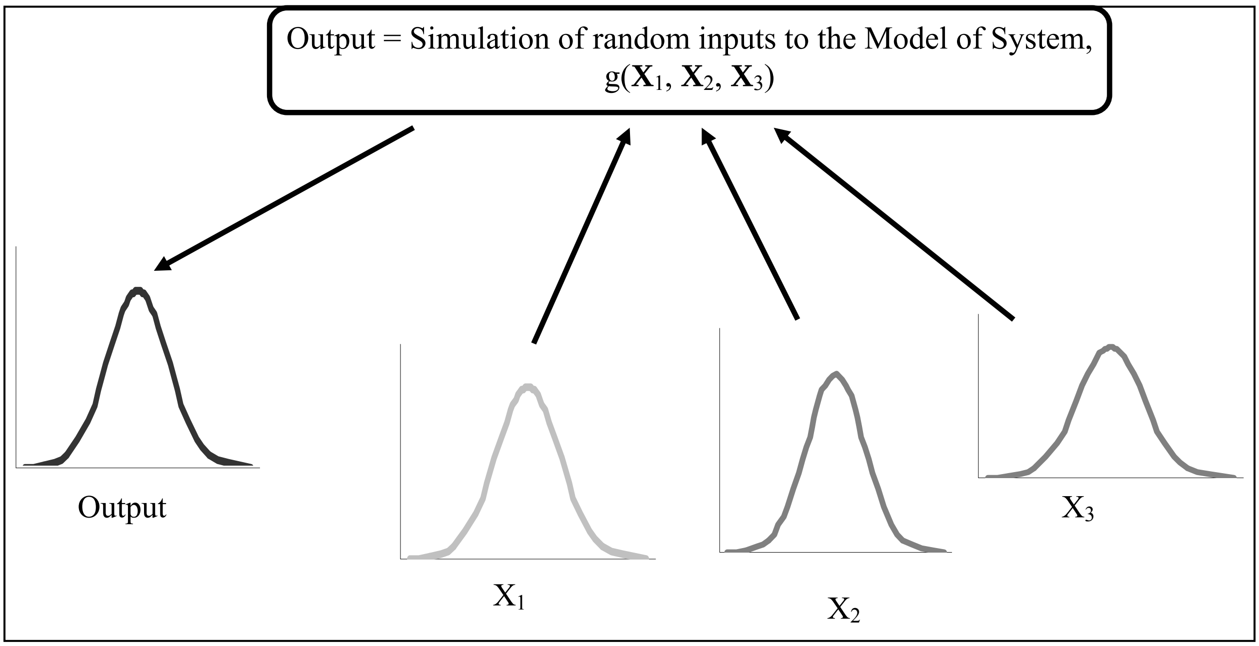

Figure 2.4: Diagram of risk analysis using simulation

As with any risk analysis, for any simulation methodology, a correct model of the system is needed to undertake the analysis. Without a correct model, the output will not be representative of how the system functions.

2.2.7.1 Consequence Frequency Assessment

One specific type of simulation risk analysis is the consequence frequency assessment (CFA). The CFA is a risk analysis method that uses statistical analysis to provide a model of the performance of multiple barriers in a system and to determine the performance level of the system. In a water treatment plant the CFA methodology models each barrier as a separate probability distribution of removal efficiencies for that barrier. This probability distribution represents the possible range of removal efficiencies that a barrier can experience and the probability that a given removal efficiency will occur; therefore, the barrier no longer "fails" or "does not fail", but the barrier performs within a range (National Research Council, 1998).

Mathematically, the performance of any treatment barrier, such as that shown in Figure 2.5, can be described as (C_1/C_0) where C_0 is the incoming concentration of the parameter and C_1 is the outgoing concentration of the parameter.

Figure 2.5: Diagram of a single barrier treatment system

However, the performance of a treatment barrier will not always remain the same, causing the treatment barrier to be represented as $F_1(C_1/C_0)$, where F_1 is a function representing the probability distribution of the treatment efficiency of the first barrier (Haas & Trussell, 1998). Calculating the effluent concentration of the treatment barrier is a matter of evaluating the integral

$$\int_{C_{1a}}^{C_{1b}} F_1\left(\frac{C_1}{C_0}\right) dC_1$$ **Equation 1**

This analysis will provide the effluent concentration probability distribution, between C_{1a} and C_{1b},, for a given influent concentration, C_0 (Haas & Trussell, 1998). If, however, C_0 is not a constant value but a function representing the influent concentration, the integral becomes

$$\iint f_0(C_0)F_1 dC_0 dC_1 \qquad \textbf{Equation 2}$$

where $f_0(C_0)$ represents the influent distribution and F_1 represents the first treatment process (Haas & Trussell, 1998).

The effluent of a multiple barrier system, such as that shown in Figure 2.6, can then be mathematically represented as

$$C_2 = \iiint f_0(C_0)F_1F_2 dC_0 dC_1 dC_2 \qquad \textbf{Equation 3}$$

where C_2 is the effluent concentration, $f_0(C_0)$ is the influent probability distribution, F_1 represents the first treatment step and F_2 represents the second treatment step (Haas & Trussell, 1998).

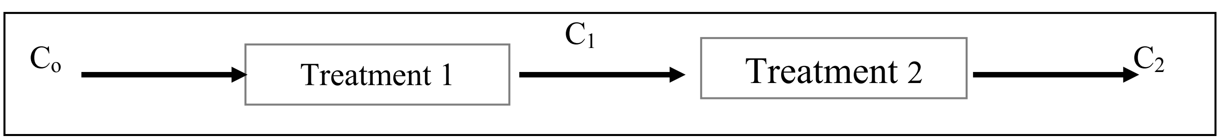

Figure 2.6: Diagram of a multiple barrier treatment system

Mathematically, the evaluation of the integrals described in Equation 3 may be difficult and/or impossible in many situations (Haas & Trussell, 1998). Therefore simulation methods are often used to determine the effluent concentration while using the CFA methodology.

Using simulation risk analysis techniques involves representing Equation 3 as:

$$C_2 = C_0\left(\frac{C_1}{C_0}\right)\left(\frac{C_2}{C_1}\right) \qquad \textbf{Equation 4}$$

where the ratios of outgoing to incoming concentrations are represented by probability distributions that show the relative treatment efficiency of that step (Haas & Trussell, 1998). Figure 2.7 describes this process, where the outgoing concentration (C_2) probability distribution function is determined by, randomly selecting an influent concentration (C_0), treatment efficiency 1 (C_1/C_0), and treatment efficiency 2 (C_2/C_1) from their representative probability distribution functions This calculation is performed a number of times to determine the probability distribution function of the effluent from the treatment train.

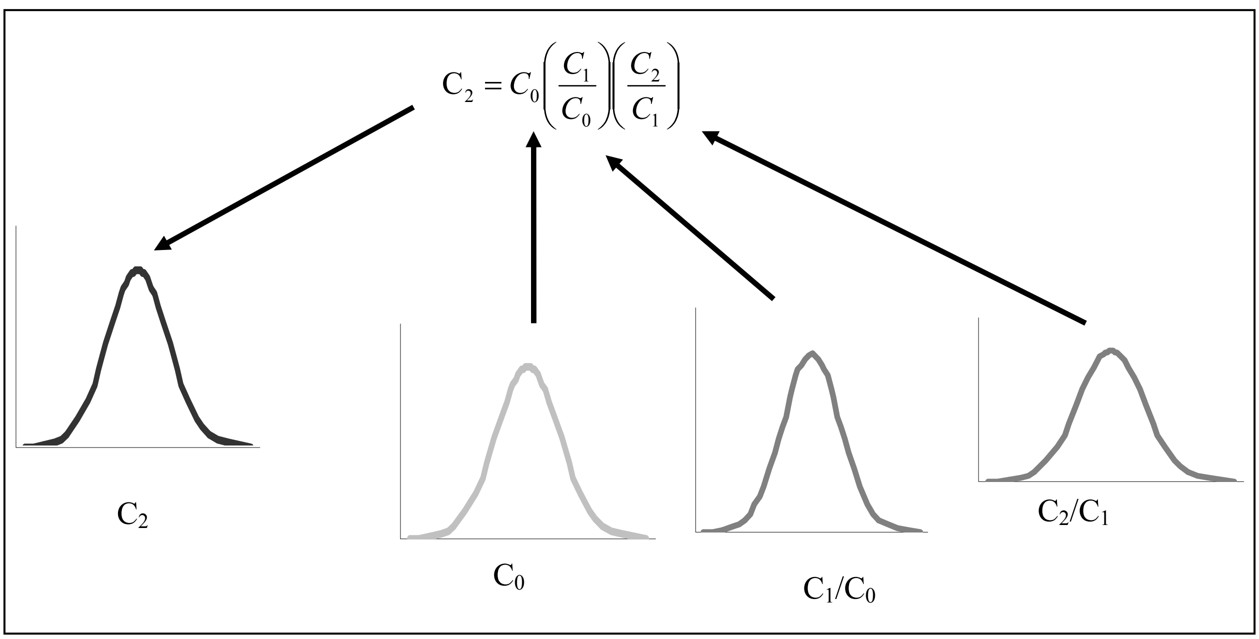

Figure 2.7: Diagram of the Consequence Frequency Assessment

2.3 Use of Risk Assessments in Water Treatment

Pollard et al. (2004) list a number of risks including financial risk, commercial risk, public health risk, environmental risk, reputation risk, and compliance/legal risk that can be experienced by water utility managers. However, a water treatment plant in operation can experience two types of risks that will affect the output water quality: risks of mechanical failures and risks of operational failures (Baxter & Barbara, 2003). Mechanical failures occur because of a mechanical defect or error within the system. These can be due to pump shutdowns or other problems associated with the mechanical operation of a component. Operational failures are connected to the operation of the system including changes in process efficiency associated with the changes in influent water quality, where the reduction is not due to an error within the mechanical equipment. Because of the differences between the two types of risks, mechanical risks focusing more on equipment and operational risks focusing on more performance, different methodologies have developed to analyze these different types of risk.

2.3.1 Algebraic Risk Assessments

Algebraic risk assessment techniques, such as those described in Section 2.2.2, are rarely used in environmental engineering or in water treatment process analysis. One example of the use of algebraic methods is by Vasquez, Maier, Lence, Tolson, and Foschi (2000), where FORM is used along with genetic algorithms to estimate the probability that a given amount of waste dumped into river in Oregon will cause environmental parameters, such as the dissolved oxygen, to drop below regulatory levels. Another example is provided by Portielje, Hvitved-Jacobsen, and Schaarup-Jensen (2000) who use the FORM methodology along with deterministic water quality models to analyze the probability that a stream will experience low levels of dissolved oxygen. However, the use of the FORM methodology is possible in both cases because a performance function, namely the Streeter-Phelps equation, is available for use. Performance functions may be available for water treatment but they are not as reliable or transferable between treatment systems because of the complex processes involved in water treatment; consequently algebraic methods are not used.

2.3.2 Evaluation of Mechanical Risks

Mercer (1988) performed a comprehensive assessment of the risks associated with the chlorination process within a water treatment plant such as the risk of the chlorine pressure falling in the headers or the risk that a chlorinator becomes plugged. These risks were evaluated using a combination of fault trees and event trees while the risks were calculated quantitatively by assigning probability values to the different sub-events. This analysis was able to provide a comprehensive analysis of the chlorination process, but the level of complexity involved in such an analysis is shown by the fact that an entire Master's thesis work was performed on one process within the treatment system.

Eisenberg et al. (1998) used the critical component analysis to evaluate the mechanical reliability of a water treatment plant. The method calculated an overall operating availability number which was a numerical way of expressing the reliability of a component. This number took into account all aspects of a components reliability including the failure rate of a component and the overall time a component was available (Eisenberg, Soller, Sakaji, & Olivieri, 2001). This analysis was able to show which components required further analysis or which components were failing at a fast rate.

Fault trees, event trees, and critical component analysis are common methods used in the analysis of mechanical risks; however, other methods have been used to assess the mechanical reliability of a water treatment system. When performing an assessment on a waste water treatment plant, Harris (1985) used availability modelling to determine the reliability of a treatment process. For each treatment component that was analyzed, a series of logic diagrams was prepared to identify how the component could fail. Using records of failure rates and repair times, the unavailability of the system was calculated. This method is a combination of critical component analysis and fault tree analysis.

The evaluation of mechanical risks within water treatment is similar to the evaluation of mechanical risks in other industries such as the nuclear industry (Keller & Modarres, 2005) or the aerospace industry (Pate-Cornell & Dillon, 2001); consequently, the methods used for this analysis are often the same. Therefore, although the evaluation of mechanical risks is an important part of a complete risk analysis, the focus of this thesis will be on evaluating risks that do not have a well-defined method of analysis, namely operational risks.

2.3.3 Evaluation of Operational Risks

The evaluation of operational risks does not have a standard method for analysis and, through an investigation of available literature; operational risks were found to be one of the lesser-known areas of risk analysis within a treatment process. Stated another way, there is not a standard method available to evaluate the risk that water which does not comply with drinking water standards will be produced by a properly functioning water treatment system.

One method to determine the risk that non-compliant water is produced by a properly operating treatment system is through a combination of modelling and probabilistic risk analysis as described in Figure 2.8. Through experimentation on a treatment processes, a model can be developed that accurately predicts output concentrations from input values. Once this model is developed, represented by the functional notation F(x), probabilistic risk analysis is performed on the model. Probabilistic risk analysis represents input parameters to the model as probability distributions. A simulation methodology is then used to randomly select the input values to the model. The output of such a probabilistic risk analysis is a probability distribution describing the different possible output concentration levels. The quantification of the risk from that parameter can then take different forms, the simplest method involves calculating the probability that the output concentration is above some defined concentration limit.

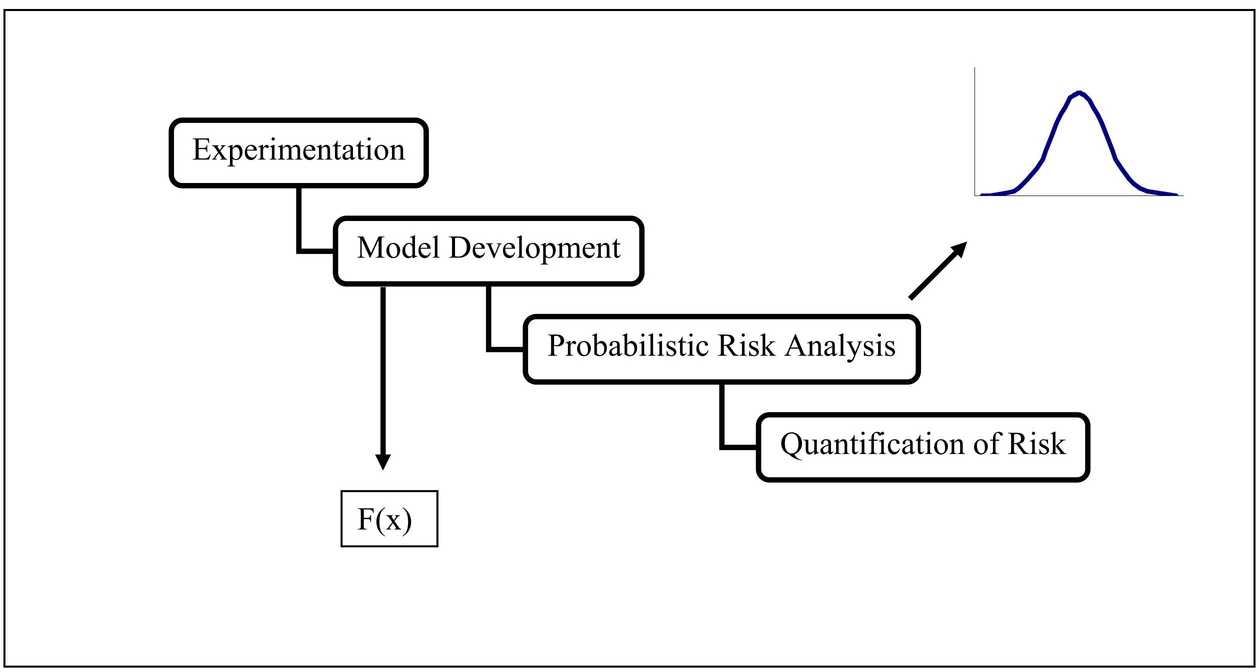

Figure 2.8: Diagram of a risk analysis methodology that combined model development with probabilistic risk analysis

This methodology is illustrated by Sadiq, Husain, Al-Zahrani, Sheikh, and Shaukat (2003), where a regression model of the average removal efficiency of total coliforms was used to model the slow sand filtration process. The model took into account filtration rate, sand bed depth, and effective media grain size. The regression equation model was then used to analyze the probability of failure through using probabilistic risk analysis. Modelling and probabilistic risk analysis was also used by Sadiq, Al-Zahrani, Sheikh, Husain, and Shauka (2004), to evaluate the performance of slow sand filters for the removal of total coliforms using fuzzy rule-based modelling. Probabilistic risk analysis and the fuzzy rule-based model were then used to analyze the probability of failure of the slow sand filter.

The use of modelling in risk analysis has also been used for non-microbial risk analysis such as the analysis by Song, Minear, Westerhoff, and Amy (1996) on the risk of bromate formation. A regression model that predicted bromate formation was developed from experimentation and then used to determine the risk of bromate formation. However, the risk was evaluated using conservative values for inputs, not through probabilistic risk analysis.

All of the above risk analyses focused on one parameter; therefore, for a complete analysis of a treatment system it would be necessary to construct a new model for each parameter of interest, unless a multiple-parameter model was developed. Thus, although use of modelling and probabilistic risk analysis is useful for focusing on one parameter, the analysis of an entire treatment system for multiple parameters could be time consuming and could overlook critical components such as the correlation of water quality variables to other parameters.

The consequence frequency assessment (CFA), as outlined by Haas and Trussell (1998) and by the National Research Council (1998), does not require an explicit model for the treatment process, but the CFA uses the distribution of removal efficiencies for a treatment process. The CFA methodology was used by Olivieri et al. (1999) to estimate pathogen removal over a water treatment facility. During this study, the removal efficiency of each treatment process was determined through a series of seeding studies. These seeding studies focused on each treatment process individually, allowing for a characterization of the removal efficiency of each particular process and a determination of the removal efficiency probability distribution function. To determine the ability of a given treatment train to remove viruses, the CFA methodology was used, allowing for a characterization of the effluent virus distribution over the full range of circumstances that the proposed treatment plant could experience.

The procedure, as outlined by Olivieri et al. (1999) and commented on by Eisenberg et al. (2001), provides a way to determine treatment efficiency under a variety of different conditions; however, the analysis focused on one parameter. Thus to implement a full CFA for a number of parameters in a water treatment plant, seeding studies would have to be performed on each process for each parameter that is included in the risk analysis.

Baxter, Barbara, and Coffey (2003) used the CFA methodology to evaluate the turbidity levels at an oxidation demonstration project plant in La Verne California. After performing this analysis Baxter et al. (2003) state that although the CFA assumes that parameter removal can be expressed as a function of incoming and outgoing concentration, parameter removal is a complex, non-linear event. This is one of the major criticisms of the CFA method. To deal with this issue, Baxter et al. (2003) performed a second analysis using a combination of modelling and probabilistic risk analysis, which is similar in methodology to that used by Sadiq et al. (2003) and Sadiq et al. (2004). The analysis by Baxter et al. (2003) used artificial neural networks as the model for the probabilistic risk analysis and included multiple variables in the analysis. By including influent temperature, influent turbidity, influent pH, ferric chloride dose, polymer dose, filter aid dose, filtration rate and filter influent turbidity Baxter et al. (2003) were able to obtain a more detailed analysis of the entire system.

Thus, the analysis by Baxter et al. (2003) avoided two of concerns of operational risk analyses in water treatment: the focus on only one parameter and the expression of a treatment process only by the efficiency of reduction of a parameter from influent to effluent.

2.3.4 Evaluation of Mechanical and Operational risks

The above discussion shows that there have been a limited number of attempts to analyze the operational risks experienced by a water treatment plant; however, a comprehensive risk analysis of a water treatment process would include an analysis of both operational and mechanical risks.

A probabilistic approach to performing a complete risk analysis is described in Laîné, Démotier, Odeh, Schön, and Charles (2002) and in Démotier et al. (2002). This approach uses a combination of fault trees and transfer functions to determine the overall probability of producing non-compliant water with respect to a standard. Transfer functions are a reduction factor applied to incoming parameter levels which describe how a treatment process operates with respect to the removal of a certain parameter.

Initially a transfer function for each treatment unit is determined. This involves determining the removal efficiency of a given treatment process for a given incoming concentration for each parameter of interest. Because the removal efficiency of a treatment process is not constant, this results in a graph of output concentration versus input concentration, where the percent reduction changes for each input value. This transfer function is called the nominal transfer function because it is the transfer function under normal operating conditions. The second step is to determine the different failure modes that can occur. These failures could be simple such as a filter failing due to a catastrophic flood. For each failure mode a degraded transfer function is determined which shows how the treatment system operates during that failure mode for each parameter of interest. During the third step the input probability distribution function of each parameter is defined. The final step is to set up fault trees for each parameter of interest, describing all the possible situations that could occur where treatment plant could produce non-compliant water. The output from an entire treatment train is then the multiplication of an incoming parameter level by the different transfer functions, whether nominal or degraded, which represent each treatment process.

This method takes into account both mechanical and operational failures of the system and is comprehensive in its analysis. However, an assumption of the methodology is that the transfer functions are constant and only change during a degraded mode. Furthermore, the transfer function focuses on the percent reduction of a parameter and does not mechanistically model the treatment system. Consequently, the effect of a particular input value such as high pH cannot be assessed through this method.

In some situations the data needed for the above described probabilistic analysis are not available. To deal with this situation Démotier et al. (2003a) and Démotier, Denoeux, and Schön (2003b) have developed a risk analysis methodology based on belief functions. According to Démotier et al. (2003a) the methodology is equivalent to the probabilistic methodology described in Laîné et al. (2002) and Démotier et al. (2002) if the data were known with perfect accuracy.

The use of belief functions allows for the representation of data if a known value of this information, such as failure rates, is not known. The final output from such an analysis provides a series of possible outcomes which cover the different plausible solutions from the input values.

The use of belief functions allows for ambiguity to be represented within a risk analysis and it also incorporates the positive aspects of the probabilistic model described by Laîné et al. (2002) and Démotier et al. (2002). However, the transfer functions are still percent reductions, which do not allow for mechanistic modelling of the system.

A final possible method to perform an overall risk analysis is described by Eisenberg et al (2001). The mechanical risk could be evaluated using CCA and then operational risk could be evaluated using CFA. Although there are criticisms of the CFA methodology, as described in Section 2.3.3, the overall method of analyzing the two systems separately provides a simple method of analyzing the risks to the entire water treatment system.

2.3.5 Water Treatment Risk Analysis as a Part of Microbial Risk Assessments

The use of risk analysis in water treatment has an important influence on the field of microbial risk assessments. In the book "Quantitative Microbial Risk Assessment," Haas, Rose, and Gerba (1999) outline the procedures for undertaking a microbial risk assessment. One of the steps that must be performed is an exposure assessment, which determines both the number of microorganisms and the frequency of exposure that a population experiences. When performing an analysis on the number of microorganisms ingested through drinking water, an exposure assessment can use raw water followed by the reduction in microorganisms through a treatment process instead of directly using the drinking water. Haas et al. (1999) state that to properly model the reduction of microorganisms during water treatment it might be necessary to construct a detailed process model which can describe all of the interactions that are experienced during the treatment process. However, Haas et al. (1999) proceeds to describe a methodology similar to the CFA, which models each treatment unit as a probability distribution of removal efficiencies and calculates the overall removal through a water treatment plant as the multiplication of a random incoming water quality concentration by each successive reduction factor. This approach is reasonable if the treatment processes are both simple and first-order (Haas et al., 1999).

Haas, Crockett, Rose, and Gerba (1996) used an average reduction value experienced by a conventional water treatment plant to calculate the associated risks of the occurrence of oocysts in drinking water. Teunis, Medema, Kruidenier, and Havelaar (1997) modeled the removal of *Cryptosporidium* and *Giardia* through a treatment plant as a beta distribution and calculated the probability of occurrence of microorganisms in the finished water using the CFA methodology.

Masago, Katayama, Hashimoto, Hirata, and Ohgaki (2002) analyzed the risk of *Cryptosporidium parvum* in drinking by modelling the treatment efficiency using a binomial distribution with a removal rate of 99.96% for an operational treatment system and a 70.6% removal rate for a failed treatment system system. Medema et al. (2003) performed three different case studies to quantitatively determine the risk of *Cryptosporidium* in surface water. The third case study fitted Beta-Binomial distributions to the removal efficiencies of *Cryptosporidium* through coagulation/lamellae separation and filtration and then used these distributions to calculate the overall risk of the occurance of *Cryptosporidium* in the treated water.

An assumption that is made throughout all of the microbial risk assessments examined above is that the complex water treatment process can be modelled using the simplified procedure of reduction efficiencies described by the CFA or by the approach used by Haas et al. (1999). Throughout the microbial risk assessments examined, although this assumption is made, there has been no justification given for its use and as Baxter et al. (2003) point out, parameter removal can be a complex, non-linear event. This assumption is important because without a proper understanding of the treatment process in a drinking water treatment plant the risk calculations associated with any risk analysis are theoretical (Teunis et al., 1997). This indicates the importance of accurately characterizing the removal process in microbial risk assessments.

2.4 Critique of Past Risk Assessments

For the evaluation of mechanical risks, the methods are well understood and have been used in many different engineering fields; therefore, no critique will be given here. Many of the operational risk analyses reported in the literature focus only on one parameter, such as the analysis performed by Sadiq et al. (2003) and Sadiq et al. (2004), or required extensive laboratory experiments to obtain the data necessary for an analysis, such as the analysis performed by Olivieri et al. (1999). Furthermore, many of the proposed operational risk analysis methodologies assumed that a distribution of reduction efficiencies was sufficient to model the treatment process. The use of reduction efficiencies does not take into account possible effects of individual changes in the treatment process that a mechanistic model would consider.

For an analysis of both mechanical and operational risks, two methods are possible; a comprehensive analysis method or an analysis of the mechanical and operational risks separately. The risk analysis methodologies outlined and used by Laîné et al. (2002), Démotier et al. (2002), Démotier et al. (2003a) and Démotier et al. (2003b) are promising in their scope of analysis. However, the methodology still models the treatment process through percent reduction and assumes no change in the transformation ratios over time. This assumption could affect any risk analysis associated with a treatment process such as a filter where the performance decreases near to the end of a filter run. The methodology proposed by Eisenberg et al. (2001) is promising, but the method used to assess operational risks still is able to evaluate only one parameter and uses a distribution of removal efficiencies to represent the treatment process.

Summarizing the criticisms of the different methods of risk analysis, an ideal risk analysis methodology should have the following characteristics: it should be available for common use, it should be able to be used on a variety of parameters, it should not be dependant on expensive and time consuming laboratory challenge studies, and it should not make the assumption that a treatment process can be expressed as a linear function of incoming and outgoing concentration but be based on the actual removal processes. Aside from combining the methodology proposed by Baxter et al. (2003) for assessing the operational risks with a separate method for evaluating mechanical risks, none of the evaluated methods are able to undertake an ideal risk analysis.

2.5 A Method of Combining Modelling and Risk Assessment

Within the wastewater treatment field, the WEST software modelling program can be used for computer modelling of treatment process. The WEST program is a modelling and simulation platform for different processes including wastewater, river and fermentation modelling (Hemmis, 2004). The program uses models developed for specific treatment processes and combines them to form a treatment train. For activated sludge, many of the models are developed in conjunction with the International Water Association (IWA) and the IWA Specialist Group on Activated Sludge Population Dynamics (IWA, 2004). One specific example of a model is described in Henze et al. (1999) and its use in conjunction with the WEST modeling platform is shown in Carrette, Bixio, Thoeye, and Ockier (2001). The combination of specialist groups, modeling programs and models allows for the widespread use of computer simulation packages in design and problem identification within the wastewater treatment field.

Rousseau et al. (2001) proposed a methodology, Figure 2.9, to help with designing or retrofitting of a wastewater treatment plant. This methodology takes raw water parameters, determines a removal value through utilizing a calibrated WEST model of the treatment plant, and then compares this value with the standard. The WEST model is a deterministic model which provides output parameter concentrations based on input data and the individual treatment processes. To incorporate the variable nature of wastewater treatment and incoming water quality, the deterministic model is used within a probabilistic risk analysis framework. A simulation engine determines a raw water data record, which is then run through the deterministic model. The result of this analysis is a cumulative distribution function of the output concentrations. The cumulative distribution function can then be used to construct a risk analysis of the parameter or parameters of interest. The procedure is similar to that described in Figure 2.8 except the model is no longer represented by the function F(x) but by a computer simulation model and a data series is generated before being input into the deterministic model. The use of this methodology, outlined in Figure 2.9, in the design of a wastewater treatment system is described in Ockier, Thoeye, and De Gueldre (2001) and Bixio et al. (2002).

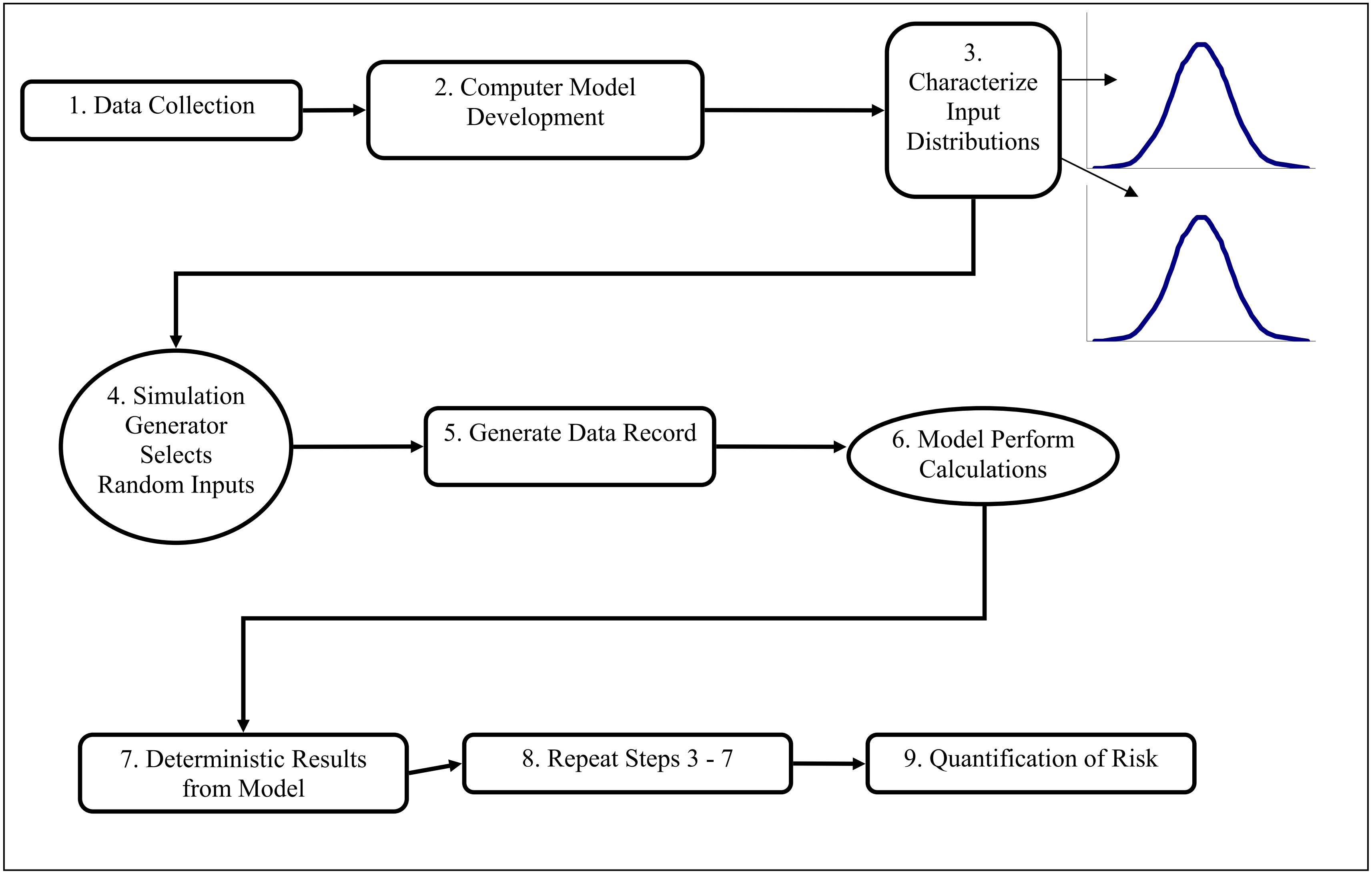

Figure 2.9: Diagram of a wastewater treatment plant risk analysis methodology

Although the methodology was developed for designing or retrofitting a treatment plant, it can be used for an analysis of an existing treatment plant by calibrating the software model to an existing system before generating a data record and running the simulations.

The described method allays the criticisms that were stated for the other risk analysis methodologies that were analyzed. Specifically, this methodology can incorporate any parameter into the assessment that the software package analyzes, it is not dependant on extensive laboratory analysis, it can function under any conditions for which it is calibrated, and it is based on mechanistic modelling, not on percent reduction. It is necessary to recognize that the above methodology focuses on operational risks and that mechanical risk still must be considered (Bixio et al., 2001). Therefore to evaluate situations that are not covered under operational risk analysis, such as a process completely failing because of mechanical defect, another analysis methodology should be used (Bixio et al., 2001).

This risk analysis methodology has not only been used in the wastewater treatment industry, but it has also been attempted in pharmaceutical production. Petrides (2006) used a combination of computer modelling and risk analysis to evaluate a batch pharmaceutical process. Here the SuperPRO Designer® modelling software from Intelligen, Inc. was used along with Monte Carlo simulations, effectively combining deterministic modelling with probabilistic simulation.

2.6 Computer Modelling in Water Treatment

Within drinking water treatment, software modeling programs are beginning to develop, but their use has been for individual treatment process, not the entire treatment train (Stimela, 2003). A few of the programs currently available for modeling an entire drinking water treatment process are OTTER, Metrex, WTP, TAPWAT, Stimela, EnviroPRO Designer® and WatPRO. A full description of the programs is not provided here, but an overview of the different computer packages that are available. One of the computer programs discussed below will be chosen and used for future analysis. This process is discussed in detail in Chapter 3, Section 3.2.

2.6.1 OTTER

OTTER is a stand-alone program that dynamically simulates specific treatment processes including, but not limited to, chemical coagulation, clarification and ozonation. MP & Associates (2005) state that OTTER can simulate treatment processes for pH adjustment, chemical coagulation, flocculation, clarification, sedimentation, plate settlers, clarifiers, rapid gravity filtration, slow sand filtration, ozone, GAC, chlorination, as well as other treatment process. Furthermore, OTTER has the ability to include over fifty (50) water quality parameters including turbidity, colour, pH, TOC, UV 254, metals, alkalinity, trihalomethanes, cysts in any model (MP & Associates, 2005). According to Head, Shepherd, Butt, and Buck (2002), the OTTER framework utilizes a variety of techniques including mechanistic equations, partial differential equations, and empirical approaches to model each individual process. Each of the individual treatment process models are coded using the FORTRAN computer language and are then linked together through a graphical interface. Therefore, a series of individual treatment processes models can be selected and combined to model an entire water treatment plant.

For site specific applications, the OTTER program can model an existing system thorough adjusting a series of calibration parameters that are determined by experimental or process data. Head et al. (2002) describe some scenarios in which OTTER has been used.

2.6.2 Stimela

Stimela is an open-source environment water treatment process computer modelling program developed by DHV Water BC and the Delft University of Technology, which uses the Matlab/Simulink® environment (van der Helm & Rietveld, 2002). The Stimela program provides models of individual water treatment process, which are then linked together in a graphical interface enabling the creation of different treatment trains. These treatment trains are then able to be calibrated to existing plants to model the performance of a given water treatment plant. An added benefit of Stimela is that it is coded in the Matlab/Simulink® structure which allows for modifications to existing models and construction of new models (Stimela, 2003). The use of Stimela is demonstrated by van der Helm and Rietveld (2002) for a gas transfer model.

Currently the models available in the Stimela program have been focused on groundwater treatment processes, thus concentrating on removal of gasses, ions, and organic micropolutants (Stimela, 2003). Thus the major processes are focused on aeration and degassing including processes such as weir aerator, packed column aerator, and other; and filtration consisting of single, double or triple media, GAC, and biofilters.

2.6.3 Metrex

The Metrex program focuses on particle removal of surface water treatment and was developed at the University of Duisburg (Stimela, 2003). Similar to Stimela, the Metrex program provides individual treatment process models, which are coded in the Matlab/Simulink® structure, and then links individual treatment processes together to form a treatment train (Stimela, 2003).

2.6.4 WTP

Water Treatment Plant Model (WTP) was developed by the Environmental Protection Agency (EPA) to help support of the Disinfectant/Disinfection Byproducts Rule (Stimela, 2003). According to the EPA, WTP is used to understand the central tendency and not for individual treatment at municipalities (USEPA, 2005). It is primarily developed for scenario studies and is based on global regression analysis, which makes it not suitable for individual design and analysis (Stimela, 2003).

2.6.5 TAPWAT

Tool for the Analysis of the Production of drinking Water (TAPWAT) has been used by the National Institute of Public Health and the Environment (RIVM) in the Netherlands. Verseegth et al. states that the model uses both percentage removals and process models to describe individual treatment processes which are then incorporated into one treatment train (as cited in Stimela, 2003). However, the model is not yet complete and that constant updates should be made on the percentage removal values to provide better results and the program is currently not used outside of RIVM (Verseegth et al. as cited in Stimela, 2003).

2.6.6 EnviroPro Designer®

EnviroPro Designer® is a computer simulation package used to simulate environmental processes produced by Intelligen, Inc. EnviroPro Designer® uses a graphical interface that combines process models to replicate actual conditions within a treatment plant including waste recycle, treatment and disposal. The individual treatment processes perform the material and energy balances associated with that particular treatment unit (Santamarina, 1997).

EnviroPro Designer® is based on the same principles of process simulators that have been used in the chemical industry. Consequently, EnviroPro Designer® describes the incoming water and subsequent treated water in terms of its individual chemical components and each treatment step modifies a particular chemical component of the water (Santamarina, 1997). The use of SuperPro Designer® v.2.7, the parent software to EnviroPro Designer®, to model a treatment plant can be seen in Flora, McAnally, and Petrides (1998).

2.6.7 WatPro

WatPro, produced by Hydromantis, Inc., can be used to model the formation of disinfection by-products, calculate Ct parameters anywhere within the treatment system, and determine the inactivation and reduction of microbiological contaminants through the use of disinfectants and treatment processes (Hydromantis, 2006). WatPro uses series of modelling equations and calibration techniques for each unit process which are then combined together in a graphical interface.

CHAPTER 3
METHOD OF ANALYSIS

This study focuses on risk analysis methods and their applicability in the water treatment field to evaluate the production of non-compliant water. As discussed earlier, these risks associated with a water treatment plant can be described as either mechanical or operational (Baxter & Barbara, 2003) and different methods are available to analyze the two types of risks. However, although methods for analyzing mechanical risks are common, such as the analysis by Mercer (1988), the use of operational risk analysis methodologies is less widespread. Therefore this study focuses on the use of operational risk analysis methodologies for water treatment plant analysis. An approach is developed and described in the following sections along with the consequence frequency assessment, which will be used to compare the new approach to existing methods

3.1 Focus of Risk Analysis Research

3.1.1 Selection of Risk Analysis Methods

The risk analysis methodology that will be used to evaluate the risk of producing non-compliant water in a water treatment plant is the method that is described in Section 2.5. As a summary, this method uses a combination of computer modelling and probabilistic risk analysis to model the complexity of the treatment process and to incorporate randomness into the risk analysis. This method uses computer modelling of treatment processes which can incorporate multiple parameters in the analysis and thus has the potential to perform a comprehensive risk analysis of a water treatment plant if it is combined with a mechanical risk analysis method. The chosen risk analysis methodology also uses proven probabilistic risk analysis techniques that are accepted by such organizations as the EPA (USEPA, 2001). To provide a frame of reference for the new risk analysis methodology, a CFA will also be performed on the system. This will be done to provide a benchmark for discussion concerning the new risk analysis methodology.

Four distinct factors are necessary to perform the two separate risk analyses: a model, a treatment train, a treatment plant, and a statistical procedure. Initially, a model of the system must be available. For the CFA this model is simply a statistical function but for the method that combines computer modelling and probabilistic risk analysis a computer model needs to be selected. Secondly, to perform a risk analysis a treatment process or series of treatment processes must be decided on. Thirdly, a treatment plant for analysis must be selected. This could be a hypothetical treatment plant or an actual treatment plant that is currently in operation. Finally, the statistical techniques that will be used throughout the analysis must be defined. Probabilistic risk analyses use many different statistical techniques; thus, before performing an analysis, the different statistical techniques that will be used need to be determined and described. These four factors are outlined in the following sections.

3.2 Computer Modelling Software Used in Analysis

A comprehensive comparison of the different water treatment plant computer models is provided by Stimela (2003) including a discussion concerning the advantages and disadvantages of each software package. This comparison did not include SuperPRO Designer® or WatPro. For the purposes of the proposed risk analysis on a water treatment system three factors were considered important: ease of use, availability of unit processes and the performance of mechanistic models. WatPro currently concentrates on the different processes associated with disinfection and the removal and inactivation of microorganisms. Thus the removal of parameters such as turbidity or metals is not included. For this reason WatPro was not considered for analysis. TAPWAT uses percentage removals and WTP uses regression analysis from experimental data; therefore, it is recommended that these two are no longer considered as they are not based on mechanistic models. Stimela and Metrex are open source code modelling platforms which would require a larger effort to model processes. Stimela (2003) indicates that in choosing between OTTER and Stimela and Metrex, OTTER provides easier calibration, optimization and learning. Finally, OTTER has more process models than Stimela or Metrex (Stimela, 2003). SuperPRO Designer® has an extensive set of process models and is based on the fundamental principles of mass and energy balance. However, this complexity, while valuable in many situations, requires a large input of resources into the modelling of the treatment unit itself. Table 3.1 shows a summary table of this comparison between computer software packages.

Table 3.1: Computer software platform comparison table

Computer Software Platform	Ease of Use (High/Low)	Sufficient Availability of Unit Processes (Yes/No)	Mechanistic Models (Yes/No)
WatPro		No	
TAPWAT			No
WTP			No
Stimela	Low	Yes	Yes
Metrex	Low	Yes	Yes
SuperPRO Designer®	Low	Yes	Yes
OTTER	High	Yes	Yes

Through this preliminary analysis of available software programs, the OTTER program is the most promising software package available to undertake a risk analysis of a water treatment plant because it incorporates a wide range of treatment processes and parameters as well as allows the risk analyst to focus on the risk analysis and not concentrate on the modelling adjustments that could be necessary with open source code programs such as Metrex and Stimela.

3.3 Treatment Process for Analysis: Rapid Gravity Filtration Unit

3.3.1 Rapid Gravity Filtration Unit

Although both the CFA risk assessment methodology and the proposed risk analysis methodology can be performed simultaneously on a number of different treatment steps, it was decided for simplicity to pick one treatment process for analysis. This would allow for a more comprehensive look at the differences between the two methodologies without complicating the analysis with a number of treatment processes.

One of the main benefits of the proposed methodology over the CFA and other methodologies is the ability to both incorporate a number of different parameters into a single analysis and to show how different external parameters influence the overall probability of producing non-compliant water. This comprehensive analysis of multiple parameters was not a part of the first phase analysis as it was decided to focus exclusively on one parameter for both the CFA and the proposed methodology to provide a direct comparison between the two methods.

Keeping these two restrictions in mind, the initial analysis was performed on a rapid gravity filtration unit, focusing on turbidity as the parameter of concern. A diagram of the process that was analyzed can be seen in Figure 3.1.

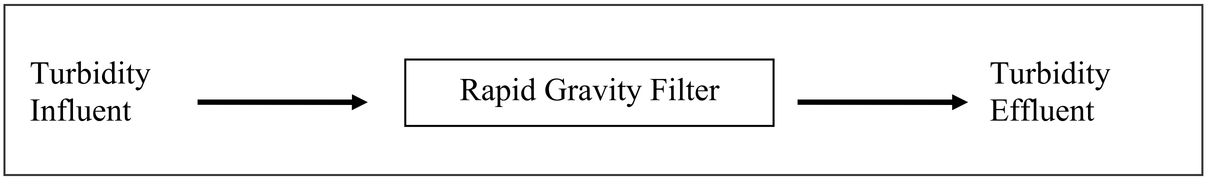

Figure 3.1: Diagram of the selected treatment process for risk analysis

The use of turbidity, a measurement of the overall clarity of water, to evaluate filter performance is advocated by Health Canada (2003). As water passes through a filtration unit the clarity improves by the amount of particles that are removed from the water. Since turbidity is a measure of the overall clarity of water, a high turbidity value can represent a large number of particles ranging from silt and sand to natural organic matter. Therefore, a reduction in turbidity can be correlated to a reduction in a large number of different parameters. Increases in turbidity can indicate increases in *Giardia* cysts and *Cryptosporidium* oocysts (MWH, 2005). High turbidity has also been associated with taste and odor problems (Atkins & Tomlinson, 1963). Furthermore, turbidity is the relevant regulated parameter by drinking water treatment guidelines such as the Ontario Drinking Water Standards (Ontario Ministry of the Environment, 2001).

Although turbidity is a useful measure of the amount of material present in water, it is not a direct measure the amount of material but relies on the principle that particles in water scatter light. Therefore a high degree of scatter would indicate a larger number of particles within the water. It is important to realize that turbidity cannot be directly related to either the number of particles or the size of particles in the water since different particles exhibit different properties when they interact with light (MWH, 2005).

3.3.2 Theoretical Description of a Rapid Gravity Filtration

The filtration process within a water treatment plant is used to remove particulate matter from the water. During the filtration process, water passes through a treatment unit that is packed with a single type or multiple types of media. This packed treatment unit, known as a filter, is then used to remove both suspended matter and microorganisms from the water source (Kawamura, 1999). This process is normally considered to proceed in two states, in the first stage particles in the water are transported to the media in the filter, and in the second stage the particles attach to the media. The first stage, known as transport, is primarily a physical process, while the second stage, known as attachment, is dependent on solution chemistry and the particle and media surface properties (O'Melia, 1985). This two stage process is shown in Figure 3.2.

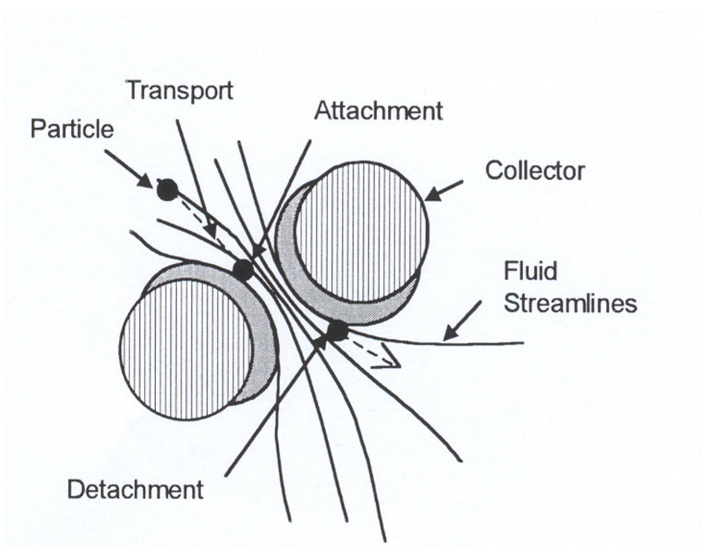

Figure 3.2: Transport and attachment of particles in a filtration bed (Amirtharajah, 1988)[1]

[1] Reprinted from *the Journal of the American Water Works Association*, Vol. 80, No. 12, from Amirtharajah, A., Some theoretical and conceptual views of filtration, pages 36-46, Copyright 1988, with permission from AWWA.

Amirtharajah (1988) describes the transportation stage of filtration through a series of mechanisms which include diffusion, a result of Brownian motion; interception, a result of particles moving close to the media particle and coming into contact with the media surface; sedimentation, a result of particle settling due to gravity; hydrodynamic action, a result of a particle rotating across streamlines; and inertia, a result of a particle's motion. Although all of these processes play a role in the transportation of a particle to the surface of the filter media, within water filtration the dominant mechanisms of transportation are diffusion and sedimentation (Amirtharajah, 1988). In an attempt to model the different processes associated with transport Yao, Tabibian and O'Melia (1971) and Rajagopalan and Tien (1976) have developed equations to predict the total transport efficiency, which is the measure of the ability to transport a particle to the media.

The attachment step is a result of a number of separate forces and interactions between the particle and the filter media. Electrokinetic, molecular forces and surface chemical interactions are significant in this step (Amirtharajah, 1988); consequently changes in the surface properties or the chemistry of either the particle or the media can have an affect on the attachment process. The attachment step is often discussed as an attachment efficiency which varies from one, where every collision results in an attachment, to zero, where no collisions result in attachment (MWH, 2005).

Filter operation is usually based on monitoring the headloss through the filter and/or the effluent water quality and/or the filter run time (Saatci & Oulman, 1980). Headloss within a filter increases during filtration from the clean-bed headloss because the accumulation of solids within the filter media decreases the porosity within the filter media (MWH, 2005). As Figure 3.3 shows, eventually, the headloss reaches a maximum value allowed within the system.

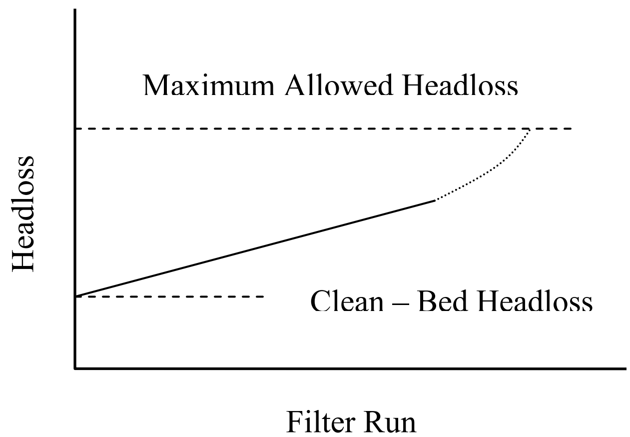

Figure 3.3: Headloss over time in a filter

Effluent water quality is measured during filtration to ensure that the output from the filter meets a standard. A typical filter effluent turbidity curve can be seen in Figure 3.4. The ripening process occurs as the clean filter media matures and becomes more efficient at capturing particles (MWH, 2005). The second step, classified as effective filtration, is where the filter is operating optimally. As the solids accumulate within a filter, eventually the output from the filter degrades and the system no longer produces water of sufficient quality. At this point the filter has experienced a breakthrough. Although Figure 3.4 seems to indicate a single peak during the ripening period, Amirtharajah and Wetstein (1980) have shown that this peak consists of two separate peaks caused by the backwash water present during the filter ripening process.

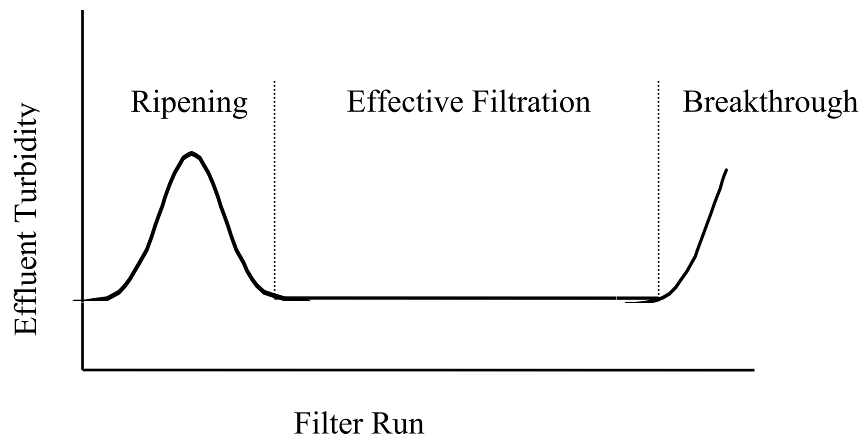

Figure 3.4: Effluent turbidity from a filter unit over time

When either the headloss or the effluent water quality becomes too great the filter cycle is complete and the filtration unit is backwashed. Backwashing involves washing the filter media so the filter is "reset" back to its original state, removing particles that have accumulated in the filter until that point. Once the filter is clean, the filtration process starts again. If the filter does not experience the maximum headloss or a breakthrough over a long time period, a backwash is sometimes initiated. Cleasby (1990) states that the initiation of a backwash based on filter run time is often initiated to avoid the growth of microorganisms or to limit the total amount of solids captured in the filter (as cited in Suthaker, Smith, & Stanley, 1995).

The discussion in Section 3.3.1 indicated that turbidity is a useful measure of the performance of a filter as it is related to the overall amount of particles and contaminants in the water. This relationship is evident during the breakthrough stage of filtration as studies have shown that as the effluent turbidity increases, there can be a corresponding decrease in the removal efficiency of *Cryptosporidium parvum* oocysts (Huck et al., 2001; Huck et al., 2002; Emelko, Huck & Douglas, 2003)

3.3.3 Rapid Gravity Filtration Design

The practical design of a filter unit is covered in considerable detail by Kawamura (1999) and MWH (2005). For the design of rapid gravity filter units the elements of concern are primarily the hydraulic loading, the filter media, the headloss, the underdrain system, and the filter backwashing (Duen, 2000).

Hydraulic loading refers to the volume of water that passes through the filter unit per surface area. Hydraulic loading rates vary from filter unit to filter unit; however filter rates usually vary from 5 – 15 m/h (MWH, 2005).

The filter media selected for a filtration unit also varies from situation to situation. Common types of filter media are silica sand, anthracite, garnet, ilmenite and granular activated carbon (Duen, 2000). However, other filter media types are possible including proprietary filter media. For the specification of filter media, the two design criteria are the effective size (d) and the uniformity coefficient. The depth of the filter media, designated as L, and the effective media size are interrelated through the parameter L/d. The L/d ratio provides a numerical rule of thumb relationship which should be between 1000 and 2000 for most filters (MWH, 2005). Increases in the L/d ratio above this range can result in higher initial headloss, longer filter backwash times with no increase in filter performance (Kawamura, 1999).

The headloss within a filter can be calculated for a clean filter bed through the Carman-Kozeny equation (MWH, 2005). This equation relates the headloss within the filter unit to a number of parameters including the size of media grains, the porosity, the flow rate and the friction within the system. The Carman-Kozeny equation is applicable only for a clean filter bed under laminar conditions. The Carman-Kozeny equation is:

$$h_L = \frac{(1-\varepsilon)}{\varepsilon^3}\frac{v_s^2}{\psi g} L \sum_{i=1}^{n} f_{fi} \frac{x_i}{d_i}$$ **Equation 5**

where:

h_L is the headloss over the filter media depth
ε is the porosity
v_s is the filtration rate
ψ is the shape factor
g is the acceleration due to gravity
L is the media depth
f_{fi} is the friction factor
x_i is the proportion of media layer by weight
d_i is the median media diameter for each segment
n is the number of segments in the filter bed

The underdrain system supports the filter media, collects the filtered water and distributives water for backwashing. The backwashing system cleans the filter media, removing the captured particles from the filter bed so the filter can begin operation again.

3.3.4 Description of how OTTER Models Filtration

There are three basic methods that have been used to model the filtration process. The first method is through phenomenological theories that use empirical expressions with empirical coefficients to model the process. This method is evident within OTTER through the use of the logistic model. The logistic model uses a logistic breakthrough curve to model the filtration process with respect to solids removal as shown in Equation 6 (Saatci & Oulman, 1980).

$$\ln\left[\frac{C_{in}(1-\zeta)}{C_{out}-\zeta C_{in}}-1\right]=r\left[\frac{kL}{\upsilon}-C_{in}(1-\zeta)t\right]$$ **Equation 6**

where:

C_{in} is the influent solids concentration (mg/L)
C_{out} is the effluent solids concentration (mg/L)
L is the filter bed depth (m)
ν is the filtration rate (m/h)
t is the filter run time (hrs)
r is the attachment coefficient (h^{-1})
k is the filter capacity (mg of solids/L of bed)
ζ is the fraction of non-filterable solids (dimensionless)

To model the headloss, the logistic model uses a relationship between headloss and the solids that are deposited in the filter as shown in Equation 7 (Adin & Rebhun, 1977).

$$H=H_o(1+\beta\sqrt{\sigma})^3$$ **Equation 7**

where:

H is the headloss (m)
H_o is the clean bed headloss (m)
σ is the solids accumulation within the filter (mg of solids/L of filter)
β is the rate of headloss build up ((L of filter/mg)$^{0.5}$)

The empirical coefficients used in this model are calculated from breakthrough curves. Saatci and Oulman (1980) recommend using pilot plant studies from at least three filters at different depths operated to breakthrough to obtain the empirical coefficients, but acknowledge that using data from an existing filter is possible but less accurate. The use of the logistic model can be considered a macroscopic approach to modelling filtration because it focuses on the overall filtration process without describing the individual transportation and attachment processes associated with filtration.

The second method that has been used to model filtration is still a macroscopic and empirical approach (Adin & Rebhun, 1977), but it includes solving the partial differential equations that are used to describe the filtration process (WRc plc, 2002). Within OTTER, this method is described as the finite difference model, and it is based on the work by Adin and Rebhun (1977). The finite difference model focuses on modelling the material balance, the rate of accumulation solids and the headloss within the filter. The material balance is described by Equation 8 (Adin & Rebhun, 1977).

$$\upsilon \frac{\partial X}{\partial Z} + \frac{\partial \sigma}{\partial t} = 0$$ **Equation 8**

where:

t is the time (hrs),
X is the concentration of solids in suspension (g/m^3)
Z is the distance from the top of the filter (m)
σ is the solid material deposited in the filter (g of solids/m^3 of bed)
ν is the filtration rate (m/h)

The rate of accumulation of solids is described by Equation 9 (Adin & Rebhun, 1977) which calculates the overall rate of accumulation by evaluating both the rate of accumulation, as described by the first term in Equation 9, and the rate of detachment, as described by the second term in Equation 9.

$$\frac{\partial\sigma}{\partial t} = k_1 \upsilon C(F-\sigma) - \left[\frac{k_2 \sigma H}{L}\right]$$ **Equation 9**

where:

F is the maximum filter capacity (g of solis/m^3 of bed)
H is the filter headloss (m)
k_1 is the attachment coefficient (m^2/g)
k_2 is the detachment coefficient (h^{-1})
L is the filter media depth (m)
C is the solids concentration (mg/L)

The filter headloss, as calculated in Equation 10, is described by an empirical equation that was determined experimentally by Adin & Rebhun (1977).

$$H = \frac{H_o}{\left[1 - \sqrt{\frac{\sigma}{F}}\right]^3}$$ **Equation 10**

The third method that has been used to model the filtration process is through trajectory theories. Trajectory theories attempt to model the filtration process without empirical coefficients. These methods use mathematical relationships that describe the different transportation and attachment mechanisms discussed in Section 3.3.2. Adin and Rebhun (1977) and Amirtharajah (1988) both indicate difficulties in using a purely physical solution to describe the complex filtration process and in OTTER purely trajectory theories are not considered.

Both the logistic method and the finite difference method include backwashing as part of modelling the filtration process; however the finite difference method is the only model that can be used to look at the affects of backwashing directly (WRc plc, 2002). The finite difference model uses a backwashing model from Amirtharajah (1985) to model the process. The logistic method, however, resets the filter to its original state after a backwash is performed.

3.4 System for Analysis: Brantford Water Treatment Plant

3.4.1 System Description

The Brantford Water Treatment Plant (WTP) treats Grand River raw water taken from the Holmedale Canal. The treatment process consists of screening, coagulation, sand ballasted flocculation (US Filter Actiflo™), sedimentation, chlorination, filtration, chloramination and fluoridation (City of Brantford, 2005). A schematic of the treatment plant layout can be seen in Figure 3.5.

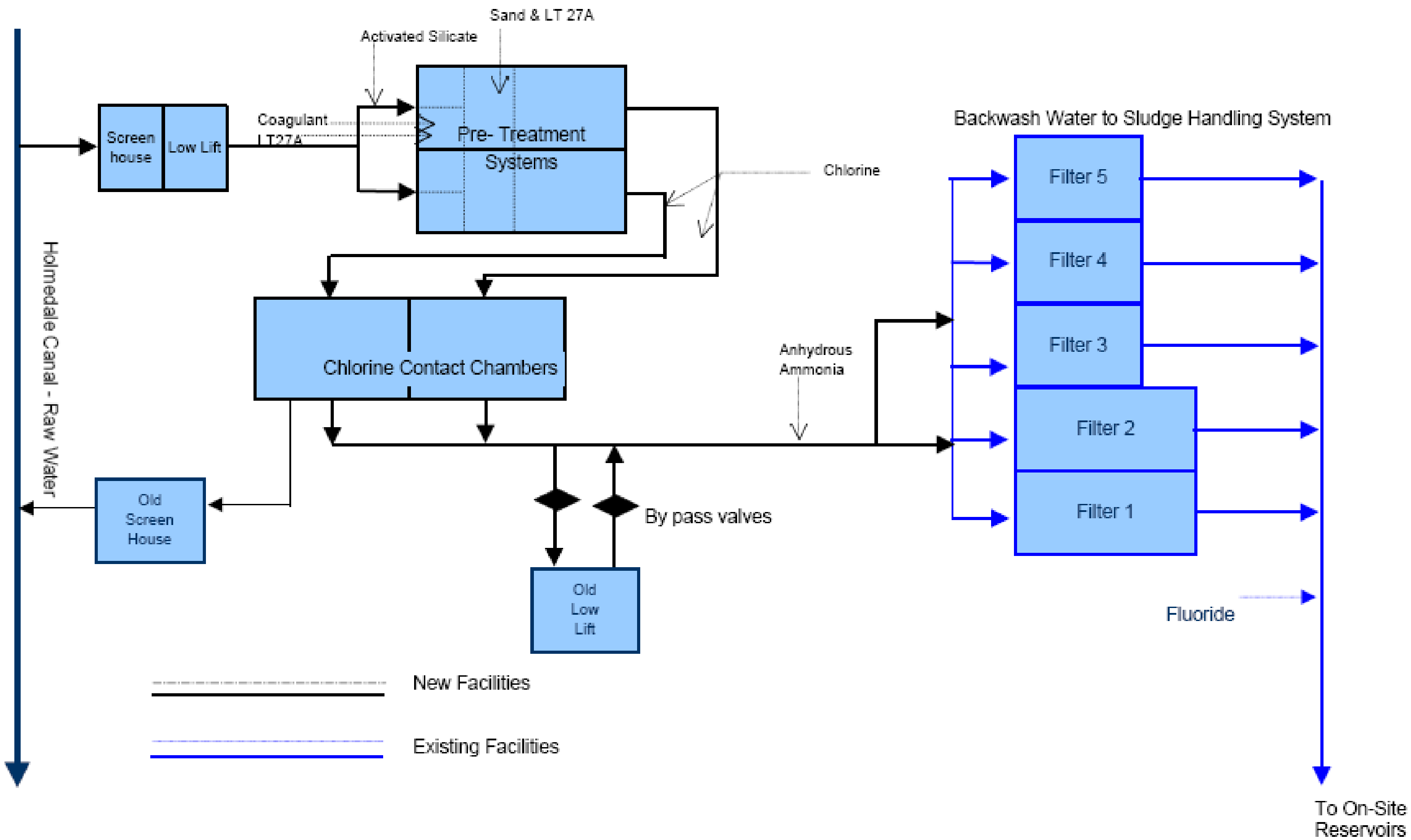

Figure 3.5: Schematic of the Brantford Water Treatment Plant as of May 1999 (City of Brantford, 2006)

3.4.2 Description of Filtration Units at Brantford

The filtration units at the Brantford Water Treatment Plant are dual media, anthracite over sand, rapid gravity filters. Some of the basic physical properties of Filter 1 are shown in Table 3.2. The other filtration units have comparable physical properties with some change in the filter surface area.

Table 3.2: Physical properties of Filter 1

Weir Height (m)	1.83
Filter Surface Area (m^2)	46.2
Media Layers	Anthracite over Sand
Anthracite Depth (m)	0.457
Sand Depth (m)	0.457
Anthracite Effective Size (mm)	0.85-0.95
Sand Effective Size (mm)	0.45-0.55

3.4.3 Data Collection

Measurements for settled water turbidity (influent turbidity), filter effluent turbidity (effluent turbidity), and filter flow rate were made for the 2004 year and were recorded as time-averaged values for every fifteen (15) minutes. This created an extensive data set covering all major seasons for a one year period. Operational and physical characteristics of the treatment units, including those described in Table 3.2, were recorded after consultation with employees at the Brantford Water Treatment Plant.

3.4.4 Choice of Filter Unit for Analysis

The data record obtained from the Brantford WTP showed that there are eight (8) separate filters in use as opposed to the five (5) indicated in Figure 3.5 since Filter 3, Filter 4 and Filter 5 are each separated into two separate filters. To perform the risk analysis it was decided to select a single filtration unit from the eight available filters. The data record showed that not every filter had its own turbidity meter for the entire duration of 2004. Consequently, the filters without their own turbidity meter (3a, 3b, 4a, 4b, 5a, 5b) were not chosen, leaving Filter 1 and Filter 2.

The summary statistics for the effluent turbidity from Filter 1 and Filter 2, as shown in Table 3.3, indicates that Filter 1 experienced a greater maximum and standard deviation of effluent turbidity for the 2004 year. Consequently Filter 1 was chosen so that the analysis would have more variability to consider.

Table 3.3: Summary statistics of Filter 1 and Filter 2 effluent during the 2004 calendar year

	Filter 1	Filter 2
Maximum (NTU)	0.25	0.17
Minimum (NTU)	0.01	0.01
Standard Deviation (NTU)	0.037	0.026

3.4.5 Filter One Influent and Effluent Turbidity Readings

The parameter of concern is the effluent turbidity from the filter. Over the 2004 year a series of measurements were made for the influent and effluent turbidity readings. Theses values were measured and recorded at fifteen (15) minute intervals for the entire 2004 year. Appendix A shows the filter influent and effluent values over time for each month period. These filter readings included a small portion of filter ripening as the filters were operated with a five (5) minute filter to waste period.

Another way to display the influent and effluent turbidity data is through a cumulative distribution function (CDF) as shown in Figure 3.6 and Figure 3.7 respectively. The CDFs were calculated using the plotting function:

$$\frac{i}{(n+1)}$$

Equation 11

where

i is the plotting point of interest
n is the number of plotting points

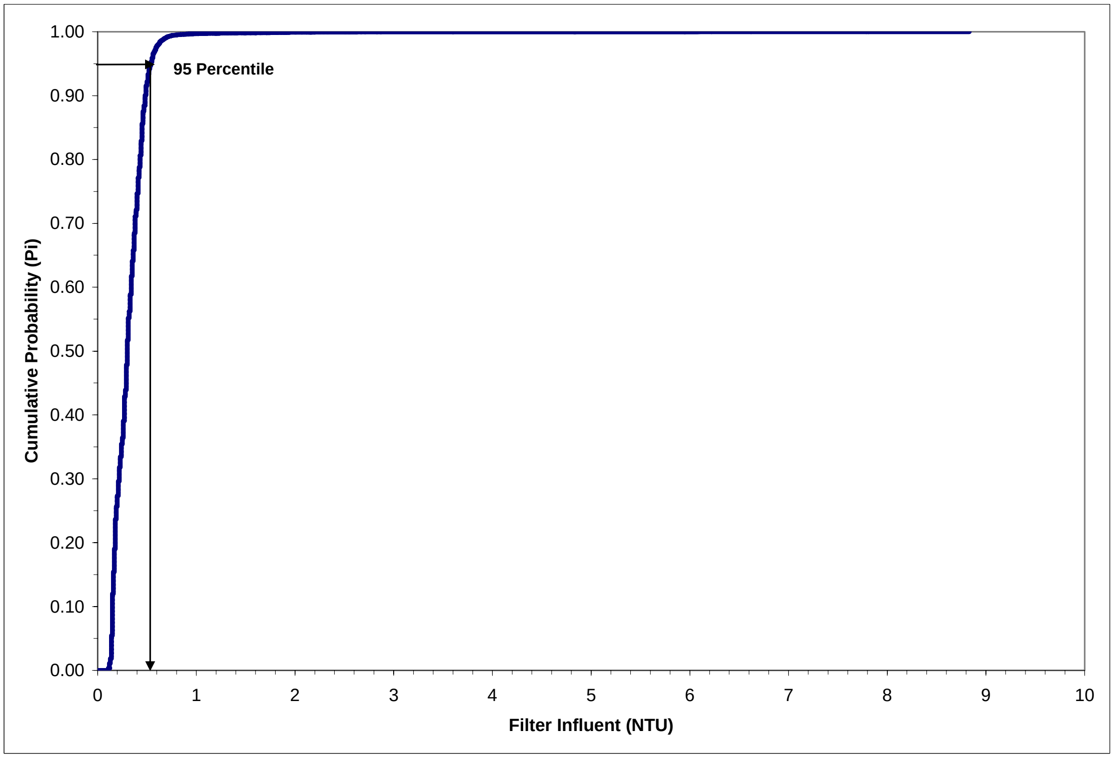

Figure 3.6: Filter 1 influent turbidity cumulative distribution function for turbidity data during the 2004 calendar year

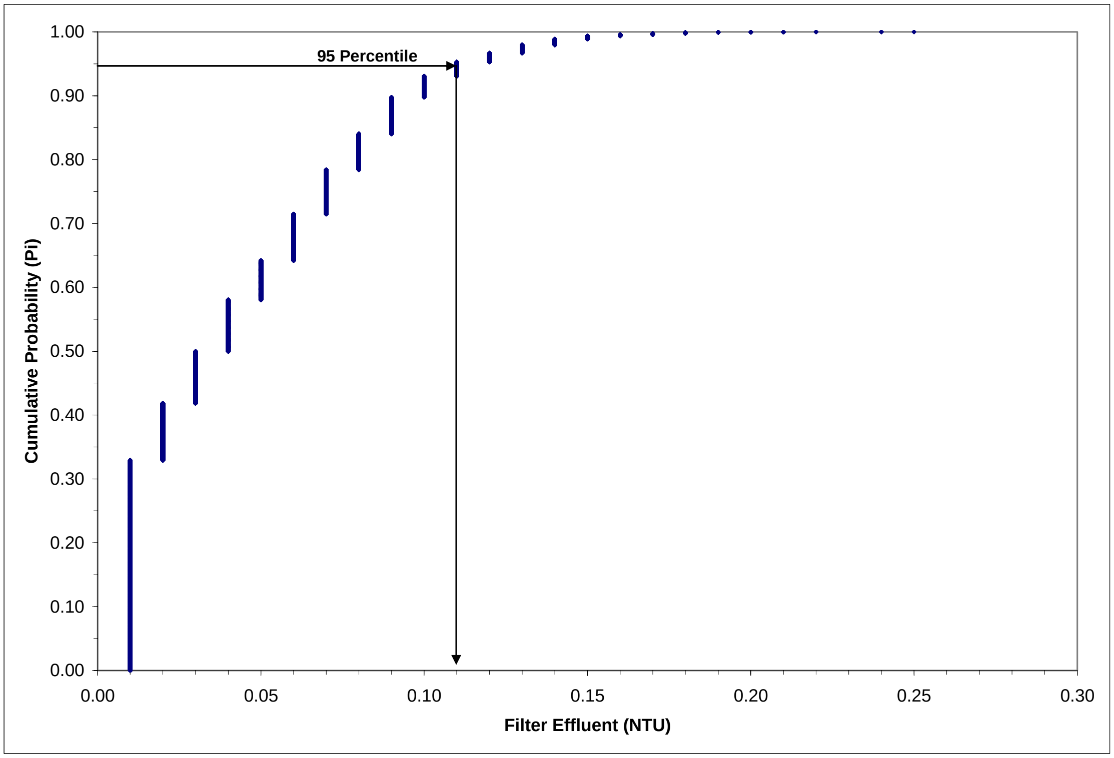

Figure 3.7: Filter 1 effluent turbidity cumulative distribution function for turbidity data during the 2004 calendar year

On the CDF for both the influent and effluent turbidity is drawn the 95 percentile level. The 95th percentile values are stated such that 95 percent of the recorded values are below the stated value. In Figure 3.6 this would mean that 95 percent of the influent to Filter 1 was below 0.54 NTU. The influent to Filter 1 is low in comparison to filters at water treatment plants also treating Grand River Water due to the performance of the Actiflo^{TM} high rate settling process. For example, the average influent for Filter 1 at the Brantford Water Treatment Plant is 0.32 NTU over the 2004 year while between August 2002 and June 2003 the influent turbidity to the Mannheim Water Treatment Plant filters ranged from 0.34 – 2.6 NTU (Li, 2004)

Aside from looking at the cumulative distribution function for the influent and effluent turbidity, some summary statistics can be calculated for both data sets. These statistics are shown in Table 3.4 and will be used for comparison to the calculated risk analysis output.

Table 3.4: Summary statistics for the influent and effluent turbidity from Filter 1 over the 2004 calendar year

	Filter 1 Influent (NTU)	Filter 1 Effluent (NTU)
Maximum	8.83	0.25
Minimum	0.01	0.01
Standard Deviation	0.18	0.04
Average	0.32	0.04
95th Percentile	0.54	0.11
99th Percentile	0.69	0.15

3.5 Statistical Analysis Techniques

Probabilistic analysis is dependent on the data source that are used for analysis and on the statistical analysis methods that are used. Discussions in books on probabilistic simulations and risk analysis provide a variety of methods to analyze and describe data sets. For a full and complete discussion of many different methods, useful references are Ang and Tang (1975), Ang and Tang (1984), Vose (1996), Cullen and Frey (1999) and Verdonck (2003). The following discussion will provide a brief overview of some methods and the rationale for the methods that will be used in further analysis.

3.5.1 Parametric and Non-Parametric Distributions

In dealing with distributions there is a distinction that can be made between distributions that are theoretically derived mathematical distributions and those that are defined directly by measured data. These are respectively known as parametric and non-parametric distributions (Vose, 1996). Fitting data to parametric distributions requires an assumption that the data fit the known distribution. The data fitting process then involves finding the parameters of the known distribution from the collected data. Non-parametric distributions make no assumption on the distribution of the data but use only the data points that are gathered.

Vose (1996) strongly recommends using non-parametric distributions, but other authors such as Verdonck (2003) provide no rule as to when to use one method over the other. However, Vose (1996) also states that the use of parametric distributions is allowable if there is evidence to suggest that the data are actually from the underlying theoretical distribution. There has been some indication that water quality parameters follow parametric distributions such as the lognormal distribution (Novotny, 2004). Therefore because of precedent and the simplicity of their use, any future analysis will use parametric distribution fitting techniques. It is important to note that the use of parametric or non-parametric methods can have a bearing on the final risk result (Verdonck, 2003).

3.5.2 Theoretical Distributions

To use parametric distributions it is necessary to determine what theoretical distribution best represents the measured data set. This is necessary as the distributional form can have a large effect on the outcome of a risk assessment, especially in situations where the relative standard deviation, the ratio of the standard deviation to the mean, is greater than one (Haas, 1997).

There are a wide range of parametric distributions that the data set can be fitted to. Some of them are the exponential, gamma, lognormal, normal, Weibull, and Gumbel (Vose, 1996). It was decided to perform distribution fitting techniques on four (4) common distributions namely the normal, lognormal, exponential, and Gumbel distribution. The lognormal and normal distributions were chosen because natural data tends to follow these distributions (Vose, 1996). The lognormal distribution has been used to model naturally occurring data by Eisenberg et al. (1998) while the normal distribution was used by Sadiq et al. (2003) to model filtration rate, even thought it was indicated that the normal distribution was used arbitrarily. The Gumbel distribution is an extreme value distribution and the exponential distribution is based on times for an occurrence of an event (Vose, 1996). These distributions are included in the analysis to cover a range of possible distributions and because extreme value distributions have been used to model removal efficiencies, such as the removal efficiency of a slow sand filter for total coliforms (Saidq et al., 2003). For the lognormal distribution, it is possible to use either the common lognormal, base 10, or the Napierian lognormal, base e, distribution. The logarithmic base 10 distribution was used because Novotny (2004) states that water quality measurements may often follow lognormal (base 10) distributions and because both base 10 and base e distributions are similar (Burmaster & Hull, 1997).

3.5.3 Parameter Estimation Methods

To determine which of the theoretical distributions best represents the data set, it is necessary to determine the numerical values for the parameters that describe an each assumed distribution. There are different parameter estimation methods for parametric and non-parametric distributions; however, since the analysis will focus on parametric distributions, only parameter estimation methods for parametric distributions will be discussed here. Further discussion on both parametric and non-parametric distributions can be seen in Cullen and Frey (1999), Vose (1996) and Verdonck (2003). Three of the most common techniques for parameter estimation are the method of moments, the probability plotting method and the method of Maximum Likelihood. Ang and Tang (1975) and Vose (1996) provide a good description of the different methods and a mathematical reason for their use.

3.5.3.1 Method of Matching Moments

For any given data set, statistical values such as the mean, standard deviation and kurtosis can be calculated. These values are known as the moments of the data set where the mean is the first moment, standard deviation is the second moment, and kurtosis is the third moment.

Any distribution is described by a set of parameters. For example the normal distribution is described by μ and σ and the exponential distribution is described by μ and β. The moments of the data set have a relationship to the parameters of the distribution, so to determine the parameters of the distribution it is possible to first determine the moments of the data set and then calculate the parameters of the distribution. Table 3.5 shows some of the relationships between the moments of the data set and the parameters of some common distributions. In Table 3.5, E(x) represents the mean and Var(x) represents the variance of the data set.

Table 3.5: Relationship between distribution parameters and the mean and variance of a measured data set (adapted from Ang & Tang, 1975)

Distribution	Probability Density Function (PDF)	Parameters	Relation to Mean and Variance*
Normal	$fx(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right]$	σ μ	E(X) = μ Var(X) = σ^2
Lognormal	$fx(x) = \frac{1}{\xi x\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{\ln x-\lambda}{\xi}\right)^2\right]$	λ ξ	E(X) = exp(λ + ½ζ^2) Var (X) = $E^2(X)\left[e^{\xi^2} - 1\right]$
Exponential	$\mathrm{f(x)} = \frac{1}{\beta}\mathrm{e}^{-\frac{(x-\mu)}{\beta}}$	μ β	E(X) = β + μ Var (X) =β^2
Gumbel	$f(x) = \frac{1}{\beta} e^{-\frac{(x-\mu)}{\beta}} e^{-e^{-\frac{(x-\mu)}{\beta}}}$	μ β	E(X) = μ + 0.5772β Var(X) = $\left(\frac{\beta^*\pi}{\sqrt{6}}\right)^2$

* E(X) represents the mean and Var(X) represents the variance

3.5.3.2 Probability Plotting Method

The probability plotting method plots the measured data set and the cumulative probability on specially constructed probability paper (Cullen & Fery, 1999). Probability paper is constructed so that if the measured data set is from the assumed distribution the plot is a straight line.

Every probability distribution has a cumulative distribution equation described as F(x) = some function of x where F(x) is the cumulative distribution of the measured data and x is some measured data point. The measured data is sorted in increasing order and then ranked from one (1) to N where N is the number of data points. The plotting position is then calculated using a plotting position equation such as m/(N+1) where m is the ranked number and N is the number of data points. This numerical value is then the plotting position for that measured data point and the combination of all the plotting position points is the cumulative distribution function, F(x), for the measured data.

When using probability plotting, the cumulative distribution function is convoluted such that it is represented as x = some function of F(x) (Pandey, 2004). Then the data is plotted with x on one axis and the function of F(x) is plotted on the other axis. Through plotting, the slope and y-intercept can be calculated for the constructed line. These values are then used to determine the parameters of the distribution. It should be noted that as the number of parameters in a distribution increases to three or more, the number of dimensions for a probability plot would have to correspondingly increase. An example for the Gumbel distribution is provided below.

The cumulative distribution function for the Gumbel distribution is

$$F(x) = e^{-e^{-\frac{(x-\mu)}{\beta}}}$$ **Equation 12**

After convolution the equation can be represented as

$$x = -\beta\left[\ln(-\ln(F(x)))\right] + \mu$$ **Equation 13**

Therefore, the data set is plotted as x (y-axis) vs $\ln\left[-\ln(F(x))\right]$ where F(x) is described by the plotting position of x. From plotting the data the slope and y-intercept can be determined. Relating the slope and y-intercept back to Equation 13, $-\beta$ is the slope and μ is the y-intercept, which are the parameters of the Gumbel distribution.

3.5.3.3 Method of Maximum Likelihood

The method of Maximum Likelihood looks to determine the parameters of the distribution that are most likely to give the observed data set. To determine the parameters of the distribution, a likelihood function is calculated which describes how likely it is that a given parameter value produces the measured data set.

The likelihood function is (Cullen and Frey, 1999):

$$L(\theta_1, \theta_2, \ldots, \theta_k) = \prod_{i=1}^{n} f(x_i / \theta_1, \theta_2, \ldots, \theta_k)$$ **Equation 14**

where:

L is the likelihood function
$\theta_1, \theta_2, \ldots \theta_k$ are the parameters of the probability distribution
n is the total number of data points in the measure data record

The best estimate of the values of the parameters is then determined by maximizing the likelihood function using a maximization methodology such as differentiation or Taylor series expansion.

3.5.3.4 Comparison of Parameter Estimation Methods

Although the above methods are all parameter estimation methods, the parameters calculated from the different methods are not always the same. Vose (1996) recommends using the Maximum Likelihood method but also acknowledges that the Maximum Likelihood method is sometimes difficult to implement and that one method is not always the best method.

Vose (1996) also indicates that if the coefficient of determination is high (0.90 or 0.95) for the straight line in the probability plotting method, the method of moments and the probability plotting method provide similar results. Cullen and Frey (1999) acknowledge that the method of moments is the most straightforward and practical method to implement. For future analysis the method of moments will be used primarily for simplicity. However, any risk analysis should be performed with the understanding that differences between the methods are possible.

3.5.4 Selecting a Theoretical Distribution

After determining the parameters for the different possible distributions, it is necessary to determine which of the distributions best represents the measured data set. To perform this analysis probability plotting will be used both to calculate an r^2 parameter and to provide a visual comparison of the degree to which the different distributions fit the data set. The r^2 parameter is defined as the coefficient of multiple determination. This parameter will be used to determine how well the measured data matches the assumed model, with 1 being a perfect match and 0 being no match at all.

3.5.4.1 Probability Plotting

Section 3.5.3.2 outlines the construction of probability plots and their use to undertake parameter estimation. Another use of probability plotting is with determining the goodness of fit of an assumed distribution to the data set. The construction of a probability plot allows for the linearity of the graph to be used as an evaluation mechanism for the goodness of fit for a distribution (Ang & Tang, 1975). Therefore, for a two-dimensional probability plot, the r^2 value of the trend line provides a useful comparison value for different assumed distributions. Since r^2 is a measure of the degree to which a line represents the data, a larger r^2 number provides a stronger indication that the data set follows the assumed distribution. Furthermore, this comparison can be performed visually.

3.5.5 Probabilistic Risk Assessment, Variability and Uncertainty

The nature of probabilistic risk assessments allows for a greater characterization of the variability and uncertainty in a population, and consequently a determination of the variability and uncertainty in a given risk.

Variability can be described as naturally occurring differences in a parameter while uncertainty is lack of knowledge in that parameter (Cullen & Frey, 1999). So while uncertainty can be reduced through further sampling, variability cannot. However, both variability and uncertainty are properties of their respective sampled populations and must be incorporated into a final risk estimate (Verdonck, 2003). The use of simulation techniques allows for both variability and uncertainty to be taken into account during a risk assessment.

3.5.6 Simulation Techniques

There are a variety of numerical simulation techniques that can be used during a risk analysis including Monte Carlo simulation, Latin Hypercube Sampling, and Importance Sampling (Cullen & Frey, 1999). Monte Carlo simulation, discussed in more detail in Sections 3.5.6.1 to 3.5.6.3, provides completely random sampling of the parent distribution or data set to generate inputs to the model. Latin Hypercube Sampling reduces the number of simulations necessary by separating the original distribution into percentiles of equal probability and one sample is taken from each percentile (Cullen & Frey, 1999). This has the effect of reducing the overall number of simulations necessary. Importance Sampling focuses the sampling on a defined area of importance. Thus this method is useful for looking at specific parts of a distribution, such as the tails, but not at a distribution as a whole (Cullen & Frey, 1999).

The Monte Carlo technique will be used for future analysis because it is commonly used and thus easily understood, is not dependent on a set of assumptions about the nature of the variability and uncertainty, and is able to deal with both uncertainty and variability either separately or together (Verdonck, 2003).

3.5.6.1 Monte Carlo Analysis

The Monte Carlo simulation technique, developed in the 1940's, was originally used to solve complex mathematical integration problems (Cullen & Frey, 1999). Monte Carlo analysis involves running a model repeatedly while constantly changing the input values which are chosen randomly from their overall parent distributions.

This analysis generates a set of output values that characterize different possible outcomes. For a more comprehensive description of the Monte Carlo simulation technique see Cullen and Frey (1999).

3.5.6.2 First Order Monte Carlo Analysis

A first order Monte Carlo analysis is another name for what is usually described as a Monte Carlo analysis. The distinction is made here because of the following discussion on second order Monte Carlo analysis. First order Monte Carlo analysis makes no distinction between uncertainty and variability (Verdonck, 2003). Input variables are assumed to be completely characterized by the assumed "best fit" distribution and the values of the parameters of that distribution. During first order Monte Carlo analysis, a random value is chosen from the distribution and run through the model.

3.5.6.3 Second Order Monte Carlo Analysis

In a Second Order Monte Carlo analysis, uncertainty and variability are separated (Verdonck, 2003). A second order Monte Carlo analysis recognizes that the values of the parameters calculated for the chosen distribution are based on a data set that may be incomplete. Therefore the values of the parameters are considered to vary within a range specified by confidence limits. The simulation procedure then uses a looped technique to account for both the variability in the data set, captured by the distribution, and the uncertainty in the parameters of the distribution

Initially, numerical values of the parameters of the distribution are randomly chosen from within the confidence limits of the individual parameters, defining a specific distribution. Once the distribution is characterized, random data values are chosen from this distribution and then input into the model. For a second run, a new set of numerical values for the parameters of the distribution are chosen defining a second distribution. The second set of random values is then chosen from this new distribution. The procedure continues until the entire analysis is complete. This research will use first order Monte Carlo analysis; however, a more comprehensive review of Second Order Monte Carlo analysis can be seen in Verdonck (2003).

3.5.7 Simulating Data from Probability Distributions

To perform a Monte Carlo simulation it is necessary to determine random values from the chosen probability distribution. One possible method to accomplish is through using the inverse transform method. The inverse transform method is described below and was used throughout this thesis.

Once the assumed distribution is known, a probability density function and a cumulative distribution function can be calculated. From the cumulative distribution function, the inverse cumulative distribution function is determined as shown in Figure 3.8.

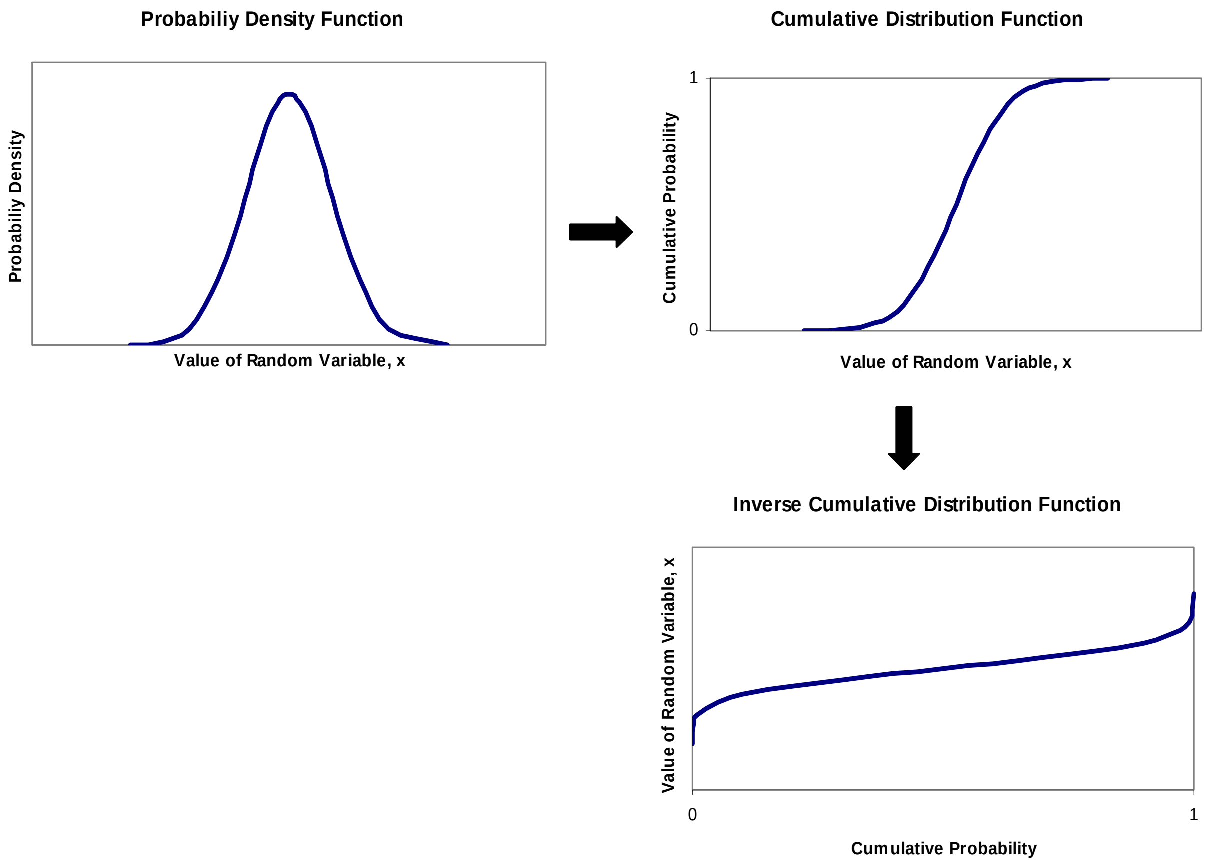

Figure 3.8: Construction of the inverse cumulative distribution function (Frey, 1992)

To choose a random data point from the assumed distribution, a random number ranging from zero (0) to one (1) is chosen from a uniform distribution. This random value is then input into the inverse cumulative distribution function to determine a random value from the original distribution. This procedure is shown in Figure 3.9.

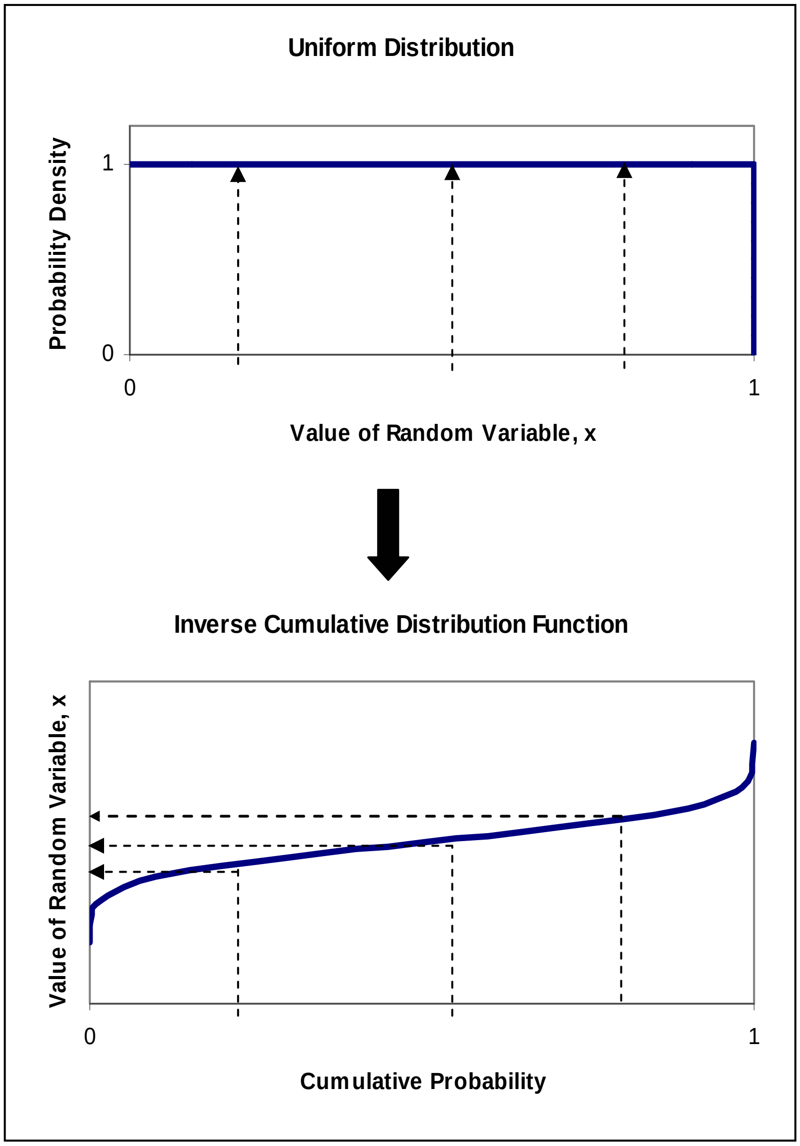

Figure 3.9: Inverse transform method

The inverse transform method is performed repeatedly until the total number of random data points needed for analysis is determined.

3.5.8 Random Number Generation

In order to simulate data from probability distributions using the inverse transform method, as described in Section 3.5.7, a random number must be generated. Therefore, it is necessary to construct a random number generator.

The research in this thesis will not focus on determining a new random number generator but will use generators that are currently available. One of these is the built in random number generator in Microsoft Excel 2002 and Microsoft Excel 2003. The use of Microsoft Excel 2002 for statistical analysis of data and specifically for the use of the random number generator is cautioned by McCullough and Wilson (2002). One of the errors noted by McCullough and Wilson (2002) is that Microsoft Excel 2002 returns highly improbable random values too frequently to be correct from a probabilistic perspective. Through an analysis of Microsoft Excel 2003 by McCullough and Wilson (2005) it was shown that this flaw was resolved for the RND function. However, McCullough and Wilson (2005) still indicate a number of flaws with the random number generator in Microsoft Excel 2003. Although the errors within the random number generator in Microsoft Excel 2003 are well documented, this random number generator will be used throughout this thesis. It is important to note that statistical errors are possible and that a more detailed analysis should use a random number generator that satisfies all statistical tests. Law and Kelton (1991) describe a series of different random number generators, along with some common problems with random number generators and methods of testing random number generators

3.5.9 Correlated Water Quality Parameters

If a risk analysis requires that a data set be generated for two or more incoming variables the concept of correlation becomes important. Correlation is the degree that one variable is related to another (Verdonck, 2003). As an example, for incoming water quality variables, this could mean that the microbial count in a water source varies directly with the temperature of the water. Performing a simple Monte Carlo simulation on these two variables would choose a random value of the microbial count independently of the temperature. Since the two variables are correlated, the assumption of independence is incorrect. Therefore, a method that takes into account the correlations between the parameters would be necessary in this situation.

The method of Iman and Canover (1982) is one method that has been developed to deal with correlated variables. This method was developed in a way that several different parameter distributions can be combined together (Haas, 1999). Restricted pairing techniques, described by Cullen and Frey (1999), are another method for dealing with correlated variables. This method works when there is an independent distribution which has any number of dependent distributions. A value is sampled from the independent distribution, and then based on the value of the independent variable, the distribution of the dependant variable can be determined. A value from the new dependent distribution is then calculated.

The risk analysis methodology used to calculate the risk of producing non-compliant water will not consider correlated incoming variables. However the importance of correlations in risk assessments is shown by Burmaster and Anderson (1994) who, as one of their fourteen principles of good practice for conducting a Monte Carlo risk assessment, state that all moderate or strong correlations between parameters should be taken into account. It is therefore recommended that any detailed risk analyses take into account correlated variables.

3.6 Summary of Analysis Methodologies

After choosing the different statistical and probabilistic techniques that will be used throughout the analysis, the final water treatment plant risk analysis methodologies can be re-stated incorporating the different factors previously determined.

3.6.1 Summary of CFA Methodology

3.6.1.1 Step 1: Define Water Treatment Plant

For the CFA methodology defining the water treatment plant involves deciding which treatment processes with the treatment plant to analyze. During this process a schematic of the treatment unit or units that are analyzed should be drawn. For the risk analysis performed in this study, the treatment process of interest is a dual media rapid gravity filtration unit.

3.6.1.2 Step 2: Determine Parameters to Analyze

The different parameters that will be used in the CFA should be determined. Although a large number of parameters would give a better picture of the overall operation of the treatment unit or plant, as the number of parameters increase the amount of time and data needed for an analysis increases as well. Currently there are no guidelines to determine what parameters to choose, but the choice will be a function of expert knowledge from both the water treatment plant operator and the risk analyst. The CFA of the filter in this study focused on turbidity as the parameter of concern.

3.6.1.3 Step 3: Determine the Influent Water Quality and the Percent Removal Distributions

Using the method of moments the theoretical distribution parameters can determined. Then using probability plotting and visual inspection of probability plots, the best fitting distribution can be determined. This study requires that the probability distribution of the influent turbidity and the percentage reduction of turbidity across the filtration unit be determined.

3.6.1.4 Step 4: Perform Monte Carlo Simulation

Using first order Monte Carlo simulation, a random influent value will be chosen from the influent distribution and a random percent reduction value will be chosen from the percent removal distribution. These two values will be multiplied together and recorded as the simulated effluent distribution. This overall process will be performed a number of times to take into account a large number of possible combinations of influent water quality and percent reduction. The relationship between influent turbidity concentration and the percent removal of turbidity across the filter was analyzed later on in this thesis to see whether or not the percent removal of turbidity is independent of the influent turbidity concentration.

3.6.1.5 Step 5: State Conclusions

For each parameter that is chosen in Step 2, a risk level can be generated. This information can then be presented to managers and operators allowing for solutions to lower either overall risk or the risk associated with one specific parameter.

3.6.2 Summary of the Risk Analysis Method which Combines Computer Modelling and Probabilistic Risk Analysis

3.6.2.1 Step 1: Define Water Treatment Plant and Set-Up Model

This step involves collecting the physical data that characterizes the system that will be analyzed and incorporating it into the computer model. For this study, the number of filters, size of filters, and other data describing the filtration process was recorded. This data was then used to accurately depict the water treatment process within the model.

3.6.2.2 Step 2: Determine Parameters to Analyze

This step is important from a risk analysis perspective. A greater number of parameters analyzed will increase the precision of the risk analysis results, but could also increase the computational time and difficulty. Currently there are no guidelines to determine what parameters to choose, but the choice will be a function of expert knowledge from both the water treatment plant operator and the risk analyst. The analysis of the filtration unit focused on turbidity as the parameter of concern.

3.6.2.3 Step 3: Calibrate the Computer Model

The calibration step is necessary to ensure accurate prediction results from the model. The procedures for calibration should follow those described for the different process models with the modelling software.

3.6.2.4 Step 4: Determine Distributions of Water Quality Parameters

Using the method of moments the theoretical distribution parameters can determined. Then using probability plotting and visual inspection of probability plots, the best fitting distribution that describes the water quality parameters can be determined. This analysis required that the influent turbidity and filter flow rate distributions be determined.

3.6.2.5 Step 5: Simulate Incoming Water Quality Data

Using a random number generator and the inverse transform method, input data can be determined. Initially a First-Order Monte Carlo simulation was done, so it was assumed that the parameters of the distribution calculated in Step 4 are correct. For the analysis of the filtration unit, the input turbidity and input filter flow rate were simulated. Since only one parameter was considered in this thesis, that of turbidity, correlation between incoming water quality parameters was not taken into account. However, a more comprehensive study which incorporates multiple parameters should look at the correlation between the influent water quality variables.

3.6.2.6 Step 6: Run Calibrated Model with Simulated Data

Once the raw water quality data have been simulated, the data is entered into the model. The model will be run for the data series and the output stored. This output can then be represented as a cumulative distribution function where the percent time that the data is less than a given level can be determined.

3.6.2.7 Step 7: State Conclusions

For each parameter that is chosen in Step 2, a risk level can be generated. This information can then be presented to managers and operators allowing for solutions to lower either overall risk or the risk associated with one specific parameter.

CHAPTER 4
RESULTS AND DISCUSSION USING THE CONSEQUENCE FREQUENCY ASSESSMENT

4.1 Application of CFA Methodology to Filter 1

The consequence frequency assessment was used on Filter 1 of the Brantford Water Treatment Plant. To perform this analysis, it was necessary to take the principles of the CFA and directly apply them to a rapid gravity filtration unit, a process that is depicted in Figure 4.1.

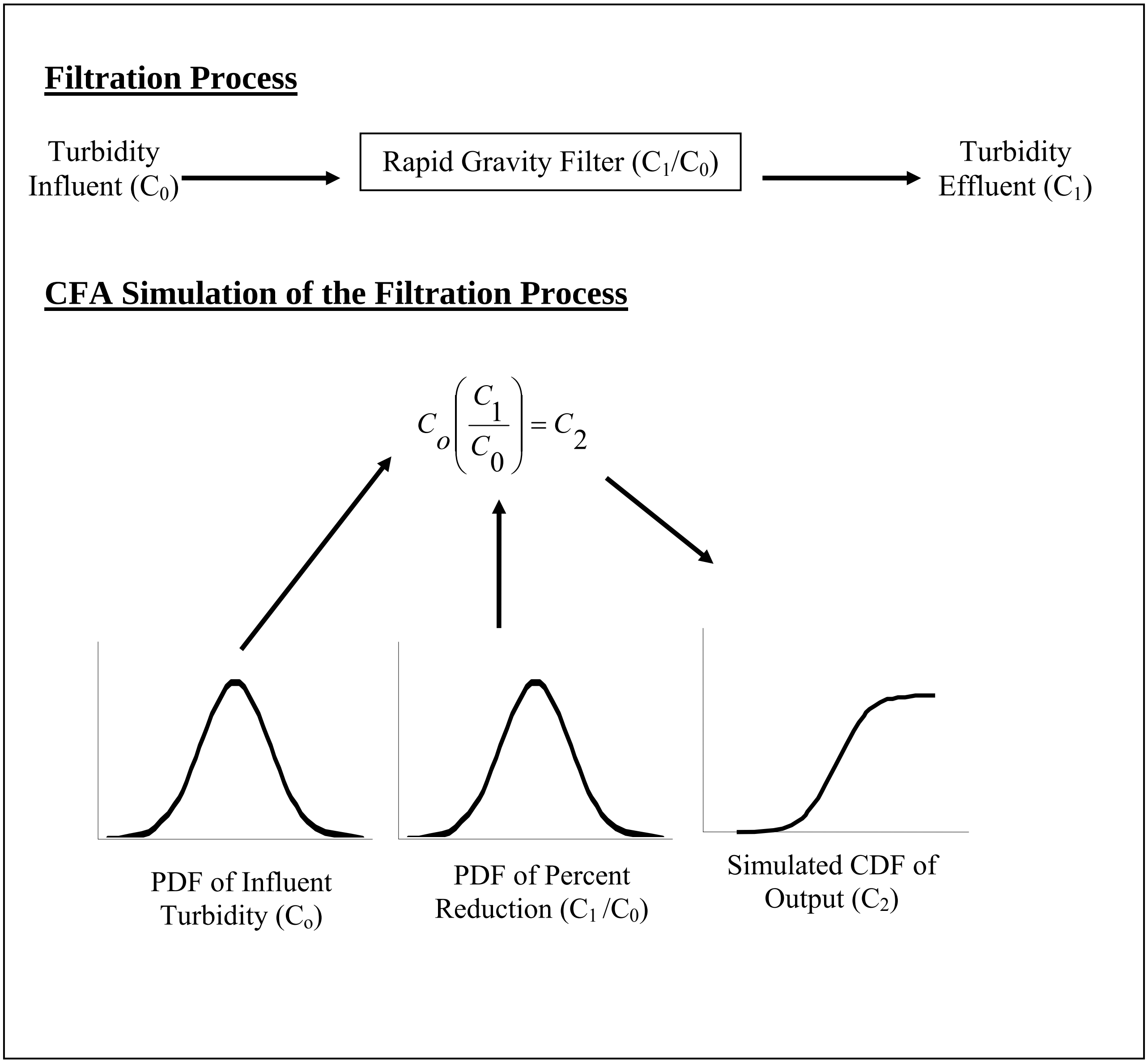

Figure 4.1: Diagram of CFA methodology applied to filtration unit

The influent turbidity (C_0) is represented as a probability distribution function (PDF) and the rapid gravity filter is modelled as a percent reduction PDF (C_1/C_0) The CFA methodology multiples a randomly selected value from the influent turbidity PDF by a randomly selected value from the percent reduction PDF to give a possible output value for the filter (C_2). After a number of simulations, all the possible effluent turbidity values (C_2) that are calculated can be represented as a cumulative distribution function (CDF) of the effluent turbidity.

4.1.1 Data Manipulation for Percent Reduction Calculation

Percent reduction is calculated by (influent-effluent)/influent. This calculation was performed for every data point over the 2004 year data record. A percentage reduction was not calculated when data were missing or not available from either the influent or effluent turbidity data record.

In some situations the percent reduction was not able to be calculated because the influent values were "0", causing the percent reduction value to be a non-integer. In these conditions a percent reduction was not recorded. An example of this occurrence is on July 25, 2004 from 10:00 am to 11:30 am. A further complication occurred when the percentage reduction values were negative, indicating that the effluent turbidity was greater than the influent turbidity. One example is on July 25, 2004 at 9:45 AM another on July 25, 2004 at 11:45 am. The influent turbidity values are 0.01 and 0.02 NTU respectively in these cases, while the effluent turbidity is around 0.60 NTU. During the analysis, the data was not offset to account for contact time in the process; however, as the use of the data was for risk analysis and the data set was large it was assumed that this assumption would have a negligible impact. Future analysis should check this assumption.

It was decided to keep all the data points, including those that gave a negative percentage reduction, since it is possible for a filter to experience detachment if captured particles are sloughed from the filter media (MWH, 2005). However, if negative percentage removal values were included, the lognormal distribution could not be used to model the process, as negative values are incompatible with the lognormal distribution. Thus, to use the lognormal distribution, a value of percent remaining as opposed to percent reduction was used. Using the percent of influent turbidity remaining in the effluent eliminated the negative values within the data record but still allowed for the effluent to be greater than the influent (Dunn, Frodsham, & Kilroy, 1998).

After performing the necessary calculations, a CDF for the percentage of influent turbidity remaining was determined. This CDF is shown in Figure 4.2, while summary statistics for the percentage of influent turbidity remaining can be seen in Table 4.1.

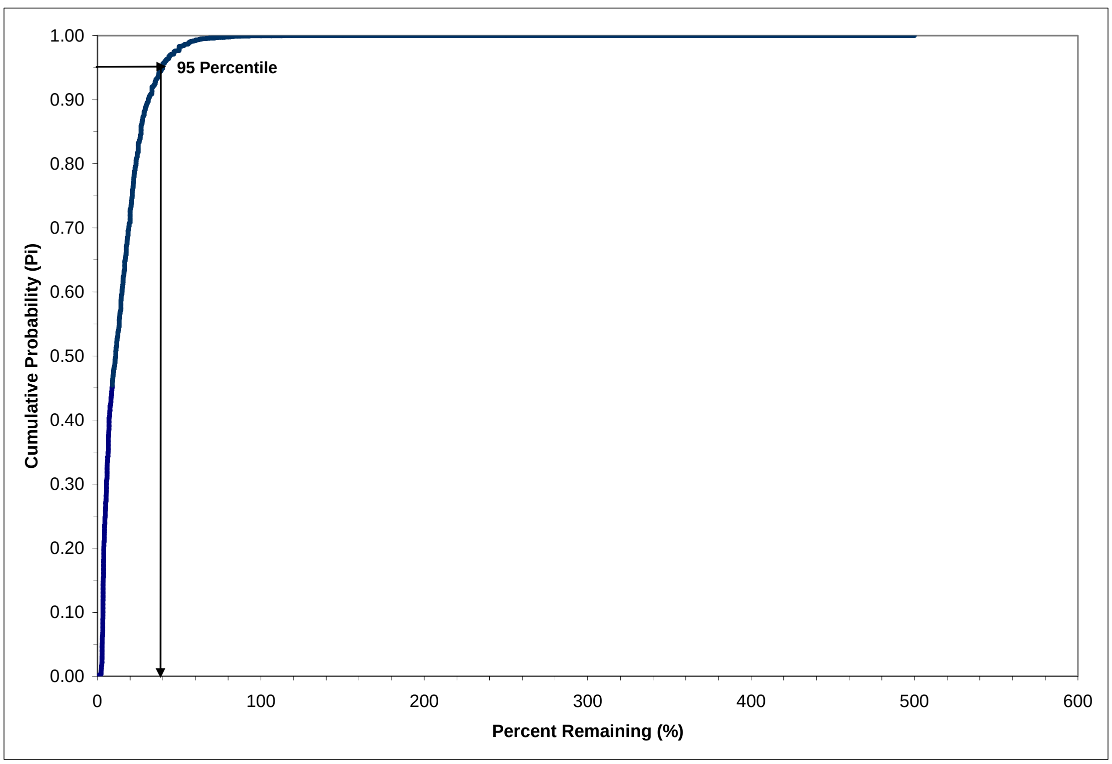

Figure 4.2: Cumulative distribution function of the percentage of influent turbidity remaining for filter 1

Table 4.1: Summary statistics for the percentage of influent turbidity remaining for filter 1

	Percent of Influent Turbidity Remaining (%)
Maximum (%)	500
Minimum (%)	0.4
Average (%)	14.8
Standard Deviation (%)	13.0
95th Percentile (%)	40.0
99th Percentile (%)	56.3

4.1.2 Distribution Fitting of Data

In order to perform the CFA, a distribution fitting process was undertaken to determine the probability distribution functions for the influent turbidity and the percent of influent turbidity remaining. This process follows the procedure that was described in Section 3.5.3 and Section 3.5.4.

Initially the method of moments was used to obtain the distribution parameters for the four selected distributions. These parameters were then used to characterize the four different distributions when undertaking the distribution fitting exercise. Table 4.2 and Table 4.3 outline the distribution fitting comparison parameters while Figure 4.3, and Figure 4.4 provide a visual comparison of the distribution fitting process. For a visual comparison, the closer the data points plot to a straight line, the better the assumed distribution fits the data set.

Table 4.2: Distribution fitting statistics for influent turbidity

	Probability Plotting (r^2)
Normal	0.613
Lognormal	0.964
Exponential	0.712
Gumbel	0.708

Table 4.3: Distribution fitting statistics for percentage of influent turbidity remaining

	Probability Plotting (r^2)
Normal	0.807
Lognormal	0.963
Exponential	0.965
Gumbel	0.938

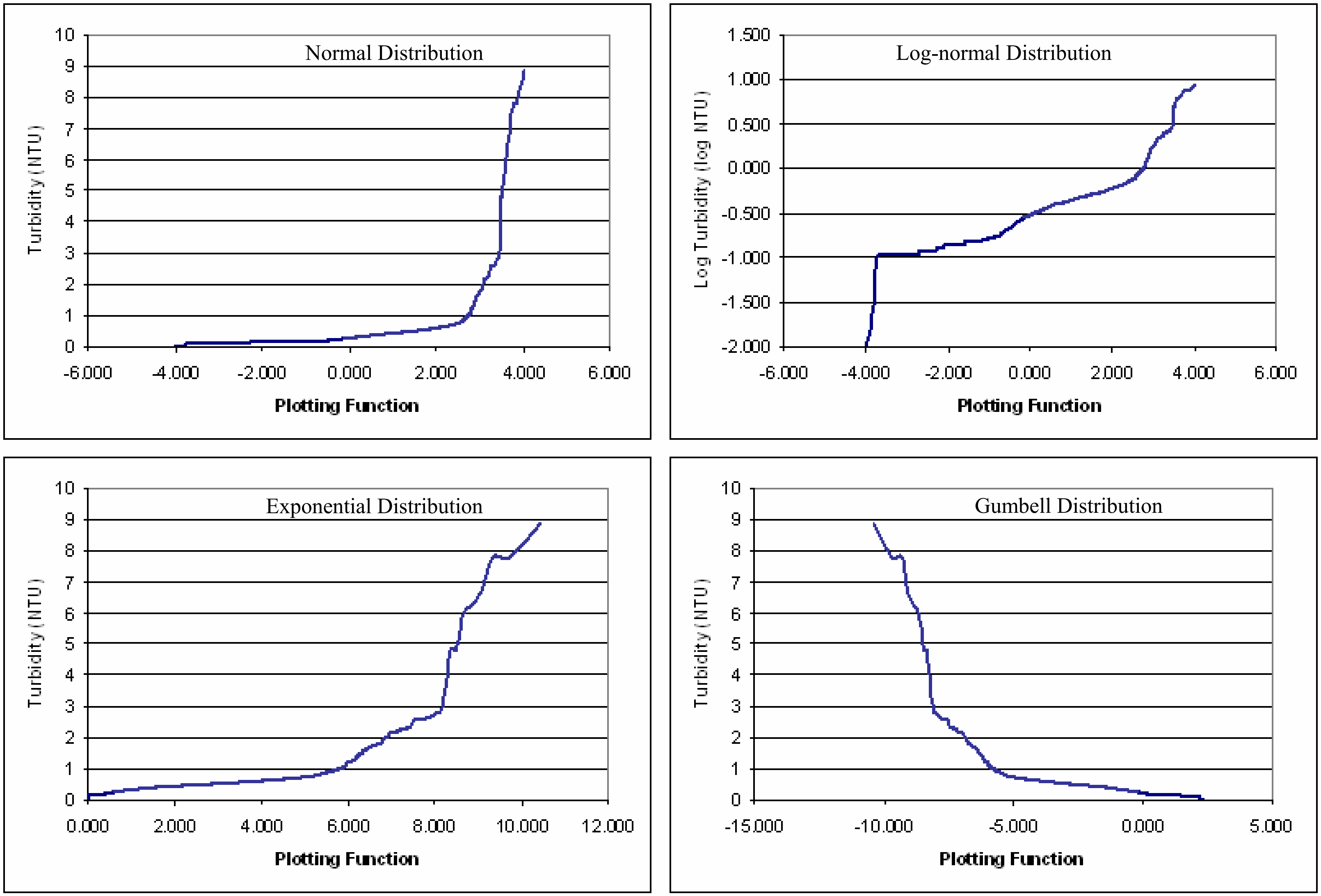

Figure 4.3: Probability plots for distribution fitting of influent turbidity data: Clockwise from top left, normal distribution, log-normal distribution, Gumbell distribution, exponential distribution

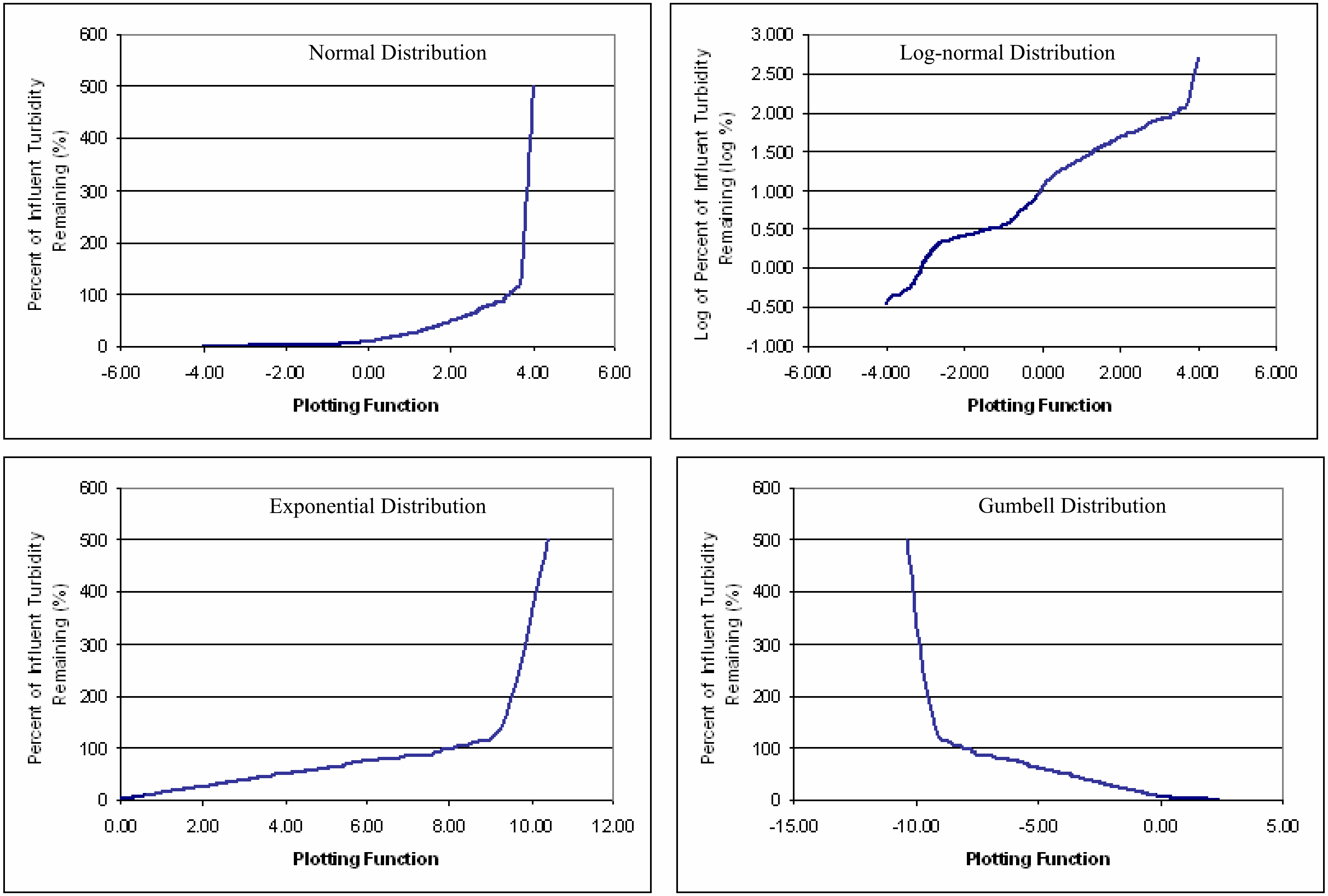

Figure 4.4: Probability plots for distribution fitting of the percent of influent turbidity remaining data: Clockwise from top left, normal distribution, log-normal distribution, Gumbell distribution, exponential distribution

From Table 4.2 and Table 4.3 it can be seen that the lognormal distribution provides the best fit to both the influent turbidity and the percentage of influent turbidity remaining data. From this analysis it was decided that the lognormal distribution would be used for future analysis. Table 4.4 shows the final distribution parameters for the lognormal distribution.

Table 4.4: Lognormal distribution parameters for influent turbidity and percentage of turbidity remaining

	Influent Turbidity (NTU)	Percentage of Influent Turbidity Remaining (%)
μ	-0.54	-0.98
σ	0.19	0.37

4.1.3 Simulation Convergence

To determine the outcome of any simulation, the issue of simulation convergence, also referred to as numerical stability, is important. Burmaster and Anderson (1994) stated, as principle twelve of their fourteen principles of good practice in the use of Monte Carlo simulation techniques, that the numerical stability of a simulation must be investigated. One method of investigating the convergence of a simulation is through plotting the output from a simulation as a function of the number of shots performed during the simulation (Verdonck, 2003). A shot is one calculation and a simulation is the entire set of calculations. For each simulation different percentile levels are calculated and tracked. Through tracking the percentile values for each simulation, the convergence of the simulation can be seen. Percentile levels are calculated such that x% of the output is below the stated level. For example, at the 95th percentile level, 95 percent of the output is below the stated value. Figure 4.5 and Figure 4.6 show the convergence of the CFA simulation for the rapid gravity filtration unit.

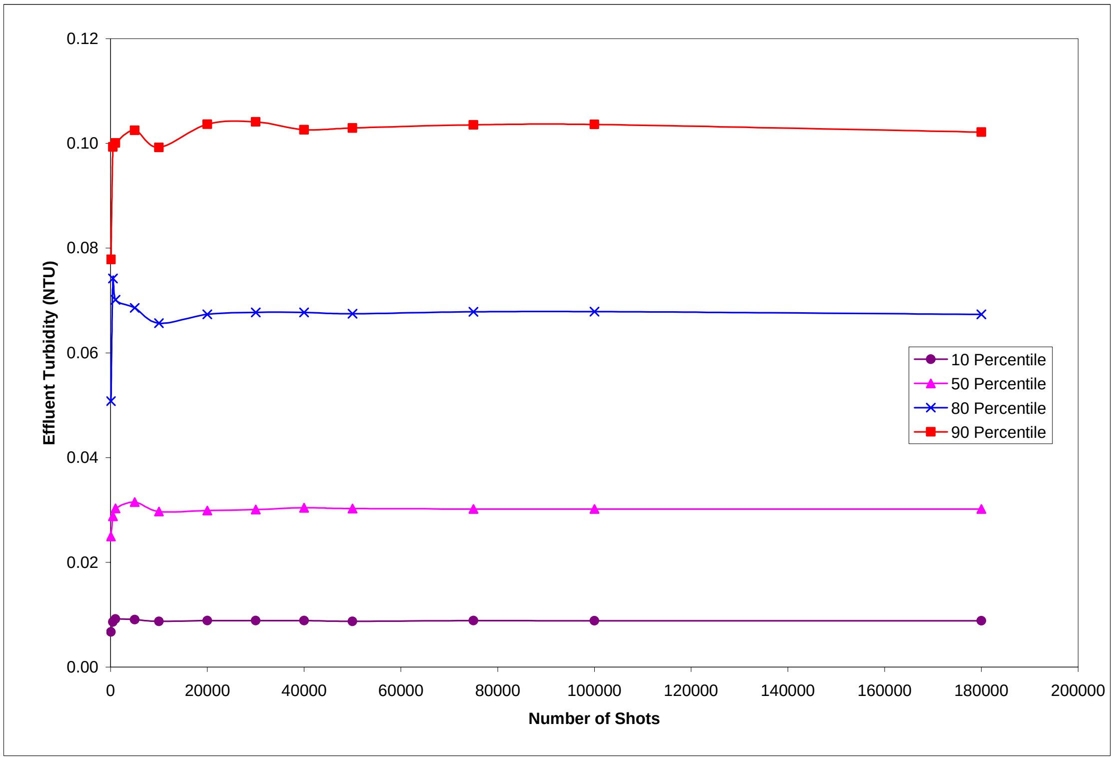

Figure 4.5: Convergence of the CFA simulation: 90th percentile and below

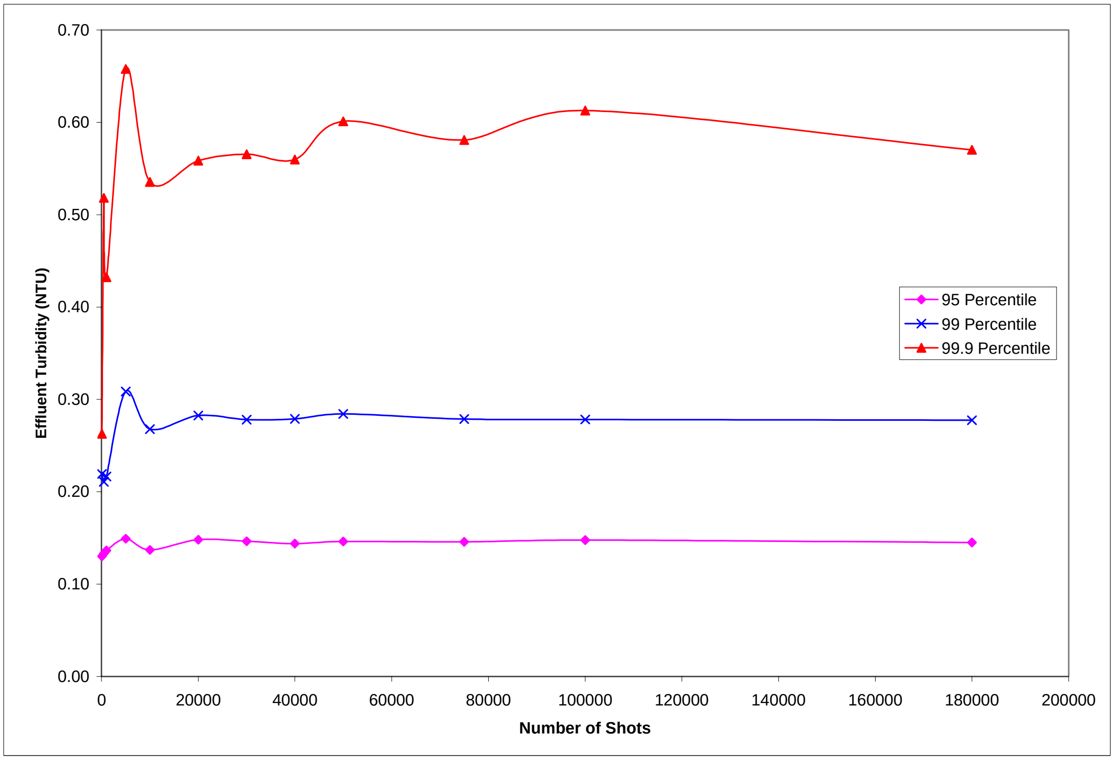

Figure 4.6: Convergence of the CFA simulation: 95th percentile and above

Figure 4.5 and Figure 4.6 show that the CFA performed on the rapid gravity filtration unit converges rapidly for low (10 – 50th) percentile levels (approximately 40,000 shots), as illustrated in Figure 4.5; however, takes a while for the 95th and 99th percentiles to converge (approximately 100,000 shots), as illustrated in Figure 4.6. For analysis purposes, the 99th percentile is the highest percentile level to be used. Thus the slight undulation of the 99.9th percentile is shown only to illustrate the difficulty that some simulations can have in stabilizing. Furthermore, because the 99.9th percentile has not yet converged at 180,000 shots, the maximum values recorded during a simulation at this number of shots should be used with extreme caution. From the simulation convergence study, it was decided to use 180,000 shots per simulation for all further CFA investigations since the 99th percentile and below have all converged by this number of shots.

4.2 CFA Simulation Output

A full CFA was performed for 180,000 shots and can be seen in Figure 4.7. From the CFA output, a set of summary statistics was calculated and compared to the actual effluent turbidity experienced by the filtration unit for the 2004 year. Table 4.5 shows these values.

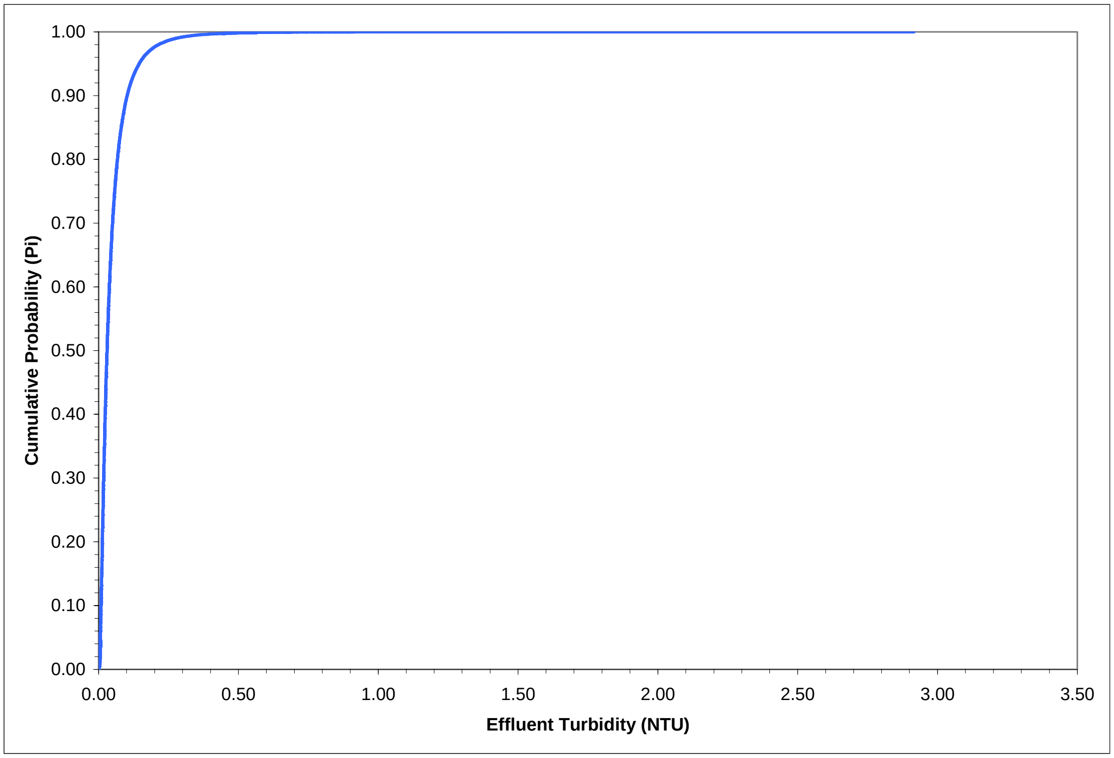

Figure 4.7: Cumulative distribution function for a full CFA simulation

Table 4.5: Summary statistics of effluent turbidity for a full CFA simulation

	Filter 1 Effluent (NTU)	CFA Effluent (NTU)
Maximum	0.25	2.92
Minimum	0.01	0.01
Standard Deviation	0.04	0.06
Average	0.04	0.05
95 Percentile	0.11	0.15
99 Percentile	0.15	0.28

The summary values from Table 4.5 show a discrepancy between what is currently experienced by the filter and what could possibly occur according to the CFA. Although the minimum, standard deviation and average turbidity values are similar, from a risk perspective, the simulation results indicate that there is a greater probability of higher effluent turbidity water being produced than what is currently experienced at the water treatment plant.

This increased probability of producing non-compliant water is illustrated by the increasing divergence in effluent turbidity values between the simulated data and the measured data at higher percentile levels, such as the 95th and 99th percentiles. For example, while the filtration unit currently operates such that 99% of the effluent turbidity is below 0.15 NTU, the simulation indicates that the filtration unit is operating such that 99% of the effluent turbidity is below 0.28 NTU. The divergence at the 99 percentile level amounts to a 0.13 NTU difference between the simulated data and the measured data. While the different in the effluent turbidity level does not seem large, this increase could have an effect on microbial contaminants as described in Huck et al., 2001; Huck et al., 2002; and Emelko et al., 2003.

This divergence is shown visually in Figure 4.8 and Figure 4.9. Figure 4.9 is identical to Figure 4.8 but it concentrates on the percentile levels between 90 and 100 where the differences between the two data series become more significant. The rest of the CDFs that will be displayed throughout this thesis will only concentrate on the area of interest; however, Appendix B displays the entire CDF for each graph shown.

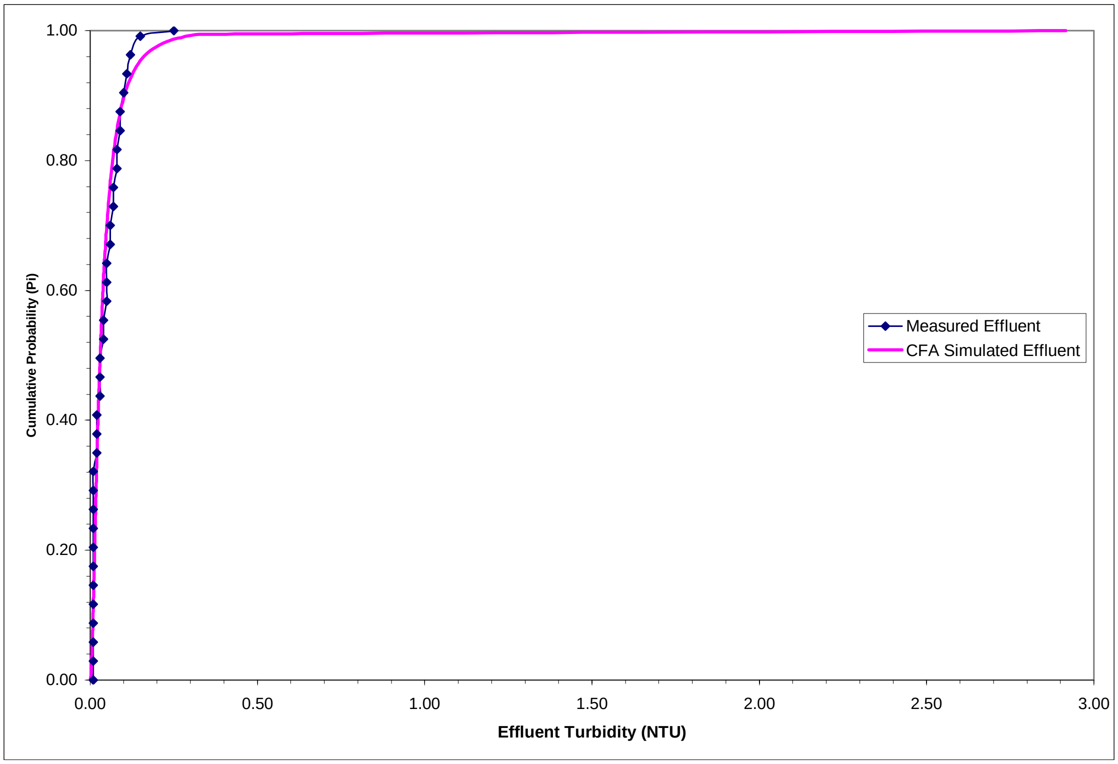

Figure 4.8: Comparison between measured turbidity effluent and CFA simulated effluent

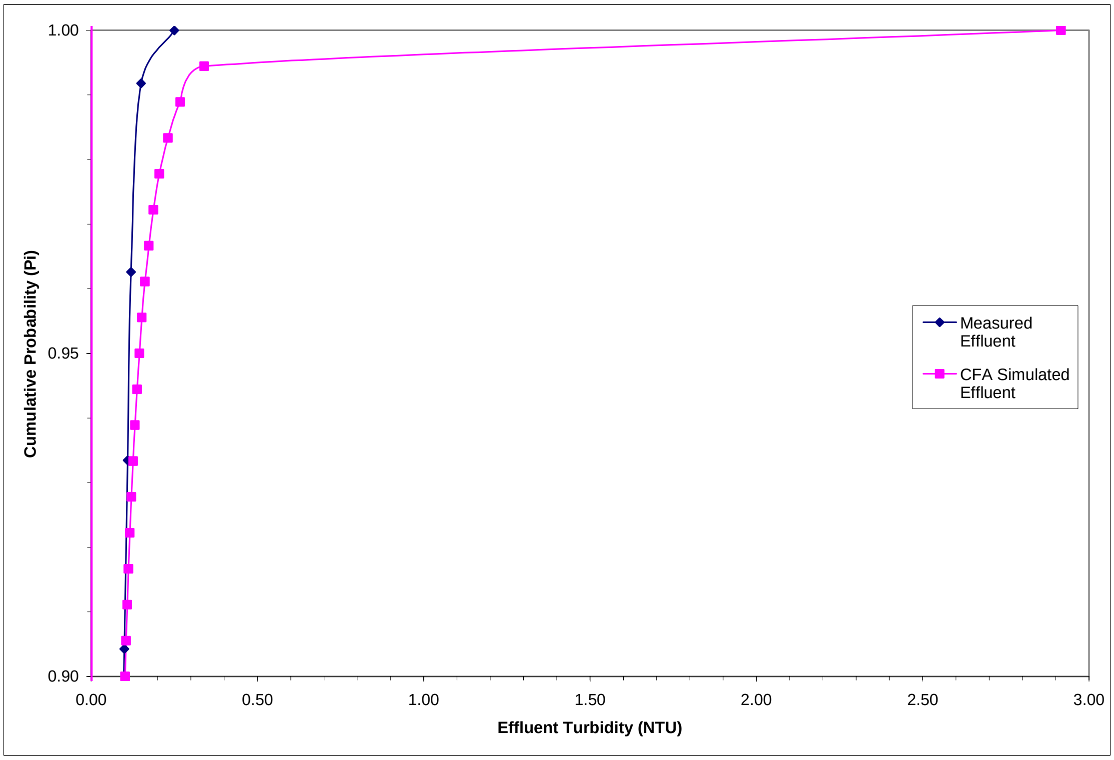

Figure 4.9: Comparison between measured turbidity effluent and CFA simulated effluent for a cumulative probability of 90% and above

While there are obvious differences between the CFA simulated effluent and the measured effluent, it is possible that some of the differences between the measured effluent and the CFA simulated effluent can be attributed to problems in the CFA methodology, not because of an increased risk level. These possible problems were investigated through a series of simulation tests.

4.3 Factors That Could Affect the CFA Output

4.3.1 Conditional Reliability Effect

One factor that could affect the CFA output is that of conditional reliability. Conditional reliability occurs when the output is conditional upon one or more parameters (Baxter et al., 2003). In the analysis of Filter 1, conditional reliability could occur if the effluent turbidity was affected by another factor, such as the influent turbidity.

To determine if there was a conditional reliability affect, the influent turbidity was separated into five percent (5%) intervals based on the range of influent turbidity values. Summary statistics of the percent of turbidity remaining within each group were then calculated. Figure 4.10 shows that although the overall percent of turbidity remaining is around 14%, as the influent turbidity increased the average percent of influent turbidity remaining decreased. Thus a greater percentage of turbidity is removed when the influent turbidity is higher. This can partially be explained by the filtration process. In the measured data set a large number of effluent turbidity values were measured to be 0.01 NTU regardless of influent turbidity. If the effluent turbidity remains approximately the same but the influent turbidity varies, then a higher influent would have a higher percentage removal.

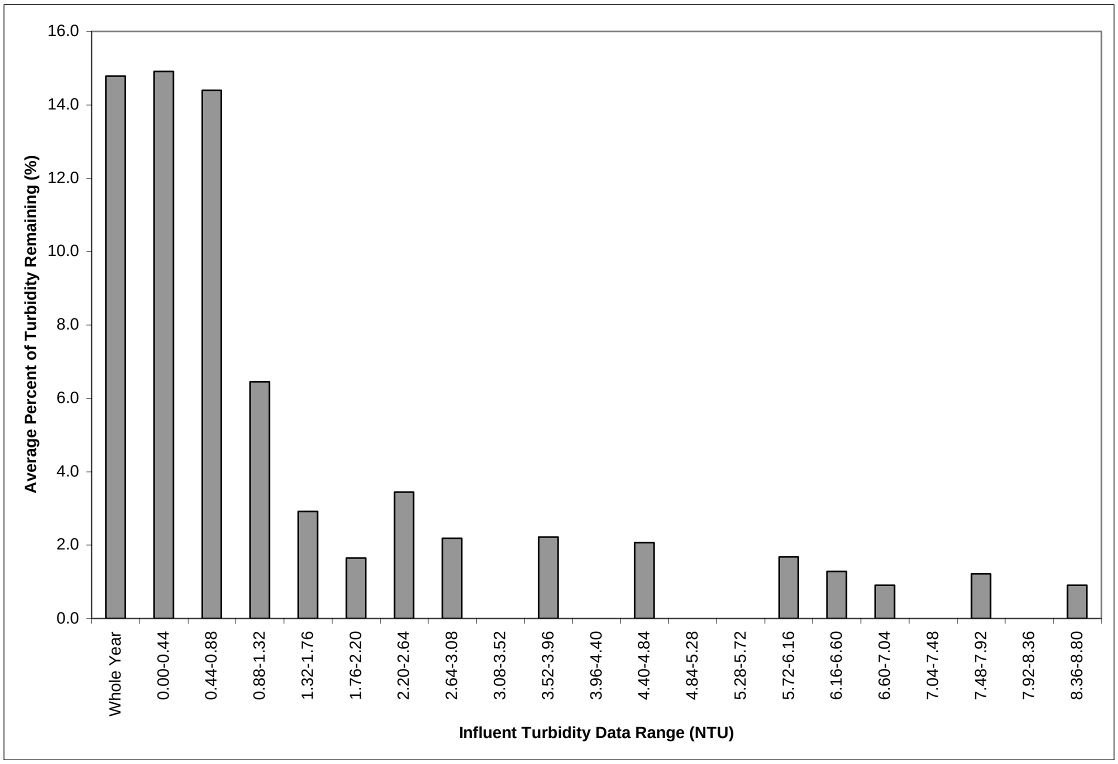

Figure 4.10: Average percent of turbidity remaining for turbidity percentiles

Because of the possible conditional reliability affect, the percent of turbidity remaining data were separated into two sections; below 0.88 NTU influent turbidity and above 0.88 NTU influent turbidity based on the analysis described in Figure 4.10. Both data sets then underwent a distribution fitting exercise similar to that described in Section 4.1.2. Table 4.6 shows the parameters of the new lognormal distributions.

Table 4.6: Lognormal distribution parameters for influent turbidity distributions modified by conditional reliability

	Below 0.88 NTU	Above 0.88 NTU	Overall
μ	-0.98	-1.56	-0.98
σ	0.37	0.45	0.37

Incorporating the principles of conditional reliability into the CFA simulation required a change in the CFA methodology. During the modified CFA simulation, a check occurred where the random influent turbidity value would simulate a percent of turbidity remaining from one distribution if the influent turbidity was over 0.88 NTU and from the other distribution if the influent turbidity was below 0.88 NTU. The CDF for the CFA modified for conditional reliability is shown in Figure 4.11.

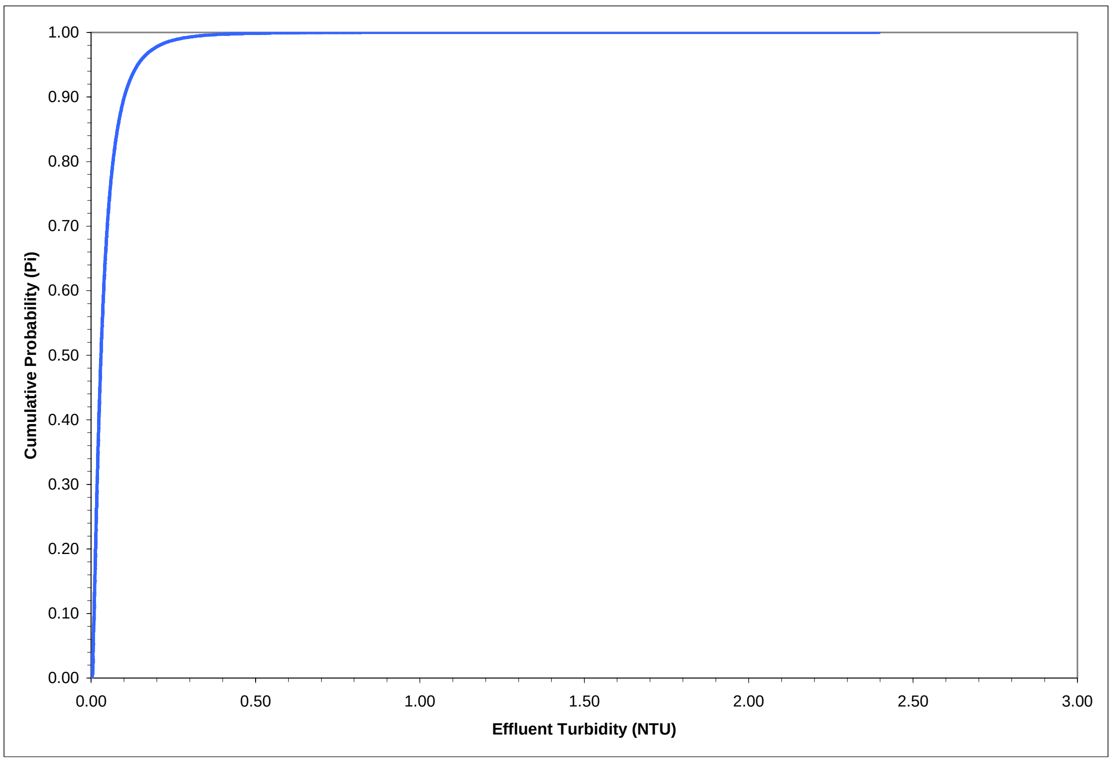

Figure 4.11: Cumulative distribution function of effluent turbidity for a CFA modified for conditional reliability

The comparison between the CFA with and without taking into account conditional reliability, as shown in Table 4.7, and Figure 4.12, shows no distinct difference between the two simulations. Although there might be a desire to use the maximum values, as shown in Table 4.7, or the divergence between the two simulations in the upper tails, as shown in Figure 4.12, as proof that the CFA which was modified for conditional reliability eliminated some of the peak values, this cannot be concretely shown as Figure 4.6 shows that at the 99.9th percentile, or essentially the maximum values, have not converged at 180,000 shots. Although there is no discernable difference between the two analyses performed for this thesis, past research, Baxter et al. (2003), has shown that the principles of conditional reliability can be used to help with the analysis of a filtration unit.

Table 4.7: Summary statistics of effluent turbidity for a CFA modified for conditional reliability

	Simulated CFA Effluent (NTU)	Simulated CFA Effluent Modified for Conditional Reliability (NTU)
Maximum	2.92	2.40
Minimum	0.01	0.00
Standard Deviation	0.06	0.06
Average	0.05	0.05
95% Confidence	0.15	0.14
99 % Confidence	0.28	0.27

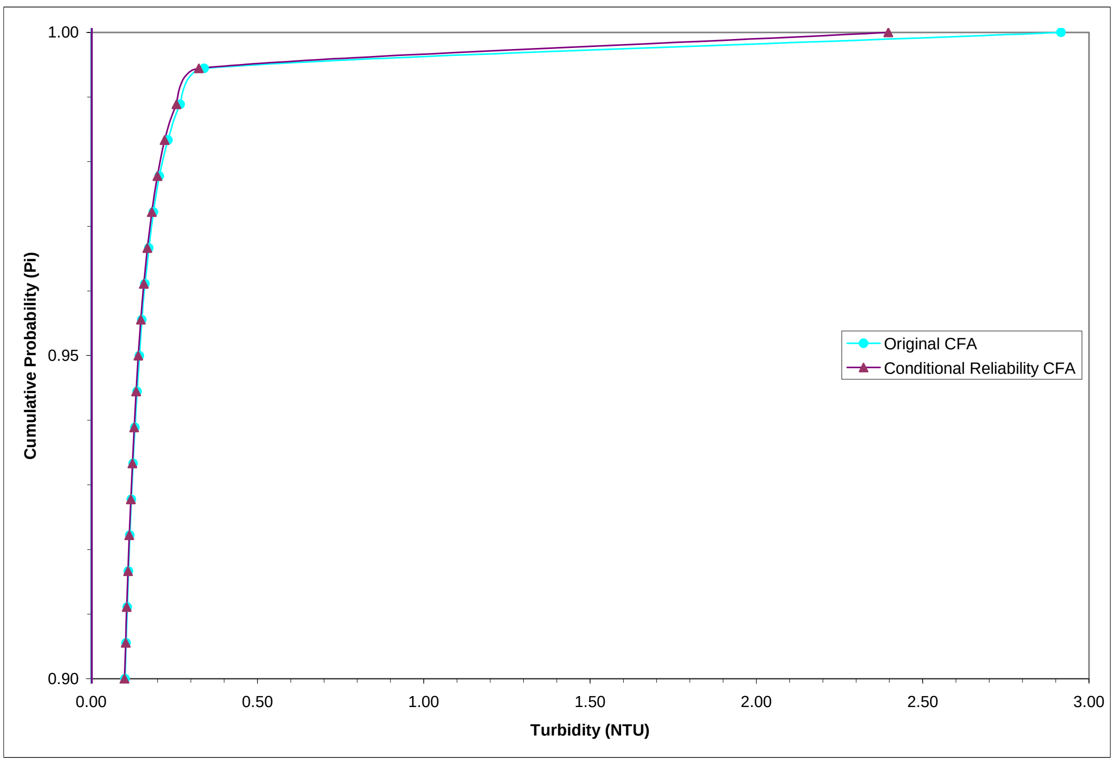

Figure 4.12: Comparison between the original CFA and CFA modified for conditional reliability: Focusing on the top 10 % of the cumulative distribution function

Part of the reason that no difference was noticed when using the principles of conditional reliability with the CFA is that the analysis used only the influent turbidity as a condition which could affect the filtration process. Effluent turbidity and the filtration process could be conditional upon a large number of other parameters that were not considered in this analysis such as filter flow rate, pH, temperature, coagulation conditions, or any number of other possibilities.

4.3.2 Influence of the Data Record

A concern with the CFA methodology is how it responds to data records collected at different times over the course of one year. To test the robustness of the CFA methodology to the number of data points collected and the season during which they were collected, a series of CFAs were performed using different sizes of data records. The outputs from these analyses were then compared to the CFA using all the data from the 2004 data record.

To perform the analysis, the influent turbidity distribution that was calculated for the entire 2004 data set in Section 4.1.2 was used for all simulations. However, a new distribution fitting procedure was performed for the percent of turbidity remaining distribution for each sub-set of data that was chosen. The sub-sets of data were chosen at even intervals throughout the year and then for one half of the year. Table 4.8 shows the calculated lognormal distribution parameters for the percentage of turbidity remaining for each data sub-set.

Table 4.8: Lognormal distribution parameters for percentage of turbidity remaining for simulations with sub-sets of the 2004 data

	2004 Year	January Data	May Data	September Data	January – June Data
μ	-0.98	-1.33	-0.85	-0.46	-1.16
σ	0.37	0.19	0.20	0.18	0.32

The CDF output from all the different simulations is shown in Figure 4.13, while Table 4.9 shows a set of summary statistics that were calculated for each of the performed simulations.

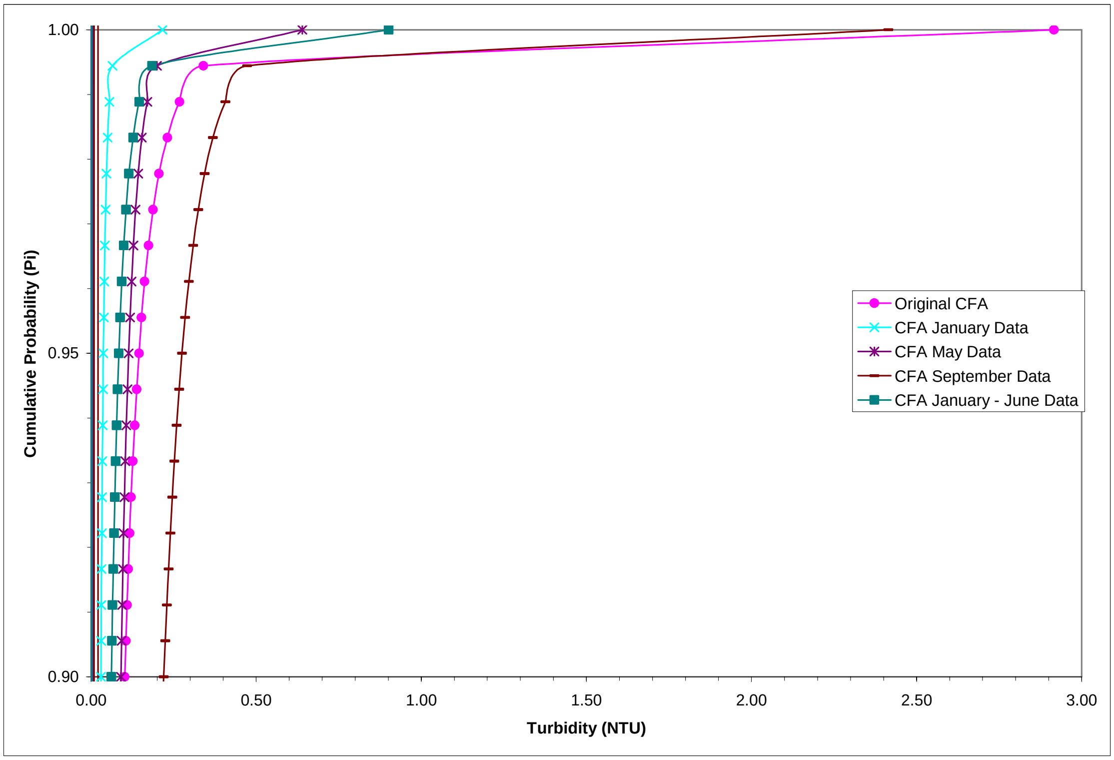

Figure 4.13: Comparison between the original CFA to the CFA with sub-sets of data using cumulative distribution functions: Focusing on the top 10 % of the cumulative distribution function

Table 4.9: Summary of output from CFA simulations with sub-sets of the 2004 data

	Original CFA (NTU)	CFA with January Data (NTU)	CFA with May Data (NTU)	CFA with September Data (NTU)	CFA with January – June Data (NTU)
Maximum	2.92	0.22	0.64	2.41	0.90
Minimum	0.01	0.00	0.00	0.01	0.00
Standard Deviation	0.06	0.01	0.03	0.08	0.03
Average	0.05	0.02	0.05	0.12	0.03
95 Percentile	0.15	0.04	0.11	0.28	0.08
99 Percentile	0.28	0.06	0.18	0.42	0.15

The data presented in Figure 4.13 and Table 4.9, show the dependence of the CFA on the data record itself. None of the sub-sets of data were able to generate output that was comparable with the original CFA. Therefore, if the CFA methodology is used in a situation where only a small sample of data is known or where data was known over a short time period, there could be difficulty in having confidence in the final results.

4.4 Discussion of the CFA Methodology

The analysis performed in Section 4.3 showed that the output from a CFA simulation can be affected by a number of different factors. This wide range of possible outputs is illustrated by Figure 4.14.

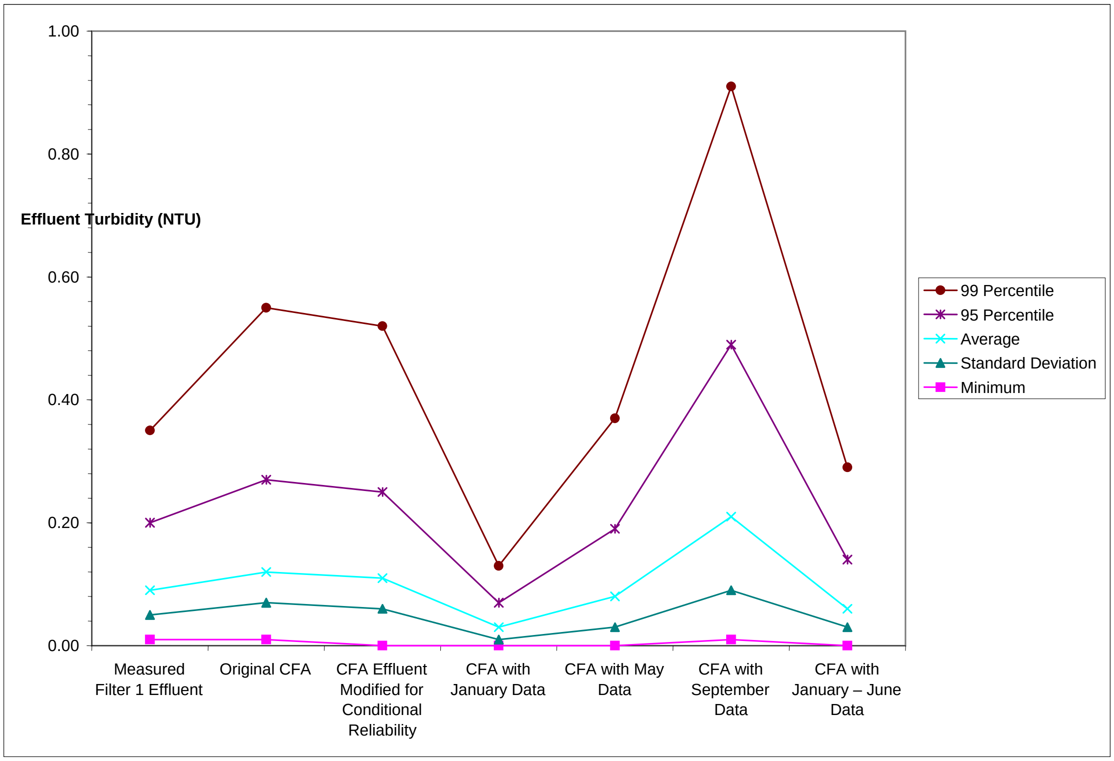

Figure 4.14: Summary of effluent values for all CFA simulations

In Figure 4.14, the largest differences between the original CFA and the different CFA simulations are provided by the CFA simulations that were performed with sub-sets of the 2004 data. The smallest differences are between the original CFA and the CFA simulation that included conditional reliability in the analysis. These two issues must be considered when performing future CFAs.

Another issue with the CFA that has not been discussed hitherto is that of the maximum values experienced by the CFA. The CFA provides a number of effluent turbidity values which are above 1.0 NTU. If a filter was analyzed that had a backwash trigger set to 1.0 NTU, these high effluent turbidity values should not be present, providing the backwashing process is properly functioning. Thus these maximum values would then be experienced as part of a breakdown in the mechanical functionally of the treatment process. Given that the breakdown of a backwashing sequence or of a mechanical component involved in the backwash should be identified through an evaluation of mechanical risks, these maximum turbidity values should not affect the operational risk analysis exercise. Consequently, the effluent values above the backwash trigger that are experienced by the CFA should not appear during a proper operational risk analysis. The filtration unit analyzed from the Brantford WTP operates on a headloss trigger, thus these maximum turbidity values cannot be directly discounted for this particular analysis, although they would normally not be expected as headloss triggers are typically set to initiate backwash before high turbidity values are experienced. It should be mentioned that high turbidity values can also occur from other factors such as a problem with a turbidity meter or due to air bubbles in the system (Scardina, Letterman, & Edwards, 2006). These issues were not taken into account at this stage of research and the extensive data set was assumed to remove these effects from the risk analysis.

Although a number of concerns have been raised concerning the CFA, Figure 4.14 shows that, if the measured effluent values are used as a benchmark, the CFA can provide a good indication of the output from a filtration unit with the possible exception of higher values at or above the 99^{th} percentile.

4.5 Risk Evaluation

One of the ways to classify the risk for a filter is to determine the likelihood that a filter will produce effluent turbidity greater than some threshold value. Table 4.10 and Figure 4.15 show the risk evaluation for Filter 1 with the CFA.

Table 4.10: Risk evaluation for target levels through the CFA

	Median (%)	95% Confidence Upper Bound (%)	95% Confidence Lower Bound (%)
Probability Effluent Turbidity > 0.05 NTU	29.9	30.1	29.7
Probability Effluent Turbidity > 0.10 NTU	10.4	10.5	10.3
Probability Effluent Turbidity > 0.30 NTU	0.81	0.77	0.85

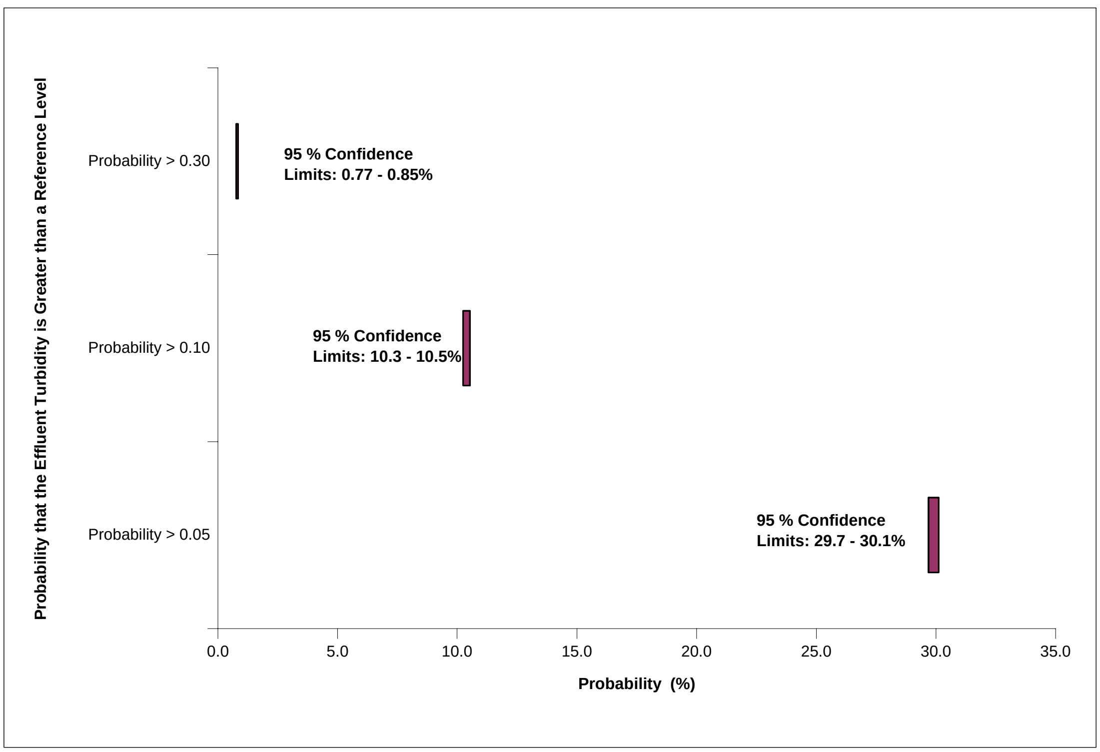

Figure 4.15: Risk evaluation for target levels through the CFA

The confidence intervals shown in Table 4.10 are calculated based on the number of shots performed for each simulation. This calculation is based on the standard deviation of the simulation where the standard deviation is calculated as described in Equation 15 (Pandey, 2005):

Equation 15

$$\sigma = \sqrt{\frac{\mu(1-\mu)}{N}}$$

where:

μ is the mean probability that the output is greater than some reference level,
N is the number of shots in the simulation,
σ is the calculated standard deviation of the simulation.

The upper and lower bound confidence intervals are then calculated using the equation:

Equation 16

$$Bound = \mu \pm k * \sigma$$

where:

k is the value from a normal distribution which corresponds to the chosen confidence level.

4.6 Implications for the Brantford Water Treatment Plant

Although some concerns related to the CFA have been stated and should be noted, some conclusions for the Brantford Water Treatment filtration unit can still be drawn.

If this analysis was performed for a regulatory agency with a requirement that the turbidity must be below 0.30 NTU 95% of the time, then, as Table 4.11 shows, the measured data and the CFA simulated data currently meet this requirement. The measured data show no observed value greater than or equal to 0.30 NTU and the CFA simulated data shows that effluent turbidity is greater than the 0.30 NTU level 0.80% of the time, which is much less than the guideline of 5%. However, if the guideline was made more stringent such that the turbidity should be less than or equal to 0.10 NTU in at least 95% of the measurements made, the guideline is not as easily met.

While the measured data indicate that the new guideline would be met approximately 93% of the time, the CFA shows that the new guideline would only be met approximately 90% of the time. While no conclusive statement can be made as to whether the CFA or the measure data set is more reliable, the measured data set is bound by the past data set while the CFA incorporates a wider range of possible effects into the analysis.

Table 4.11: Risk evaluation for target levels for measured data and CFA simulated data

	Measured Data (mean %)	CFA Simulated Data (mean %)
Probability Effluent Turbidity > 0.10 NTU	6.9	10.4
Probability Effluent Turbidity > 0.30 NTU	0.0	0.81

Another way to analyze the results from the risk analysis is to incorporate the output from the risk analysis and combine it with the idea of conditional reliability. Table 4.12 shows this analysis with the CFA. The influent turbidity was broken down into three categories, less than the mean minus one standard deviation, between the mean minus one standard deviation and the mean plus one standard deviation, and greater than the mean plus one standard deviation. Within each of the sections a cumulative distribution function was calculated such that the probability of producing water greater than some standard could be calculated.

Table 4.12: Conditional reliability analysis of CFA methodology

Condition	Probability Effluent Turbidity > 0.05 NTU	
Influent Turbidity		
	Influent Turbidity Less than (-0.732); $\upsilon-\sigma$ in the lognormal distribution	0.09
	Influent Turbidity Between (-0.732 and -0.353); $\upsilon-\sigma$ and $\upsilon+\sigma$ in the lognormal distribution	0.28
	Influent Turbidity Greater than (-.353); $\upsilon+\sigma$ in the lognormal distribution	0.56

From the results of Table 4.12, the indication is that the output is primarily dependent on the influent water quality since once the influent water quality is greater than the mean plus one standard deviation the probability of the turbidity effluent is greater than 0.05 NTU is 56%. Thus, to reduce the probability of producing high effluent turbidity, the influent turbidity should be lowered; however, this analysis can be misleading since only one condition is evaluated, which is an inherent constraint of the CFA.

CHAPTER 5
RESULTS AND DISCUSSION USING COMPUTER MODELLING AND PROBABILISTIC RISK ANALYSIS

5.1 Application of the Computer Modelling and Probabilistic Risk Analysis to Filter 1

Before undertaking an analysis, it was necessary to adapt the principles of computer modelling and probabilistic risk analysis directly to a rapid gravity filtration unit. This process, performed for Filter 1 of the Brantford Water Treatment Plant, is depicted in Figure 5.1.

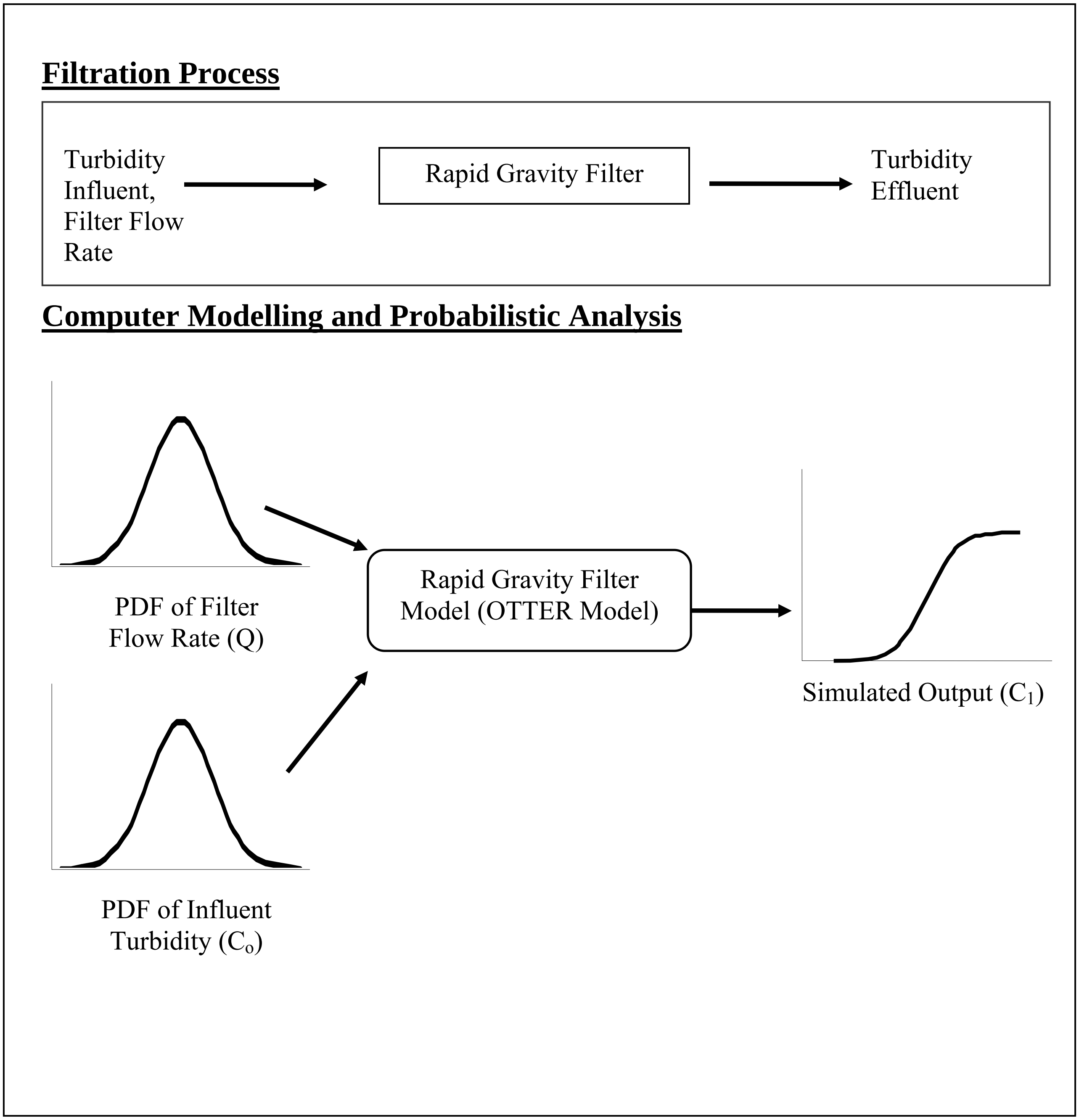

Figure 5.1: Diagram of computer modelling and probabilistic analysis methodology applied to filtration unit

Initially, the probability distribution functions of the filter flow rate (Q) and influent turbidity (C_0) are determined. From these distributions, random values are selected and input into a calibrated filtration model which was then run. The output from this process is a CDF representing different possible effluent turbidity values (C_1). Although the filter flow rate was not used in the CFA, the filter flow rate was used in this analysis as the OTTER model uses the filter flow rate to model the filtration process, as described in Section 3.3.4.

5.2 Model Set-Up

To set-up the OTTER filtration model, there were four separate categories of data that were determined: static data, which are the physical properties of the filter; operating data, which focus on the operation of the filter; calibration data, which allow OTTER to model the filtration process for the filter of interest; and input data. However, before determining this information, a series of preliminary experiments were undertaken to determine how the OTTER model would perform under different conditions.

5.2.1 Preliminary Experiments

The preliminary experiments evaluated how the output from the filter model would be affected by choosing either the logistic or finite difference model within the OTTER software, how water quality parameters that were not included in the overall risk analysis would affect the output, and how the method of input, either hourly or every fifteen minutes, would affect the output. A summary of the findings are presented here, the entire analysis can be seen in Appendix C.

During the discussion of the logistic and finite difference models in Section 3.3.3, it was noted that the two different models use different mathematical relationships to model the filtration process. Furthermore, because of the modelling procedure; the finite difference model was the only model able to evaluate the effects of backwashing as the logistic model re-sets the filter to its original state while the finite difference model uses equations to determine how the filter is backwashed. The analysis showed that the two models provided different output for the headloss build up within the filter and the effluent turbidity itself, even though in some cases these differences were small. However, this analysis was performed on an uncalibrated model. Since calibration attempts to induce the model output to match the physical output, both calibrated models should theoretically operate similarly. It was decided to use the logistic model primarily for its ease of use and because backwashing was not explicitly looked at during this analysis.

Although the parameters of interest in this risk analysis are the input turbidity and the filter flow rate, the OTTER model allows for an analysis of a large number of other parameters. These other water quality parameters were not included within the risk analysis but their presence within the OTTER model could have some effect on the output. From the preliminary analysis, external water quality parameters were shown to have an effect primarily on the headloss build up within the filter but not on the effluent turbidity values. This can be expected since parameters such as temperature were included in the analysis. The temperature will affect the properties of water and thus affect the filtration process, particularly the headloss. However, although some effect was noticed during the preliminary study, most water quality parameters analyzed would not affect the modeled filtration process described in Section 3.3.4 since the modelling equation focuses on the influent and effluent turbidity. To compensate for any possible affect of external water quality parameters, all further simulations were performed using identical, input values for water quality parameters that were not directly included in the analysis.

Within OTTER there is the ability to change the timing of inputs to the model. Therefore, hourly data can be entered into a data record but fifteen minute inputs to the system can be chosen. This causes OTTER to interpolate between two successive data points for the other input values. It was assumed that this method of interpolation should not be used because it strayed from the truly probabilistic methodology; thus a fifteen minute time frame was chosen for both the data record and the inputs to the filter.

5.2.2 Static and Operational Data

The calibrated OTTER filter model used static and operational data that were consistent with the basic characteristics of the Brantford WTP. The initial static data were the same as was used for preliminary analysis and can be seen in Table 5.1, which was also depicted in Table 3.2.

Table 5.1: Parameters for initial model set-up

Weir Height (m)	1.83
Filter Surface Area (m^2)	46.2
Media Layers	Anthracite over Sand
Anthracite Depth (m)	0.4572
Sand Depth (m)	0.4572
Anthracite Effective Size (mm)	0.85-0.95
Sand Effective Size (mm)	0.45-0.55

Operational data were primarily concerned with the method of backwashing. Since the specifics of backwashing were not looked at explicitly, it was not necessary to completely characterize the backwashing cycle but only to determine when a backwash occurred. For backwashing, the headloss trigger was set to 2.2 m after consultation with Brantford Water Treatment Plant employees. No other backwash trigger was used, as was consistent with the treatment plant operating policy.

5.2.3 OTTER Model Calibration

5.2.3.1 Recommended Calibration Procedure

The calibration procedures necessary for any OTTER model are described in WRc OTTER 2.1.3: Process Model Description (WRc plc, 2002). For the logistic filter model, the calibration procedures are based on a series of parameters:

- the attachment coefficient (r),
- the filter capacity (κ),
- the non-filterable solids fraction (ζ),
- the hydraulic conductivity (β), and
- the ripening period (tr).

The attachment coefficient and the filter capacity are determined through analyzing a filter breakthrough curve for turbidity, the ripening period is determined through comparing model and experimental value for different trials, and hydraulic conductivity is determined from a regression equation comparing a modified headloss parameter to a modified solids accumulation parameter (WRc plc, 2002). The non-filterable solids fraction must be assumed, however WRc plc (2002) recommends a value less than 0.1. Along with the above five (5) parameters, the properties of the media voidage (ε) and sphericity (ϕ) can be used to help the calibration procedure.

Saatci and Oulman (1980) recommend using pilot studies from at least three different filters at different depths to determine the calibration parameters of a filter. However, the recommended calibration procedure could not be used for the calibration of the Brantford filtration model because no pilot studies were available for the filters. Although less accurate, Saatci and Oulman (1980) state that it is possible to use data from an existing filter to determine the calibration parameters. This modified process is described in WRc plc (2002). However, even this modified process could not be used on the filter of interest. This occurred as the process recommended by WRc plc (2002) needs a filter breakthrough curve to be implemented. The current operation of the Brantford Water Treatment Plant backwashes the filter before such an event occurs. Thus a different method was developed to calibrate the existing data to the OTTER filter model with using the 2004 data record. Within the 2004 data record there were 142 different filter runs to evaluate. Time constraints did not permit an analysis of all 142 filter runs, thus the modified calibration method was developed to determine the calibration parameters from a smaller number of filter runs. Appendix D shows the modified calibration procedure. This procedure involved selecting four different filter runs from the 2004 data record which would cover the range of conditions experienced by the filter. The modified calibration procedure then determined the calibration parameters for the four selected filter runs.

5.2.3.2 Calibration Parameters

The following values are the calibration parameters calculated using the modified calibration procedure:

- the attachment coefficient (r), 0.06 h^{-1};
- the filter capacity (κ), 1100 mg/L;
- the non-filterable solids fraction (ζ), 0.0;
- the hydraulic conductivity (β), 0.06 $(L/mg)^{1/2}$; and
- the ripening period (tr), 5 hrs.

Furthermore, the voidage and sphericity values were changed from their default values for both anthracite and sand. These values were modified using data from Cleasby and Fan (1981) as a reference for modification. Cleasby and Fan (1981) provide a series of values for different parameters of sand and anthracite over a large number of sieve size ranges. The data from

Cleasby and Fan (1981) that correspond to the media size in the Brantford Water Treatment Plant can be seen in Table 5.2. These values were used in the calibrated model.

Table 5.2: Modified values for voidage and sphericity

	Calculated Values from Cleasby and Fan (1981)	
	Sand	Anthracite
Porosity [voidage] (ε)	0.468	0.564
Shpericity (ϕ)	0.773	0.645

Visually, the ability of the calibrated model to duplicate the output from the 2004 data record can be seen in Figure 5.2 for the headloss and Figure 5.3 for the effluent turbidity. These two figures are plotted using the same vertical scale for comparison. Appendix D provides the figures with varying scales to focus in on the differences between the filter runs. Figure 5.2 indicates that the headloss comparison is reasonable for the average and maximum accumulation filter runs, but the model predicts lower headloss for the low filter run and higher headloss for the high filter run. Figure 5.3 indicates that the effluent turbidity values are again reasonable for the average and maximum accumulation filter runs, but that the model predicts higher effluent turbidity for the low filter run and lower effluent turbidity for the high filter run. Figure 5.3 does show that for the average filter run, the 5 hour ripening period specified for the model differs from the ripening period that can be determined from the graph of approximately 20 hrs. A 5 hr filter ripening period was used for future simulations since, although it does not seem reasonable for the average filter runs, it was the calibrated value that best represented the range of filter runs described in Appendix D. It is important to note that all work was performed with the assumption of a completely clean filter at the start of each filter run. Thus, if a filter run in the data record did not start out as completely clean, the calibrated values would be incorrect. This is an assumption that could have a large effect and so should be checked in future work. For a discussion on average, low and high filter runs see Appendix D.

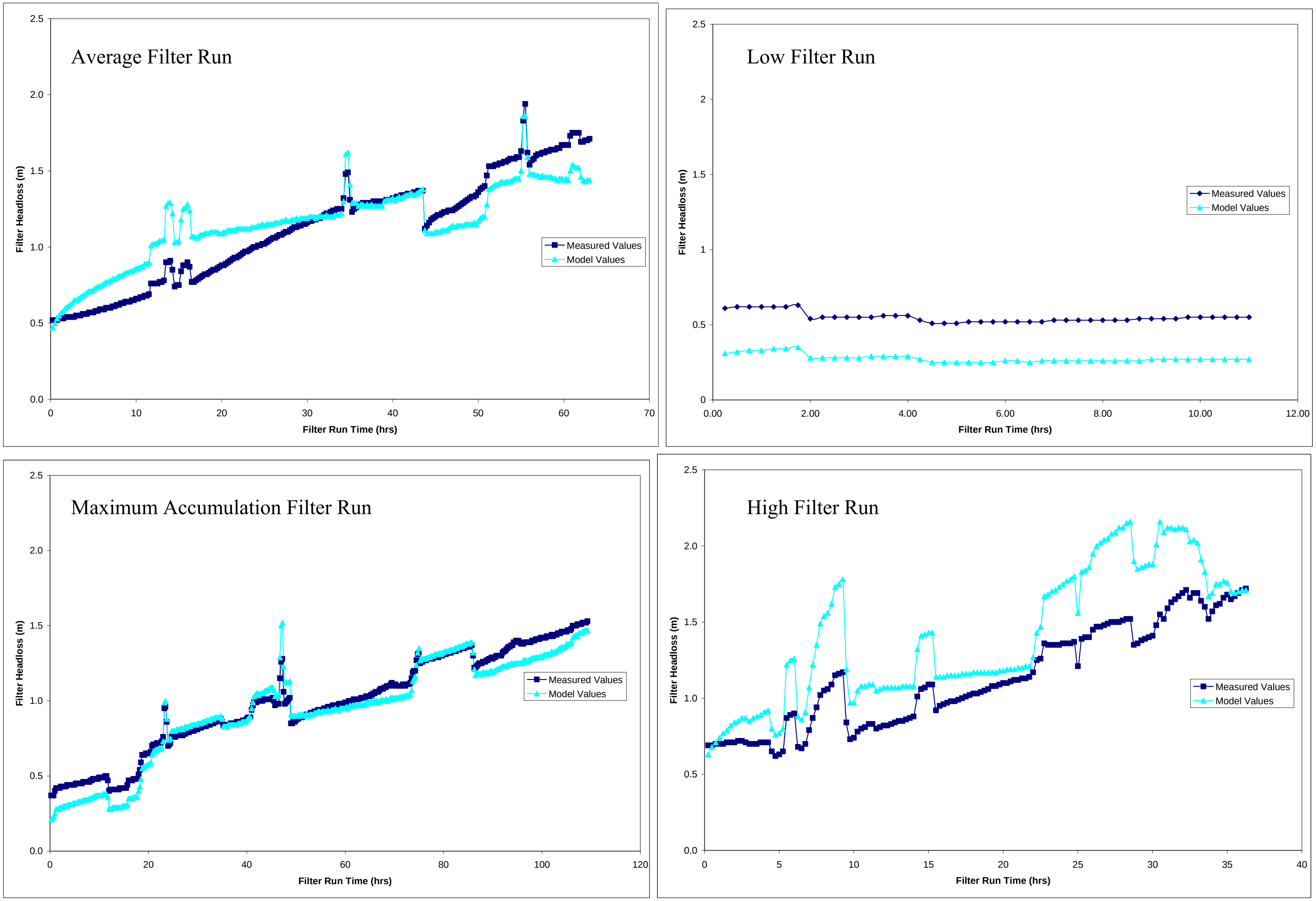

Figure 5.2: Comparison of measured vales and model calculated values for filter headloss: Clockwise from top left, average filter run, low filter run, high filter run, maximum accumulation filter run

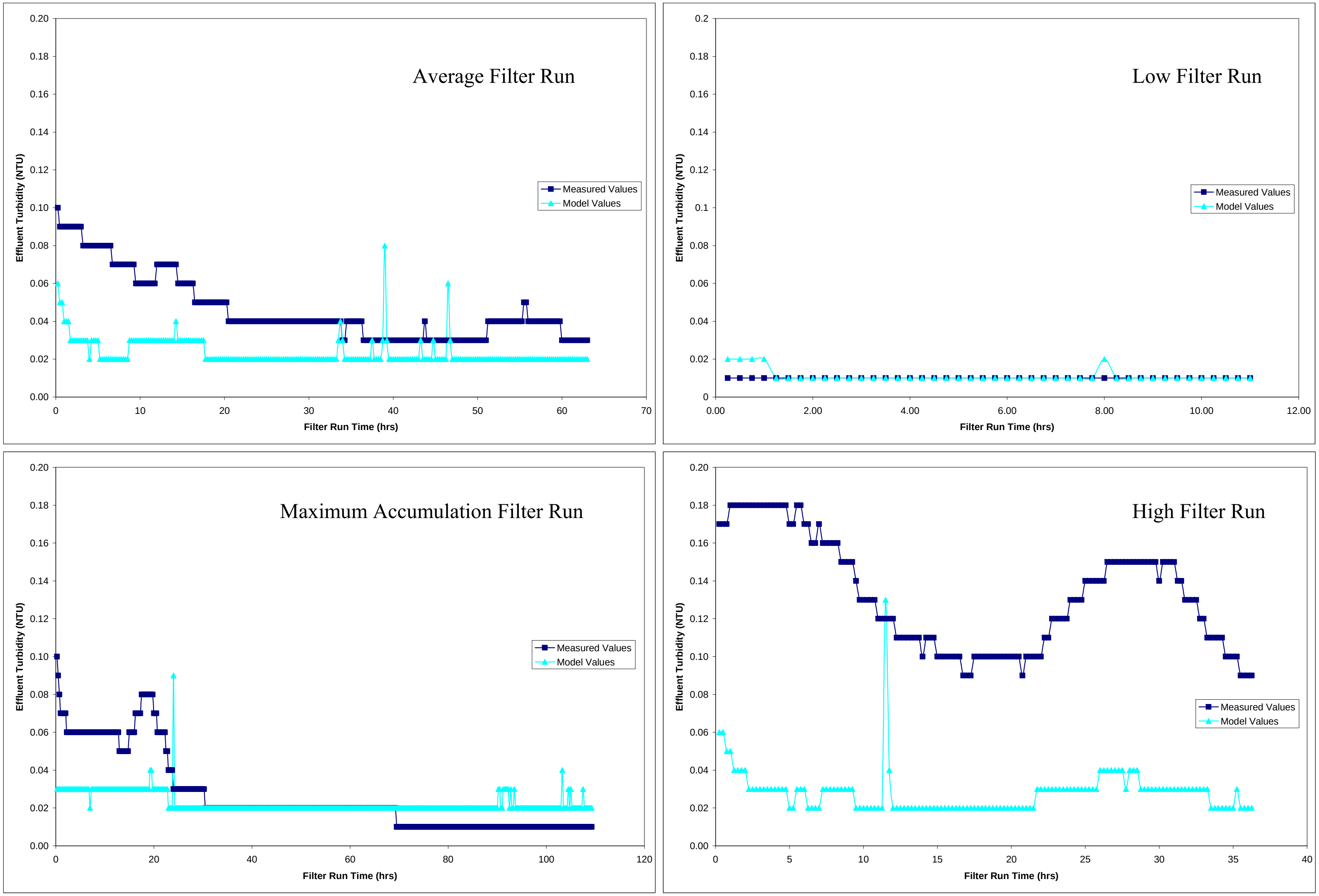

Figure 5.3: Comparison of measured vales and model calculated values for filter effluent: Clockwise from top left, average filter run, low filter run, high filter run, maximum accumulation filter run

5.2.4 Input Data Record

5.2.4.1 Distribution Fitting of Data

The influent turbidity was previously fit to a distribution in Section 4.1.2; however to use the OTTER model, simulated filter flow rates were needed. The use of simulated filter flow rates used in conjunction with simulated influent turbidity created a random input data record for use in the risk analysis, allowing for a wide range of possible inputs to be evaluated. The process of simulating a water demand curve is a topic that in itself has experienced detailed research. There has been research into determining water demand through models which correlate to other measurable parameters. Protopapas, Katchamart, and Platonova (2000) looked at the effect of weather on daily water use while Alvisi, Franchini, and Marinelli (2003) used the Neyman-Scott stochastic process to model residential demand. However, the above research focuses on the demand within distribution systems, not demand as it is experienced by a filter, which could differ significantly from the overall demand from a treatment system. Since it was not the intent of this research to evaluate water demand simulation methodologies, the filter flow rate was determined in the same method as that of the influent turbidity distribution and percent of turbidity remaining distribution as discussed in Section 4.1.2.

The distribution fitting statistics for the water demand distribution can be seen in Table 5.3. According to the r^2 parameter, the Gumbel distribution provides the best-fit distribution. However, this analysis can be misleading as all the chosen distributions provide a reasonable fit to the data. In looking at other research in simulated water demand profiles, it was seen that water demand has been modeled as a normal distribution, although this was an assumption of the research (Kapelan, Savic, & Walters, 2005; Xu and Goulter, 1998; and Lansey, Duan, Mays, and

Tung, 1998). Xu and Goulter (1998) state that a large number of simulated flow demands had to be rejected because negative flows were simulated by the assumed normal distribution. Again, the above research focuses on water demand, not the filter flow rate which would differ from water demand. Therefore, to maintain continuity between the distributions chosen for the influent turbidity and the percentage of turbidity remaining, it was determined that the lognormal distribution would be used for future simulations.

Table 5.3: Lognormal distribution fitting statistics for filter flow rate

	Probability Plotting (r^2)
Normal	0.948
Log-Normal	0.959
Exponential	0.932
Gumbel	0.986

Table 5.4 shows the lognormal distribution parameters for the influent turbidity and the filter flow rate distributions which were used to simulate inputs to the OTTER model.

Table 5.4: Lognormal parameters fused for simulating inputs to the OTTER model

	Water Demand	Turbidity
μ	0.78	-0.54
σ	0.10	0.19

5.2.4.2 Data Record

The input data record consisted of a series of simulated values from the previously determined lognormal distributions for the influent turbidity and the water demand. Along with the simulated data, a numerical value for water quality parameters that were not explicitly included in the analysis needed to be entered. As stated in Section 5.2.1, these values were kept constant for all the simulations. The lognormal parameters for the influent turbidity and filter flow rate were shown in Table 5.4 while the default values allocated to the water quality parameters that were not explicitly included in the analysis are shown in Table 5.5. These values are the default values provided by the OTTER program.

One parameter that was maintained as a constant over the course of the simulations which could provide some concern was that of temperature. This simplification was applicable for this study since the thesis focused on the operation of a filter unit over the course of time, not with respect to one filter run at a specific time of the year. However, although an average temperature value was maintained as a constant over the simulations, the temperature could affect the risk analysis output and should be considered in any future analysis.

Table 5.5: Water quality parameters used in the OTTER model

Parameter	Amount	Parameter	Amount	Parameter	Amount
pH	7.5	Nitrate	0	Chlortoluron (μg/L)	0
Temperature (°C)	15	Nitrite	0	Diuron (μg/L)	0
Apparent Colour (°Hazen)	50	Chloride	0	Isoproturon (μg/L)	0
True Colour	20	Chlorite	0	MCPA (μg/L)	0
Hardness (mg/L as $CaCO_3$)	150	Chlorate	0	MCPB (μg/L)	0
Alkalinity (mg/L as $CaCO_3$)	100	Bromide (mg/L)	0	Mecoprop (μg/L)	0
Conductivity (μS/cm)	400	Bromate (mg/L)	0	2,4-D (μg/L)	0
Total Suspended Solids (mg/L)	Solids:Turbidity Ratio set at 2	Sulphate (mg/L)	0	Diazinon (μg/L)	0
Settleable Suspended Solids (mg/L)	95% of the total suspended solids	Dissolved Oxygen (mg/L)	0	Chlorfenvinphos (μg/L)	0
Filtereable Suspended Solids (mg/L)	95% of the total suspended solids	Orthophosphate (mgP/L)	0	Propetamphos (μg/L)	0
Free Chlorine (mg/L)	0	UV Adsorbance at 254 nm (/m)	12	Cysts (number/L)	0
Combined Chlorine (mg/L)	0	Total Organic Carbon (mg/L)	5	Coliforms (number/mL)	0
Chlorine Dioxide (mg/L)	0	Dissolved Organic Carbon (mg/L)	3	*E. coli* (number/mL)	0
Total Aluminium (mg/L)	0	Particulate Organic Carbon (mg/L)	2	Viruses (number/mL)	0
Total Iron (mg/L)	0	Trihalomethanes (μg/L)	0	Heterotrophs (number/mL)	0
Total Manganese (mg/L)	0	Trihalomethane Formation Potential (μg/L)	0	Algae (cells/mL)	0
Dissolved Aluminium (mg/L)	0	Haloacetic Acids (μg/L)	0	Chlorophyll-A (μg/L)	0
Dissolved Iron (mg/L)	0	Assimilable Organic Carbon (μg/L)	0	Taste (number)	0
Dissolved Manganese (mg/L)	0	Atrazine (μg/L)	0	Odour (number)	0
Ammonia (mg/L)	0	Simazine (μg/L)	0	Particle Size	2

5.2.5 Description of Calibrated OTTER Model

Visually, the calibrated OTTER model of Filter 1 can be seen in Figure 5.4. Raw water is passed through a flow control valve which modifies the flow into the filter. From the filter the treated water is collected in the process marked "final." The "wash water" is used for backwashing and the "waste water" shows the solids accumulation after backwash.

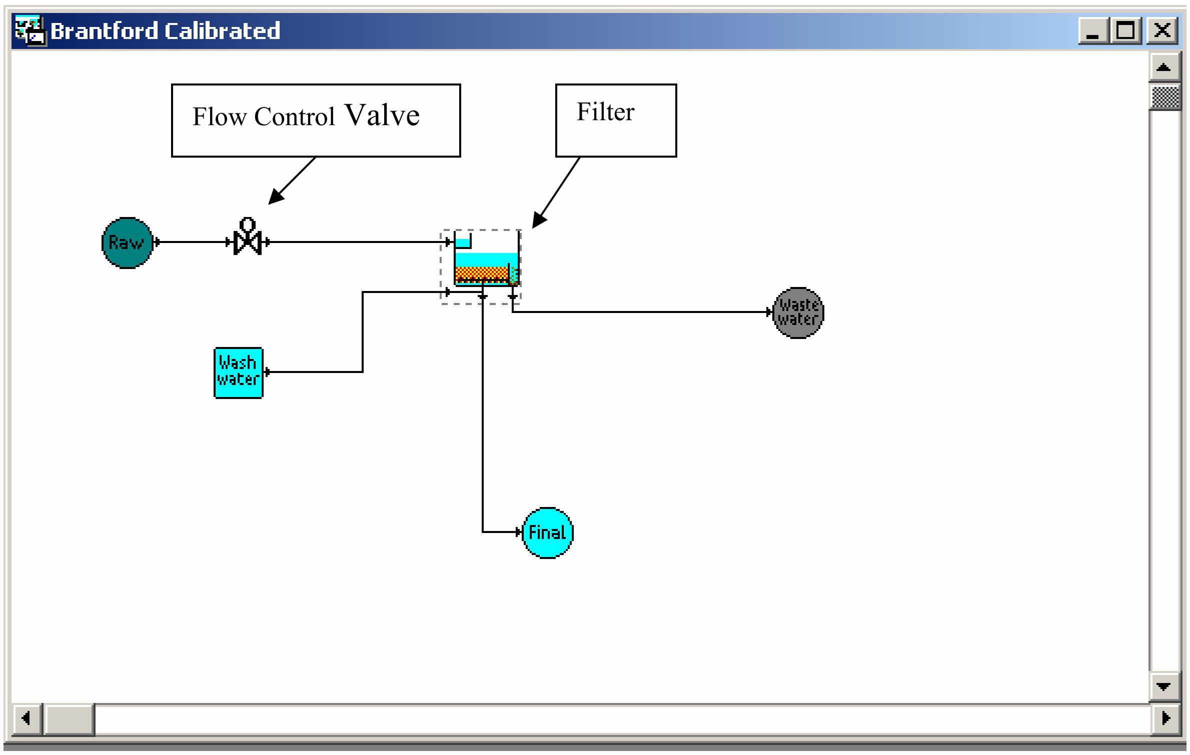

Figure 5.4: OTTER model of Brantford Filter 1

Figure 5.5, Figure 5.6, and Figure 5.7 show the set-up for Filter 1 including all the entered calibration data. These parameters were constant throughout all the simulations. The model value, number of CSTR stages, was kept to one (1) for all simulations as discussed in Appendix C.

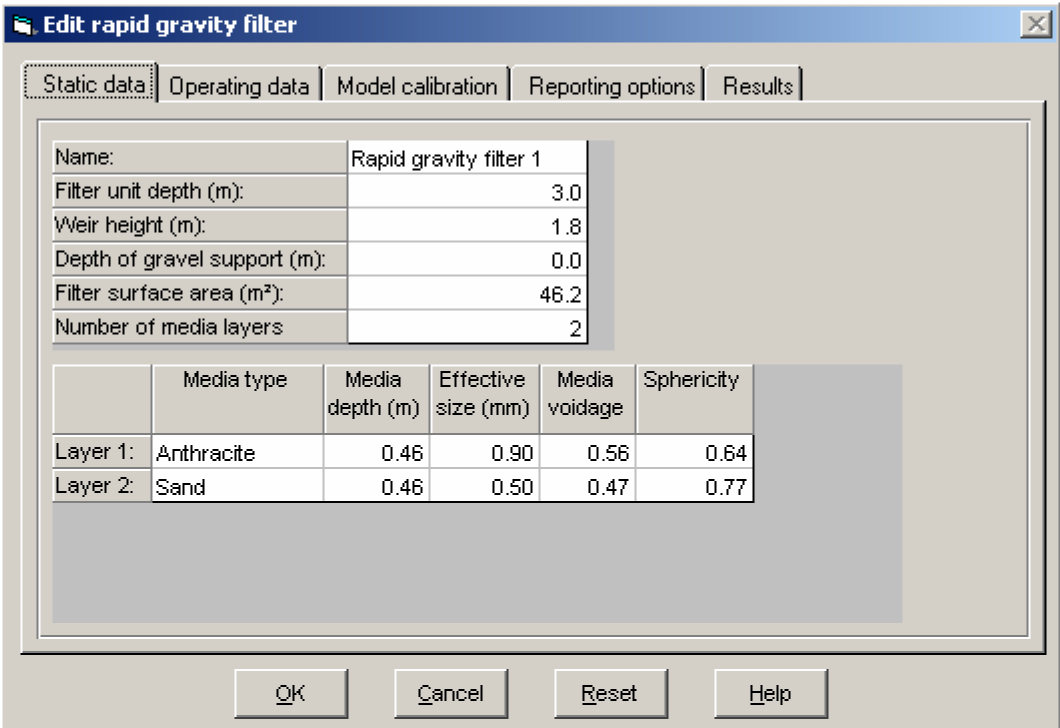

Figure 5.5: Static data for calibrated Brantford WTP OTTER model

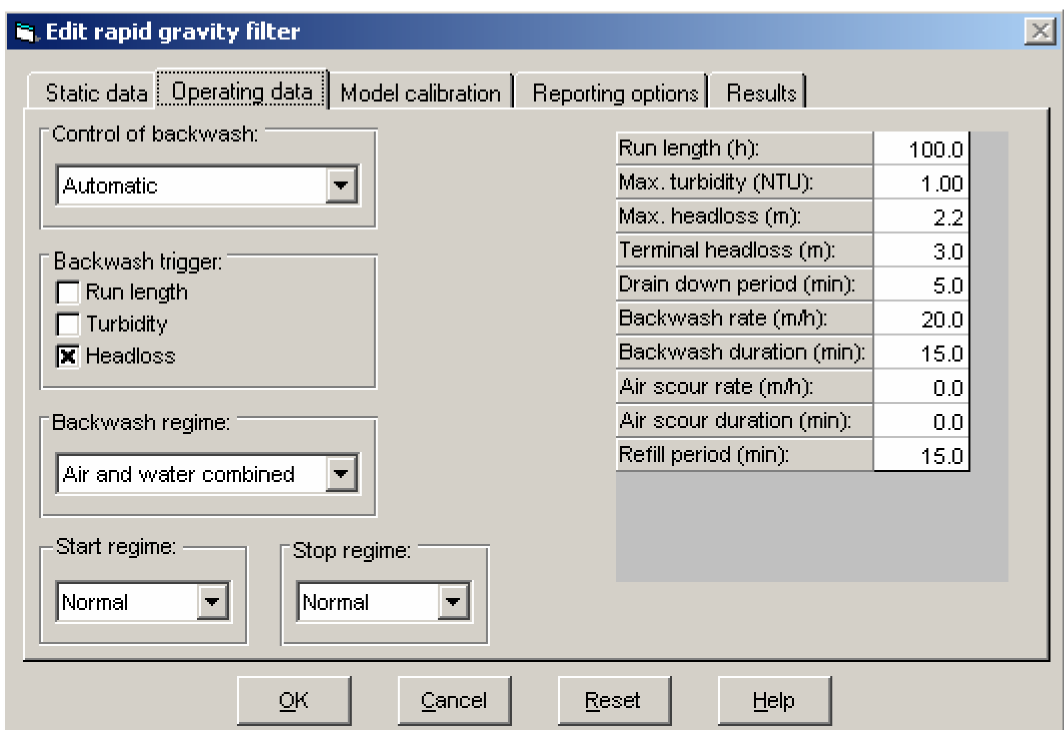

Figure 5.6: Operating data for calibrated Brantford WTP OTTER model

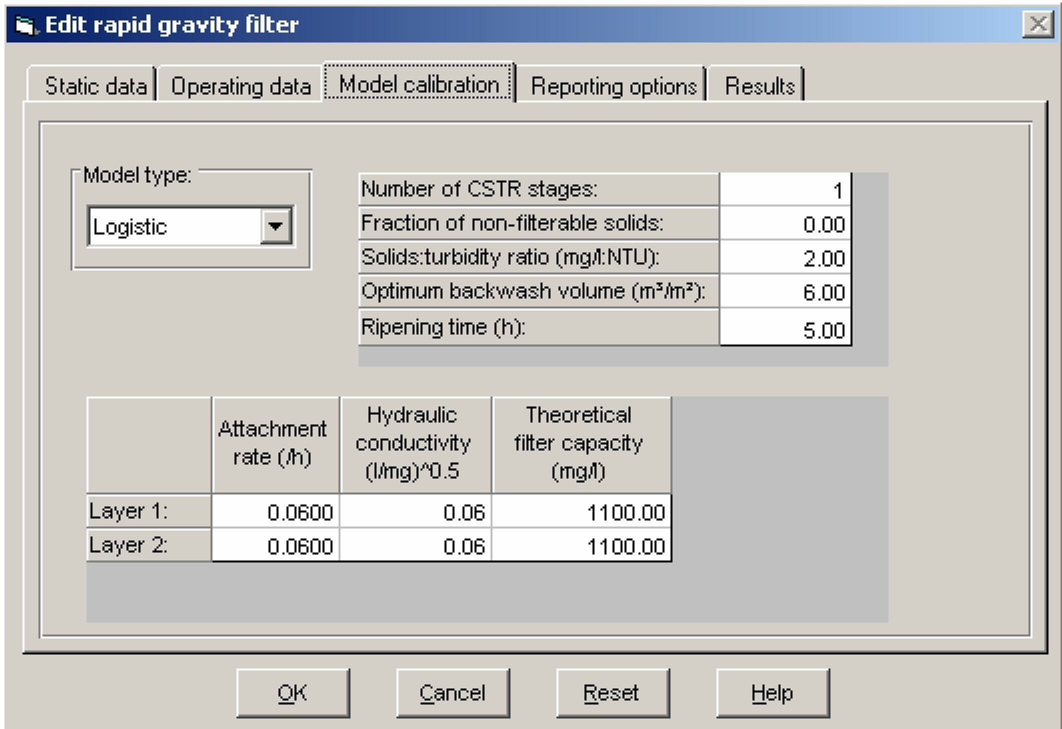

Figure 5.7: Calibration data for calibrated Brantford WTP OTTER model

5.2.6 Simulation Convergence Study

Similar to the CFA analysis, a simulation study was performed to see where the simulation converged. To perform this study, a series of simulations was performed with varying number of shots. New data sets were developed for each simulation and run through the calibrated OTTER model. Figure 5.8 and Figure 5.9 show the results from the simulation study. It can be seen that most percentiles converge well around 13,000 shots; however, as with the simulation study performed in Chapter 4, this does not hold true with the 99.9th percentile. Future simulations will use around 13,000 shots but because the 99.9th percentile is not converged, the maximum values should not be relied on.

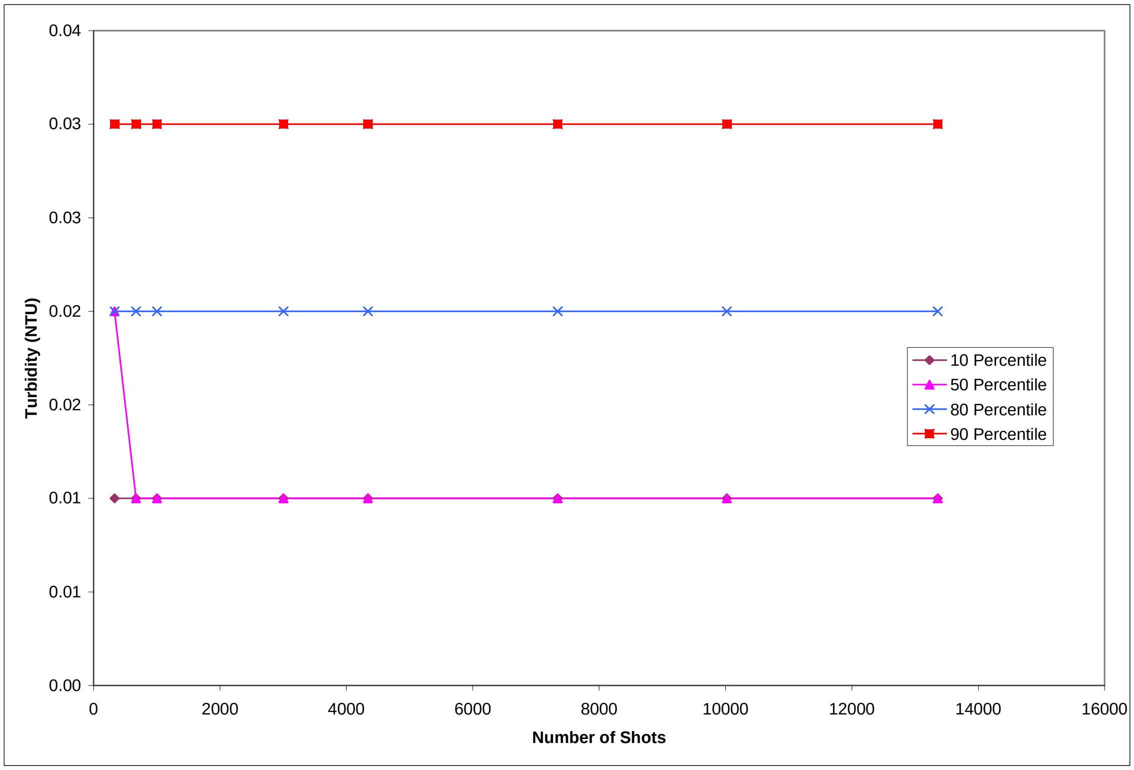

Figure 5.8: Convergence of the calibrated OTTER model simulation: 90 percentile and below

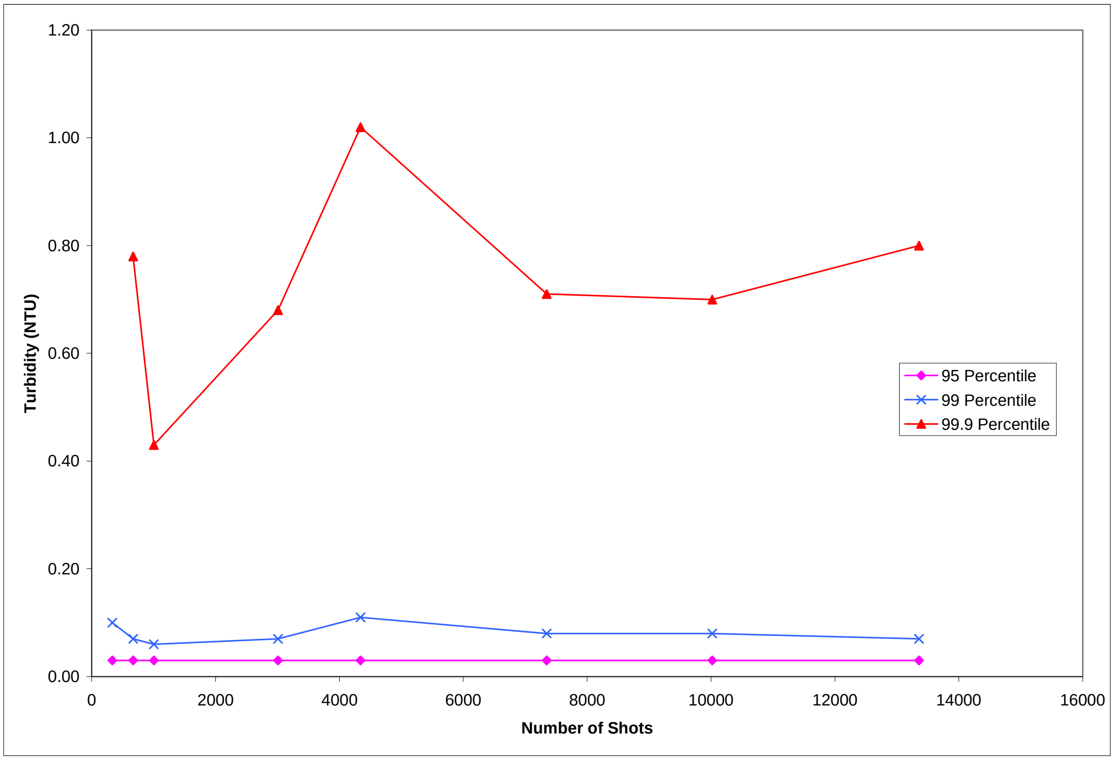

Figure 5.9: Convergence of the calibrated OTTER model simulation: 95 percentile and above

5.3 Simulation Results for a Full System Analysis

The output from a full simulation with 13,358 shots is displayed as a CDF in Figure 5.10 and summary statistics of the simulation along with measured effluent summary statistics are presented in Table 5.6. For the calibrated model the number of shots used varied from simulation to simulation because of the method that OTTER uses to handle backwashes. When a backwash is triggered, for the next two time periods no water is produced from the filtration unit and the effluent turbidity is recorded as zero. Thus when performing an analysis on the output, these effluent turbidity values are removed from the data record. Since the number of backwashes varied from simulation to simulation, the total number of shots also varied from simulation to simulation.

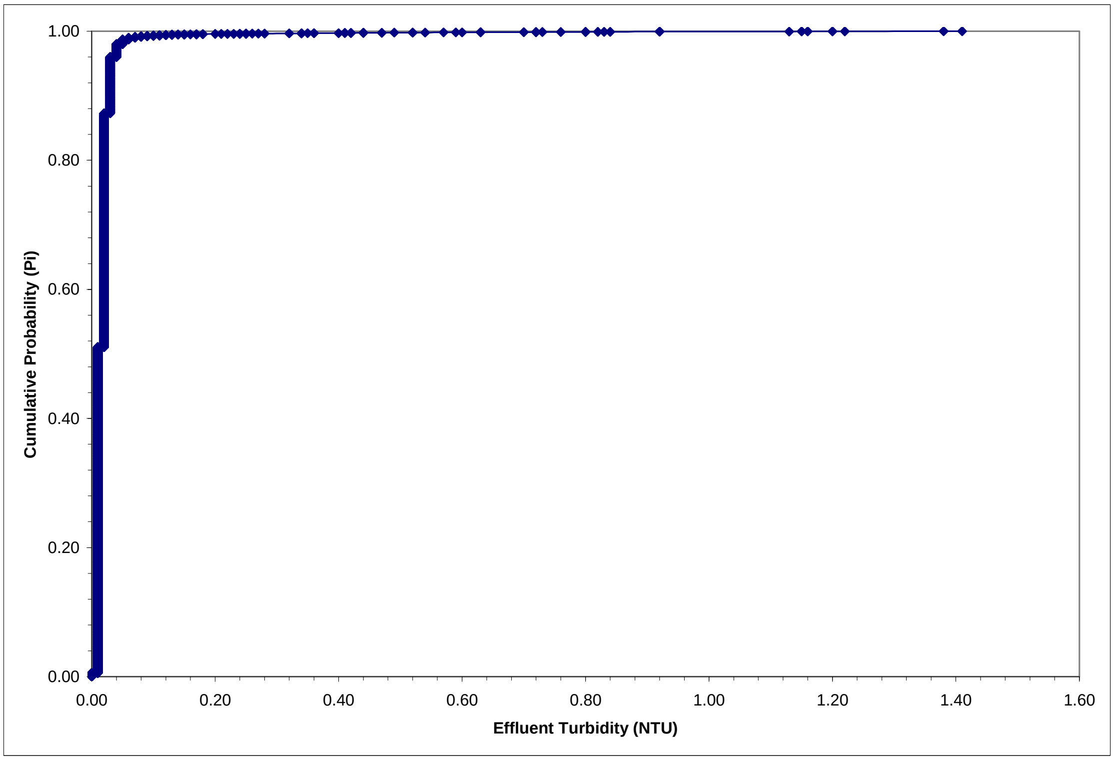

Figure 5.10: CDF of turbidity effluent from calibrated OTTER simulation using 13,358 shots

Table 5.6: Summary of output from calibrated OTTER simulation

	Simulated Output from Calibrated OTTER Model (NTU) *	Measured Filter 1 Effluent (NTU)
Max	1.41	0.25
Min	0.00	0.01
Standard Deviation	0.04	0.04
Average	0.02	0.04
95 Percentile	0.03	0.11
99 Percentile	0.07	0.15

* Simulation performed using 13,358 shots

The summary values from Table 5.6 show a discrepancy between what is currently experienced by the filter and what could possibly occur according to the modelling and probabilistic risk analysis process. Although the minimums and standard deviations are similar, from a risk perspective, the results indicate that the measured water quality, at the 95th and 99th percentile level, produces higher effluent turbidity water than what the model indicates. In other words, the model predicts a lower actual probability of producing non-compliant water than what is currently experienced at the water treatment plant.

This lowered probability of producing non-compliant water is illustrated by the divergence in effluent turbidity values between the simulated data and the measured data with increasing percentile levels, as shown visually in Figure 5.11. Figure 5.11 shows that as the percentile levels increase the measured effluent values increase more rapidly than the simulated values. Chapter 6 provides a detailed discussion on the possible reasons for this difference, primarily focusing on the ideal versus non-ideal performance of the fitler.

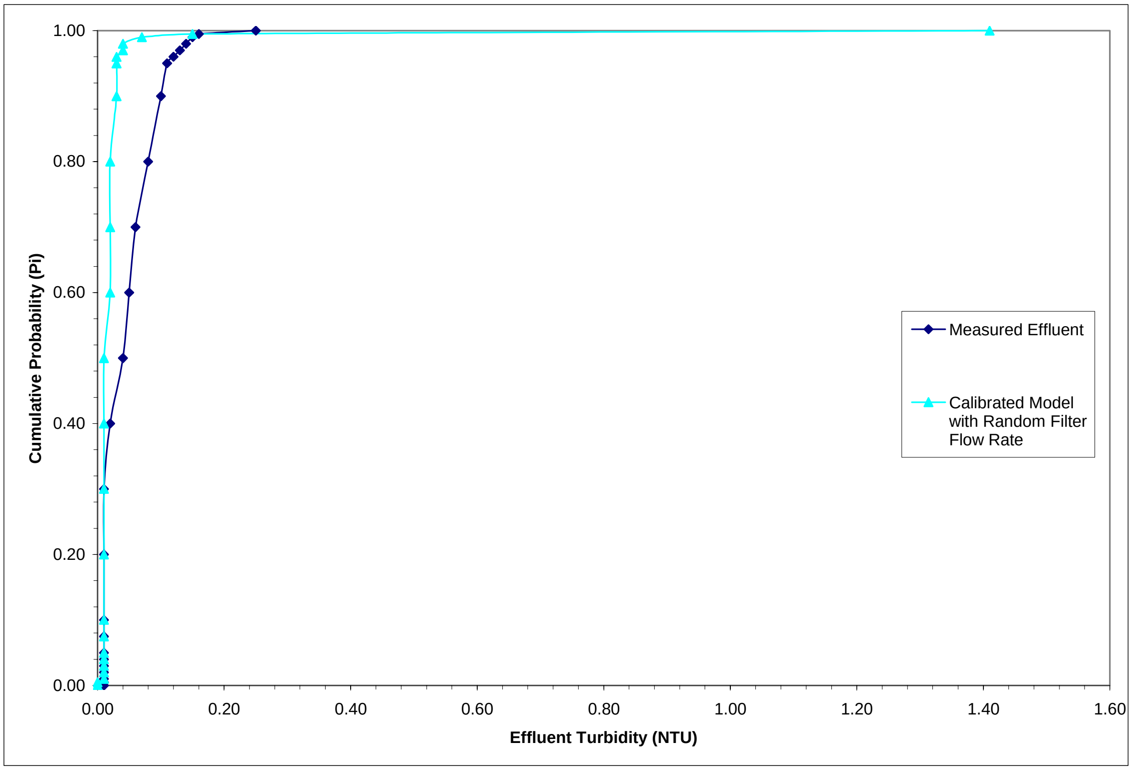

Figure 5.11: Comparison between measured turbidity effluent and turbidity effluent simulated with a calibrated model and random filter flow rate

5.3.1 Risk Evaluation

The output from the simulation can be used to evaluate the probability of producing effluent turbidity greater than a reference level for the filter. Table 5.7 compares the probability of producing water greater than a reference value between the simulated output and the measured data for different effluent turbidity targets.

Table 5.7: Risk evaluation for target levels through the calibrated OTTER model

	Simulated OTTER model Effluent (%)	Measured Filter 1 Effluent (%)
Probability Effluent Turbidity > 0.05 NTU	1.3	35.8
Probability Effluent Turbidity > 0.10 NTU	0.67	6.9
Probability Effluent Turbidity > 0.30 NTU	0.64	0.0

* Simulation performed with 13,356 shots

The output indicates that the filter is operating at a low probability of producing non-compliant water but this could be misleading especially when comparing the simulated level with the measured level calculated for the probability of effluent turbidity greater than 0.05 NTU. The calculated value, 1.3%, differs considerably from that currently experienced by Filter 1, 35.8%. One possible condition that was evaluated to see if it affected the output was inputting the filter flow rate as a time-series.

5.3.2 Effect of Time Series Filter Flow Rate

One concern throughout the above analysis involved the filter flow rate that was inputted to the simulation. This flow rate was assumed to be completely random; however, this assumption is incorrect. Figure 5.12 shows the flow experienced by Filter 1 over January 2004 while Figure 5.13 shows a simulated flow for approximately one month. Figure 5.12 shows that while the filter flow rate is slightly random, there is a pattern to the flow which is not visible in Figure 5.13.

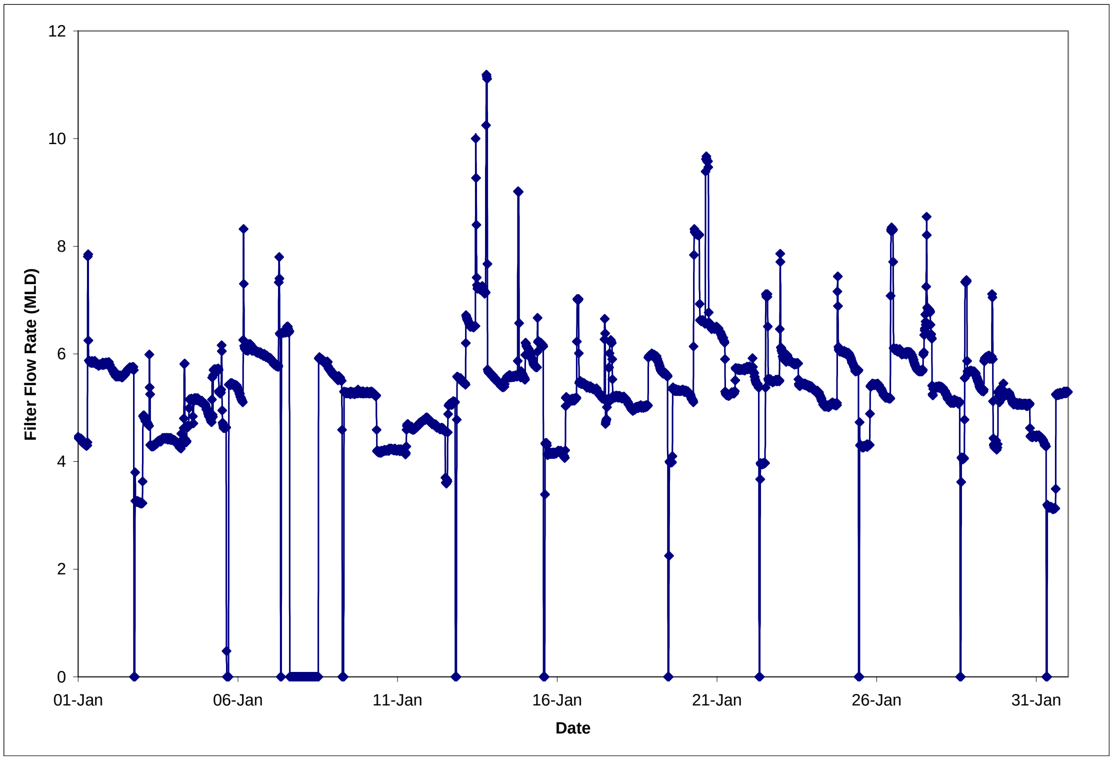

Figure 5.12: Measured Filter 1 flow rate for January 2004

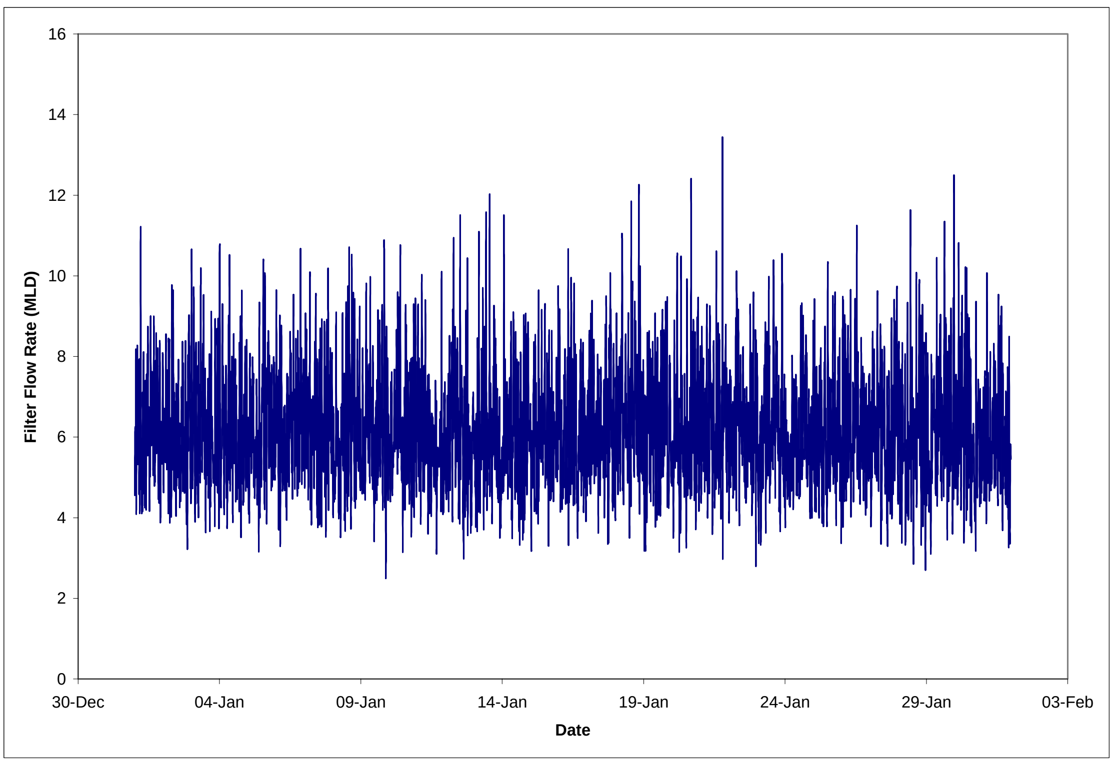

Figure 5.13: Simulated Filter 1 flow rate for approximately 1 month

5.3.2.1 Results from Filter Analysis by Modified Probabilistic Methodology with Pseudo-Time Series for Flow Demand

The model set-up and input data initialization was performed as explained in Sections 5.2. The difference for this simulation was that the filter flow rate profile was not simulated using the lognormal distribution, but the measured filter flow rate data from 2004 was used as input to the simulation. It should be noted that by using the 2004 filter flow rate profile the simulation was no longer completely random and some bias could be input to the simulation. The results from the simulation can be seen in Figure 5.14 and in Table 5.8.

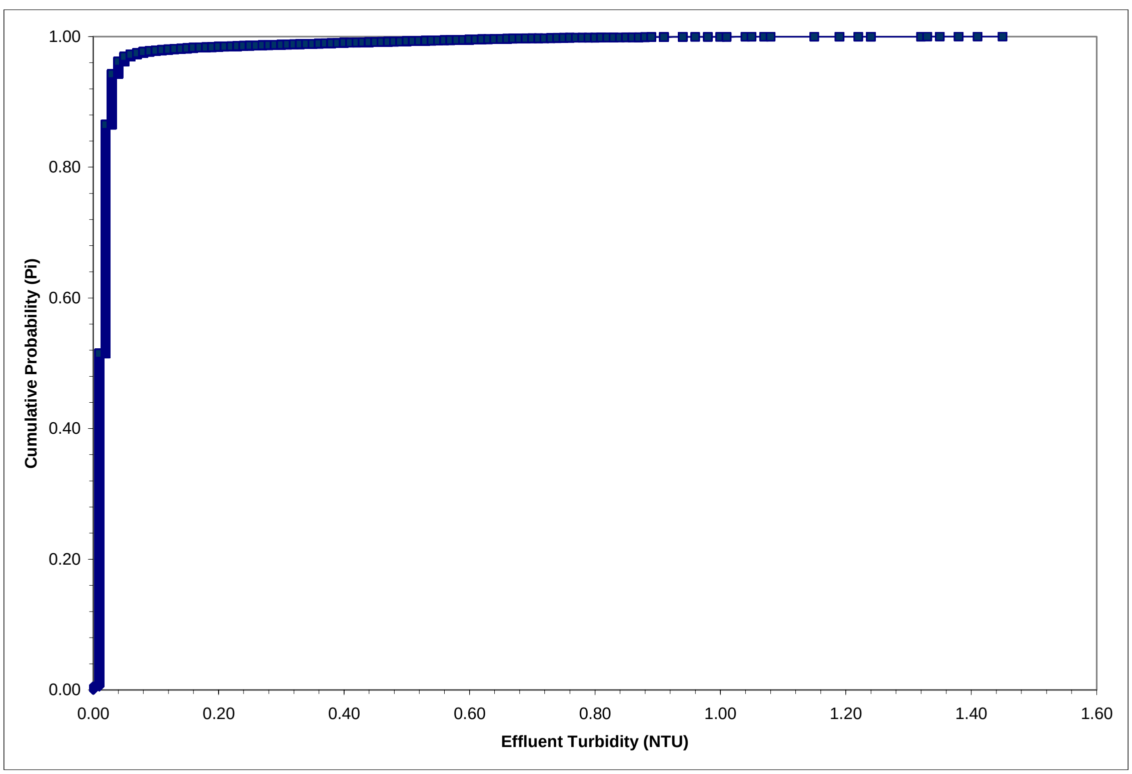

Figure 5.14: CDF of turbidity effluent from calibrated OTTER simulation with time-series filter flow rate profile

Table 5.8: Summary of output from calibrated OTTER simulation with time series filter flow rate profile

	Simulated Effluent Turbidity (NTU)*
Max	1.45
Min	0.00
Standard Deviation	0.07
Average	0.03
95	0.04
99	0.39

*Simulation Run for 2004 Filter Flow Rate Profile

5.3.2.2 Risk Evaluation

The probability of Filter 1 exceeding target levels can then be calculated. Table 5.9 shows the calculated and measured levels for Filter 1. The levels that were calculated using a time-series for the filter flow rate have increased from the completely random filter flow rate shown in Table 5.7; however, there is still some discrepancy between the simulated levels and the measured Filter 1 levels.

Table 5.9: Risk evaluation for target levels through the calibrated OTTER model using a time series for filter flow rate

	Simulated OTTER Effluent (%)	Measured Filter 1 Effluent (%)
Probability Effluent Turbidity > 0.05 NTU	3.1	35.8
Probability Effluent Turbidity > 0.10 NTU	2.1	6.9
Probability Effluent Turbidity > 0.30 NTU	1.2	0.0

* Simulation performed with one year of actual water demand (34,296 shots)

5.3.3 Comparison between Calibrated OTTER model with random flow demand and calibrated OTTER model with time-flow series

The differences between using a time series for the filter flow rate and not using a time series can be seen in Table 5.10 and Table 5.11. The numerical values of the probability of producing non-compliant water, as seen in Table 5.10, change by approximately 1-2 percentage points for the three different levels. However, it is in the numerical effluent turbidity output that differences can be seen. Table 5.11 shows that the time-series filter flow rate curve allows for slightly higher turbidity effluent on average and at the 95 percentile level and substantially higher effluent turbidity at the 99 percentile level. This occurs because the time-series causes a greater percentage of the output values to be larger, as can be seen in Figure 5.15.

Table 5.10: Comparison between probabilistic risk evaluation using a calibrated OTTER model with and without a time series for water flow

	Calibrated OTTER Model*				Calibrated OTTER Model Time Series **			
	Median (%)	Upper Bound (%)	Lower Bound (%)	Range (%)	Median (%)	Upper Bound (%)	Lower Bound (%)	Range (%)
Probability > 0.05 NTU	1.3	1.5	1.1	0.4	3.1	3.3	2.9	0.4
Probability > 0.10 NTU	0.7	0.8	0.5	0.3	2.1	2.3	2.0	0.3
Probability > 0.30 NTU	0.6	0.8	0.5	0.3	1.2	1.4	1.1	0.2

* Simulation performed using 13,358 shots
** Simulation performed with 2004 year of actual filter flow rate (34,296 shots)

Table 5.11: Comparison of probabilistic risk analysis output using a calibrated OTTER model with and without a time series for water flow

	Calibrated OTTER Model*	Calibrated OTTER Model Time Series **
Max (NTU)	1.41	1.45
Min (NTU)	0.00	0.00
Standard Deviation (NTU)	0.04	0.07
Average (NTU)	0.02	0.03
95 Percentile (NTU)	0.03	0.04
99 Percentile (NTU)	0.07	0.39
Average Filter Run Time (hrs)	80	100

* Simulation performed using 13,358 shots
** Simulation performed with 2004 year of actual filter flow rate (34,296 shots)

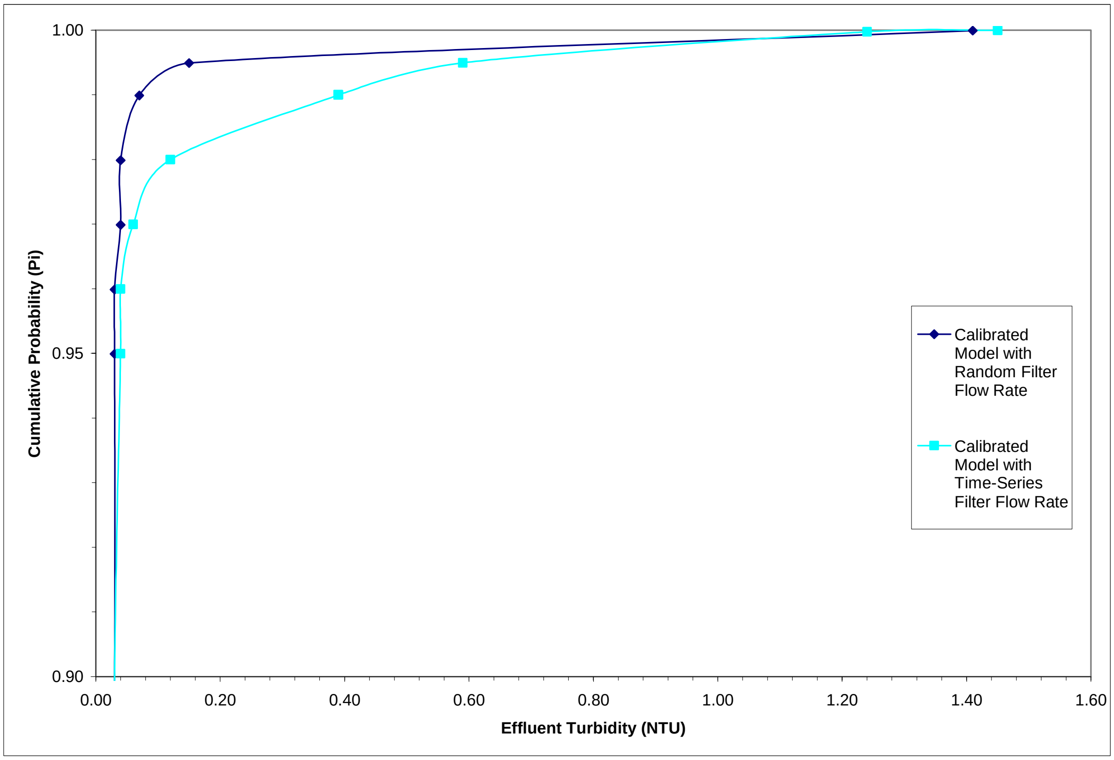

Figure 5.15: Comparison of the CDF output from the probabilistic risk assessment for the calibrated OTTER models with and without using a time series: Focusing on the top 10% of the CDF

One possible reason for the difference between the simulations with and without a time-series filter flow rate can be deduced from the average filter run times. The calibrated model with random filter flow rate has an average of 80 hours per filter run, while the calibrated model using the time series has an average of 100 hours per filter run. The longer filter runs for the time-series flow rate allowed for higher effluent turbidity output and thus a higher probability of producing non-compliant water.

This analysis shows how the mechanism used to model the filter flow rate can affect the output from the analysis. However, because the 2004 data record is not random the rest of the thesis will use the results from the simulations performed with the completely random filter flow rate.

Any future study should evaluate in more detail the mechanism of incorporating filter flow rate into the analysis.

5.4 Predictive Modelling and Risk Analysis

The use of a calibrated computer model allows for a more comprehensive analysis of the treatment process, which is not possible with other risk analysis methodologies such as the CFA. One area of further analysis is through using the computer model and the risk analysis methodology to analyze predictive scenarios. Predictive scenarios would involve changing the input or calibrated parameters within the computer model and determining how the final output would be affected. It is possible to choose any number of different parameters to evaluate including any physical, operational or calibration parameters. For the analysis three factors were changed: influent water turbidity, filter flow rate, and filter depth. These three factors were chosen because Letterman (1987) mentions them during his evaluation of factors that affect filtered water quality and headloss development and because time constraints limited the analysis to only three factors.

5.4.1 Predictive Study Set-Up

The predictive study was set up in a manner similar to a 2^3 factorial study. The three parameters were combined together to form eight different simulations which cover the range of input values for these parameters. Table 5.12 shows the simulation set-up. The simulation numbers in Table 5.12 were chosen arbitrarily to identify the different filter runs. They start at number 6 because numbers 1 through 5 were used during some preliminary analysis that is not reported on in this thesis.

Table 5.12: Predictive study using computer modelling set-up

Simulation #	Filter Depth	Influent Turbidity	Filter Flow Rate
11	Low	Low	Low
13	Low	Low	High
12	Low	High	Low
10	Low	High	High
7	High	Low	Low
9	High	Low	High
8	High	High	Low
6	High	High	High

Saatci and Oulman (1980) caution against extrapolating data beyond the depths and filter flow rates used to generate the calibrated parameters. Thus low and high values were chosen to be 20% above and below the original values respectively. Because the influent turbidity and filter flow rate are distributions and not single values, it was decided to increase and decrease the mean of the measured data and not modify the standard deviation. Thus, increasing or decreasing the mean by 20% would represent a series of new measurements where the average would be 20% higher or lower than the original average but with the same standard deviation.

Since the chosen distribution was lognormal, this required that both the mean and standard deviation of the lognormal distribution be modified so that only the mean of the data that is not logged would change. Figure 5.16 shows this visually for simulated data for influent turbidity. The same procedure was followed for filter flow rate.

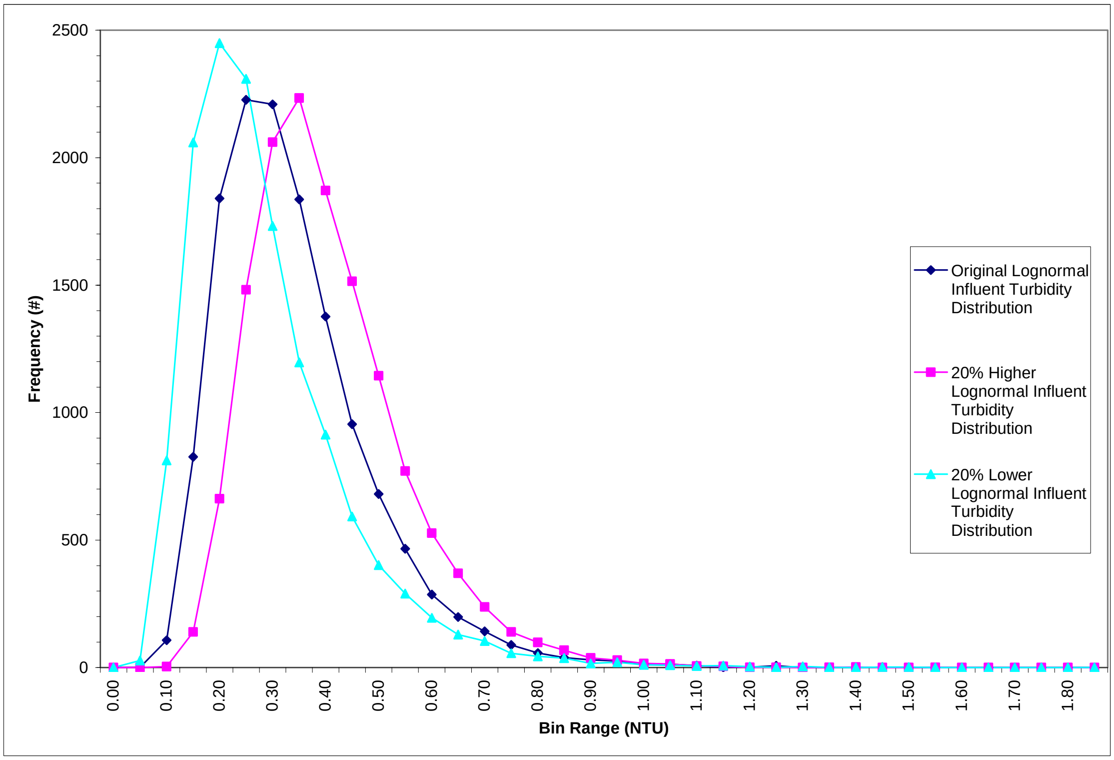

Figure 5.16: High and low distributions for influent turbidity for the predictive study

The input data for the eight different simulations can be seen in Table 5.13. For influent turbidity and filter flow rate, the values in Table 5.13 show the mean of the simulated data set.

Table 5.13: Input data for the different simulations for the predictive study

Simulation #	Filter Depth (m)	Influent Turbidity (NTU)	Filter Flow Rate (MLD)
11	0.7312	0.252	4.94
13	0.7312	0.252	7.42
12	0.7312	0.378	4.94
10	0.7312	0.378	7.42
7	1.0968	0.252	4.94
9	1.0968	0.252	7.42
8	1.0968	0.378	4.94
6	1.0968	0.378	7.42

5.4.2 Simulation Output

The output from the simulations was evaluated using Yates method. This analysis determined the effects and sums of squares for each parameter of interest. Appendix E shows the full calculations for all the simulations, while Table 5.14 and Table 5.15 provide an overview of the findings. Table 5.14 shows the output from the analysis while Table 5.15 shows the calculated effects and interactions of each parameter in the analysis.

Table 5.14: Results from predictive study: calculation of probability values for each simulation at three chosen reference levels

Simulation #	Filter Depth	Influent Turbidity	Filter Flow Rate	Probability > 0.05 NTU (%)	Probability > 0.10 NTU (%)	Probability > 0.30 NTU (%)	Backwashes
11	Low	Low	Low	4.84	3.64	1.95	23
13	Low	Low	High	2.56	1.34	0.49	48
12	Low	High	Low	4.91	3.25	1.6	34
10	Low	High	High	2.84	0.74	0.19	68
7	High	Low	Low	1.58	1.19	0.9	23
9	High	Low	High	0.55	0.25	0.14	48
8	High	High	Low	0.83	0.56	0.31	34
6	High	High	High	0.37	0.05	0.02	63

Table 5.15: Significance of the three evaluated parameters for the predictive study

Source	Probability > 0.05 NTU (Effect/Interaction)	Probability > 0.10 NTU (Effect/Interaction)	Probability > 0.30 NTU (Effect/Interaction)
Filter Flow Rate (A)	-1.460	-1.565	-0.980
Influent Turbidity (B)	-0.145	-0.455	-0.340
Filter Depth (C)	-2.955	-1.730	-0.715
Flow x Turbidity(AxB)	0.195	0.055	0.130
Flow x Depth (AxC)	0.715	0.840	0.455
Depth x Turbidity (BxC)	-0.320	0.040	-0.015
Flow x Turbidity x Depth (AxBxC)	0.090	0.160	0.105

5.4.3 Discussion of Predictive Study

Some of the results presented in Table 5.14 could be expected. On average the high filter depth produced better quality water then the low filter depth. This is consistent with theoretical expectations, as shown in Section 3.3.4, and other findings (e.g. Letterman, 1987); however, some of the results are not what would be expected. When the filter rate is increased the removal rates should decrease (Letterman, 1987), causing a higher probability of producing non-compliant water; however, the filtration unit experienced a higher probability of producing water above a stated level when the filter flow rate was low as opposed to when it was high. It would also be expected that the best scenario would be with a high filter depth, low filter flow rate, and low influent turbidity, but this did not occur.

The seemingly improbable observation that a low filter flow rate produced a worse situation than a high flow rate can be explained through the understanding of backwashes. Initially, it is important to remember that an increase in filter flow rate increases the rate of headloss development (Letterman, 1987) which is also consistent with the Carman Kozeny equation as shown in Section 3.3.3. This effect of filter flow rate on headloss development can be seen in Figure 5.17, as the low filter flow rate scenario in Simulation 11 has a lower rate of headloss build up than the high filter flow rate scenario (Simulation 13).

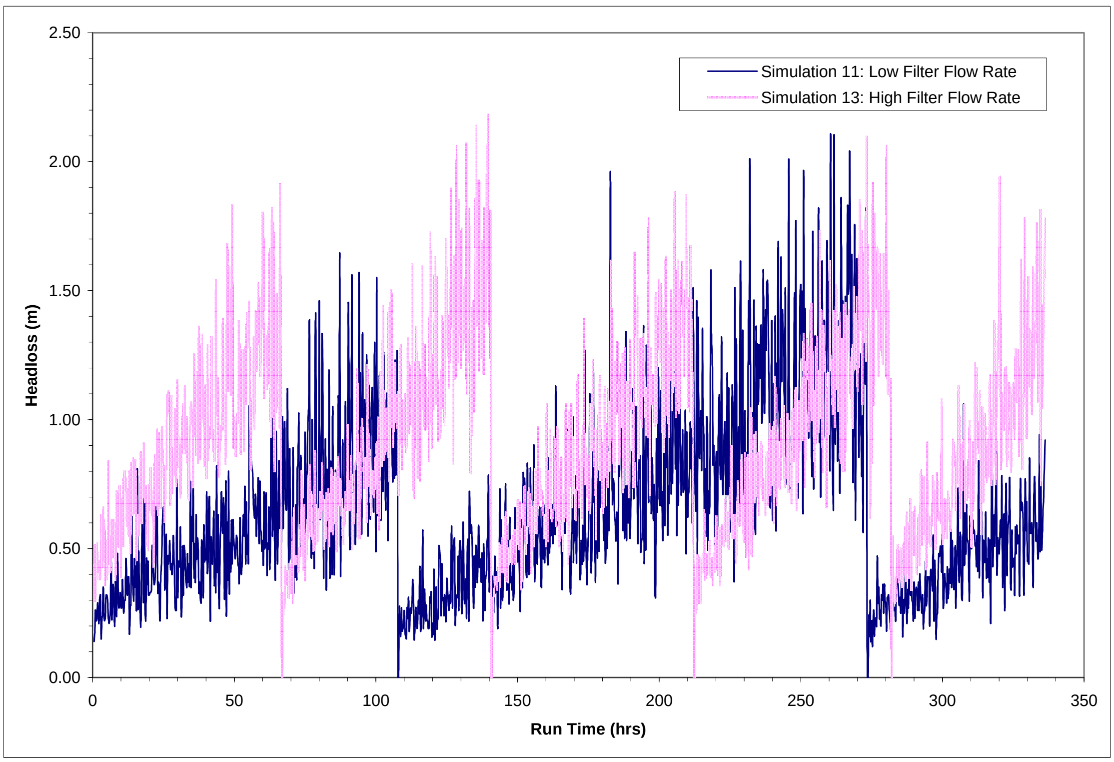

Figure 5.17: Headloss build up in the filtration unit over time for Simulations 11 and 13

Since the filtration unit in question operates under a headloss trigger only, the model study shows that the filter flow rate is a major contributor to the number of backwashes. For example, Simulations 11 and 13 have the exact same characteristics except for the filter flow rate and the high filter flow rate causes a greater number of backwashes per volume of water filtered. This can be seen in Figure 5.18.

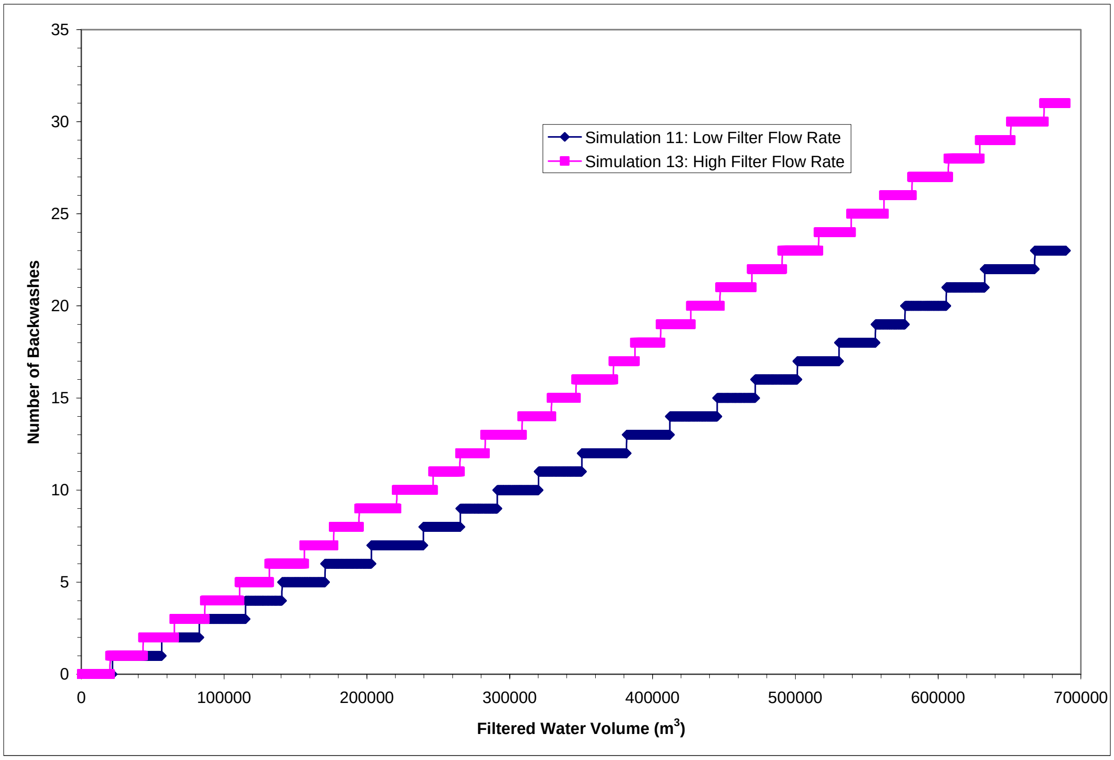

Figure 5.18: Backwashes over time for Simulations 11 and 13

A calculation for Simulation 11 and Simulation 13 showed that for equivalent filtered water volumes the two simulations removed the same amount of total solids. This was determined by looking at the average turbidity removed per volume of water filtered for a series of filter runs for both simulations such that the total amount of water filtered was similar. The unit of comparison is the ratio of the average amount of solids removed per filtered water volume, averaged for the total number of filter runs for Simulation 11 and for the number of filter runs for Simulation 13 which corresponds to approximately the same amount of total water filtered for Simulation 11. This analysis is shown in Table 5.16. Since the calculated t-statistic is below the critical t-statistic, the two simulations are shown to remove approximately the same amount of solids per filtered water volume over an equal amount of filtered water volume. The calculations performed in Table 5.16 were performed for the condition where the variances of the different simulations cannot be assumed to be equal.

Table 5.16: T-test to compare the turbidity removal between simulation 11 and simulation 13

	Simulation 11	Simulation 13
N (number of filter runs)	22	29
Average ratio of kg of solids removed per volume of water filtered (kg/m3)	4.50E-04	4.59E-04
Standard Deviation of the ratio of kg of solids removed per volume of water filtered	1.75E-05	4.32E-05
Observed T statistic	1.030	
Degrees of freedom	39	
Critical T statistic for $t_{39,0.025}$	2.021	

Although the amount of solids per filtered water volume is similar, the higher filter flow rate in Simulation 13 caused a greater number of backwashes and lowered effluent turbidity values. Figure 5.19, although hard to evaluate, shows this decrease in turbidity by the larger proportion of higher effluent turbidity values from Simulation 11 as opposed to Simulation 13.

With a fewer number of backwashes per unit volume, the lower flow rate allows the filter to experience more time with a higher solids loading in the bed. As described in Section 3.3.4, the total attachment of particles to a filter bed is a function of the attachment and detachment. With a longer period of time in the filter bed, there is the possibility that a greater number of particles could detach, contributing to the higher effluent water quality. With the high filter flow rate, this condition is not experienced. Therefore, for the current filter operation, the situation of concern is one of low filter flow rate, which allows higher effluent turbidity.

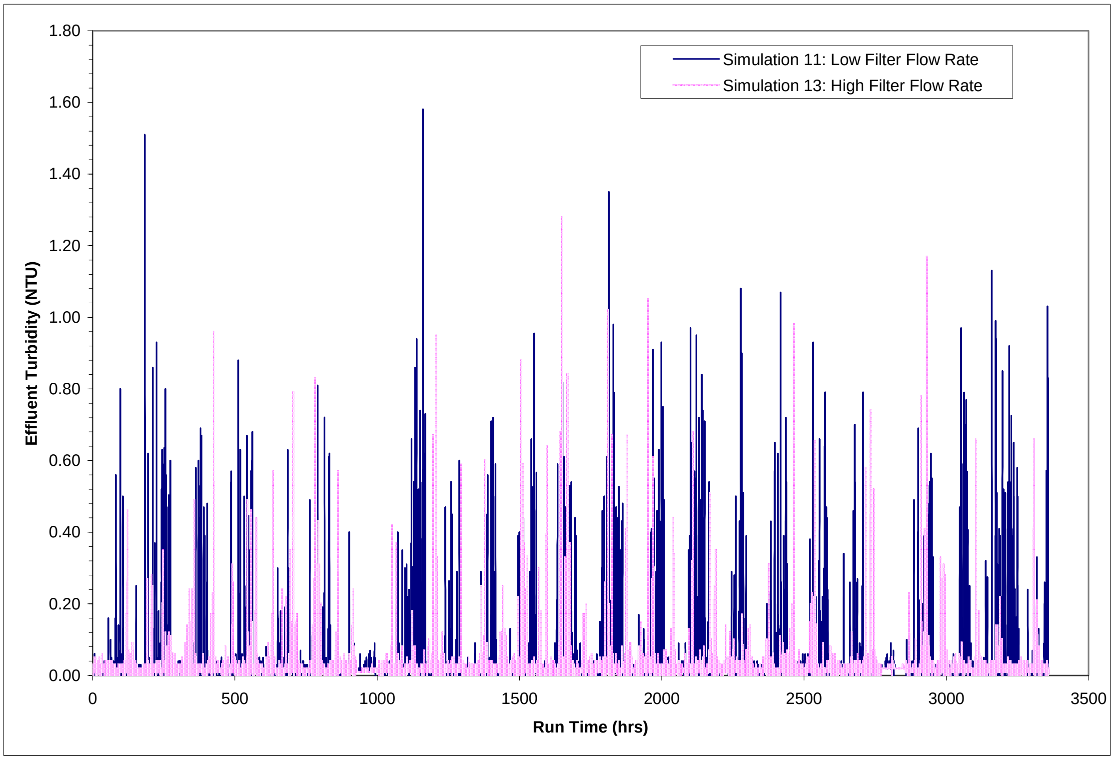

Figure 5.19: Turbidity effluent from the filtration unit over time for Simulations 11 and 13

One difficulty in using the factorial study methodology with simulated data occurred during the evaluation of the output. Although each simulation was performed for the same number of input values, each time a backwash occurred the filter did not produce water for that time period. This effectively lowered the total number of shots for the effluent turbidity. Since each simulation had a different number of backwashes, each simulation also had a different number of shots.

The evaluation of a factorial study uses a mean square error, a measurement related to the standard deviation, to determine whether a parameter is significant or not. Since the standard deviation is based on the number of shots and the mean of the simulation, see Section 4.5, each simulation will have a different standard deviation. Over the course of the eight different simulations, the total number of shots varied by 90, but the standard deviation between one simulation and another varied by a factor of 100. Thus a standard deviation or mean square error was not determined directly from the simulations.

To calculate the significance of the different effects and interactions, a normal probability plot was used. The normal probability plot evaluates the different calculated effects and interactions with the expectation that the differences between them are from to random variation (e.g. Montgomery, 2001), consequently the change of one or more variable would not have an effect on the output. If this was true then all the effects and interactions would fall on a straight line on a normal probability plot while any factors that do not fall on a straight line can then be determined to be significant (Montgomery, 2001). The normal probability plot can also be used to gain an estimate of the error associated with the analysis by using the insignificant effects as an estimate of the error (Montgomery, 2001), allowing for the use of an F-test to determine the significant effects. Both of these methods were used in this analysis.

Table 5.17, Table 5.18, and Table 5.19 provide the F-tests at the 5% significance level for the three different conditions. The error was estimated in all situations from the three most insignificant effects: BC, ABC, AB. These tables show that the filter flow rate (A) and filter depth (C) are both significant factors while the filter flow rate by filter depth interaction (AC) is significant for one of the conditions. If the significance level was lowered, the filter flow rate by filter depth interaction would be significant for all three conditions.

Table 5.17: F-test for the probability of effluent turbidity greater than 0.05 NTU

Source	Effect	SS	DF	MS	F	Significant
Filter Flow Rate (A)	-1.460	4.263	1	4.263	14.352	Yes
Influent Turbidity (B)	-0.145	0.042	1	0.042	0.142	No
Filter Depth (C)	-2.955	17.464	1	17.464	58.792	Yes
Flow x Turbidity(AxB)	0.195	0.076	1	0.076	0.256	No
Flow x Depth (AxC)	0.715	1.022	1	1.022	3.442	No
Depth x Turbidity (BxC)	-0.320	0.205	1	0.205	0.689	No
Flow x Turbidity x Depth (AxBxC)	0.090	0.016	1	0.016	0.055	No
Error			3	0.297		

Note: $f_{crit} = f_{1,3,0.05} = 10.13$

Table 5.18: F-test for the probability of effluent turbidity greater than 0.10 NTU

Source	Effect	SS	DF	MS	F	Significant
Filter Flow Rate (A)	-1.565	4.898	1	4.898	81.033	Yes
Influent Turbidity (B)	-0.455	0.414	1	0.414	6.849	No
Filter Depth (C)	-1.730	5.986	1	5.986	99.021	Yes
Flow x Turbidity(AxB)	0.055	0.006	1	0.006	0.100	No
Flow x Depth (AxC)	0.840	1.411	1	1.411	23.345	Yes
Depth x Turbidity (BxC)	0.040	0.003	1	0.003	0.053	No
Flow x Turbidity x Depth (AxBxC)	0.160	0.051	1	0.051	0.847	No
Error			3	0.060		

Note: $f_{crit} = f_{1,3,0.05} = 10.13$

Table 5.19: F-test for the probability of effluent turbidity greater than 0.30 NTU

Source	Effect	SS	DF	MS	F	Significant
Filter Flow Rate (A)	-0.980	1.921	1	1.921	34.117	Yes
Influent Turbidity (B)	-0.340	0.231	1	0.231	4.107	No
Filter Depth (C)	-0.715	1.022	1	1.022	18.161	Yes
Flow x Turbidity(AxB)	0.130	0.034	1	0.034	0.600	No
Flow x Depth (AxC)	0.455	0.414	1	0.414	7.354	No
Depth x Turbidity (BxC)	-0.015	0.000	1	0.000	0.008	No
Flow x Turbidity x Depth (AxBxC)	0.105	0.022	1	0.022	0.392	No
Error			3	0.056		

Note: $f_{crit} = f_{1,3,0.05} = 10.13$

Figure 5.20, Figure 5.21, and Figure 5.22 show the normal probability plots for three different conditions. In all three conditions the factors of filter flow rate (A) and filter depth (C) appear to be significant while it can not be determined if the interaction effect between filter flow rate and influent turbidity (AC) is significant. The lines in these figures were drawn by hand to provide further understanding to the tables shown above.

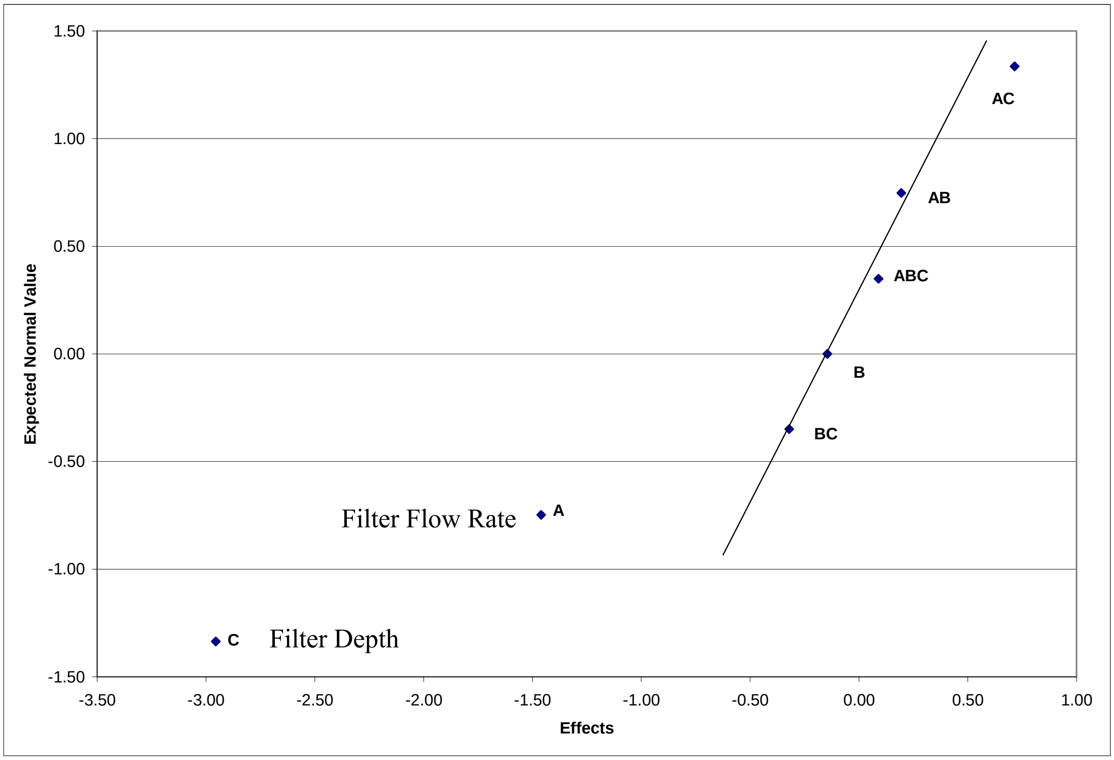

Figure 5.20: Normal probability plot for the probability of effluent turbidity greater than 0.05 NTU (A: filter flow rate, B: filter depth, C: influent turbidity)

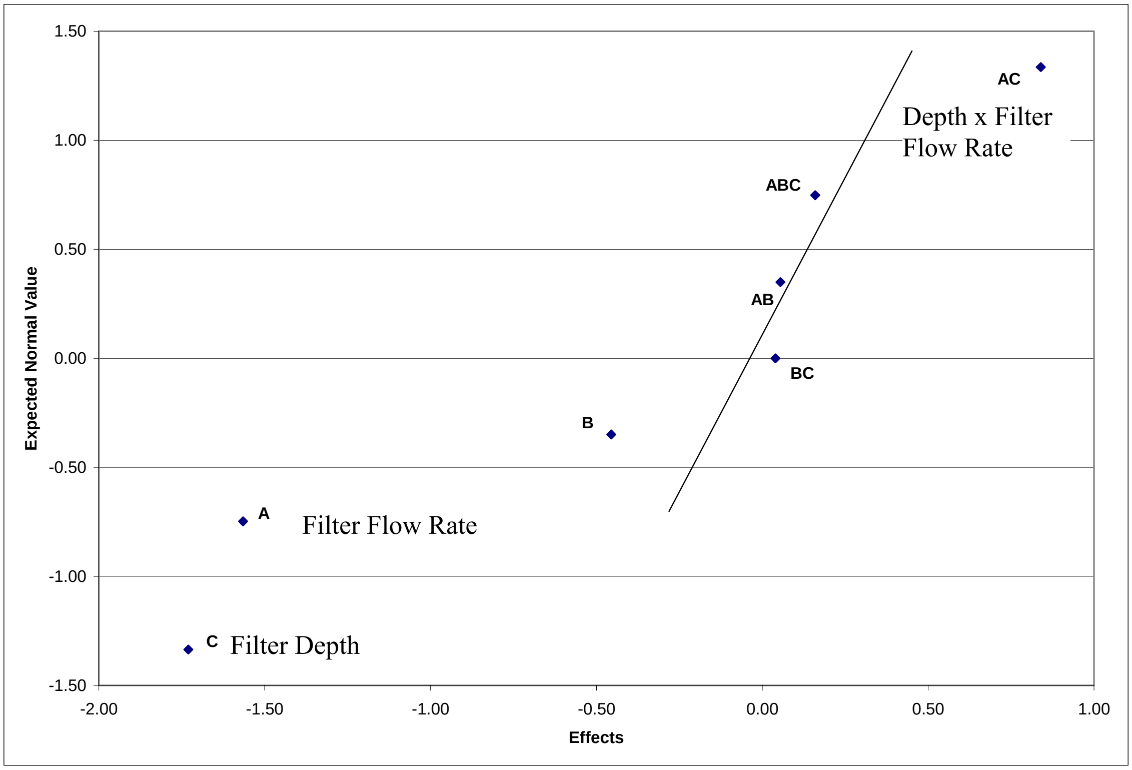

Figure 5.21: Normal probability plot for the probability of effluent turbidity greater than 0.10 NTU (A: filter flow rate, B: filter depth, C: influent turbidity)

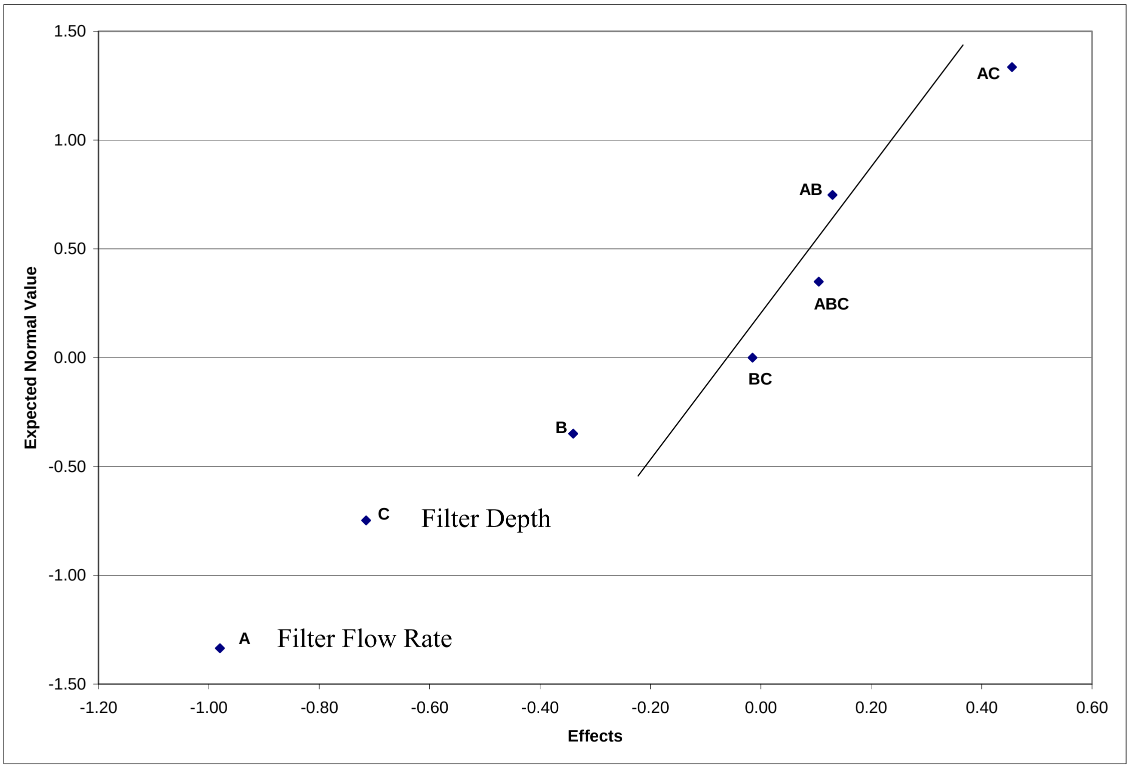

Figure 5.22: Normal probability plot for the probability of effluent turbidity greater than 0.30 NTU (A: filter flow rate, B: filter depth, C: influent turbidity)

5.5 Risk Analysis Implications for the Brantford Water Treatment Plant

If this analysis was performed for a regulatory agency with a requirement that the turbidity must be below 0.30 NTU 95% of the time, then the risk analysis methodology using a random filter flow rate in conjunction with the OTTER model and the measured data would satisfy this criteria. However, if the regulatory requirement was 0.10 NTU 95% of the time, then the probabilistic analysis with the OTTER model would satisfy this criterion but the measured data would not. This is described in Section 5.3.1. The difference between the regulatory acceptance or rejection depending on whether measured or simulated data is used illustrates the importance that should be placed on determining how the calculations for compliance should be performed.

The results from the risk analysis methodology using a random filter flow rate in conjunction with the OTTER model can be incorporated with idea of conditional reliability in a similar way that the results from the CFA were. However, to analyze the results from the calibrated OTTER model, the methodology used for the CFA was expanded upon to evaluate three different conditional situations. The first looked at the filter flow rate, the second at the influent turbidity, and the third analyzed a combination of the filter flow rate and the influent turbidity Table 5.20 shows the output from this analysis.

Table 5.20: Conditional reliability analysis of calibrated OTTER model

Condition	Probability Effluent Turbidity > 0.05 NTU	
Filter Flow Rate	Filter Flow Rate Less than (0.679); υ–σ in the lognormal distribution	0.00
	Filter Flow Rate Between (0.679 and 0.880); υ–σ and υ+σ in the lognormal distribution	0.01
	Filter Flow Rate Greater than (.880); υ+σ in the lognormal distribution	0.04
Influent Turbidity	Influent Turbidity Less than (-0.732); υ–σ in the lognormal distribution	0.01
	Influent Turbidity Between (-0.732 and -0.353); υ–σ and υ+σ in the lognormal distribution	0.01
	Influent Turbidity Greater than (-.353); υ+σ in the lognormal distribution	0.02
Combination	Filter Flow Rate Less than υ–σ and Influent Turbidity Less than υ–σ	0.00
	Filter Flow Rate Less than υ–σ and Influent Turbidity Between υ–σ and υ+σ	0.00
	Filter Flow Rate Less than υ–σ and Influent Turbidity Greater than υ+σ	0.01
	Filter Flow Rate Between υ–σ and υ+σ and Influent Turbidity Less than υ–σ	0.01
	Filter Flow Rate Between υ–σ and υ+σ and Influent Turbidity Between υ–σ and υ+σ	0.01
	Filter Flow Rate Between υ–σ and υ+σ and Influent Turbidity Greater than υ+σ	0.01
	Filter Flow Rate Greater than υ+σ and Influent Turbidity Less than υ–σ	0.04
	Filter Flow Rate Greater than υ+σ and Influent Turbidity Between υ–σ and υ+σ	0.04
	Filter Flow Rate Greater than υ+σ and Influent Turbidity Greater than υ+σ	0.06

The output from the calibrated model, as shown in Table 5.20, shows the probability of producing effluent turbidity greater than 0.05 NTU for a series of conditions. Although 0.05 NTU is not important from a regulatory prospective, it was used for this analysis as it might be important from an operational perspective. Table 5.20 shows that the probability of producing effluent turbidity greater than 0.05 NTU increases with influent turbidity as would be expected. However, while the probability increases by a factor of two for the influent water quality between the low influent and the high influent, the filter flow rate shows an increase by a factor of four. This indicates that filter flow rate has a greater effect on the effluent water quality than the influent turbidity, for the data analyzed. This observation is illustrated more succinctly when the filter flow rate is greater than the mean plus one standard deviation. Under these conditions, the probability of producing water quality greater than 0.05 NTU remains above 4% regardless of the influent turbidity.

The predictive study, discussed in Section 5.4.3, corroborates the findings of the conditional reliability study by showing the significance of the filter flow rate and furthers this understanding by showing the importance of the filter depth for this filtration unit. However, some discrepancies are noticed. It should be mentioned that the conditional reliability methodology uses the output from the risk analysis with the OTTER model directly without any extrapolation of the input data. However, the predictive study uses a series of inputs that result in higher and lower influent turbidity and filter flow rates than are seen through the 2004 data record. This could account for some of the discrepancies.

Nevertheless, the predictive study indicates that the a decrease in the filter flow rate increases the probability of producing water above a stated level while an increase in filter flow rate decreases the probability. The conditional reliability study shows a relationship where an increase in filter flow rate results in an increase in the probability of producing water above a stated level. So while the predictive study indicates that a low flow condition is of concern, the conditional reliability study indicates that a high flow condition is of concern.

In an attempt to reconcile this difference, two of the predictive simulations were run a second time with an added 0.30 NTU backwash turbidity trigger. Table 5.21 shows that the backwash turbidity trigger lowered the probability of producing effluent turbidity greater than a standard. In the case of Simulation 11, a backwash turbidity trigger decreased the probability of producing effluent turbidity greater than 0.10 NTU from 3.46% to 0.46%.

Evaluating Table 5.21 for the relationship between Simulations 10 and 11 without backwash turbidity triggers, it can be seen that Simulation 11, a low flow rate simulation, exhibits more risk than the high flow rate Simulation 10. However, after including the backwash turbidity triggers, the high flow rate Simulation 10, contains more risk than the low flow rate Simulation 11. This is what was originally expected and what was seen in the conditional reliability study; a higher flow rate increases the probability of producing effluent turbidity greater than some value. Thus the discrepancy between the conditional reliability study and the predictive study is partially resolved by adding a turbidity trigger.

Theoretically, this study illustrates that a measure of caution should always be used before utilizing an analysis method. Practically, this study illustrates that one method to decrease the risk associated with producing effluent turbidity greater than a reference is to ensure no low flow conditions occur, while another method is to add a backwash turbidity trigger to the filtration unit. Adding a time trigger for backwashing would also lower the probability of producing effluent turbidity greater than some level however this condition was not evaluated in this thesis.

Table 5.21: Simulations 10 and 11 from the predictive study run with a 0.30 NTU turbidity backwash trigger compared to the original Simulations 10 and 11

Simulation	Average (NTU)	75 Percentile (NTU)	95 Percentile (NTU)	99 Percentile (NTU)	Probability Effluent > 0.30 NTU	Probability Effluent > 0.10 NTU	Probability Effluent > 0.05 NTU
11 with Turbidity Trigger (Low Filter Flow Rate)	0.01	0.02	0.03	0.05	0.00	0.46	1.00
11 without Turbidity Trigger (Low Filter Flow Rate)	0.03	0.02	0.05	0.5	1.95	3.64	4.84
10 with Turbidity Trigger (High Filter Flow Rate)	0.02	0.03	0.04	0.08	0.00	0.50	2.44
10 without Turbidity Trigger (High Filter Flow Rate)	0.02	0.03	0.04	0.09	0.19	0.74	2.84

CHAPTER 6
DISCUSSION OF RISK ANALYSIS METHODOLOGIES

6.1 Numerical Differences

A comparison of the two different risk analysis methodologies and the measured data can be seen in Table 6.1 and a comparison of the risk evaluation from the different methodologies for three different levels can be seen in Figure 6.1, Figure 6.2, and Figure 6.3. From looking at Table 6.1, it is difficult to determine which risk analysis methodology should be used for future analysis. The output from the CFA generally matches the turbidity effluent that is currently experienced by Filter 1; however, there are extremely high effluent values that are above anything seen presently by Filter 1. The output from the probabilistic methodology using the calibrated OTTER model seems to underestimate the actual turbidity effluent, except for the maximums values.

A comparison of the risk evaluation methodologies shows that at the 0.05 NTU level (Figure 6.1), the CFA and the measured effluent are reasonably similar but the probabilistic methodology using the calibrated OTTER model differs considerably. As the level increases to the 0.10 NTU (Figure 6.2), and the 0.30 NTU range (Figure 6.3), the different methodologies begin to produce similar results. In evaluating the Figure 6.1, Figure 6.2, and Figure 6.3 it should be noted that the confidence limits in Figure 6.1, Figure 6.2, and Figure 6.3 remain reasonably similar as they are based on the number of simulations, as discussed in Section 4.5, and that the scale changes from one figure to another.

Table 6.1: Comparison of risk analysis methodologies using output from the simulations

	Consequence Frequency Assessment*	Calibrated OTTER Model**	Measured Filter 1 Effluent
Max	2.92	1.41	0.25
Min	0.00	0.00	0.01
Standard Deviation	0.06	0.04	0.04
Average	0.05	0.02	0.05
95 Percentile	0.15	0.03	0.11
99 Percentile	0.28	0.07	0.15

* CFA performed for 180,000 shots
** Calibrated OTTER simulation performed for 13,358 shots

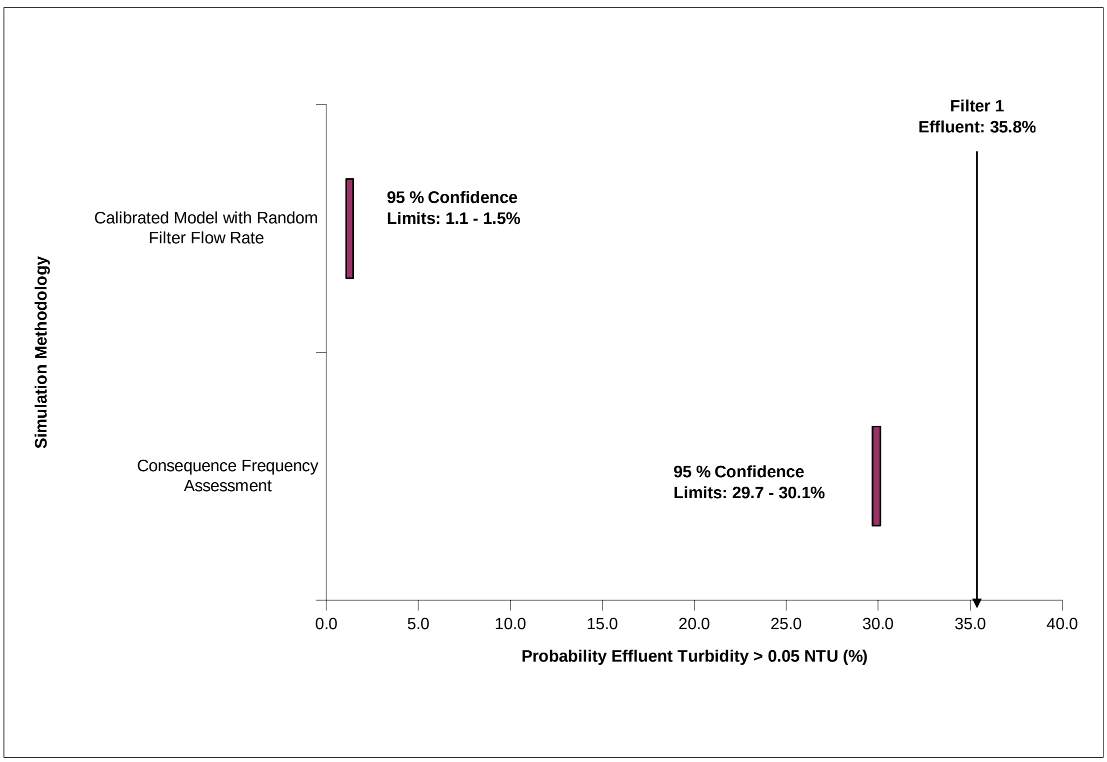

Figure 6.1: Comparison of risk evaluation from different analysis methodologies for probability of producing water greater than 0.05 NTU

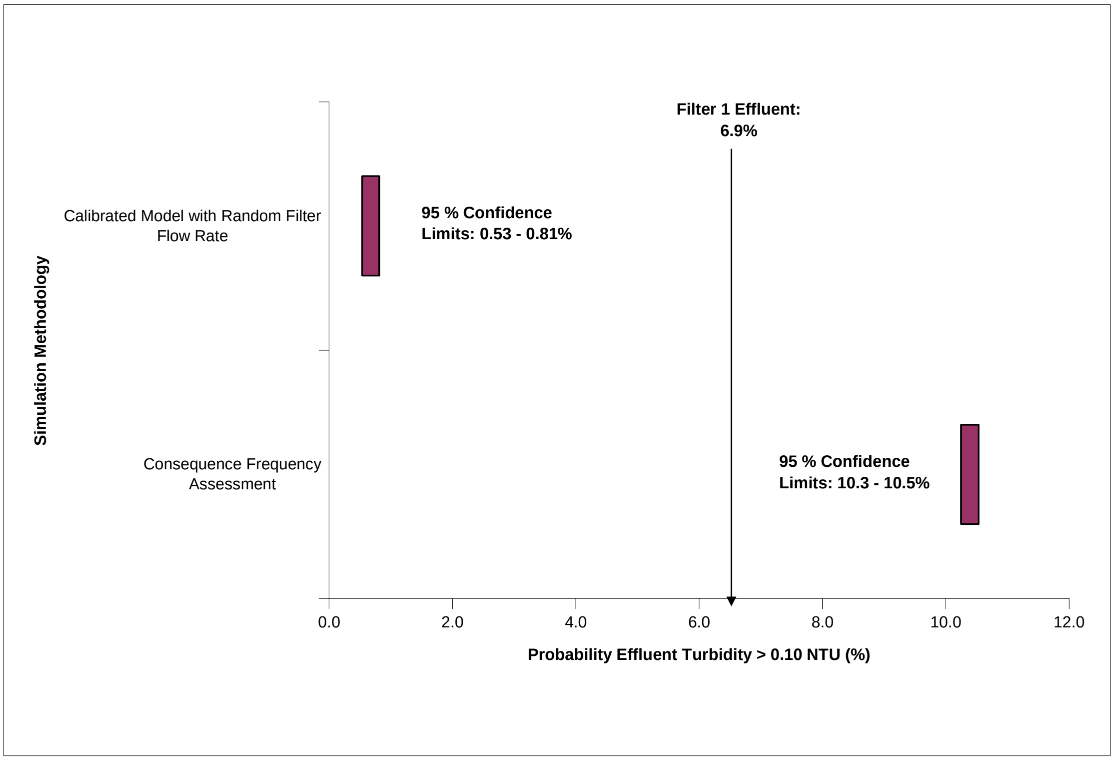

Figure 6.2: Comparison of risk evaluation from different analysis methodologies for probability of producing water greater than 0.10 NTU

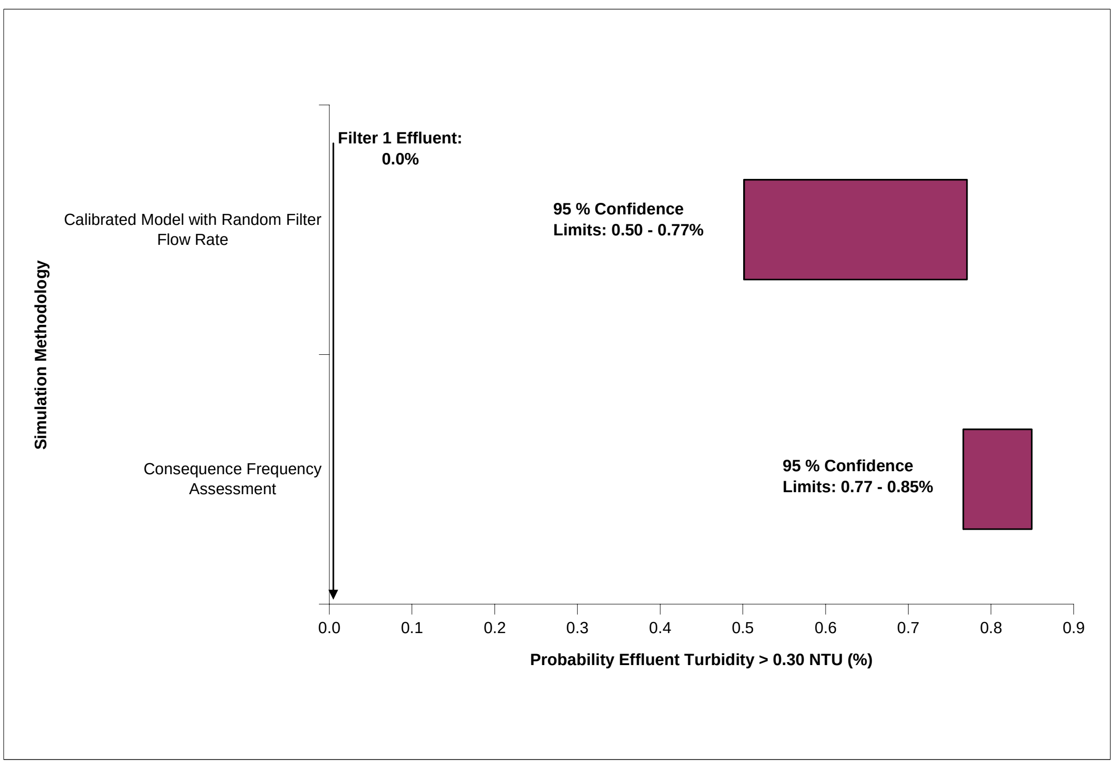

Figure 6.3: Comparison of risk evaluation from different analysis methodologies for probability of producing water greater than 0.30 NTU

A more comprehensive understanding of the different methodologies can be seen by looking at Figure 6.4. In this figure, it is evident that until around the 95th percentile the measured effluent and the CFA are closely related while the probabilistic analysis with the OTTER model seems to underestimate the measured effluent until around the 99th percentile, above which it greatly exceeds it. Figure 6.5 shows this difference more explicitly by limiting scale along the x-axis of Figure 6.4 to 0.5 NTU.

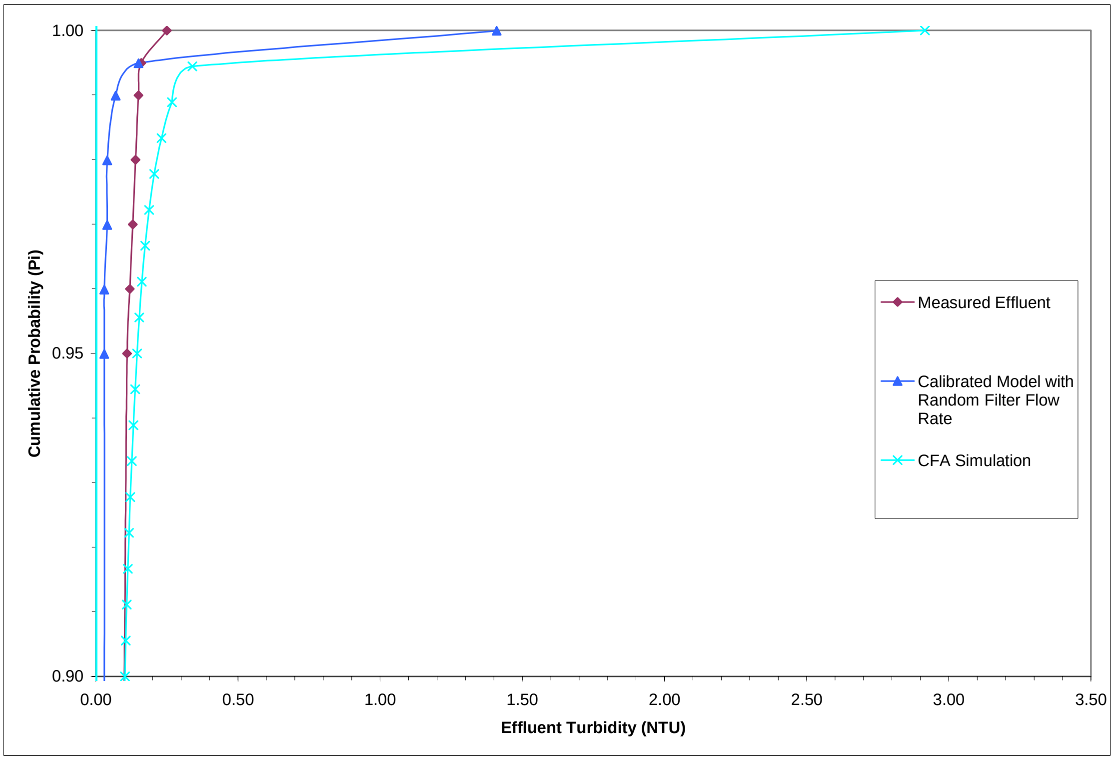

Figure 6.4: CDF of the output from the different risk analysis methodologies and the measured effluent: Focusing on the top 10% of the CDF

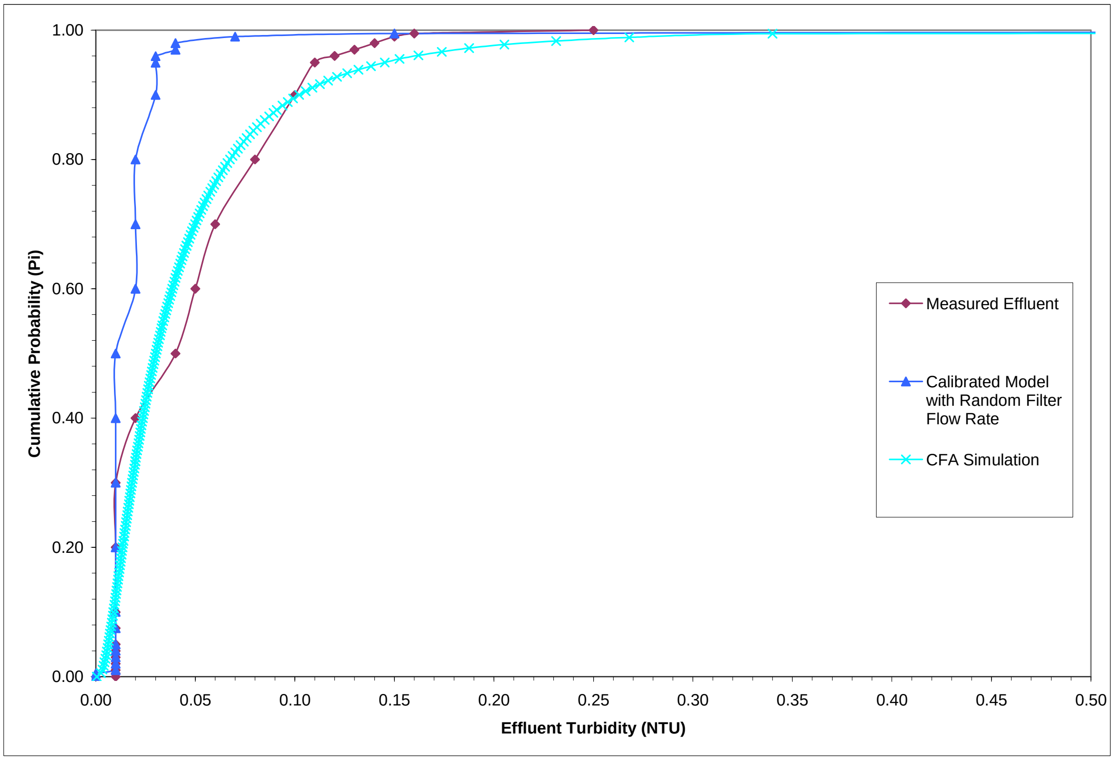

Figure 6.5: CDF of the output from the different risk analysis methodologies and the measured effluent: Focusing on the top 10% of the CDF and between 0 - 0.5 NTU

The question is which methodology to use and what the different methodologies are measuring. There are three possible outcomes from this analysis and comparison:

1) Combining modelling and probabilistic simulation produces more reasonable values from a risk perspective in comparison to other methodologies such as the CFA or in comparison to past measured data.

2) The discrepancies between the CFA and the combination of probabilistic simulation with modelling can be accounted for because of the assumptions that were necessary to perform the analysis.

3) The different methodologies are measuring different aspects of risk.

The first possible outcome cannot be stated with certainty before the assumptions of the analysis are checked and the other two possible outcomes are discounted. Therefore to eliminate the second possible outcome, the basic assumptions of the OTTER modelling procedure and risk analysis procedure should be checked. Some of the basic assumptions are that the modified calibration procedure was reasonable, that a time series filter flow rate curve could be simplified to be completely random, and that the OTTER filter model sufficiently describes the filtration process. The assumption that a completely random filter flow rate could be used was tested by using the 2004 data record and some differences were seen between using the two different methods of generating filter flow rates. However, the 2004 data record was not completely random and thus a random filter flow rate curve which incorporates the time-series component should be used in a future study to see of the output is affected.

The third possible outcome provides an interesting discussion that should require more investigation. In using a calibrated software model, the risk analysis is performed on a set of ideal operating conditions. This was an initial goal of the analysis, to determine the probability of producing water above a specified reference level from a properly operated water treatment plant. The simulations show that this probability for the filtration unit analyzed is between 1% and 3% depending whether the reference level is 0.3 NTU of 0.05 NTU. However, the CFA is based on the past data record exclusively, which will include non-ideal conditions or situations where operational procedures were modified. For example, the backwashing of a filter manually because the operator perceives it is necessary. The discrepancy between the CFA and the modelled risk evaluation would then be those conditions that could be classified as non-ideal. One assumption in making this comparison is that the data record used in the CFA would have no instances where the output would be affected by a mechanical failure, which would need to be analyzed using a mechanical risk analysis methodology. There was no way of knowing this for the gathered data set.

Therefore, the difference in output from the risk methodologies would converge when the modelled probabilistic methodology found a mechanism to incorporate non-ideal conditions into the analysis. If, after further analysis, the third possible outcome was deemed to be reasonable, then a recommendation might be that an analysis mechanism such as the CFA is sufficient for simplified risk analysis, but that for a more comprehensive understanding of the system a risk methodology using modelling and probabilistic analysis could be performed with the understanding that it focuses on the ideal conditions.

6.2 External Differences

One of the major differences between the CFA and using modelling and probabilistic risk analysis is the wider range of capabilities with the use of computer modelling. Using computer modelling allowed the effect of external parameters, such as filter flow rate, to be included in the overall analysis. In this instance it showed that the filter flow rate was a greater contributor to producing non-compliant water than influent turbidity. Also, using computer modelling allowed for predictive studies. In this case, it was shown that adding a backwash turbidity trigger to the filtration unit would greatly reduce the probability of producing non-compliant water for low filter flow rate scenarios. Furthermore, the predictive studies showed that the filter flow rate and filter depth were the most significant effects on the probability of producing effluent turbidity greater than a reference level. Influent turbidity, although not significant in this study, could be important in other situations. The CFA, in its current form, is unable to analyze any of these things.

6.3 Risk Analysis Implications for the Brantford Water Treatment Plant

The results from the risk analysis using the two methods showed results that were at times highly divergent. An example of this is the probability of producing turbidity effluent greater than 0.05 NTU. The consequence frequency assessment calculated a value of approximately 30% while the probabilistic methodology with model simulation calculated a value of approximately 1%. The Brantford WTP filtration unit is directed by the Ontario Drinking Water Standards which have a 5 NTU maximum turbidity at the point of consumption (Ontario Ministry of the Environment, 2003). However a more comprehensive regulation of turbidity is provided by the Guidelines for Canadian Drinking Water which, for chemically assisted filtration, direct that turbidity "shall be less than or equal to 0.3 NTU in at least 95% of the measurements made, or at least 95% of the time each calendar month, and shall not exceed 1.0 NTU at any time" (Health Canada, 2003). The results previously presented with respect to 0.05 NTU are not necessarily of concern, but they do illustrate a difference between the risk analysis methods.

In looking at the 2004 turbidity data record for the filter of interest, it can be seen that these criteria are met as the maximum effluent turbidity is 0.25 NTU and the effluent turbidity is less than 0.11 NTU 95% of the time. However, the application of risk analysis methods to the filtration unit demonstrates the possibility that the filter unit might violate these guidelines. The

CFA and the calibrated OTTER model risk analysis methods indicate that the effluent turbidity is less than 0.3 NTU 95% of the time, but both risk analysis method show maximum turbidity levels over 1.0 NTU. If the turbidity guideline was lowered to 0.10 NTU, or if an internal operational guideline was set at that value, the analysis shows that the filtration unit could either be in compliance of the guideline, or be in violation of the guideline depending on the analysis method chosen. A problem with risk analysis that arises out of this research is that, depending on the method chosen, a water treatment plant could be in compliance or out of compliance. A situation could occur where the predicated ability to achieve regulatory compliances, and potentially substantial related capital expenditures, could depend on the analysis method chosen.

This illustrates the importance that should be placed on determining how the calculations for compliance should be performed. Furthermore, this illustrates that risk analysis cannot be used as an arbitrary judgment tool for decision making. As Hrudey (2004) states: risk analysis should guide risk management. For the Brantford Water Treatment Plant, the overall analysis indicates that there is currently little probability of producing non-compliant water at the 0.30 NTU regulatory level, but any lowering of the guideline, or adoption of a stricter internal operating guideline, would require further analysis of the system.

CHAPTER 7
CONCLUSIONS

In this study, risk analysis methods that have been used in other engineering disciplines were evaluated for their ability to be used in analyzing a water treatment plant to evaluate the risk that a properly operated water treatment plant produces water that does not comply with a stated standard. From a literature review, two risk analysis methods were chosen and evaluated; the consequence frequency assessment (CFA) and a method that combines water treatment plant modelling with probabilistic simulation. Both of these methods were then applied to a full-scale anthracite/sand filter unit that was evaluated based on the effluent turbidity. From this overall study, conclusions can be drawn for the Brantford Water Treatment Plant filtration unit specifically and for risk analysis in water treatment plants.

7.1 Conclusions for Risk Analysis in Water Treatment

For risk analysis in water treatment, the study highlights some broader points for consideration in future risk analyses which are the most significant conclusions for any future work in risk analysis and water treatment.

1. The quantitative output of risk analysis is highly dependent on the methodology used. This principle is exemplified through the different results that were obtained using the different analysis methods.

2. Until the results from a risk analysis are better understood, risk analysis results should be used as a guiding tool, not a directive map to the “right” result: risk analysis should guide risk management (Hrudey, 2004). Thus the risk analysis itself should not be the determining factor in deciding whether or not a system is operating acceptably but should be one component of a risk assessment and thus an entire risk management framework for drinking water.

3. Risk analysis, regardless of methodology, can produce results that provide information to managers. A beneficial understanding of the filtration unit can be acquired by using the idea of conditional reliability with risk analysis. This idea focuses on what external conditions contribute to the probability of producing effluent water above a stated level and thus what external conditions contribute to the risk of producing non-compliant water to the greatest extent.

4. Risk analysis, regardless of methodology, shows that a past data record might not be completely indicative of future performance. Current drinking water guidelines base performance on the past monitoring record. The use of risk analysis techniques attempt to examine the filtration unit under all possible conditions that are likely to occur. Consequently, the risk analysis can provide an estimation of the probability that the system would produce water not meeting the standard, regardless of the past data record.

7.2 Conclusions for Risk Analysis Performed in on a Filtration Unit

The following conclusions can be drawn with respect to performing a risk analysis on a dual media rapid gravity filter.

1. Undertaking a risk analysis with the CFA is a simpler procedure then undertaking a risk analysis with computer modelling and simulation.

2. The use of percentage remaining as opposed to percentage reduction is a better parameter for use during the CFA as it allows for the incorporation of instances in the data record where the effluent turbidity is greater than the influent turbidity.

3. The CFA methodology is dependent on the seasonality of the measured data used for analysis. It was found that because the CFA uses the past data record, if the CFA is performed with a data set consisting of a portion of a year, the results could vary significantly from the results of a CFA that uses a data set consisting of an entire year

4. Future risk analyses using computer modelling should incorporate the use of a random time series filter flow rate curve into the analysis.

5. A two tiered risk analysis method is proposed for future analysis. The CFA methodology can be used to gain an overview understanding of the probability of producing non-compliant water, while the use of modelling and probabilistic risk analysis can be used to focus in on the specifics.

7.3 Conclusions for the Brantford Water Treatment Plant

The following conclusions can be drawn with respect to the Brantford Water Treatment Plant.

1. The filter flow rate and filter depth are the most significant effects when evaluating the probability of producing effluent water with turbidities greater than a reference level for the conditions analyzed.

2. For the conditions analyzed, the influent turbidity was not a major factor when evaluating the probability of producing effluent water with turbidities greater than a reference level.

CHAPTER 8 RECOMMENDATIONS AND FUTURE WORK

The analysis performed on the filtration unit at the Brantford Water Treatment Plant was able to provide insight into its overall performance. However, there are a number of possible future actions that will increase the understanding of risk analysis methodologies in water treatment and increase the ways that the methodologies can be used.

8.1 Recommendations for the Brantford Water Treatment Plant

1. Although the filtration unit is currently operating at a high level, the operation of the filtration unit should be evaluated if a new turbidity standard or internal operational guideline is introduced.

2. Under low filter flow rate conditions a backwash turbidity trigger should be installed to reduce the potential for turbidity breakthrough.

8.2 Recommendations for Regulatory Agencies and Risk Assessors

1. Recognize that risk analysis should guide risk management decisions and not be used as the single tool that determines what action to perform.

2. Recognize the wide range of outputs that are possible from using different risk analysis methods.

3. Begin the process of developing risk analysis methods that can be used to evaluate drinking water treatment processes.

8.3 Future Work: Strengthen Methodology and Current Results

For the different risk analysis methodologies a number of statistical techniques and assumptions were used. Future research should determine the extent to which these decisions affect the final output.

Initially, the effect of the method of simulating the input water parameters should be looked at. This will include describing the affect of choosing a parametric or non-parametric distribution. Furthermore, if parametric distributions are used, the affect of the distribution type and distribution parameters should be looked at. This analysis, although statistical in nature, should be looked at closely. During the analysis it was decided that the influent turbidity, which is the settled water turbidity, could be modelled as a lognormal distribution. Although the lognormal distribution has been used to model naturally occurring water quality parameters in the past (Eisenberg et al., 1998; Novotny, 2004), in this case the water quality parameter is not truly naturally occurring because it is a function of the previous treatment steps. It may be more realistic to use a non-parametric bootstrapping method for the analysis.

Regardless of the type of distribution, the effect of the type of random number generator should be investigated if the analysis requires one. This study used a random number generator developed for Microsoft Excell, even though there have been errors noted in this random number generator (McCullough and Wilson, 2002, 2003).

The choice in the analysis to assume that incoming water quality parameters were not correlated was stated explicitly; however, literature such as Burmaster and Anderson (1994) and Verdonk (2003) state the need to see the effect of the correlation among incoming water quality parameters. Therefore the incorporation of correlation should be analyzed as well.

The water flow profile for the 2004 year was used as the input water demand in an attempt to show how a time-series water profile would affect the results from an analysis. However, in using a past data record the analysis was no longer a true random simulation. Therefore, a methodology should be developed to simulate a water flow profile that is realistic and random by using some time-series simulation mechanism. A methodology to include correlation and time series data is shown by Rousseau et al. (2001).

Finally, since the combination of probabilistic simulation and computer modelling is dependent on the output from the site specific model, more focus should be paid to the calibration of the filtration unit to the existing data. The OTTER program provides a calibration procedure (WRc plc, 2002); however, because the data that was needed to follow the calibration procedure was not available a different mechanism was used.

To provide a greater level of confidence in the risk analysis, the calibration procedures outlined by WRc plc (2002) should be followed. This calibration procedure would require a pilot study to look at filter breakthrough curves for the filter of interest. The experiment would need to measure the flowrate through the filter, the influent turbidity, the effluent turbidity, the headloss through the filter and the run time along with the basic filter parameters of length and area. The voidage and sphericity values can affect the output from the filtration unit; thus, instead of relying on past literature, the actual parameters of the media should be analyzed. The calibration parameters,

- the attachment coefficient (r),
- the filter capacity (κ), and
- the hydraulic conductivity (β)

are dependant on the media itself as well as the conditions under which the filter is operated. Therefore, although the parameters could be calculated for the entire filter unit, realistically they would change from the anthracite to the sand. To fully characterize the filter process, the parameters should be calculated for each media layer. Furthermore, water quality parameters not included in the risk analysis should be investigated further so that the calibrated models are as accurate as possible. There is the possibility that if these values change considerably during the analysis, a change in the risk analysis could be seen.

Finally, the suitability of the OTTER software program to adequately evaluate the filtration process should be more thoroughly investigated. A comprehensive analysis would also incorporate a second or third modeling package to determine how extensive the effect of the modelling program is on the output.

REFERENCES

Amirtharajah, A., & Wetstein, D. P. (1980). Initial degradation of effluent quality during filtration. Journal of the American Water Works Association, 72(9), 518-524.

Amirtharajah, A. (1985). The interface between filtration and backwashing. Water Research, 19(5), 581-588.

Amirtharajah, A. (1988). Some theoretical and conceptual views of filtration. Journal of the American Water Works Association, 80(12), 36-46.

Adin, A., & Rebhun, M. (1977). A model to predict concentration and head-loss profiles in filtration. Journal of the American Water Works Association, 69(8), 453-457.

Alvisi, S., & Franchini, M., & Marinelli, A. (2003). A stochastic model for representing drinking water demand at residential level. Water Resources Management, 17(3), 197-222.

Ang, A. H-S., & Tang, W. H. (1975). Probability Concepts in Engineering Planning and Design, Volume I. New York: John Wiley & Sons, Inc.

Ang, A. H-S., & Tang, W. H. (1984). Probability Concepts in Engineering Planning and Design, Volume II. New York: John Wiley & Sons, Inc.

Atkins, P. F., & Tomlinson, H. D. (1963). Evaluation of daily carbon chloroform extracts with CAM. Water Sewage Works, 110(8), 281-284.

Baxter, W. C., & Barbara, J. L. (2003). A framework for risk analysis in potable water supply, World Water and Environmental Resources Congress 2003. Philadelphia, United States, June 23-26, 2003.

Baxter, W. C., & Barbara, J. L., & Coffey, B. M., (2003). Analyzing operational risk in potable water supply using conditional reliability. World Water and Environmental Resources Congress 2003, Philadelphia, United States, June 23-26, 2003.

Bixio, D., & Parmentier, G., & Rousseau, D., & Verdonck, F., & Meirlaen, J., & Vanrolleghem, P. A., et al. (2001). Integrating risk analysis in the design/simulation of activated sludge systems, In: Proceedings 2nd IWA World Water Congress. Berlin, Germany, October 15-19 2001.

Bixio, D., & Parmentier, G., & Rousseau, D., & Verdonck, F., & Meirlaen, J., & Vanrolleghem, et al. (2002). A quantitative risk analysis tool for design/simulation of wastewater treatment plants. Water Science and Technology, 46(4-5), 301-307.

Burmaster, D. E., & Anderson, P. D. (1994). Principles of good practice for the use of Monte Carlo techniques in human health and ecological risk assessments. Risk Analysis, 14(4), 477-481.

Burmaster, D. E., & Hull, D. A. (1997). Using LogNormal Distributions and LogNormal Probability Plots in Probabilistic Risk Assessments. Human and Ecological Risk Assessment, 3(2), 235-255.

Carrette, R., & Bixio, D., & Thoeye, C., & Ockier, P. (2001). Full-scale application of the IAWQ ASM No. 2d model. Water Science and Technology, 44(2-3), 17-24.

City of Brantford. (2006). http://www.city.brantford.on.ca/environmental/pdf/Layout.PDF, accessed January 31, 2006.

City of Brantford (2005). Holmedale Water Treatment Plant Quarterly Report for the period of July to September, 2005. http://www2.brantford.ca/environmental/pdf/reports/ holmedaletreatment_jul_sep_05.pdf

Cleasby, J. L., & Fan, K. (1981). Predicting fluidization and expansion of filter media. Proceedings of the American Society of Civil Engineers. Journal of the Environmental Engineering Division, 107(3), 455-471.

Considine, R. (2004). Development of a water quality risk management framework. Engineers Australia, 76(3), 54.

Cullen, A. C., & Frey, H. C. (1999). Probabilistic Techniques in Exposure Assessment: A Handbook for Dealing with Variability and Uncertainty in Models and Inputs. New York: Plenum Press.

Démotier, S., & Odeh, K. & Schön, W., Charles, P., & Fotoohi, F., & Allious, J-F. (2002). Risk assessment for drinking water production process. In Proceedings of European Conference on System Dependability and Safety, Lyon, France, March, 2002.

Démotier, S., & Denoeux, T., & Schön, W., & Odeh, K. (2003a). A new approach to assess risk in water treatment using the belief function framework. In Proceedings of the IEEE International Conference on Systems, Man and Cybernetics v 2, 2003, Washington, United States, October 2-5, 2003.

Démotier, S., & Denoeux, T., & Schön, W. (2003b). Risk assessment in drinking water production using belief functions. In Proceedings of ECSQARU. Aalborg, Denmark, July 2-5, 2003.

Duen, J. (2000). Pilot Filter Assessment at the City of Brantford Water Purification Plant. General Engineering Project 503, University of Waterloo. Waterloo, Canada.

Dunn, A. J., & Frodsham, D. A., & Kilroy, R. V. (1998). Predicting the risk to permit compliance of new sewage treatment works. Water Science and Technology, 38(3), 7-14.

Egerton, A. (1996). Achieving reliable and cost effective water treatment. Water Science and Technology, 33(2), 143-149.

Eisenberg, D., & Olivieri, A., & Soller, J., & Gagliardo, P. (1998). Reliability analysis of an advanced water treatment facility. Proceedings of the 1998 National Conference on Environmental Engineering, 297-302.

Eisenberg, D., & Soller, J., & Sakaji, R., & Olivieri, A. (2001). A methodology to evaluate water and wastewater treatment plant reliability. Water Science and Technology, 43(10), 91-99.

Emelko, M. B., & Huck, P. M., & Douglas, I. P. (2003). Cryptosporidium and microsphere removal during late in-cycle filtration. Journal of the American Water Works Association, 95(5), 173-182.

Flora, J. R. V., & McAnally, A. S., & Petrides, D. (1999). Treatment plant instructional modules based on SuperPro Designer v 2.7. Environmental Modelling and Software, 14(1), 69-80.

Frey, H. C. 1992. Quantitative Analysis of Uncertainty and Variability in Environmental Policy Making. AAAS/EPA Environmental Science and Engineering Fellow.

Haas, C. N., & Crockett, C. S., & Rose, J. B., & Gerba, C. P., & Fazil, A. M. (1996). Assessing the risk posed by oocysts in drinking water. Journal of the American Water Works Association, 88(9), 131-136.

Haas, C. N. (1997). Importance of distributional form in characterizing inputs to Monte Carlo risk assessment. Risk Analysis, 17(1), 107-113.

Haas, C. N., & Trussell, R. R. (1998). Frameworks for assessing reliability of multiple, independent barriers in potable water reuse, Water Science and Technology. 38(6), 1-8.

Haas, C. N. (1999). On modeling correlated random variables in risk assessment. Risk Analysis, 19(6), 1205-1214.

Haas, C. N., & Rose, J. B., & Gerba, C. P. (1999). Quantitative Microbial Risk Assessment, New York: John Wiley & Sons, Inc.

Harris, J. P. (1985). The application of reliability and availability analysis techniques in the waste water treatment industry. Reliability Engineering, 10(4), 193-217.

Head, R., & Shepherd, D. & Butt, G. & Buck, G. (2002). OTTER mathematical process simulation of potable water treatment. Water Science and Technology: Water Supply, 2(1), 95-101.

Health Canada (2003) Guidelines for Canadian Drinking Water Quality: Supporting

Documentation — Turbidity. Water Quality and Health Bureau, Healthy Environments and Consumer Safety Branch, Health Canada, Ottawa, Ontario.

Hemmis (2004). http://www.hemmis.com/products/west/default_west.htm, accessed November 15, 2004.

Henze, M., & Gujer, W., & Mino, T., & Matsuo, T., & Wentzel, M. C., & Marais, G. v. R., et al. (1999). Activated sludge model No. 2d, ASM2d. Water Science and Technology, 39(1), 165-182.

Hrudey, S. E. (2001). Drinking water quality: A risk management approach. Water, 26(1), 29-32.

Hrudey, S. E. (2004). Drinking-water risk management principles for a total water quality management framework. Journal of Toxicology and Environmental Health, Part A, 67(20-22), 1555-1566.

Huck, P. M., & Coffey, B. M., & O'Melia, C. R., & Emelko M. B., & Maurizio, D. D. (2001).Filtration Operation Effects on Pathogen Passage. American Water Works Association Research Foundation and American Water Works Association, Denver, Colorado.

Huck, P. M., & Coffey, B. M., & Emelko, M. B., & Maurizio, D. D., & Slawson, R. M., & Anderson, W. B., et al. (2002). Effects of filter operation on Cryptosporidium removal. Journal of the American Water Works Association, 94(6), 97-111.

Hydromantis. (2006). http://www.hydromantis.com/software08.html, accessed May 16, 2006.

Iman, R. L., & Conover, W. J. (1982). A Distribution-free approach to inducing rank correlation among input variables. Communications in Statistics – Simulation and Computation, 11(3), 311-334.

International Water Association (2004). http://www.iwahq.org.uk/template.cfm?name=sg17, accessed November 15, 2004.

Jardine, C. G., & Hrudey, S. E. (1997). Mixed messages in risk communication. Risk Analysis, 17(4), 489-498.

Kaplan, S., & Garrick, J. B. (1981). On the quantitative definition of risk. Risk Analysis, 1(1), 11-27.

Kapelan, Z. S., & Savic, D. A., & Walters, A. G. (2005). Multiobjective design of water distribution systems under uncertainty. Water Resources Research, 41(11), W11407.

Kawamura, S. (1999). Design and operation of high-rate filters. Journal of the American Water Works Association, 91(12), 77-90.

Keller, W., & Modarres, M. (2005). A historical overview of probabilistic risk assessment development and its use in the nuclear power industry: a tribute to the late Professor Norman Carl Rasmussen, Reliability Engineering and System Safety. 89(3), 271-285.

Krewski, D., & Balbus, J., & Butler-Jones, D., & Haas, C., & Isaac-Renton, J., & Roberts, K. J., Sinclair, M. (2002). Managing health risks from drinking water – a report to the Walkerton inquiry. Journal of Toxicology and Environmental Health, Part A, 65(21), 1635-1823.

Laîné, J. M., & Démotier, S., & Odeh, K., Schön, W., & Charles, P. (2002). Risk assessment for drinking water production: assessing the potential risk due to the presence of Cryptosporidium oocysts in water. Water Science and Technology: Water Supply, 2(3), 55-63.

Lansey, K. E., & Duan, N., & Mays, L. W., & Tung, Y.-K. (1989). Water distribution design under uncertainty. Journal of Water Resources Planning and Management, 115(5), 630-345.

Law, A. M., & Kelton, W. D. (1991). Simulation Modeling and Analysis, Second Edition, New York: McGraw-Hill.

Letterman, R. D. (1987). An overview of filtration. Journal of the American Water Works Association, 79(12), 26-32.

Li, T. (2004). Quantifying Robustness of Water Treatment Systems, M.A.Sc Thesis, University of Waterloo. Waterloo, Ontario, Canada.

Masago, Y., & Katayama, H., & Hashimoto, A., & Hirata, T., & Ohgaki, S. (2002). Assessment of risk of infection due to *Cryptosporidium parvum* in drinking water. Water Science and Technology, 46(11-12), 319-324.

McCollough, M.C., & Wilson, B. (2002). On the accuracy of statistical procedures in Microsoft Excel 2000 and Excel XP. Computational Statistics and Data Analysis, 40(4), 713-721.

McCollough, M.C., & Wilson, B. (2005). On the accuracy of statistical procedures in Microsoft Excel 2003. Computational Statistics and Data Analysis, 49(4), 1244-1252.

Medema, G. J., & Hoogenboezem, W., & van der Veer, A. J., & Ketelaars, H. A. M., & Hijnen, W. A. M., & Nobel, P. J. (2003). Quantitative risk assessment of *Cryptosporidium* in surface water treatment, Water Science and Technology, 47(3), 241-247.

Mercer, S., (1988). Demonstration of quantitative risk assessment to Some municipal water treatment plant process, MS Thesis, University of Alberta. Edmonton, Alberta, Canada.

Montgomery, D. C. (2001). Design and Analysis of Experiments, Fifth Edition, New Jersey: John Wiley & Sons Inc.

MP & Associates. (2005). Water Treatment Software: OTTER, accessed February 25, 2005, http://www.mpassociates.gr/software/environment/otter.html

MWH. (2005). Water Treatment: Principles and Design, Second Edition, New Jersey: John Wiley & Sons Inc.

National Health and Medical Research Council. (2004). Australian Drinking Water Guidelines (NHMRC Publication No. EH19, EH39). http://www.health.gov.au:80/nhmrc/ publications/ synopses/eh19syn.htm.

National Research Council. (1998). Issues in Potable Reuse: the Viability of Augmenting Drinking Water Supplies with Reclaimed Water. Washington, D.C: National Academy Press.

Novotny, V. (2004). Simplified databased total maximum daily loads, or the world is Log-Normal. Journal of Environmental Engineering, 130(6), 674-683.

O' Melia, C. R. (1985). Particles, pretreatment, and performance in water filtration. Journal of Environmental Engineering, 111(6), 874-890.

Ockier, P., & Thoeye, C., & De Gueldre, G. (2001). Key tools to accelerate fulfilment of the EU Urban Water Treatment Directive in the Flemish region of Belgium. Water Science and Technology, 44(1), 7-14.

Olivieri, A., & Eisenberg, D., & Soller, J., & Eisenberg, J., & Cooper, R., & Tchobanoglous, G., et al. (1999). Estimation of pathogen removal in an advanced water treatment facility using Monte Carlo simulation. Water Science and Technology, 40(4-5), 223-233

Ontario Ministry of the Environment. (2001). Ontario Drinking Water Standards. (Ontario Ministry of the Environment Publication # 4065e).

Ontario Ministry of the Environment. (2003). Technical Support Document for Ontario Drinking Water Standards, Objectives, and Guidelines. (Ontario Ministry of the Environment Publication # 4449e).

Pandey, M. (2004). CIVE 601 Engineering Risk and Reliability Class Notes. University of Waterloo.

Pate-Cornell, E., & Dillon, R. (2001). Probabilistic risk analysis for the NASA space shuttle: a brief history and current work. Reliability Engineering and System Safety, 74(3), 345-352.

Petrides, D. (2006). Analysis and Evaluation of Batch Pharmaceutical Processes under Uncertainty using Process Simulation, Scheduling, and Risk Analysis Tools, accessed February 23, 2006, http://www.intelligen.com/literature.shtml

Pollard, S. J. T., & Strutt, J. E., & Macgillivray, B. H., & Hamilton, P. D., & Hrudey, S. E. (2004). Risk analysis and management in the water utility sector a review of drivers, tools and techniques. Process Safety and Environmental Protection, 82(6B), 453-462.

Portielje, R., & Hvitved-Jacobsen, T., & Schaarup-Jensen, K. (2000). Risk analysis using stochastic reliability methods applied to two cases of deterministic water quality models. Water Research, 34(1), 153-170.

Protopapas, A. L., & Katchamart, S., & Platonova, A. (2000). Weather effects on daily water use in New York City. Journal of Hydrologic Engineering, 5(3), 332-338.

Rajagopalan, R., & Tien, C. (1976). Trajectory analysis of deep-bed filtration with sphere-in-cell porous media model. AIChE Journal, 22(3), 523-533.

Rak, J., (2003). A study of the qualitative methods for risk assessment in water supply systems. Environment Protection Engineering, 29(3-4), 123-133.

Rousseau D., & Verdonck, F., & Moerman, O., & Carrette, R., & Thoeye, C., & Meirlaen, J., et al. (2001). Development of a risk assessment based technique for design/retrofitting of WWTPs. Water Science and Technology, 43(7), 287-294.

Saatci, A. M., & Oulman, C. S. (1980). The bed depth service time design method for deep bed Filtration. Journal of the American Water Works Association, 72(9), 524-528.

Sadiq, R., & Husain, T., & Al-Zahrani, M. A., & Sheikh, A. K., & Shaukat, F., (2003). Secondary effluent treatment by slow sand filters: performance and risk analysis. Water, Air and Soil Pollution, 143(1-4), 41-63.

Sadiq, R., & Al-Zahrani, M. A., & Sheikh, A. K., & Husain, T., & Shaukat, F., (2004). Performance evaluation of slow sand filters using fuzzy rule-based modeling. Environmental Modelling & Software, 19(5), 507-515.

Saskatchewan Environment. (2005). 2005-2006 Provincial Budget Performance Plan – Safe Drinking Water Strategy (Document ID No. 9657). http://www.se.gov.sk.ca/environment /protection/water/2005-06PerformancePlan-DrinkingWater.pdf.

Scardina, P., & Letterman, R. D., & Edwards, M. (2006). Particle count and on-line turbidity interference from bubble formation. Journal of the American Water Works Association, 98(7), 97-109.

Santamarina, V. E. (1997). Modeling and optimization of a municipal treatment plant using EnviroPro Designer. Environmental Progress, 16(4), 268-273.

Sinclair, M., & Rizak, S. (2004). Drinking-water quality management: The Australian framework. Journal of Toxicology and Environmental Health, Part A, 67(20), 1567-1579.

Song, R., & Minear, R., & Westerhoff, P., & Amy, G. (1996). Modeling and risk analysis of Bromate formation from ozonation of Bromide-containing waters. Water Science and Technology, 34(7-8), 79-85.

Stimela (2003). Report WP2. www.stimela.com, accessed November 15, 2004.

Suthaker, S., & Smith, D. W., & Stanley, S. J. (1995). Filtrate turbidity improvement of existing mono-media filters based on a pilot plant study. Canadian Journal of Civil Engineering, 22(6), 1051-1062.

Teunis, P. F. M., & Medema, G. J., & Kruidenier, L., & Havelaar, A. H. (1997). Assessment of the risk of infection by *Cryptosporidium* or *Giardia* in drinking water form a surface water source. Water Research, 31(6), 1333-1346.

U.S. Presidential/Congressional Commission on Risk Assessment and Risk Management. (1997). Framework for Environmental Health Risk Management. Volume. 1. Washington, DC.

United States Environmental Protection Agency (2001). Risk Assessment Guidance for Superfund: Volume III – Part A, Process for Conducting Probabilistic Risk Assessment (EPA Document No. 540-R-02-002). www.epa.gov/superfund/RAGS3A/index.htm.

United States Environmental Protection Agency. (2005). Water Treatment Plant Model for MS Windows 3.1: Version 1.55. http://yosemite.epa.gov/water/owrccatalog.nsf/0/80acea46c3412a1185256b06007259ee?OpenDocument, accessed February 25, 2005.

Vasquez, J. A., & Maier, H. R., & Lence, B. J., & Tolson, B. A., & Foschi, R. O., (2000). Achieving water quality system reliability using genetic algorithms, Journal of Environmental Engineering. 126(10), 954-962.

van der Helm, A. W. C., & Rietveld, L. C. (2002). Modelling of drinking water treatment processes within the Stimela environment. Water Science and Technology: Water Supply, 2(1), 87-93.

Verdonck, F., (2003). Geo-Referenced Probabilistic Risk Assessment, PhD Thesis, Ghent University, Belgium.

Vose, D. (1996). Quantitative Risk Analysis: A Guide to Monte Carlo Simulation Modelling. New York: John Wiley & Sons, Inc.

WRc plc. (2002). WRc OTTER 2.1.3: Process Model Descriptions. Wiltshire, Great Britain.

Xu, C., & Goulter, I. C. (1998). Probabilistic model for water distribution reliability. Journal of Water Resources Planning and Management, 124(4), 218-228.

Yao, K.-M., & Habibian, M. T., & O'Melia, C. R. (1971) Water and waste water filtration: concepts and applications. Environmental Science and Technology, 5(11), 1105-1112.

ACRONYMS

ADWG	Australian Drinking Water Guidelines
AFOSM	Advanced First-Order Second Moment Method
CDF	Cumulative Distribution Function
CFA	Consequence Frequency Assessment
EPA	United States Environmental Protection Agency
E(x)	Mean of a data set
FOSM	First-Order Second Moment Method
FORM	First-Order Reliability Method
F(x)	Defines a cumulative distribution function of the variable “x”
f(x)	Defines a probability distribution function of the variable “x”
IWA	International Water Association
MCRA	Monte Carlo Risk Assessment
PDF	Probability Distribution Function
r^2	Coefficient of multiple determination
TAPWAT	Tool for the Analysis of the Production of drinking WaTer
Var(x)	Variance of a data set
WTP	Water Treatment Plant Model

APPENDIX A:
BRANTFORD WATER TREATMENT PLANT RAW DATA FOR 2004

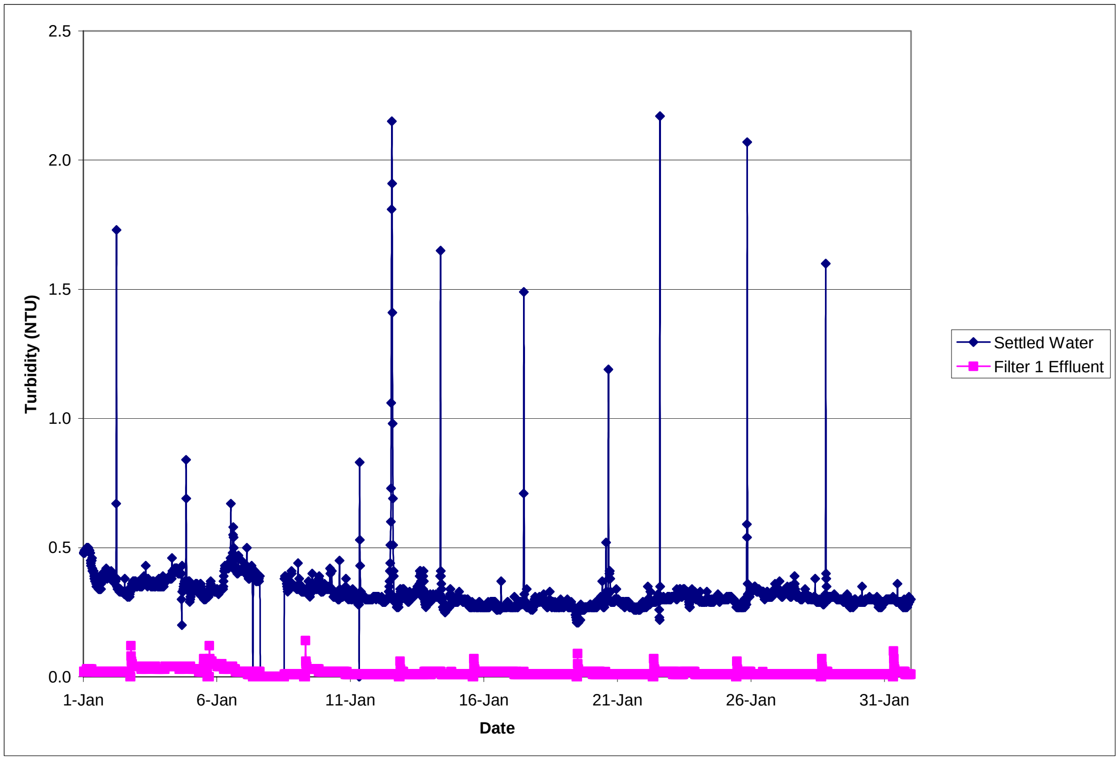

Figure A. 1: Fifteen minute influent and effluent turbidity values for Filter 1 for the month of January, 2004

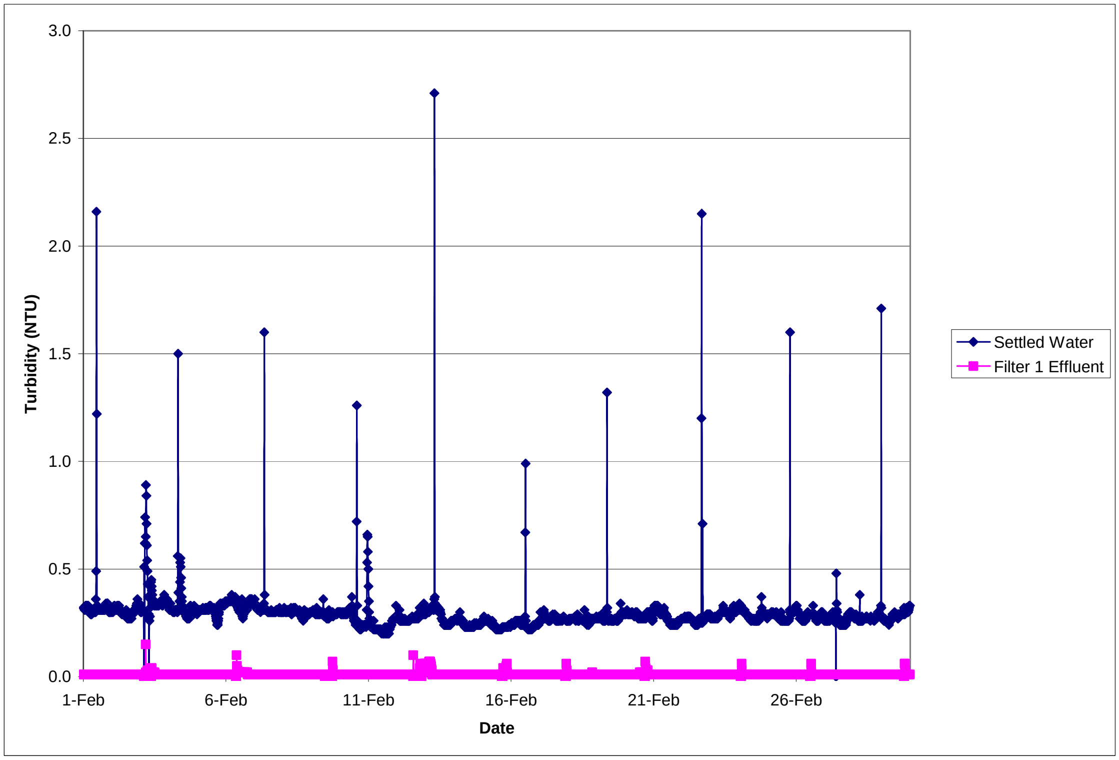

Figure A. 2: Fifteen minute influent and effluent turbidity values for Filter 1 for the month of February, 2004

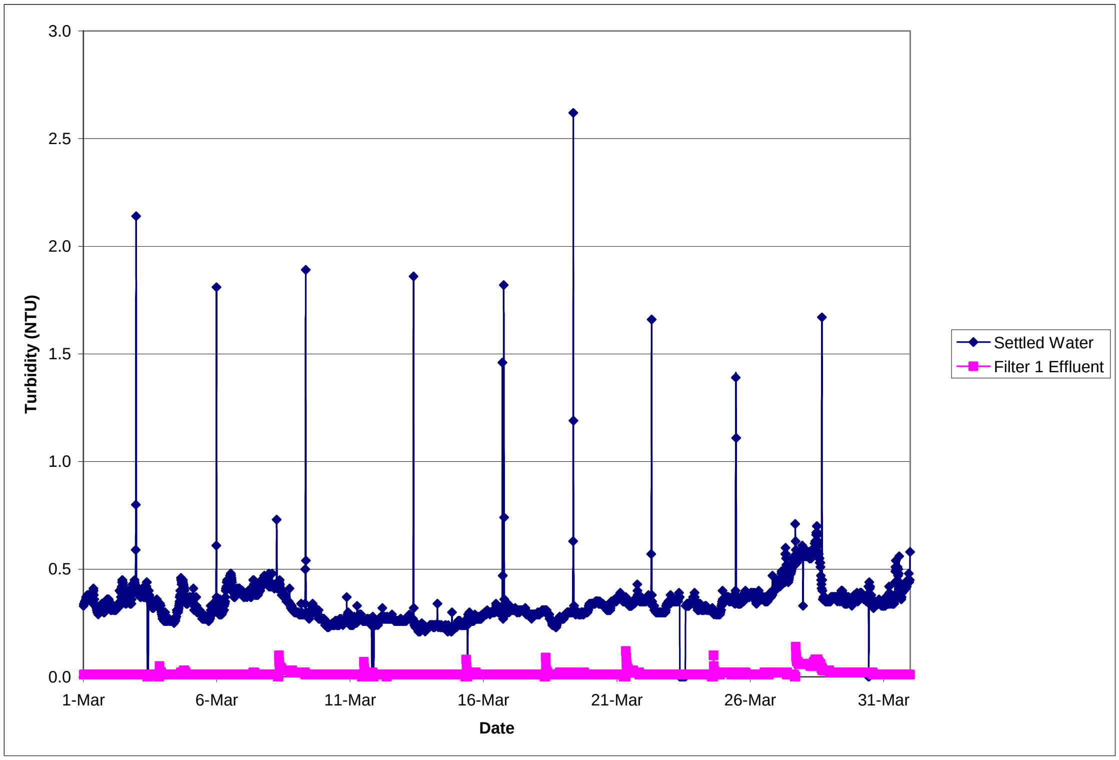

Figure A. 3: Fifteen minute influent and effluent turbidity values for Filter 1 for the month of March, 2004

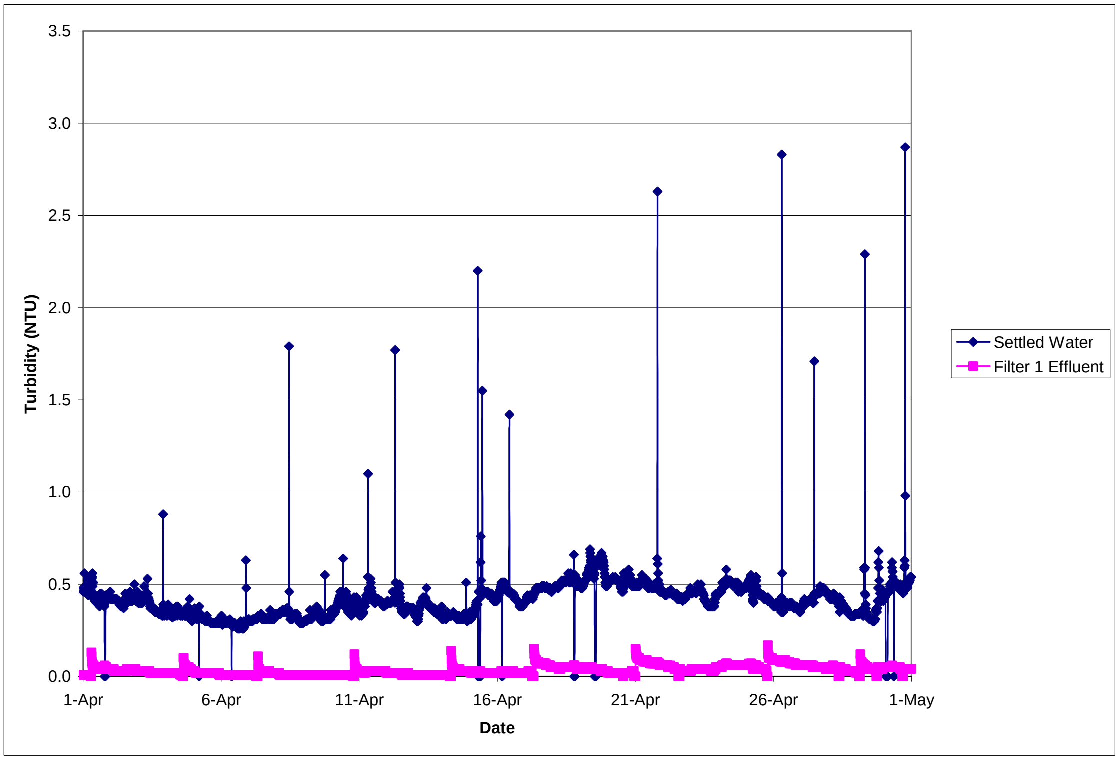

Figure A. 4: Fifteen minute influent and effluent turbidity values for Filter 1 for the month of April, 2004

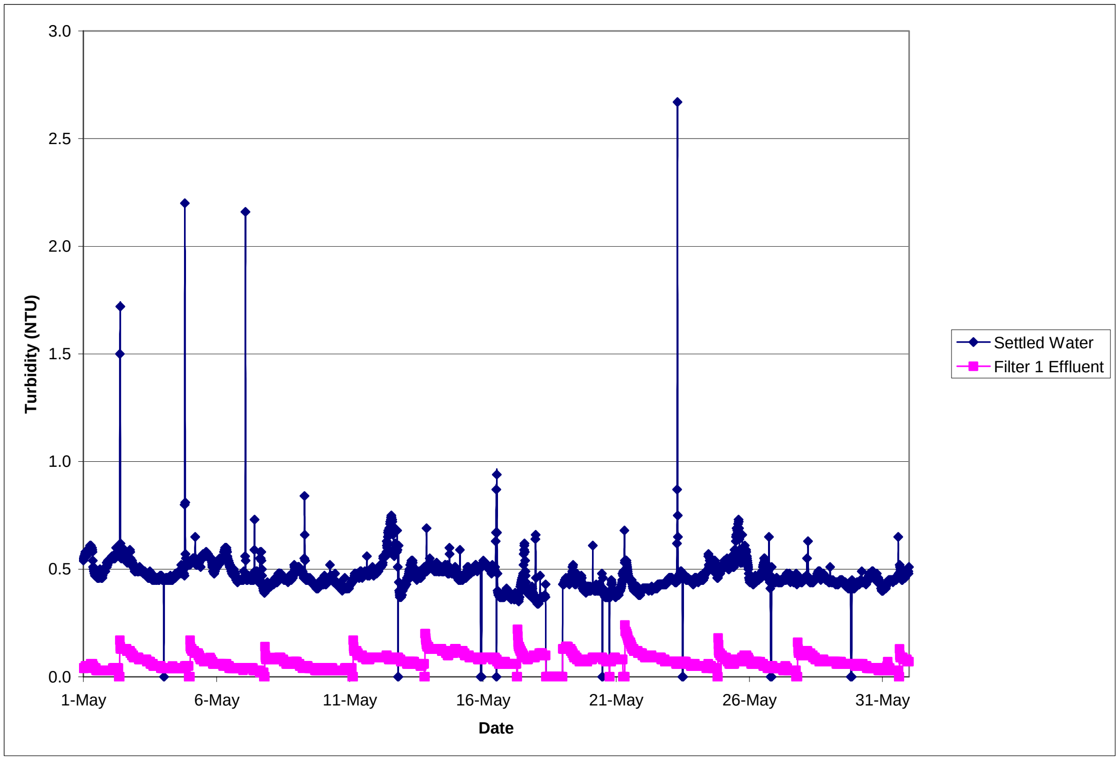

Figure A. 5: Fifteen minute influent and effluent turbidity values for Filter 1 for the month of May, 2004

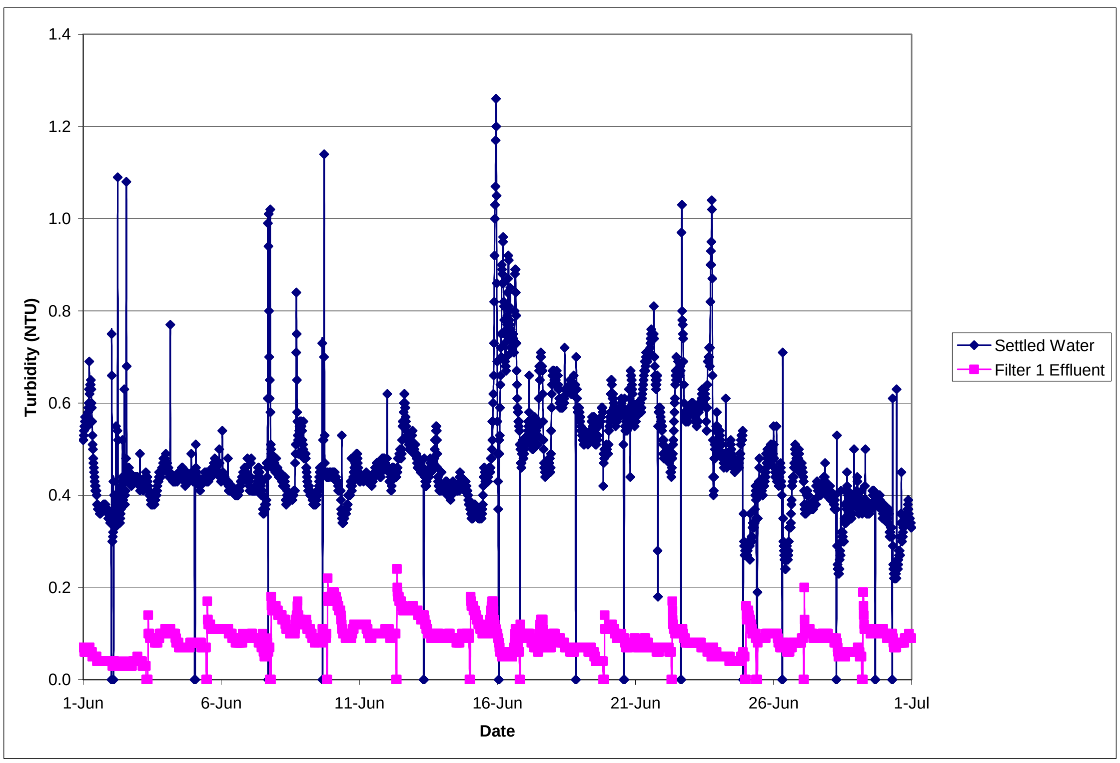

Figure A. 6: Fifteen minute influent and effluent turbidity values for Filter 1 for the month of June, 2004

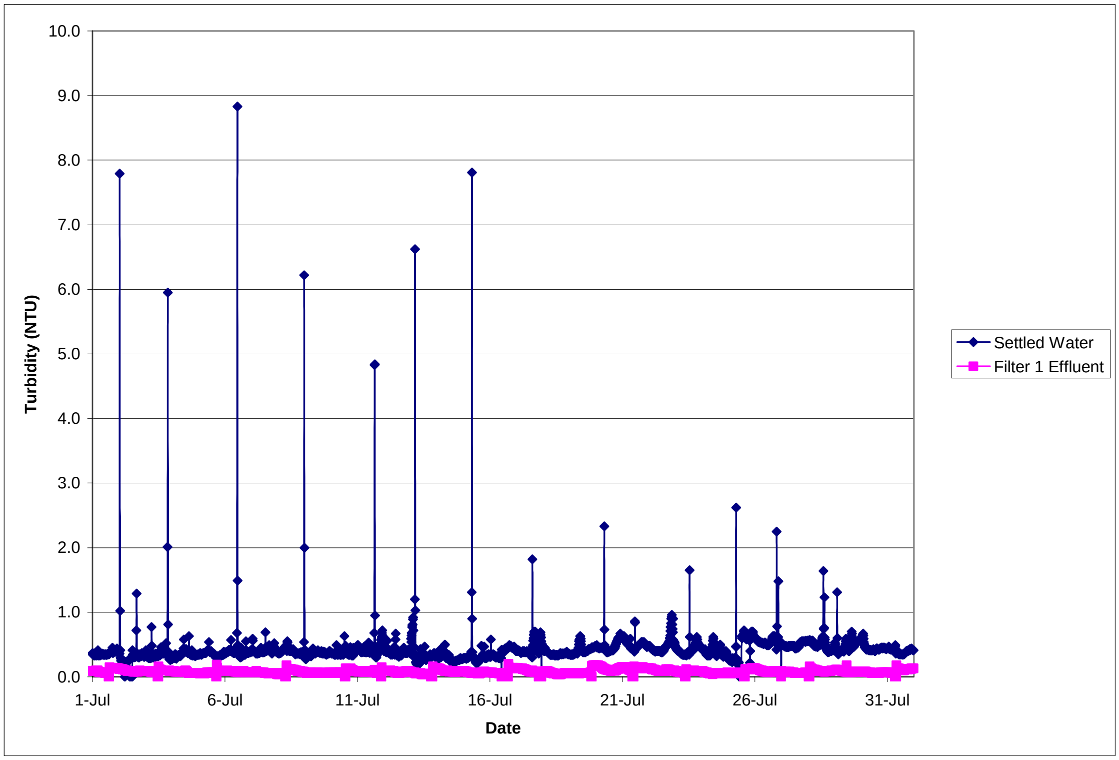

Figure A. 7: Fifteen minute influent and effluent turbidity values for Filter 1 for the month of July, 2004

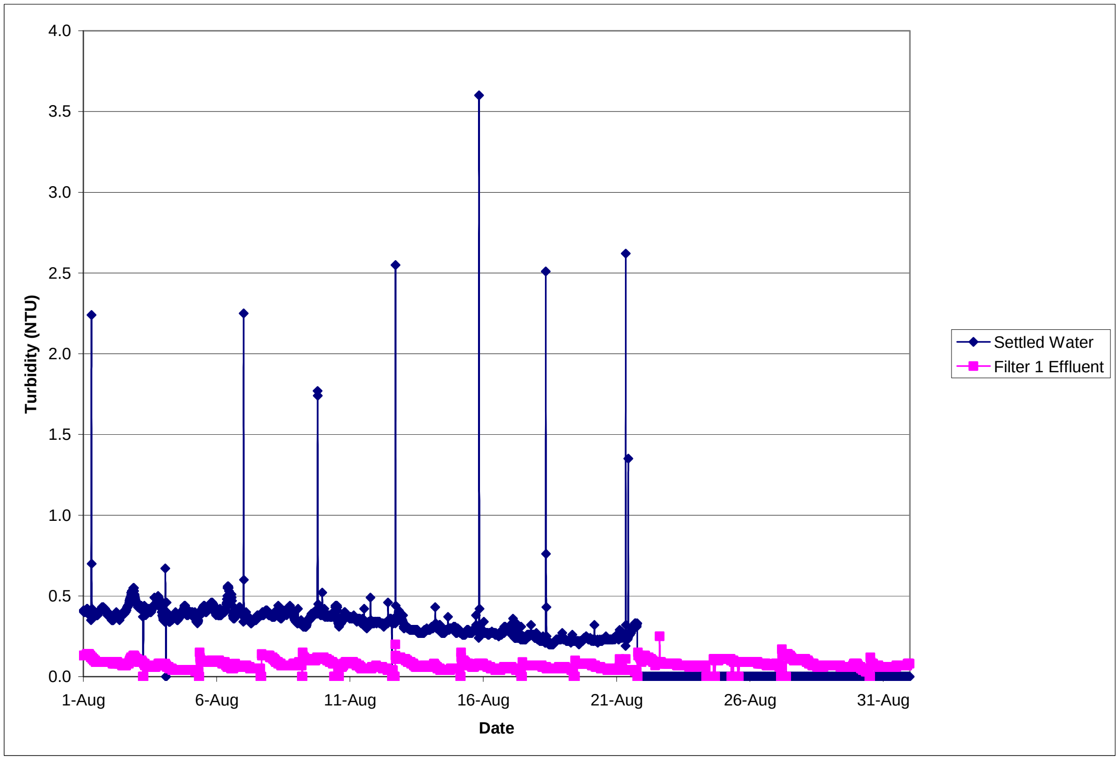

Figure A. 8: Fifteen minute influent and effluent turbidity values for Filter 1 for the month of August, 2004

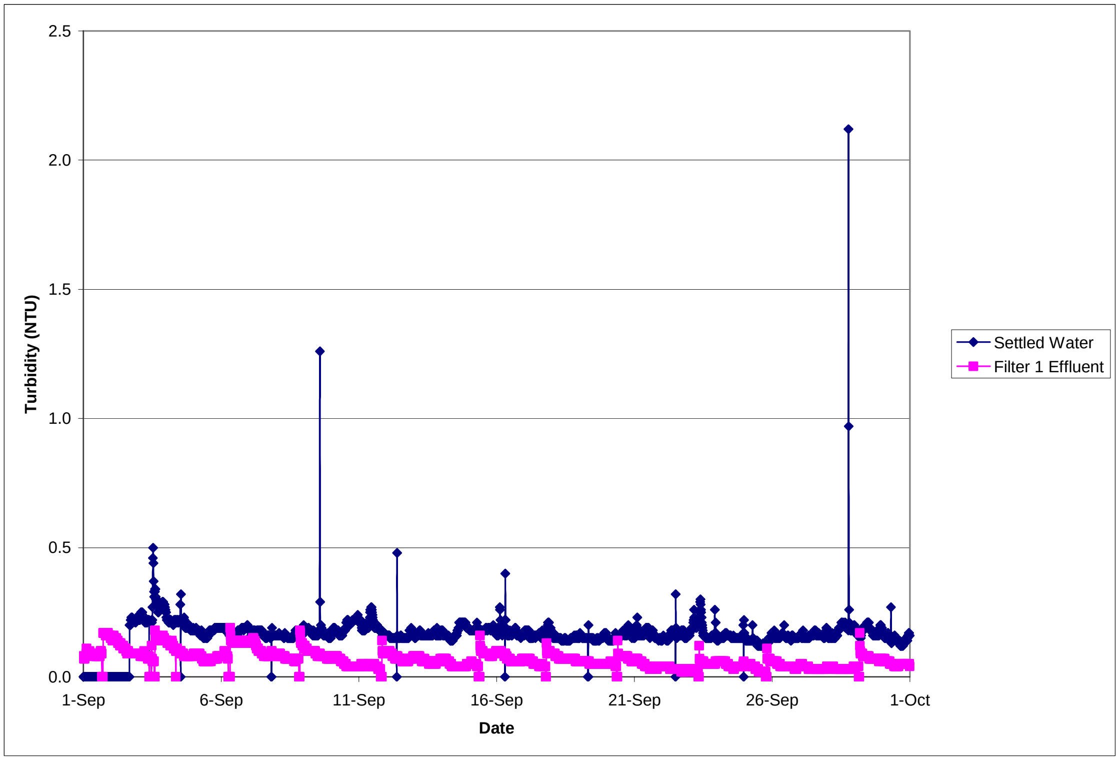

Figure A. 9: Fifteen minute influent and effluent turbidity values for Filter 1 for the month of September, 2004

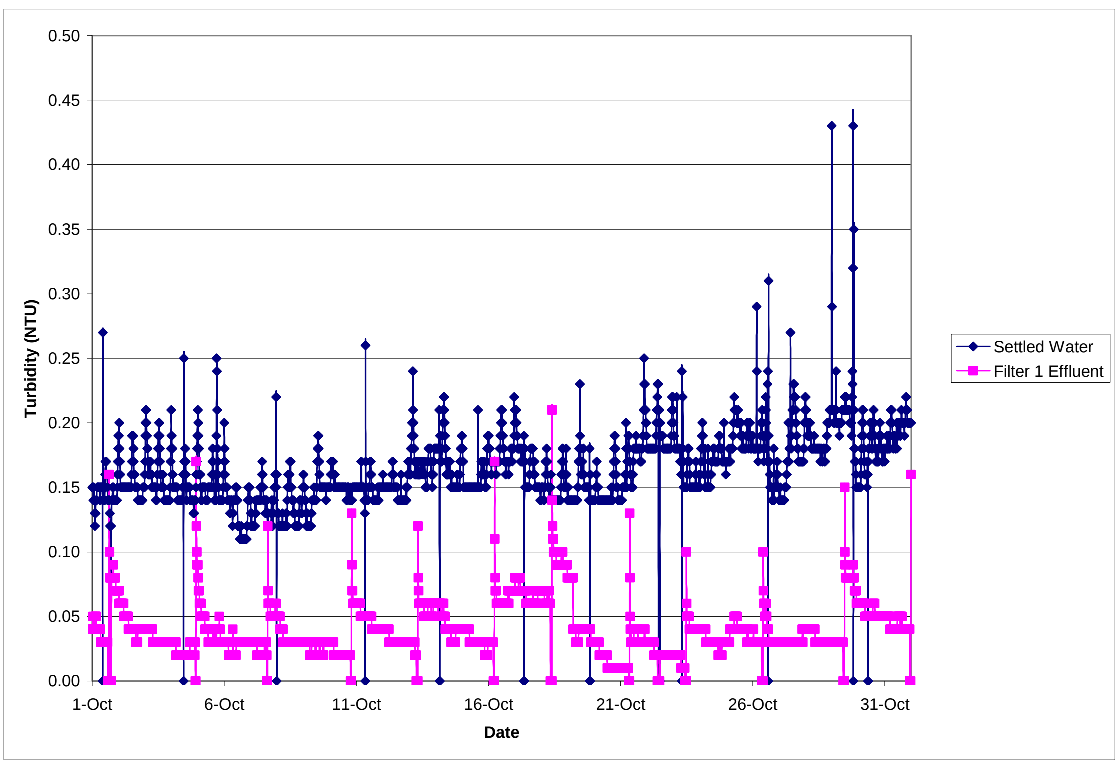

Figure A. 10: Fifteen minute influent and effluent turbidity values for Filter 1 for the month of October, 2004

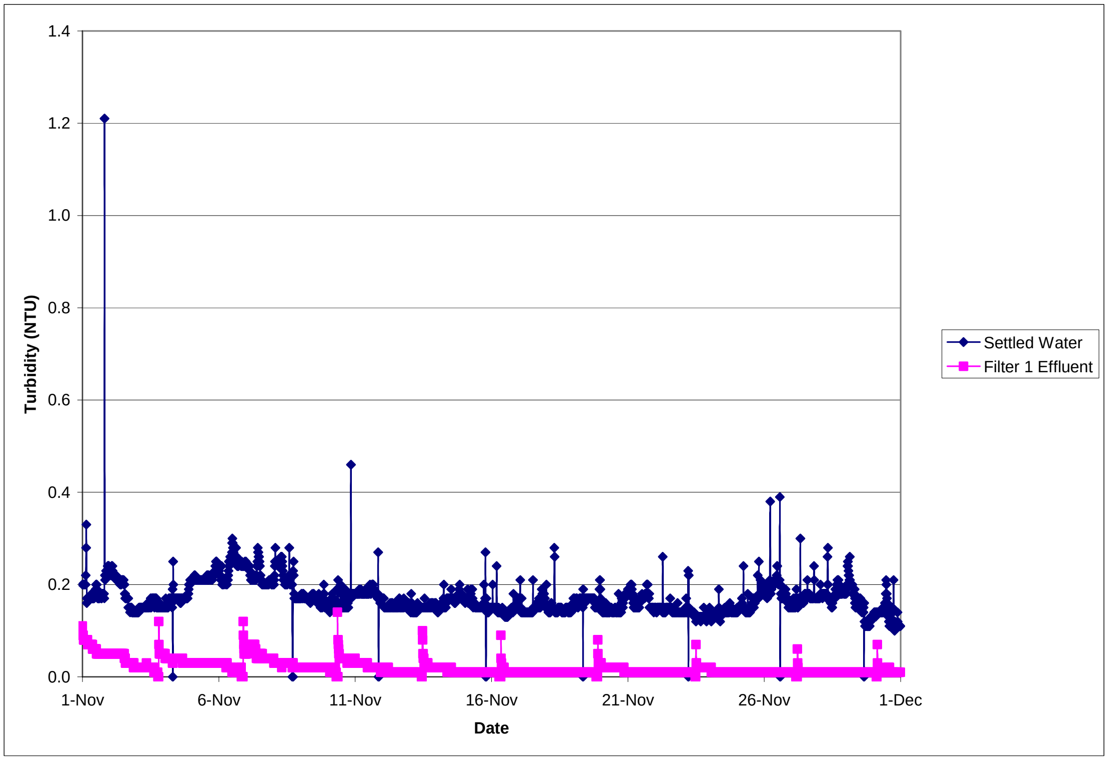

Figure A. 11: Fifteen minute influent and effluent turbidity values for Filter 1 for the month of November, 2004

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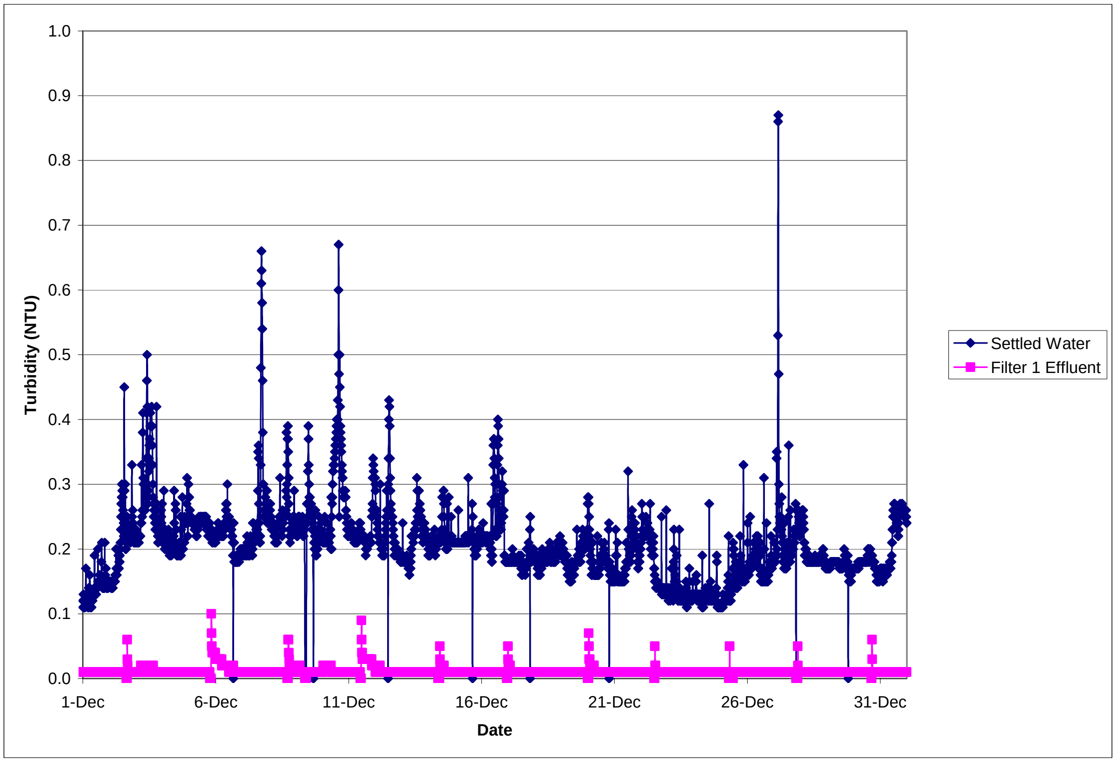

Figure A. 12: Fifteen minute influent and effluent turbidity values for Filter 1 for the month of December, 2004

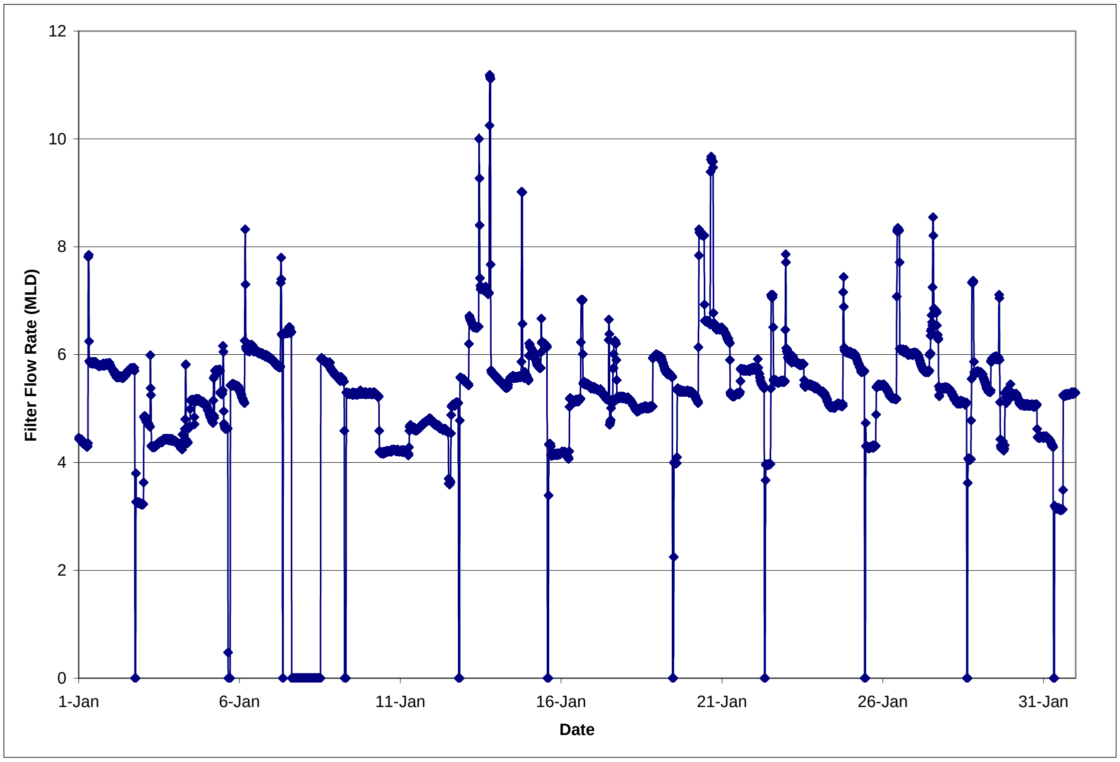

Figure A. 13: Fifteen minute filter flow rate values for Filter 1 for the month of January, 2004

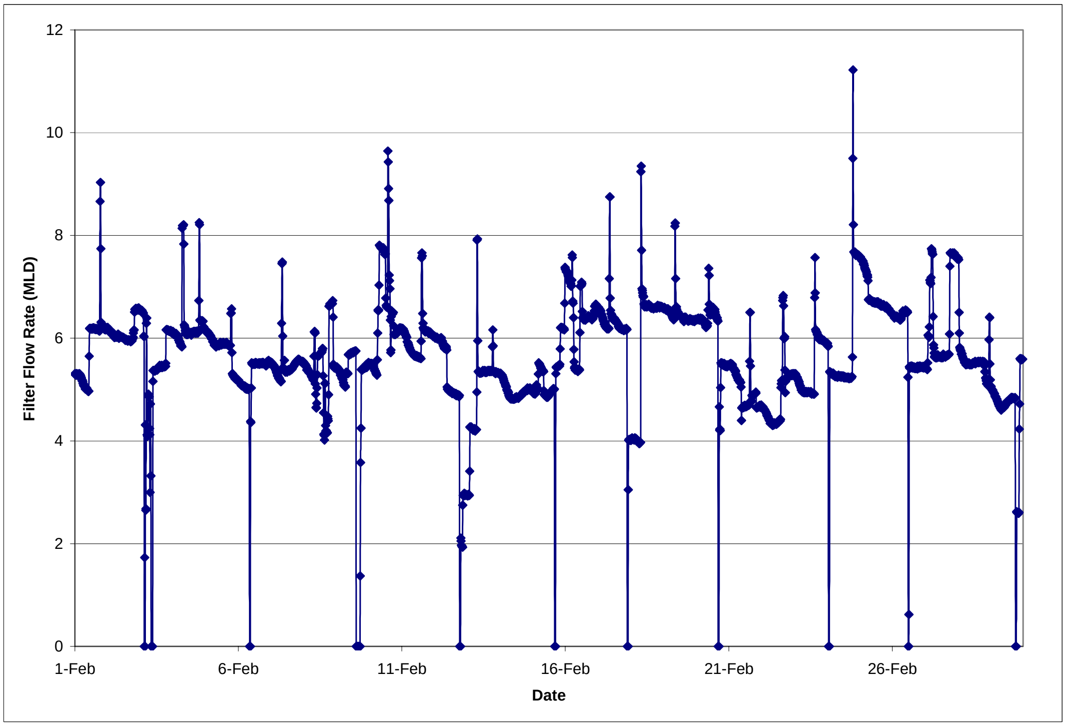

Figure A. 14: Fifteen minute filter flow rate values for Filter 1 for the month of February, 2004

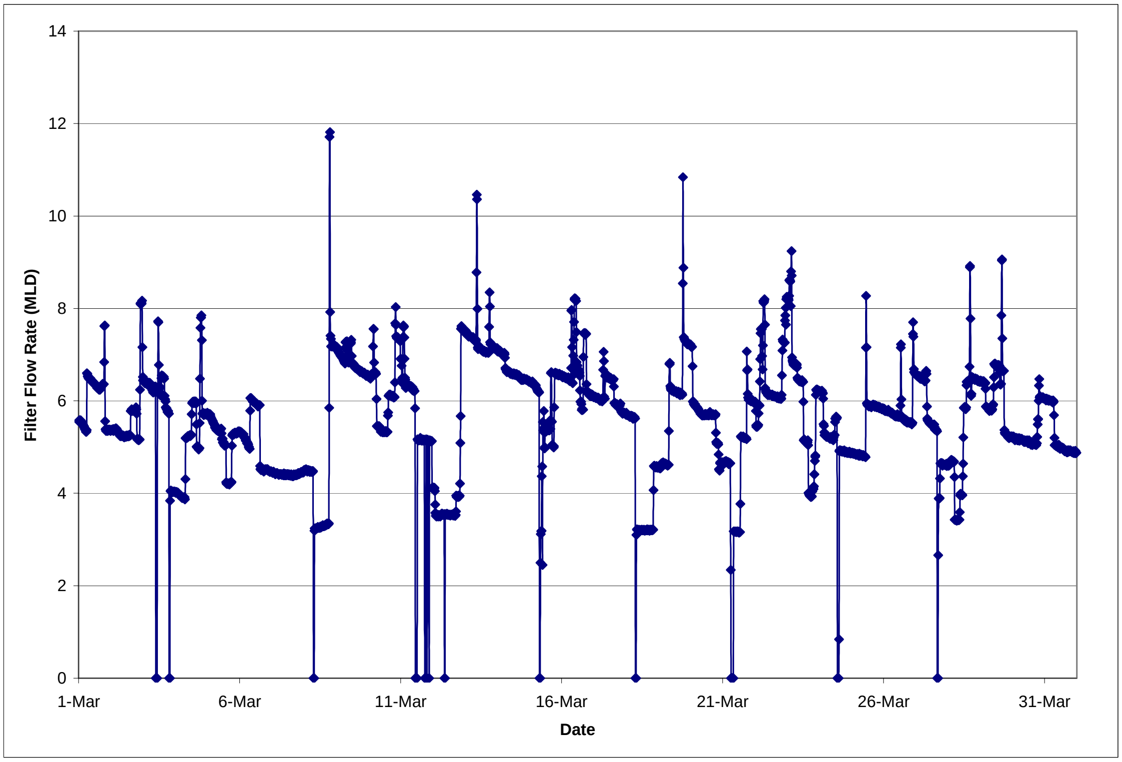

Figure A. 15: Fifteen minute filter flow rate values for Filter 1 for the month of March, 2004

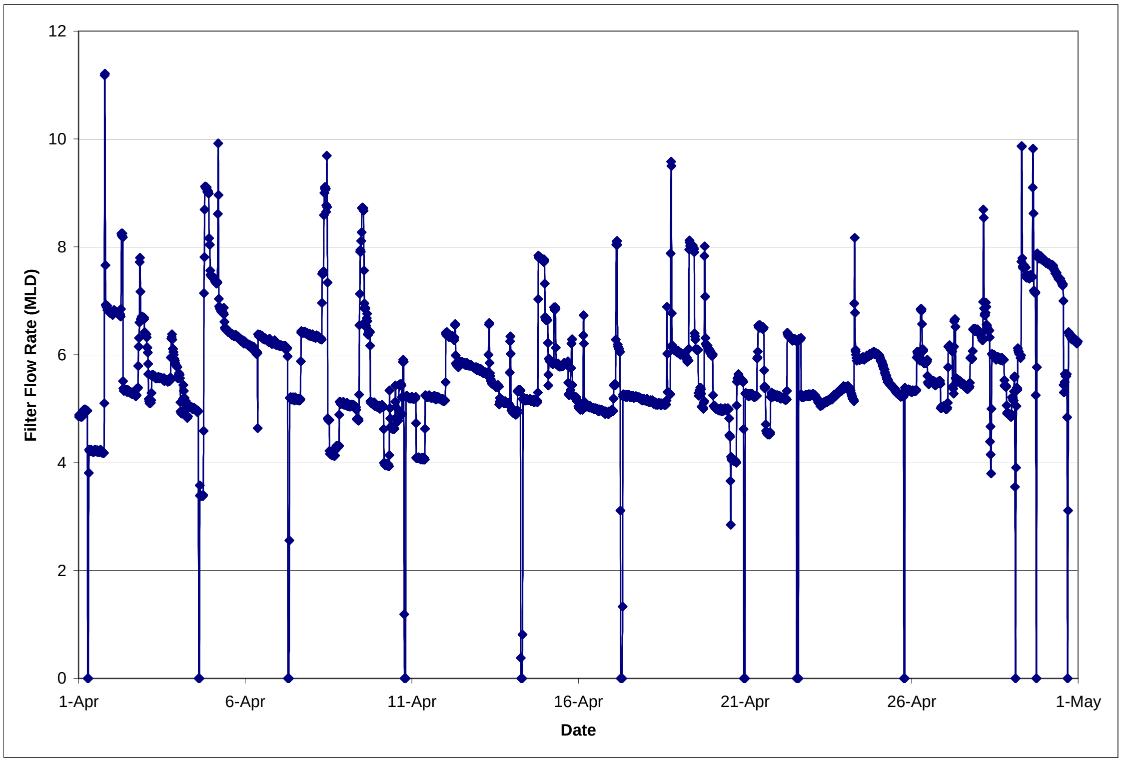

Figure A. 16: Fifteen minute filter flow rate values for Filter 1 for the month of April, 2004

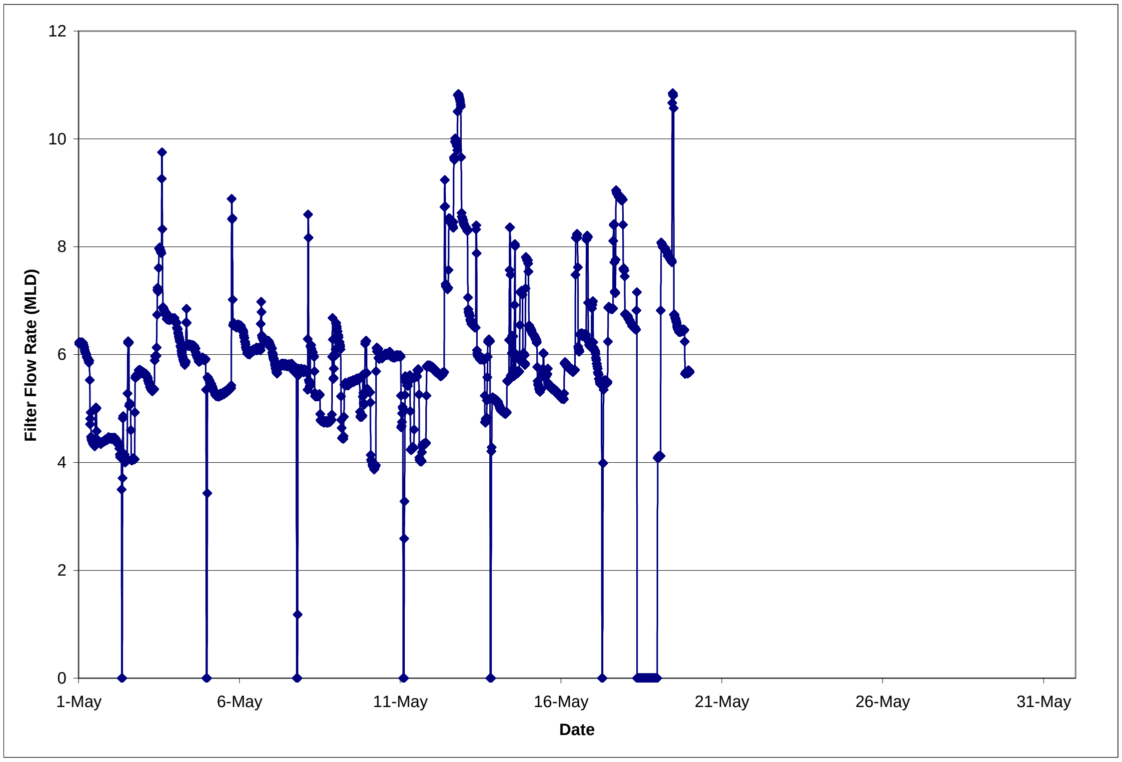

Figure A. 17: Fifteen minute filter flow rate values for Filter 1 for the month of May, 2004

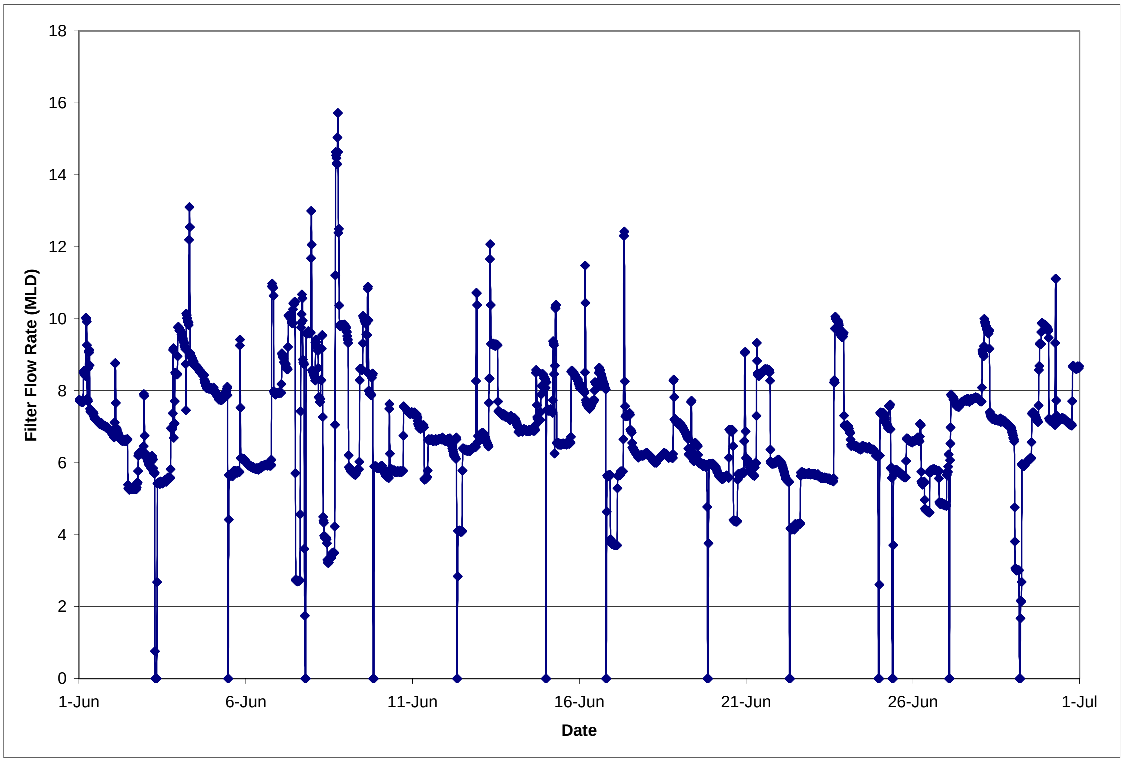

Figure A. 18: Fifteen minute filter flow rate values for Filter 1 for the month of June, 2004

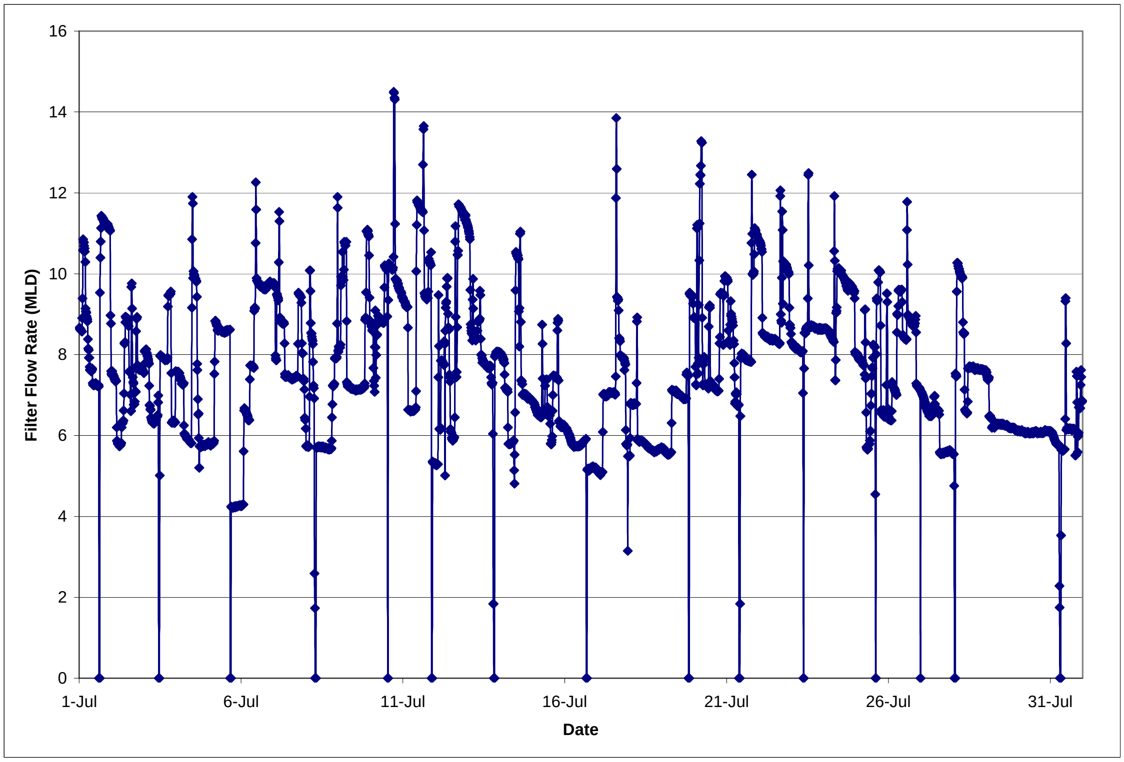

Figure A. 19: Fifteen minute filter flow rate values for Filter 1 for the month of July, 2004

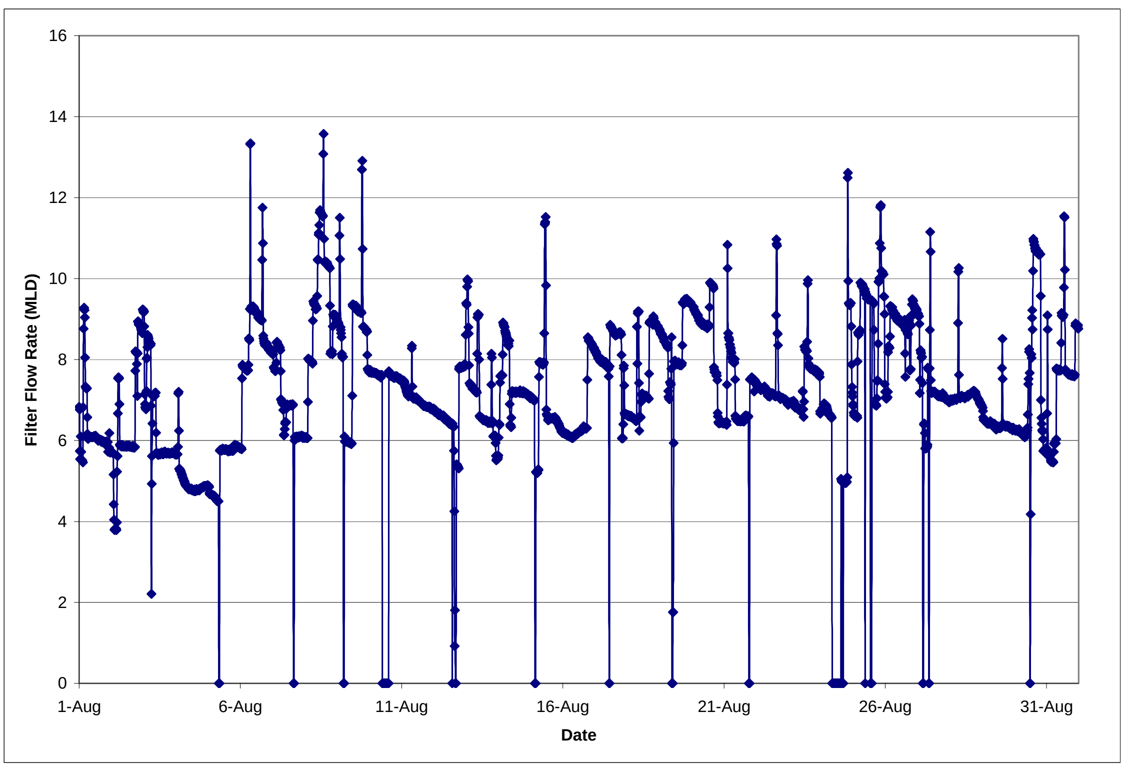

Figure A. 20: Fifteen minute filter flow rate values for Filter 1 for the month of August, 2004

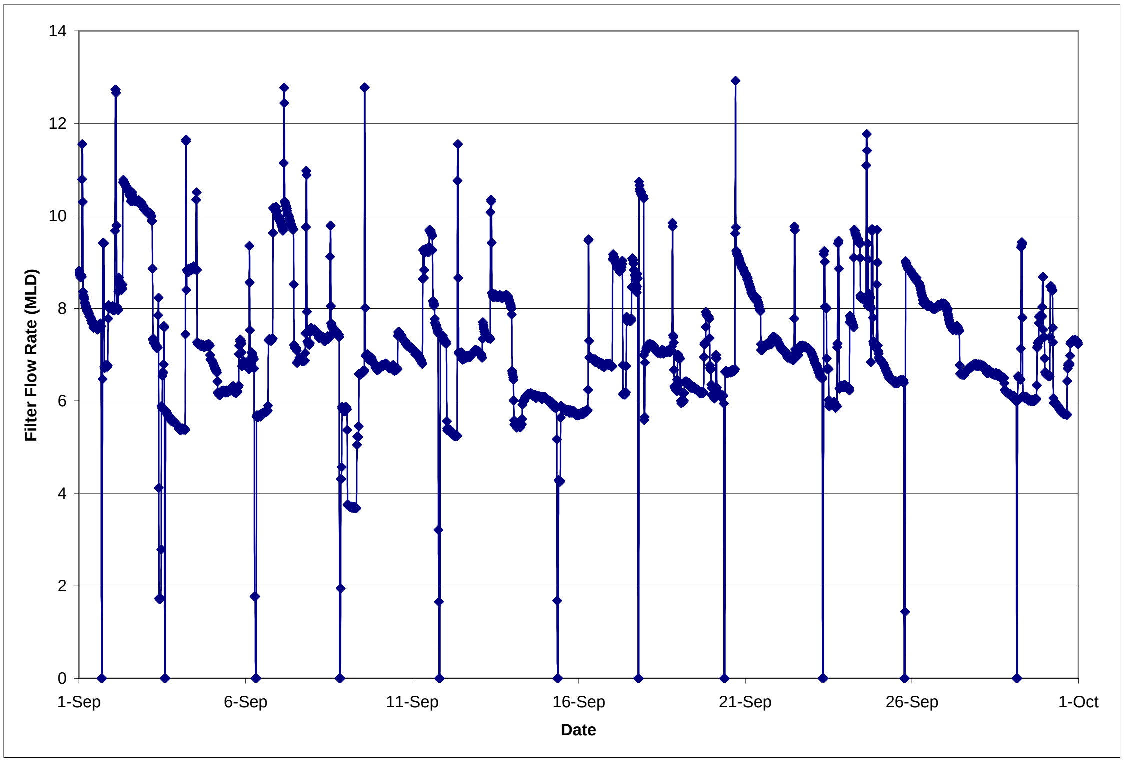

Figure A. 21: Fifteen minute filter flow rate values for Filter 1 for the month of September, 2004

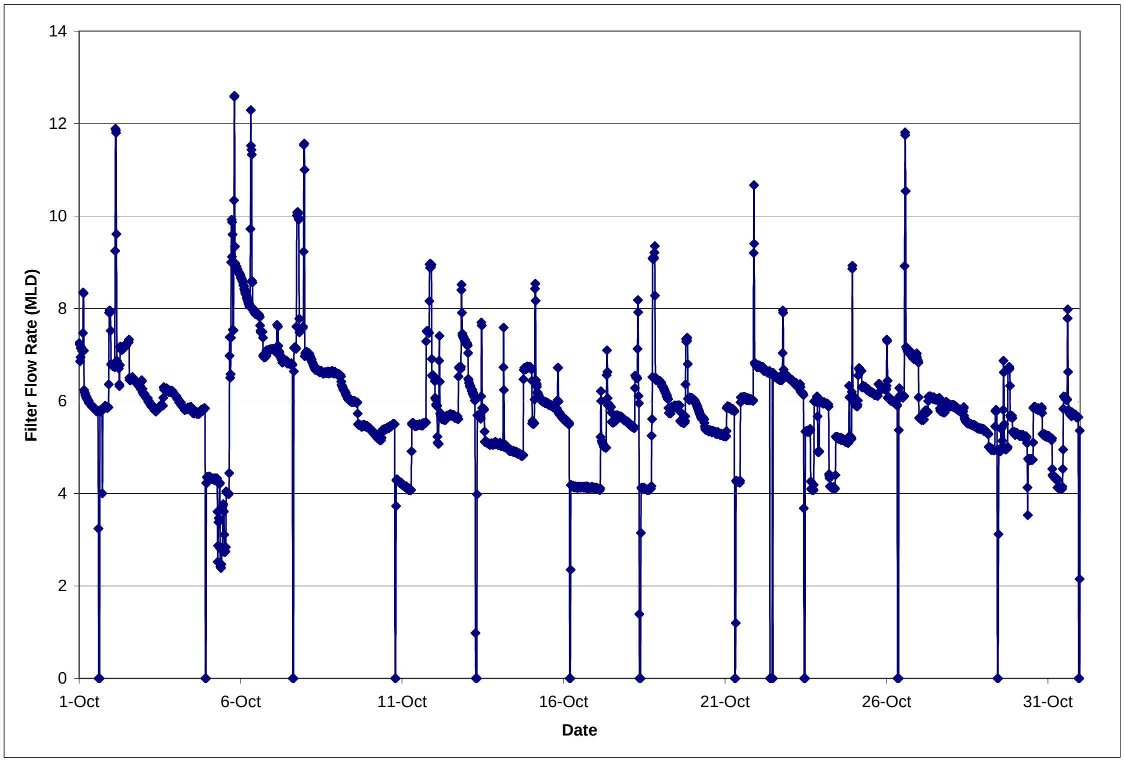

Figure A. 22: Fifteen minute filter flow rate values for Filter 1 for the month of October, 2004

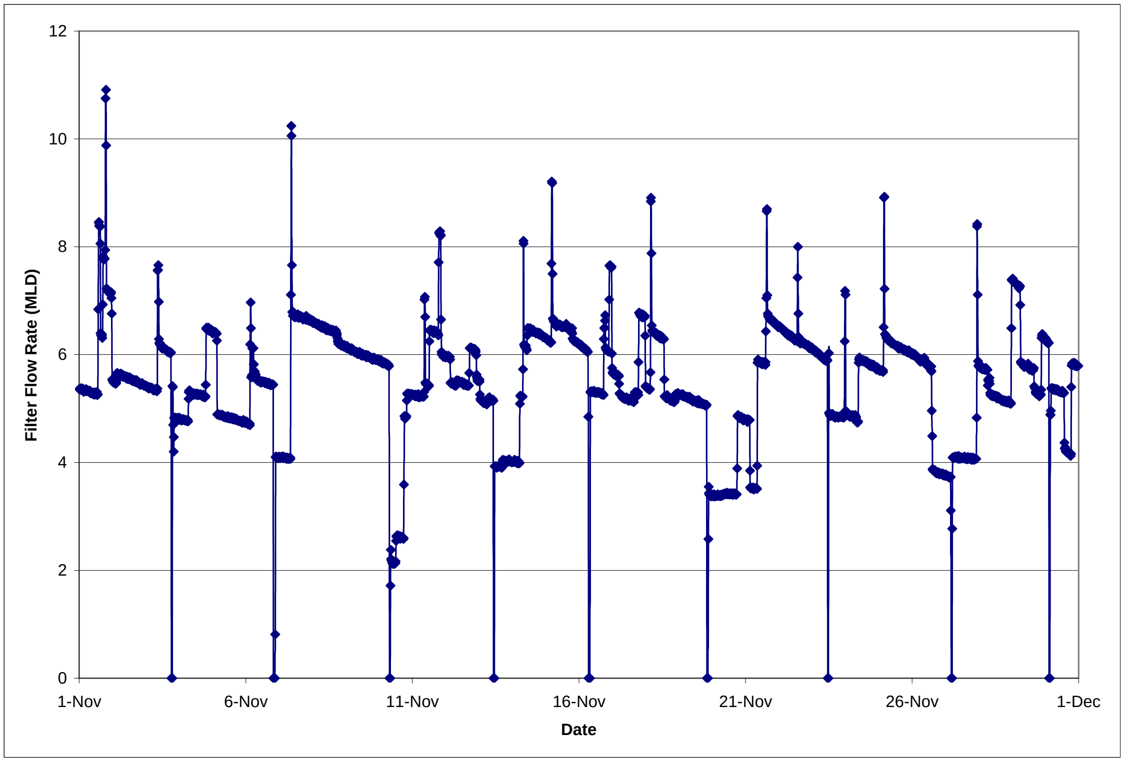

Figure A. 23: Fifteen minute filter flow rate values for Filter 1 for the month of November, 2004

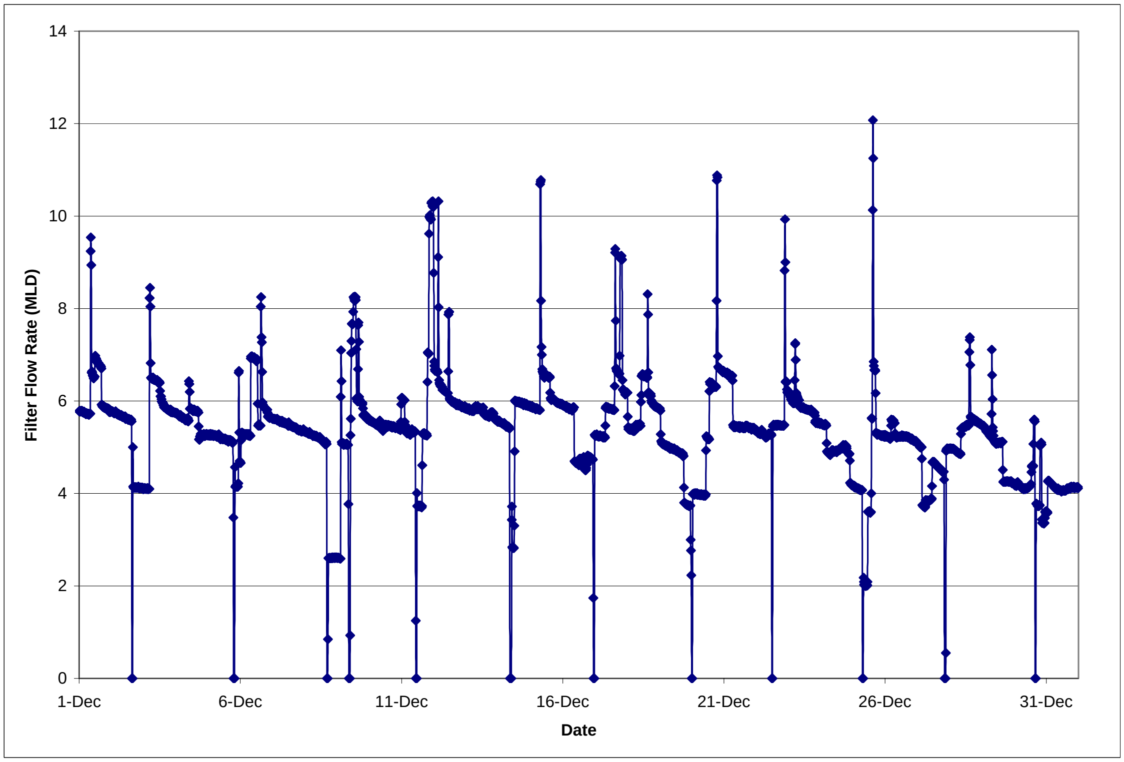

Figure A. 24: Fifteen minute filter flow rate values for Filter 1 for the month of December, 2004

APPENDIX B:
FULL CUMULATIVE DISTRIBUTION FUNCTIONS FOR ALL SIMULATOINS AND SIMULATION COMPARISONS

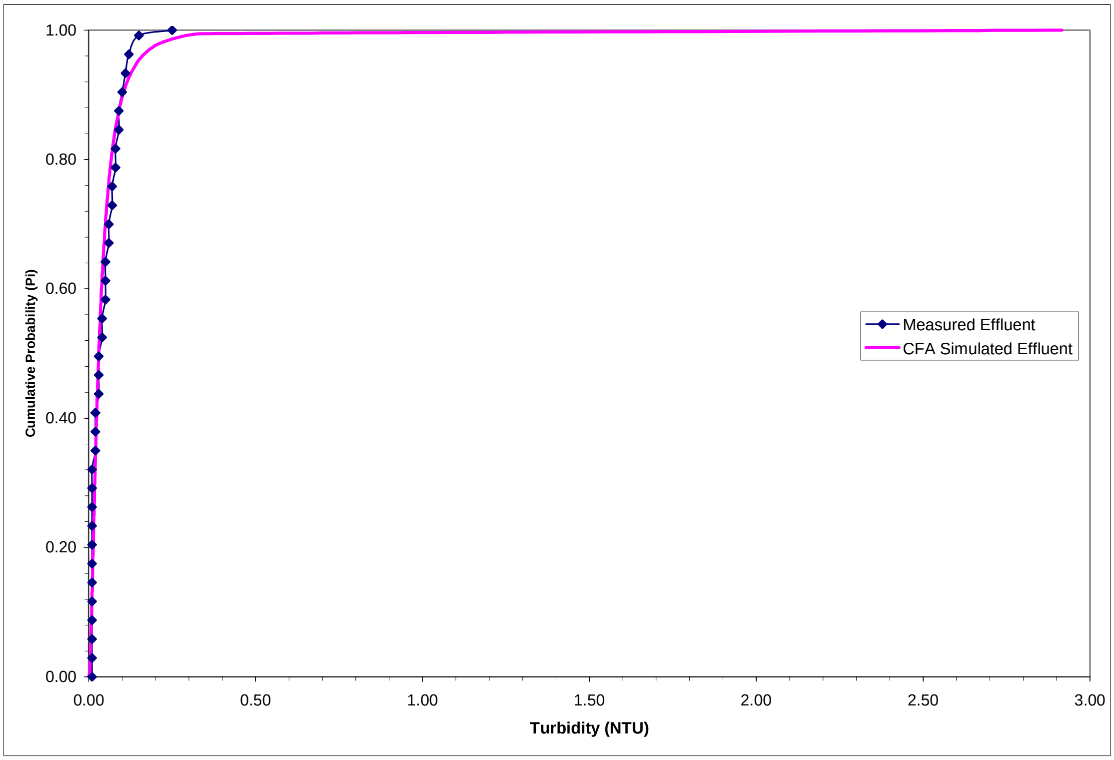

Figure B. 1: Comparison between measured turbidity effluent and CFA simulated effluent: Associated with Figure 4.8

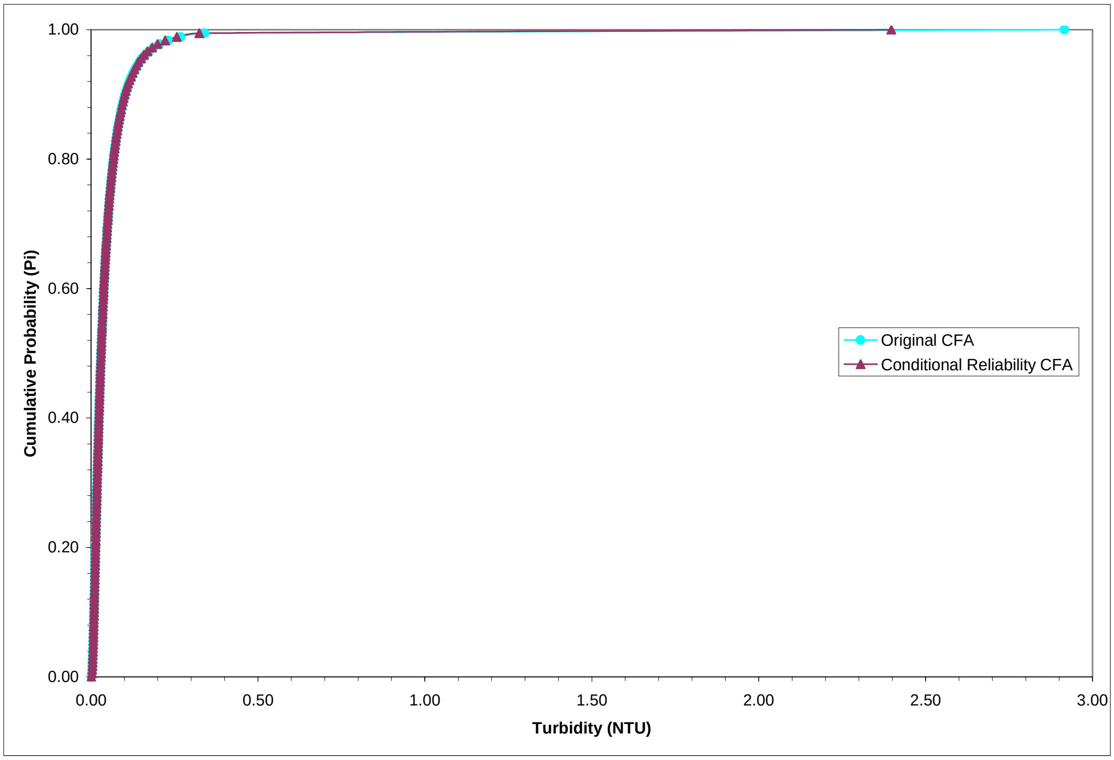

Figure B. 2: Comparison between CFA and CFA modified for conditional reliability: Associated with Figure 4.12

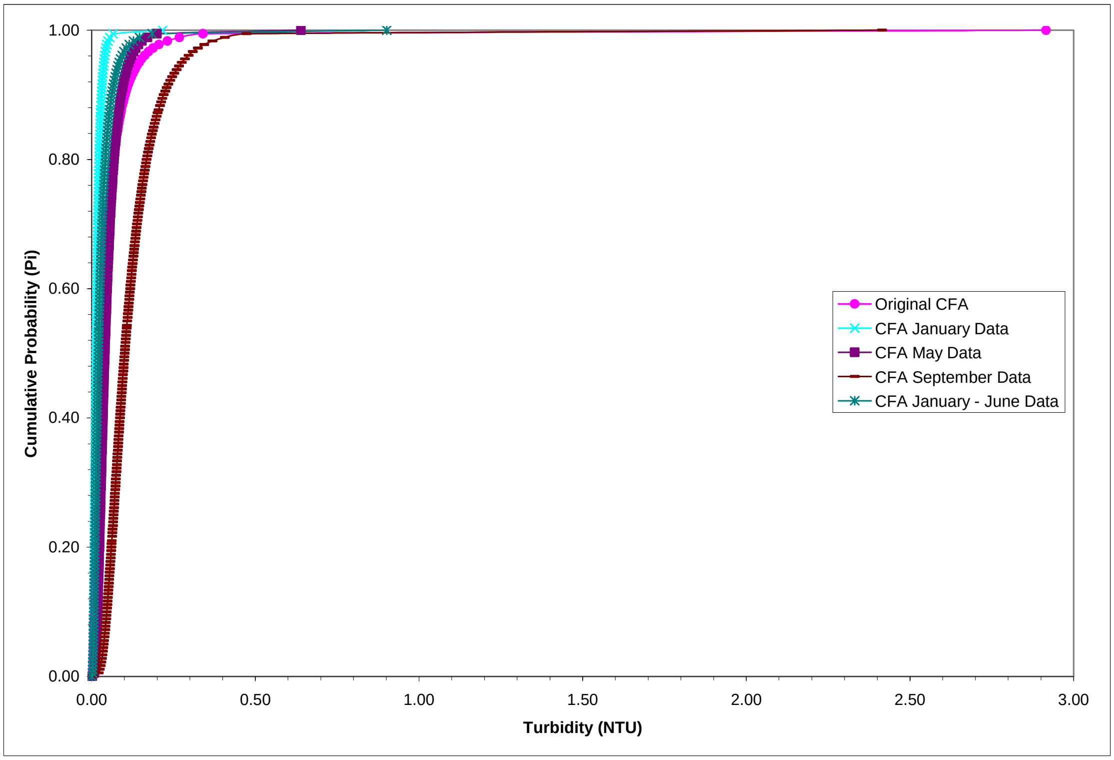

Figure B. 3: Comparison the original CFA to CFA with sub-sets of data using cumulative distribution functions: Associated with Figure 4.13

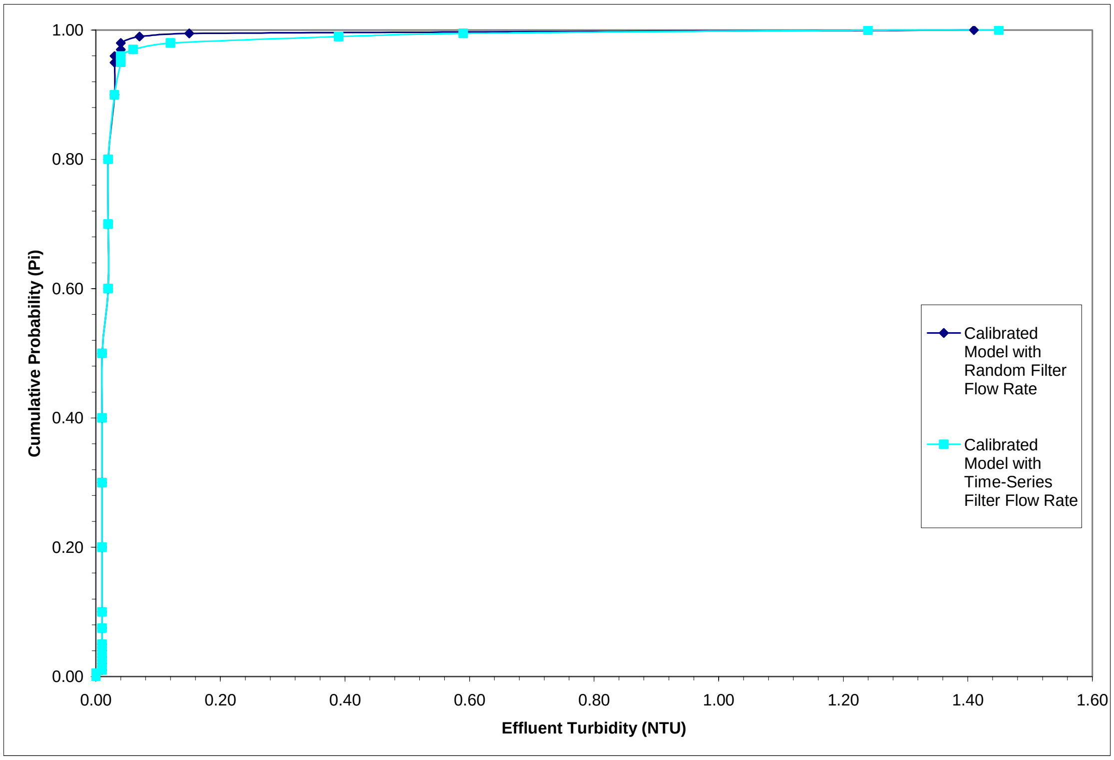

Figure B. 4: Comparison of the CDF output from the probabilistic risk assessment for the calibrated OTTER models with and without using a time series: Associated with Figure 5.14

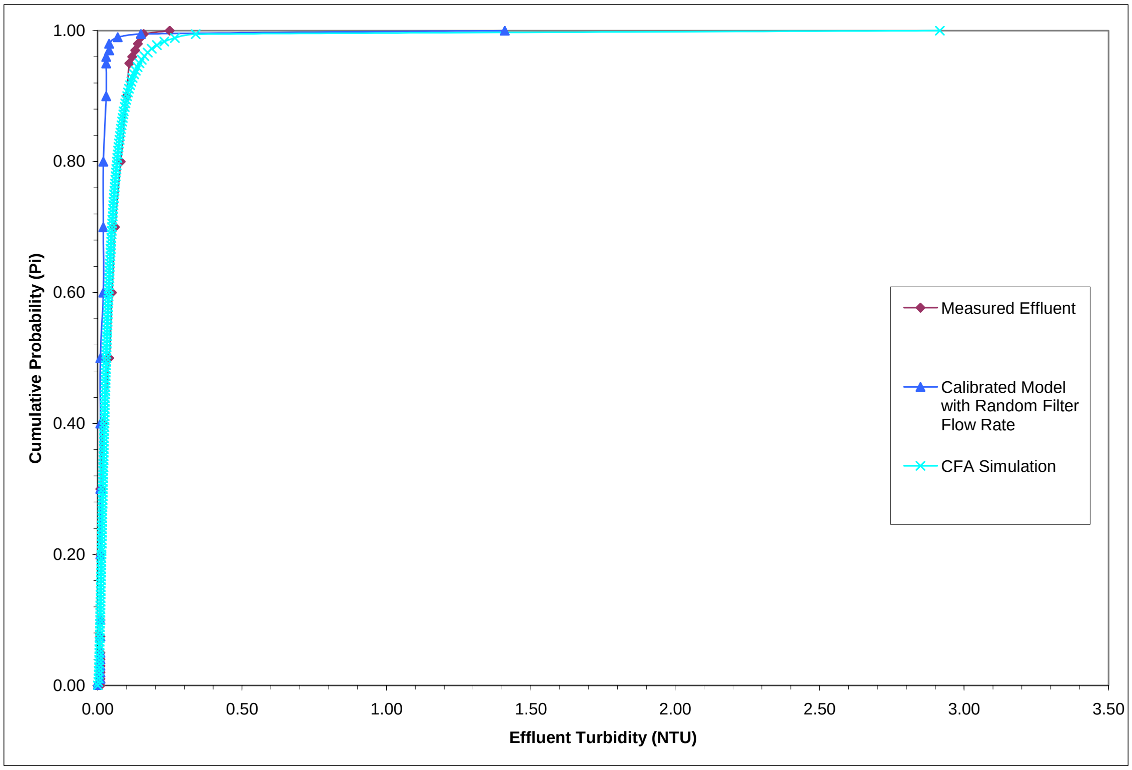

Figure B. 5: CDF of the output from the different risk analysis methodologies and the measured effluent: Associated with Figure 6.4

APPENDIX C: PRELIMINARY ANALYSIS WITH THE OTTER FILTRATION MODEL

C.1 Preliminary Experiments with the OTTER Model

The OTTER filter model developed to undertake the preliminary experiments used static that was consistent with the basic characteristics of the Brantford WTP, but without any of the calibration that would be necessary for a full system analysis. Other parameters such as media voidage and sphercity were kept as their default values from the OTTER software model itself. The static data as used in the analysis can be seen in Figure C. 1.

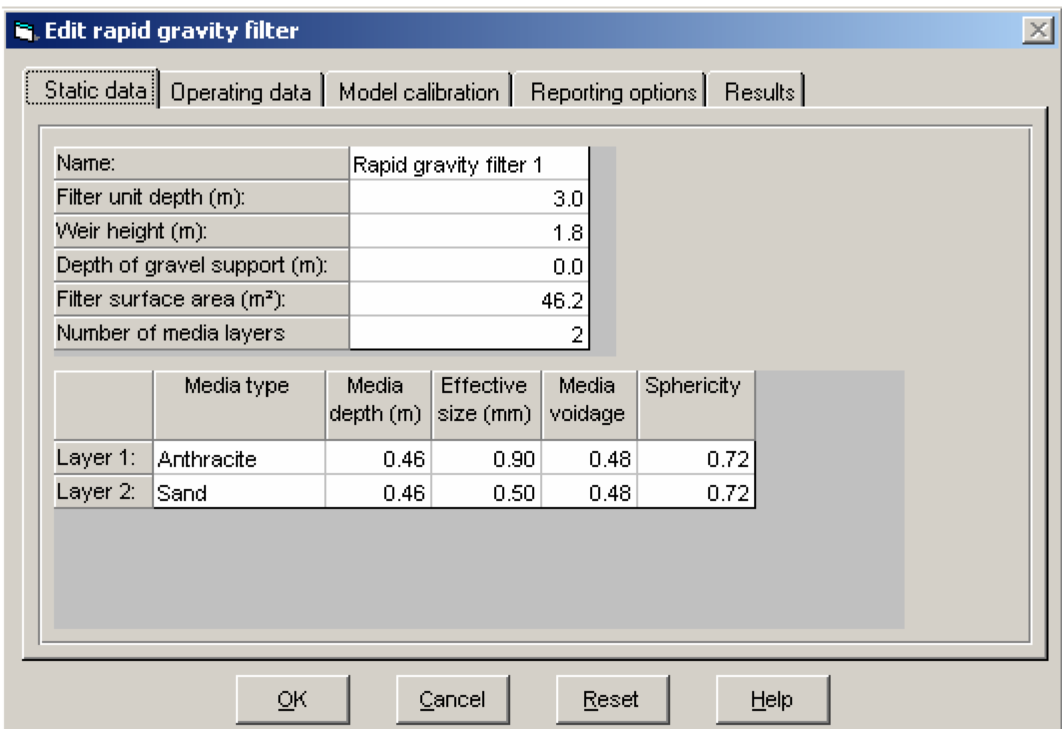

Figure C. 1: OTTER static data for preliminary analysis

Operating data was also inputed and this data was kept close to model defaults. One change was made with respect to the backwash triggers. An automatic backwash trigger of 2.20 m headloss was used, from discussion with the Brantford WTP staff. Furthermore, 1.0 NTU backwash trigger was also chosen in this preliminary analysis. The full set of operating data that was chosen can be seen in Figure C. 2.

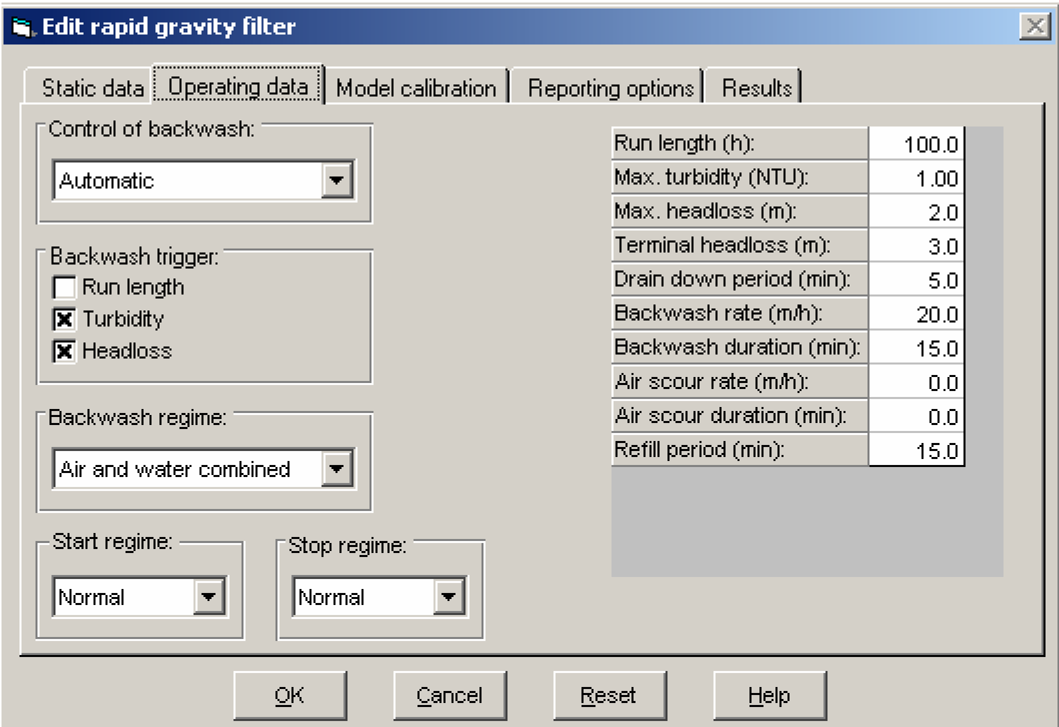

Figure C. 2: OTTER operating data for preliminary analysis

Model calibration data was set to defaults; however, as Section 3.3.4 describes, the OTTER model uses two different methods to model the filtration process, finite difference and logistic. The model calibration data can be seen in Figure C. 3, but the model type was changed from finite difference to logistic to determine if there was an observable difference between the two.

One calibration value that was not changed for either the preliminary analysis or for any future analysis is that of the number of CSTR stages. This value was kept to the model default of one (1) for all simulations. WRC plc (2002) states that calibration value, number of CSTR stages, is used for parameters that are not otherwise affected by the performance of the filter. The concern during this analysis is with turbidity removal, which is directly affected by the performance of the filter as can be seen in Section 3.3.4, thus according WRC plc (2002) the number of CSTR stages was did not need to be changed. This assumption was checked using two identical simulations with CSTR numbers of one (1) and ten (10). The outputs from both simulations were identical, thus the comments in WRc plc (2002) were verified and the number of CSTR stages was not modified for any future simulations.

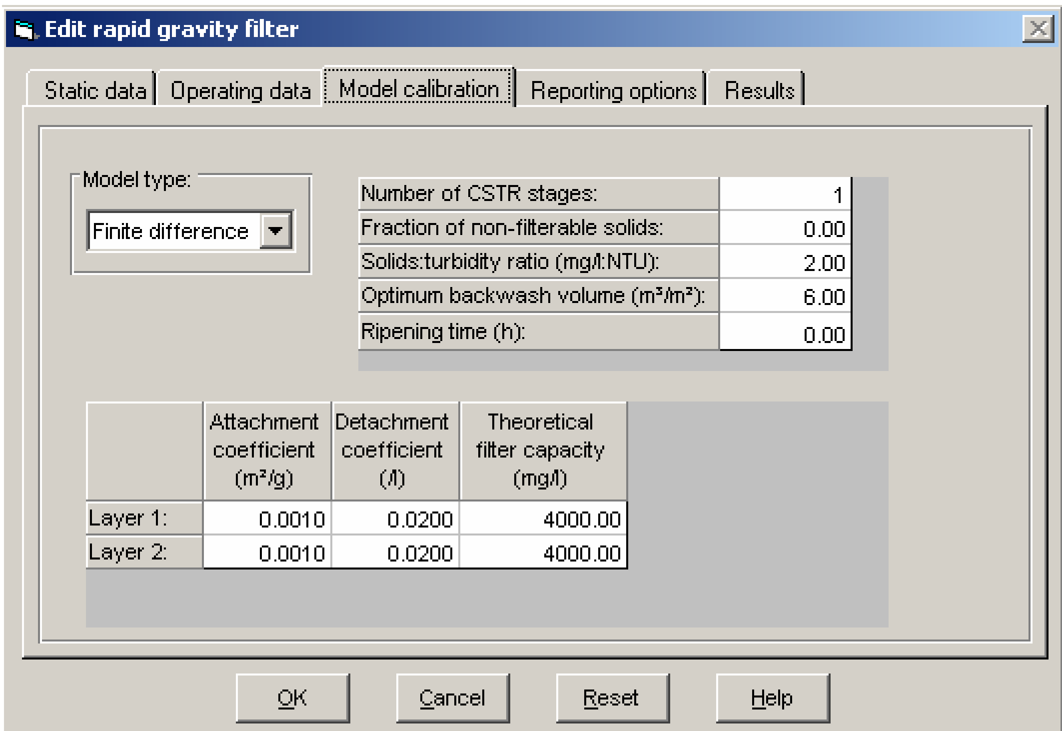

Figure C. 3: OTTER model calibration data for preliminary analysis

C.2 Comparison Between the Logistic Model, the Finite Difference Model, and Measured Data using an Uncalibrated OTTER Model

C.2.1 Input Data Record

To provide a comparison to actual data, the incoming water turbidity and water demand was taken directly from the data record between Jan 15 at 15:00 to Jan 19 at 10:00. This time was arbitrarily chosen, but the length of the data record was limited to 365 data points because in the OTTER model, flow control valves are necessary to change the flow and they are limited to a maximum of 365 data points. Other water quality parameters were kept to the default values presented by OTTER. The input water turbidity and demand can be seen in Appendix A or in Figure C. 4 and Figure C. 5, while values of the input water quality parameters that were not directly changed are shown in Table C.1. The water quality parameters shown in Table C.1 were kept constant throughout the simulation.

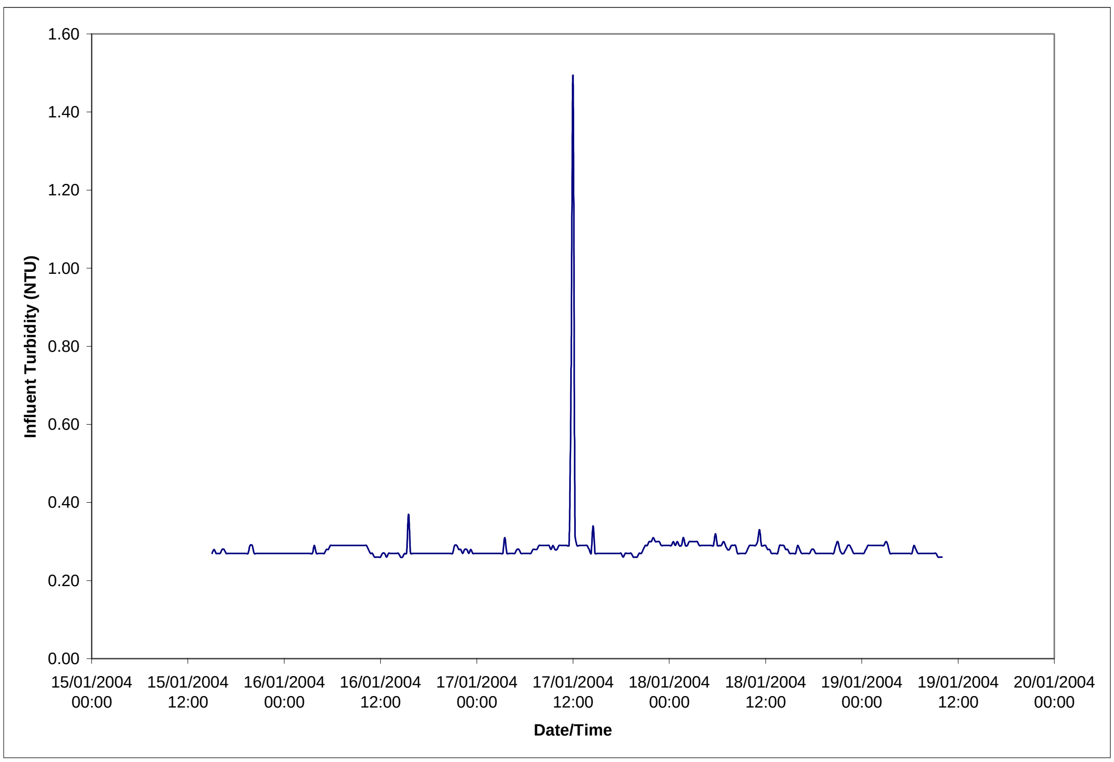

Figure C. 4: Influent turbidity to filter 1 from January 15 at 15:00 to January 19 at 10:00, 2004

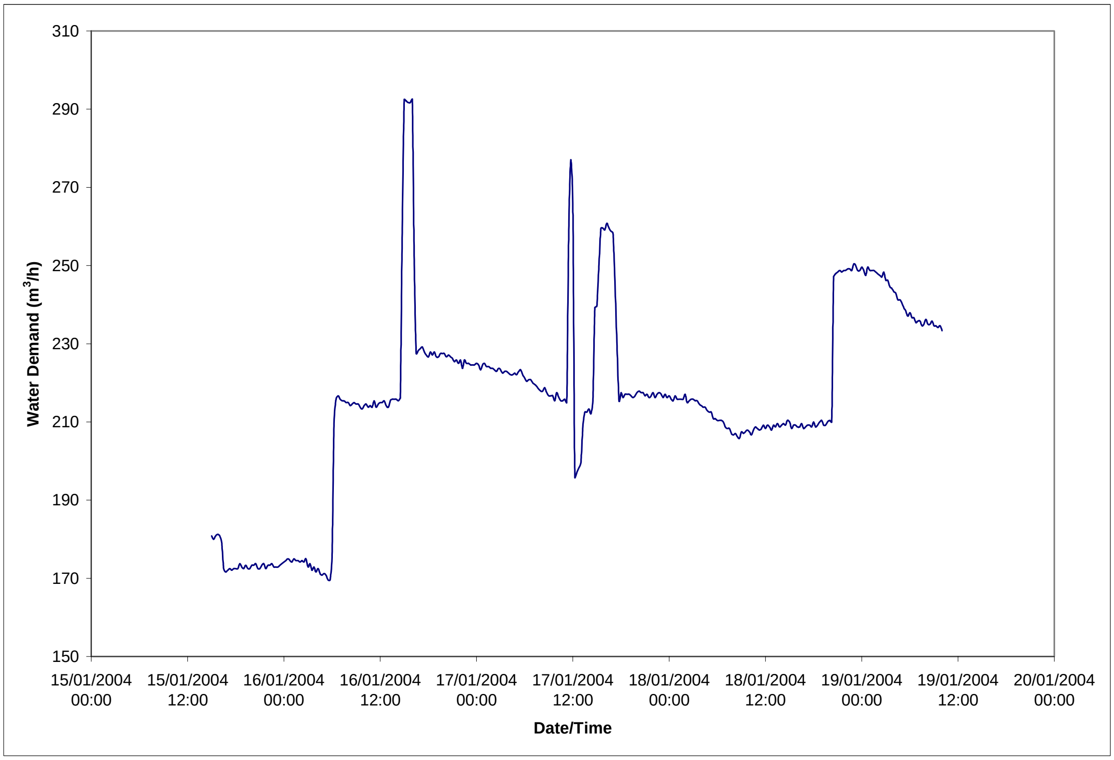

Figure C. 5: Filter flow rate for filter 1 from January 15 at 15:00 to January 19 at 10:00, 2004

Table C. 1: Water quality parameters used in OTTER model

Parameter	Amount	Parameter	Amount	Parameter	Amount
pH	7.5	Nitrate	0	Chlortoluron (μg/L)	0
Temperature (^oC)	15	Nitrite	0	Diuron (μg/L)	0
Apparent Colour (^{o}Hazen)	50	Chloride	0	Isoproturon (μg/L)	0
True Colour	20	Chlorite	0	MCPA (μg/L)	0
Hardness (mg/L as $CaCO_3$)	150	Chlorate	0	MCPB (μg/L)	0
Alkalinity (mg/L as $CaCO_3$)	100	Bromide (mg/L)	0	Mecoprop (μg/L)	0
Conductivity (μS/cm)	400	Bromate (mg/L)	0	2,4-D (μg/L)	0
Total Suspended Solids (mg/L)	Solids:Turbidity Ratio set at 2	Sulphate (mg/L)	0	Diazinon (μg/L)	0
Settleable Suspended Solids (mg/L)	95% of the total suspended solids	Dissolved Oxygen (mg/L)	0	Chlorfenvinphos (μg/L)	0
Filtereable Suspended Solids (mg/L)	95% of the total suspended solids	Orthophosphate (mgP/L)	0	Propetamphos (μg/L)	0
Free Chlorine (mg/L)	0	UV Adsorbance at 254 nm (/m)	12	Cysts (number/L)	0
Combined Chlorine (mg/L)	0	Total Organic Carbon (mg/L)	5	Coliforms (number/mL)	0
Chlorine Dioxide (mg/L)	0	Dissolved Organic Carbon (mg/L)	3	*E. coli* (number/mL)	0
Total Aluminium (mg/L)	0	Particulate Organic Carbon (mg/L)	2	Viruses (number/mL)	0
Total Iron (mg/L)	0	Trihalomethanes (μg/L)	0	Heterotrophs (number/mL)	0
Total Manganese (mg/L)	0	Trihalomethane Formation Potential (μg/L)	0	Algae (cells/mL)	0
Dissolved Aluminium (mg/L)	0	Haloacetic Acids (μg/L)	0	Chlorophyll-A (μg/L)	0
Dissolved Iron (mg/L)	0	Assimilable Organic Carbon (μg/L)	0	Taste (number)	0
Dissolved Manganese (mg/L)	0	Atrazine (μg/L)	0	Odour (number)	0
Ammonia (mg/L)	0	Simazine (μg/L)	0	Particle Size	2

C.2.2 Output from OTTER Models

The effluent turbidity from the two models is shown in Figure C. 6, while the headloss within the filter is shown in Figure C. 7. The output from the two models and the comparison between the two model types is not meant to show which model best represents the data, but to show that the different calculation mechanisms between the logistic and the finite difference models cause differences in uncalibrated outputs. It also shows that calibration is necessary to accurately represent a system, regardless of the model type that is used. Furthermore, the lower headloss and higher effluent turbidity values shown by both models in Figure C. 6, Figure C. 7 and Table C. 2 with respect to actual measurements makes sense because if the attachment efficiency was increased, through calibration, the headloss would increase and more particles would be removed by the filtration process. It was decided to use the logistic model for future simulations and calibration, primarily for the simplicity of its use.

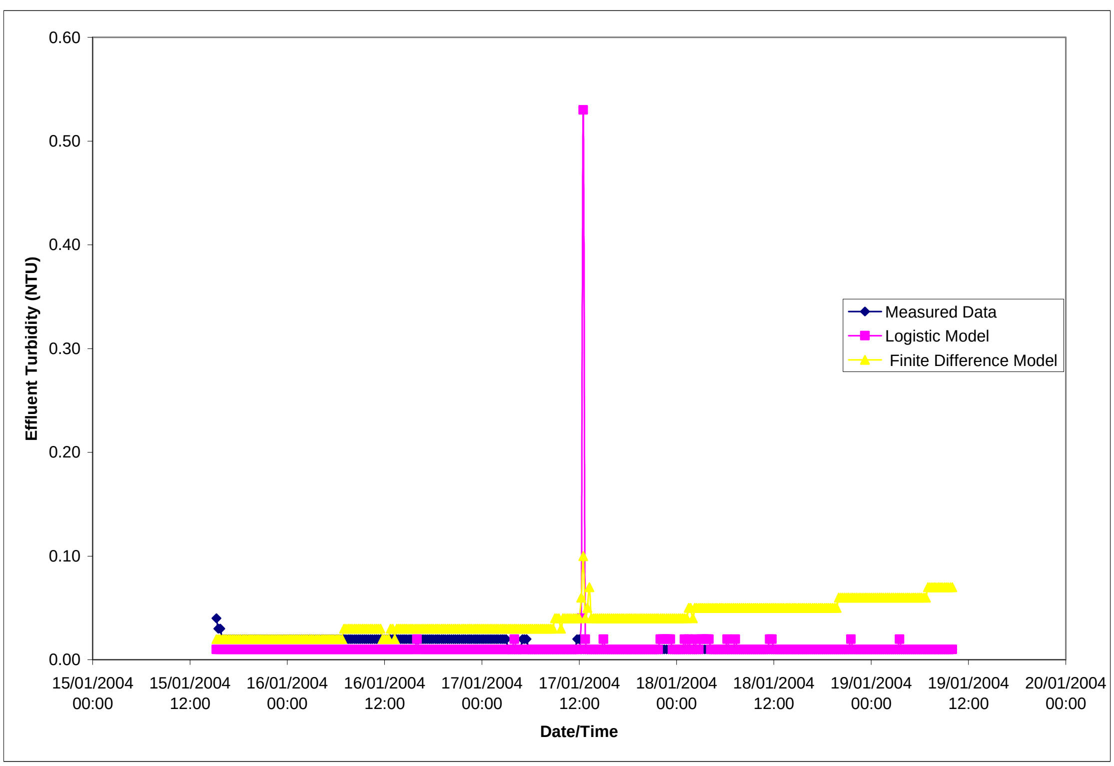

Figure C. 6: Comparison between output from uncalibrated OTTER models and measured effluent turbidity

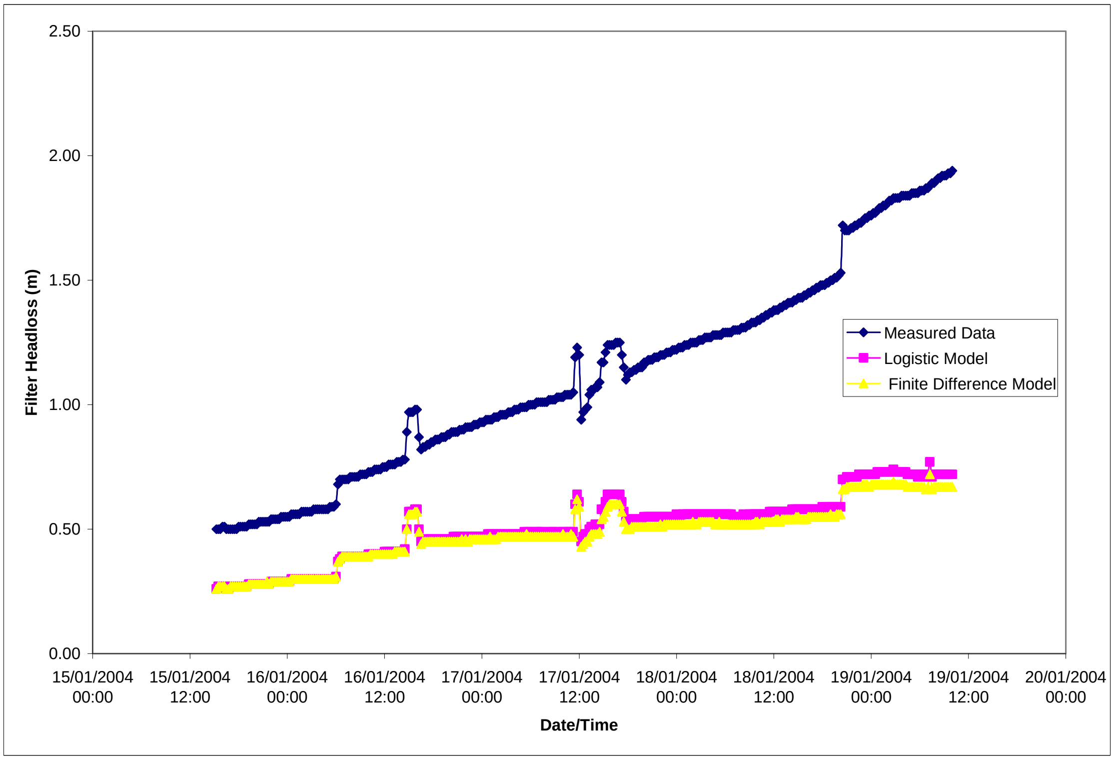

Figure C. 7: Comparison between output from uncalibrated OTTER models and measured headloss

Table C. 2: Summary of output from simulations with Sub-Sets of the 2004 Data

	Measured Effluent (NTU)	Logistic Model Effluent (NTU)	Finite Difference Model Effluent (NTU)
Maximum Turbidity	0.04	0.53	0.10
Minimum Turbidity	0.01	0.01	0.02
Turbidity Standard Deviation	0.01	0.03	0.01
Average Turbidity	0.01	0.01	0.04
Turbidity 95% Confidence	0.02	0.02	0.06
Turbidity 99 % Confidence	0.02	0.02	0.07
	Measured Effluent (m)	Logistic Model Effluent (m)	Finite Difference Model Effluent (m)
Maximum Headloss	1.94	0.77	0.72
Minimum Headloss	0.50	0.26	0.26
Headloss Standard Deviation	0.41	0.13	0.12
Average Headloss	1.11	0.51	0.49

C.3 Effect of Changes in Input Water Quality on Model Outputs

C.3.1 Input Data Record

Although different water quality will ultimately change the output from a treatment system, a preliminary test was carried out on the filtration system. This test was to see how the filter effluent would change from a large change in the water quality characteristics that are not directly associated with the filtration as described in the OTTER model. This meant changing the water quality values that were described in Table C.1, Section C.2.1. Similar to the first preliminary experiment, the water quality parameters, once changed, were kept constant during the simulation. For comparison, the same water demand and influent turbidity profile as for the first experiment was used. Table C. 3 shows the changed water quality inputs. Most of the parameters described in Table C. 3 are expected to have little or no effect as they are not directly related to the modelled filtration process described in Section 3.3.4.

Table C. 3: Changed water quality parameters used in the OTTER model

Parameter	Amount	Parameter	Amount	Parameter	Amount
pH	6	Nitrate	5	Chlortoluron (μg/L)	5
Temperature (°C)	10	Nitrite	5	Diuron (μg/L)	5
Apparent Colour (°Hazen)	100	Chloride	5	Isoproturon (μg/L)	5
True Colour	40	Chlorite	5	MCPA (μg/L)	5
Hardness (mg/L as $CaCO_3$)	300	Chlorate	5	MCPB (μg/L)	5
Alkalinity (mg/L as $CaCO_3$)	200	Bromide (mg/L)	5	Mecoprop (μg/L)	5
Conductivity (μS/cm)	800	Bromate (mg/L)	5	2,4-D (μg/L)	5
Total Suspended Solids (mg/L)	Solids:Turbidity Ratio set at 2	Sulphate (mg/L)	5	Diazinon (μg/L)	5
Settleable Suspended Solids (mg/L)	95% of the total suspended solids	Dissolved Oxygen (mg/L)	5	Chlorfenvinphos (μg/L)	5
Filtereable Suspended Solids (mg/L)	95% of the total suspended solids	Orthophosphate (mgP/L)	5	Propetamphos (μg/L)	5
Free Chlorine (mg/L)	5	UV Adsorbance at 254 nm (/m)	24	Cysts (number/L)	100
Combined Chlorine (mg/L)	2	Total Organic Carbon (mg/L)	10	Coliforms (number/mL)	100
Chlorine Dioxide (mg/L)	2	Dissolved Organic Carbon (mg/L)	6	*E. coli* (number/mL)	100
Total Aluminium (mg/L)	5	Particulate Organic Carbon (mg/L)	4	Viruses (number/mL)	100
Total Iron (mg/L)	5	Trihalomethanes (μg/L)	5	Heterotrophs (number/mL)	100
Total Manganese (mg/L)	5	Trihalomethane Formation Potential (μg/L)	5	Algae (cells/mL)	100
Dissolved Aluminium (mg/L)	5	Haloacetic Acids (μg/L)	5	Chlorophyll-A (μg/L)	100
Dissolved Iron (mg/L)	5	Assimilable Organic Carbon (μg/L)	5	Taste (number)	100
Dissolved Manganese (mg/L)	5	Atrazine (μg/L)	5	Odour (number)	100
Ammonia (mg/L)	4	Simazine (μg/L)	5	Particle Size	4

C.3.2 Output from OTTER Models

Table C. 4 outlines the results from the simulation after changing the input data. From Table C. 4 it can be seen that the turbidity effluent does not change with the changing water quality, but that the water quality changes affect the headloss values. For future analysis, it should be noted that introducing changes in the water quality can have an effect, depending on the input parameter that is changed. However, further analysis was performed using the model defaults as shown in Table C.1, Section C.2.1, noting that other water quality parameters could have some effect.

Table C. 4: Summary of output from simulations with sub-sets of the 2004 data

	Measured Effluent (NTU)	Logistic Model Effluent (NTU)	Logistic Model Effluent New Water Quality (NTU)	Finite Difference Model Effluent (NTU)	Finite Difference Model Effluent New Water Quality (NTU)
Maximum Turbidity	0.07	0.53	0.53	0.10	0.10
Minimum Turbidity	0.01	0.01	0.01	0.02	0.02
Turbidity Standard Deviation	0.01	0.03	0.03	0.01	0.02
Average Turbidity	0.01	0.01	0.01	0.04	0.04
Turbidity 95% Confidence	0.02	0.02	0.02	0.06	0.07
Turbidity 99 % Confidence	0.02	0.02	0.02	0.07	0.07
	Measured Effluent (m)	Logistic Model Effluent (m)	Logistic Model Effluent New Water Quality (m)	Finite Difference Model Effluent (m)	Finite Difference Model Effluent New Water Quality (m)
Maximum Headloss	1.93	0.77	0.88	0.72	0.82
Minimum Headloss	0.50	0.26	0.30	0.26	0.30
Headloss Standard Deviation	0.41	0.13	0.15	0.12	0.14
Average Headloss	1.11	0.51	0.58	0.49	0.55

APPENDIX D: MODIFIED CALIBRATION PROCEDURE

The modified calibration procedure methodically looked at the different calibration parameters to determine a combination of parameters that provided similar output to what was seen by the measured turbidity effluent and headloss values in the 2004 data record.

It was necessary to compare the calibration parameters to the full data set; however, running each set of calibration parameters through all 142 filter runs experienced in the 2004 year was not practical or desirable. Therefore, the different combinations of calibration parameters were assessed for their ability to model different runs chosen from the 2004 data record through a linear optimization model. This linear optimization model was performed to find the most "average" filter run and the filter runs that deviated from the "average" run the greatest.
A linear optimization model can be viewed as:

Minimize or Maximize $\sum c_j x_j$

Where x_j is the parameter of interest
And c_j is the weight applied to the parameter.

In terms of the model, the filtration process can be described by and is affected by a combination of the turbidity influent, turbidity effluent, filter headloss and filter flowrate. An average filter run would then be one that had an average turbidity influent, average turbidity effluent, average headloss, and average filter flowrate over the filter run. To determine this specific filter run, the median turbidity influent, turbidity effluent, filter headloss, and filter flowrate was calculated for the 2004 year. The median values were then calculated for each filter run and the percent difference between the filter run median and the overall median value was determined. The average filter run was then determined using linear optimization, where the goal was to minimize the percent difference over all four parameters. The linear optimization can be seen in Equation

17, where all c_i values were equal to provide equal weighting to each parameter that could affect the filtration process.

$$\sum c_i I_i + c_i E_i + c_i H_i + c_i F_i$$ **Equation 17**

Where I is the percent difference in average turbidity influent from the run of interest to the overall average, E is the percent difference in average turbidity effluent from the run of interest to the overall average, H is the percent difference in average headloss from the run of interest to the overall average, F is the percent difference in average filter rate from the run of interest to the overall average.

Through this procedure, filter run 59 was found to be the most average filter run. The procedure also allowed for the determination of the filter runs that deviated from the average the greatest both above and below the median values provided absolute value differences were not used. Thus the "high" filter run was determined to be filter run 80 and the "low" filter run was determined to be filter run 31. Table D.1 shows the output from the analysis.

Table D.1: Filter Run Linear Programming for OTTER Model Calibration

	Filter Run Characteristics				Absolute Value Percent Difference Between Filter Run Characteristics and Averge Values				Percent Difference Between Filter Run Characteristics and Averge Values			
Filter Run	Influent Mean (NTU)	Effluent Mean (NTU)	Headloss Mean (m)	Flowrate Mean (MLD)	Influent (%)	Effluent (%)	Headloss (%)	Flowrate (%)	Influent (%)	Effluent (%)	Headloss (%)	Flowrate (%)
31 (low)	0.26	0.01	0.55	3.94	18.0	79.3	48.7	37.3	-18.0	-79.3	-48.7	-37.3
59(average)	0.45	0.05	1.11	6.87	39.2	3.4	3.7	9.3	39.2	-3.4	3.7	9.3
80 (high)	0.50	0.13	1.14	8.54	55.5	173.5	5.8	36.1	55.5	173.5	5.8	36.1
Overall	0.32	0.05	1.07	6.28								

Table D.1 continued

Linear Programming	
ABS*	Non ABS*
45.8	-45.8
13.9	12.2
67.7	67.7

*ABS stands for Absolute Value

The modified calibration procedure also took into account the accumulation within the filter. For each filter run in 2004 the total amount of solids accumulated during the filter run was calculated assuming the filters were clean at the start of each filter run. This allowed for the filter run which caused the maximum amount of accumulation to be determined.

Visually, the ability of the calibrated model to duplicate the output from the 2004 data record can be seen in Figure D.1 for the headloss and Figure D.2 for the effluent turbidity

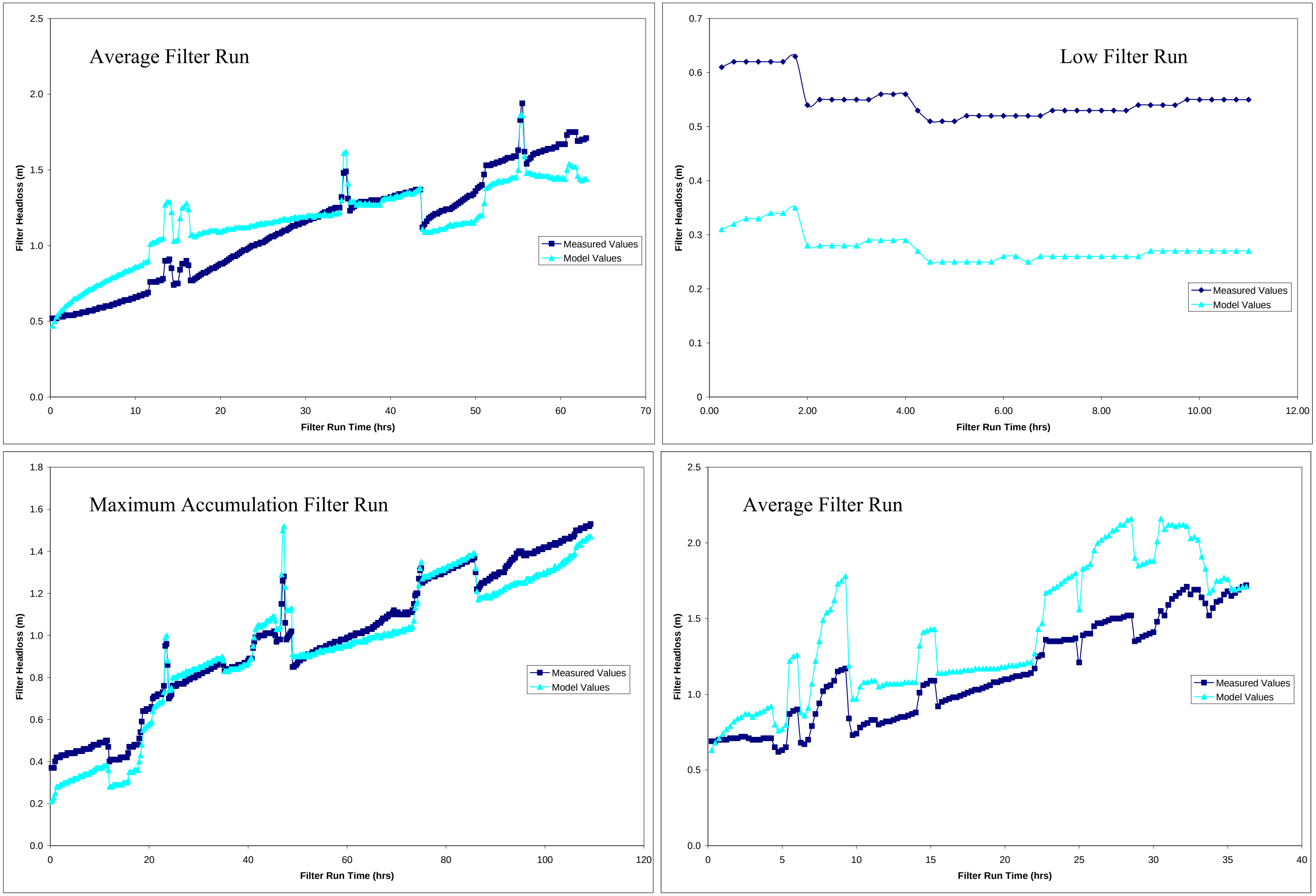

Figure D.1: Comparison of measured vales and model calculated values for filter headloss: Clockwise from top left, average filter run, low filter run, high filter run, maximum accumulation filter run

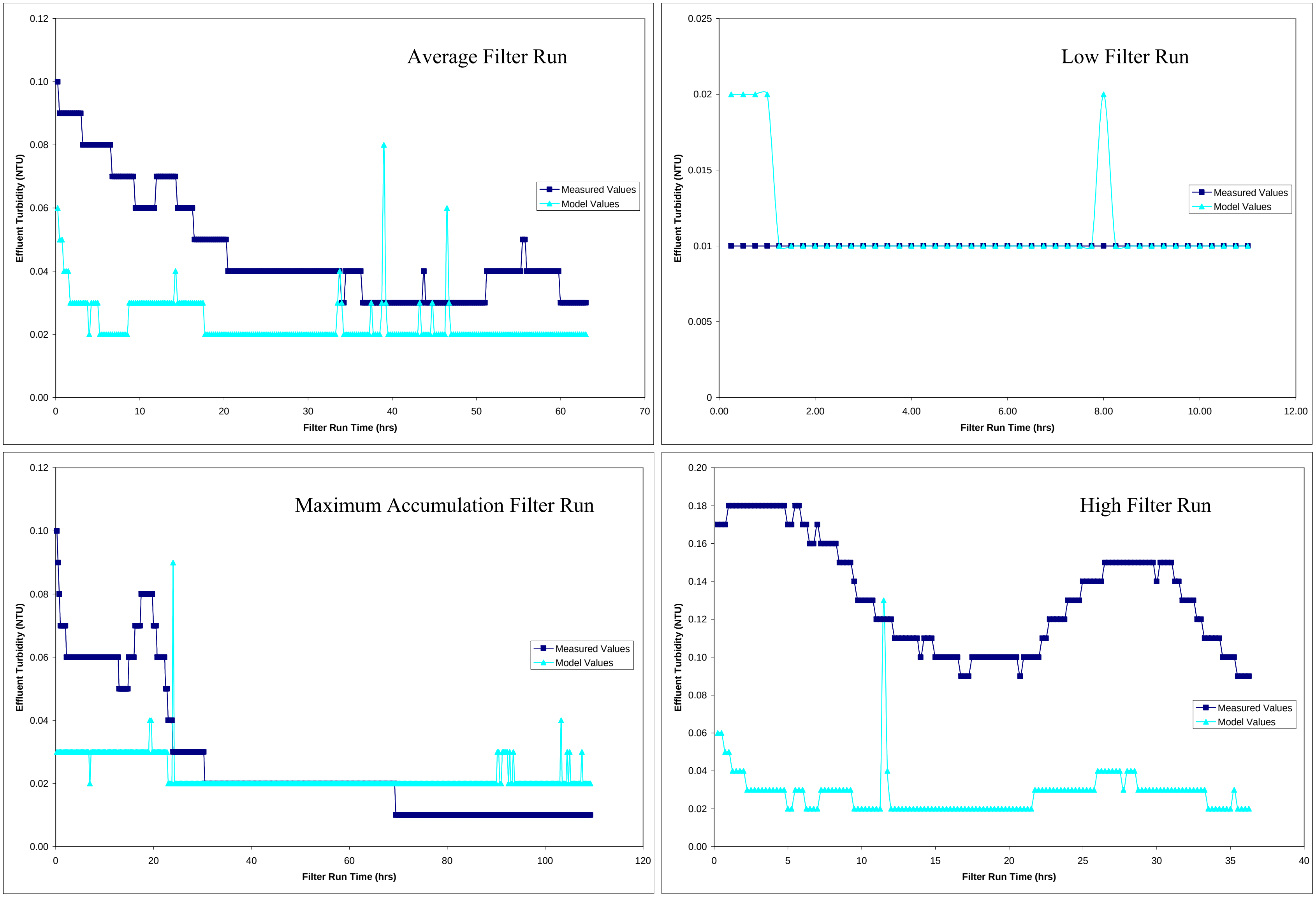

Figure D.2: Comparison of measured vales and model calculated values for filter effluent: Clockwise from top left, average filter run, low filter run, high filter run, maximum accumulation filter run

APPENDIX E:
YATE'S METHOD CALCULATIONS FOR PREDICTIVE MODELLING AND RISK ANALYSIS

Table E.1: Yate's method for calculating effect estimates for the probability that the effluent turbidity is greater than 0.05 NTU

Simulation #	Filter Depth (m)	Influent Turbidity (NTU)	Filter Flow Rate (MLD)	Probability > 0.05 NTU (%)	[1]	[2]	[3]	Divisor	Effect Estimate	Source
11	-1	-1	-1	4.84	0.0740	0.1515	0.1848	8	0.0231	Mean
13	-1	-1	1	2.56	0.0775	0.0333	-0.0584	4	-0.0146	Flow
12	-1	1	-1	4.91	0.0213	-0.0435	-0.0058	4	-0.0015	Turbidity
10	-1	1	1	2.84	0.0120	-0.0149	0.0078	4	0.0020	Flow x Turbidity
7	1	-1	-1	1.58	-0.0228	0.0035	-0.1182	4	-0.0296	Depth
9	1	-1	1	0.55	-0.0207	-0.0093	0.0286	4	0.0072	Flow x Depth
8	1	1	-1	0.83	-0.0103	0.0021	-0.0128	4	-0.0032	Depth x Turbidity
6	1	1	1	0.37	-0.0046	0.0057	0.0036	4	0.0009	Flow x Turbidity x Depth
Sum of Squares					0.0132	0.0263	0.0526			

Table E.2: Yate's method for calculating effect estimates for the probability that the effluent turbidity is greater than 0.10 NTU

Simulation #	Filter Depth (m)	Influent Turbidity (NTU)	Filter Flow Rate (MLD)	Probability > 0.10 NTU (%)	[1]	[2]	[3]	Divisor	Effect Estimate	Source
11	-1	-1	-1	3.64	0.0498	0.0897	0.1102	8	0.0138	Mean
13	-1	-1	1	1.34	0.0399	0.0205	-0.0626	4	-0.0157	Flow
12	-1	1	-1	3.25	0.0144	-0.0481	-0.0182	4	-0.0046	Turbidity
10	-1	1	1	0.74	0.0061	-0.0145	0.0022	4	0.0006	Flow x Turbidity
7	1	-1	-1	1.19	-0.0230	-0.0099	-0.0692	4	-0.0173	Depth
9	1	-1	1	0.25	-0.0251	-0.0083	0.0336	4	0.0084	Flow x Depth
8	1	1	-1	0.56	-0.0094	-0.0021	0.0016	4	0.0004	Depth x Turbidity
6	1	1	1	0.05	-0.0051	0.0043	0.0064	4	0.0016	Flow x Turbidity x Depth
Sum of Squares					0.0056	0.0112	0.0224			

TableE.3: Yate's method for calculating effect estimates for the probability that the effluent turbidity is greater than 0.30 NTU

Simulation #	Filter Depth (m)	Influent Turbidity (NTU)	Filter Flow Rate (MLD)	Probability > 0.30 NTU (%)	[1]	[2]	[3]	Divisor	Effect Estimate	Source
11	-1	-1	-1	1.95	0.0244	0.0423	0.0560	8	0.0070	Mean
13	-1	-1	1	0.49	0.0179	0.0137	-0.0392	4	-0.0098	Flow
12	-1	1	-1	1.6	0.0104	-0.0287	-0.0136	4	-0.0034	Turbidity
10	-1	1	1	0.19	0.0033	-0.0105	0.0052	4	0.0013	Flow x Turbidity
7	1	-1	-1	0.9	-0.0146	-0.0065	-0.0286	4	-0.0072	Depth
9	1	-1	1	0.14	-0.0141	-0.0071	0.0182	4	0.0046	Flow x Depth
8	1	1	-1	0.31	-0.0076	0.0005	-0.0006	4	-0.0002	Depth x Turbidity
6	1	1	1	0.02	-0.0029	0.0047	0.0042	4	0.0011	Flow x Turbidity x Depth
Sum of Squares					0.0015	0.0030	0.0061			