RESEARCH ARTICLE

Performance based modelling of long-term deterioration to support rehabilitation and investment decisions in drinking water distribution systems

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Managing the urban drinking water system in the long-term in order to maintain system performance can be challenging due to the difficulty of modelling future deterioration of the networks. This paper establishes a methodology for cohort survival models where historical (empirical) data on decommissioning ages of pipes are used to calibrate survival functions of pipe cohorts according to service level targets. The benefit of the approach is that remaining useful life of pipes, future renewal rates and investment needs can be governed by a required level of service in the network. A case study shows how the methodology can be applied to a cohort of drinking water pipes to create a 'calibration curve', which is a survival function calibrated with empirical data

Keywords: asset management, survival function, cohort survival model

1. Introduction

An important objective for managing urban water systems is to maintain the reliability of the pipes in such a way that the system has an acceptable level of performance, cost and risk. Understanding and modelling the deterioration of pipes, which supports the likelihood side of risk, is essential to achieve such a goal. The method presented in this paper deals with maintaining a long-term required level of system performance through the modelling of pipes' deterioration. The objective of the paper is to improve the quality of the existing long-term deterioration modelling by using historical data on decommissioned pipes to produce empirical survival functions, and relating that to the current service level of the network.

The paper addresses long-term modelling of pipe deterioration and remaining useful life, where a number of approaches exist. Comprehensive reviews of deterministic, statistical and probabilistic modelling approaches for asset lifetimes are available in Kleiner and Rajani (2001), Burn *et al.* (2010) and St.Clair and Sinha (2012). One of the prominent methods applied in Europe is the 'cohort survival model'. This modelling approach was first applied in demography to forecast population growth based on fertility and mortality data (Herz, 1998). In 1987 it was adapted to describe the deterioration process of infrastructure assets (Baur and Herz, 2002). As the name suggests, the model is based on a division of assets into homogenous groups, called 'cohorts'. In 1996, Herz (1996) presented a parametric function to describe the deterioration process of water and wastewater pipes. The Herz function is referred to as a 'survival function', and is illustrated in Figure 4. Other mathematical distributions are also used to describe survival functions for water pipes. In Le Gat *et al.* (2013) a non-parametric Turnbull distribution and a parametric Weibull distribution was used and compared to the Herz function. A Weibull parametric function was also used in Large *et al*. (2015b). The non-parametric distribution is built purely on empirical observed data of decommissioning ages between a and b, where no information on decommisioning ages is available before or after the observation window [a, b]. This distribution is 'a decreasing step function that jumps down at each observed lifetime value, while remaining constant (horizontal) between two successive lifetime values' (Le Gat *et al.*, 2013). The parametric Herz and Weibull functions are however based on theoretical probablity distributions of the time T. These two functions are based on different parameters. While the Herz function is based on the ageing, failure and resistance parameters, as described in section 2.2, the Weibull function is based on a scale and a shape parameter.

Every cohort has their own defined survival function, which calculates the probability that a pipe will survive beyond a given age and describes the expected service life of all pipes within a cohort. The work in this paper focuses on survival functions and how historical data can be used to optimize these functions with regard to network service level in order to assure a good long-term performance of the network.

2. Literature

2.1 Cohort survival models

Cohort survival models have been applied in a number of projects for urban water infrastructure in Europe and North America (AWWA, 2010, Baur *et al*., 2004, Deb *et al*., 2009, Herz, 2002, Herz, 1998, Herz, 2003, Large *et al*., 2015, Malm *et al*., 2012, Malm *et al*., 2013). Two of the most commonly used models in the European water sector are the software packages CARE-W LTP (Sægrov, 2005) and KANEW (Herz, 2003, Sægrov, 2005, Sægrov *et al*., 2003),both of which apply the Herz function and are the same models with modifications (Baur *et al*., 2004). In Norwegian water utilities, results from the calculations with KANEW or LTP are implemented in municipal master plans, which normally spans for 10 years. The Herz model is specifically tailored to urban water systems and is the most applied version of the survival function in the European market, which is the reason that this model alone is the focus of the review in this section, and the focus of the calibration.

The cohort survival model is by Ugarelli and Bruaset (2010) and Kleiner and Rajani (2001) defined as a probabilistic single-variate group processing model, which use probability distributions on cohorts. The model is defined as single-variate since, once cohorts have been formed based on several variates such as construction period, material, diameter, failure rates or soil conditions, the type of cohort is the only variate affecting the allocation of survival function. Being probabilistic, the model possesses some randomness in that a probability distribution describes the range of varying expected lifetimes of the pipes. In Large *et al.* (2014) the KANEW approach is referred to as a deterministic deterioration model. Both the 'statistical' and 'deterministic' definitions are acceptable of the cohort survival model. The deterministic deterioration approach involves fitting a function to the observed data, in this case the Herz function, which allows for no randomness on cohort level. At the same time, the cohort survival model is referred to as a statistical model (Burn *et al*., 2010) since the use of survival functions instead of average lifetimes makes place for natural randomness and variability in service lives of single pipes.

2.2 The Herz survival function

Pipes within the same cohort can be rehabilitated for a number of different reasons, e.g. level of service, coordination of rehabilitation work, cost and risk, which leads to a variety of service lives. Such a variety of service lives is best represented by a survival function (Renaud *et al.* 2014). The x-axis of the survival function displays expected service life in years, while the y-axis displays the accumulation of the length of pipes in the cohort, from 100 % in operation (no rehabilitation), down to 0 % in operation (all pipes rehabilitated), see Figure 4.

The Herz function is based on the parameters a, b and c:

a: ageing factor describing the smoothness of the start of the ageing process beyond the resistance time.
b: Failure factor describing the final failure rate of the oldest and most durable pipes.
c: Resistance time describing the time until first rehabilitation.

The Herz function calculates the probability P that the age T of a pipe will be higher than the time t, and is defined as (Herz, 1996):

$$F(t) = P(T \geq t) = 1 \quad when\ t \leq c \tag{1}$$

$$F(t) = P(T \geq t) = \frac{a+1}{a+ e^{b(t-c)}} \quad when\ t > c \tag{2}$$

$$F(t = \infty) = 0 \tag{3}$$

3. Method

3.1 Calibration of survival functions for water pipes in literature

Some work in recent years has focused on the calibration of survival functions for drinking water pipes. Large *et al*. (2015) presents a methodology for the calibration of survival functions with historical data on decommissioned pipes. The paper corrects historical data from left truncation and right censoring, and assumes that rehabilitation decisions in the future will be the same as in the past. It does however not consider if past rehabilitation decisions have caused a satisfactory service level or not. Correction of left truncation and right censoring are also used to calibrate survival functions for water pipes with historical data in Le Gat *et al*. (2013), where the link between failure rates and parametric survival functions for different water utilities is investigated. They conclude that ‘water main replacements have been highly influenced by the segment failure rates’ and use that as an argument to apply parametric survival functions based on empirical data to plan future renewal.

3.2 Calibration

The construction of a historical survival function is based on the recorded age of pipes at decommissioning and can be used to calibrate the Herz survival function, namely the a, b and c parameters. The first step is to split the network into suitable cohorts. The recorded age of decommissioned pipes within a cohort can then be used to create a historical survival function. The historic condition of a cohort, measured for example as the average and annual failure rate of the cohort over the past 10 years, indicates the effect of the rehabilitation performed on that cohort. As long as the performance of the cohort has been sufficient in the past, it is reasonable to assume that the historical rehabilitation rate has been sufficient (Malm *et al*., 2012) or possibly too high.

Service levels can be measured with performance indicators. If a performance indicator for a cohort is less favorable than for other cohorts it might point to a non sufficient past rehabilitation rate for that cohort. Furthermore, it is necessary to look closer at the development of the performance indicator over time and correlate that to the rehabilitation efforts. The first part of the calibration process consists of the following steps:

(1) Assess **historical service level**, represented by one or several performance indicators (See Figure 1).
(2) Identify **historical rehabilitation rates** and how they affect performance indicators.
(3) Construct **historical survival functions** based on recorded data (see Figure 3). These are based on recorded empirical data on the age of pipes at decommissioning. The curve is created by accumulating the length of pipes (related to total length) decommissioned at every time step.
(4) Identify the cumulative length distribution (related to total length) of pipes currently in operation, labeled as an **operational curve** (see Figure 3). The pipes in operation have a certain length and have reached a certain age. The curve is created by accumulating the length of pipes (related to total length) currently in operation versus their age.

The total length of pipes refers to the sum of the length of decommissioned and operational pipes, which constitutes the total stock length of all constructed pipes in a cohort. The future decommissioning ages of pipes currently in operation is not known. In order to construct a calibration curve, the amount of pipes to be decommissioned annually in the future, and their decommissioning ages, must be estimated. The estimation of this future decommissioning is illustrated with the curve 'Estimation of future decommissioning' in Figure 3. The curve represents the predicted accumulated distribution of length (related to total length) of these pipes at decommissioning. The combination of the historical decommissioned pipes and the predicted decommissioning of pipes in the future constitute a calibration curve for the survival function. In Figure 3 the calibration curve is the combination of the 'Historical survival function' and the curve 'Estimation of future decommissioning'.

3.3 How to predict future decommissioning of pipes

In order to predict the annual future decommissioning of pipes which are currently in operation, a future rehabilitation rate is chosen based on how past rehabilitation rates have been able to maintain a good level of service or not (Figure 1). Assuming the historical service level met the service level target, the corresponding rehabilitation rate applied in the same period can be adopted for the future as adequate to maintain the required service, as also stated by Malm *et al.* (2012). The survival and failure functions of the Herz model (Herz, 1998) support this assumption by suggesting a steady rehabilitation and failure rate of cohorts until the most durable pipes are to be replaced, in which both the rehabilitation and failure rates do not increase, but decrease. Based on this assumption, the average historical rehabilitation rates of cohorts can be applied also for the next 10 years if past service levels are satisfactory. The adopted long-term rehabilitation rate should be revised in accordance with water utility master plans to ensure it is still sufficient to meet set targets of service level. In Norway, master plans are normally produced in 10 year intervals.

The development of past service level through an observation period reveals something about the effect of past rehabilitation efforts. In the following, five different descriptions of past service levels representing possible development through an observation period, are defined. This development is termed 'historical service level development'. Below, these five illustrative developments are described for recorded failure rates on drinking water pipes, followed by a suggestion for measure on the future rehabilitation rate. As decision support on adopting a future rehabilitation rate to predict future decommissioning of pipes, the following is recommended:

- Steady decreasing failure rate observed: keep the same rehabilitation rate until the failure rate starts to even out, or reduce it if the cost-benefit ratio is too low.

- Steady, flat and non changing failure rate observed: If the failure rate is low enough to meet targets, the rehabilitation rate can be kept at the same level, or even reduced. A steady reduction in rehabilitation rate can be imposed while observing effects on failure rates.

- Steady increasing failure rate observed: rehabilitation rate should be increased in reasonable steps while observing effects on failure rates.

- First decreasing, then flattening out failure rate observed: the rehabilitation rate should be kept at the same level or reduced cautiously while observing the effect on failure rate.

- First increasing, then flattening out failure rate observed: if the failure rate is at an acceptable level, the current rehabilitation rate should be maintained. If not, the rehabilitation rate should be increased.

In order to construct a calibrated survival function based on decommissioning ages not yet known, we have to estimate which pipes will be decommissioned at each time step in the future. During the modelling a certain length of pipes are decommissioned every year. When these pipes are decommissioned, they are removed from the operational pipe data. The length of pipes remaining in operation at any time step can be estimated by equation 4. Based on their age and length, the decommissioned pipes are plotted into the data for the curve 'Estimation of future decommissioning'. The length of pipes in this curve can be estimated at any time step by equation 5. An annual length of pipes are selected from the operational curve based on the selected future rehabilitation rate. This rate can vary with time. At each time step the remaining pipes in the operational curve gain one year of age. This process is repeated until all pipes in operation are decommissioned.

In order to predict how pipes are selected out from all the pipes in operation, we have looked at historical data for decommissioned pipes. For the case study, which is further described in section 4.1, the average age of decommissioned pipes over the observation period was 52 years. A trend curve for the data shows that the average age of decommissioned pipes has increased, as is normal for a material which is no longer in use (asbestos cement). The average age of pipes selected for decommissioning from the operational curve in the first year of estimation should therefore at minimum be 52 years, i.e. in line with the average age of earlier decommissioned pipes. A study by Le Gat *et al.* (2013) shows that decommissioned pipes have a higher failure rate than pipes in operation. It is therefore assumed that pipes still in operation, on a general level, constitute the better part of a cohort with prolonged lifetime and that decommissioned pipes for the most part will constitute the youngest part of a survival function. The group of pipes from where future decommissioning is estimated is therefore selected from the oldest pipe in the operational curve up until the pipe where the selection reaches an average age of 52 years. This is called the 'selection window'. When selecting pipes evenly distributed throughout this selection at every time step we make sure that the trend of increasing average age of decommissioned pipes is continuing since the youngest pipes are left for further operation. Furthermore, this ensures that pipes are decommissioned with a range of varying service lives to comply with the survival function principles.

When we estimate the future decommissioning of pipes, the length of pipes in operation (Eq 4) at every time step and the length of decommissioned pipes (Eq 5) at every time step can be determined:

$$\text{Length } (OP)\ at\ t = Length\ OP - \big((RR_1 \times Length\ OP) * \Delta t_1\big) - \big((RR_2 \times Length\ OP) * \Delta t_2\big) - \ \dots\ - \big((RR_X \times Length\ OP) * \Delta t_x\big) \qquad (4)$$

where

Length (OP) at t = Total length of pipes in operation at any time step t, where t = years and goes from 0 to n.

Length OP = total length of pipes in operation at t=0

Δt = time period defined between two time steps of t. The period is defined by a constant RR. A change in RR initiates a new time period.

RR = rehabilitation rate between time steps of t. The rate can vary according to targeted service level. The rate varies x number of times. Every time the rate changes, a new link is established where a new RR and a new time period is defined. This can be calculated up until time step n where there are no more pipes left in operation.

$$\text{Length (DEC)}\ at\ t = \ Length\ DEC + \big((RR_1 \times Length\ OP) * \Delta t_1\big) + \big((RR_2 \times Length\ OP) * \Delta t_2\big) + \ \dots + \big((RR_X \times Length\ OP) * \Delta t_x\big) \qquad (5)$$

where

Length (DEC) at t = Total length of decommissioned pipes at any time step t

Length DEC= Length of decommissioned pipes at t=0. Total length of historically decommissioned pipes.

4. Results

4.1 Calibration case study

In Figure 1, the ‘historical service level development’ for a cohort of asbestos cement pipes is presented for a Norwegian case study. The cohort is defined by a single variate, the material, and contains all pipes with the material of asbestos cement. The observation period of failures in the city is from 1993 to 2014. It can be observed that the failure rate for the cohort decreased from 1993 to 2000, and that it has been kept at around 0.1 failures/km/year since. Thus, the ‘historical service level development’ can be described as decreasing, then flattening.

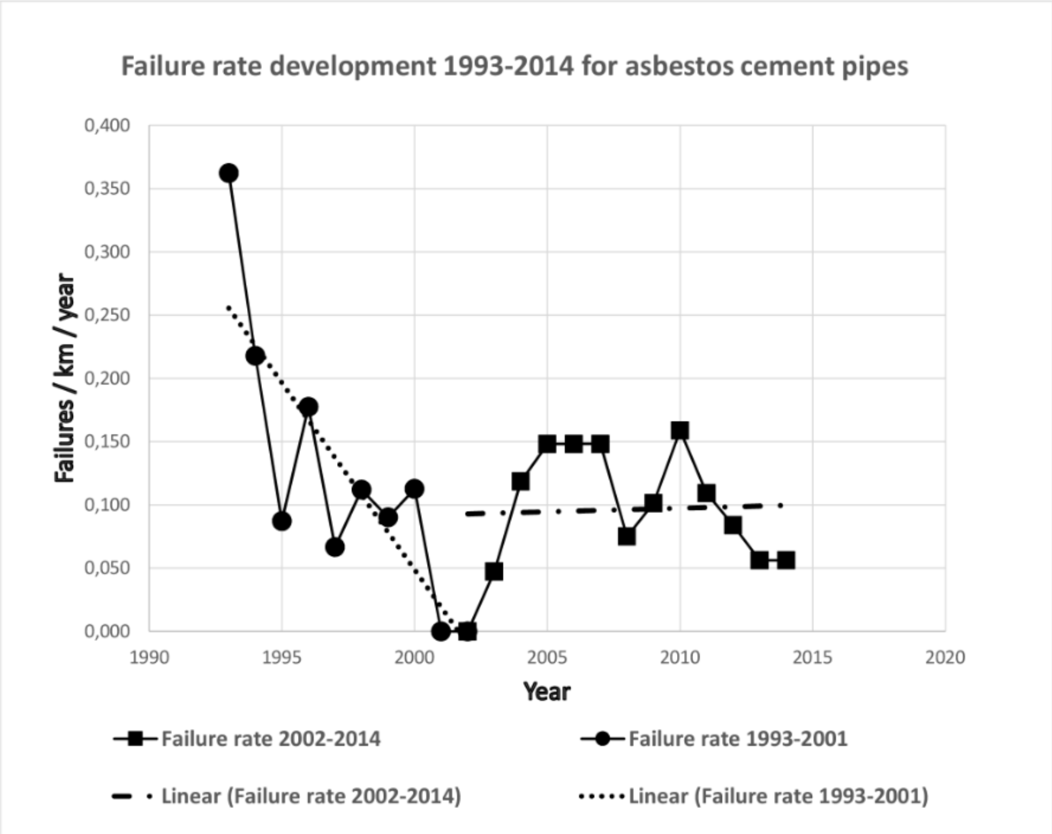

Figure 1. 'Historical service level development' for asbestos cement pipes in the case study.

The failure rate has varied from year to year. In the 1990's the utility worked in a reactive approach with regards to failures, whereas lately it has moved to proactive maintenance. This can explain some of the higher failure rates early in the observation period.

To maintain a good level of service it is not only important to keep a certain rehabilitation rate, but also to select the right pipes for rehabilitation. Figure 2a shows that the variation in failure rates more or less follows the variation of the failure rates of the network. Figure 2b shows that the increase and decrease in number of failures on the asbestos cement pipes follow the same pattern as total number of failures in the network, with minor deviations. However, both graphs show a decreasing trend in number of failures the first decade. Figure 2c indicates that an increased rehabilitation rate causes a reduced failure rate the following year. When the utility has increased the rehabilitation efforts on the cohort, they have to some degree succeeded in rehabilitating the right pipes. Figure 2d shows a moderate correlation between the average age of the cohort and failure rates, meaning an increasing average age affects failure rates negatively. There is an indication in the data that the utility has been able to rehabilitate the right pipes. This is based on the observation that the increase of failure rates as average age increases are modest, and that rehabilitation rate has dropped significantly during the five years with the highest average age, which is the last five years of the observation period. The utility has been able to increase accuracy in the last decade concerning the selection of pipes for rehabilitation, which is a fundamental premise in order to see improved results by increasing the rehabilitation rate.

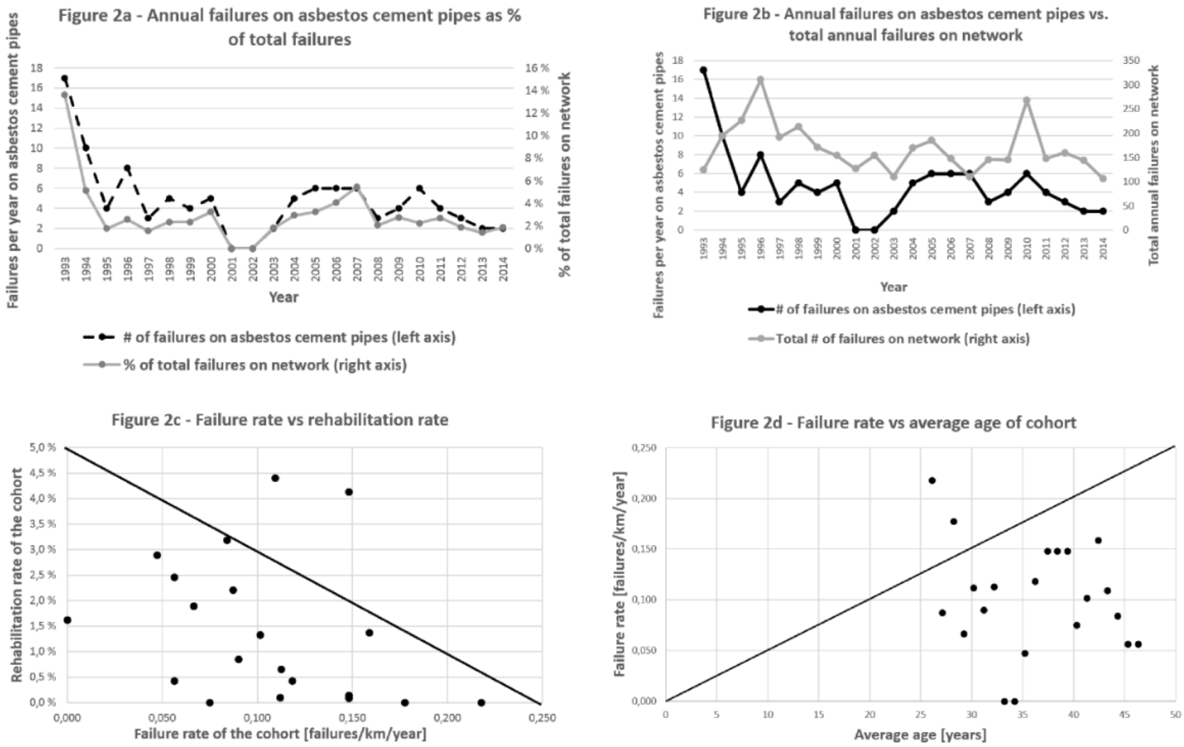

Figure 2. Data analysis of failures on asbestos cement pipes in the case study.

Figure 3 shows the cumulative distribution of total pipe length versus age for all asbestos cement pipes that have been constructed in the case study city. The data is split into pipes that have been renewed, labeled as decommissioned, and pipes that are still in operation, labeled as operational. As shown by the y-axis, decommissioned pipes constitute about 25 % of the total length of all constructed asbestos cement pipes in the city. About 75 % of the total length of all constructed asbestos cement pipes are still in operation in the water supply system. Together they constitute 100 % of the total length of asbestos cement pipes ever constructed. We can also see from the figure that 10 % of the total length were renewed before they reached the age of 33, and that 10 % of the total length are 50 years or older and still in operation. The figure also shows that the oldest pipe currently in operation is 60 years old (Operational curve) and that the ‘Estimation of future decommissioning’ shows that the oldest asbestos cement pipe is estimated to become 147 years old.

The challenge is to forecast and model at what age asbestos cement pipes will be decommissioned in the future. To do this, we follow the procedure suggested in section 3.3.

The average failure rate of asbestos cement pipes over the observation period was 0.113 failures/km/year, compared to the average of the network at 0.207 failures/km/year, which indicates a good relative condition of the cohort. The average rehabilitation rate through the observation period was at 1.3 %, which was higher than the network average, which sat at around 0.7 % for the past 12 years. From these numbers and from Figure 1 it is apparent that the cohort has been managed in a way that has not reduced service level of the network. Based on the low failure rate for the cohort through the observation period and the shape of the ‘historical service level development’, the rehabilitation rate of the cohort can therefore be reduced since the failure rate can be allowed to moderately increase. Rehabilitation rates start at 1.3 % during the first years, which corresponds to the current rehabilitation rate on the cohort, and are lowered down to 1 % after five years. As a starting point we assume these values to be suitable to maintain the current level of service. It is not recommended to lower the rehabilitation rate down to the network average of 0.7 % since asbestos cement pipes in general are considered among the worst in the network and may need more rehabilitation than the best quality pipes. However, the rehabilitation rate may be lowered more at a later time, when the effect of this rehabilitation plan is reviewed against new data. Based on these selected rehabilitation rates we can calculate the future length of pipes to be decommissioned annually. The estimated future decommissioned pipes are illustrated with the curve ‘Estimation of future decommissioning’ in Figure 3. The calibration curve consists of pipes that have been decommissioned in the past (the curve ‘Historical survival function’), and pipes that are estimated to be decommissioned with a specific age in the future (the curve ‘Estimation of future decommissioning’).

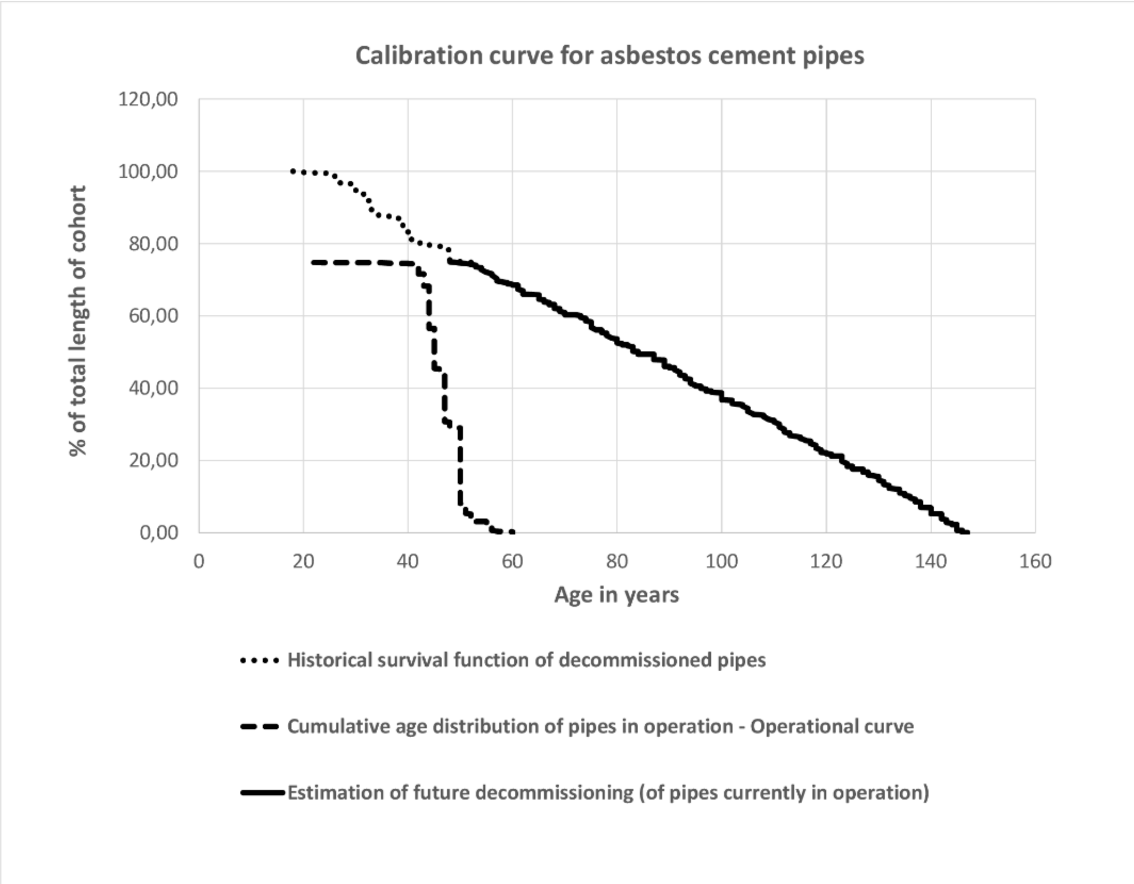

Figure 3. Historical-, operational- and calibration curve for asbestos cement pipes in the case study.

Figure 3 illustrates the following:

- ‘Historical survival function’ for asbestos cement pipes that have already been decommissioned. The curve shows the cumulative distribution of length of decommissioned pipes out of total length of asbestos cement pipes, and constitutes the first part of the calibration curve for the asbestos cement pipes. Observation window of decommissioning ages is from 1994 to 2014.
- The cumulative distribution of length (out of total length) of asbestos cement pipes which are currently in operation, where the length of pipes is accumulated versus their age. This

is the ‘Operational curve’. The curve illustrates the portion of operational pipes in relation to total asbestos cement pipes.

- Curve for the future estimation of pipes currently in operation, labeled ‘Estimation of future decommissioning’. This curve is the estimation of the cumulative distribution of length (out of total length) versus age of asbestos cement pipes that will be decommissioned in the future. This estimation is based on the process described in section 3.3 and the data discussed in this section. The pipes that are estimated for future decommissioning are the ones that are currently in operation (currently part of the ‘Operational curve’).

4.2 Model goodness of fit

The ‘calibration curve’ is now the basis to construct a calibrated model for the cohort with the Herz function. The validation was done by analyzing the goodness of fit of the regression. The least squares method was applied in the case study to find the best fit of the Herz function to the data. The best fit produced a coefficient of determination R^2 of 0.9967, showing a good approximation of the Herz model to the calibration curve data. Together with the data plot of Figure 4, this validates the goodness of fit of the model to the data. Since the calibration process does not yet consider the effect of reduced failure rates of the most durable pipes, which results in a reduction of the incline of the Herz curve in its final stage, the goodness of fit analysis was cutoff when 20 % survival was reached.

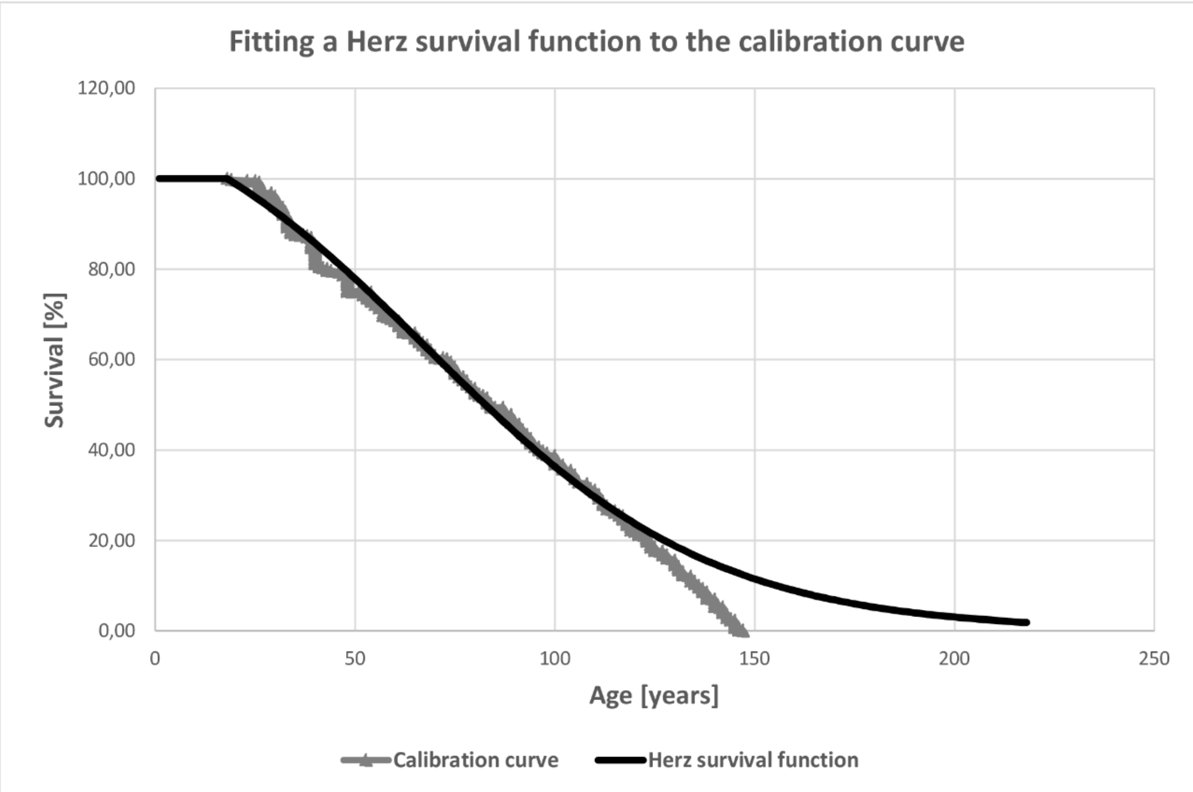

Figure 4. The Herz function fitted to the calibration curve by the least squares method.

5. Discussion

It is assumed that the use of empirical data on decommissioning ages, as applied in this paper, instead of expert knowledge alone, will help to improve long-term deterioration modelling. By basing survival functions on empirical data it is expected that the uncertainty of the cohort survival model input will be reduced, and by conforming the functions to service level targets, it facilitates utilities in maintaining a long-term required performance of the distribution network. In instances where little data exist on historical survival functions, failure rates and rehabilitation rates, as is the case for young cohorts, it is harder to apply the calibration process. However, the iteration process at 10 year intervals (coinciding with the master plans of water utilities) to review service levels will help to improve the calibration process even for young cohorts.

When addressing aspects into the future, it is important to assess if the future will mirror the past, or if there will be changes, both internal in the system, and in the external factors that affect the system. A survival function is forecasting what we expect the deterioration to be in the future, and are thus addressing future aspects with associated uncertainty. Historical survival functions are based on past rehabilitation work initiated on the basis of not only pipe condition, but also by coordination practices with other infrastructures, section wise rehabilitation, need for capacity increase, phaseout of old materials, and so on. These are a product of past rehabilitation practices and strategies. By calibrating survival functions with historical survival functions we are able to include the effect of these practices on the rehabilitation rate also in the future. This means that we assume the same rehabilitation practices will be applied in the future as in the past. If the contrary will be the case, an analysis on how future rehabilitation practices will deviate from the past will have to be assessed.

When using historic data to predict the future, external factors influencing the cohort deterioration processes and rehabilitation needs such as demographic changes and climate change, are normally assumed to be stationary. This however, does not reflect reality. Demographic changes will occur, and the stationarity of climate change is 'dying' (McCarl *et al*., 2008). A study by Milly *et al*. (2008 cited Hallegatte, 2009) demonstrates that water management cannot keep using the stationary hypothesis in its investment decisions, and the effect of climate change (and other factors) on future deterioration of pipes must therefore be assessed.

6. Conclusion

The main challenge of the cohort survival model is the determination of the survival functions. This paper has addressed how survival functions can be calibrated with empirical data on decommissioning ages of pipes and data on selected performance indicators. In this process, the utility is able to consider service quality as basis for future rehabilitation and investment decisions by managing survival functions according to service level targets.

A limitation of the proposed calibration process is the absence of considering the effects of external factors on future rehabilitation needs. Stationary hypothesis of climate change should not be applied in future investment decisions of the water industry. Another limitation of the calibration process is the disregard of the reduced failure rates of the most durable pipes with longest lifespans. As more data is collected on the decommissioning of pipes, empirical data will be available to support the inclusion of this aspect in the calibration.

In Large *et al*. (2015) the historical survival function was corrected from left truncation and right censoring with the Turnbull statistical method. It would be interesting to see if this approach can be merged with the process presented in this paper in order to further improve calibration of survival functions.

New available data at the tool implementation intervals (~10 years) should be included to improve historical survival functions and consequently the calibration curves. It is therefore recommended that the process described in this paper should be repeated on a 10 year interval in an iterative process where service levels are re-evaluated according to required targets.

7. Acknowledgements
The authors would like to thank the ten largest municipalities in Norway, the Norwegian interest group for water 'Norsk Vann', and the Norwegian Research Council for the financing and support of this work.

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