

4

Performance models

This chapter describes two models for microbial removal or inactivation by water treatment processes. Section 4.2 describes a model for removal of particles by granular filtration, and shows how it can be used to predict the effect of process variables on the removal of microbial pathogens. Section 4.3 discusses a number of different models used to describe experimental disinfection data.

4.1 REMOVAL PROCESS MODELS

The removal process model described here is based on a mechanistic performance model that was first developed and applied in water filtration by O'Melia and co-workers (O'Melia & Stumm, 1967; Yao, Habibian & O'Melia, 1971). Substantial modifications have been made by Fitzpatrick & Spielman (1973), Rajagopalan & Tien (1976) and others. An extensive review of these theoretical models is available (Elimelech et al., 1995). The version described here is that of Rajagopalan & Tien (1976). It considers particle removal by

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granular filters to involve two steps: transport and attachment. This section describes these two steps, and then considers each of the process variables in terms of their effect on the removal of microbial pathogens.

4.1.1 Transport

In the removal process, particles are first transported from suspension to a nearby media grain. The transport step, which is physical–hydrodynamic in nature, involves three main mechanisms:

- *interception* — particles following the streamline of fluid flow come into contact with a media grain (this mechanism is affected by the size of the particle);
- *sedimentation* — particles with density greater than that of water deviate from the streamline of fluid flow by gravity and come into contact with a media grain;
- *diffusion* — particles subjected to random motion by their thermal energy come into contact with a media grain.

Single collector efficiencies (defined as the ratio of the number of successful collisions between particles and a filter media grain to the total number of potential collisions in the projected cross-sectional area of the media grain) have been well developed to describe these transport mechanisms.

4.1.2 Attachment

To be removed, a particle must not only come into contact with a media grain, but must also attach to it. Not all contacts between particles and media lead to attachment; an attachment efficiency (α) is used to represent the fraction of successful contact. The value of α varies from one (all contact results in attachment) to zero (no contact results in attachment). In drinking-water treatment, chemical coagulation pretreatment promotes attachment efficiency, with optimized coagulation conditions increasing the value of α . A predictive equation for removal efficiency can be derived from single collector efficiency, attachment efficiency and the total number of media collectors.

4.1.3 Effects of process variables on removal efficiency

Variables that can affect the efficiency of removal of microbial contaminants by granular filtration include coagulation conditions, filtration rate, diameter of medium, filter depth and water temperature. Figure 4.1 illustrates the effects of these variables, as a function of particle size, and Table 4.1 shows the

parameters used in these simulations. The theoretical results give some indication of removal of microbial pathogens by granular filtration, but the model has limitations. First, it was developed for a clean bed and a monodisperse suspension, and thus does not take into consideration temporal variation in filter performance. Second, it was developed for passive (nonmotile) particles; however, some microbes (e.g. some species of coliform bacteria) are motile. Cell motility may change both transport mechanism and removal efficiency. Little is known of the effects of cell motility on filter performance, and the model does not take this factor into account. Finally, the model has been successfully tested for nonmicrobial particles but has yet to be systematically tested with microbes. Each of the process variables, and its effect on removal efficiencies, is considered in detail below.

Particle size

Model calculations indicate that particle diameter has a dramatic effect on removal mechanisms and efficiency (Figure 4.1a). Microbes that are submicron in size (e.g. viruses) are transported to media particles by molecular diffusion (Brownian motion). For such particles, removal efficiency decreases as particle size increases, because small particles diffuse faster than large ones. Assuming that microbes do not change in size before entering the filter, and that coagulation conditions are optimal ($\alpha = 1.0$), model predictions suggest the filter could remove 6.38 logs of MS2 bacteriophage (2.5×10^{-8} m diameter), 3.21 logs of rotavirus (7.0×10^{-8} m) and 2.53 logs of PRD1 bacteriophage (10^{-7} m).

Microbes with a diameter larger than about a few microns (e.g. protozoan cysts, algae and some bacteria) are removed by interception (Figure 4.1a). Removal efficiency of such particles increases as microbial size increases, because larger particles are more easily intercepted by the filter medium. When the filter is operated under optimal chemical coagulation, the predicted removal efficiencies are 1.44 logs for *Cryptosporidium* oocysts (5×10^{-6} m) and 4 logs for *Giardia* cysts (10×10^{-6} m). Numerous studies (e.g. Nieminski & Ongerth, 1995; Swertfeger et al., 1999) show that *Giardia* cysts are removed more efficiently than *Cryptosporidium* oocysts. Removal by gravity is never a dominant mechanism in these simulations; even for large microbes such as *Balantidium coli* cysts (6×10^{-5} m), the density of the particles (1.05 g/cm^3) is similar to that of water. The effect of gravity is insignificant for most microorganisms in the influent to filters, unless they are associated with dense particles.

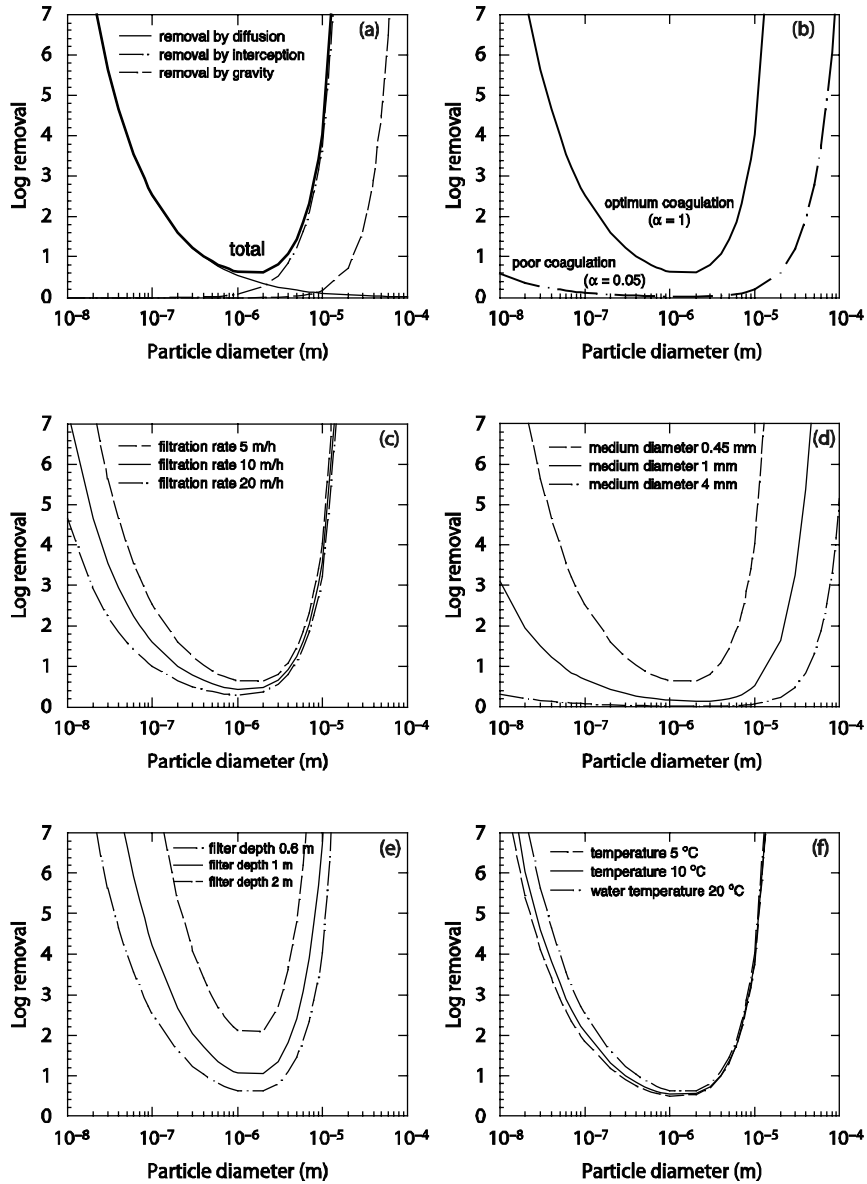


Figure 4.1 Effects of process variables on removal efficiency of granular filtration (simulation parameters are shown in Table 4.1).

Table 4.1 Parameters used in model calculations for Figure 4.1

Process variables	Values
Coagulation condition (α)	1.0 ^a
Filtration rate	5 m/h ^b
Medium diameter	0.45 mm ^c
Filter depth	0.6 m ^d
Water temperature	20°C ^e
Media configuration	monomedia
Particle density	1.05 g/cm ³
Hamaker constant	10 ⁻²⁰ J
Filter porosity	0.4

^a 1.0 and 0.05 in Figure 4.1b

^b 5, 10 and 20 in Figure 4.1c

^c 0.45, 1 and 4 mm in Figure 4.1d

^d 0.6, 1 and 2 m in Figure 4.1e

^e 5, 10 and 20°C in Figure 4.1f

Removal efficiency is lowest for microbes with a diameter of about 1 μm (Figure 4.1a). Particles of about this size are too large for diffusion to be effective and too small for interception to be effective. Thus, even with optimal coagulation conditions ($\alpha = 1.0$), the model predicts that the filter removes only 0.64 logs of coliform bacteria (1.0×10^{-6} m). Some bacteria in this size range will be motile, which will influence their removal, but the model does not take this into account.

Pretreatment with chemical coagulants

The calculations shown in Figure 4.1b illustrate the significant effect on filtration performance of pretreatment with chemical coagulants. When coagulation conditions change from optimal ($\alpha = 1.0$) to poor ($\alpha = 0.05$), log removals deteriorate from 6.38 to 0.20 for MS2 bacteriophage, from 0.64 to 0.03 for coliform bacteria, from 1.44 to 0.07 for *Cryptosporidium* oocysts, and from 4.00 to 0.20 for *Giardia* cysts. These simulated effects of chemical coagulation on filtration performance are qualitatively consistent with many experimental results (e.g. Al-Ani et al., 1986; Ongerth, 1990).

Filtration rate

The effect of filtration rate on filter performance depends on the size of the particle (Figure 4.1c). For microbes greater than a few microns in diameter, with a density close to that of water, removal is mainly by interception, and is therefore not strongly affected by filtration rate. Thus, increasing the filtration rate from 5 m/h to 20 m/h decreases the modelled removal efficiency only

slightly. For example, the removal of *Giardia* cysts reduces from 4.03 logs at a filtration rate of 5 m/h, to 3.58 logs at 10 m/h and to 3.22 logs at 20 m/h. A similar result has been observed experimentally by Al-Ani et al. (1986). However, the effects of filtration rate on removal efficiency are much more pronounced for submicron microbes, where removal is mainly due to diffusion, which is strongly affected by filtration rate. For example, the modelled removal of rotavirus decreases from 3.21 logs at a filtration rate of 5 m/h to 1.27 logs at 20 m/h.

Filter medium size and depth

Filter medium size (Figure 4.1d) and depth (Figure 4.1e) strongly affect microbial removal by filtration. Decreasing the size of the medium or increasing the depth of the filter increases the removal efficiency. This is in part because the number of filter media collectors increases, favouring the capture of particles. Decreasing the medium size also enhances the contact opportunity between particles and media grains due to diffusion and interception.

Temperature

Temperature has some effect on the removal of submicron microbes, but almost no effect on the removal of those larger than 1 μm (Figure 4.1f). When the modelled temperature was reduced from 20°C to 5°C, the removal efficiency of MS2 bacteriophage decreased from 6.38 logs to 4.66 logs, although the removal of *Cryptosporidium* oocysts was only reduced from 1.44 logs to 1.31 logs. This is partly because particle removal by diffusion (important for removal of submicron microbes) is strongly dependent on temperature, with an increase in temperature decreasing water viscosity and thus increasing the rate of diffusion. Particle removal by interception (important for larger microbes) is, on the other hand, not affected by temperature.

4.2 DISINFECTION MODELS

A number of researchers have used models to describe experimental disinfection data (Haas & Karra, 1984; Haas et al., 1995). The simplest disinfection model (Equation 1) is a combined one proposed by Chick (1908) and Watson (1908). In the Chick–Watson model, the rate of inactivation of a microorganism is dependent upon the concentration of the disinfectant and contact time. Equation 2 represents the integrated form of Equation 1, and simplifies to CT (the disinfectant concentration multiplied by contact time) when n (the coefficient of dilution) is equal to 1.

$$(1) r = -kC^n N$$

$$(2) \ln(N/N_0) = -kC^n t$$

where:

r = rate of microorganism inactivation

k, n = empirical constants

C = disinfectant concentration, M/V

N = microorganism concentration at time t , #/V

N_0 = microorganism concentration at time t , #/V

Another disinfection model, represented in equations 3 and 4, was proposed by Hom (1972). It provides for a relationship between disinfectant concentration and contact time, and empirical constants m and n . The Hom model successfully described the disinfection of *Giardia* (Haas et al. 1995) and *Cryptosporidium* (Finch et al., 1993), and converts to the Chick-Watson model when m is equal to 1. In a typical disinfection experiment, disinfectant concentration decreases with time and a first order decay rate is generally assumed (Equation 5). Haas et al. (1995) presented the integrated form (Equation 6) after substitution of Equation 5 into Equation 3.

$$r = -kmNC^n t^{m-1} \quad (3)$$

$$\ln(N/N_0) = -kC^n t^m \quad (4)$$

$$C = C_0 e^{-k't} \quad (5)$$

$$\ln(N/N_0) = -(m/nk')^m k C_0^n [1 - e^{(-nk't/m)}]^m \quad (6)$$

where:

k' = first order decay rate of disinfectant, 1/t

C_0 = initial disinfectant concentration, M/V

k, m, n : empirical constants for Hom model

t = contact time

Variations on these disinfection models are possible but are rarely used. The simple Chick-Watson model was the most appropriate model for comparing *Cryptosporidium* disinfection data from a number of research groups, because of the inherent variation in experimental data (unpublished data, International *Cryptosporidium* CT Workshop, Washington, DC, January 12–14, 1998).

4.2.1 Integrated disinfection design framework

The integrated disinfection design framework (IDDF) model incorporates disinfection kinetics into a hydraulic model of the treatment process (Bellamy, Finch & Haas, 1998). The four steps in implementing the framework are:

1. Determine the contactor hydraulics.
2. Determine the disinfectant characteristics.
3. Determine the inactivation kinetics.
4. Develop a disinfection model.

The advantage of the IDDF model is that it more accurately predicts microbial inactivation because it accounts for basin hydraulics, the decay of the disinfectant within the basin and non-linear disinfection kinetics. The model can be run as a spreadsheet calculation or with an easy-to-use operator interface. Because of the need to balance disinfection efficiency with disinfection by-product formation, a variation of the IDDF model will probably be used to estimate *Cryptosporidium* inactivation under future regulatory scenarios.

5

Treatment variability

Maintaining reliable treatment performance is critical for minimizing microbial risk, because health effects associated with microbial contaminants tend to be due to short-term, single dose exposure rather than long-term exposure. However, drinking-water treatment is a dynamic process and the treatment efficiency for removal or inactivation of microbial pathogens is variable. This is illustrated by an on-site survey of 100 water treatment plants across the USA, which found that the removal efficiency of particles greater than 2 μm ranged from 0.04 to 5.5 logs, with a median value of 2.8 logs (McTigue et al., 1998). The study also found significant variation in the removal efficiencies of *Cryptosporidium* oocysts and *Giardia* cysts, although the removal of these pathogens did not necessarily correlate directly with the removal of particles.

Some process variation is normal and expected; however, too much variability can result in treatment failures, leading to waterborne disease outbreaks. It is the objective of drinking-water standards, therefore, to keep process variability within acceptable limits.