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QMRA-based reliability analysis to assess the performance of an ultrafiltration plant

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ABSTRACT

In the drinking water treatment industry, it is becoming increasingly important to evaluate the reliability of different water treatment processes. This paper extends the use of quantitative microbial risk assessment (QMRA) as part of a reliability analysis, to assess the capacity of alternative water treatment technologies to minimize risk of microbial infection. The approach is demonstrated, in the Canadian context, for an ultrafiltration (UF) technology used for the removal of the protozoon *Cryptosporidium* spp., for which the removal is quantified using real operational data. The performance of the UF facility is compared with that of reference conventional trains, for which the removal performance is reported in the literature. The UF physicochemical process appears to reliably provide water with lower levels of *Cryptosporidium* spp. than the conventional trains. However, many issues such as the time scale at which the removals are measured and the methods used to establish the removal for different technologies impose moderation on the strength of this conclusion.

Key words | drinking water, membranes, pathogens, reliability, ultrafiltration, water treatment plants

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NOTATION

α:	alpha parameter of a Beta probability distribution
β:	beta parameter of a Beta probability distribution
CF:	hydraulic concentration factor
C_{raw}:	mean oocyst concentration in raw water
$C_{treated}$:	mean oocyst concentration in treated water
$g()$:	reliability analysis performance function
i:	index of the volunteer feeding study
$infection$:	number of subjects infected at dose j in study i
j:	index of the dose level of the study
$L(\,)$:	likelihood function
LRV:	log reduction value
$LRVtotal$:	total log reduction value achieved by a plant
n:	number of dose levels of each study
N:	mean dose of oocysts ingested
P_{acc}:	acceptable risk of infection
P_{inf}:	computed risk of infection
Q_{breach}:	untreated flow of water through the breach of the membrane
Q_{filt}:	total flow of water through the membrane
r:	ratio of ingested pathogens that survive the host's defences and start an infection
$subject$:	number of subjects exposed to dose j in study i
V:	ingested volume of cold drinking water
X:	vector of random variables in a reliability analysis

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INTRODUCTION

Decision making in the water treatment industry has become increasingly more complex with the discovery of previously unidentified pathogens and substances, new concerns of

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consumers, the emergence of novel treatment technologies and the initiation of new standards and regulations. Each new technology is accompanied by a significant level of uncertainty given the relatively low level of experience with these technologies. Nevertheless, decisions involving considerable economical, environmental and social implications, such as the selection of a water supply system, the modification of an existing system, or the development of regulations overseeing the practices of the industry, must be made despite such uncertainty. Risk assessment approaches have been developed to address these uncertainties.

As noted by Haas & Trussell (1998), the possibility that an engineered system performs out of prescribed specifications always exists. In this context, reliability is usually defined as the probability of proper functioning of a system, called success. This is a quantitative definition that demands a probabilistic and/or statistical approach. Two points of view can be adopted when quantitatively evaluating the reliability of an engineered system. First, the system can be seen as a black box and the variability of its output can be measured and quantified. Comparing the output variability with a regulation that differentiates the normal state from the failure state, one can determine the probability of compliance, or inherent reliability (Eisenberg *et al.* 2001). Alternatively, a system can be decomposed into many sub-systems assembled in series or in parallel, each with its own probability of failure. The probability of proper functioning of the whole system can be calculated by conflating the probability of failure of its components, called mechanical reliability (Eisenberg *et al.* 2001). In this paper, it is proposed that inherent reliability analysis, which considers uncertainty of the different variables involved in the protection of public health, can provide useful information for decision-makers.

In recent decades, an important focus of research in the field of microbial quality of drinking water has been the investigation of protozoan parasites, mostly *Giardia spp.* and *Cryptosporidium* spp. These protozoa infect the digestive tracts of warm-blooded animals, including humans. They reproduce in their host and are excreted through feces in a resistant stage, called a cyst (*Giardia*) or oocyst (*Cryptosporidium*). The symptoms of giardiasis and cryptosporidiosis, their respective illnesses, are gastrointestinal. It is now known that (oo)cyst-contaminated water is an important route of infection, along with direct or indirect contact with feces of infected individuals. Disinfection using traditional chlorination technologies at practical dosages and retention times has some effect on *Giardia* cysts but no significant effect on *Cryptosporidium* oocysts. Ozone is effective against both in warm waters but becomes much less effective under cold water conditions, such as those encountered in Canadian winters. Physical removal or alternative disinfection, such as ultraviolet (UV) radiation, is required to effectively treat water contaminated with protozoan (oo)cysts. Among the new technologies developed to remove (oo)cysts, membrane ultrafiltration (UF) is gaining popularity.

Quantitative evaluation of exposure to these pathogens, of the consequences of exposure and of the concentration reduction achievable by the different technologies is required when treatment alternatives are being considered. Quantitative microbial risk assessment (QMRA) is the application of principles of risk assessment to evaluate the consequences of an exposure to microbial infectious agents. The major developments in the application of QMRA for drinking water took place during the 1980s and 1990s (Haas 1983; Rose *et al.* 1991; Haas *et al.* 1996; Teunis *et al.* 1997). Haas *et al.* (1999) summarized the state of knowledge of QMRA at the time, and reported on the microbial world, the different steps involved in a risk assessment, the models used in the process of QMRA, and the previously published data regarding dose-response relationships. Since then, QMRA has been used in the United States to develop technical standards (USEPA 1989, 2006) and in Europe to develop a regulation framework (MicroRisk Consortium 2003). In Canada, provincial drinking water regulations are strongly influenced by the USEPA approach (Alberta Environment 2006; MDDEP 2006).

In this paper, QMRA is applied to a full-scale UF plant in a Canadian setting, chosen to provide an example of the use of a new physicochemical process removing *Cryptosporidium parvum* oocysts. To take variability and uncertainties related to the model variables into account, it is proposed to integrate the QMRA model into a reliability-based approach. This approach provides a sound basis for comparison of treatment technology performance, to quantify the importance of different model variables, and to improve our understanding of the risk associated with microbiological water quality. The risk level computations by the QMRA model are based on day to day operational data from a real full-scale UF system

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and take into account parameter uncertainties. The resulting reliability is compared with that of conventional treatment train reference cases to demonstrate the possible uses of the method.

The remaining sections of this paper are organized as follows. First, the development of the reliability point of view of the QMRA approach is described. Next, the inputs for the application of the approach for analysing the reliability of a UF plant are described and the results are presented and compared with reliability estimates for conventional treatment under different operating scenarios. A discussion follows, where the results are analyzed in light of the objectives and assumptions of the study, and the value of reliability analysis in decision-making is discussed.

RELIABILITY APPROACH FOR APPLYING THE QMRA MODEL

In the application of QMRA, the most common and widespread model used to estimate the ratio of infection in the population is the exponential model (Haas *et al.* 1996; Teunis *et al.* 1997; Barbeau *et al.* 2000; Medema *et al.* 2003). The mathematical expression for this model is:

$$P_{inf} = 1 - \exp(-r \times N) \tag{1}$$

where P_{inf} is the ratio of infection in the population; r is the infectivity parameter, defined as the ratio of ingested pathogens that will survive the host's defences and start an infection, and N is the mean dose of oocysts. The mean dose, while easier to determine in experimental settings, cannot be measured at the consumer's tap in a drinking water context and is usually expressed as the product of the mean of the treated water concentration of oocysts ($C_{treated}$) and the intake volume of cold drinking water (V). Moreover, $C_{treated}$ is impractical to measure for *Cryptosporidium parvum*, because common concentrations are well below the detection limits of modern analytical methods. The alternative to direct measurement of pathogens in treated water is to measure concentrations in raw water and to estimate the removal achieved by the treatment plant. The resulting dose is shown in Equation (2), where C_{raw} is the oocyst concentration in raw water, and *LRVtotal* is the performance of the whole plant for this pathogen, expressed in a base-10 logarithmic scale (log reduction value, LRV):

$$\mathrm{N} = V \times C_{raw} \times 10^{-LRVtotal} \tag{2}$$

This model is based on two important assumptions. The first is the "single hit" hypothesis. That is that two or more pathogenic microorganisms of the same species, even if ingested together, act independently, and that any of them may cause an infection. Second, it is assumed that pathogens in the treated water are randomly distributed and the quantity of oocysts in a given volume exhibits a Poisson distribution with an average concentration $C_{treated}$. The time scale at which this model may be applied is the choice of the analyst. If one wishes to know the yearly risk of infection, then yearly values of variables V (total intake volume of cold water over one year), C_{raw} (total number of oocysts in the total volume of raw water / total volume of raw water treated over one year) and *LRVtotal* (total number of oocysts in the total volume of treated water / total number of oocysts in the total volume of raw water over one year) must be used. The infectivity parameter, r, is independent of time. In the current study, the model is applied at a daily time scale, i.e. distribution functions of daily values of the variables described earlier are used. However, results are presented as yearly risk of infection to facilitate comparison with previously developed benchmarks of acceptable risk of infection (Haas 1996).

To perform a reliability analysis, a performance function separating the failure domain from the success domain must be defined. In this case, failure is defined as the production of water leading to an unacceptable risk of infection for the consumers. Its mathematical expression is shown in Equation (3), where $g(X)$ is the performance function, X is the vector of random input variables, and P_{acc} is the acceptable risk of infection. Failure occurs when $g(X) \leq 0$. Finally, the extended expression including all random variables is shown in Equation (4).

$$g(X) = \mathrm{P}_{acc} - \mathrm{P}_{inf} \tag{3}$$

$$g(X) = P_{acc} - 1 + \exp(-r \times V \times C_{raw} \times 10^{-LRVtotal}) \tag{4}$$

This model may be categorized as an inherent reliability model. It uses quantification of the system output (*LRVtotal*)

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and compares it to a standard (P_{acc}) to differentiate failure from success. To investigate system performance in the face of uncertain standards, a range of values of P_{acc} may be examined.

Different methods have been developed to assess the reliability of engineered systems. In this study, the First-Order Reliability Method (FORM), developed by Hasofer & Lind (1974), is used. Briefly, FORM uses marginal distributions of random variables and correlations between these variables to numerically evaluate the probability of failure of a system. A hyperplane approximates the performance function (i.e., first order approximation), and the joint probability of being on the failure side of the plane is found numerically. The advantages of this method over widely-used Monte Carlo Simulation (MCS) are its computational efficiency, and the other measures that may be determined during the analytical process, such as the importance of each random variable in the probability of failure. The disadvantage of FORM is that it gives a first order approximation of the probability of failure. However, in many applications of FORM to water engineering problems, FORM results differ only slightly from MCS results, while computing efficiency is improved (Vasquez *et al.* 2000; Maier *et al.* 2001; Sarang *et al.* 2008; Thorndahl *et al.* 2008).

The program used to execute the FORM analysis herein is the Open System for Earthquake Engineering Simulation (OpenSees) developed at the University of California at Berkeley (OpenSees 2006). The reliability tools of this program, although originally intended for structural reliability, can be used to solve any reliability problem.

APPLICATION OF THE RELIABILITY APPROACH TO A FULL-SCALE UF PLANT

Input variable probability distributions

Figure 1 shows the distribution functions of the input variables. Each graph shows the cumulative distribution function (CDF), i.e., the probability that the random variable is lower than a given value, on the right ordinal scale, and the probability density function (PDF), i.e., the derivate of the CDF, on the left ordinal scale.

Infectivity

The distribution of infectivity is based on the dose-response relationship found in volunteer challenge studies (Dupont *et al.* 1995; Okhuysen *et al.* 1999) and is assumed valid for the entire population (Gale 2001). The USEPA (2005) estimates different distributions of infectivity, *r*, by applying different probability models to data from six human volunteer challenge studies. Oocysts found in the raw water are

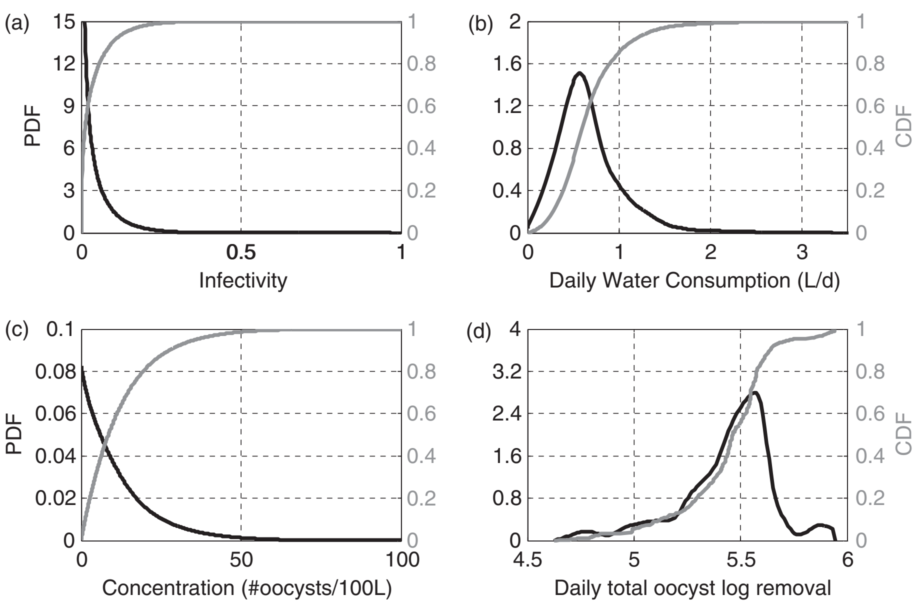

Figure 1 | Probability density and cumulative distribution functions of input variables.

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assumed to be the mix of the genotypes used in these challenge studies (Messner et al. 2001; Aboytes et al. 2004). Among the models based on the exponential equation (see Equation (1)), the best fit was found when r followed a Beta distribution. Hence, a Beta distribution is assumed herein and the infectivity distribution used in the reliability analysis is shown in Figure 1(a). This distribution was found using the maximum log-likelihood technique based on results from the volunteer feeding studies presented in USEPA (2005). The likelihood function is:

$$L(\alpha, \beta) = \sum_{i=1}^{6} \left[\ln \left(\int_{r=0}^{1} Beta(r, \alpha, \beta) \times \prod_{j=1}^{n} Bin(infection_{i,j}, subject_{i,j}, 1 - \exp(-r \times N)) dr \right) \right] \tag{5}$$

where r is the infectivity parameter, α and β are the Beta distribution parameters, *infection* is the number of subjects infected at dose j in study i, *subject* is the number of subjects exposed to dose j in study i, i is the index of the volunteer feeding study, j is the index of the dose level of the study, n is the number of dose levels of each study, and N is the dose. Maximizing the function results in the following parameters: $\alpha = 0.383$, $\beta = 10.829$.

Tap water consumption

The distribution of daily cold tap water consumption for the Canadian population is shown in Figure 1(b). As suggested by Mons et al. (2007), country-specific tap water consumption data and distributions should be used for QMRA applications when available. In Canada, the Environmental Health Directorate (EHD) conducted the most complete survey of tap water consumption in 1977 and 1978 (EHD 1981). The tap water consumption was shown to vary according to factors such as age, geographical location, and level of physical activity. The ratio of tap water consumed cold, versus boiled or through food, also varies with age. Statistical distributions of total daily tap water consumption are available (EHD 1981) for different age groups (less than 6, 6 to 17, and 17 years-old and over). In our work, to account for the quantity of boiled water, consumption levels for each age group were multiplied by the ratio of cold to total tap water for this particular age group (82%, 83%, and 45%, respectively). To produce Figure 1(b), a weighted average of the "cold-water-adjusted" distributions was calculated where the weights are based on the 2005 demographical percentage of each age group (6.4%, 15.2%, and 78.4%, respectively) provided by Statistics Canada (2006).

Pathogen concentration

Monitoring raw water concentrations of protozoa is not common practice in Canada. For the plant studied herein, one monitoring campaign of *Cryptosporidium* oocysts in its raw water was conducted in 1997 before commissioning of the plant. One sample per month was taken between July and December inclusively, for a total of six samples. The results from this sampling campaign were used to obtain the probability distribution shown in Figure 1(c). For each day, oocysts are assumed to be randomly distributed in the water with an unknown average concentration, C_{raw}. Each measurement is therefore the result of a Poisson process. For every sample, the likelihood of possible values of C_{raw} was computed, resulting in a probability distribution between 0 and 100 oocysts/100 L. Assuming all six distributions are equally likely to represent the variation in daily mean concentration, they are averaged to obtain the distribution shown in Figure 1(c). It is important to note that although Figure 1(c) represents a possible contamination scenario, it does not necessarily characterize a typical or all Canadian source waters. Nonetheless, the computational approach could be used to obtain distributions for other source waters with similar monitoring data.

Full-scale UF system performance

Full-scale plant data are used to obtain the distribution for the performance variable (*LRVtotal*). This plant is not necessarily representative of all plants using UF but represents a plausible scenario of performance resulting from the operation of this technology under Canadian jurisdiction. The treatment facility is not identified for confidentiality reasons.

The treatment process of the plant consists of the following steps: 2.5 mm screening, coagulation, flocculation, UF, and chlorination. The type of membranes used is hollow fibre

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operated in an outside-in mode. Membranes are immersed in a water tank and a vacuum is applied on the inside of the fibres, which causes the water to permeate through the fibres and flow to the permeate collector. A total of twelve parallel trains, of six cassettes each, can be operated independently. The filtered water is then chlorinated by the addition of a sodium hypochlorite solution. Chlorinated water passes through a contact tank and ends up in a reservoir from which it is pumped to the distribution system.

Integrity tests are conducted on hollow-fibre UF membranes using the standard pressure-decay test technique described in ASTM International (2003). This test consists of pressurizing the inside of the fibres with air and measuring the decay of pressure occurring when air flows through pores and possibly breaches. Air will flow through wetted pores and breaches if capillary forces cannot resist the air pressure applied during the test. Because these capillary forces are a function of the diameter of the holes, it is possible to compute the air pressure that will detect holes of 3 μm or more, which is the minimum size of an oocyst, as required in ASTM international (2003). During operation, it is assumed that water flowing through the detected breaches is untreated. Both the airflow during the integrity testing and the equivalent water flow during water filtration are assumed to pass through the same breaches, with the same characteristics (i.e., breach diameters, lengths, shapes, etc.). Using compressible and incompressible flow hydraulics, the equivalent flow of water is modeled. Assuming both flows are laminar, the Hagen-Poiseuille equation for laminar flow is used to calculate the equivalent water flow from the pressure-decay rate measured during the integrity test. Details of the mathematical derivation of the equivalent water flow can be found in ASTM International (2003). The log reduction value for this test is computed by Equation (6), where LRV is the log reduction value of the unit, Q_{filt} is the total flow of water through the membrane, Q_{breach} is the untreated flow through the breach, and CF is the concentration factor, a dimensionless term, dependant on the hydraulic configuration of the system, which takes into account the increase in solids concentration on the feed side of the membrane.

$$LRV = \log_{10}\left(\frac{Q_{filt}}{CF \times Q_{breach}}\right) \qquad (6)$$

At this plant, an integrity test is conducted on each train every week. The LRV values were obtained from pressure-decay tests conducted between May 2005 and June 2007. The minimum and maximum LRV for individual trains are 4.01 and 7.81, respectively, with a mean of 5.52 and a standard deviation of 0.507. The result of each integrity test is assumed to represent the performance of the tested train for the entire period between the given test and the previous test. An LRV value is therefore assigned to each train for every day between May 1st 2005 and June 30th 2007. A value of *LRVtotal*, the average removal achieved by the 12 trains, was computed for each day. The resulting historical data of the total removal (*LRVtotal*) achieved by the UF plant is shown on Figure 2. These values were used to obtain the probability distribution of the performance of the whole plant (*LRVtotal*) as shown on Figure 1(d).

Results of FORM analysis

The results of the reliability analysis are shown in Figure 3. For different values of the acceptable risk, P_{acc}, the reliability, or probability of success for the UF membrane system is given by the curve "UF Membrane". The other curves in Figure 3 are the results of reliability analyses for different operating scenarios of a conventional physicochemical treatment train, as explained in the following section. Success is defined as the production of water leading to a risk lower than the

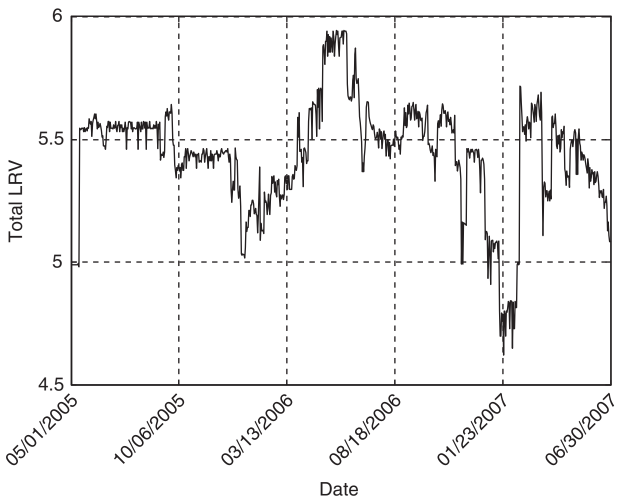

Figure 2 | Total removal of Cryptosporidium oocyst (LRVtotal) achieved by the UF system between May 2005 and June 2007.

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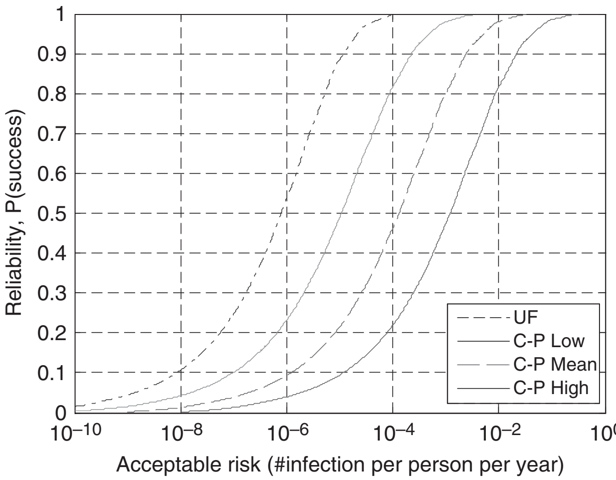

Figure 3 | Reliability of treatment for different infection risk levels under a UF and conventional physicochemical (C–P) systems based on low, mean and high performance distributions.

acceptable value. Hence, the curves in Figure 3 can be viewed as the CDF of the risk of infection by *Cryptosporidium parvum*, given the input variables described previously. For example, at a reliability level of 0.9, the risk of infection is $10^{-4.93}$. That is, there is a 90% probability that less than one in 85,114 people become infected by *Cryptosporidium parvum* by drinking water produced by this UF plant.

Reference cases for conventional physicochemical system performance

Because UF is a new treatment technology, it is useful to compare its reliability with a reference technology for which experience is more abundant. The conventional physicochemical treatment train, which can be viewed as the traditional technology providing physical removal of oocysts, is used in this work as such a reference. It consists of the following steps: screening, coagulation, flocculation, clarification, and rapid granular media filtration.

In many jurisdictions, turbidity of the filter effluent is monitored and used as a surrogate to compute credited log reduction of pathogens (Alberta Environment 2006; MDDEP 2006; USEPA 2006). However, in the Microrisk project and in other sources (Huck *et al.* 2002; Emelko *et al.* 2005; Smeets *et al.* 2006), it is recognized that although turbidity is a good indicator of plant optimization, it is not suitable for directly informing quantitative assessment of oocysts removal. In this work, rather than using effluent turbidity data to establish a conventional treatment reference performance, an approach developed in the Microrisk project (Smeets *et al.* 2006) is used. To our knowledge, this approach is the most comprehensive reference on pathogen removal for use in quantitative risk analysis, and is illustrated in the probability density functions of conventional treatment system removal shown in Figure 4. In the Microrisk project a literature review of 15 studies of *Cryptosporidium* oocyst removal by bench-, pilot-, and full-scale conventional physicochemical treatment trains was conducted to obtain the range of possible performance. Based on the full range of removal values obtained in the studies, the basic log-triangular PDF shown in Figure 4(a) was constructed. Then, given the turbidity abatement achieved by a system, Smeets *et al.* (2006) suggest that this PDF could be adjusted. Following the same approach, we assume that, when effluent turbidity of the physicochemical process is consistently maintained constantly below 0.1 NTU, the plant is assumed to be performing well and is likely to provide removal in the high range of the basic distribution and therefore the distribution is shifted as in Figure 4(b). On the contrary, when the filtrate turbidity is unstable, varying by a few tenths of NTU around the regulatory limit, indicating that filtration does not work effectively, we assume that the plant is poorly optimized and the removal is likely to be in the low range of the basic distribution and is therefore the performance distribution is shifted as in Figure 4(c). A third reference case of mean performance is developed in our study, as shown in Figure 4(d), which may be thought of as an intermediate case between optimal and poor operation. This approach is general because performance distributions, although based on actual measurements from studies, are adjusted arbitrarily to represent different operational scenarios. Turbidity values are used as an indicator to adjust the basic performance distribution based on the degree of plant optimization but do not provide an actual assessment of the achieved removal.

Results of the reliability analyses for the conventional treatment reference cases based on the high, low, and mean performance distributions in Figure 4(b), (c) and (d), respectively are shown in Figure 3. They indicate that the UF system studied provides water with low concentrations of *Cryptosporidium parvum* more reliably than would the reference conventional trains treating the same water.

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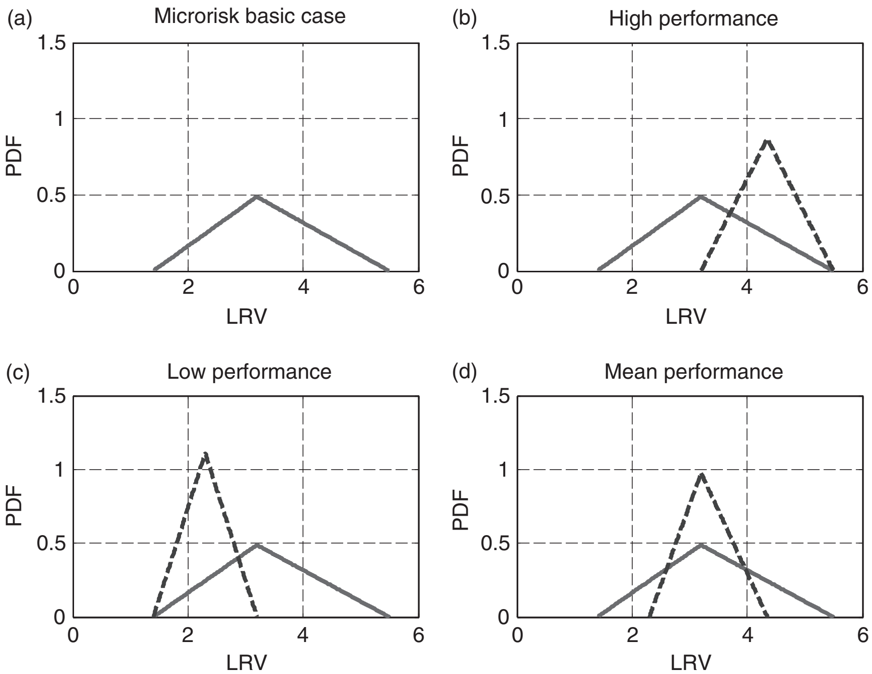

Figure 4 | Probability density functions of conventional treatment system removal.

If all other variables (i.e., C_{raw}, V, and r) are fixed and the intention is only to determine which technology provides the highest removal, then the *LRV* probability distributions are sufficient representations of reliability. This approach acknowledges variability and recognizes the importance of conferring pathogen removal credits to a system not only based on the capacity of the technology but on the operational reality. When the reliability of two plants in different settings (i.e., different C_{raw}, V, and r) is to be assessed, incorporating the QMRA model in the reliability analysis is valuable, because this allows the health impact to be used as a reference point of comparison. In the context of advancing regulations that consider operational changes, conducting the complete reliability analysis is also advised, given a standardized approach to reliability analysis is established and a reliability target is determined.

Finally, Figure 5 shows the absolute values of the importance vector, which represents sensitivity information regarding the input variables, for the UF system. The importance vector is the gradient, a unit vector, of the performance function $g(X)$ at the point where it is approximated by a hyperplane. The gradient represents, for an infinitesimal increase in the value of the random variable, the resulting change in the value of the risk of infection. Hence, the higher the value of the importance vector for a given variable, the more sensitive the risk of infection is to this variable. The infectivity parameter is the variable with the highest value regardless of the level of acceptable risk. The raw water concentration is the second most important variable, except for the highest value of acceptable risk, where the plant performance is slightly more important. The intake volume is, in all cases, the least important of the random variables. The importance vectors for the conventional treatment scenarios, not shown here, exhibit almost identical patterns.

DISCUSSION

Value of the approach in decision-making

Risk and regulations

Traditionally, compliance with water treatment objectives was assured when monitoring of treated water for undesired contaminants achieved a certain standard, developed to reach a desired health target. Nowadays, it is known that

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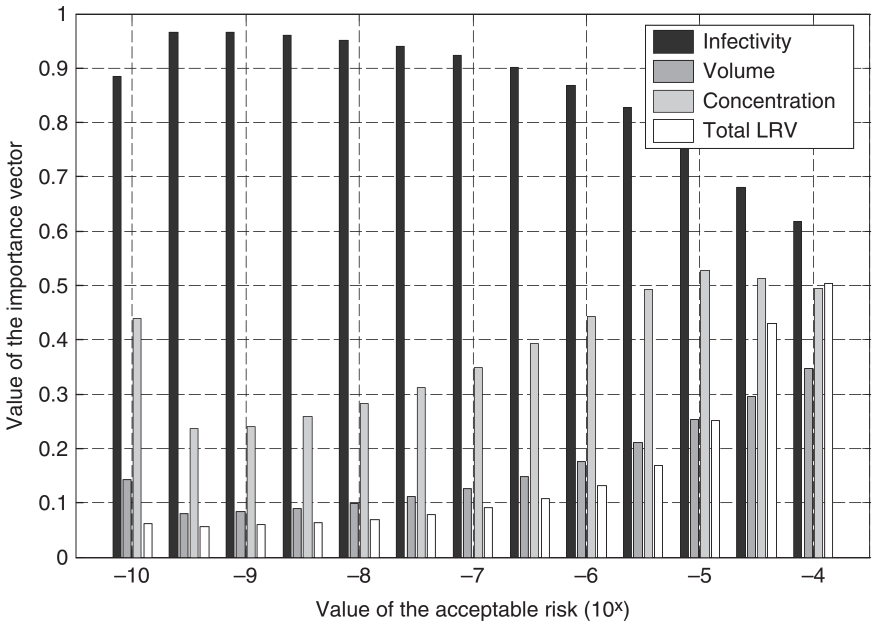

Figure 5 | Importance of random variable for UF system reliability analysis.

the economically or technologically feasible sampling of treated water is not statistically significant to detect disease-causing organisms that are a health concern at very low concentrations, such as *Cryptosporidium*. Instead of sampling-based standards, performance-based standards are now the norm. Yet, performances and other factors influencing health risk vary. LeChevallier & Buckley (2007) recommend that risk assessors should quantify uncertainties involved in the QMRA process and "define variables in terms of increasing or decreasing degree of certainty". The model proposed herein is a direct response to this recommendation, where uncertainty is addressed through reliability analysis.

While the mean risk of infection can be driven by one or two low performance events of low probability (Smeets 2008), reliability, defined earlier as the probability of producing water leading to an acceptable risk of infection, has the advantage of not being as sensitive to the precise evaluation of these low treatment plant performances (Jaidi 2007). Even if the risk values associated with these events is miscalculated by an order of magnitude due to incorrect evaluation of the low performances, they do not influence the probability of failure if their probability is neither extremely high nor extremely low. That is, the distribution of the risk of infection is more stable than the mean risk of infection. One value of the reliability approach is the fact that it provides a more stable output while addressing uncertainties.

Comparison of treatment technologies

Some authors working in the field of QMRA and in other engineering disciplines suggest that results from reliability analyses should only be used as a means of comparison because of the various assumptions in the structure of the model and in the input probability distributions (Faber 2006; Jaidi 2007). Yet, it is of the upmost importance to recognize that determining *LRV* distributions for both technologies poses many challenges. For example, in the present comparison, *LRV*s for the UF system were obtained from tests conducted weekly, for which the results are computed with a hydraulic model involving many assumptions. On the other hand, the performance distributions for the conventional treatment scenario were derived from a compilation of research studies where removals were computed using influent and effluent sampling data from one-time experiments on different systems. These two approaches for representing performance differ in the time scale at which the data are obtained and in the techniques for obtaining such data. It is

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reasonable to ask if a comparison based on such different sources of information is valid.

When conducting a comparison of operational reliability for two different technologies, the time scale and method used to assess the performance of the technologies should be similar. In this work, and in many regulatory approaches, this condition is not met. The results presented here should therefore be interpreted carefully, taking into account that the removal achieved by the UF and conventional technologies have not been assessed with similar methods. Finally, it is important to mention that time scales are also significant for other variables, such as C_{raw} and V. Yearly, monthly, daily, and even hourly averages of a single variable can be quite different from one another. To our knowledge, this issue has not been explicitly recognized for treatment performance, pathogen concentrations or water intake. Thus, when conducting a QMRA-based reliability analysis, the time scale of interest needs to be determined and data need to be collected in accordance with this time scale. As mentioned by Haas & Trussell (1998): "For contaminants with health effects associated with acute, or single dose, exposures, the presence of variability becomes important". We suggest that a relatively short time scale (daily) generally be considered, since risk analysis based on an annual time scale may fail to account for undesirable short-term variations in the risk of infection.

Reliability

Incorporating correlations

An aspect of reliability analysis that was not considered here is correlations between random variables. For example, the water consumption peaks could occur simultaneously with the raw water contamination peaks, or contrarily, consumption peaks could coincide with periods of low contamination, which would result in a risk distribution different from that shown in Figure 3. Correlations between raw water concentrations and performance of the treatment plant could also be observed. Moreover Haas & Kaymak (2003) found that inactivation of *Giardia muris* cysts by ozone decreased as the initial number of cysts in the water decreased. Our data set did not allow the computation of such correlations. Nonetheless, correlations should be considered in future research, as they may have a significant impact on reliability.

Use of FORM

The technique used to conduct the reliability analyses may also provide sensitivity information regarding the parameters. Figure 5 shows that in our analyses the risk is more sensitive to infectivity, r, and raw water concentration, C_{raw}, and less sensitive to the plant performance, *LRVtotal*, and water intake, V. Low values of the importance vector do not mean that a variable does not influence the result of the analysis but rather that more is known regarding this variable in comparison with other variables. Given the high values of the importance vectors for infectivity and raw water concentrations, more information regarding them would narrow their respective probability distributions and be the most beneficial when seeking to reduce the range of risk of infection obtained through the reliability analysis. For example, the raw water concentration distribution is highly uncertain, and would be undeniably improved by more comprehensive monitoring campaigns.

CONCLUSIONS

The reliability point of view for applying QMRA is demonstrated for estimating the reliability of a UF plant based on operational data and for comparing it with the reliability of three reference conventional treatment cases in terms of their ability to provide a tolerable risk of infection by *Cryptosporidium parvum*. In all cases, the UF system studied exhibited a higher reliability than the reference conventional physico-chemical treatment cases for a wide range of risk of infection. However, many issues such as the time scale at which the removals are measured and the methods used to establish the removal for different technologies impose moderation on the strength of this conclusion. It is our understanding that the current regulatory approaches for establishing removal credits do not adequately recognize the variability of the treatment processes and that this approach should be updated. The uncertainty associated with the computation of *LRV*s from integrity testing on UF membranes should also be quantified and incorporated in the reliability analysis. In general, the prediction of pathogen concentrations in treated water is a task that will require more attention if a QMRA-based reliability approach is widely adopted in Canadian provinces.

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Variability needs to be acknowledged, and regulators should base their choices on the operational reality of the different treatment plants. Other issues raised that will need to be addressed by decision-makers are the choice of an "acceptable" or "tolerable" level of risk of infection and its associated reliability, the time scale at which the model should be applied, the necessary amount of data to gather regarding the different input variables to reduce uncertainty and quantify variability satisfactorily, and the quantification of correlations among these variables.

In the end, the method presented here provides a sound basis on which to evaluate one criterion in what can be considered a multi-criteria decision problem. Choices such as the selection of a treatment technology or the modification of an existing water treatment system involve many other considerations, such as (in no particular order) cost, environmental impact, other acute or chronic health issues, aesthetic concerns, operability, operator safety, and consumers' perception of the technology.

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