# Modeling and optimization of membrane lifetime in dead-end ultra filtration

Zondervan, Edwin; Roffel, Brian

*Published in:*
Journal of Membrane Science

*DOI:*
10.1016/j.memsci.2008.05.023

Journal of Membrane Science 322 (2008) 46–51

Contents lists available at ScienceDirect

Journal of Membrane Science

journal homepage: www.elsevier.com/locate/memsci

# Modeling and optimization of membrane lifetime in dead-end ultra filtration

Edwin Zondervan [a,*], Brian Roffel [b]

[a] Eindhoven University of Technology, Department of Chemical Engineering and Chemistry, P.O. Box 513, 5600 MB Eindhoven, The Netherlands
[b] Groningen University, Chemical Engineering Department, Institute for Technology & Management, Nijenborg 4, 9747AG Groningen, The Netherlands

ARTICLE INFO

*Article history:*
Received 9 July 2007
Received in revised form 28 April 2008
Accepted 7 May 2008
Available online 21 May 2008

*Keywords:*
Ultra filtration
Membrane lifetime
Modeling
Optimization

ABSTRACT

In this paper, a membrane lifetime model is developed and experimentally validated. The lifetime model is based on the Weibull probability density function. The lifetime model can be used to determine an unambiguous characteristic membrane lifetime. Experimental results showed that membrane lifetime shortens if the average membrane fouling status increases. The lifetime modeling results are then used to determine the economic lifetime of membranes. Subsequently, the economic lifetime of a membrane is used to optimize membrane lifetime, i.e. minimizing the total costs. Based on the experimental results it can be concluded that the total costs are minimal if the average membrane fouling status is approximately 1.7× the membrane resistance.



## 1. Introduction

Ultra filtration (UF) is increasingly used as an intermediate or complete surface water purification technique. UF membranes have high selectivity and became economically attractive as a water purification technique during the last fifteen years. Membrane performance, however, is influenced by fouling. For this reason membranes have to be frequently cleaned. In the short term this is done by backwashes, and in the long term cleaning chemicals are used.

Currently UF operating settings are based on rules of thumb and pilot plant studies. It is expected that overall operating costs may be reduced by means of process optimization.

Recently attention has been directed towards optimization of filtration [1], backwashing [2] and chemical cleaning [3] of UF membranes. Intermediate term optimization, where membrane performance is optimized over multiple production cycles was also reported [4,5]. Long term optimization of UF membranes, where membrane ageing/lifetime is incorporated, is another area of research interest.

In ref. [6] the setup and execution of an experimental design, in which potential ageing factors were evaluated by means of accelerated lifetime testing was discussed. These results showed that the membrane fouling resistance is a significant ageing factor, influencing lifetime.

In this paper we will develop and validate a statistical membrane lifetime model. From the model a clear definition of membrane life time can be derived. Subsequently, the model is used to evaluate the capital costs and the operational costs of an ultra filtration membrane as function of the fouling resistance. This result may be useful in the development of a long-term fouling control strategy.

## 2. Theory

### 2.1. Lifetime modeling

Statistical analysis and modeling based on data collected by means of accelerated ageing tests has been done in different fields of science and engineering [7–12].

An example of a commonly used lifetime model is the so-called Weibull distribution. There exist several other classes of lifetime models, for example the exponential distribution, log-normal distribution, log-logistic distribution, gamma distribution, inverse Gaussian distribution, log-location distribution, piecewise constant distribution and polynomial distribution. Besides that, there are the so-called mixture models (combining several model classes). However, many of those models can only be used in specific situations. The Weibull model is robust, can be applied to many types of lifetime data and has only two model parameters.

Application to the lifetimes or durability of manufactured items such as ball bearings, automobile components and electrical insulation is very common. It is also used in biological and medical applications, for example, in studies on the time to the occurrence of tumors in human populations or in laboratory animals [13].

* Corresponding author. Tel.: +31 40 247 5433.
*E-mail address:* e.zondervan@tue.nl (E. Zondervan).

0376-7388/$ – see front matter © 2008 Elsevier B.V. All rights reserved.
doi:10.1016/j.memsci.2008.05.023

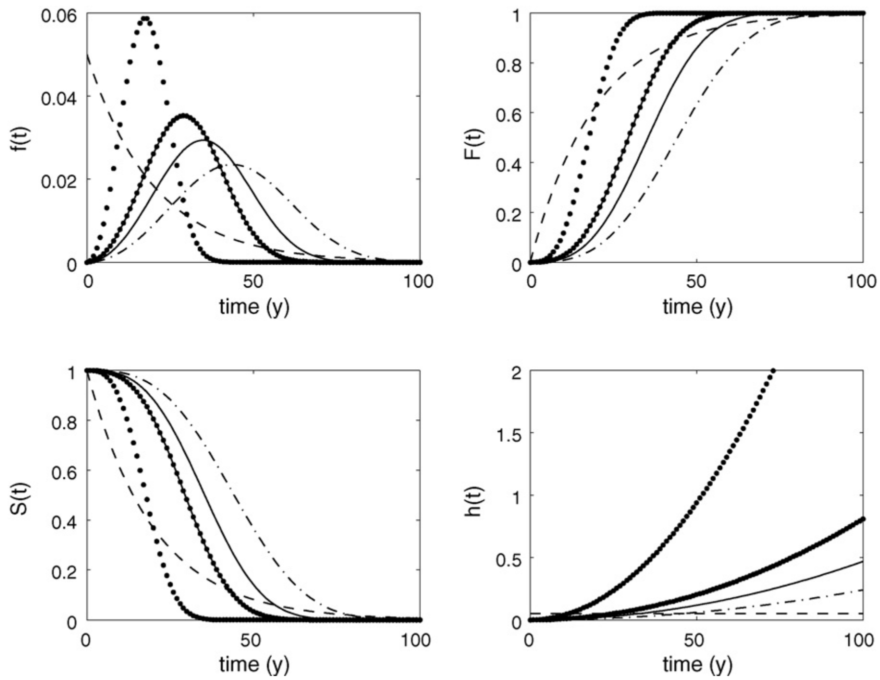


**Fig. 1.** Examples of the Weibull probability density function, the cumulative density function the survivor function and the hazard function for different values of λ and β. *Legend:* (—) $\lambda = 0.05$, $\beta = 3$; (···) $\lambda = 0.05$, $\beta = 2$; (- - -) $\lambda = 0.05$, $\beta = 1$; (- ·- ·-) $\lambda = 0.03$, $\beta = 3$; (●●●●) $\lambda = 0.02$, $\beta = 3$.

*2.2. Definitions*

Consider the case of a single continuous lifetime variable, *T*. Specifically, let *T* be a nonnegative random variable representing the lifetimes of individuals in some population. All functions are defined over the interval $[0, \infty\rangle$. Let $f(t)$ denote the probability density function (p.d.f.) of *T* and let the (cumulative) distribution function (c.d.f.) be:

$$F(t) = \int_0^t f(x)\,dx \tag{1}$$

The probability of an individual surviving to time *t* is given by the survivor function or reliability function:

$$S(t) = \int_t^\infty f(x)\,dx \tag{2}$$

The hazard function specifies the instantaneous rate of death or failure at time *t*:

$$h(t) = -\frac{d}{dt}\log[S(t)] \tag{3}$$

*2.3. The Weibull distribution*

The Weibull distribution is perhaps the most widely used lifetime distribution model. The Weibull distribution has a hazard function of the form:

$$h(t) = \lambda\beta(\lambda t)^{\beta-1} \tag{4}$$

where $\lambda > 0$ and $\beta > 0$ are distribution model parameters. It includes the exponential distribution as the special case when $\beta = 1$. By Eqs. (1) and (2), the p.d.f. and survivor functions of the distribution are:

$$f(t) = \lambda\beta(\lambda t)^{\beta-1}\,\exp[-(\lambda t)^\beta] \tag{5}$$

and

$$S(t) = \exp[-(\lambda t)^\beta] \tag{6}$$

The Weibull hazard function is a monotone increasing function when $\beta > 1$, decreasing when $\beta < 1$ and constant when $\beta = 1$. In Fig. 1 different Weibull models are shown for different values of β and λ.

The model is flexible and has been found to provide a good description of many types of lifetime data. This property and the fact that the model gives simple expressions for the p.d.f. and survivor and hazard functions partly account for its popularity. The Weibull distribution arises as an asymptotic extreme value distribution and in some instances this can be used to provide motivation for it as a model. The scale parameter $\alpha = \lambda^{-1}$ is often used instead of λ. In some areas, especially in engineering α is termed the characteristic life of the distribution. The shape of the Weibull p.d.f. and hazard function depends only on β, which is sometimes called the shape parameter for the distribution. The effect of λ is to change the scale of the horizontal axis and not the basic shape of the distribution.

## 3. Experimental

In an earlier performed study [6], accelerated ageing tests were performed to determine, by means of experimental design and analysis of variance, which potential ageing factors significantly influenced membrane integrity. The potential factors were varied at two levels (high and low): the membrane fouling status (clean membranes and severely fouled membranes), the number of applied back pulses (backwashes) (100,000 and 300,000 pulses), the magnitude of the applied back pulses (50 and 200 kPa (0.5 and 2.0 bar)) and the concentration of oxidative cleaning agent used for back pulsing (0 and 1000 $\mu l\,l^{-1}$ (0 and 1000 ppm) sodium hypochlorite, pH 12).

Each experiment was performed in threefold. During the tests membrane integrity was evaluated by means of permeability measurements, pressure decay tests and bubble tests. Also tensile tests were performed to investigate mechanical properties of the fibers. The research showed that the number of back pulses, the fouling status of the membrane and the combination of those two factors were significant within the 95% and 99% range of the F-test.

Based on those outcomes was concluded that a model describing membrane lifetime as a function of time should most probably depend on the average fouling status of the membrane.

Specifically the data from the bubble tests was useful, as it directly showed the number of defected fibers as a function of the number of applied back pulses.

Because the number of data points from the experimental design was limited, an additional series of accelerated tests had to be performed.

In this study we include bubble point data obtained from an extra series of experiments, where we have measured integrity frequently as a function of the applied number of back pulses.

### 3.1. Pressure pulse unit

In Fig. 2 the pressure pulse unit (PPU) is shown. The main part of the PPU is the membrane pump, which can pump sodium hypo chlorite – or water – at a pressure of 0–300 kPa (0–3 bars) through membrane modules with a frequency of approximately 20–30 pulses per minute (in normal operation a back pulse is applied 4 times per hour). Pulse tests are performed, reflecting a plant's "worst case scenario", where valves open and close frequently, while generating fast pressure changes (from 0 to 200 kPa (0 to 2 bars) in 2–3 s). Using two pressure restrictions, two sets of experiments can be simultaneously performed in threefold at two different pressures. The used PES membrane modules were Norit-Xiga RX300 PSU hollow fiber UF modules with a membrane surface of 0.07 $m^2$. The Xiga fibers have a polysulfone housing and PES/PVP flow distributors (fibers). Every test module contains 100 fibers with a length of 30 cm. Potting procedures and materials for clean and fouled fibers were the same.

Three series of pulse tests were performed with clean fibers, intermediately fouled fibers and severely fouled fibers. The average initial membrane resistance was determined to be $5 \times 10^{11}$, $1.25 \times 10^{12}$ and $2 \times 10^{12}$ $m^{-1}$, respectively.

Severely fouled modules were assembled from fibers that were taken from a module that was operated in a pilot pant. Intermediately fouled modules were obtained from a module operating in a full scale installation. Both modules were filtrating canal water. The water is known to have a high organic content (TOC and DOC values of approximately 10 mg $l^{-1}$).

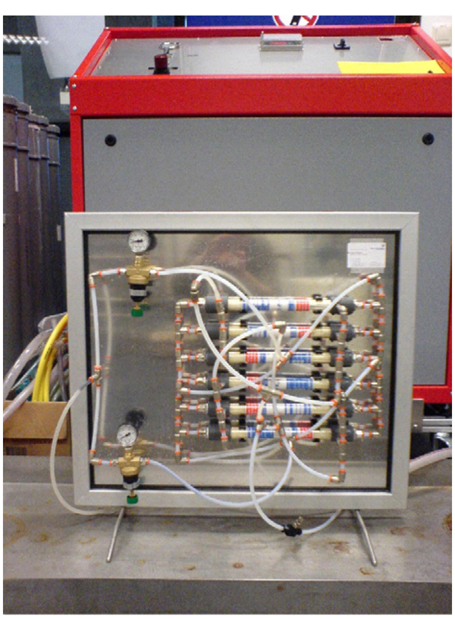

**Fig. 2.** Graphic representation of the pressure pulse unit.

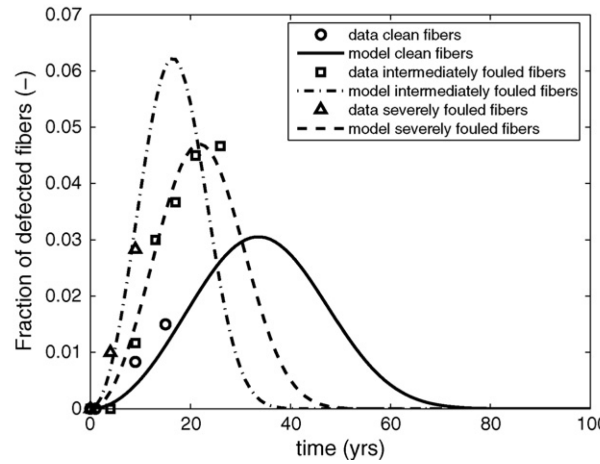


**Fig. 3.** Experimental data and fitted lifetime models.

The module from the pilot plant was operated over a 6-month period, and was only cleaned with sodium hydroxide. The module taken from the full scale installation was operated over a 7-year period, the cleaning history was not exactly known, but it is assumed that the module was cleaned frequently (every 24 h) with sodium hydroxide (0.05 M) and hydrochloric acid (0.05 M), while sodium hypochlorite (100 $\mu$l $l^{-1}$ (100 ppm)) cleaning was only done occasionally. The standard operating conditions for both modules were: filtration flux: 60 l $h^{-1}$ $m^{-2}$, backwash flux: 200 l $h^{-1}$ $m^{-2}$, duration of a filtration run: 20 min, backwash duration: 1 min.

### 3.2. Procedure

At frequent intervals, the pulse tests were interrupted and membrane integrity was evaluated by means of permeability testing, pressure decay testing and bubble point testing. In this research only bubble test date is presented, as bubble test data can be used to determine the number of defected fibers in a module as function of the number of applied back pulses. Defected fibers were detected and closed with special pins, before experimentation continued.

## 4. Results and discussion

### 4.1. Lifetime modeling

In Fig. 3 the experimental data and the fitted Weibull models are plotted. Table 1 shows the calculated model parameters. During accelerated ageing tests, fibers take a long time to fail. To collect data within acceptable experimentation time, it is necessary to terminate the experiment before all fibers have failed. Consequently, certain fiber lifetimes are *censored*. Censoring is not an uncommon practice in the collection and analysis of lifetime data. A robust model, such as the Weibull model, is able to cope with the effects of censoring.

Although censoring takes place, data can be interpreted and fitted correctly because a proper model structure has been chosen, the Weibull model. The Weibull model has properties that, for example, a linear approximation does not have, e.g. the surface below the curve should be equal to one (100% of the fibers have defected).

The results of Table 1 show that the characteristic life time ($\alpha$), as well as $t_{1/10}$ and $t_{1/100}$ decrease when the fouling state of the membrane increase: membrane lifetime shortens when the membrane is increasingly fouled.

**Table 1**
Calculated model parameters and characteristic lifetimes

| | $R$ ($m^{-1}$) | $\lambda$ ($year^{-1}$) | $\beta$ ($year^{-1}$) | $\alpha$ (years) | $t_{1/10}$ (years) | $t_{1/100}$ (years) |
|---|---|---|---|---|---|---|
| Clean | $5.00 \times 10^{11}$ | 0.026 | 3.0 | 38.5 | 18.1 | 8.3 |
| Intermediate fouling | $1.25 \times 10^{12}$ | 0.040 | 3.0 | 25.0 | 11.8 | 5.4 |
| Severe fouling | $2.00 \times 10^{12}$ | 0.050 | 3.0 | 20.0 | 9.5 | 4.3 |

In Fig. 4 the cumulative density function, the survivor function and the hazard function are plotted for the specific experimental cases.

### 4.2. Lifetime optimization

The cumulative density function reflects the total number of defected fibers in a module as a function of operating time. The costs for fiber reparation are proportional to the number of defected fibers. In Fig. 5, the upper left figure shows the reparation costs as a function of time in €/m$^2$. The reparation costs are calculated from the cumulative density function according to:

$$C_{REPA} = \frac{Nc}{A} F(t) \quad (7)$$

where $N$ is the number of fibers present in a module, $c$ are the costs for reparation of a single fiber and $A$ is the membrane surface. Calculations were performed for a commercially available model with $N = 10,000$, $c = 5$ € and $A = 40\,m^2$. In the upper left corner of Fig. 5 also a horizontal line is shown, expressing the costs for membrane replacement $C_{replace} = 75$ € $m^{-2}$ (based on costs for repair, downtime, bubble testing and isolation of the compromised fiber). The point where the horizontal line intersects with the curve, determines the economic lifetime $t_L$ of a module. For increased fouling, the economic lifetime becomes shorter, as shown in the upper right corner of Fig. 5.

The capital costs (or investment costs) are correlated to the economic lifetime of a module by a simple hyperbolic relationship:

$$C_{CAP} = \frac{K}{t_L} \quad (8)$$

with $K = 350$ (€ year) $m^{-2}$. If the economic lifetime is 7 years, the capital costs will be around 53 € $m^{-2}$. A module element with a membrane surface of 40 $m^2$ has capital costs of around 2100 €.

If the economic lifetime is short, the capital costs will be high, if the lifetime is long, the capital costs will be low, as shown in the lower left corner of Fig. 5.

The operational costs are calculated from energy requirements, materials usages (cleaning chemicals, flocculant dosing, waste) and depreciation costs. The cost calculation is quite extensive, and perhaps out of the scope of this paper. However, in a paper recently published [5], we discuss in detail how operational costs can be calculated and optimized. Using these models, we have evaluated how operational costs change when the maximum allowed fouling level (resistance) is changed. These results are graphically represented in Fig. 6.

Combining the results of the upper right figure and the lower left figure of Fig. 5 the relationship between the fouling resistance and the capital costs can be obtained, as shown in the lower right corner of Fig. 5.

Capital costs increase as the membrane fouls more (where fouling is expressed as an increase of the fouling resistance), but operational costs decrease if more fouling is allowed.

In Fig. 6 the capital costs $C_{CAP}$ and an operational costs approximation $C_{OP}$ are plotted together with the total costs $C_{TOT}$. In refs. [4,5] a detailed description can be found on how the operational costs as function of the average membrane irreversible fouling state were calculated using a fouling model and cost function, based on energy consumption, material costs (feed water, waste water, coagulant, cleaning chemicals, etc.) and depreciation costs, over multiple chemical cleaning cycles. It is finally noted that, in this

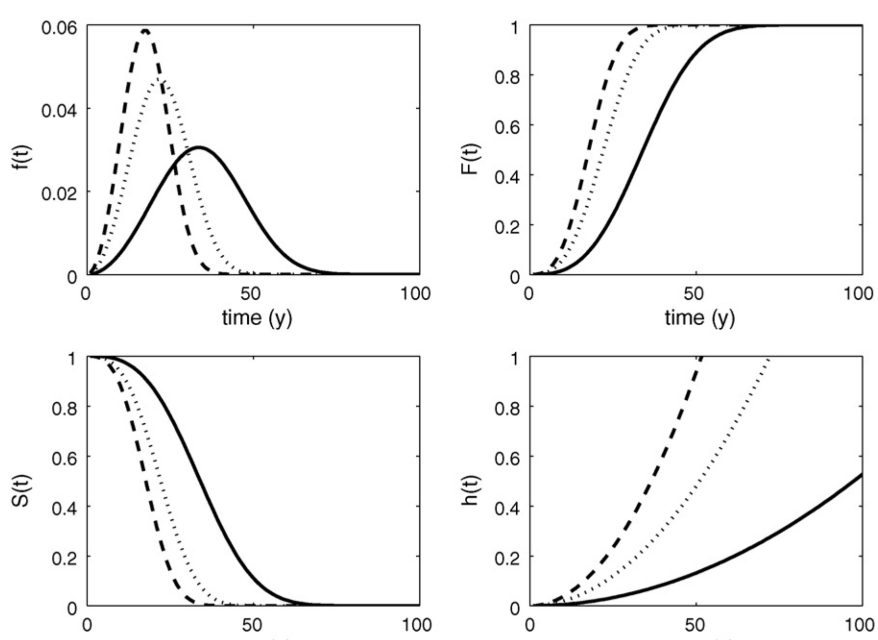


**Fig. 4.** The Weibull probability density function, the cumulative density function the survivor function and the hazard function for different membrane fouling states. *Legend:* (—) $R = 5 \times 10^{11}\,m^{-1}$; (···) $R = 1.25 \times 10^{12}\,m^{-1}$; (- - -) $R = 2 \times 10^{12}\,m^{-1}$.

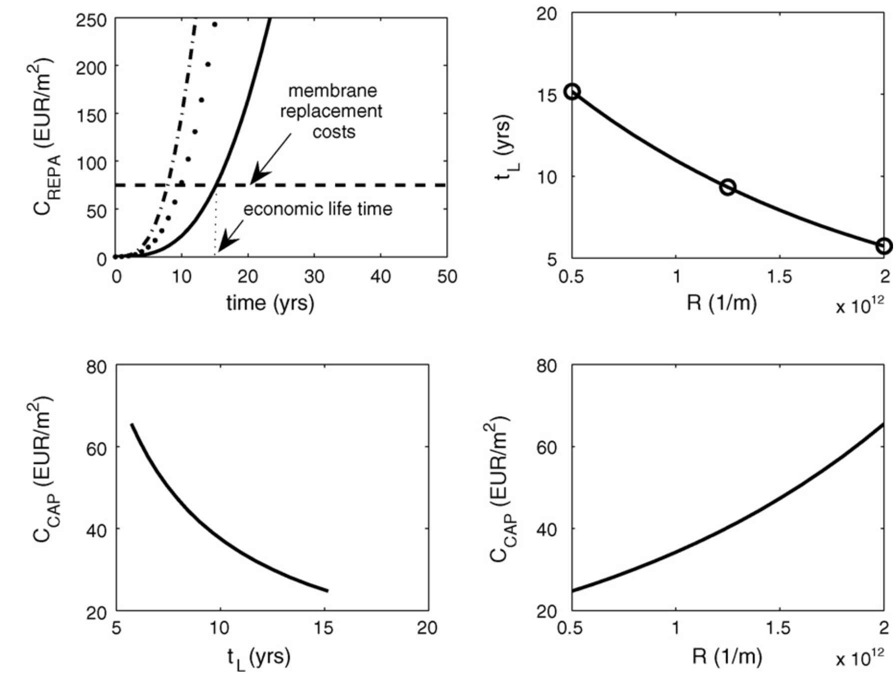


**Fig. 5.** Upper left: reparation costs as function of operating time for different fouling resistances. *Legend:* (—) $R = 5 \times 10^{11}$ m$^{-1}$; (···) $R = 1.25 \times 10^{12}$ m$^{-1}$; (- - -) $R = 2 \times 10^{12}$ m$^{-1}$, upper right: resistance as function of economic lifetime, lower left: capital costs as function of economic life time and lower right: capital costs as function of fouling resistance.

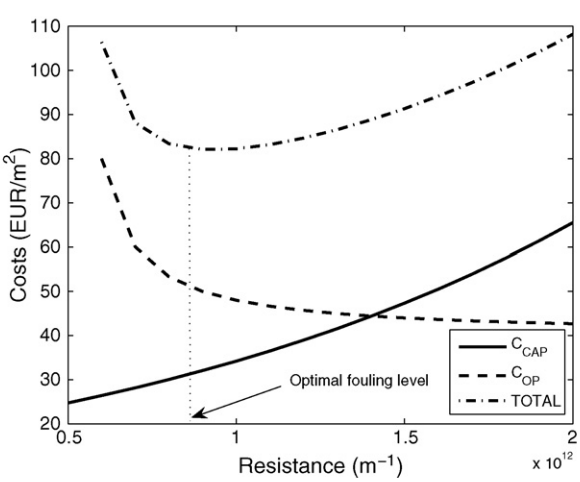


**Fig. 6.** Optimal fouling resistance calculated from the capital costs and operational costs.

study, inflation effects were not incorporated. From Fig. 6 it can be seen that the total costs are minimal at a fouling level of around 1.7× the membrane resistance ($5 \times 10^{11}$ m$^{-1}$).

## 5. Conclusions

A membrane lifetime model was developed and experimentally validated. The lifetime model is based on the Weibull probability density function. The lifetime model can be used to determine an unambiguous characteristic membrane lifetime. Experimental results showed that membrane lifetime shortens if the average membrane fouling status increases. The lifetime modeling results are then used to determine the economic lifetime of membranes. Subsequently, the economic lifetime of a membrane is used to optimize membrane lifetime, which means minimization of the total costs. Based on the experimental results presented, the total costs are minimal if the average fouling status is approximately 1.7× the membrane resistance ($5.10^{11}$ m$^{-1}$).

## Acknowledgments

The financial support of NWO/STW, Aquacare Europe, Hatenboer-Water, Norit membrane Technology and Vitens Laboratory & Process technology is gratefully acknowledged.

## Nomenclature

| | |
|---|---|
| $\alpha$ | characteristic lifetime (years) |
| $A$ | membrane surface (m$^2$) |
| $\beta$ | shape parameter |
| $c$ | repair costs (€) |
| $C_{CAP}$ | capital costs (€/m$^2$) |
| $C_{REPA}$ | repair costs (€/m$^2$) |
| $C_{OP}$ | operational costs (€/m$^2$) |
| $f$ | probability density function |
| $F$ | cumulative density function |
| $h$ | hazard function |
| $\lambda$ | Scale parameter (year$^{-1}$) |
| $N$ | number of fibers in a module |
| $R$ | membrane fouling resistance (m$^{-1}$) |
| $S$ | survivor function |
| $t$ | time (years) |
| $t_L$ | economic lifetime (years) |
| $t_R$ | reference time (years) |

## References

[1] B. Blankert, C. Kattenbelt, B.H.L. Betlem, B. Roffel, Dynamic optimization of a dead-end filtration trajectory: non-ideal cake filtration, Journal of Membrane Science 290 (1–2) (2007) 114–124.
[2] B. Blankert, Short to medium term optimization of dead-end ultrafiltration, Ph.D. dissertation, 2007, Groningen University, the Netherlands (Chapter 5).
[3] E. Zondervan, B.H.L. Betlem, B. Roffel, Development of a dynamic model for cleaning ultrafiltration membranes fouled by surface water, Joural of Membrane Science 289 (1–2) (2007) 26.
[4] B. Blankert, Short to medium term optimization of dead-end ultrafiltration, Ph.D. dissertation, 2007, Groningen University, the Netherlands (Chapter 8).
[5] E. Zondervan, B. Blankert, B.H.L. Betlem, B. Roffel, Modeling and optimization of a sequence of chemical cleaning cycles in dead-end ultrafiltration, Journal of Membrane Science 308 (1–2) (2008) 207.
[6] E. Zondervan, A. Zwijnenburg, B. Roffel, Statistical analysis of data from accelerated ageing tests of PES UF membranes, Journal of Membrane Science 300 (1–2) (2007) 111.
[7] G.U. Crevecoeur, A model for the integrity assessment of ageing repairable systems, IEEE Transactions on reliability (42) (1993) 1.
[8] L. Lee, Testing adequacy of the Weibull and log linear rate models for a Poisson process, Technometrics 22 (2) (1980) 195.
[9] D. Ryu, S. Chang, Novel concepts for reliability technology, Microelectronics reliability 45 (2005) 611.
[10] K.S. Wang, F.S. Hsu, P.P. Liu, Modeling the bathub shape hazard rate function in terms of reliability, Reliability Engineering and System Safety 75 (2002) 397.
[11] Z. Chen, A new two-parameter lifetime distribution with bathtub shape or increasing failure rate function, Statistics & Probability Letters 49 (2000) 155.
[12] R. Jiang, P. Ji, X. Xiao, Aging property of unimodal failure rate models, Reliability Engineering and System Safety 79 (2003) 113.
[13] J.F. Lawless, Statistical Methods and Models for Life Time Data Analysis, Wiley, 2006.