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STATISTICAL MODELLING OF PIPE FAILURES IN WATER NETWORKS

by

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Abstract

European cities spend in the order of one billion Euros a year to rehabilitate water supply networks. Rehabilitation costs will increase in the coming decades as networks age and deteriorate. The rational behind today's rehabilitation decisions is unclear. In the best case, decisions are based on practical experience like failure frequency**.** During the past 10-20 years, most of the larger European water utilities have implemented Automated Mapping/Facilities Management (AM/FM) system for recording and managing inventory and maintenance data for their distribution networks. The information registered in these systems can be used to predict future pipe failures in the network, improving network management decisions. This thesis aims to make a modest contribution to improving the prediction of pipe failures in water networks.

This thesis presents an evaluation of statistical methods for modelling pipe failures for each individual pipe in a water distribution network and shows whether the existing data in Gemini VA (a Norwegian AM/FM system for water- and sewerage utilities) is sufficient input for these models. Statistical methods that are appropriate for modelling pipe failures are described, and the models are applied in a case study using data for the water distribution network in Trondheim, Norway.

This thesis introduces the Non Homogeneous Poisson Process (NHPP) with covariates (i.e. explanatory variables) as an appropriate method for modelling pipe failures in water networks. The NHPP has been successfully used to model other minimal repair processes. I.e., the system is not restored to a 'good-as-new' state after the repair, and the intensity of failures for the repaired object is unchanged. This is the normal situation for pipe repairs in water distribution systems. As part of this research, a computer program has been developed that estimates the parameters in the NHPP ("Power law" model). The results from this NHPP model are compared to the results obtained from a modified Weibull Proportional Hazards Model (PHM), where the hazard function is allowed to continue beyond the pipe's first failure.

The statistical models have been calibrated, verified and used to predict failures for both networks (i.e. group of pipes) and individual pipes. Covariates that have a significant influence on the rate of occurrence of failures (ROCOF) are documented. Both the Weibull PHM and the NHPP are capable of modelling pipe failures. In the case study, the Weibull PHM shows a tendency to overestimate failures compared to NHPP. Model results fit the observed data best at network level, but are also satisfactory at pipe level when there is adequate calibration data. The NHPP can easily be used to predict the expected number of future failures by directly integrating the function defining the intensity of failures. The intensity function in the Weibull PHM is a step function, and can not be directly integrated. A time- consuming Monte Carlo simulation is required to predict future failures. Based on the results from the case study, NHPP is recommend over the Weibull PHM for modelling failures in water networks.

The case study showed that the grey cast iron and unprotected ductile iron pipes in the Trondheim water network are deteriorating. Unprotected ductile iron pipes installed before 1975 are in the most advanced stage of deterioration. These pipes have been, and will continue to be, be the most likely candidates for replacement/renovation. The ROCOF for these newer pipes is much higher than the ROCOF for the old, grey cast iron pipes in the system, demonstrating once again that age can not be used as the sole criterion for replacement.

The output from the statistical models can be used for a variety of purposes in water network management. In the long term the models can be used to estimate future budget needs for rehabilitation. In the short term the models can be used to define candidates for replacement based on poor structural condition. Information about failure intensity is also required for carrying out network reliability analysis. For this purpose reliability data for each individual pipe is required, which is exactly what the predictive models described in this thesis provide.

In order to improve the interpretation of the results, the output from the predictive models is imported to Gemini VA. This makes it easy to generate plots showing the future number of failures for each pipe. In the future predictive models should be integral part of management information systems for the water industry, a step towards a more proactive rehabilitation strategy, where pipes can be rehabilitated before they wear out.

The predictive models for pipe failures can be further improved by applying new statistical models appropriate for repairable systems.

Preface

This thesis gives a summary of literature reviews and statistical analyses/calculations carried out during the period 1996 to 1999, for the study of pipe failures in water supply networks. I have been enrolled as a doctoral student at the Norwegian University of Science and Technology (NTNU), Department of Hydraulic and Environmental Engineering. The study has been financed by the Research Council of Norway as an integrated part of the strategic research programme *"Maintenance and service life of the built environment"* carried out by NTNU and SINTEF.

Special thanks go to Professor Wolfgang Schilling at NTNU, Department of Hydraulic and Environmental Engineering, under whose supervision the studies in this thesis has been carried out. I thank him in particular for involving me in his "baby", the series of "European Junior Scientist Workshops" (EJSW), where young scientists, typically doctoral students, present own works and solve scientific problems in a co-operative and non-competitive environment. As a part of my research I arranged the 10th EJSW on "Deterioration of Built Environment: Buildings, Roads and Water Systems" at the island of Tautra, Norway 24-28 May 1997. The EJSW have initiated an international network, which has been invaluable for my personal and scientific development.

Based on the international contacts made during the 10th EJSW, I stayed at Cemagref, Bordeaux for two months during the autumn of 1998, visiting Patrick Eisenbeis and Yves Le Gat. Beside the social aspects of such a visit I am also thankful for the fruitful academic discussions and comments concerning statistical modelling of pipe failures. The workshop at Tautra was later followed up by the 13th EJSW on "Service-Life Management of Water Mains and Sewers: Decision Criteria and Strategies for Rehabilitation" held in Dresden in the autumn of 1999 and arranged by Rolf Baur, one of the participants from Tautra.

I am very grateful for the good working atmosphere created by my friends and colleagues at the Department of Hydraulic and Environmental Engineering. I would like to give special thanks to Sveinung Sægrov at SINTEF for his help and co-operation during the last 3 years. Also thanks to Jørn Vatn at SINTEF for fruitful statistical discussions and for helping me in programming the equations for the NHPP model.

European contacts made as a part of the strategic research programme at NTNU/SINTEF have resulted in a project proposal for EU 5th framework called CARE_W (Computer Aided Rehabilitation of Water networks). The guidelines for the Norwegian degree of "Doktor ingeniør" stress the importance of building international contacts, and this has been an important part of this thesis work.

Thanks to Trondheim municipality for providing me with the necessary data for the case study.

Special acknowledgements are due to Sandy McCarley for proofreading the thesis for spelling and grammar mistakes, and for her constructive comments.

Last but not least, I thank Hilde and our kids Ola (6), Pauline (4) and Sivert (0.75) for their patience in my work.

Table of content

Nomenclature

β	Vector of regression coefficients, β= [β_1, β_2,... β_p]
α	Transformed interception parameter, (-ln(λ)) (reported by SAS/SYSTAT)
σ	Transformed interception parameter, (1/p), (reported by SAS/SYSTAT)
θ	Likelihood function parameter
λ	Interception parameter in the Weibull distribution
λ	Interception parameter in the "power law " model (NHPP)
$\Lambda(t)$	Cumulative intensity function
$\lambda(t)$	Intensity function
$\lambda_0(t)$	Baseline intensity function
Δt	Time step
a	Regression parameter
A	Regression parameter
A_{av}	Average availability
a_i	Point of time
b	Regression parameter
$B(t)$	Break rate
$B(t_0)$	Initial break rate
b_i	Point of time
C	Regression parameter
c($\mathbf{z}'\beta$)	Covariate function
C_1	Correction factor
C_2	Correction factor
$f(x)$	Probability density function
$H(x)$	Cumulative hazard function
$h(x)$	Hazard function
$h_0(x)$	Baseline hazard function
i,j,n,m,p,r	Integers
k	Year of pipe installation
$L(t)$	Structural reliability
MTTF	Mean time to failure
MTTR	Mean time to repair
$N(t)$	Number of failures in the time interval (0, t]
P	Probability
$R(t)$	Resistance
ROCOF	Rate of occurrence of failures
$S(t)$	Loads (used in literature review)
$S(t)$	Survival function or reliability function
$S(t,\beta,\mathbf{z})$	Survival function in the presence of a covariate vector **z**
Scale, (δ)	Parameter in the "power law" model (NHPP)
Scale, (p)	Parameter in the Weibull distribution

t	Global time, age of a system or cumulative sum of x
T_i	Failure times
t_0	Initial year
$v(t)$	Intensity function
$V(t)$	Cumulative intensity function
W	Random variable with an extreme value distribution
x	Local time, operating time between failures
z'	Column vector of covariates, transposed vector of **z**
z	Vector of covariates, **z**= [z_1, z_2,...z_p]

Glossary of terms

Automated Mapping/Facilities Management (AM/FM) System: A term used in the infrastructure management disciplines (e.g. utilities and public works) to describe Geographical Information Systems (GIS) that processes graphic and non-graphic data for a variety of purposes, such as managing geographically distributed facilities, overlaying combinations of features and recording resultant conditions, analysing flows or other characteristics of networks and defining districts to satisfy specified criteria. AM/FM systems are more user- adjusted and more specific than GIS systems.

Availability: The availability, $A(t)$ at time t is the probability that an object (e.g. pipe) is functioning at time t. The average availability $A_{av}(t)$ denotes the mean proportion of time the object is functioning. If we have an object that is repaired to an "as good as new" condition every time it fails, the average availability is

$$A_{av} = \frac{MTTF}{MTTF + MTTR}$$

where MTTF (mean time to failure) denotes the mean functioning time and the MTTR (mean time to repair) denotes the repair time of the object. The average availability, $A_{av}(t)$ is used in network reliability analysis.

Bad-as-old: If the hazard function of a repairable system is the same after each repair carried out as it was just before the failure, the system is said to be in a bad-as-old condition after the repair. The corresponding repair is called a *minimal repair*.

Break: A failure on a pipe resulting in loss of water. Examples of types of breaks might be a hole or a crack in the pipe wall.

Break rate: The term break rate is widely used in analyses of pipe breaks in water distribution networks. Break rate for a given pipe or set of pipes is normalised for pipe length and time. The unit for breaks rate is often expressed as number of breaks per kilometre per year [*number of breaks/length/time*]. In this work break rate is also used when leakage is considered as the failure type and not only breaks. Break rate is not equivalent to the statistical terms ROCOF and FOM explained later in this glossary.

Burst: Used analogous to break.

Censored lifetime: The *lifetime* of a component is defined to be the time from the component is put into service until it fails. In many situations we do not observe the full lifetime. One example would be when the component has not failed at the termination of the experiment. Different types of censoring may occur. In this work only *left* and *right* censoring is mentioned. Left censoring means that we do not exactly know when the component was put into operation.

Right censoring means that we know that the component has survived up till some time, say X, but we do not know the history after X. Censoring also applies to repairable systems modelled by the statistical methods presented in this thesis.

Covariates: All those factors, which may have an influence on the reliability characteristics of a system, are called covariates. Covariates are also called variables, explanatory variables or risk factors. Examples of covariates are environmental factors (e.g. soil condition), hydraulic factors (e.g. pressure) and structural variables (e.g. diameter)

Cut set: A cut set is a set of components (e.g. pipes) which by failing causes the system (e.g. water distribution system) to fail. The cut set is said to be minimal if it can not be reduced without loosing its status as a cut set. The term is used within reliability analysis.

Failure: The term *failure* is in this work used for a break or leakage on a pipe.

Failure rate: The term failure rate is in the statistical literature often used for both ROCOF (i.e. repairable systems) and FOM (i.e. non-repairable systems), which might cause some confusion. In order to avoid confusion the term will not be used in this work with a few exceptions in the literature review where it is explicit mentioned by an author.

Failure time: T_i, i=1,2,3,..., measures the total time from 0, a convenient fixed origin, to the ith failure and is called the failure time for the ith failure (see also *interfailure times*).

Good-as-new: If the hazard function of a repairable system is reset to that of a new system by each repair carried out after a failure, the system is said to be in a good-as-new condition after the repair.

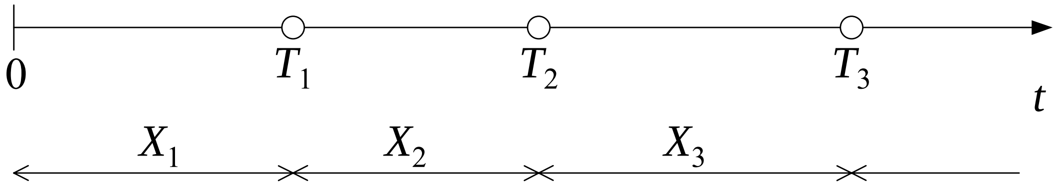
Hazard function: The hazard function $h(x)$ or the force of mortality (FOM) is defined as the conditional probability that at time x the component (pipe) will fail in a small time interval $(x,x+\Delta x)$, provided that it has not failed up to time x:

$$h(x) = \lim_{\Delta x \to 0} \frac{P[x \le X < x + \Delta x \mid X \ge x]}{\Delta x}$$

The term $h(x)\Delta x$ can best be interpreted as the probability that the *first* failure occurs in $(x, x+\Delta x)$.

Intensity function: The intensity function at time t is a measure of the probability that a repairable system will fail in a small time interval $(t, t+\Delta t)$. It is also called the *rate of occurrence of failures*.

Interfailure times: The interfailure time is the time between each failure in a stochastic point process. The interfailure times are denoted as X_1, X_2,... A graphical description of the failure history of a system, starting from time t=0 is shown bellow. The "o"'s correspond to failure times (T_i) of the system. T_i is the time from 0 to the time of the *i*th failure.



Lifetime: The concept of *lifetime* applies only for components which are discarded the first time they fail. The lifetime of a component is the time from when the component is put into function until the component fails. The lifetime of a component is treated as a random variable. In this work the time between failures (i.e. interfailure times) is also used as a lifetime in order to model repairable systems with PHM. By doing so we are able to model successive failures for a component.

Minimal repair: When the reliability is exactly the same just before and immediately after the corresponding repair. The situation is termed *minimal repair*.

Monte Carlo simulation: A statistical technique that randomly generates values for uncertain variables over and over to simulate a model. The results approximate the full range of possible outcomes.

Network level: Term used for predictive models that predict reliability measures for group of pipes or the whole network.

Non- repairable system: A system which is discarded the first time it ceases to perform satisfactorily.

Path set: A path set is a set of components (e.g. pipes) which by functioning ensures that the system (e.g. water distribution system) is performing. The path set is said to be minimal if it can not be reduced without loosing its status as a path set. The term is used within reliability analysis.

Pipe: From one node in the water network to another (e.g. manhole, change in pipe diameter). Typically length is 50 – 150 m. Each pipe will normally consist of many pipe segments or lengths.

Pipe level: Term used for models that are able to predict reliability measures for each individual pipe in the network.

Predictive models: Models used for prediction of future failures. In this work applied for statistical models.

Proactive strategy: In water network management a strategy is proactive if action is taken before a failure occurs.

Reactive strategy: In water network management a strategy is reactive if action is taken after a failure has occurred.

Rehabilitation: All methods for restoring or upgrading the performance of an existing pipeline system. The term rehabilitation includes repair, renovation, renewal and replacement.

Reliability: According to ISO 8402 the reliability of a system is defined as "The ability of the system to perform a required function, under given environmental and operational conditions and for a stated period of time".

Renewal: Construction of a new pipe, which fulfils the same function in the distribution system but does not necessarily have an identical path as the pipe it is replacing.

Renewal process: A failure process for which the times between successive failures are independent and identically distributed with an arbitrary distribution. When a component fails, it is replaced by a new component of the same type, or restored to "good as new" condition. When this component fails, it is again replaced, and so on.

Renovation: Methods of rehabilitation in which all or part of the original fabric of a pipeline are incorporated and its current performance improved. Relining is a typical example of pipe renovation.

Repair: An unplanned maintenance activity carried out after the occurrence of a failure. After the repair the system is restored to a state in which it can perform a required function (e.g. supplying water). (Rectification of local damage).

Repairable system: A system which, after failure to perform at least one of its required functions, can be restored to performing all of its functions by any method, other than replacement of the entire system.

Replacement: Construction of a new pipe, on or off the line of an existing pipe. The function of the pipe will incorporate that of the old, but may also include improvements.

***Risk*:** According to the Norwegian Standard, NS5814 "Risk shall be defined as a list of consequences and their probability".

ROCOF (Rate of occurrence of failures): The ROCOF is the time derivative of the expected cumulative number of failures and is defined as:

$$v(t) = \frac{dV(t)}{dt} = \frac{d}{dt} E(N(t)) \overset{def}{\equiv} ROCOF$$

Where *V(t)*= *E(N(t))* denotes the mean number of failures in the interval (0,*t*]. It follows that the ROCOF may be regarded as the mean number of failures per time unit at time *t*.

To best interpret the ROCOF, write:
v(t)*dt* = E[N(t+dt)] - E[N(t)]= expected number of failures in (t, t+dt]

or in terms of probabilities
v(t)*dt* = P(failure in (t, t+dt]

Sometimes it is called the *intensity function* (i.e. unconditional).

Service life: According to ISO Standard 15686 defined as “The period of time after installation during which a building or its parts meet or exceed the performance requirements”. Analogously for water networks: “The period of time after installation during which a water network or its parts meet or exceed the performance requirements”.

Stochastic point process: In this context a stochastic point process is a mathematical model for highly localised events (failures) distributed randomly on the time axis. By “highly localised” what is meant is that the failures occur instantaneously in time. This will, however, be an approximation to the real life where a failure is considered to be a deterioration process.

Stratification: The stratification of a data is obtained by grouping the data on the basis of the discrete value of a single covariate or a combination of a set of covariates. This covariate can be used to categorise the failure data.

Worse-than-old: If the hazard function of a repairable system is worse after each repair than it was just before the failure, the system is said to be in a worse-than-old condition after the repair.

1 Introduction

1.1 Background

According to the Norwegian guide for water supply (Miljøverndepartmentet, 1988), the overall objective of a water distribution system is to supply each consumer with *enough* water of *good* quality. The *safety* of the water network should be considered and the overall *costs* should be acceptable. The term "enough" water means fulfilling pressure and water demands. The water quality must comply with the established drinking water regulations and standards. The safety shall be considered by means of reliability analysis, risk analysis and vulnerability analysis. According to Norwegian regulations, consumers shall pay all the costs of water supply, including operation, maintenance and administration. In Norway all large water works are non-profit, publicly owned and operated utilities. In order to fulfil these objectives, the water distribution system has to be satisfactorily operated, maintained and rehabilitated. The water distribution system is built of pipes, valves, storage tanks and pumping stations. The water network (i.e. pipes) plays the most important role in the system.

The water distribution networks in Norway (public) have a combined length of about 35.000 kilometres, with an estimated replacement value of 70 billion NOK (US $ 9 billion). Serving 3.8 million persons (ca 88 % of population) with high quality drinking water, is a task that is difficult to value in money terms. Nevertheless, the networks are ageing and need maintenance in order to comply with present and future demands. Typically, water pipes in fully developed networks are being rehabilitated at an annual rate of 0.5 to 1 % of the existing length of the water distribution network, which indicates that the average service life of these water mains is expected to lie in the range from 100 to 200 years. Several water works have concluded that the rehabilitation rate must be increased up to 1.5-2% within 10-20 years corresponding to annual cost of 0.7-1.4 billion NOK. Some of the pipes are up to 150 years old but may still function satisfactorily. The older parts of the networks have been built under standards and construction practices, and with technologies that are no longer appropriate. Nevertheless, to replace this part of the networks is beyond the economic capabilities of the water utilities. It will, therefore, be necessary to handle older networks in other, more appropriate ways. Age cannot be used as the sole criterion for replacement of a pipe.

A comprehensive list of criteria to be considered in deciding whether a pipe should be replaced, was outlined by Stacha (1978). These criteria include: comparison of costs (maintenance and capital), evaluation of hydraulic carrying capacity of the pipe, effect of pipe condition on water quality, risks of pipe condition to the safety of people and property, evaluation of system performance in predicted future demands and frequency of failure.

Some of these criteria are explicitly quantifiable (i.e. maintenance cost, capital cost, investment, hydraulic carrying capacity at present and future demands). Others like safety, reliability and the social costs associated with failure may require surrogate or implicit evaluation techniques to be quantified. A criterion not mentioned by Stacha, but well known for the practitioner, is the opportunistic rehabilitation of pipes, motivated by other underground works carried out in the area (e.g. road, gas, electricity).

The challenge is to develop reliable models for predicting the future renewal requirements for each individual pipe in the water network. Experience has shown that a significant number of network repairs are performed on an unscheduled basis. This reactive maintenance has the disadvantage that damage has to occur before measures are taken (i.e. "putting out fires"). Using this maintenance strategy, the rehabilitated pipes are selected according to emergency criteria, such as the number of breaks on the actual pipe. An alternative to the reactive strategy is a proactive strategy (Sægrov et al., 1999). In a proactive strategy the service determines the maintenance requirements by taking into account the state of the pipes and forecasting their degradation. Pipe failures cause considerable cost and inconvenience. Since it is not practical or economically possible to rehabilitate the entire length of the network, a targeting of rehabilitation resources is required. With limited resources, the ability to avoid damage and to optimise the use of available funds for preventative maintenance by employing predictive models is a preferred option for water network management. The proactive strategy requires a good knowledge of the network characteristics including the deterioration factors and the failure record. This means the installation of a computerised database, preferably in the form of a geographical information system. To this date, the benefits of a proactive over a reactive approach have not been demonstrated. However, this might be as a result of the inadequate evaluation models used to date.

In Scandinavia, major cities have practised computer assisted reporting on water main bursts and leaks for the last ten years. The same holds for France, Germany and United Kingdom, where network information systems have been established, though not yet completed by most water utilities. The systems include statistics on pipe failures and condition as well as rehabilitation work that has been done. In Norway the Automated Mapping/Facilities Management (AM/FM) system Gemini VA is widely used for managing the water and wastewater system in the municipalities. Technical data for the water and wastewater system are registered in Gemini VA. Gemini VA has a management module containing failure records (what, where and when it happened) and work done on the pipe (repair, TV- inspections, flushing). In Norway 210 municipalities of a total of 435 use the AM/FM system Gemini VA. All of the biggest municipalities in Norway are using Gemini VA and approximately 85 - 90 % of all Norwegian public water and wastewater pipes are registered using this system (Røstum, 1997). This data, collected from many municipalities using the same system, is a good platform for developing statistical methods for describing the structural state of pipes.

The research work presented in this thesis belongs to the specific area of statistical modelling of pipe failures in water distribution networks, taking into consideration the effects of different factors that may influence the technical state of the water network.

There are various factors that may have an influence on the technical state of a water distribution network. These factors include external/environmental conditions (e.g. soil corrosion, air temperature), internal variables (e.g. water temperature, water quality), structural characteristics (e.g. pipe diameter, pipe length, pipe material) and maintenance variables (e.g. number of failures, type of repair).

As pipes age, the technical (material properties) and functional state (transport capacity) of water distribution networks deteriorate. This is a general rule that applies to most systems. Only exceptionally, as with the famous Bordeaux wines, will quality improve with age, due to the maturing process for the wine. During my stay in Bordeaux, I learned that this is because age has a positive affect on the Cabernet Sauvignon grape. This effect is not present in water networks, which generally deteriorate with age. If you are in the lucky position of having a wine cellar, it is important to find the optimum age for consuming your wine. In order to determine the optimum age, the wine expert has to open a bottle and taste. Depending on the subjective evaluation of the quality of the wine, the decision might either be "ready to drink " or "store for some more years". The same principle applies to water pipe rehabilitation. We want to find the optimum time for rehabilitation of the pipe or to answer the question "*Shall we keep on with spot repairs or shall we renew the whole pipe*?" If the pipe is replaced too early, there is an economic loss due to money being spent sooner than necessary, since the service life of the pipe has not expired. If the replacement of the pipe is left too long, there is an economic loss when additional money is spent for emergency repairs that should have been avoided. The pipe should not be rehabilitated too early and neither too late. An analogy to the tasting of wine will then be to take out pipe samples and to analyse them. However, it is not realistic to take out pipe samples for the entire network. Predictive models are an alternative to the expensive alternative of extensive pipe sampling and structural evaluation. Predictive models could also be useful for identifying critical elements for more detailed evaluation. Since tasting of wine is more or less an art and not so much science, it is not so realistic to come up with models describing the time evolution for the quality in the wine, but for water pipes there is potential.

1.2 Rehabilitation of water networks

The following paragraphs give an introduction to water network rehabilitation. Rehabilitation includes all methods for restoring or upgrading the performance of an existing pipeline system. The term rehabilitation includes maintenance and repair as well as renovation and replacement (Figure 1-1). The definitions used in the figure follow the Norwegian Standard NS-EN752-1:1996 (also a European Standard) and the International Standard ISO/TR 11295, which is also in accordance with the conventional use of the terms in the field of trenchless technology. Since the different rehabilitation actions have different properties and thereby improve the pipe in different ways, it is, as it will be shown later in this thesis, important to know how the rehabilitation of the pipe actually was carried out.

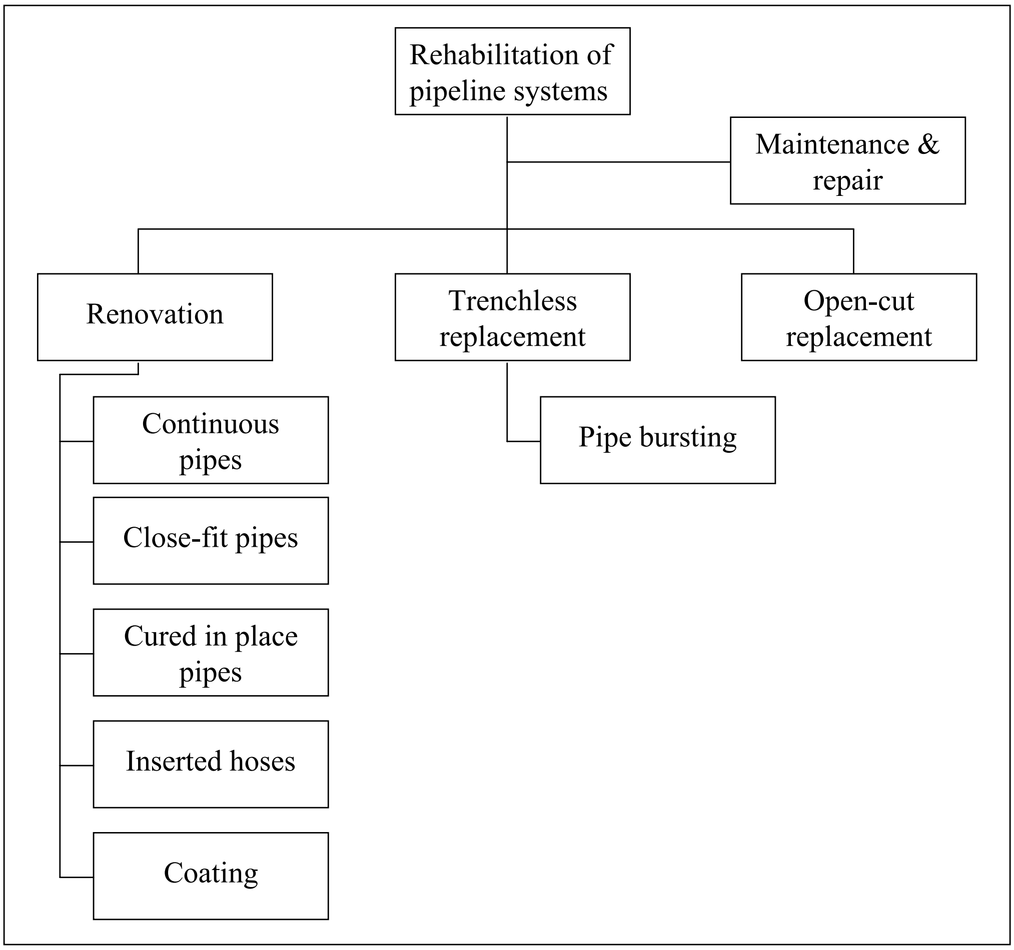


Figure 1-1. Illustration of the terms rehabilitation, repair, replacement and renovation in water networks.

When a pipe breaks or a leak is observed, the pipe has to be repaired. For pipes with cracks normal to the pipe length (shear cracks) or pipes with pitting corrosion, a repair is often carried out using a repair sleeve. These repair sleeves have a typically length of length of 0.2-0.5m depending on the original pipe diameter. The sleeve stops the leak, but the overall strength of the pipe has not been appreciably improved.

When cracks parallel to the pipe length and also due to practical reasons, pipe segments are replaced instead of using sleeves. The length of these pipe segments depends on the type of pipe being replaced and is usually in the range of 1-6 meter. In some cases several pipe segments might be replaced. The replaced pipe segments will normally have higher strength than the remaining pipe.

When a simple repair is not sufficient to repair a pipe, renovation or replacement of the pipe is required. The two basic types of procedures available are called *open trench* or *trenchless technology*.

Replacement means the construction of a new pipe on or off the line of an existing pipe. Replacements are carried out by open cut (open trench) or a trenchless technology like pipe bursting. In both cases the pipe can be considered as a new pipe. The old pipe might either be removed or left in the ground.

Renovation is the term used for rehabilitation methods where the original fabric of a pipeline is incorporated and its current structure is improved. Two sub-groups of renovation techniques exist, namely structural and non-structural methods. The structural methods improve the strength of the pipe and the resulting pipe can be considered as a new pipe. Structural methods include continuous pipes, inserted hoses and lose-fit pipes. The non-structural methods do not significantly improve the strength of the pipe and resulting pipe can considered as it was previous to the rehabilitation with respect to structural condition. These methods include relining with cement mortar or epoxy. The functional performance is of course improved as a result of reduced hydraulic friction and improved water quality due to a new and smoother internal surface. A wide assortment of renovation methods exists.

1.3 Introduction to modelling pipe failures in water networks

Great complexities arise when one attempts to analyse and predict the future behaviour of individual pipes in a system. There is a high variability in failure patterns among different water distribution networks (cities) and also among the various pipes of a given network. Nevertheless, an analysis at the individual pipe level is clearly needed, both for making maintenance decisions under economical criteria and for network reliability analysis.

In situ observations of the physical condition of the water pipes could reveal some information about the structural state. With new non-destructive techniques it is possible to measure the average pit depth and also the maximum pit depth caused by internal corrosion. However, these techniques are time consuming and rather expensive and are only realistic for the most critical water mains.

Figure 1-2 presents a schematic of the temporal development of the technical state of a pipe and the rate of occurrence of failures (ROCOF). Failure incidents (i.e. break or leakage) are marked with a circle on the time axis.

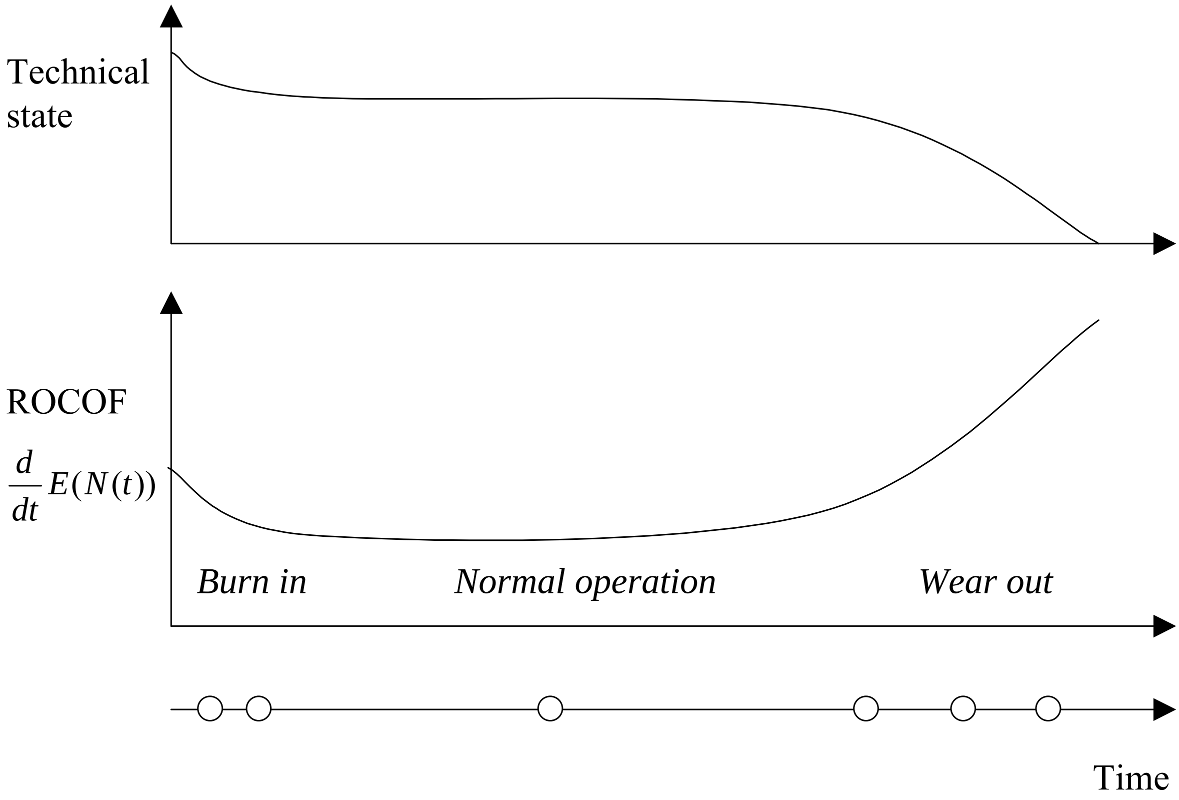


Figure 1-2. Service life of pipes in a water network.

The temporal development of the rate of occurrence of failures (ROCOF) in a water network over the service-life can be illustrated as a *bathtub* curve; a term used due to its characteristic shape (Figure 1-2). ROCOF is the time derivative of the expected cumulative number of failures and is defined as:

$$ROCOF \overset{def}{\equiv} \frac{d}{dt} E\left(N(t)\right) \qquad (1.1)$$

where *E(N(t))* denotes the mean number of failures in the interval (0,*t*].

It is important to notice that two different bathtub curves exist (Ascher and Feingold, 1984). The curve shown in Figure 1-2 represents repairable systems where the system can fail several times. The other type of bathtub curve represents non-repairable systems where the force of mortality (FOM) or hazard function is considered (see Chapter 3).

The ROCOF is often high in the initial phase. This can be explained by the fact that new pipes may have undetected manufacturing or installation defects (also known as “infant mortality”). The period from installation and a short time afterwards is often called *burn in* period. In this period the ROCOF is decreasing. The reasons for the initial failures might be poor production and poor workmanship during installation. In the period of normal operation the ROCOF is low and almost constant. Failures happening in this period are normally random events, such as unusual external loads on the pipe (Mosevoll, 1994; Lidström, 1996; Rausand and Reinertsen, 1996). For the majority of components the ROCOF will show a slight increase during this period (Høyland and Rausand 1994). In the “wear out” period the pipes have increasing ROCOF due to deterioration of the pipe material (e.g. corrosion) which finally leads to the collapse of the pipe. The bathtub curve in Figure 1-2 can be applied to an individual pipe, a group of pipes with similar characteristics or the whole population of a pipe network.

The shape of the bathtub curve in Figure 1-2 is a theoretical behaviour. Analysis of historical failure data does not normally allow us to identify all three stages in the bathtub curve unless we have a complete failure data history going back to when the pipes where laid. For grey cast iron pipes, which have been in useful service for well over 100 years, complete failure data history are normally not available. For more recently installed pipe types like PVC and PE only the first part of the bathtub curve is observable. The observation of a real bathtub curve becomes even more complex due to pipe rehabilitation. Replaced pipes are taken out of service, and of course no more failures are recorded for these pipes. Pipe replacement has a direct influence on the end of the bathtub curve. Only rarely are we able to observe a “non-rehabilitated” version of the bathtub curve. One example of this type of curve is available from the former East Germany, which had a very high level of acceptance for the break rate (Baur and Herz, 1999) (i.e. social costs were not considered!). For most water network this is not the case since replacement and renewal are regular parts of maintenance and operation plans.

From a management point of view failures caused by *wear out* are of special interest, since these failures are important for maintenance and renewal strategies. Therefore, the focus in this work is on failures happening in the wear out phase, i.e. on the right-hand side of the bathtub curve. The proposed models are also applicable for pipes in the earlier stages. However, when no trend in the data is observable, less sophisticated models can be used. Failures happening in the first years after construction (i.e. burn in period) will be under warranty from pipe producers and/or contractors. In Norway the warranty period for pipelines is three (3) years. Failures happening in the burn-in period will of course influence the reliability and availability of the whole network and may also influence the remaining service life of the pipe.

A frequently occurring problem in the analysis of failure data is that not all parts of the data have been collected under similar conditions. Pipes in the same network differ in pipe material, ground conditions, maintenance history, year of construction, frost penetration, way of construction, joint method, water quality and traffic loading. While many of these covariates are not significant enough to cause failure of a pipe in good condition, their combined effect, especially in the case of corroded pipes, can cause failure.

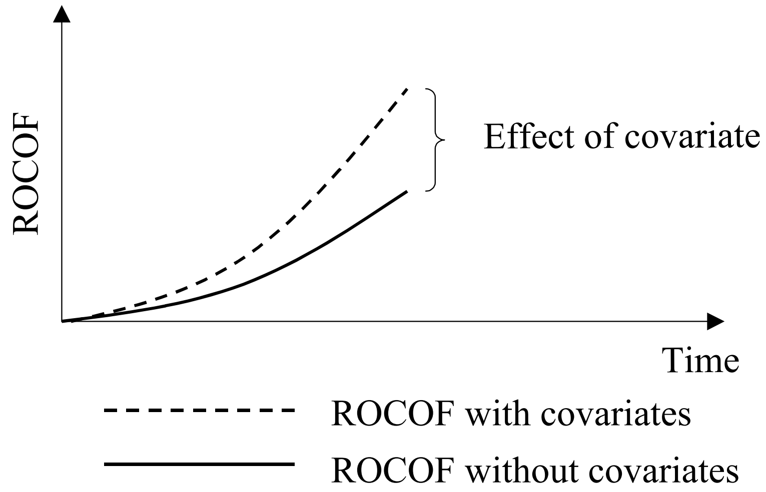


Figure 1-3. The effect of covariates on the tail end of the bathtub curve.

In Figure 1-3 the tail end (right-hand side) of the bathtub curve (Figure 1-2) is shown. The covariates described in the preceding paragraph may influence the ROCOF so that the observed ROCOF (with covariates present) is either larger (e.g. unprotected ductile iron pipe laid in clay) or smaller compared to the ROCOF without covariates present. It is therefore essential to choose a model which includes these covariates. Covariates result in a horizontal shift in the bathtub curve, and the *wear out* period tends to start earlier.

For making maintenance decisions in a water network it will be useful to know the development for the following reliability measures as a function of time for each pipe:

- Rate of occurrence of failures (ROCOF)
- Number of failures in the time interval (0,t], $N(t)$
- Availability
- Probability of a new failure

The above mentioned measures are all related, but they are used in different ways within water network management.

The ROCOF is the key measure and serves as input for the other measures. For the manager the ROCOF tells about deteriorating trends in the network.

A good estimate of the expected number of failures in a given time period can be used in an economic analysis of repair versus replacement for individual pipes. This analysis can also be used in budgeting for future rehabilitation and replacement needs for the entire network.

In order to calculate the reliability of the water distribution network it is necessary to determine the availability for each pipe in the network. Since the deterioration of pipes in the existing network varies according to environmental factors it is important to come up with appropriate statistical models to describe the failure characteristics of each pipe. Statistical models are a first step in network reliability analysis and serve to generate availability data for each component (i.e. pipe) in the network. Since the availability of each pipe varies with time, the reliability of the water supply network should be calculated for different future time intervals.

The probability of failure and its consequences, determine the risk of failure. According to the Norwegian Standard, NS5814 “Risk shall be defined as a list of consequences and their probability”. When carrying out risk analysis for water supply networks, statistical models should be used for assessing the probability of failures for different scenarios.

1.4 Objectives, scope and organisation of study

The main objective of the study is to develop/evaluate statistical models that can be used to predict failures for each individual pipe in a water distribution network. A second objective is to determine whether the maintenance data that is normally collected and registered in AM/FM systems in Norway (using Gemini VA) is sufficient input for these predictive models. The models can be used by water utilities to improve maintenance decisions. Although several statistical methods for analysing systems in terms of covariates have been proposed in medicine, their use in water engineering has been very limited.

Models for describing the technical state of pipelines will be important tools for maintenance planning. The models described in this thesis are applied to a test data set from Trondheim, with the aim of enabling planners to predict how the technical state of the pipes will change and, as a consequence, which are in most urgent need of repair.

A schematic diagram showing the structure of this thesis is shown in Figure 1-4.

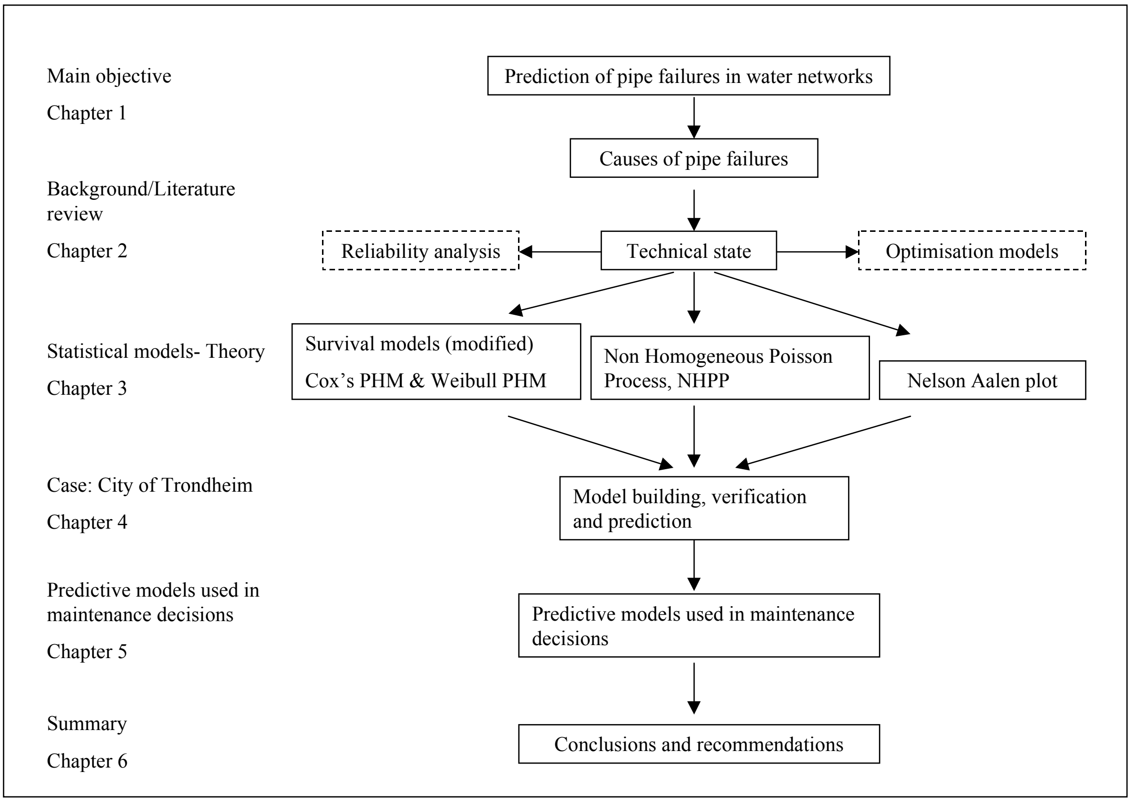


Figure 1-4. Thesis structure.

The necessary background for statistical modelling of pipe failures in a water distribution network are reviewed and presented in Chapter 2. The relevant statistical models used for modelling pipe failures are described in Chapter 3. These statistical models have been applied in a case study of the water distribution network in the city of Trondheim, Norway. The procedure for processing the data and the results from the statistical analysis (including calibration, verification and prediction) is described in Chapter 4. The use of the predictive models for making maintenance decisions and a proposal for their integration in existing AM/FM systems like the Norwegian Gemini VA is described in Chapter 5. Finally the results are discussed and conclusions and recommendations are given in Chapter 6.

2 Literature review

2.1 Introduction

This chapter reviews some of the existing literature on modelling pipe failures in water networks. The first section describes the conditions that cause pipe failures. Existing models for describing the technical state of pipes are reviewed in section 2.3. This review is followed by a discussion of the analysis of water distribution system reliability. This section also shows how models for assessing the structural condition of pipes are coupled to reliability analysis of networks. Existing optimisation models for rehabilitation of water distribution networks are discussed in section 2.5. The purpose of this discussion is to illustrate the breadth of each of these topics and to provide the reader with some idea about the complexity of integrating all these issues into one single optimisation model.

2.2 Causes of pipe failures

The causes of pipe failures have been identified by a number of authors (Morris, 1967; Shamir and Howard, 1979; Kelly and O'Day, 1982; Goulter and Kazemi, 1988). A variety of factors causing failures have been reported. Morris (1967) suggested a number of possible causes for water main breaks, but underlined that "the cause of water main breaks cannot always be ascertained".

A detailed discussion of what causes the failures in the water distribution network is beyond the scope of this thesis. However, a general explanation of the varied causes is helpful. A thorough description of causes for pipe failures for the most common materials used within water supply is given in Mosevoll (1994). In the international literature the main focus is on failures on grey cast iron and ductile iron pipes since these materials have been most frequently used in the past. There is, however an increasing trend in using plastic materials (PE and PVC) and in the future we will have to expect failure of these pipes due to ageing.

The most important variables describing the structural deterioration of water networks can be grouped into four (4) categories; structural or physical variables, external or environmental variables, internal or hydraulic variables and maintenance variables (Røstum et al., 1997). A list of possible factors causing pipe failures is given in Table 2-1.

Table 2-1. Factors affecting structural deterioration of water distribution pipes.

Structural variables	External/environmental variables	Internal variables	Maintenance variables
Location of pipe	Soil type	Water velocity	Date of failure
Diameter	Loading	Water pressure	Date of repair
Length	Groundwater	Water quality	Location of failure
Year of construction	Direct stray current	Water hammer	Type of failure
Pipe material	Bedding condition	Internal corrosion	Previous failure history
Joint method	Leakage rate		
Internal protection	Other networks		
External protection	Salt for de-icing of roads		
Pressure class	Temperature		
Wall thickness	External corrosion		
Laying depth			
Bedding condition			

Most of the factors are constant with time, but some might also be time dependent (e.g. loading, water quality, water velocity).

The following paragraphs describe the factors which are commonly assumed to have the greatest impact on pipe failure.

Age and installation period
Different installation periods or eras, show different failure characteristics. These characteristics are more dependent on the construction practice for each era than on time since installation (age). Some construction periods have a higher break rate than others (Andreou et al., 1987b; Mosevoll, 1994). In some cases, older pipes are more resistant to failure than younger pipes. For grey cast iron pipes this can be explained by the thinner walls produced by newer casting methods. The thinner walls lead to a greater effect of corrosion and higher stress level for the same external loads. The importance of backfill on pipe lifetime was not realised until the 1930s. Jointing techniques have improved over the years, allowing greater deflections at joints. During the postwar housing boom of the 1950s and 1960s, quantity was more important than quality of the construction. Poor bedding conditions and quality of workmanship are reported for this era (Mosevoll, 1994; Sundahl, 1997). Andreou et al. (1987b) reported a tendency of pipes with failures at early ages to perform better than pipes failed at later ages. Wengström (1993a) found that pipe records are unable to show age dependency and concluded that repair strategies might mask age dependency,

i.e. few pipes are allowed to stay in the ground after more than approximately four (4) repairs. Goulter and Kazemi (1988) also concluded that age should not be the single factor used for assessing pipe condition.

Corrosion
Corrosion is one of the main reasons for pipeline replacements (Ræstad, 1995). External and internal corrosion cause degradation of pipes made of grey cast iron, ductile iron and steel (Mosevoll, 1994). The internal corrosion depends on the characteristics of the transported water (e.g. pH, alkalinity, bacteria and oxygen content) and external corrosion depends on the environment around the pipe (e.g. soil characteristics, soil moisture, and aeration). Kaara (1984) argued that external corrosion is an important factor to incorporate in predictive models as its intensity, unlike that for internal corrosion, will vary from pipe to pipe as soil conditions vary.

Diameter
There seems to be total agreement in the literature that highest number of failures is found in pipes with small diameters (e.g. Andreou, 1986; Eisenbeis, 1994). Pipes with diameters less than or equal to 200 mm have particularly large number of failures. The high frequency of failures for small pipe dimensions is explained by reduced pipe strength, reduced wall thickness, different construction standards and less reliable joints for smaller pipes (Wengström, 1993b). Another reason might be the lower velocities in smaller pipes resulting in settlement of suspended materials from the water, creating a great environment for bacteria to grow. In addition, larger pipes are heavier, and settlement occurs during or immediately after installation.

Pipe length
The pipe length differs from pipe to pipe within a network and also between networks. For long pipes (e.g. >1000 m) external conditions like soil conditions and traffic might vary along the pipe. Røstum et al. (1997) recommended pipe lengths on the order of 100m in order to avoid different conditions for the same pipe. Andreou (1986) found the hazard function to be approximately proportional to the square root of length. Similar findings are reported by Eisenbeis (1994), Lei (1997) and Eisenbeis et al. (1999).

Pipe material
Most water works consists mainly of cast iron pipes (i.e. grey cast iron and ductile iron pipes) and long records of failures exist for these pipes. Many researchers have focused on grey cast iron pipes (Andreou, 1986; Goulter and Kanzemi, 1988; Eisenbeis, 1994; UtilNets, 1997). In more recent times, new materials like PVC and PE have been introduced on a large scale for water networks. The material characteristics of these pipes differ widely, and the different materials must be analysed separately (Mosevoll, 1994). Statistical analysis of pipes made of PVC and PE are the focus of recent studies (Eisenbeis

et al., 1999). In a Swedish survey (Sundahl, 1996) the highest break rates were observed on grey cast iron pipes and PVC pipes.

The manufacturing techniques for the different pipe material have changed considerably over the years. The evolution of casting methods for grey iron pipes is a good example of this. The first pipes were horizontally cast in sand moulds resulting in uneven wall thickness. Later, vertical casting was introduced, resulting in more even wall thickness and allowing the production of pipes with thinner walls. The development of centrifugal casting methods resulted in improved pipe strength and greater consistency of wall thickness (WRc, 1998). Production techniques, as well as materials need to be considered when analysing grey cast iron pipe failures. The production method is correlated to the year of production, which again is related to the laying-year available in most pipe records.

Seasonal variation

A seasonal pattern with the greatest number of failures occurring during the winter is common for many water distribution networks (Eisenbeis, 1994; Sægrov et al., 1999). Andreou (1986) found that smaller diameter pipes (less that 8 inches) have higher break rates in the winter. Sundahl (1996) analysed five (5) water networks in Sweden. The number of breaks was correlated to air temperature, but no correlation was found to precipitation and snow depth. In Trondheim, most of the failures are reported in the summer season, in spite of the expected frost load in wintertime due to the cold climate (Røstum, 1997). This is explained due to an intensive leakage control program carried out in the summer season detecting a lot of external corrosion of unprotected ductile iron pipes. Wengström (1993b) analysed Swedish water networks and reported the higher break rates for ductile iron pipes during the summer, but higher breaks during winter for pipes made of grey cast iron. The author concluded that this could give a change in the seasonal break rate, as more ductile iron pipes are used.

Sægrov et al. (1999) observed both a winter and a summer peak in break rate in UK. The summer peak was attributed to drying and uneven shrinkage of clay soils, whilst the winter peak may have been due to frost loading or thermal contraction effects. In addition, the annual break rate over a period of ten years was found to be related to the mean annual daytime temperature and inversely related to the total annual rainfall.

Climatic effects should be used at a preliminary stage in order to determine pipe failure causes. However, for prediction of future failures it is not easy to include climatic effects as a covariate since the time evolution of these factors are unknown. Sundahl (1996) in her thesis tried to model the seasonal variations in leakage using a sinus curve. From the manager’s point of view the existence of seasonal variation in pipe failures might be useful for the daily planning/organising of the management of the water network. However, when calculating the future needs for rehabilitation and for prioritising between pipes it is less useful to know the actual day of failure.

Soil conditions

Soil conditions affect external corrosion rates, and play an important role in pipe degradation. Clark et al. (1982) used the presence of corrosive soil environments in their analysis of pipe failure, but found a low correlation between length of pipe laid in corrosive environments and breaks. Malandain et al. (1998) used GIS to relate soil conditions to the break rate for pipes in the water network in Lyon, France. Eisenbeis (1994) used ground condition, (defined as the presence or absence of corrosive soil) as an explanatory variable in the analysis of pipe failures.

Previous failures

The number previous failures or the failure history of a pipe is a significant factor for the predicting future failures (Walski and Pelliccia, 1982). Andreou (1986) used Cox's proportional hazards model to analyse breaks in the water network. The break rate increased with each break, up to the third break after which the break rate was constant, but high. At this point the pipes were assumed to be in a "fast breaking state". The number of previous breaks was found to significantly affect the hazard function of the pipes. Eisenbeis (1994) observed a similar pattern. Malaindain et al. (1999) included these findings from Andreou and Eisenbeis in a break rate model.

Goulter and Kanzemi (1988) observed the temporal and spatial clustering of water-main breaks, indicating that a previous break increased the likelihood of future breaks in its immediate vicinity. About 60% of all subsequent breaks occurred within 3 months of the previous break. They suggested that the subsequent breaks are caused by damage during repair operations, such as pressure surge while refilling the pipe after repair or ground movements caused by excavation, backfilling and the movement of heavy vehicles. Sundahl (1996, 1997) also reportes an increase in break rates after a break due to maintenance activity on the network (e.g. repair, replacement).

Several factors unrelated to repair activities are also responsible for the clustering of breaks in the network. Pipes in the same location often have the same age and materials and are laid with the same construction and joining methods. Pipes in the same location are also likely to be exposed to the same external and internal corrosion conditions.

Nearby excavation

Excavations in the vicinity of pipelines disturb bedding conditions, resulting in pipe failure. Research in the U.K. (WRc, 1998) showes that work on adjacent services (e.g. gas, electricity) can cause pipe failure.

Pressure
Static water pressure and pressure surges in a distribution system can affect pipe failure. Pressure surges can occur when water and air valves open and close during network operations. These surges can be one of the factors in failure clustering, as valves are closed and opened during repair activities. Andreou (1986) found static pressure as significant when modelling pipe failures, but the importance of the variable was found to be low. Clark et al. (1982) used both the absolute pressure and the pressure differential (surge) when modelling time to first failure.

Land use
Land use (e.g. traffic areas, residential areas, and commercial areas) is used as a substitute for external loads on pipes. Eisenbeis (1994, 1997) used land use over the pipe (i.e. no traffic vs. heavy traffic), as a variable in failure models.

2.3 Existing models for describing the technical state of pipes

There have been three main approaches to modelling the technical state of water networks with respect to pipe failures: descriptive analysis, physical analysis and predictive analysis. A summary of these approaches is given in Wengström (1993a). Descriptive analysis organises and summarises the data and can be used to indicate various trends in failures and factors affecting pipe failures. Every effort to model the structural condition of a pipe network should begin with this basic analysis. Physical analysis uses estimates of the external loading, amount of internal and external corrosion and the pipe stress to model the structural state of the pipe material. Predictive analysis uses statistical techniques to predict future system failures.

One of the most sited references concerning pipe failure modelling is the so-called *Shamir and Howard* approach (Shamir and Howard, 1979), a method used to determine the optimal time of replacement for water pipes. Both existing and replaced pipes are considered in this model. Based on failure data, the number of breaks per unit length per year is forecasted by:

$$B(t) = B(t_0) \cdot e^{A(t-t_0)} \tag{2.1}$$

where $B(t)$ denotes the break rate (breaks/year/km) in year t and $B(t_0)$ the initial break rate in year t_0 . A is a constant with the unit year^{-1}. (Shamir and Howard used the notation $N(t)$ instead of $B(t)$ for break rate. Since the term $N(t)$ is widely used for counting processes as the cumulative number of failures during $(0,t]$, $B(t)$ is substituted for $N(t)$ in this work). After replacement, the pipe is considered “virtually break free” within the planning horizon. Shamir and Howard combined the break forecast with economic data to find the optimum time for replacement. This break regression equation has been recommended by other authors (Walski, 1987).

The main limitations of the proposed break regression model are:

- Basing break predictions on pipe age alone is very limited. Other factors such as pipe diameter, length, pressure, material, soil, aggressiveness of the water, number of previous breaks are significant factors in pipe break, and should then be included in the model.

- The method does not include information about pipes that have not yet failed (i.e. censored failure times).

The failure regression model is however, simple to apply and in spite of its limitations has been widely used in research projects to predict the number of future failures in water supply networks (Kaara, 1984; Smith, 1994; Kleiner, 1997; Kleiner and Rajani, 1999).

Walski and Pelliccia (1982) proposed an approach similar to that of Shamir and Howard (1979), which includes factors for the break history and pipe diameter. Their model takes the form:

$$B(t) = C_1 C_2 a e^{b(t-k)} \qquad (2.2)$$

Where $B(t)$ denotes break rate (breaks/year/mile) at time t, C_1 is the correction factor for previous breaks and C_2 is the correction factor for pipe size, a and b are regression parameters and k is the year of pipe installation. (t-k) is the age of the pipe. (Walski and Pelliccia used the notation $N(t)$ instead of $B(t)$ for break rate. In order to avoid confusion with the counting process terminology, the notation has been changed in this work).

Clark et al. (1982) propose a regression model based on the observation that a lag period occurs between the pipe installation and the first break. Two equations are developed, one to predict the time elapsed until the first break occurs and the second to predict the number of subsequent breaks. As in the previously described models an exponential growth in the break rate is assumed (after the first break). Several demographic variables such as industrial development and residential development are used as covariates in the equations. However, models which include these variables fit the observed data poorly (i.e. low R^2- value).

Kaara (1984) in his thesis and Andreou (1986) in his thesis and the accompanying papers (Andreou, 1987; Andreou et al., 1987a; Andreou et al., 1987b) introduced Cox's semi-parametric Proportional Hazards Model (PHM) (Cox, 1972) for analysing pipe breaks in water networks. Andreou developed a model for predicting failure probability for each individual pipe in the network for two large water utilities in the Northeastern U.S. In this model, the life span of a pipe is divided into a slow break-stage and a fast break-stage. The fast break-stage starts after three breaks. A Proportional Hazards Model (PHM) is used to describe the "break rate" *h(x)* for each pipe as a function of time (The author used the term break rate for *h(x)* which is not in accordance to my *Glossary of terms* where hazard function is used).

$$h(x,\mathbf{z},\boldsymbol{\beta}) = h_0(x)\exp(\mathbf{z}'\boldsymbol{\beta}) \tag{2.3}$$

where $h_0(x)$ is the baseline hazard function, $\mathbf{z}'$ is a column vector of covariates or independent variables ($\mathbf{z}'=[z_1,z_2,z_3,..z_p]$), and $\boldsymbol{\beta}$ is a vector of unknown regression parameters ($\boldsymbol{\beta}=[\beta_1,\beta_2,\beta_3..\beta_p]$) that have to be fitted using field observations. A *bathtub* shaped curve gives the best description of the baseline hazard function. The case study finds the following variables to be most significant in analysing breaks: pressure in the pipe, number of previous breaks, age of pipe at the time of the second break, installation period, land use and pipe length. The "break rate" does not increase after the third break. The pipes used in the analysis vary greatly in length. Some of the pipes are too long (i.e. >1000 m) to be analysed as one component, as conditions affecting break rate could vary along the pipe length.

Andreou developed this model to predict failure probability and to assess explanatory variables in pipe failure. The model is not intended to predict the expected number of failures in a network.

Al-Humoud et al. (1990), use a PHM to model failure for the same two water utilities as Andreou (1987). The sensitivity of the model parameters to sample size and percent censoring are examined through random sampling from a database. The hazard function varies with sample size and percentage of censored observation.

Li and Haimes (1992) developed a semi-Markov model to describe the deterioration process in a water supply network. The Markov "states" represented are the state of operation (functioning or under repair) and the number of breaks that have occurred. A PHM as used by Andreou (1986) is applied to identify two stages of deterioration and their accompanying hazard functions. The authors used the formulas of Walski and Pelliccia (1982) to estimate the repair time (i.e. time that it takes to repair the pipe) of a pipe, and to estimate the accompanying cost of repair and replacement. The steady state probabilities obtained from the Markov model are used in a linear optimisation model, which maximises the availability of the system and includes the expected costs as a constraint. This analysis does not include a hydraulic network model, and can not account for alternate supply (system availability) while a pipe is under repair.

Wengström (1993b) presents an analysis of the system behaviour of water distribution networks using the Additive Hazards Model (AHM). In this regression model the covariates are linked to time between failures is an additive way. The aim of the work is to investigate whether or not pipe repairs renewed the system. In contrast to the PHM, the AHM does not consider the ageing of the pipes, but evaluates the time between failures/repairs. The author claims that a PHM should be used for analysing individual pipes while the AHM should be used to analyse system behaviour in terms of break history and the influence of repairs. The results from the analysis show that repair activity carried out in the network increases the probability of failures.

Goulter et al. (1993) developed a method for quantifying the variation in pipe break rates associated with temporal and spatial clustering of water-main breaks. This method is also discussed by Goulter and Kanzemi (1988). The first step of this method uses a "cross referencing scheme" to determine the mean number of breaks that occur on a pipe after the first break. In the second step, a non-linear regression is used to determine the values of coefficients for an equation that captures the changes in the mean number of subsequent breaks with variation in time and space. These parameters are applied to a non-homogeneous Poisson distribution that predicts the probability of a subsequent break in a pipe, given that the first break already occurred. The model is restricted to predicting the subsequent breaks, and cannot be used to predict the first break. The non-homogeneous Poisson distribution used does not include explanatory variables.

A new statistical distribution, named the Herz distribution, was introduced by Herz (1996, 1997, 1998) and used by Trujillo (1995) for describing the ageing of water pipes. The model is based on a mathematical cohort survival model developed at Karlsruhe University ("Karlsruhe Procedure"). In this model the network is divided into cohorts of pipes, i.e. groups of pipes with the same year of installation, pipe material and other characteristics which affect their performance over time. The Herz distribution was developed specifically for the ageing of infrastructure elements and has the feature that the failure rate/renewal rate increases with age more and more before it increases more gradually and finally approaches asymptotically a boundary value. What the author called the failure rate/renewal rate, is in statistical terms the hazard function for the *service life* of a pipe. The pipe is replaced when the service life is expired. The renewal rate is given by:

$$h(t) = \frac{be^{b(t-c)}}{a + e^{b(t-c)}} \quad \text{for } t \geq c = 0 \tag{2.4}$$

Where the value of a, b and c may be derived empirically for the past periods and particular types of pipes. When used to forecast, they must be based on expert judgement, i.e. on pipe survival estimates of managers and engineers (Herz, 1996). The ageing function (with upper and lower boundaries) must be established for each group of pipes. The model predicts the residual life (i.e. remaining lifetime) for each pipe cohort and can be used to estimate rehabilitation requirements.

Several major European cities have used the Herz distribution for planning pipeline renovation and rehabilitation. The procedure has been cast into the user-friendly software KANEW in a research project sponsored by AWWARF (Deb et al., 1998). The model was used in five (5) case studies in the U.S. as part of this project. The authors concluded that KANEW is useful for assessing future rehabilitation needs, but could be improved by developing better methods for determining survival function parameters using operation and maintenance records.

The main disadvantages of the Herz distribution/KANEW are:

- KANEW does not provide for the analysis of individual pipes, as no covariate structure is included in the model. Ageing functions are specified for each type of pipes, not for individual pipes. This implies that the model should only be used when analysing rehabilitation needs and strategies for the entire water distribution network (i.e. network level).

- KANEW does not consider important factors like hydraulic capacity, water quality and reliability analysis of the network in the analysis of rehabilitation/renewal needs. The model assumes that these properties are a function of age (for each cohort), and are accounted for by the probability density function of the service life.

- The parameters in the Herz distribution are based on historical renewal rates and not historical break rates. The renewal rates reflect the rehabilitation policies in the past (e.g. often tending to maintain a fixed average age of the stock) and the economic and technical condition of the period. Furthermore the rehabilitation policies are likely to change in the future. So the parameters would have to be changed in order to reflect future standards and policies. This is a forecasting problem that might be tackled with Delphi technique.

Based on the needs for improvements outlined by Deb et al. (1998), Gustafson and Dale (1999b) suggest that survival curves be generated by using a Monte Carlo simulation as input for KANEW.

Eisenbeis (1994 and 1997), proposed an approach similar to Andreou's application of the proportional hazard model (Andreou, 1986), but assumed a Weibull distribution for the baseline hazard function, $h_0(x)$. This model also includes three-stages. The first stage describes hazard functions for pipes that have not experienced a failure. The second stage describes hazard functions for the second to forth failure, while the third stage describes the hazard functions for pipes after their forth failure. The water supply network in Bordeaux is used as a case study for the analysis. The study demonstrates that the most important factor for predicting failures is the number of previous failures. Age is the most important factor for forecasting the first failure. For pipes with two to four failures, the hazard function is less dependent on age. For pipes with more than four breaks, the hazard function is constant. For predicting the future failures for each pipe a method assuming the failures to come from an exponential distribution is used. Since the baseline hazard function is actually a Weibull model, the procedure for predicting new failures is only valid in the case where the Weibull distribution is reduced to an exponential distribution.

Andreou (1986) and Eisenbeis (1994) both distinguish between a slow and a fast break stage, which reflects the different stages in the *bathtub* curve. Both authors limited their analyses to the failure of grey cast iron pipes.

Vagnerini (1996) modelled the evolution of break rate using the exponential distribution with an *a priori* categorisation by pipe material. This model assumes a constant break rate, and the mean time to failure (MTTF) is calculated for each group of pipes. The assumption of a constant break rate could not be verified. The model was originally developed as an aid in choosing pipe materials.

Lei (1997) and Lei and Sægrov (1998) use Cox's Proportional Hazards Model and the Weibull accelerated model to analyse the water distribution network in Trondheim. In the survey only the first failure is analysed, and all maintenance activity is considered as a failure. In addition to lifetime analysis, Nelson-Aalen plots are used to analyse for trends in the network. A linear regression is fitted to the Nelson–Aalen plot to predict the number of failures within a time horizon, assuming no trend in the data. The study is limited by the decision to treat all maintenance activities (including non-repair activities like flushing) in the network as failures. For some of the models proposed, the covariates are included even if they are not significant.

A *Reliability Based System for the Maintenance Management of the Underground Networks of Utilities* funded by the European Union under the Brite/Euram programme named UtilNets is reported in UtilNets (1997). A structural reliability module for water mains, a hydraulic reliability module and a network reliability module (Camarinopoulos et al., 1996b) have been integrated into a decision support system for water network rehabilitation decisions called UtilNets. The program has routines for simple water quality analysis, optimisation of rehabilitation works and calculation of rehabilitation/replacement and social costs.

The module for describing the structural reliability of water mains is explained in Camarinopoulos et al. (1996a). The time dependent structural reliability (*L*), for each pipe is defined as the probability that the overall resistance of the pipe

(*R*), (representing. pipe thickness, strength, etc.) is greater that the overall load effects (*S*) (e.g. traffic load, water loads, etc.):

$$L(t) = P(R(t) - S(t)) \tag{2.5}$$

The variables, or loads, exhibit a stochastic behaviour and are assumed to occur according to a Poisson process. The authors introduced the term *failure surface*, to define the set of variables where failures occurred.

UtilNets was originally limited to the analysis of grey cast iron pipes. Both pitting and uniform pipe corrosion are included in the model. A pipe is assumed to have failed when the maximum pit depth becomes equal to the pipe wall thickness. 16 variables are used to describe the performance of the main (i.e. earth load, traffic load, water load, working pressure, truck load, surge pressure, frost load, thermal load, pit depth, stress, wall thickness, strength, unsupported length, external radius, internal radius, and corrosion coefficient) (Figure 2-1). The model calculates the life expectancy for each pipe as the number of years from when the pipe was laid until it reaches a structural failure probability of 50 %.

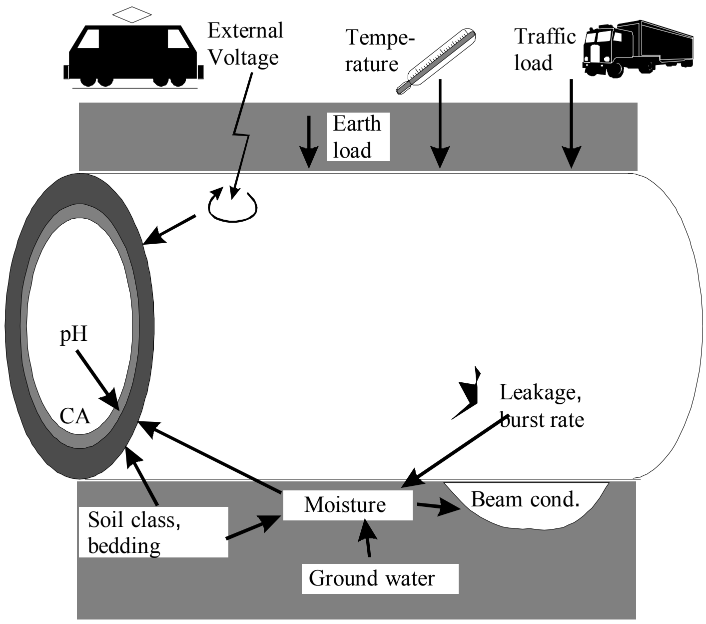


Figure 2-1. Pipe loads used in UtilNets (Preston et al., 1999).

UtilNets also includes a simple hydraulic module. The actual state of behaviour is compared to the maximum demand requested, minimum operating pressure and maximum velocity permitted for each pipe. A hydraulic failure is assumed to have occurred when the loading exceeds the resistance.

UtilNets main limitations are:

- No goodness of fit for the model is documented.

- Only the first failure of each pipe is considered.
- The structural model is deterministic and requires extensive data for each pipe (16 variables). Corrosion depth for specific pipes must be found by analysing pipe samples.
- The model only simulates grey cast iron pipes.
- The hydraulic analysis is carried out without a hydraulic network simulator.

In a more recent paper, Preston et al. (1999), propose that the scope of UtilNets be somewhat reduced. The authors state that, *"UtilNets in its current prototype form is too rigid, over complex and requires impracticable amounts of data"*. They conclude that collecting the vast amounts of data required for the analysis is too resource intensive. The model will only be practical if utilities start to collect similar data as part of their normal operation. Therefore, Utilnets will be modified in terms of reduction in number of modules and reduced number of variables used in the analysis.

Le Gat (1998) describes the application of the Weibull PHM for the analysis of irrigation pipes in the southern part of France. The expected number of failures for each pipe is predicted. The work follows the principles of Eisenbeis (1994) and Andreou (1986). A Monte Carlo simulation based on the survival functions is introduced to predict pipe failures.

Eisenbeis et al. (1999) present an analysis of two French networks and one Norwegian network using a Weibull PHM. The model uses a stratification of the failure data according to the number of previous failures recorded. Quite good agreements between observed and predicted failures are reported. The results from the Norwegian study are also presented in this thesis.

Malaindain et al. (1998, 1999) and Malandain, 1999 use a Poisson regression model to quantify the influence of the variables diameter, material, and position of the pipe (i.e. located in a road or not) on the break rate. The time since installation is not included in the regression. The water network of Lyon is used as case study. Prior to the analysis the pipes are grouped according to structural and environmental factors. In order to model the break rate (i.e. hazard function) as a function of time, the break rate function was divided into three different intervals (Figure 2-2), and each interval is analysed separately, resulting in a step function for the break rate. In the early stage the hazard function increases and a Weibull model is assumed based on the results from Eisenbeis (1994). In the following stages an exponential model (i.e. constant hazard function) is used. The author points out that the proposed approach should only be used at *network* level and not at *pipe* level.

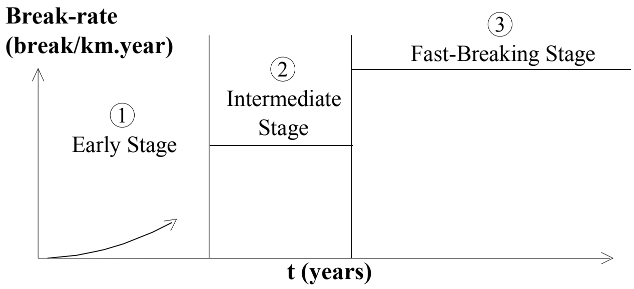


Figure 2-2. Evolution of break rate for water network of Lyon (Malaindain et al., 1999).

The authors use a Geographic Information Systems (GIS) for identifying the spatial variation for the break rate caused by environmental variables (e.g. soil condition).

Gustafson and Clancy (1999a) describe a method to model the occurrence of pipe failures in grey cast iron pipes with a semi-Markov model, where the "state" of the water mains is represented by the number of failures and the time between failures is used as the "holding time". The required probability distributions are estimated using survival analysis. The time to first failure is modelled with a 3-parameter gamma-distribution and the subsequent failures with an exponential distribution. The data set is divided into three (3) groups of pipes, depending on the original wall thickness. No explanatory variables are included in the analysis, due to lack of data. The authors report that the mean failure time is strongly related to the failure number and conclude that these grey cast iron pipes are deteriorating. The model's reliability is reduced by the poor time resolution (i.e. one year) available for recorded failures.

2.4 Reliability of water networks

Water distribution networks are traditionally designed to be completely reliable. However, the increasing scarcity of public money for construction and maintenance and the advanced age of many water supply systems are causing system operators to focus on reliability analysis. The reliability of a system, according to ISO 8402 (Høyland and Rausand, 1994) is defined as *the ability of the system to perform a required function, under given environmental and operational conditions and for a stated period of time*.

Reliability models have been adopted in other fields involving networks (e.g. power supply, computer engineering). Some of these approaches may prove useful for analysing water distribution networks, although one must bear in mind the different physical laws that govern flow in the various networks and the different effect that the failures have in these networks. The reliability analysis of water distribution systems must include hydraulic network models. The analyses of ring systems common to water supply networks are more complex than traditional mechanical reliability analysis, where one considers the reliability of a single route between source and supply. Hydraulic network models allow analysis of both alternate supply routes, and the hydraulic capacity of these routes. The mechanical reliability corresponds to an upper bound estimate for the true hydraulic reliability of the network.

Water distribution network reliability is measured relative to failure. Failure can be of the physical type (e.g. break or leakage). The reliability of the network might then be interpreted as the probability that *all* demand points are connected to the source. This is sometimes called the connectivity definition (Wagner et al., 1988a). The connectivity reliability results in one single value of reliability for the whole network and should be used when designing new systems (Quimpo, 1996). Reliability might also be defined as the probability that a given demand point is connected to the source. Although a fully operational path may exist between a water source and a given demand node, the demand node may not receive any water if there is insufficient pressure in the network. This definition is sometimes called the reachability definition. According to Quimpo (1996) the reachability definition is suitable as a reliability measure in maintenance optimisation. Both connectivity and reachability need to be considered in any reliability analysis of water distribution networks.

Most published research has concentrated on the analysis and decision process for improving the mechanical reliability of a water distribution network. Research on inclusion of capacity in the reliability analysis, has among others been carried out by Wagner et al. (1988a, b), Wu et al. (1993), Schneiter et al. (1996) and Hansen and Vatn (1999, 2000).

The methods used for analysing the reliability of water distribution networks can be divided into two groups: simulations (i.e. Monte Carlo) or analytical methods (e.g. cut sets). The basic principle behind the analytical methods is to transform the topology of the systems into a model that consists only of series and parallel structures.

Wagner et al. (1988a, b) propose a simulation model of system reliability in water supply networks which focuses on pipe and pump failures. The simulation program is divided into two parts; a simulation section, which generates failures and repair events according to specified probability distributions (i.e. Monte Carlo simulation) and a hydraulic network solver, which calculates the flows throughout the network and the pressures at each node for a specific demand in the completely or partially failed system. The pipe failure data is generated based on an exponential distribution. The authors define three operating states for each node; “normal”, in which demand is fully supplied, “reduced service”, in which the pressure falls below a threshold value but is still above a minimum value and a “failure mode”, in which the pressure falls below a specified minimum and the supply is shut off. Similarly, three operational states are defined for the entire system. “Normal” is defined as the system state when all nodes are functioning normally. A state of “failure” exists when one or more nodes are in failure mode. The system is considered to be in “reduced mode” when one or more nodes are in a state of reduced service, but no nodes are in a state of failure. During a simulation session, various outcomes are continuously recorded. Events such as the time duration in which each node is in any operational mode and total demand shortfall are calculated and relevant statistics are computed.

Quimpo and Shamsi (1991) used the exponential distribution when describing the break rate for each pipe, in order to estimate the reliability of the water supply network. This reliability model uses the minimal cut set or the minimal path set approach to calculate the reliability of the system. Their approach includes a hydraulic simulation for determining the flow through all pipes. Reliability surface plots (i.e. contour lines with equal reliabilities) are used for visualising the results. The reliability model is then used as a tool for assigning priority to maintenance activities based on a predefined level of acceptable reliability. Low points on the surface highlight areas of unacceptable reliability. Pipes located in these areas are identified as priority candidates for preventive maintenance or replacement. One deficiency of Quimpo and Shamsi’s method is that the reliability surface developed in the analysis is based solely on connectivity between a demand point and a water source. Hydraulic capacity (reachability) is not considered.

Wu et al. (1993) address the problem of quantifying the reliability of water distribution networks on the basis of the connectivity of the demand point to the water source alone. The authors introduce a capacity weighted index that takes into account partial satisfaction of demand in addition to a minimal path set method to calculate the connectivity from source to a point in the network. The capacity for each *path* is calculated and thereby the ability for each path to transport the required flow to the demand node. The reliability of each pipe is assumed to be known and constant. Wu et al. (1993) conclude that the addition of a of hydraulic capacity model would make the reliability measure more realistic.

In a network reliability analysis carried out for the water network in the city of Trondheim (Vatn and Tveit, 1997) only rough estimates of pipe availability are used. The study considers mechanical reliability only, and hydraulic reliability is not included in the analysis.

Camarinopoulos et al. (1996b) developed a capacity based reliability measure for water supply networks. Both the probability that the demand point is connected to a source (connectivity) and the probability that the system could meet a specified level of flow at each demand point (capacity) are considered. The method of minimal cut sets is used to solve the connectivity problem. Applying this method to large, real world networks required some speeding up techniques. The term “flow cut set”, meaning the minimal set of edges whose failure cause insufficient supply at the demand points was introduced.

Camarinopoulos et al. (1996b), do not use a hydraulic simulator for flow calculation in their reliability calculations. Their method for measuring reliability will be included in the decision support system UtilNets (1997), as a network reliability module.

Walski (1993) pointed out the importance of valve location when assessing the reliability of water distribution networks. He argued a description of the valve system provides a better representation of reliability than the link-node approach normally used. Walski introduced the concept of segment (i.e. collection of pipes) to describe the portion of a water distribution network that could be isolated by closing valves.

Hansen and Vatn (1999, 2000) combine a hydrostatic model with a network reliability model to calculate a network's ability to supply the demand point with sufficient amounts of water. The EPANET simulator from the US EPA Drinking Water Research Division is used as the hydrostatic engine. A software tool, named AQUAREL was developed to carry out the calculations. Their method uses modularization to reduce calculation times. This involves modelling the water distribution network in two stages. In the first stage a global model is defined where the nodes in the network are larger areas such as leakage zones. In the second stage each zone is modelled in detail. The water distribution network in Trondheim, Norway is used as a case study. Like other network reliability analyses, the model requires availability data for each individual element such as pipes, pumps and valves. Availability data for pipes is supplied from the statistical models described in this thesis (Chapter 3). Availability data for pumps and valves have not been collected for the water network in Trondheim. The authors use data collected for similar, offshore installations (OREDA database) to estimate availability for these elements.

2.5 Optimisation models for rehabilitation and replacement of water distribution networks

The first attempt for determining the optimal time for pipe replacement was presented by Shamir and Howard (1979). This model includes break rate data for each pipe (see Eq. (2.1)) and the present value costs of replacement and maintenance (Figure 2-3). This is a highly simplified approach which omits many important elements in rehabilitation planning.

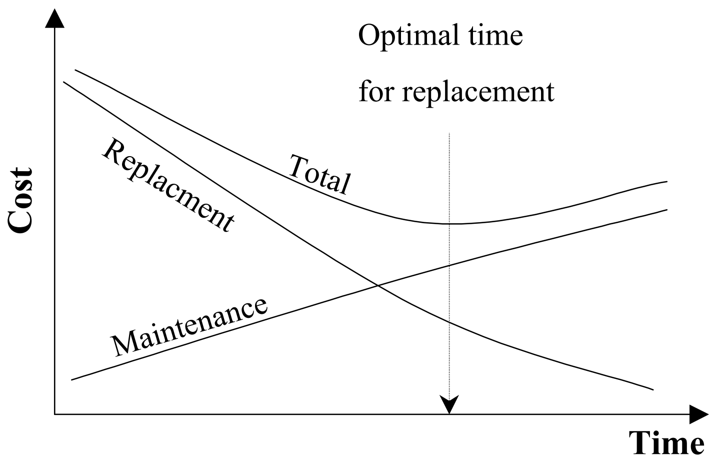


Figure 2-3. Conceptual curves for determining the optimal time for replacement (Shamir and Howard, 1979).

A more comprehensive attempt to optimise the rehabilitation/replacement of pipes in a water distribution network was carried out by Woodburn et al. (1987). The objective function of this model is cost minimization, where the cost function includes the costs of rehabilitation, replacement, repair and pumping. The model uses a non-linear programming procedure in combination with a hydraulic simulation program (KYPIPE) to determine if a pipe should be rehabilitated, replaced or left alone (i.e. no action). Only hydraulic constraints are included in the model. The proposed model is not designed to optimise future rehabilitation/replacement schemes, but indicates whether a pipe should be rehabilitated or replaced at the present time. The model allows for rehabilitation/replacement of a portion of a pipe.

Kim (1992), in his dissertation, describes a methodology to select the pipes to be rehabilitated/replaced in an existing water distribution network which minimises the total rehabilitation and energy cost at given water demand and pressure requirements. A hydraulic simulator (KYPIPE) is joined with a non-linear programming model to solve the non-linear problem. The model has been tested on an artificial network with 43 pipes. The author states that the model has the ability to find optimal solutions, but global optimality is not guaranteed. The proposed model differs from previous work by using the whole pipe section as a decision variable instead of pipe length (Woodburn et al., 1987). Kim does not describe the method used to predict the future failures that are needed as input for the model. The model does not include network reliability analysis.

Smith (1994) integrates the methods of pipe failure analysis, network reliability and optimisation to develop optimal design and replacement strategies that meet hydraulic requirements under different demand and failure scenarios. Smith uses a modified version of the basic exponential failure model developed by Shamir and Howard (1979) for predicting pipe breaks. Smith uses a critical number of breaks (20 breaks/km) and a critical break rate (10 breaks/year/km) as the reliability criteria. Pipes with this many breaks or break rate are automatically replaced. This method does not include a comprehensive network reliability model. Previous methods for optimising pipe replacement and rehabilitation provide local optimal solutions. Smith's model is aimed at producing a global optimal solution.

Kleiner (1997) in his dissertation and in the accompanying papers Kleiner et al. (1998a, b) proposes an optimisation method which includes the deterioration of structural integrity and hydraulic capacity for every pipe in the network over time. The maintenance and capital investment cost associated with each pipe is calculated as the present value of an infinite stream of costs. Dynamic programming is used to define the optimal time of replacement for each pipe in order to minimise the cost (energy, rehabilitation, replacement and repair). Dynamic programming allows the use of time as an explicit variable. This approach differs from previous methods for optimising rehabilitation of water distribution pipes, which do not include time as a variable. The author states that the proposed model (called the "multistage network rehabilitation analysis procedure" (MNRAP)) promises to provide a valuable decision support system for long-term rehabilitation planning of water distribution networks.

MNRAP assumes that pipe age alone can serve as surrogate measure for the pipe condition. The pipe break prediction model developed by Shamir and Howard (1979) is used in the procedure, but the parameters for break prediction are assigned on an individual basis without any grouping of pipes. Kleiner assumes that the historical failure record for each pipe is comprehensive enough to allow a fit of Eq. (2.1) to the observed failure data. According to the author, the analysis procedure was too time-consuming to be carried out for a complete water supply network. The maximum number of pipes analysed with the model was 12. The method does include the deterioration of hydraulic capacity over time, but does not consider network reliability criteria.

The model was validated in two ways:

- For a small network (3 pipes) all feasible combinations of rehabilitation were compared to the results received by MNRAP. Good agreement was found between the methods.

- A study was conducted in which six water utility managers were presented with a sample water distribution network. The participants were required to use their best engineering judgement and analysis tools in determining an optimal rehabilitation strategy. MNRAP gave good results compared to the existing analysis practices for the test data.

Halhal et al. (1997), address the issue of choosing the best possible network improvements within a limited budget. A generic algorithm was developed to maximise benefits and minimise costs subject to limited budget. Four types of benefit were considered in the analysis; a pressure benefit, derived from better network hydraulics, a maintenance benefit, derived from better physical condition of the pipes, an operation benefit, derived from greater network flexibility and a water quality benefit derived from pipe replacement. A weighting system was introduced for to account for the relative importance of the different benefits. The authors assume a constant break rate in their analysis.

2.6 Conclusions

A pipe failure (i.e. break) in a water distribution network is a complicated event, which usually results from a combination of several factors. Failure patterns between different water distribution networks, and also among the pipes of a given network, are highly variable. Water network must be analysed individually to determine which variables are responsible for pipe failures. The main obstacles in developing a physical model for pipe failures are the lack of knowledge of the strength of the system and the many external variables which act to stress each pipe. To overcome this difficulty, a statistical model based on analysis of historical failures can be used.

The literature review shows that the break rate function developed by Shamir and Howard (1979) is used in many of the proposed models for optimisation of rehabilitation/replacement of water pipes (Kaara, 1984; Smith, 1994; Kleiner, 1997). The limitations of this failure model have been reported in the literature and the equation should be used with care. The existing methods for optimising the rehabilitation of water pipes all use simple models for describing the occurrence of failures. Estimates of the number of future breaks and future reliability values are required as input data in the optimisation models. The reliability of all models is highly dependent on the quality of the input data. The same is true of network reliability analyses, which generally use poor pipe availability data. The reliability study carried out in Trondheim (Hansen and Vatn, 2000), which uses statistical methods for estimating future pipe break and reliability values, is an exception.

To date, there have been no successful attempts to incorporate all of the criteria for pipe replacement outlined by Stacha (1978) into a single model that would provide a comprehensive analysis of distribution network rehabilitation strategies. In Europe there is a trend towards using "decision support systems" (DSS) for improving the maintenance process (e.g. UtilNets (1997)). The UtilNets (1997) program is an attempt to implement all of Stacha's criteria into a single decision support system. The project is ambitious, but the modules completed to date are not comprehensive and have not been validated with observed data. A crucial point in a DDS for pipe replacement and rehabilitation is the calculation of structural failures (i.e. pipe breaks). We still lack the knowledge and computational tools required to build an adequate decision support system.

The most promising method available for modelling pipe failures is the Proportional Hazards Model (PHM). During the past ten years, the PHM has become increasingly popular as a tool for modelling pipe breaks. However, from a statistical point of view it is intuitively better to model failures in a water distribution network as a non-homogeneous Poisson process (NHPP). NHPP is well known in the fields of reliability analysis and medicine. The NHPP can be used to model minimal repair processes, i.e. processes where intensity of failures remains the same after a repair. These methods are discussed in detail in the next chapter.

3 Statistical models for analysis of failure time data in water networks

This chapter reviews statistical methods for analysing failure time data in water distribution networks. These methods also provide information on the value and significance of the covariates, or explanatory variables used in these methods. Broken water pipes are expensive to replace, and it is rarely cost-efficient to replace a pipe after the first failure. The usual approach is to repair pipes until the failure costs clearly outweigh the replacement costs, or until other underground projects make replacement economically attractive. A water distribution network can therefore be considered as a repairable system. A repairable system is defined to be a system which, after failure to perform at least one of its required functions, can be restored to performing all of its functions by any method, other than replacement of the entire system (Ascher and Feingold, 1984).

When modelling a repairable system like a water distribution network it is important to know how the repair action actually is carried out since the method used for repairing a pipe can influence the likelihood of successive failures.

A common assumption after a repair is that the underlying hazard function is refreshed, i.e. the system is returned to a *good-as-new* state, indicating a perfect repair. Typically a Weibull distribution with or without a covariate structure is used to model a system with "perfect repairs" (renewal process).

There are many situations, however, when a *good-as-new* assumption may not be appropriate. This is particularly true when dealing with a highly complex water distribution network where *wear out* behaviour is common. A more appropriate assumption may be to model the system as a *bad-as-old* regime (i.e. minimal repair). The *bad-as-old* regime is modelled as a non-homogeneous Poisson process (NHPP). In a system with minimal repair, the failed system is restored to a condition, which statistically is the same as its condition just prior to failure. The failure intensity function after repair is the same as it was just before the failure and repair. Only a major equipment overhaul, which typically takes the form of a planned preventive maintenance shutdown (e.g. rehabilitation), will refresh the intensity function. Most water pipes are repaired by replacing a very small segment of the pipe, or by using a repair sleeve. The whole pipe from one node to another is not refreshed to a good-as-new state. A renovated or replaced pipe can be treated as a new pipe, and the system is refreshed to a good-as-new state. The *bad-as-old* regime is the most appropriate for normal pipe repair procedures.

For each pipe in the water network the failure history with the failure times T_1, T_2, T_3, T_i is recorded (see Figure 3-1) and each pipe has a vector of covariates or explanatory variables $\mathbf{z}$ ($\mathbf{z}=[z_1,z_2,z_3,..z_p]$). We are interested in modelling the relationship between the failure history and the covariates $\mathbf{z}$. This relationship is determined by analysing a group of pipes. Models for describing the relationship between the failure history and the covariates **z** are called regression models. Two general classes of regression models are considered in order to relate the hazard function or intensity function to the covariates. The first approach can be thought of as a generalisation of survival data analysis in which the hazard function modelling is continued beyond a subject's first failure (i.e. lifetime) to second and subsequent failures (i.e. PHM). The second approach is a counting process (i.e. NHPP). Both models can also estimate the significance of the covariates that influence system failure times.

3.1 Failure times and interfailure times

A graphical description of the failure history of a repairable system, starting from time t=0 is shown in Figure 3-1. The "o" 's correspond to failure times (T_i) for the system. T_i is the time from 0 to the time of the ith failure. The interfailure times are the times between each failure. The interfailure times are denoted X_1, X_2,.., and given by $X_i = T_i - T_{i-1}$, i=1,2,...

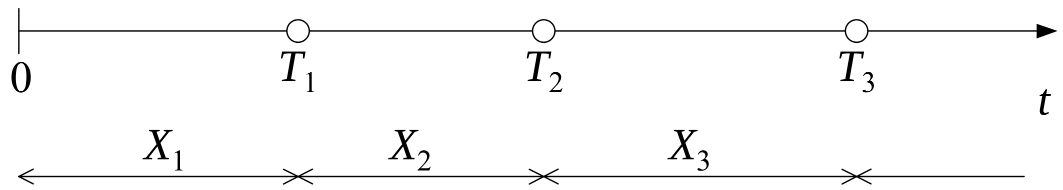


Figure 3-1. Failure times T_i and interfailure times X_i of a repairable system.

The different approaches use different terminology and notations. The failure times (T_i) are used as input for NHPP and the interfailure times (X_i) are used when modelled with PHM. Regardless of the notation being used, the sequence of failure times and the sequence of interfailure times contain the same information about the failure history.

For the statistical analysis we assume that the water network is repaired immediately after experiencing a failure. This implies that the repair times are negligible compared to the failure and interfailure times, a reasonable assumption for water networks.

3.2 Incomplete failure data availability

A frequently observed problem when analysing failure time data in water networks, is that we do not know the complete failure history. The statistical models we choose should be able to handle incomplete failure data.

Figure 3-2 shows an example of the failure data typically available for water distribution networks. The failure events are marked with an "o" on the time axes. The time window reflects the period where failure data is available.

The failure data on the left side of the time window is not known. Failures may have occurred in this period, but are unrecorded. We call this left-censored failure data. The right side of the time window corresponds to an upper bound of time for which failure data is available. Failure data will be recorded in the future, but these data are not included in the analyses. This means that the data is also right censored.

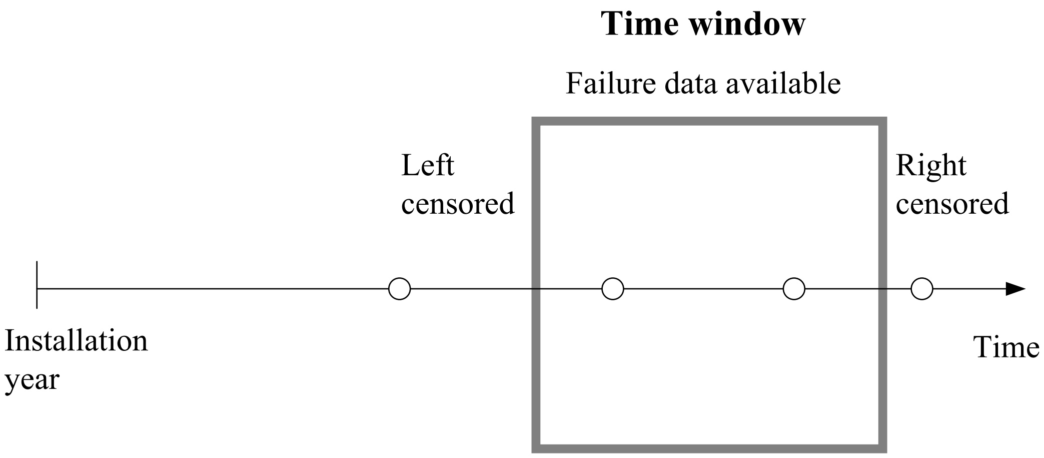


Figure 3-2. Typically availability of failure data in water networks.

A data set might also consist of some wrong/false data such as impossible inventory data, typing errors, etc. Before the data can be analysed, these *false* data must be detected and then discarded or corrected. Otherwise the results can be distorted with the presence of false data.

Missing failure time data for some days will not cause such great problems like when missing precipitation and runoff data in urban drainage modelling. If missing data is believed to be a problem and the extent of missing data is known, it can be handled by introducing interval censoring (SYSTAT, 1997).

3.3 Survival analysis approach

The analysis of survival data is a traditional statistical theme. However, in 1972 D. R. Cox introduced the Proportional Hazards Model (PHM) in order to estimate the effects of different covariates on the the time to failure of a system. The model has been used extensively in medical statistics, where the benefit of the analysis of data on such factors as life expectancy and duration of periods of freedom from symptoms of a disease as related to treatment applied, individual histories and so on, is obvious. Kaara (1984) and (Andreou (1986) introduced the use of proportional hazards model for analysing failures in water distribution networks.

In survival analyses, interest centres on a group or groups of individuals for each of which there is defined a point event (e.g. failure), occurring after a length of time. In survival analyses failures can occur at most once for any individual. The survival time for a pipe is the time from the installation year to the time of failure. Pipes in the network have different installation years, in statistical terms this is called *staggered* entry.

The lifetime X denotes the time between installation, and the time at which a pipe fails to function properly. The concept of *lifetime* applies only for components that are discarded after the first failure (Cox, 1972; Kalbfleisch and Prentice, 1980). However in order to model repairable systems with survival models, the time between failures is also denoted as a *lifetime* (Chapter 3.3.7). In the following the concept of survival analysis and the different measures are described in more detail.

3.3.1 Survival function

The basic quantity employed to describe time-to-event phenomena is the survival function (i.e. component reliability). This is the probability that an individual will survive beyond time x. It is defined as:

$$S(x) = \Pr(X > x) \tag{3.1}$$

The survival function is a non-decreasing function with a value of one at the origin and zero at infinity. When X is a continuos random variable, the survival function is the complement of the cumulative distribution function, that is, $S(x)=1-F(x)$, where $F(x)=\Pr(X\leq x)$.

3.3.2 Hazard function

Another fundamental element in survival analysis is the hazard function. This function is known as the conditional failure rate in reliability theory, the force of mortality (FOM) in demography, or simply the hazard rate. The hazard function is defined by:

$$h(x) = \lim_{\Delta x \to 0} \frac{P[x \leq X < x + \Delta x \mid X \geq x]}{\Delta x} \tag{3.2}$$

The term $h(x)\Delta x$ can best be interpreted as the probability that the *first* failure occurs in $(x, x+\Delta x)$.

If X is a continuous random variable, then

$$h(x) = {f(x)}/{S(x)} = -\delta \ln[S(x)] \tag{3.3}$$

Where *f(x*) is the density function. A related quantity is the cumulative hazard function *H(x)*, defined by

$$H(x) = \int_0^x h(u)du = -\ln[S(x)] \tag{3.4}$$

Thus, for continuos life times,

$$S(x) = \exp[-H(x)] = \exp\left[-\int_0^x h(u)du\right] \tag{3.5}$$

The failure time distribution of pipes in a water distribution network may be investigated through the survival function *S(x)*, or the hazard function *h(x)*.

The hazard function can be constant, increasing, decreasing or bathtub- shaped. When the hazard function is constant, *S(x)* reduces to the survival function for the exponential distribution. For many types of components the hazard function increases with time as a result of component ageing. Figure 3-3 illustrates a bathtub curve shaped hazard function. It should be noticed that two different bathtub curves exist. One for repairable systems (i.e. ROCOF) as described in Chapter 1.3 and one for non-repairable systems (i.e. FOM). Non-repairable systems include those where objects have only one lifetime, or for systems which after repair is returned to a good as new state. For the FOM curve the time since last repair is considered. These two curves should not be mixed together.

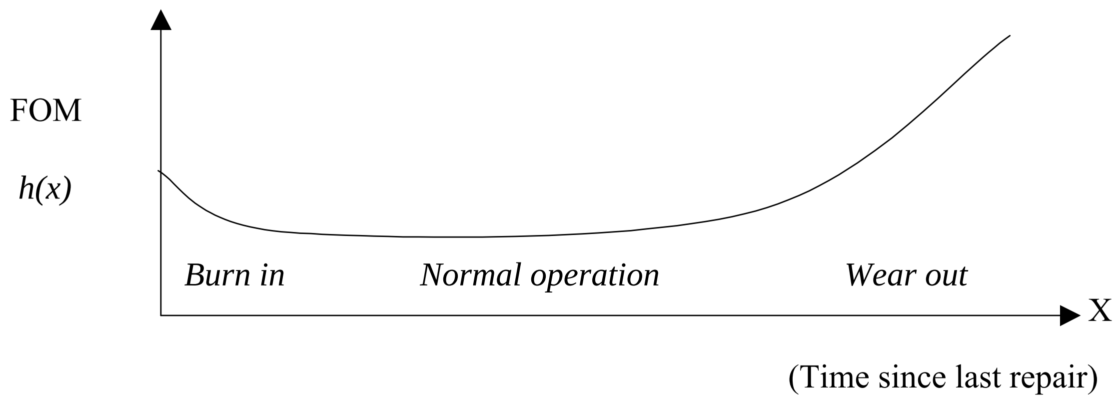


Figure 3-3. Bathtub shape of the hazard function or FOM.

3.3.3 Censoring in lifetime analysis

In traditional *lifetime* analysis only the first failure is considered. Essentially data are said to be “censored” when there are individuals in the sample where only a lower or upper bound on lifetime is available (Cox, 1972; Kalbfleisch and Prentice, 1980).

Assume that *n* identical pipes are installed at different given points in time (i.e. staggered entry) and followed until the *first* failure or until the time when the study period ends (Figure 3-4). X_i , $i\neq 1$ and 4 are observed lifetimes. Lifetimes X_1^* and X_4^* are right censored lifetimes.

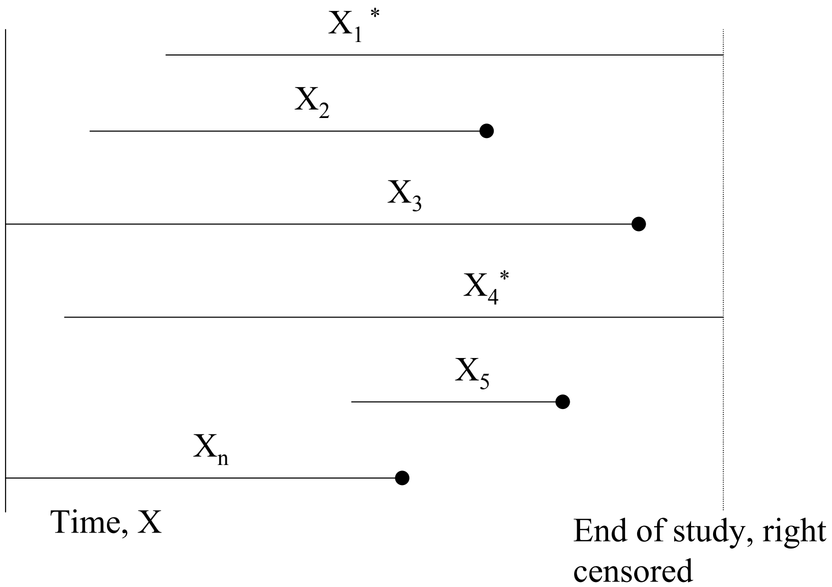


Figure 3-4. Censored (right) data with staggered entry.

For water distribution networks, the following types of censoring is relevant:

- Left censoring
- Right censoring

By left censoring we mean that there is a period of time after installation when no data is recorded. When a case is right censored the dependent variable is known to be greater than a specific value, but its true value is not known (i.e. pipe has not failed by the time the maintenance record ends). More accuracy is achieved by including cases in which the event has not happened yet (right censored data). If the event has occurred the censoring value, C is set equal to 1, else C=0 (right censored).

In this work survival models are used to model successive pipe failures (i.e. repairable system). In this case, censorship may also occur after the first failure. The censoring scheme explained in this chapter, is extrapolated to apply to repairable systems (Chapter 3.3.7).

3.3.4 Cox's Proportional Hazards Model

The most widely used model for survival analysis is the Cox model. This model is semi-parametric, since its hazard function is the product of an unspecified baseline hazard function, and a parametric function relating the hazard function and the covariates. Let $h(x|\mathbf{z})$ be the hazard function at time x for a pipe with covariate vector **z**. The basic model according to (Cox, 1972) is as follows:

$$h(x\,|\,\mathbf{z}) = h_0(x)c(\mathbf{z}'\boldsymbol{\beta}) \tag{3.6}$$

where $h_0(x)$ is the baseline hazard function. $\boldsymbol{\beta}=(\beta_1, \beta_2 ... \beta_p)$ is a parameter vector, $\mathbf{z}'$ is a column vector of covariates or independent variables ($\mathbf{z}=[z_1,z_2,z_3,..z_p]$) and $c(\mathbf{z}'\boldsymbol{\beta})$ is a known function. The baseline hazard function represents the hazard function that a system would experience if the effects of all covariates in the model are equal to zero. Depending on how a covariate is defined in the model, this may correspond to either a natural zero or an arbitrarily assigned zero value. This is called a semi-parametric model because a parametric form is assumed only for the covariate effect.

A common model for $c(\mathbf{z}'\boldsymbol{\beta})$ is:

$$c(\mathbf{z}'\boldsymbol{\beta}) = \exp(\mathbf{z}'\boldsymbol{\beta}) = \exp\left(\sum_{i=1}^{p} \beta_i z_i\right) \tag{3.7}$$

Yielding

$$h(x\,|\,\mathbf{z}) = h_0(x)\exp(\mathbf{z}'\boldsymbol{\beta}) = h_0(x)\exp\left(\sum_{i=1}^{p} \beta_i z_i\right) \tag{3.8}$$

The Cox model is often called a proportional hazard model (PHM) because if we look at two pipes with covariate values **z** and **z*** the ratio of the hazard functions is:

$$\frac{h(x\,|\,\mathbf{z})}{h(x\,|\,\mathbf{z}^*)} = \frac{h_0(x)\exp(\boldsymbol{\beta}_i\mathbf{z}_i)}{h_0(x)\exp(\boldsymbol{\beta}_i\mathbf{z}_i^*)} = \frac{h_0(x)\exp\left(\sum_{i=1}^{p} \beta_i z_i\right)}{h_0(x)\exp\left(\sum_{i=1}^{p} \beta_i z_i^*\right)} = \exp\left(\sum_{i=1}^{p} \beta_i (z_i - z_i^*)\right) \tag{3.9}$$

which is a constant and the hazard functions are proportional.

The regression coefficients are estimated by maximising the partial likelihood that does not include the baseline function, $h_0(x)$. The likelihood function is maximised by using the Newton- Raphson method for numerical estimation (SAS, 1994; SYSTAT, 1997).

The effect of time on the survival process is captured by the baseline hazard function, $h_0(x)$. This function has to be estimated in order to use Cox's PHM for predicting failures and to evaluate the effect of pipe ageing. Given the baseline function, the survival function and the hazard function for components with certain set of conditions (covariates) can be estimated.

A major advantage of the Cox's PHM is that one need not assume a specific form of the baseline hazard function, $h_0(x)$ in order to evaluate the effects of covariates. When the objective is to evaluate the effect of covariates on the hazard function, Cox's Proportional Hazards Model should be used. When the objective is to predict future failures within a certain time horizon, a parametric assumption about the form of the baseline hazard function is more convenient (Kumar and Klefsjö, 1994). An example of this type of PHM is the Weibull proportional hazards model, where the baseline function is a Weibull hazard function.

In SAS and SYSTAT it is not possible to handle left censoring for Cox's PHM. To work around this problem, a variable called *age_left* is introduced which means the time from installation year to the time when failure recording starts. For the Weibull PHM it is possible to include left censoring as a special case of interval censoring. Left censoring does not improve the analysis for pipe groups where all of the pipes are left censored (e.g. grey cast iron pipes, all of which were installed long before failure recording began).

3.3.5 Weibull Proportional Hazards Model/accelerated model

The Weibull distribution is a flexible model for describing failure data. It has a hazard function, which either is monotone increasing, decreasing, or constant. It is the only parametric regression model which has both a proportional hazards representation and an accelerated failure time representation. The Weibull hazard function is expressed as

$$h_0(x) = \lambda p(\lambda x)^{p-1} \tag{3.10}$$

where λ is the interception and p is the scale parameter (Kalbfleisch and Prentice, 1980). In Figure 3-5 the hazard function for the Weibull distribution is shown for the case where $\lambda=1$ and for different values of p. When p=1, the Weibull distribution reduces to an exponential distribution, where the hazard function is constant with time.

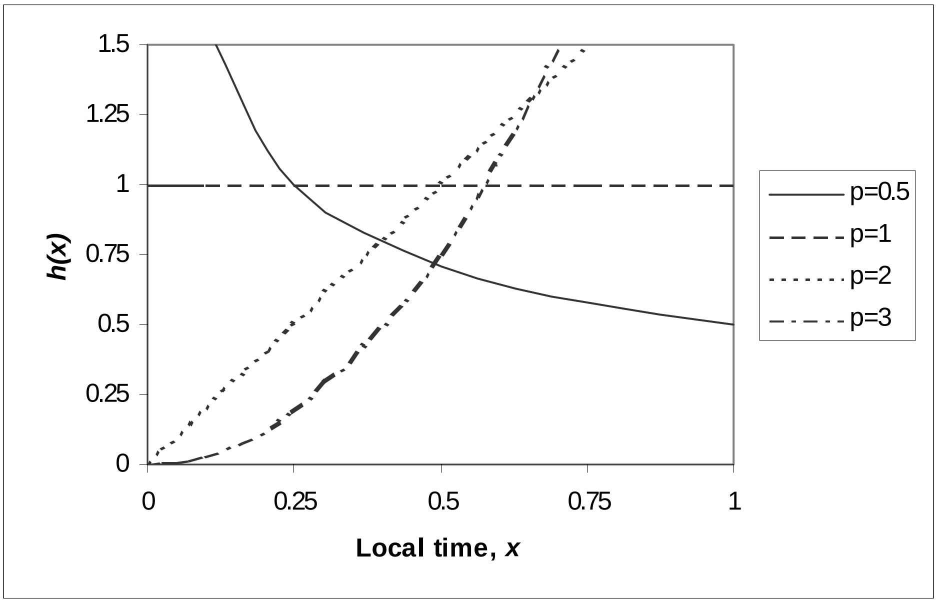


Figure 3-5. Hazard function of the Weibull distribution, λ=1.

The Weibull model with a proportional hazards representation has the following hazard function.

$$h(x,\boldsymbol{\beta},\mathbf{z}) = \lambda p(\lambda x)^{p-1} \exp(\mathbf{z}'\boldsymbol{\beta}) \tag{3.11}$$

where **z'** is a column vector of covariates or independent variables ($\mathbf{z}=[z_1,z_2,z_3,..z_p]$), and $\boldsymbol{\beta}$ is a vector of unknown regression parameters ($\boldsymbol{\beta}=[\beta_1,\beta_2,\beta_3..\beta_p]$).

Accelerated lifetime models assume that ln*X* (natural logarithm) is related to the covariates **z'** via a linear model

$$\ln X = \alpha + \mathbf{z}'\boldsymbol{\beta}^* + \sigma \mathbf{W} \tag{3.12}$$

where $\alpha=-\ln\lambda$ (interception parameter), $\sigma=1/p$ (scale parameter), $\boldsymbol{\beta}^*=-\sigma\boldsymbol{\beta}$ and W has the extreme value distribution (Kalbfleisch and Prentice, 1980).

Writing

$$w(x) = (\ln x - \alpha - \mathbf{z}'\boldsymbol{\beta}^*)/\sigma \tag{3.13}$$

And using the extreme value distribution with survival function (Klein and Moeschberger, 1997).

$$S(w) = \exp[-\exp(w)] \tag{3.14}$$

Inserting for *w(x)* gives the survival function for the Weibull accelerated model for each individual pipe as a function of time

$$S(x, \boldsymbol{\beta}^*, \mathbf{z}) = \exp\left[-\exp\left(\frac{\ln x - \alpha - \mathbf{z}'\boldsymbol{\beta}^*}{\sigma}\right)\right] = \exp\left[-x^{1/\sigma}\exp\left(\frac{-\alpha - \mathbf{z}'\boldsymbol{\beta}^*}{\sigma}\right)\right] \tag{3.15}$$

Accelerated lifetime models are log-linear models, i.e., the explanatory variables act additively on ln*X* (or multiplicatively on *X*). It is assumed that the covariates accelerate the time to failure.

The method for estimating the vector $\boldsymbol{\beta}^*$ and the parameter α and σ uses the maximisation of the log-likelihood function, which is the log-transform of the joint density of probability of the observations. The right-censored data contribute to this function by the value of their survival function at the censored time. The analysis is performed with the statistical software SAS and SYSTAT (SAS, 1994; SYSTAT, 1997).

3.3.6 Stratified Proportional hazards model

The discrete values of a covariate can be used for grouping a data set. The number of groups that can be formed is defined as the number of strata of a data set. If a stratum specific PHM is assumed, the corresponding model is called stratified PHM. In this model, it is assumed that the hazard functions are proportional within the same stratum, but not necessarily across strata. The hazard function of a system in the j^{th} stratum can be expressed as:

$$h_j(x \mid \mathbf{z}) = h_{0j}(x)\exp(\mathbf{z}'\boldsymbol{\beta}) \tag{3.16}$$

The concept of stratification is very useful for modelling a repairable system with a PHM. The following section presents a more detailed discussion of the application of PHM.

3.3.7 Survival models (PHM) for analysing repairable systems/successive failures

In traditional life time analysis failures can occur at most once for any individual (Cox, 1972). In order to apply survival models to simulate a repairable system (e.g. water network), some changes in notations and terminology are required. The following procedure follows the extension of the stratified PHM suggested by Prentice et al. (1981) for modelling failures in a single system. This method can be thought of as a generalisation of survival data analysis in which the hazard function is continued beyond an object's first failure (i.e. lifetime) to second and subsequent failures. The terms survival function (Eq. 3.1) and hazard function (Eq. 3.2) are also used with respect to the interfailure time for modelling a repairable system and not strictly according to the definitions used by Cox (1972). The interfailure time used in the analysis might be either an observed or a right-censored interfailure time, i.e. pipes that are still intact at the end of the observation period. Figure 3-6 illustrates this procedure.

In this work the number of previous failures is used as the stratification variable. A pipe moves to the next stratum immediately following a failure (i.e. break or leakage) and remains there until a new failure occurs or until the data is censored. This allows the baseline hazard function to depend on the number of previous failures.

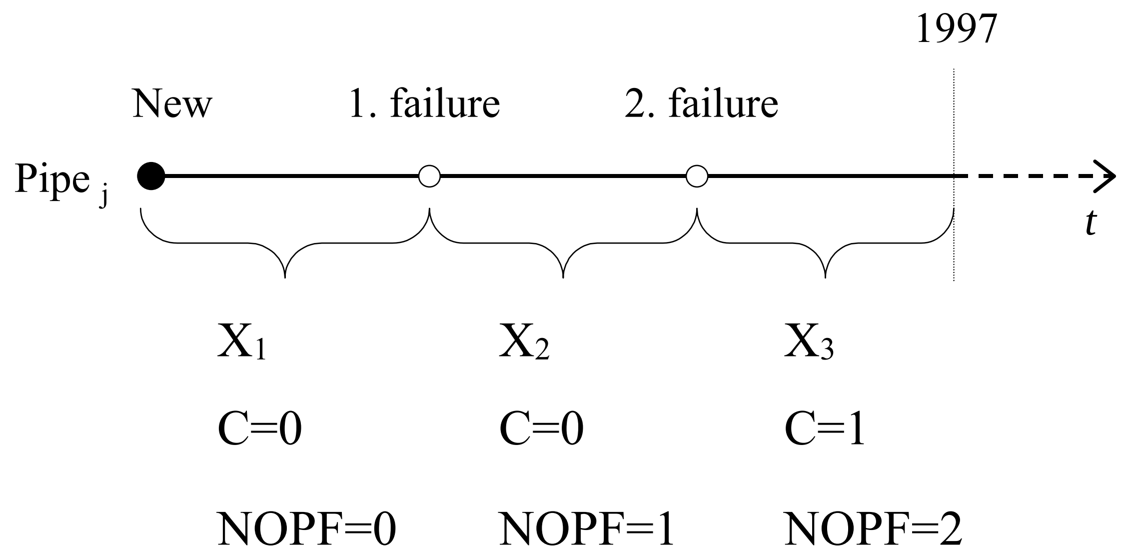


Figure 3-6. PHM used for modelling successive failures in water networks.

$Pipe_j$ is installed, represented by time "New". After a time *t* a failure is recorded. The time from laying year to first failure is called interfailure time X_1. The pipe is repaired and put into service again. After some time a new failure occurs. The time from the first failure to the second failure is called interfailure time X_2. The pipe will again be repaired and returned to service. After this no more failures are recorded and the time period from the second failure to the end of the analysis period is called interfailure time X_3 which is a right censored interfailure time (C=1). X_3 is not an exact interfailure time, but a right censored failure time. The fact that the interfailure time is censored and not an exact interfailure time is an important factor in this analysis. All of these interfailure times refer to the same pipe and inventory data.

In addition a new variable "Number Of Previous Failures" (NOPF) is included. This covariate plays a special role, serving as a stratification variable, as much as a covariate. The stratification consists in splitting the data into two or more subsets, allowing for separate analyses (the parameters vary according to the stratum). Since NOPF act both as stratification variable and covariate, the hazard function will have horizontal shifts after each failure. An illustration of the hazards functions for a deterioration network with a increasing hazard function within each stratum is shown in Figure 3-7. The "o" on the time-axes indicates the time of the failure. The hazard function in each time interval might either be decreasing, constant or increasing and the actual shape will depend on the failure data being analysed.

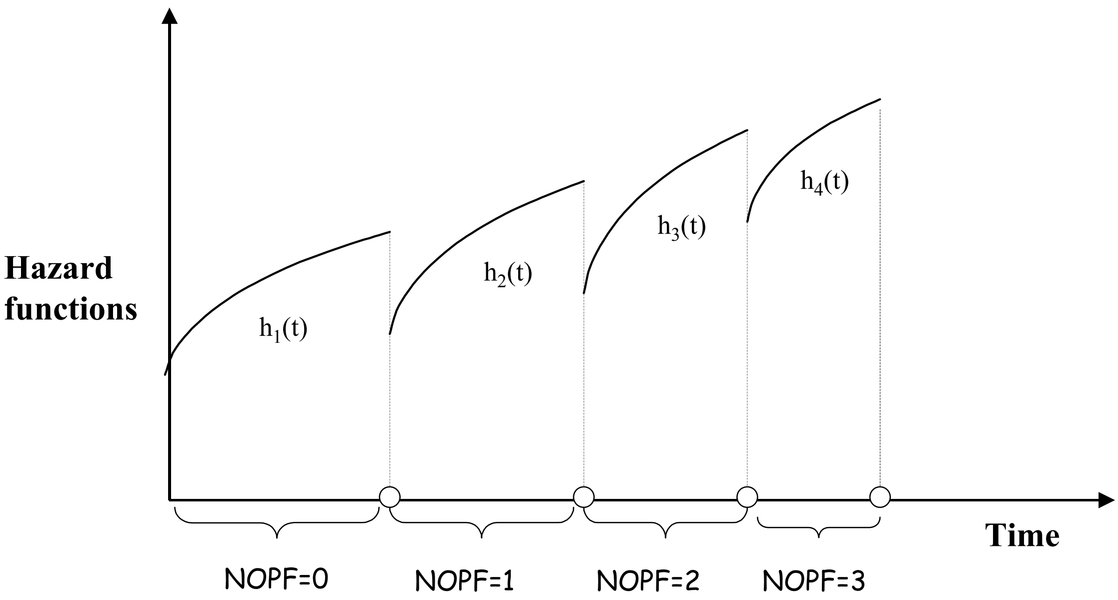


Figure 3-7. An illustration of the pattern of the hazard function for survival models of a repairable system including stratification by the number of previous failures.

Without the inclusion of NOPF as a covariate in the modified PHM this approach would have been reduced to an ordinary renewal process where it is assumed that the hazard function is reset to that of a new system after repair. The result is a more flexible model that has good-as-new, bad-as-old and even worse-than-old as special cases. However, as a result of the stratification, more parameters and coefficients are required and must be estimated since each interfailure time is modelled separately.

The area under the hazard functions in Figure 3-7 is equivalent to the expected number of failures in the time interval. Since the curve is a step function, integration of the curve is not a straightforward process. The PHM failure prediction is carried out by using a Monte Carlo simulation based on the survival functions. This procedure is described in Chapter 3.3.8.

Le Gat (1999) referred to this PHM approach as an "Event dependent renewal process" which is an extension of what Cox (1980) called a "Time dependent renewal process". The term "event" was used instead of "time" since the interfailure times have different distribution functions depending on the rank of the event.

3.3.8 Prediction of failures in a PHM using Monte Carlo simulation

For the stratified PHM is difficult to derive an analytic solution for failure prediction. Therefore a Monte Carlo simulation based on survival functions is carried out (Le Gat, 1998; Eisenbeis et al., 1999).

To predict the number of failures we are using the regression parameters $\boldsymbol{\beta}^*$ and the individual set of covariates **z** for each pipe. The regression parameters $\boldsymbol{\beta}^*$ are found by analysing a group of pipes. Based on each pipe's individual set of covariates **z** a survival function for each pipe is calculated. If the number of previous failures is included as a covariate, the survival function will change after a failure. Monte Carlo simulation based on the survival function is then used to predict the expected number of failures within a given time horizon. Only pipes which are still in use are included in the analysis. For predicting the expected number of failures within a certain time horizon it is convenient to use a parametric model like Weibull and not a semi- parametric model like Cox PHM. The recourse to Monte Carlo simulation is justified by the use of the number of previous failures (NOPF) as highly significant covariate, which complicates the calculation of the distribution of the number of future failures.

The survival function for the Weibull accelerated model is:

$$S(x, \boldsymbol{\beta}^*, \mathbf{z}) = \exp\left[-\exp\left(\frac{\ln x - \alpha - \mathbf{z}'\boldsymbol{\beta}^*}{\sigma}\right)\right] = \exp\left[-x^{1/\sigma}\exp\left(\frac{-\alpha - \mathbf{z}'\boldsymbol{\beta}^*}{\sigma}\right)\right] \tag{3.17}$$

where

$$\mathbf{z}'\boldsymbol{\beta}^* = \beta_1^* z_1 + \beta_2^* z_2 + ..\beta_n^* z_n \tag{3.18}$$

The parameters of the underlying Weibull distribution are the following functions of these extreme value parameters, λ=exp(-α), p=1/σ.

If we solve for x we get the failure time corresponding to a given survival probability.

$$x = \left(\ln\left(\frac{1}{S}\right)\exp\left(\frac{\alpha + \mathbf{z}'\boldsymbol{\beta}^*}{\sigma}\right)\right)^{\sigma} \tag{3.19}$$

The Monte Carlo simulations is carried out in the following way:

- A random number (0,1) is chosen. The corresponding failure time for the given survival function is calculated (Figure 3-8)
- If the failure time is shorter than the time horizon, a new failure time is calculated using an updated version of the survival function (number of previous failures might be a covariate in the model). This is repeated until we reach the time horizon for the analyses. The cumulative number of failures within the time horizon is calculated.
- For each pipe this elementary scheme is repeated 1000 times.
- The mean value of the 1000 simulations will then be an estimator for the expected number of failures within the time horizon. The upper and lower confidence limits and the standard error can also be estimated based on the results from the simulations. By applying Monte Carlo simulations we are thus able to establish a prediction interval.

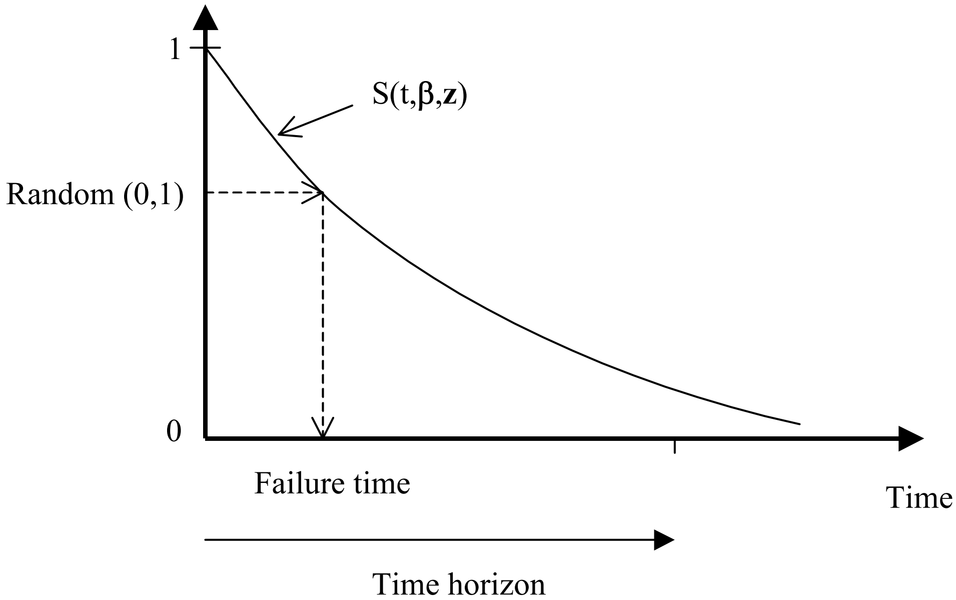


Figure 3-8. Prediction of failures based on survival functions.

For prediction of the first new failure after the calibration period we have to take into consideration the conditional survival function. If a pipe has already lived some time when the prediction starts, the survival function has to be modified and a conditional survival function has to be calculated. The time from the last recorded failure to the time when the calibration period stops is called *LIFE* in the survival analysis (equivalent to interfailure time X_3 in Figure 3-6). This lifetime is a right censored lifetime. The survival probability corresponding to the time *LIFE*, *S(LIFE)*, is then used when calculating the conditional survival probability, *S(t)**. The conditional survival function is shown in Figure 3-9. The conditional survival function has the value 1 for the time corresponding to the *LIFE*, since we know for sure that the pipe will survive the time *LIFE*. The conditional survival function is then given by:

$$S(t)^* = \frac{S(t)}{S(LIFE)} \tag{3.20}$$

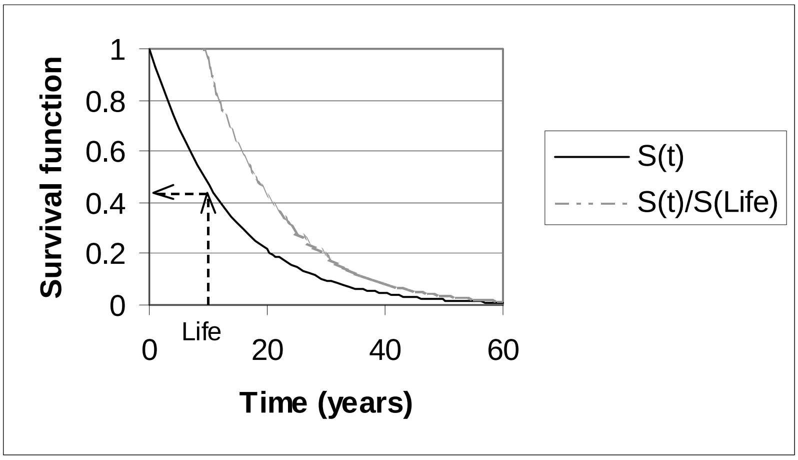


Figure 3-9. Conditional survival probability.

3.4 Counting process

In this chapter the statistical family of counting process is considered which applies for repairable systems. The events observed are starting time of operation, starting time of observation and failure times. The objective is to model the number of failures within a time interval. The random variable *N(t)*, number of failures during (0,*t*] is of special interest. The process {*N(t)*, $t \geq 0$} is called a stochastic process, or more specifically a counting process. A stochastic process {*N(t)*, *t*≥0} is said to be a counting process if *N(t)* satisfies (Høyland and Rausand, 1994):

1. *N(t)* ≥ 0
2. *N(t)* is integer valued
3. If *s*<t then *N(s)*≤*N(t)*
4. For *s*<*t*, [*N(t)* – *N(s)*] represents the number of events that have occurred in the interval (*s*,*t*].

3.4.1 Non-Homogeneous Poisson Process

When analysing a repairable system one ought to be interested in characteristics of the pattern of successive failures in the system. If the systems exhibits a trend (i.e. a tendency for failures to occur more closely or less closely) one clearly has to use non-stationary methods. The model, which is mostly used to take account for trend in repairable systems, is the non-homogeneous Poisson process.

3.4.1.1 Introduction and definitions

A counting process $\{N(t), t \geq 0\}$ is a non-homogeneous Poisson process (NHPP) with intensity function $\lambda(t), t \geq 0$ if

1. $N(0) = 0$, The number of experienced failures in a unused system is zero
2. $\{N(t), t \geq 0\}$ has independent increments.
3. $P(N(t+\Delta t)- N(t) \geq 2) = o(\Delta t)$, that is, the system will not experience more than one failure at the same time.
4. $P(N(t+\Delta t)- N(t) = 1) = \lambda(t)\Delta t + o(\Delta t)$,

The basic "parameter" of the NHPP is the rate of occurrence of failures (ROCOF). ROCOF is the time derivative of the expected cumulative number of failures and is defined as:

$$v(t) = \frac{dV(t)}{dt} = \frac{d}{dt}E(N(t)) \stackrel{def}{\equiv} ROCOF$$

Where $V(t)= E(N(t))$ denotes the mean number of failures in the interval $(0,t]$. It follows that the ROCOF may be regarded as the mean number of failures per time unit at time t.

To best interpret the ROCOF, write:
$v(t)dt = E[N(t+dt)] - E[N(t)]=$ expected number of failures in $(t, t+dt]$

or in terms of probabilities
$v(t)dt = P($failure in $(t, t+dt]$

The ROCOF function is also called the intensity function (unconditional) of the NHPP ($v(t)=\lambda(t)$).

The cumulative intensity of the process is:

$$\Lambda(t) = \int_0^t \lambda(u)du \qquad (3.21)$$

It is important to notice that the NHPP model does not require stationary increments. This means that the failures may be more likely to occur at certain times than others, and hence the interfailure times (i.e. times between failures) are generally neither independent nor identically distributed.

The NHPP differs from the Homogeneous Poisson Process (HPP) only in that the intensity varies with time rather being a constant. It is thus possible with a NHPP to model trends through specifications of the intensity function. For example, a deteriorating system corresponds to an increasing function $\lambda(t)$, while an improving system corresponds to a decreasing function $\lambda(t)$.

The term $\lambda(t)\Delta t$ can be interpreted as the probability that a failure, not necessarily the first, occurs in $(t+\Delta t)$.

3.4.1.2 Modelling with Non-Homogeneous Poisson Process

In a non-homogeneous Poisson process each pipe is studied within the time interval (a_i,b_i), i.e. time interval where observations are available (Figure 3-10). Time 0 corresponds to the laying year of the pipe. Each pipe has its own covariate vector $\mathbf{z_i}$ and a number n of recorded failures, with the time of their occurrence: $T_1<T_2<...<T_n$. The components of the covariate vector are all independent variables that have a significant influence on the pipe's service-life. The effect of the covariates on the rate of occurrence of these failures (ROCOF) is of interest.

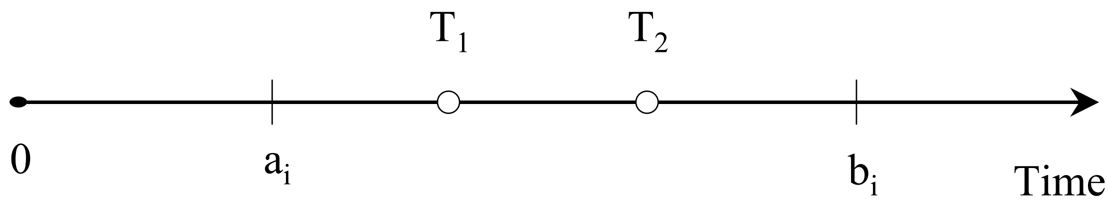


Figure 3-10. Definition of terms used in NHPP.

The main assumption is that n failures occur in a period of time according to a non-homogeneous Poisson process, with the intensity of failures given by:

$$\lambda(t,\boldsymbol{\beta},\mathbf{z}_i) = \lambda_0(t)c(\mathbf{z}_i'\boldsymbol{\beta}) \tag{3.22}$$

The model is sometimes referred to a Proportional Intensity Model (Lawless, 1987). The model is an extension of the Proportional Hazards Model (Cox, 1972) for modelling repairable systems. λ_0 is denoted as the baseline intensity. For the function defining the proportional intensity assumption an exponential form is often used. This allows avoidance of restrictions on β in order to make $\lambda(t,\mathbf{z_i},\beta) > 0$.

$$c(\mathbf{z}_i'\boldsymbol{\beta}) = \exp(\mathbf{z}_i'\boldsymbol{\beta}) \tag{3.23}$$

The covariates are assumed to be constant during the entire operation period.

We can think of the intensity function $\lambda(t)$ as the hazard function of the time to first failure, the rate of subsequent failures is unaffected by the first failure. After a failure, the system is restored to a state where it is exactly as good (or bad) as it was immediately before the failure.

3.4.1.3 Power law process

Several parametric models have been established to describe the intensity of the NHPP; the power law model, the linear model and the log-linear model. The power law model is most commonly discussed in the literature. In this work the power law model has been chosen for the time dependent function $\lambda_0(t)$, defined as:

$$\lambda_0(t) = \lambda\delta t^{\delta-1} \tag{3.24}$$

for $\lambda>0$, $\delta>0$ and $t\geq0$. Some authors use β instead of δ as the parameter for the intensity function (Samset, 1988). Since β is used for the coefficients for the covariates this parameterisation is not used here. The chosen parameterisation follows the example of Lawless (1987) and Ciampi et al. (1992). The intensity function, when covariates are included is then:

$$\lambda(t,\mathbf{\beta},\mathbf{z}_i) = \lambda\delta t^{\delta-1}\exp(\mathbf{z}_i{}'\mathbf{\beta}) \tag{3.25}$$

The power law model is sometimes referred to as a Weibull process, since the intensity function has the same functional form as the hazard function of the Weibull distribution. In the power law model the time to first failure follows a Weibull distribution. However, according to Ascher and Feingold (1984) the use of Weibull process might lead to confusion, creating the impression that the Weibull distribution can be used to model *trend* in the interfailure times of a repairable system. Note that for $\delta=1$ the intensity function reduces to an exponential model, corresponding to a Homogeneous Poisson Process, HHP.

A repairable system modelled by the power law model is improving if $0<\delta<1$ and deteriorating if $\delta>1$. The normal method of parameterisation is to use the transformation $\lambda=e^{\beta_0}$ and include it in the regression function $e^{\mathbf{\beta z}}$ as an interception while letting the covariate z_0 be equal to one. By doing so the term β_0 has no limits while fulfilling the assumption $\lambda>0$. Due to computational problems caused by data overflow, Eq. 3.25 was used without transformation. In the calculations some extra tricks are included in order to achieve $\lambda>0$. Indeed, this works quite well in practice.

The cumulative or integrated intensity function is

$$E(N(t)) = \Lambda(t,\mathbf{\beta},\mathbf{z}) = \int_0^t \lambda(u,\mathbf{\beta},\mathbf{z})du \tag{3.26}$$

where $N(t)$= number of failures in $(0,t]$. The integrated intensity function for the interval (a_i,b_i), corresponding to the expected number of failures in the interval (a_i,b_i) is given by:

$$E\left(N(b_i)-N(a_i)\right)=\int_{a_i}^{b_i}\lambda(u,\mathbf{\beta},\mathbf{z})du=\lambda\left(b_i^{\delta}-a_i^{\delta}\right)\exp(\mathbf{z}'\mathbf{\beta}) \tag{3.27}$$

An illustration of the intensity function for the NHPP is shown in Figure 3-11. The area under the curve is equivalent to the expected number of failures for the time interval. For the NHPP model, this curve can be integrated using Eq. (3.27).

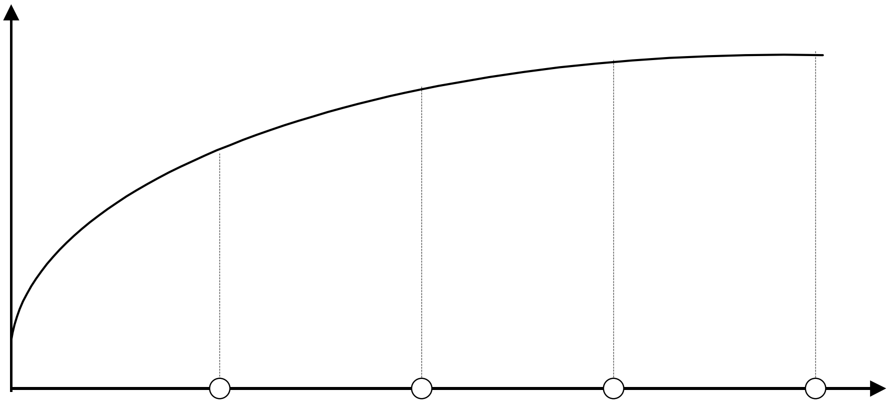


Figure 3-11. An illustration of the pattern of the intensity function for NHPP in the case of minimal repair or "bad-as-old" condition of a repairable system.

3.4.1.4 Estimation of parameters in NHPP/Maximum likelihood method

To estimate the unknown parameters (λ, δ and β) in the chosen NHPP, the principle of *maximum likelihood* is used. The likelihood function when covariates are present is denoted as $L(\theta;\mathbf{z},t)$. We might think of the likelihood function as a measure of how "likely" θ is to have produced the observed T values.

Information about m independent observations with identical intensity function $\lambda(t)$ is available (i.e. inventory and failure data). Individual (e.g. pipe) i is observed over the time interval (a_i, b_i) and n_i events are registered at the times t_{ij}, where j=1,2,…n_i and i=1,2,…m.

The likelihood function for the power law model for all m processes is given by (see Lawless (1987) or Samset (1988)):

$$L(\theta;t)=\prod_{i=1}^{m}\left[\cdot\prod_{j=1}^{n_i}\left[\lambda\left(t_{ij}\right)\right]\cdot e^{-\int_{a_i}^{b_i}[\lambda(u)du]}\right] \tag{3.28}$$

The maximisation of Eq. 3.28 is achieved taking the logarithm of L and maximising the new function (l=ln$L$). The log- likelihood function (l) for the power law model is given by:

$$l(\theta;\mathbf{z},t)=\sum_{i=1}^{m}\left[n\mathbf{z}_i\beta+n\ln\lambda+n\ln\delta+(\delta-1)\sum_{j=1}^{n}\ln t_{ij}-e^{\mathbf{z}_i\beta}\lambda\left(b^{\delta}-a^{\delta}\right)\right] \tag{3.29}$$

The maximisation of the log-likelihood function is performed in the program by an optimisation algorithm (for details see Press et al. (1992)), which only requires the following formulas for the first derivative of $l(\theta;\mathbf{z},t)$:

$$\frac{\partial l}{\partial\lambda}=\sum_{i=1}^{m}\left[\frac{n}{\lambda}-e^{\mathbf{z}_i\beta}\left(b^{\delta}-a^{\delta}\right)\right] \tag{3.30}$$

$$\frac{\partial l}{\partial\delta}=\sum_{i=1}^{m}\left[\frac{n}{\delta}+\sum_{j=1}^{n}\ln t_{ij}-e^{\mathbf{z}_i\beta}\lambda\left(b^{\delta}\ln b-a^{\delta}\ln a\right)\right] \tag{3.31}$$

$$\frac{\partial l}{\partial\beta_r}=\sum_{i=1}^{m}\left[n\mathbf{z}_i-e^{\mathbf{z}_i\beta}\lambda\mathbf{z}_i\left(b^{\delta}-a^{\delta}\right)\right] \tag{3.32}$$

As there is no statistical software available for handling NHPP, a computer program for solving these equations was developed as part of this research. A description of the program, named WINROC, is given in Appendix A.

3.4.2 The Nelson-Aalen estimator: a non-parametric estimate of the cumulative intensity

Any statistical model, which is adopted in order to examine a set of observations, is based on a set of assumptions. The model results depend on whether or not the assumptions made are correct. Non-parametric models or distribution-free methods have been developed to free modelling from this constraint. For NHPP the so-called Nelson-Aalen estimator was introduced by Aalen (1978), as an estimator for the cumulative intensity of counting processes in general.

Assume that m different and independent NHPPs with a common intensity $\lambda(t)$ have been observed. The ith process is observed in the time interval $(a_i, b_i]$, and n_i failures have occurred by time t_{ij} where j=1,2,…n_i and i=1,2,…m. A non-parametric estimator for the cumulative intensity function $\Lambda(t,Z)=\int_0^t\lambda(u,Z)du$ for the NHPPs in the time interval considered is given by:

$$\hat{\Lambda}(t) = \sum_{t_{ij} \le t} \frac{1}{Y(t_{ij})} \tag{3.33}$$

where $Y(t_{ij})$ is the number of processes which are in operation immediately before time t_{ij}. When there is only one sample (m=1), the Nelson–Aalen estimator coincides with $N(t)$, which is the number of failures during (0,t]. A further discussion of the Nelson-Aalen estimator is given in Samset (1988).

If only one system is to be analysed, plotting the Nelson-Aalen estimator is just the same as a plot of cumulative failures versus cumulative operating time. A cumulative failures ($N(t)$) plot or a Nelson-Aalen plot often gives a good indication of whether or not there is a trend in the interfailure times of the system. When the curve $N(t)$ is convex, the system is deteriorating. In the same way $N(t)$ will tend to be a concave function of t when the system is improving (failures become less frequent). If $N(t)$ is linear, the system is steady.

3.5 Techniques for evaluation of the models

When a model for the observed data is established and the unknown parameters estimated we are of course interested in how well the model fits the observed data. The goodness of fit depends on whether or not the assumptions made are reasonable or not. In order to evaluate the models different checks can be carried out.

The traditional statistical checks are:

- Log-likelihood value comparison
- Significance of parameters

In order to chose between different models (i.e. NHPP versus Weibull PHM) comparison between predicted and observed failures can be carried out. Following techniques are useful for this:

- Cumulative plots for observed versus predicted failures (Nelson-Aalen plot)
- Annual plots for observed failures versus predicted failures for each year
- Plotting the pairs (observed failures, predicted failures) for each pipe

In Chapter 4 these methods will be applied in a case study for the water network in Trondheim, Norway. I refer to this chapter for further details about the different techniques.

3.6 Conclusion statistical models

Both the PHM approach and the NHPP model can be used to model failures in a repairable system like a water distribution network. It is not practical to use Cox's semi-parametric model to model successive failures, since the baseline hazard function has to be estimated separately before prediction takes place. A parametric model is more practical for predicting failures, and in this work a Weibull PHM is applied. The application of the Weibull PHM to failure prediction includes a Monte Carlo simulation based on the survival functions for each stratum. Failure prediction with the NHPP is achieved by integrating the intensity function with respect to time.

The PHM approach and the NHPP describe different failure regimes. For the PHM the underlying failure regime is found to be something between *good-as-new* and *worse-than-old*. The stratification used in the PHM gives the model flexibility with respect to number of previous failures. The NHPP is known to model *bad-as-old* regimes, which intuitively suits the failure processes in water networks very well. A comparison of these two methods PHM and NHPP as applied to predicting breaks in the water network is therefore both interesting from a scientific point of view and required from a practical point of view.

4 Case: City of Trondheim

A case study is carried out for the water distribution network of the city of Trondheim, Norway. The water distribution in Trondheim is fortunate to draw high quality raw water from the lake Jonsvannet. One treatment plant and three reservoirs provide the treatment and the primary distribution for the city. The water is mainly supplied by gravity, but pumping is required for some areas. The distribution network has 808 km of pipes (see Figure 4-1), serving a population of 160 000 and also industry. The pipes in the system are predominantly ductile iron, grey cast iron and plastic (PVC and PE) although there are smaller amounts of pipes made of asbestos, steel and concrete (Figure 4-2). The average length of a pipe (link) is 88 m and the average pipe age is 35 year (Røstum, 1997). It is well worth noticing that the average pipe laying depth in Trondheim is 2.5 meter to prevent freezing. Even at that level, frost has been known to cause pipe failures in severely cold winters. In central Europe a value between 0.5 to 1.0 m is more common. The difference in laying depth between Norway and central Europe will also influence pipe failures caused by traffic loads. The level of leakage has been decreasing the last three years from a level at 0.32 l/s/km in 1996 to close to 0.14 l/s/km in 1998. The break rate measured as number of breaks/km/year is about 0.3.

In Figure 4-1 the length of pipe being laid per year and the corresponding cumulative network length is shown. A typical postwar housing boom can be observed in the 50’s and the 60’s.

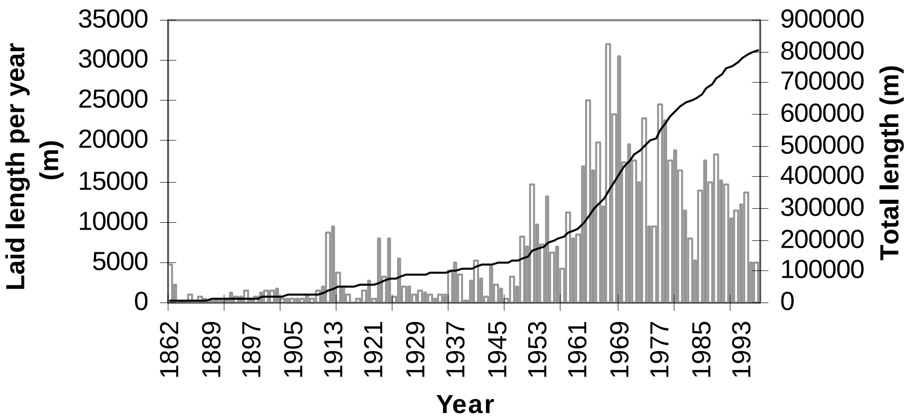


Figure 4-1. Network data for the water distribution network in Trondheim per 1/1/1997.

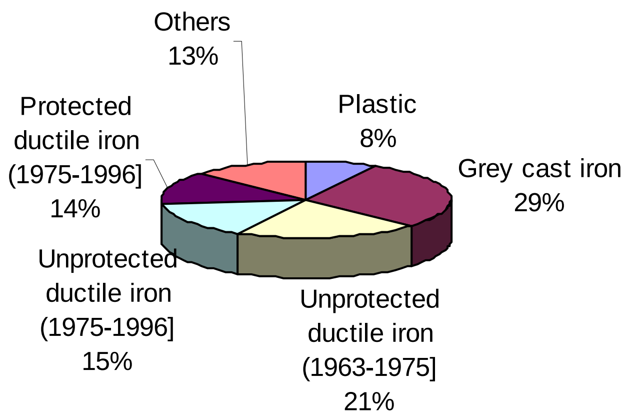


Figure 4-2. Distribution of pipes according to material for the water distribution network in Trondheim per 1/1/1997.

4.1 Processing the data

Pipeline data from Trondheim's Gemini VA database per January 1, 1997 is used in the analysis. This database contains structural data for the pipes (e.g. diameter, length of pipe, material, laying year, soil conditions, co-ordinates, joint type) and maintenance data (e.g. type of failure, date of failure, type of repair, data of repair). The approach outlined by Lei (1997) and Lei et al. (1998) is used to process the data from the GEMINI VA database (Figure 4-3). The Gemini VA system uses DataFlex as its database. The software program WinQL (Core Software Inc., Version 1.0) is used to access these files and export them in an ASCII format which can be used directly by statistical software.

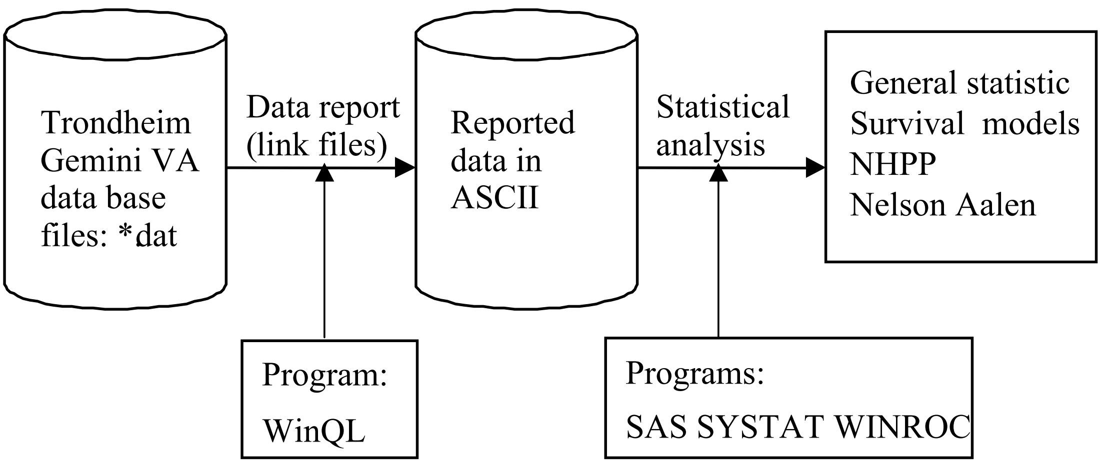


Figure 4-3. Data processing.

An alternative to using WinSQL is to export data from Gemini VA using Gemini VA's report option. However, in the current version of Gemini VA, the predefined report format is relatively inflexible, and the exported files would require considerable editing to convert them to the appropriate format for using with statistical software.

Statistical software like SAS or SYSTAT provide the necessary data management procedures and functions for processing the pipeline data.

During the processing of the data the following assumptions is made:

- Only one failure has occurred at the same day for each pipe. The Gemini VA database contains the exact date of failure and of repair. This allows for exact analyses of failure times. The raw data includes some cases where successive failures are recorded on the same day for a single pipe. In the analysis these failures are considered as one failure. According to information received from Trondheim municipality, successive failures on the same day for a single pipe are rare and the recorded successive failures are most likely a result of typing errors.

- In this work a failure is defined as a break/leakage and coded in GEMINI VA as “DBR”. A pipe failure leads to repair or replacement after a short time. The failure may be a leak, a cracked joint, a blowout, a longitudinal split, or a shear break. Each failure type is recorded with a separate code in the database. The analysis in this work does not, however, differentiate between types of failures. In the literature, failures are defined differently and there isn’t a clear-cut definition of “failure”.

- Due to the structural organisation of rehabilitation data in Gemini VA renovated pipes are not included in this analysis, as it was not possible to determine the original pipe material. Renovated pipes can be excluded from the analysis since the pipe attribute *STATUS* will change from “D” (i.e. in use) to “N” (i.e. not in use) when the pipe is replaced. The new pipe is assigned a new, unique system identification number (SID). Currently, the number of renovated pipes in Trondheim is small. In the future it will be important to improve the data recorded for renovated pipes as more pipes will be renovated instead of replaced.

- For some failures, one or more pipe segments are replaced (i.e. partly replacement). This new part of the total pipeline will normally have improved material properties, but in the existing Gemini VA database it was not possible to analyse this. Partly replaced pipes are thus treated as a normal repair in this work.

The data set is divided into 5 different groups according to pipe material, protection and installation year (Table 4-1). The grouping is established based on a combination of statistical analysis, theoretical knowledge and practical field experience about the different failure pattern for the groups. Statistical analysis is carried out separately for each group.

Table 4-1. Pipe groups.

Group	Short name	Material (coding in Gemini VA)	Installation year
Unprotected grey cast iron	Grey cast	SJG	<=1963
Unprotected ductile iron	UDI 1	SJA, SJB and SJK	(1963,1975]
Unprotected ductile iron (simple external/internal protection used)	UDI 2	SJA, SJB and SJK	(1975,1996]
Protected ductile iron	PDI	SJC and SJD	(1975,1996]
Plastic	Plastic	PEH, PEL, PRE and PVC	(1975,1996]

Table 4-2 shows the recorded number of failures in Trondheim for each year. The first failure recorded in the database is from 1975. Unfortunately less than 10% of all failures in the period 1975-1987 have been recorded, and only data from the period with "complete" data (1988-1996) are used in the analysis. Analysis of the incomplete failure data from 1975-87 would have lead to false results. 90% of the failures recorded before 1988 occurred on unprotected ductile iron (UDI 1).

Table 4-2. Number of failures recorded per year for Trondheim.

Year	**1975**	**1977**	**1978**	**1979**	**1980**	**1981**	**1982**	**1984**	**1985**	**1986**
Failures	2	4	1	1	4	3	1	17	28	26

Year	**1987**	**1988**	**1989**	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**
Failures	13	144	187	153	221	227	220	303	218	224

The recorded failures per year for each group are shown in Table 4-3. The total number of failures in the observed period is 1897. For pipes made of plastic only 2 failures are recorded. The term *other pipes* refers to pipes which have different materials and cannot be treated as one group. These pipes will not be analysed with the statistical models since they differ too much to be considered as a group.

Table 4-3. Number of failures per year for each group.

	Number of failures per year for each group (after 1988)									
	1988	**1989**	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**SUM**
Grey cast	40	60	45	66	55	50	93	62	44	515
UDI1	87	109	81	118	139	132	165	112	153	1096
UDI2	1	4	5	3		12	5	8	8	46
PDI	3		3	1		1	4	6	5	23
Plastic									2	2
Other pipes	13	14	19	33	33	25	36	30	12	215
									SUM	1897

Table 4-4. Number of pipes according to failures for each group.

	Number of pipes with *X* failures									# pipes	# failures
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**total**	**total**
Grey cast	2301	298	55	18	8	3	1			2684	515
UDI 1	1811	298	136	77	34	16	7	3	2	2384	1096
UDI 2	728	21	5	2	1	1				758	46
PDI	1216	16	2	1						1235	23
Plastic	564	2								566	2
Sum										7627	1682

The total number of pipes covered by these groups is 7627. The total number of pipes in Trondheim is 8451 pipes. This means that 90 % of all pipes in the network are covered by the analyses.

It is interesting to notice that out of 566 plastic pipes in Trondheim only two of these have recorded failures. Nowadays, there is an increasing trend in using plastic pipes for new construction and for renovation of pipes. In the future it will be interesting to analyse whether the increased use of plastic pipes will have any effect on the recorded failures for this group.

The number of recorded failures varies slightly compared to the work done by Lei (1997) due to a modification in the definition of a failure. In this work a failure is defined as a break/leakage and coded in Gemini VA as "DBR". Lei et al. (1998) treat every maintenance activity in the network as a failure. This means that maintenance activities like pipe flushing are treated as failures. Lei et al. (1998), also used all recorded failures, including data from periods with incomplete records. This leads to over-optimistic survival functions.

The pipe inventory and failure data available for Trondheim is representative of the status for many other water works in Norway and in Europe. The failure history available in database form is relatively short, and most of the pipes have no recorded failures. Only a few pipes have several failures. The inventory data is not complete and probably contains errors.

4.1.1 The extent of clustering of failures in the water distribution network

The literature shows (e.g. Goulter and Kanzemi, 1988; Sundahl, 1996) that there is a high probability of a subsequent failure immediately after a pipe failure. These subsequent failures are a direct result of the activities carried out during replacement or repair of a previous failure. Goulter and Kanzemi (1988) observed the temporal and spatial clustering of water-main failures and developed a method for quantifying the variation in pipe break rates (Goulter et al., 1993). The temporal variation in pipe failures is analysed for the Trondheim data set (all pipes). The analysis is carried out for each pipe and not restricted to a specific distance from the previous failure like in Goulter et al. (1993). Subsequent failures for the same pipe within 1 week, 2 weeks and 1 month are shown in (Table 4-5).

Table 4-5. Subsequent pipe failures in Trondheim.

Total number of failures	1 week	2 weeks	1 month
1897	48 (2.5 %)	62 (3.3 %)	94 (5 %)

The temporal clustering of subsequent failures in Trondheim is low compared to other studies (Goulter and Kanzemi, 1988). Further analysis of this phenomena is not included in this study. For systems where temporal clustering is significant, it should be taken into consideration when making rehabilitation/maintenance plans.

Based on material characteristics, temporal and spatial clustering of failures due to maintenance activities are most likely to occur on grey cast iron pipes rather than ductile iron pipes. Ductile iron pipes are as the name states *ductile* and are more resistant to fracturing than grey cast iron pipes.

4.2 Procedure for calibration and verification of the statistical models

The statistical models are calibrated (established) using the failure data for a nine year period (1988- 1996). The models are verified by predicting pipe failures for the following two years (1997 and 1998), and comparing the results with the observed data. This procedure is illustrated in Figure 4-4. Unfortunately the verification period is relatively short due to the fact that a minimum number of years are required in order to establish the models. When the statistical models are calibrated and verified, they can be used for the prediction of future failures.

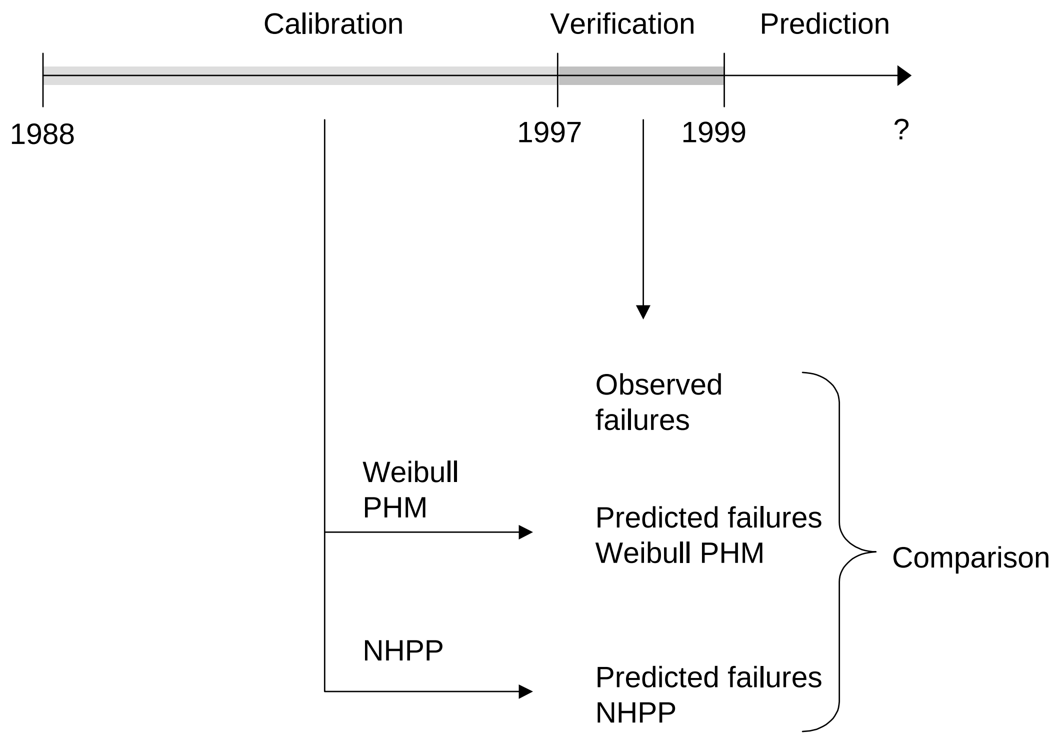


Figure 4-4. Procedure for calibration and verification of the statistical models.

Statistical models with different sets of covariates are evaluated and the best model is found by standard techniques, e.g. test of significance of parameters, log-likelihood comparison and prediction goodness.

The estimates of the regression parameters are tested for their significance at 5% p-value on the basis of the t-statistic. The reported p-value may be interpreted as the probability of obtaining such an extreme value for the estimate of β, if it is equal to zero. The covariates whose p-values are less than 5% are discarded from the model.

For the log-likelihood comparison, the set of covariates that give the highest log-likelihood value is chosen. The log-likelihood values can only be compared for different alternatives of the same statistical model. It does not make sense to compare the log-likelihood values for PHM and NHPP since the likelihood functions are different.

The models are also calibrated in terms of their ability to predict failures and how well the models fit the observed data. Graphics comparing predicted and observed values are useful for evaluating the model results (e.g. cumulative plots for observed failures versus predicted, year plots for observed failures versus predicted, plotting the number of observed and predicted failures for each pipe).

4.3 Covariates used in the models

All covariates that could have an influence on the rate of occurrence of failures should be included in the statistical models. The model results will reveal the significance of each covariate on the failure history. This study has included only the covariates that can be extracted from the pipeline database (Gemini VA). Potentially significant variables like water pressure and velocity are not included in this study, since a hydraulic model of the distribution system is not available. These covariates can easily be included in the models as they become available.

The variables included in the analysis are:

LnLength:	The length of the pipe (in *m*) is transformed by taking the natural logarithm, since the length is known to act proportionally on the hazard function of a pipe.
Diameter:	Diameter of the pipe in *mm*.
Age_left:	Time between construction and start of records, i.e. left-censored data. Might be a surrogate for other effects such as construction methods etc.
LnNOPF:	The Number Of Previous Failures (NOPF) of the pipe. The transformation, LnNOPF= Ln(NOPF+1) is taken to avoid the logarithm of zero in cases where no previous failures are recorded.
Clay:	Variable indicating whether the native soil around the pipe is coded as clay or not (Gemini VA code = ”LE”). This variable indicates the presence or absence of clay, i.e. 1 if clay, 0 if other material.
OM:	Variable indicating if the native soil around the pipe is coded as artificial masses (Gemini VA code = ”OM”). (Norwegian: “*oppfyllingsmasser*”) or not. If it is *OM* the variable is 1, else 0.
Intercept (α):	The interception parameter (α) for the Weibull distribution estimated by SAS and SYSTAT (reports the same value).
Scale (σ):	The scale parameter (σ) for the Weibull distribution estimated by SAS and SYSTAT. If $\sigma<1$ the hazard function is increasing, otherwise decreasing.
Interception (λ):	“Power law” parameter used for modelling NHPP.
Scale (δ):	“Power law” parameter used for modelling NHPP.

Note that the covariates reported as significant vary between models and between pipe groups. For the PHM, the significant covariates also differ between strata for the same pipe group.

4.3.1 A physical interpretation of some of the covariates

4.3.1.1 Ground conditions

Corrosion caused by sulphate reducing bacteria (SRB) has been a problem for the ductile iron pipes in Trondheim that lack external protection. Many of the pipes are exposed to marine clay deposits, which foster SRB corrosion, resulting in heavy external pitting. 50% of these pipes failed within 17 years of installation. Corrosion rates due to SRB-corrosion have been reported to be as high as 1mm/year (Gukild, 1978). The wall thickness of ductile iron pipes (100mm – 400mm) ranges from 6-8 mm, and the first failures occurred only a few years after installation.

Environmental conditions conducive to SRB corrosion include:

- Anaerobic conditions (clay is used as backfill material)
- Organic material present (mixed during construction)
- Sulphate present
- pH of 5.5 - 9

The chemical process for SRB corrosion is

$$2\mathrm{H} + \mathrm{Fe} + \mathrm{CaSO}_4 + \mathrm{SRB} \rightarrow \text{ferrous sulphide} + \text{ferrous hydroxide} \tag{4.1}$$

Before 1980 clay was used as backfill for pipe trenches in Trondheim. This backfill always included some organic material as well. Since 1980, only sand is allowed as backfill. After 1975 there has been an increasing use of polyethylene or polyurethane coating for ductile iron pipes in order to protect against external corrosion in Trondheim (Bjørgum, 1988).

4.3.1.2 Diameter

In general the time to failure of a pipe increases with increasing pipe diameter. Ductile iron pipes and grey cast iron pipes have different failure patterns. The spherical shape of the graphite in ductile iron pipes results in remarkable mechanical properties. These pipes have high tensile strength, are impact resistant and have a high elastic limit. Ductile iron pipes with poor internal/external protection corrode but do not experience fracture. The nominal wall thickness of pipes (and corresponding resistance to failure) increases with increasing pipe diameter.

When grey cast iron pipes fail, they tend to burst and not leak like ductile iron pipes. The graphite is present in the form of flakes. When abnormal stress is concentrated at a point on the pipe, each of these flakes may initiate fracturing. Pipe stiffness is also an important factor in resisting pipe fracture. Stiffness increases with increasing diameter.

Most large diameter pipes are trunk or transmission mains. The quality of the construction for these mains is often better than that for smaller pipes. This is especially true for pipe diameters greater than 500 mm.

4.3.1.3 Age_left

The *age_left* variable is equivalent to the time between laying year and start of failure recording. When the value is high, the pipe has already shown its resistance against failures, and will therefore tend to last longer than pipes with low age_left values. The age_left covariate is a surrogate for variables which have not been included in the model, for example time dependent changes in the quality of workmanship. The variable is only considered for pipes installed before the failure record starts.

4.3.1.4 Length of pipe

The length of a pipe has an effect on the number failures per pipe since we are measuring failures per pipe and not per pipe length. There is also a difference between grey cast iron and ductile iron pipes caused by different material properties. The material in ductile iron pipes is homogeneous throughout the pipe length. Grey cast iron pipes are less homogeneous, and the probability of failure is greater for a longer pipe than for a shorter one.

4.4 Results for the Weibull PHM/accelerated model

The analysis is based on historical failure data from the period from 1988 to 1996 (9 years). The pipes in each age/material group are divided into two strata depending on the number of previous failures (NOPF) recorded. Each strata, or subset, is analysed separately. The parameters β, α and σ vary from stratum to stratum. Stratum 1 includes pipes with no previous failures (NOPF = 0) and stratum 2 includes pipes that have failed one or more times (NOPF >= 1). Due to the small numbers of pipes with more than two failures (Table 4-4), including a third stratum for pipes with multiple failures did not improve the models. The lifetime used in the analysis might either be an observed interfailure time or a right-censored interfailure time, i.e. pipe which still is functioning at the end of the observation period.

The different groups of pipes are analysed using the statistical packages SAS PROC LIFEREG ver. 6.12 (SAS, 1994) and SYSTAT SURVIVAL ver. 7.01 (SYSTAT, 1997). The packages provide maximum likelihood estimates of intercept parameter α and scale parameter σ associated with the extreme value distribution, the error distribution for the Weibull model.

In the following the parameters and the regression parameters are given according to an accelerated model (Eq. 3.12) and not a PHM (Eq. 3.11).

However, it is easy the transform the parameters according to the following functions: $\lambda=\exp(-\alpha)$, $p=1/\sigma$ and $\beta=-\beta^{*}/\sigma$.

4.4.1 Unprotected ductile iron pipes laid between 1963 and 1975

Unprotected ductile iron pipes laid between 1963 and 1975 (UDI1) are analysed as one group. The estimates of the parameters, coefficients and the corresponding p- values (i.e. significance level) are given in Table 4-6. The results have also been compared to a similar analysis carried out for two French water networks, where some of the same variables were found to be significant (Eisenbeis et al., 1999).

Table 4-6. Results Weibull PHM for UDI1 (Decimals after decimal point are not cancelled in order to allow comparison with Table 4-10).

Stratum	Parameters and coefficients	Estimate	p- value
NOPF =0	**Intercept (α)**	5.45317633	0.0001
	LnLength, log transformed of length of pipe (in *m*)	-0.5114362	0.0001
	Diameter of pipe (in *mm*)	0.00387284	0.0001
	Age_left (i.e. time (years) from construction to beginning of observations)	0.03312558	0.0104
	"Clay" or not (i.e. indication if pipe is laid in clay)	-1.1002885	0.0009
	Scale (σ)	0.97286216	
NOPF ≥ 1	**Intercept (α)**	2.8732128	0.0001
	LnLength, log transformed of length of pipe	-0.2952295	0.0041
	LnNOPF, log transformed of number of previous failures	-1.0162046	0.0001
	Age_left (i.e. time from construction to beginning of observations)	0.04819655	0.0223
	Scale (σ)	1.28981313	

All covariates in the model are significant and behave in the expected way. Pipe length has a negative effect on the interfailure time in both strata (i.e. longer pipes fail more often). Pipe diameter is only significant for pipes with no previous failures (stratum 1). A larger pipe diameter prolongs the time to the first failure. Interfailure times also increase with larger age_left values. Pipes that have been in service for many years are less likely to fail than pipes that are recently installed. The previous number of failures (NOPF) has an important positive effect on failure probability. The hazard function increases with increasing number of previous failures. The clay parameter is significant only for stratum 1. Soil conditions in Trondheim promote SRB corrosion, with subsequent external pitting. When the first leakage occurs, many other pits have developed that are close to a breakthrough in the pipe wall. Most of the pipes experiencing successive failures are located in clay. Since these pipes have the same value for the clay variable, the model cannot show that it is significant within the stratum for pipes with multiple breaks. The shape parameter (σ) for stratum 1 is close to one, corresponding to a near-constant hazard function. For stratum 2, σ is greater than 1, indicating a decreasing hazard function between each failure.

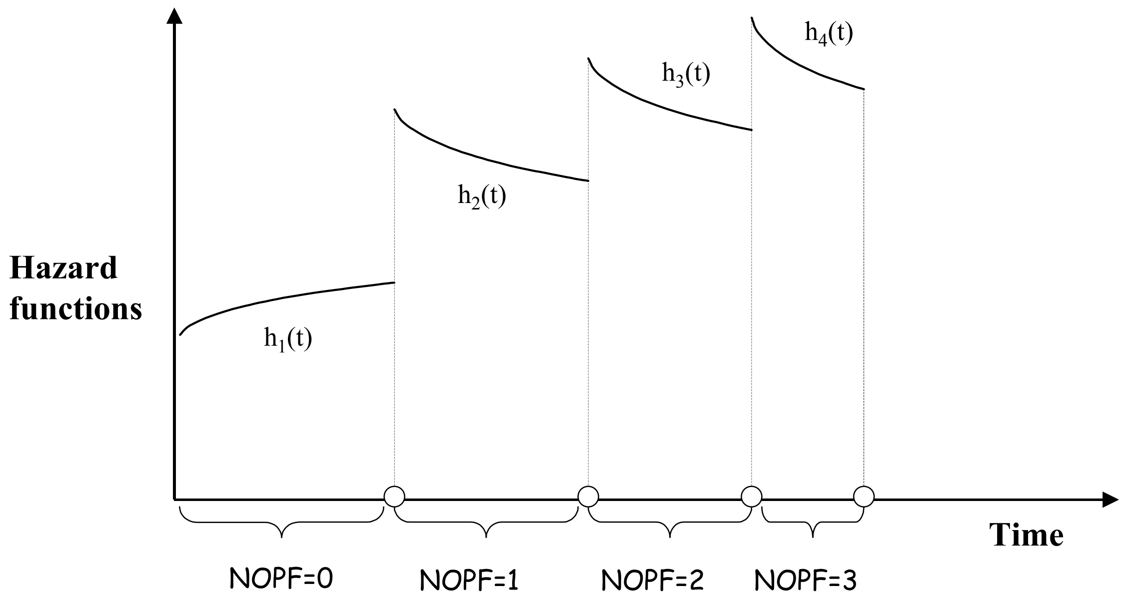


Figure 4-5. Weibull PHM hazards functions for unprotected ductile iron pipes laid between 1963 and 1975.

The actual shape of the hazard functions for the Weibull PHM is shown in Figure 4-5. For the first interval (time to first failure) the hazard function increases slightly with time. In the subsequent intervals the hazard functions decrease with time. The horizontal shift after each failure is due to the fact that *NOPF* acts as a covariate, increasing the probability of failure. After each failure *NOPF* is increased by one. The results show that this group of pipes is deteriorating.

4.4.2 Grey cast iron pipes laid between 1870 and 1963

All of the grey cast iron pipes were installed before 1964 and are analysed as one group. The parameters and the corresponding estimates are given in Table 4-7.

Table 4-7. Weibull PHM results for grey cast iron.

Stratum	Variables	Estimate	p- value
NOPF =0	**Intercept (α)**	5.9683	0.0001
	LnLength, log transformed of length of pipe (in *m*)	-0.5749	0.0001
	Diameter of pipe (in *mm*)	0.0022	0.0029
	"OM" or not (i.e. indication if pipe is laid in "OM")	-0.4373	0.0056
	Scale (σ)	0.8972	
NOPF ≥ 1	**Intercept (α)**	7.6797	0.0001
	LnLength, log transformed of length of pipe (in *m*)	-0.5353	0.0307
	LnNOPF, log transformed of number of previous failures	-2.2403	0.0002
	Scale (σ)	1.8321	

All covariates in the model are significant and behave the way we expect. Pipe length has a negative effect on interfailure times for both strata. The pipe diameter is only significant for the first stratum. A larger pipe diameter prolongs the time to the first failure. The variable age_left is not significant for either stratum. Number of previous failures is an important variable for pipes in the second stratum. Pipes laid in an area with native soil material have a longer time to first failure than pipes in an area with imported material (i.e. OM). The hazard function for pipes in stratum 1 increases with time ($\sigma<1$), while the hazard function for stratum 2 decreases with time ($\sigma>1$). The hazard function for this group of pipes, as a function of time and NOPF, exhibits the same pattern as group UDII (Figure 4-5).

4.4.3 Unprotected ductile iron pipes laid between 1975 and 1996

Unprotected ductile iron pipes laid between 1975 and 1996 (UDI2) are analysed as one group. The significant variables and parameters for this analysis are presented in Table 4-8.

Table 4-8. Weibull PHM results for unprotected ductile iron pipes laid between 1975 and 1996.

Stratum	Variables	Estimate	p- value
NOPF =0	**Intercept (α)**	7.9001	0.0001
	Age_left (i.e. time (years) from construction to beginning of observations)	-0.3129	0.0234
	Scale (σ)	0.8224	
NOPF ≥ 1	**Intercept (α)**	4.0371	0.0001
	LnNOPF, log transformed of number of previous failures	-2.2916	0.0207
	Scale (σ)	1.2687	

In stratum1 the age_left parameter is found to be significant, but has the opposite sign as for the two previous groups. For this group a high age_left covariate reduces the time to the first failure. The result is surprising, but we have to consider the relatively low number of pipes failing for this stratum (30 observed failures out of 729) The scale parameter for stratum 1 indicates an increasing failure ($\sigma<1$) rate with time. For the second stratum the hazard function is decreasing ($\sigma>1$). For pipes in the second stratum the number of previous failures plays an important role. The hazard functions will have the same behaviour as in Figure 4-5.

4.4.4 Protected ductile iron pipes laid between 1975 and 1996

Protected ductile iron pipes laid between 1975 and 1996 (PDI) are analysed as one group. The parameters and the corresponding estimates are given in Table 4-9.

Table 4-9. Weibull PHM results for protected ductile iron pipes laid between 1975 and 1996.

Stratum	Variables	Estimate	p- value
NOPF =0	**Intercept (α)**	5.7382	0.0001
	Scale (σ)	0.8494	
NOPF ≥ 1	**Intercept (α)**	3.8423	0.0079
	Scale (σ)	1.7184	

The number of pipe failures for this group is low. In the first stratum, there are only 19 pipes with failures out of a total of 1235 pipes. Stratum 2 has only four failures. No significant covariates could be determined for this small number of observed failures, and only the Weibull parameters are reported. The scale parameter for stratum 1 indicates an increasing failure ($\sigma<1$) rate with time. For the second stratum the hazard function is decreasing ($\sigma>1$). The hazard functions will have the same pattern as shown in Figure 4-5, but for the failure intervals after the first failure the hazard functions will be identically.

4.4.5 Plastic pipes laid between 1975 and 1996

For plastic pipes only two failures are recorded for a sample set of 566 pipes. There are no pipes with more that one failure. It is not possible to fit a model to this small sample set. A rough estimate of the survival function assumed as a horizontal line equal to one.

In the work of Lei (1997) the same data set is used for analysing the first failure of a pipe (equivalent to stratum 1). Lei reported parameters for plastic pipes, even when the covariates were not significant.

4.4.6 Failure prediction using Monte Carlo simulation

For each pipe in each group, the expected number of failures for different time horizons (i.e. 2,5,10 and 20 years) is calculated using the method described in Chapter 3. An example of this approach for a typical, unprotected ductile iron pipe (length=100m; diameter=150mm; year of construction=1970; laying in clay; no previous failures recorded) is shown in the following paragraphs.

Figure 4-6. shows the survival functions for this "average" unprotected ductile iron pipe for successive failures. S1(t) refers to the survival function for first failure, S2(t) refers to the second failure and so on. Since the number of previous failures is a covariate in the model, the survival functions will differ from each other. As shown in Figure 4-6 the survival functions become steeper as the failure number increases. This implies that the time between failures on the average become shorter and shorter.

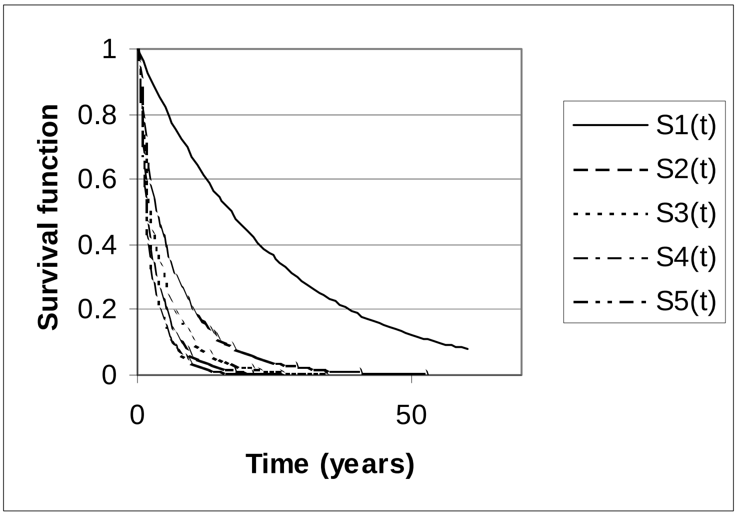


Figure 4-6. Survival functions for an "average" ductile iron pipe.

The expected number of future failures is calculated for the "average" pipe using the survival functions in Figure 4-6. The results are shown in Figure 4-7. For each year the number of failures are simulated 100 000 times (increased from 1000 to 100 000 in order to get a smooth curve for illustration purposes) and the mean value of the simulations is equal to the line *N(t)*. Upper and lower bounds (90% confidence interval) for the predicted values are also shown. From Figure 4-7 we can see that about eight failures can be expected over the next 30 years. The concave curve indicates a deteriorating network. Similar analyses are carried out for each individual pipe in the network using each individual pipe's set of covariates.

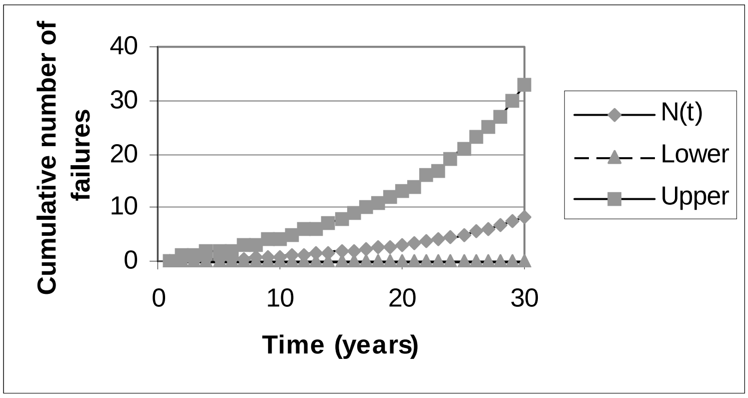


Figure 4-7. Predicted new failures for an "average" UDI1 pipe.

Based on the predicted failures the rate of occurrence of failures (ROCOF) for this "average" pipe is calculated. The ROCOF will be the slope of the curve *N(t)* (see Eq. (1.1)). As seen in Figure 4-8. the ROCOF increases with time. The local peak before 30 years is a result of the Monte Carlo simulation. If we increased the number of simulations even more the curve would have been smoothed. It should be noticed the ROCOF for the pipe is increasing even if the scale parameter (σ) for the second stratum (NOPF≥1) is greater then 1, indicating a decreasing hazard function between each failure. The explanation for this is that the number of previous failures (NOPF) act as covariate in the model, and the hazard function will therefore have a horizontal shift upward after a failure (see also Figure 3-7).

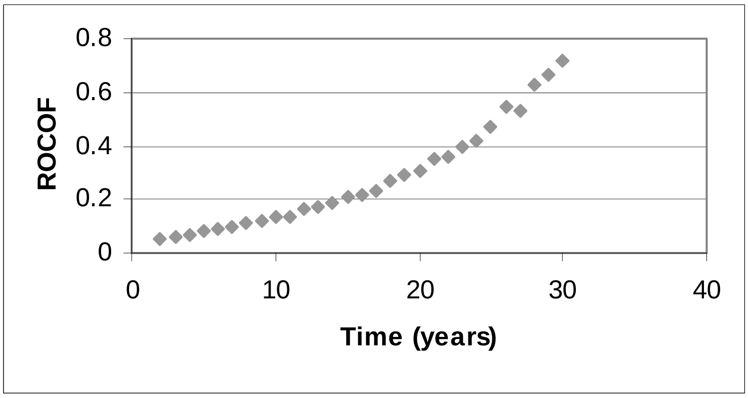


Figure 4-8. Rate of occurrence of failures (ROCOF) for an "average" UDI1 using the Weibull PHM approach.

The ROCOF in Figure 4-8. corresponds to the right hand side of the "bath tube" curve. The ROCOF is increasing indicating that unprotected ductile iron pipes in Trondheim are deteriorating.

4.5 Result for Cox's Proportional Hazards Model

Cox's proportional hazards model does not require any assumptions about the form of the baseline hazard function and is useful for evaluating the effects of covariates on the hazard function. Cox's model, however, is not appropriate for predicting failures (section 3.3.4). The following paragraphs present a comparison of the estimates for covariates given by the Cox and Weibull proportional hazard models, as applied to group UDI1 (unprotected ductile pipes laid between 1963 and 1975). The stratification used in the model is the same as the one described in section 4.4.1. The results for the Cox model are presented in Table 4-10, together with the transformed estimates for the corresponding results from the Weibull PHM/accelerated model (Table 4-6).

Table 4-10. Covariate values for Cox's PHM and Weibull PHM, pipe group UDI1.

Stratum	Variables	β_{Cox}	$-\beta^*_{Weibull}/\sigma$
NOPF =0	**LnLength**, log transformed of length of pipe (in *m*)	0.52389	0.52570
	Diameter of pipe (in *mm*)	-0.00399	-0.00398
	Age_left (i.e. time (years) from construction to beginning of observations)	-0.03648	-0.03405
	"Clay" or not (i.e. indication if pipe is laid in clay)	1.13094	1.13098
NOPF ≥ 1	**LnLength**, log transformed of length of pipe (in *m*)	0.2352	0.22889
	LnNOPF, log transformed of number of previous failures	0.83168	0.78787
	Age_left (i.e. time from construction to beginning of observations)	-0.04034	-0.03737

When comparing the parameter estimates of Cox's PHM with those of the fully parametric model of Weibull PHM it is important to notice that the coefficients will have opposite signs and will differ by a scale factor related to the Weibull shape parameter, i.e. β_{Cox} is equivalent to $-\beta^*_{Weibull}/\sigma$. As shown in Table 4-10, the two models give similar results.

4.6 Results Non Homogeneous Poisson Process

The failure data is also analysed with the program WINROC, which estimates the parameters using the Non-Homogeneous Poisson Process (NHPP), (Chapter 3.4.1). The best results are achieved by resetting all a_i's and b_i's, letting the time of observation start at time *0*, rather than at the installation year. The results are also relatively good without resetting the time scale. A new variable, *age_left,* equivalent to the time from laying year to the time when observations starts, was introduced in order to account for the age of the pipe at the time of the start of observations. Good results were also achieved by excluding the *age_left* variable. The final results from all groups are shown in Table 4-11.

Table 4-11. NHPP model results for all pipe groups.

Variables	Estimates of the parameters and coefficients			
	Grey cast	**UDI1**	**UDI2**	**PDI**
Lambda, λ (i.e. "Power law" parameter)	0.01619	0.02719	0.00174	0.00251
Scale, δ (i.e. "power law" parameter)	1.12859	1.28145	1.48759	1.0022
Length of pipe	0.00194	0.00423		
Diameter of pipe	-0.00067	-0.00364	-0.0073	
"OM" or not (i.e. indication if pipe is laid in deposits)	0.14240			
"Clay" or not (i.e. indication if pipe is laid in clay)		0.41176	-0.02023	
Age_left (i.e. time from construction to beginning of observations)	-0.00084	-0.0083	0.15499	

The parameters and the explanatory variables behave in a technically logical way. Increasing the pipe length increases the intensity of failures. Increasing the diameter of the pipe decrease the intensity of failures. The presence of clay is an important variable for predicting failures for pipe group UDI1, while presence of deposits (i.e. OM) is an important variable for grey cast iron pipes. The structural reasons for these patterns are presented in section 4.4. For grey cast iron pipes, and the pipes in group UDI1, an increasing *age_left* variable tends to decrease the intensity of failures. Reasons for this might be that the poorly resistant pipes in these groups have been replaced earlier, and the remaining pipes are resistant to failures. The variable *age_left* might also be a surrogate for other effects not included in the models. The general pattern of the results accord well with the corresponding results from the Weibull PHM.

4.6.1 Relative risks NHPP

The covariates presented in Table 4-11 are not dimensionless, and it is difficult to evaluate their relative importance. Calculating the relative risk (RR) for a range of values for the significant covariantes ($\mathbf{z}_i \vee \mathbf{z}_i^*$), makes it easier to interpret their influence on the rate of occurrence of failures. In the following examples, the relative risks associated with different values of the covariates are presented (Table 4-12). The relative risk (RR) is defined as the change that would occur in the intensity function for a given change in one of the model covariates. The other covariates are held constant while varying the covariate $\mathbf{z}_i$. Relative risk is calculated as:

$$RR = \frac{\lambda(t, \boldsymbol{\beta}, \mathbf{z}_i)}{\lambda(t, \boldsymbol{\beta}, \mathbf{z}_i^*)} = \frac{\lambda \delta t^{\delta-1} \exp(\boldsymbol{\beta}\mathbf{z}_i)}{\lambda \delta t^{\delta-1} \exp(\boldsymbol{\beta}\mathbf{z}_i^*)} = \frac{\exp(\boldsymbol{\beta}\mathbf{z}_i)}{\exp(\boldsymbol{\beta}\mathbf{z}_i^*)} \tag{4.2}$$

Table 4-12. Relative risks (RR) for different covariate values.

Covariate	$z_i \vee z_i^*$	$RR_{Grey\ cast}$	RR_{UDI1}	RR_{UDI2}
Length (m)	50 ∨ 150	0.82	0.66	
Diameter (mm)	100 ∨ 300	1.14	2.07	4.31
OM (“OM” or not)	0 ∨ 1	0.87		
Clay (“Clay” or not)	0 ∨ 1		0.66	1.02
Age_left (years)	5 ∨ 15	1.01	1.09	0.21

The results of this table can be interpreted as follows: decreasing the diameter for a specific UDI1 pipe from 300 mm to 100 mm will double (2.07) the intensity of failures. For a UDI1 pipe not located in clay the intensity of failures will be only 66% of that of an identical pipe which is located in clay.

4.6.2 Calibration NHPP

In Table 4-13 the total number of predicted and observed failures for the calibration period 1988- 1996 is shown.

Table 4-13. Predicted (NHPP) and observed failures for the period 1988-1996.

	Grey cast	UDI1	UDI2	PDI
Predicted failures with NHPP	506	1078	46	23
Observed failures	515	1096	44	23

The total number of failures predicted by the model, and the number of observed failures are very similar. It is also interesting to investigate whether the model also is good during the period. For evaluation of this, cumulative plots and years plots are good graphical tools for a visual inspection.

4.6.2.1 Cumulative plots

Cumulative plots can be used to graphically evaluate the model results with observed failures. These plots can also show trends in interfailure times for the network. Figure 4-9 displays the *observed* cumulative failures (Nelson- Aalen estimator) and the predicted (NHPP) cumulative failures for UDI1 pipes. The model fits the observed data very well. 1096 failures were observed compared to the NHPP model estimate of 1078. In this case the observed curve is convex, indicating a *deteriorating* network. For these pipes, the future failures will occur more and more frequently. Similar plots are also made for the other pipe groups. A complete set of cumulative plots for all groups are shown in Appendix B. Based on the cumulative plot we might conclude that the NHPP model is able to reproduce the total failure time history for this case study.

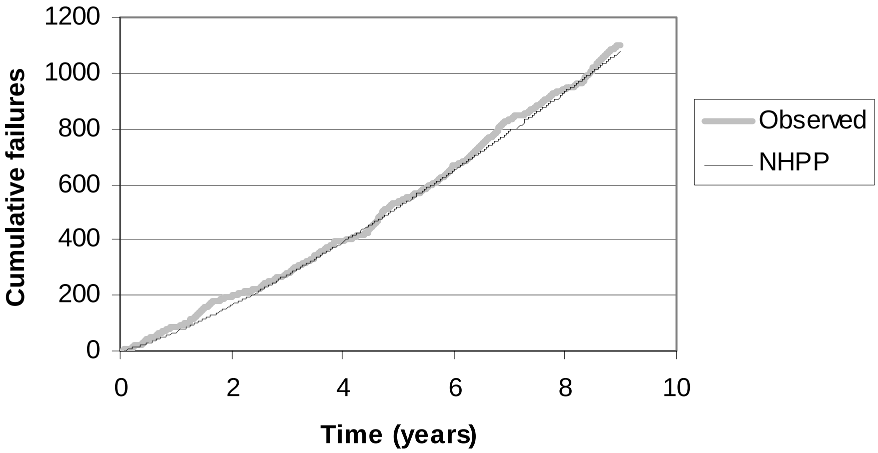


Figure 4-9. Cumulative failures plot for UDI1 pipes for the period 1988-1996.

A number of tests have been developed to determine whether the observed trend is statistically significant (e.g. Laplace test and Military Handbook test, see Ascher and Feingold (1984) for details). In this work statistical tests for trends are not calculated and graphical/visual examination of the data is assumed to give sufficient evidence of failure trends.

4.6.2.2 Annual plots

As an indication of the goodness of fit of the model, annual plots are constructed showing the predicted number of failures and the observed number of failures for each year. In Figure 4-10 the results for UDI1 pipes are shown. The number of failures per year is increasing, and it is evident that the NHPP model is able to reproduce this process. It is not realistic to expect the model to match all the peaks, since seasonal effects (e.g. temperature) are not included as covariates. A complete set of annual plots for all groups is shown in Appendix C.

It should be noted that the curve in Figure 4-10 is not produced by curve fitting to the observed number of failure per year (e.g. least square method) but is based on a maximum likelihood estimation which considers the failure time for each pipe. In some cases it will be possible to fit a curve to the observed values to improve the prediction of failures for each year. However, this type of model does not include covariates and will not be applicable for individual pipes, one of the main goals of this study.

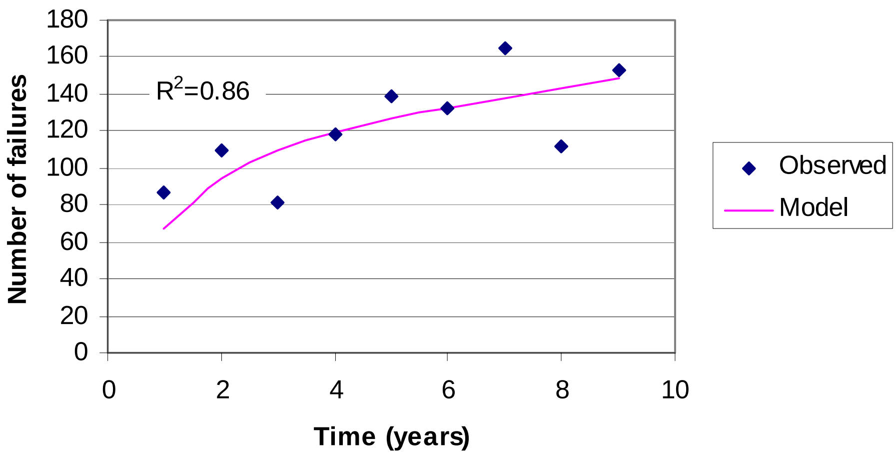


Figure 4-10. Annual plot for UDI1 for the period 1988-1996 (9 years).

4.7 Weibull PHM versus NHPP at network level for the calibration period.

It is interesting to compare the capabilities of prediction for the NHPP and the Weibull PHM. In Figure 4-11 a cumulative plot for Weibull PHM, NHPP and observed failures is shown for UDI1 pipes. The upper line is Weibull PHM, which has an uneven shape resulting from the Monte Carlo simulation. The smooth line is the parametric form of the NHPP. The calculations for producing cumulative plots with the Weibull PHM is extremely time consuming due to the inclusion of Monte Carlo simulation. Cumulative plots have only been generated for UDI1 pipes. Cumulative plots for the NHPP are easily calculated using Eq. (3.27).

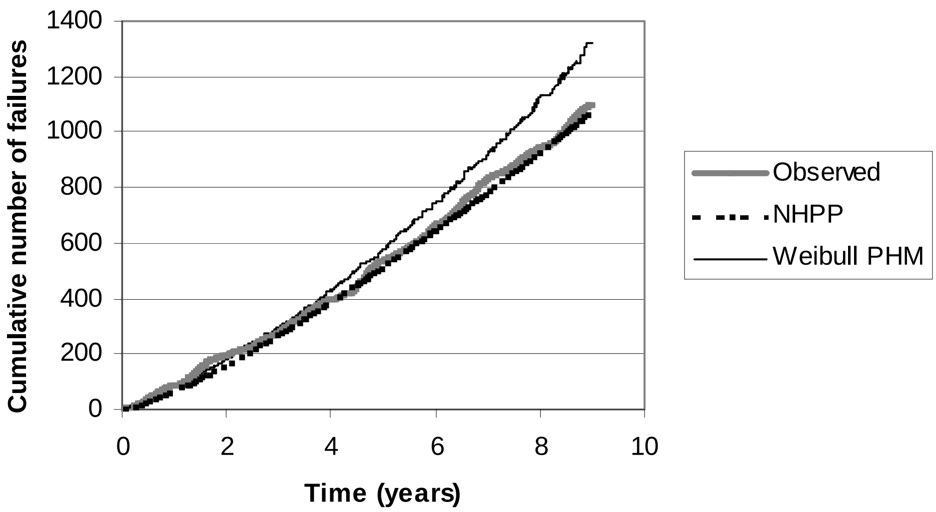


Figure 4-11. Cumulative plot for Weibull PHM, NHPP and observed failures for UDI1 pipes for the period 1988-1996.

For UDI1 pipes, the Weibull PHM has a systematic tendency to overestimate the number of predicted failures compared to the NHPP. The same trend is evident when the models are used for predicting new failures. The cumulative number of predicted failures for the calibration period 1988-96 are 1078 and 1322 respectively for NHPP and Weibull PHM. 1096 failures actually occurred during this period.

When using Weibull PHM, stratification depending on number of previous failures is required. The number of strata is limited by the sample size (i.e. few pipes with two or more failures). In order to improve the model, more pipes with multiple failures recorded are required.

Whether the Weibull PHM will overestimate, underestimate or estimate correct the number of predicted failures I believe will be site specific.

4.8 Verification of Weibull PHM and NHPP at network level

After calibration, the models are verified using failure data for 1997 and 1998. The results are shown in Table 4-14.

Table 4-14. Predicted (NHPP and Weibull PHM) and observed failures for 1997 and 1998.

	Grey cast	UDI1	UDI2	PDI
Observed failures	94	306	8	8
NHPP	132	309	15	6.2
Weibull PHM	141	377	21	7.1

NHPP gives the best results while the Weibull PHM consistently overestimates the number of failures.

4.9 Prediction at network level

The calibrated and verified models are used to predict future failures for each group (i.e. network level). In Figure 4-12 the results from calibration, verification and prediction for UDI1 pipes in Trondheim using NHPP is shown. The model is calibrated using nine years of failure data. The calibrated model is tested against failure data for the following two years. This verified model is then used to predict the total number of failures for all unprotected ductile iron pipes within a given time horizon. A typical master plan has a plan period of about ten years. The maximum time horizon for prediction should be based on the validity of the model. The results displayed in Figure 4-12 show that the model is good enough to use in master plans for pipe renovation and replacement.

The failures presented in Figure 4-12 are calculated with the assumption that no replacement/renovation is carried out in the prediction period. However, since this model can also be used to predict failures for individual pipes, the effect of replacement/renovation for specific pipes can easily be calculated.

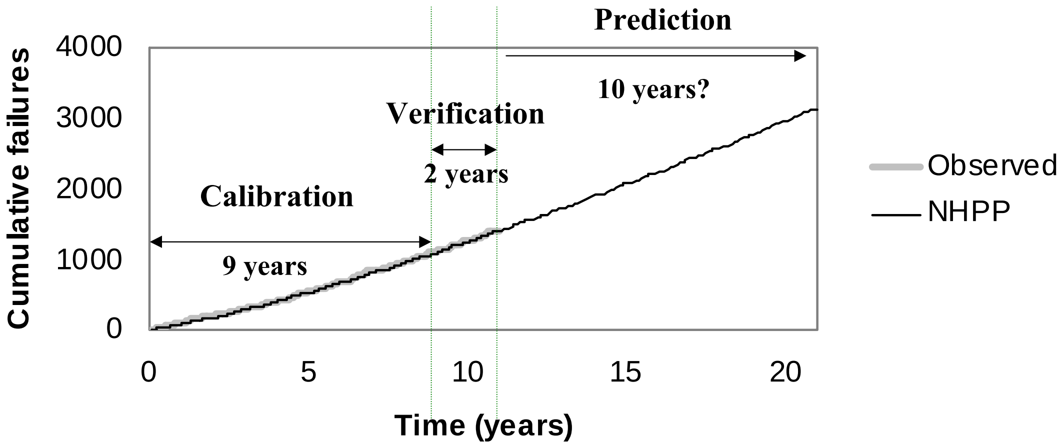


Figure 4-12. NHPP model results (calibration, verification and prediction) for unprotected ductile iron pipes (UDI1) in Trondheim.

A complete set of cumulative plots showing the model results for calibration, verification and prediction for all pipe groups is shown in Appendix D.

4.10 Weibull PHM and NHPP at pipe level

The cumulative plots shown so far display the sum of failures for all pipes in a group. This value is the sum of the failures for each individual pipe, based on that pipe's set of covariates. In the following sections, the model's ability to correctly predict failure for individual pipes is evaluated. This evaluation includes a graphical test and a test on quartiles.

4.10.1 Graphical test at pipe level

In the following a simple plotting technique is used as a graphical check of the models prediction capabilities at pipe level. For each pipe the observed number of failures are compared with the predicted number of failures by plotting the "pairs" (observed, predicted). A plot where the pairs are distributed around the line "Y=X" (i.e. straight line with slope equal to 1) indicates a good model. It should be pointed out that the predicted values might be decimal numbers, but the observed number of failures for each pipe is always an integer.

In Figure 4-13 the results from modelling UDI1 with the Weibull PHM approach for the two years 1997 and 1998 is shown (i.e. verification period). In Figure 4-

14 similar results are shown for the NHPP. Similar results were also observed for the other pipe groups.

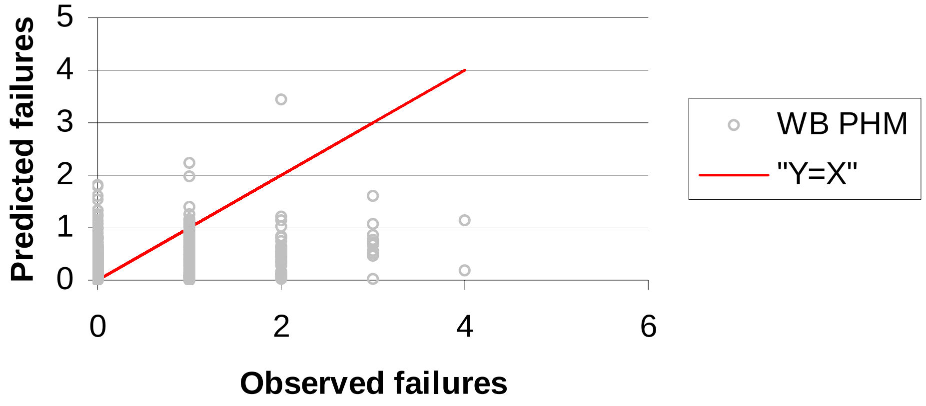


Figure 4-13. Plot of the pairs (number of observed failures, number of predicted failures) for each UDI1 pipe in Trondheim for the years 1997-1998 using Weibull PHM for prediction.

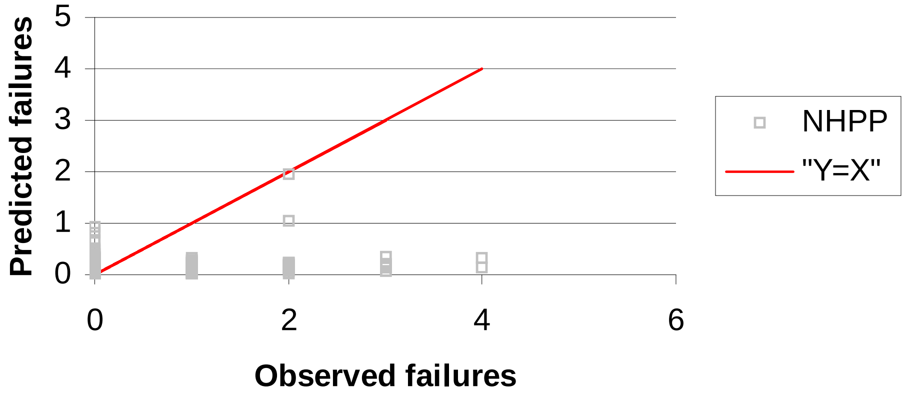


Figure 4-14. Plot of the pairs (number of observed failures, number of predicted failures) for each UDI1 pipe in Trondheim for the years 1997-1998 using NHPP for prediction.

Figure 4-13 and Figure 4-14 require for some comments:

- The verification data includes information for only two (2) years.
- Most of the observations are on pipes with 0 or 1 observed failures. 90 % of all pipes have 0 failures and 98% of the pipes have 0 or 1 failure. So the plots contain an element of "optic" effect.
- We might get the impression that the Weibull PHM fits the data better than the NHPP. However, since Weibull PHM for UDI1 has a tendency to overestimate failure at the network level the same tendency also holds at pipe level.

- Some pipes have been renovated and for these pipes no failures have been observed after the time of renovation. In the present study it was not possible to consider renovated pipes and therefore the models overestimate failures for these pipes.
- For pipes with high number of predicted failures but even higher number of observed failures, underestimating the number of failures is of little consequence as these pipes will anyway be candidates for renewal.
- The predicted values are equal to the expected values, so this is a sole mean prediction. For each of the predicted values an upper and lower bound (i.e. prediction interval) may be given. In spite of this methodical problem, the pair plots point out some of the points where the models do not fit the observed data.

A discussion of the underlying data for some of the extreme points (observed and/or predicted) on the graphs is presented in the following paragraphs. An explanation of the most relevant Gemini VA codes is given in Appendix E.

The point (0,0.94) in Figure 4-14 represents the pipe with system identification number (SID) 433428. A resumé of the information in Gemini VA recorded for this pipe is given bellow.

SID	Status	Length	Material	Dimension	Year	Soil	Date_warning	Date_execution	Code
433428	D	572.72	SJK	200	1969	LE	16-Nov-94	18-Nov-94	**DBR**
433428	D	572.72	SJK	200	1969	LE	18-Nov-94		U61
433428	D	572.72	SJK	200	1969	LE	18-Nov-94		U33
433428	D	572.72	SJK	200	1969	LE	18-Nov-94		**R76**
433428	D	572.72	SJK	200	1969	LE	18-Nov-94		QA4

In the database records for this specific pipe a failure (code = ”DBR”) is observed on November 16, 1994. Two days later the whole pipe was replaced (code = ”R76”). After this date, no more data is recorded. This is also what is expected for a new pipe. Normally when a pipe is replaced, the procedure is to generate a new SID for the new pipe and change the *Status* for the original pipe from “D” to “N”. A “D” means that the pipe is still in use and a “N” is used when the pipe is taken out of service. For this specific pipe the procedure has not be followed correctly. As a result of this error, the “old” vector of covariates is used for prediction of failures and not a modified one with new covariates (e.g. laying year, pipe material). This explains why the predicted value is too high for this pipe. When the procedure is followed correctly, the old pipe is kept in the database as a historical data and can be used in statistical analysis.

The point (4,0.19) in Figure 4-13 or point (4,0.32) in Figure 4-14 is equivalent to the pipe 448862. The recorded data in Gemini VA for this pipe is given bellow.

SID	Status	Length	Material	Dimension	Year	Soil	Date_warning	Code	Attention
448862	D	265.8	SJA	150	1974	LE	18-Aug-97	DBR	Two failure before at the same point
448862	D	265.8	SJA	150	1974	LE	25-Aug-97	DBR	
448862	D	265.8	SJA	150	1974	LE	8-Dec-97	DBR	
448862	D	265.8	SJA	150	1974	LE	1-Sep-98	DBR	

In the database no failures are recorded for the calibration period (1988-96). When the pipe fails, on August 18, 1997 operation and maintenance crew report that there have been two earlier failures on this pipe which have gone unrecorded. Obviously, these instances of unrecorded and missing data will affect the calibration and usefulness of the statistical models. The Weibull PHM will be the most seriously affected by this type of incomplete failure records, since the number of previous failures act as a covariate.

As illustrated for the pipes 433428 and 448862, the quality of the output of the models is strongly dependent on the quality of the input data, i.e. Garbage in = Garbage out, "GIGO".

The point (4,1.14) in Figure 4-13 and point (4,0.15) in Figure 4-14 represent pipe 424617. The data recorded in the Gemini VA database for this pipe is given bellow.

SID	Status	Length	Material	Dimension	Year	Soil	Date_warning	Code	Attention
424617	D	82.14	SJA	150	1974	LE	7/1/94	DBR	
424617	D	82.14	SJA	150	1974	LE	7/6/94	DBR	
424617	D	82.14	SJA	150	1974	LE	5/18/95	DBR	
424617	D	82.14	SJA	150	1974	LE	6/28/96	DBR	
424617	D	82.14	SJA	150	1974	LE	6/16/97	DBR	
424617	D	82.14	SJA	150	1974	LE	8/29/97	DBR	4 m pipe replaced
424617	D	82.14	SJA	150	1974	LE	10/2/98	DBR	
424617	D	82.14	SJA	150	1974	LE	10/5/98	DBR	

Four failures are recorded in the period 1988-1996 with four more failures occurring in 1997 and 1998. It should be pointed out that the PHM approach, which includes NOPF as a covariate is able to predict these multiple failures. According to the NHPP model, this pipe should not have a high intensity of failures, as its set of covariates places it at low risk. In statistical terms this pipe is considered as an "outlier".

"Pair"-plot analysis is a useful graphical tool. A thorough evaluation of the extreme points give valuable information about the deterioration process and about which covariates should be included in the model. These extreme values help to point out inaccuracies in the pipeline database.

4.10.2 Prediction for quartiles of pipes

Another test for evaluating the prediction at pipe level is to carry out a test on quartiles of pipes. In this test, failures are predicted for the verification period for each pipe. Within each group the pipes are ranked according to the number of predicted failures. Pipes that are at greatest risk are grouped in quartile 1. If a model works at pipe level, the model should be able to identify pipes where most of the failures occur. The model should be considered as valid at pipe level if the pipes predicted to be at greatest risk also experience the most failures. Table 4-15 and Table 4-16 show the quartile results from the NHPP and Weibull PHM predictions together with the observed failures. . Since the quartiles are ranked according to predicted failures, the observed failures for a quartile differ from NHPP to Weibull PHM.

Table 4-15. Comparison of the predicted number of failures with NHPP and the observed number of failures that occurred in 1997 and 1998.

	UDI1		CAST		UDI2		PDI	
	NHPP	OBS	NHPP	OBS	NHPP	OBS	NHPP	OBS
1st quartile	113.3	103	39.2	43	4.1	2	1.6	4
2nd quartile	80.3	106	33.6	31	3.7	1	1.6	0
3rd quartile	67.2	54	31.2	12	3.7	2	1.6	2
4th quartile	47.7	43	28.1	8	3.8	3	1.6	2
Sum	308.5	306	132.0	94	15.3	8	6.2	8

Table 4-16. Comparison of the predicted number of failures with Weibull PHM and the observed number of failures that occurred in 1997 and 1998.

	UDI1		CAST		UDI2		PDI	
	PHM	OBS	PHM	OBS	PHM	OBS	PHM	OBS
1st quartile	260.4	208	71.1	46	4.9	2	1.9	4
2nd quartile	60.8	47	36.1	28	3.8	1	1.7	0
3rd quartile	39.1	24	23.7	14	7.8	2	2.0	2
4th quartile	17.0	27	10.1	6	4.9	3	1.5	2
Sum	377.4	306	141.1	94	21.4	8	7.2	8

The tables show that both models are relatively good at prediction at quartile level. The results are best where the sample size is largest (i.e. UDI1 and grey cast iron pipes). For these groups most failures are predicted in the 1st quartile and least in the 4th quartile. The results from the groups UDI2 and PDI are poorer because less data is available for calibration. The model for PDI pipes has no significant covariates which obviously is not sufficient for modelling the complex deterioration process in a water network.

The tables show that the models can be used as a prioritisation tool at pipe level. Pipes in the first quartile are the most likely candidates for renewal based solely on poor structural condition. Some failures will also occur for the other quartiles.

Using these models for planning the rehabilitation of pipes before they fail will reduce the need for a reactive, or “fire-fighting” maintenance style.

4.11 Analysis of individual pipes in cases of small samples

The statistical models Weibull PHM and NHPP described in this thesis are only applicable when there is a large sample size is large. For networks with highly variable pipe characteristics (e.g. material), the pipes must be grouped into many, small groups and statistical models will not be valid. The future failures for pipes in these systems can be evaluated by plotting cumulative failures over time (e.g. *N(t)*). This method requires failure data for each pipe. A cumulative failure plot can indicate whether there is a trend in the failure times for each individual pipe. From a practitioner’s point of view, these plots could be a convenient tool for making maintenance decisions for individual pipes (e.g. “Should we keep on with spot repairs or should we replace/renovate the whole pipe?”). The methodology is too time-consuming to be carried out for each pipe in the entire network.

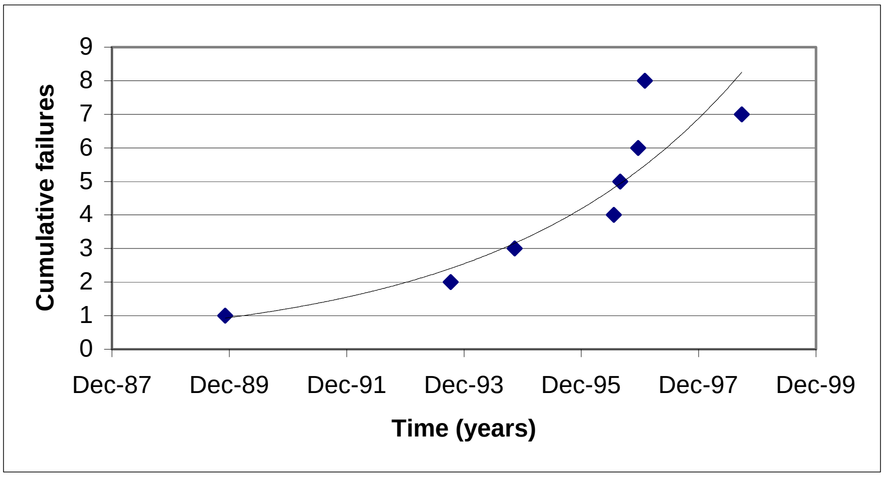


Figure 4-15. Cumulative failure plot for a single pipe in Trondheim.

Figure 4-15 is an example of a cumulative failure plot for a single pipe in the Trondheim water distribution system. The curve is convex, indicating a deteriorating pipe. In order to predict future failures it is possible to fit a curve to the data set and extrapolate. For some pipes, this simple procedure may provide better information about future breaks than the more sophisticated statistical models.

This procedure can only be used for pipes with several previous breaks, and will be most useful for making decisions about distribution and service lines. Multiple breaks cannot be accepted on transmission and trunk mains, where the consequence of failure is high.

The existing version of Gemini VA has no routines for generating *N(t)* plots. Creating these plots for all of the pipes in a system requires extensive data analysis and manipulation.

4.12 Summary and conclusion for the case study

The water distribution network in Trondheim is analysed using different statistical models. The water network is divided into five groups that are analysed separately. The statistical models show which covariates (i.e. explanatory variables) affect the rate of occurrence of failures (ROCOF). The Cox' s PHM, Weibull PHM and the NHPP assign similar values to the significant covariates. In the PHM, the variable NOPF is important for modelling successive failures, since NOPF serves as both a stratification and explanatory variable. Increasing pipe *length* shortens the time to failure, increasing pipe *diameter* prolongs the time to failure. Variables, which represent ground conditions also, behave in the same way in all of the models. In Trondheim, corrosion caused by sulphate reducing bacteria (SRB) has resulted in extensive external pitting. The statistical models described in this study have been able to model this phenomenon by including *clay* as a covariate. Pipes located in clay have a higher ROCOF.

The rate of occurrence of failures (ROCOF), the expected number of failures within a given time horizon (*N(t)*) and the average availability is calculated for each pipe belonging to the groups shown in Table 4-1 (excepting plastic pipes). These reliability measures are all calculated at the individual pipe level. The models are also used for predicting the expected number of future failures for each of the groups (i.e. network level).

Weibull PHM and NHPP are used for predicting failures. These statistical models have been calibrated using the failure data for a nine-year period. Two subsequent record years are used for verifying the models. The verified models are then used to predict new failures. Since the models are based on each pipe's individual set of covariates, the same model can be applied at the network and the individual pipe level.

At network level, good results are obtained with both the Weibull PHM and NHPP. The Weibull PHM has a tendency to overestimate the total number of failures compared to NHPP. When analysing for trends in the rate of occurrence of failures a non-parametric technique like the Nelson-Aalen plot gives valuable information about the deterioration process. By extrapolating the trend in such a plot, estimates for future rehabilitation needs might be found. However, the effect of rehabilitation on individual pipes can not be included in this simple plot. For that purpose a prediction model like Weibull PHM or NHPP is required.

At pipe level the best results are obtained for pipes where the sample size is large (UDI1 and grey cast iron pipes in the Trondheim network). For these pipe classes, the models can be applied at the individual pipe level. For the other groups the results are more dispersed due to small sample size and fewer recorded failures. The failure process in a water network is stochastic, and the result at pipe level will always be poorer than at network level. This is also the case for Trondheim. Models that are valid at the individual pipe level require more information about the variables responsible for failure. At network level it is possible to get "good" results using just a few covariates. More data, and more accurate data is required for modelling at pipe. A model that is valid at pipe level will also be valid at the network level.

The models can be improved by including other significant variables. In this work only data easily obtained from Gemini VA have been used. An analysis with the hydraulic model EPANET is underway for the water network in Trondheim. The data from this model will allow the inclusion of hydraulic variables like water pressure and velocity in the failure models. Water pressure is reported to be significant in previous studies (Andreou, 1986; Le Gat, 1999), while low velocities, and the resultant settling of suspended solids, may increase the rate of internal corrosion for unprotected iron pipe.

The state of deterioration for each of the pipe groups, or place along the "bathtub curve", is shown in Figure 4-16. A wide range of deterioration states is found within each group, as the deterioration variables are different for each individual pipe. Figure 4-16 displays all of the groups on the same curve for illustration purposes. In reality the different groups will have different bathtub curves.

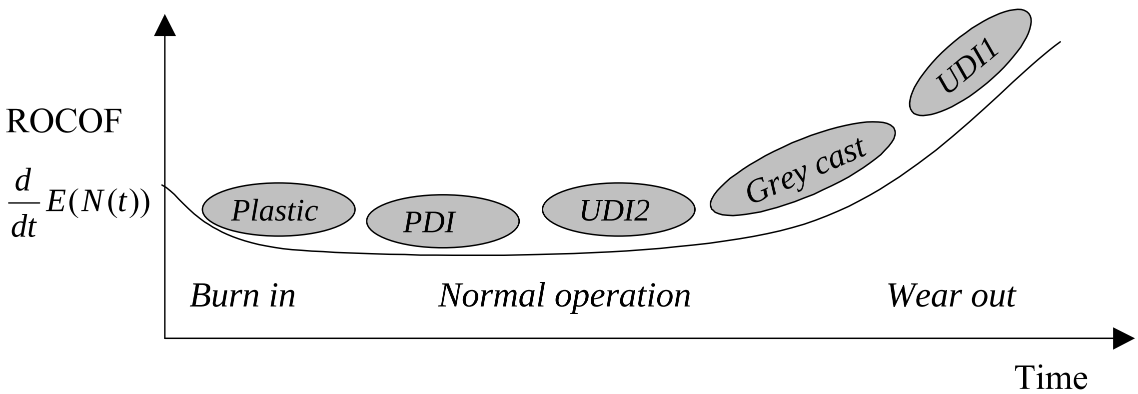


Figure 4-16. A comparison of the state of deterioration for the different pipe groups in Trondheim's water network.

Plastic, PDI and UDI2 pipes are in general in the stage of normal operation since there is no trend in the failure data. How long this period will last, can not be concluded based on the available data. Grey cast iron and UDI1 pipes are deteriorating, and are said to be in *wear out* phase. The rate of occurrence of failures (ROCOF) for these groups will continue to accelerate, i.e. failures will occur more and more frequently. Grey cast iron pipes exhibit a lower ROCOF than UDI1 pipes, in spite of their being much older. This demonstrates that age should not be the sole criteria for replacement. Most of the candidates for renewal in the near future will come from the UDI1 and grey cast iron pipe groups.

The above conclusions apply to pipe groups only, and should not be used for decisions about each individual pipe. For example, a large diameter UDI1 pipe laid in good soil conditions (i.e. not clay in combination with organic matter) may have a low deterioration rate.

Simple graphical techniques like cumulative plots are convenient tools for evaluating the condition of a group of pipes and also for single pipes. For some pipes a cumulative plot may provide better information than the more sophisticated statistical models.

As of 1999, 11 years of complete failure history data are digitally recorded for Trondheim's distribution system. A longer data series will improve the quality of the predictive models. The database for Gemini VA includes fields for recording inventory data which are still unused (e.g. pipe depth). These additional variables could also improve the predictive models.

The data for normal repairs and replacement of pipelines (node to node) are properly recorded for this case study. Data collection for renovated pipes and partly replaced pipes has been poor, as the earlier database structure in Gemini VA was not designed for structuring this information. The recently released version of Gemini VA (released 1999) eliminates this problem.

5 The role of predictive models in maintenance management

In this chapter the role of predictive models in improving maintenance decisions is discussed. Few water utilities in Europe have a rehabilitation policy. The policies that do exist are reactive, and do not include strategies for rehabilitating pipes before they wear out. Pipes are rehabilitated only when the break rate is higher than an arbitrary value or when other works in the street are planned. The use of predictive models is a step towards a proactive maintenance strategy, where replacement/renovation is carried out where failures are most likely to occur. A proactive or preventative rehabilitation strategy should be more cost-effective than the reactive strategies used today.

The success of a proactive approach obviously depends on the criteria used for rehabilitation planning. These criteria should be linked to the prediction of future pipe failures, the reliability of the water network serving the customers and the cost of improvements. If this information is available, it will be possible to optimise rehabilitation programs.

5.1 How predictive models can be used to improve maintenance decisions

The predictive models described in this thesis can be used in the water industry for improving maintenance decisions in several ways. Applying these models will increase knowledge about the network and the deterioration processes. The models can also be used to predict different reliability measures of the network (Chapter 1.3). Predictive models can be used to:

- Assess factors causing pipe failure. Estimating the magnitude of the effects of a covariate can help management to decide which factors should be controlled or improved to avoid pipe failures (e.g. reduce operational pressure). From a network planner's point of view, some of these factors should be considered in the design process (e.g. choosing the right pipe material for different conditions).

- Rank pipes in the network according to predicted failures in order to decide which pipes to rehabilitate. (e.g. replace pipes with more than 4 failures or replace pipes where break rate is higher than 0.2 breaks/km/year).

- Calculate the probability of failure for specific pipes based on risk coefficient estimates obtained from the models. These numbers can be used as input in risk analyses. Using statistical models to quantify the probability of failure will improve the quality of the risk analyses.

- Provide data for comparing rehabilitation costs versus the cost of continual repair. Model results can be used to assess the structural status of the pipes in need of rehabilitation and aid in choosing the best rehabilitation strategy.

- Predict failures for both short term and long term planning periods. Model results can be used for long term budget planning (i.e. 10- 20 years). Cumulative plots for pipe groups can aid in this assessment. In the short term (i.e. one year) the models can be used for defining candidates for replacement/renovation due to poor structural condition.

- Serve as input data in optimisation models for rehabilitation and replacement of water distribution systems (e.g. Kleiner, 1997). These models require data for future break rate. The optimisation processes used to date suffer from poor models for describing the failure development (Chapter 2.5). The predictive models described in this thesis could improve the optimisation models.

- Serve as input data for reliability analysis of the water network. Network reliability analyses require data for average availability for each individual pipe in the network. The average availability $A_{av}(t)$ denotes the mean proportion of time the object is functioning. If an object that is repaired to an "as good as new" condition every time it fails, the average availability is: $A_{av} = \frac{MTTF}{MTTF + MTTR}$, where MTTF (mean time to failure) denotes the mean functioning time and the MTTR (mean time to repair) denotes the repair time of the object. MTTF is found by taking the inverse of the intensity function, $MTTF = 1/\lambda$. As shown earlier in this thesis, the intensity is both time dependent and also varies from pipe to pipe as a result of the covariates. The predictive models are well suited for generating these intensity data. The average availability can be calculated for both present time and for a defined time period. Since the intensity function is not constant, an estimate of the intensity function for a specific year might be found by integrating the intensity function for the given year (expected number of failures). Estimates for the MTTR could be based on repair data found in automated mapping and facilities management (AM/FM) systems like Gemini VA. This particular system contains information about when the failure was observed and when it was repaired. A network reliability analysis is under way for the water network in Trondheim and a computer tool, named AQUAREL is being developed (Hansen and Vatn, 1999; Hansen and Vatn, 2000**).** The results from the NHPP model in this thesis are used as input data for the availability for each specific pipe in the Trondheim network.

5.2 The interplay between predictive models and other factors influencing the rehabilitation decision

5.2.1 Factors influencing the rehabilitation decision

Predictive models define candidates for replacement/renovation based solely on poor structural condition. The rehabilitation plans for a specific pipe must consider multiple criteria which cannot be directly compared. Figure 5-1 shows the different factors influencing the rehabilitation decision. A decision as to whether to replace/renovate the pipe, or continue with repairs may be based on a single factor (e.g. insufficient hydraulic capacity, poor structural condition) or a combination of several, related factors.

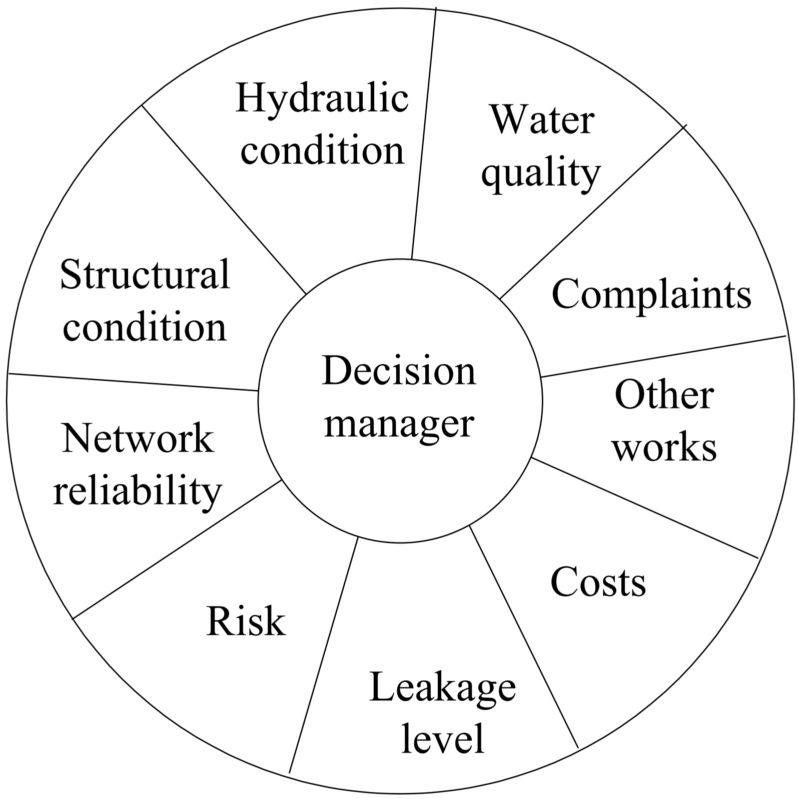


Figure 5-1. Factors influencing the rehabilitation decision for a water pipe.

The factors influencing the choice are basically directly comparable. Some of the factors can be assigned an economic cost or benefit, while others are non numeric. This is a typical multi-criteria problem. The relations between the different factors are complex. A change in one will often affect the other factors. For example, renovating a water pipe might improve the water quality, change the hydraulic capacity, reduce leakage, improve the pipe's structural strength and increase network reliability. A change in a pipe's hydraulic characteristics can have both long-term and short-term effects on the pipes structural condition and affect water quality in the network.

Complaints

There is a trend towards using level of service (i.e. “serviceability”) as a criterion for rehabilitation in addition to more traditional criteria like economics and structural condition. After privatisation was introduced in the UK water industry, ‘service’ has received a special focus. In Norway there is a trend towards including service levels as a management objective. In Gemini VA a new module is being introduced for managing customers complaints, and this data is expected to play a more important role in decision making.

Water quality

In some cases poor water quality may be the only criteria for replacement/renovation of a pipeline. Predicting the effect of individual pipe rehabilitation requires the water quality analysis and modelling. Water quality data have so far not been implemented in Gemini VA. A water quality module is already being used in the corresponding Swedish program VABAS/DUF.

Leakage level

Leakage level is strongly correlated to the structural condition and intensity of failures of the network. Leakage level is reduced by carrying out leakage control programs. Leakage control programs are costly, and from an exclusively economic perspective, it is well known every water network has an optimum leakage level.

Hydraulic condition

The hydraulic conditions in a water network may influence other factors such as water quality, leakage level, structural condition, operation costs, complaints and network reliability.

Network reliability

As previously shown, network reliability analysis is directly related to the predictive models, and these models can be used for estimating availability data for each individual pipe in a network.

Structural condition

The results from other methods for measuring the structural condition of a pipe like pipe sample analysis and non-destructive techniques for pipe condition evaluation (e.g. radar), can provide the statistical models with valuable input data. For the Weibull PHM and NHPP it is possible to include covariates that vary with time rather than remaining constant. This allows modellers to use the results from pipe measurements (e.g. time evolution of pipe wall thickness) as a time dependent covariate. This is a good example of the ability of statistical models to include the results of other investigations as input data.

Other works
Some pipes may be prioritised as a result of plans for reconstruction or renewal of other infrastructure like roads, gas and electricity. These pipes may have been rehabilitated at a later date without these other underground works.

Decision manager
The decision manager knowledge and experience play an important role. The manager may prefer some rehabilitation techniques over others, based on past experience with the network. The decision manager must also consider political and economic issues when making decisions about rehabilitation. Political demands can result in replacement strategies where technical considerations play a minor role.

Costs
Candidates for replacement/renovation are chosen as the result of a multi-criteria analysis. Once the candidates are identified, an economical analysis can be carried out for choosing the best rehabilitation technique for each pipe. A program like *Waterfowl* developed at Water Research Centre (WRc) can be used for this purpose. The total cost of the rehabilitation program is limited by the available budget for the specific year.

5.2.2 Reporting improved performance after rehabilitation

After a replacement/renovation of the water network has been carried out, it is important verify improved system performance in terms of the factors mentioned in Figure 5-1. For this purpose performance indicators related to rehabilitation of pipelines (Alegre et al., 2000) should be calculated. Reporting trends in these factors, such as improved water quality, reduced break rate, reduced number of complaints or reduced leakage can be serve to justify rehabilitation expenditures for customers and politicians.

5.3 Predictive models incorporated in GIS

An important task when using predictive models, is to present the results in a way that facilitates interpretation of the results. Geographical Information Systems (GIS) are good tools for displaying model results. In Norway, the AM/FM system Gemini VA includes thematic mapping functions which have been used in this work. Many of the standard GIS packages available today can also be used to create thematic maps of the predictive models results.

The current version of Gemini VA does not include a predictive model. Gemini VA does provide space in the database for registering data for up to five user-defined fields. The model results for the expected number of failures in two, five, ten and 20 years can be registered in Gemini VA for analysis and thematic map production. The following example details this procedure for the water network in Trondheim shows how a GIS can improve the traditional way of presenting failure data.

As previously mentioned, Gemini VA includes a register for pipe failures and repairs. Thematic maps, are the standard way to visualise observed failures. The left side of Figure 5-2 is a typical example of a Gemini VA pipe failure map, based on data for a small district in Trondheim (Utleira). Most of the pipes in this area are made of unprotected ductile iron, and several pipe failures have been observed. A failure map, which displays the number of failures for each pipe, is sometimes used to locate the "worst" pipes, i.e. pipes with an unacceptable number of failures which are candidates for renewal or replacement. These maps can also be used to detect "hot spots", or areas where there is a spatial clustering of pipe failures. Failure maps are easy to generate with Gemini VA. This approach to identifying pipes for rehabilitation is reactive, since decisions are based on failures that have already occurred. Thematic maps showing predicted, or future failures would allow proactive rehabilitation strategies. Pipes could be rehabilitated before they wear out. Incorporating model results in Gemini VA, as described earlier, allows planners to locate pipes that are likely to fail in the future. The right side of Figure 5-2 shows the expected number of failures in 2 years for each individual pipe, based on the NHPP model.

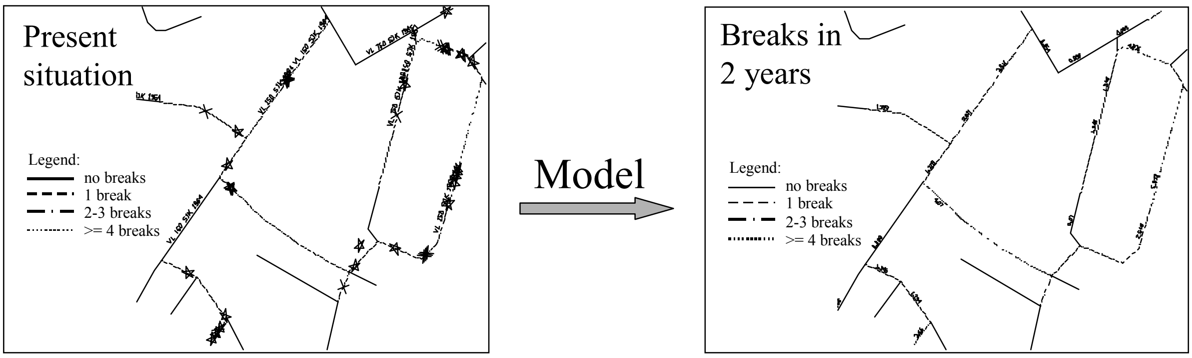


Figure 5-2. Trondheim, Utleira: Number of failures for each pipe. Data for the present situation is taken from Gemini VA. The future state is predicted using the NHPP model.

The time frame that a planner needs to visualise depends on the purpose of the investigation. For master plans a time horizon of ten (10) years might be useful. A shorter time horizon may be more appropriate for analysing special problem. The uncertainty of the predictions will of course increase with an increase the time horizon.

Figure 5-2 shows the predicted number of failures are shown, but similar plots can easily be made for reliability measures such as ROCOF, probability of failure and average availability.

In the future I believe that thematic maps which visualise models results will be an integrated part of management information systems for the water industry. Lyonnaise des Eaux, France, is already working on including the model described by Eisenbeis (1994) in their GIS (Madiec et al., 1997).

6 Summary, conclusion and recommendations for future work

6.1 Summary and conclusions

The purpose of this study was to examine statistical models for predicting failures for each pipe in a water distribution network and to determine whether or not the already existing data in Gemini VA is sufficient input for these models.

Two general classes of regression models were considered in an effort to relate the influence of explanatory variables to the failure times of a water network. The first approach can be thought of as a generalisation of survival data analysis (i.e. Proportional hazards models (PHM)). The second approach is a counting process (i.e. Non homogeneous Poisson process (NHPP)). Since the models include covariates, they can be applied at both the network and pipe level. For prediction of failures using the Proportional hazard model (PHM), it was found to be most convenient to use a parametric model like Weibull PHM instead of Cox's semi-parametric model. A computer program was developed to estimate the maximum likelihood for the parameters in the NHPP.

The statistical models were used in a case study for the water network in Trondheim, Norway. The pipes in the network were divided into groups based on different failure characteristics. The following covariates were found to be significant: pipe length, pipe dimension, soil condition, pipe age when digital recording started and the number of previous failures. The significant covariates varied from group to group. For the PHM approach, the significant covariates also varied from strata to strata within the same pipe group. The relative importance of the covariates was reported and all covariates acted in a physically logical way. The statistical methods were able to model the effect of sulphate reducing bacteria (SRB) corrosion on unprotected ductile iron pipes by using the presence or absence of clay as a representative variable.

The case study showed that the grey cast iron and unprotected ductile iron pipes in the network are deteriorating. Unprotected ductile iron pipes installed before 1975 are in the most advanced stage of deterioration.

The models were calibrated using the failure data from a nine year period, verified with data from the following two years and later used for predicting new failures at both the network and pipe level. The predictive power of the models has been evaluated. Both the Weibull PHM and the NHPP were capable of modelling the failure history of the water network, but in the case study the Weibull PHM showed a tendency of overestimation compared to NHPP. A nice feature with the Weibull PHM compared to the NHPP was the inclusion of NOPF as a covariate. With Weibull PHM it was possible to model pipes where the covariates had a "positive" effect and where several failures had already occurred.

Model predictions were more reliable for groups of pipes (network level) than they were for individual pipes. However, at pipe level the models were also considered to give satisfactory results. The models predict the *expected* number of failures, and there is no guarantee that these failures will actually occur. Nevertheless, predictions at the pipe level are necessary for prioritising pipes to be rehabilitated, risk analyses and for network reliability analyses.

A minimum number of observations are required to obtain reliable model results. The number of observations available is a function of the available failure records and the number of pipes in the network. For a relatively large water network like Trondheim, a failure history in the order of about 10 years should be sufficient. For smaller networks a longer failure history will be required. Each network should be analysed separately in order to decide whether or not there is enough failure data available.

The models could be improved by including additional covariates like water pressure and velocity. This data is now available for Trondheim's distribution network

It is difficult to draw definitive conclusions from a case study. Nevertheless, the NHPP appears to be better at predicting pipe failures than the Weibull PHM approach. Based on the results from the case study, NHPP is recommend over the Weibull PHM for modelling failures in water networks. Direct integration of the intensity function in the NHPP simplifies future failure calculation, while the Weibull PHM requires a time consuming Monte Carlo simulation.

Statistical methods like Weibull PHM and NHPP are currently being tested at Cemagref (Le Gat, 1999). Preliminary efforts show similar results to those in this work.

Since the proposed techniques are empirical, the derived predictive models will always be site specific. Water distribution networks have very different pipe materials and pipe age, different soil conditions, different construction standards, etc. A general prediction model, which could be applied to any water network cannot be generated from the statistical methods described in this thesis. Parameterisation can not be transposed from one system to another. The significance of SRB corrosion in the Trondheim models is an example of the site-specific nature of these models.

The results from the predictive models have been incorporated into Gemini VA to make it easier to present and interpret the results. In the future, predictive models should become an integrated module in the automated mapping/facilities management (AM/FM) tools for water networks.

If statistical models are to be used in the water industry, it is important that the necessary input data is easily obtained. Data collection for the sole purpose of failure prediction would not be effective or cost efficient. Models should be designed to use data that is routinely collected and stored in AM/FM systems like Gemini VA.

Water utilities that have not begun collecting pipe maintenance data should start recording data for pipes, should start right away. Utilities that collect and store this important information will give future generations the opportunity to manage the network in a cost efficient way.

The predictive models should be used as one *tool* out of many in the decision process. Other criteria for renewal also exist. Methods for automatically generating priority lists for pipe rehabilitation do exist, but are not recommended. The expert judgement of the system manager, who has many other tools and information sources, is the best basis for deciding when and where to rehabilitate. The statistical models are not a substitute for good judgement, but provide a framework within which good decisions can be made.

6.2 Suggestions for improvements in Gemini VA

Even though Gemini VA can provide data for statistical analyses of pipe failures, there is some room for improvement. Gemini VA would benefit from an improved data structure and should allow for the addition of new modules and options.

The results of this thesis show that the integration of a statistical, failure prediction model would make Gemini VA an important tool for rehabilitation planning. The larger Norwegian water utilities, together with other user of Gemini VA provide the commercial basis for such an integration.

Gemini VA should also include an option for generating cumulative plots of the number of failures for each individual pipe. Such an option will certainly be used on a day to day basis for making decisions about individual pipes. The data required for these plots is already recorded in Gemini VA, but an automatic routine generating the graphics would be a welcome addition to the program

There is also a need to improve the data structure in Gemini VA. During the last few years, many new pipe materials, and a wide range of external and internal protective coatings have become available. The existing coding system for pipe materials must be expanded to include descriptions for these new pipes. Today's poor material coding system creates many problems for system managers.

If the predictive models are to be used, it is important that the data used as input (i.e. covariates and failure times) is easily obtained. Storing all the relevant data in Gemini VA will fulfil this criterion. Gemini VA should be expanded to include the water quality and hydraulic data required by predictive models and necessary for the daily management of a network.

In the existing version of Gemini VA it is not possible to record failure data for pumps and valves (i.e. pressure reducing valves). In order to manage the whole water distribution system, reliability data for these components must be available. Gemini VA should altered to allow for registration of these failure data.

6.3 Recommendations for future work

The goal of this thesis was to develop tools for improving rehabilitation strategies for water networks. The statistical models developed in this work are a step towards a more proactive maintenance strategy. However, much work is left to be done.

Though the statistical models evaluated in this work are able to model pipe failure satisfactorily, improvements can be made. The newly proposed Trend Renewal Process (TRP) may provide better models for pipe failure. TRP is a general tool for modelling repairable systems, which has recently been introduced by Lindqvist (1997) and is thoroughly described in Elvebakk (1999). The TRP is a generalisation of the model proposed by Lawless and Thiagrarajah (1996), and can be seen as an extension of the renewal process and the non-homogeneous Poisson process, having both as special cases. NHPP and renewal processes are strictly speaking only valid under minimal repair and perfect repair conditions, respectively.

The intensity of the TRP is given by

$$\lambda(t) = z\left(\Lambda(t) - \Lambda\left(T_{N(t-1)}\right)\right)\lambda(t) \tag{6.1}$$

where $\Lambda(t) = \int_0^t \lambda(u)$

The intensity function of the TRP is the product of two factors, the age of the system and the time since the last failure. The time from the last failure provides much of the same information as the NOPF variable used in the PHM approach. Since the TRP is dealing with the intensity of failures it will be easy to use the model for prediction of failures by integrating the intensity function.

So far the TRP does not include covariates, which we know effect the rate of occurrence of failure in a water network. The TRP can easily be extended to include covariates by adding the term "exp(**z'**β)" to the equation and develop the corresponding likelihood function. It would have been interesting to see if better predictions can be obtained by apply the TRP in modelling pipe failure data. For further information about TRP the reader is invited to read the thesis of Elvebakk (1999).

In this work only the pipes in the water distribution network are considered. Although pipes failures are an important factor in water network reliability, elements like pumps, tunnels and valves also play a role. Statistical analysis of failure time data can be used to generate reliability data for these elements. Reliability analysis for the entire water distribution network requires data for pumps and valves as well as pipes. Failure data needs to be recorded for pumps, valves and tunnels, which includes failure date and failure type. Until reliability data for pumps, valves and other installations used in water networks are available, data from similar systems could be used as an approximation. The Offshore Reliability Data (OREDA) handbook contains data for a wide range of components and systems used on offshore installations (Vatn, 1993). These data can be used as *a priori* estimates, until data becomes available from water distribution systems.

Further research is required on the influence of renovation methods on the rate of occurrence of failures (ROCOF). Since a wide range of renovation methods, and resulting structural improvements exist, they can not be treated as one group. Separate statistical analyses for the different renovation techniques have to be carried out. For proper treatment of renovated pipes, it is important that all of the necessary information about the renovation method can be stored in a database like Gemini VA.

The optimisation models for rehabilitation decisions have so far been suffering from "poor" models describing the development of failures for each pipe. Integrating the NHPP for failure prediction will improve these optimisation models.

Water utility managers need more tools to help them make the right decisions about network rehabilitation. A proposal called CARE-W (Computer Aided Rehabilitation of Water networks) for the EU 5th framework, has been initiated by leading European research organisations, universities and water companies to address this issue. Hopefully, new and better tools will become available in the coming years.

References

Aalen, O.O. (1978). Non-parametric inference for a family of counting processes. *Ann. Statist*, **6**, 701-726.

Alegre, H., Hirner, W., Baptista, J. and Parena, R. (2000). *Performance indicators for water supply services*. Operations & Maintenance Committee, International Water Association (in press).

Al-Humoud, J., Wu, S. and Quimpo, R.G. (1990). Failure modeling of hydraulic systems. In: *Proceedings of the 1990 National Conference on Hydraulic Engineering*, New York, pp. 204-209.

Andreou, S. (1986). *Predictive models for pipe break failures and their implications on maintenance planning strategies for deteriorating water distribution systems*. PhD thesis, MIT, Cambridge, MA.

Andreou, S. (1987). Maintenance Decisions For Deteriorating Water Pipelines. *Journal of Pipelines*, **7**, pp. 21-31.

Andreou, S., Marks, D.H. and Clark, R.M. (1987a). A New Methodology for modelling Break failure Patterns in Deteriorating Water Distribution Systems: Theory. *Journal of Advanced Water Resources*, **10**, March, pp. 2-10.

Andreou, S., Marks, D.H. and Clark, R.M. (1987b). A New Methodology for modelling Break failure Patterns in Deteriorating Water Distribution Systems: Applications. *Journal of Advanced Water Resources*, **10**, March, pp. 11-20.

Ascher, H. and Feingold, H. (1984). *Repairable systems- Modeling, inference, misconceptions and their causes*. Marel Dekker, New York.

Baur, R. and Herz, R. (1999). *Service Life Management of Water Mains and Sewers. Decision Criteria and Strategies for Rehabilitation.* Proceedings of the 13th EJSW, 8 September – 12 September, Dresden University of Technology. ISBN: 3-86005-238-1.

Bjørgum, F. (1988). Korrosjon av vannledninger i Trondheim. Årsmøte, Norsk kommunal teknisk forening.

Camarinopoulos, L., Chatzoulis, A., Frontistou-Yannas, S. and.Kallidrornitis, V. (1996a). Structural Reliability of Water Mains. In: *Proceedings of ESREL'96*, Probabilistic Safety Assessment and Management.

Camarinopoulos, L., Pampoukis, G. and Preston, N. (1996b). Reliability of a Water Supply Network. In: *Proceedings of ESREL'96*, Probabilistic Safety Assessment and Management.

Ciampi, A., Dougherty, G., Lou, Z.Y., Negassa, A. and Grondin, J. (1992). NHPPREG - a computer program for the analysis of nonhomogeneous Poisson process data with covariates. *Computer Methods and Programs in Biomedicine*, **38**(1), June 1992, pp. 37-48

Clark, R.M., Stafford, C.L. and Goodrich, J.A. (1982). Water Distribution systems: A spatial and Cost Evaluation. *Journal of the Water Resources Planning and Management Division*, **108**, pp. 243-256.

Cox, D.R. (1972). *Regression Models and Lifetables (with discussion).* Journal of the Royal Statistical Society.

Cox, D.R. (1980). *Point processes.* In series: *Monographs on applied probability and statistics.* Chapman and Hall, London.

Deb, A.K. et. al. (1998). *Quantifying future rehabilitation and replacement needs of water mains.* AWWA Res. Fdn., Denver.

Eisenbeis, P. (1994). *Modélisation statistique de la prévision des défaillances sur les conduites d'eau potable.* Thése de doctorat, Université Louis Pasteur, Strasbourg.

Eisenbeis, P. (1997). Estimating the aging of a water mains network with the aid of a record of past failures. In: *Proceedings of the 10th EJSW at Tautra. "Deterioration of Built Environment: Buildings, Roads and Water Systems"*, Norwegian University of Science and Technology, IVB-report B2-1997-2, ISBN 82-7598-040-2, pp.125-133.

Eisenbeis, P., Røstum, J. and Le Gat, Y. (1999). Statistical Models for Assessing the Technical State of Water Networks - Some European Experiences. In: *Proceedings of annual conference of AWWA*, Chicago, Illinois, 20 – 24 June 1999.

Elvebakk, G. (1999). *Analysis of Repairable Systems Data: Statistical Inference for a Class of Models Involving Renewals, heterogeneity and Time Trends*. PhD thesis, 1999:69, Norwegian University of Science and Technology, Trondheim, Norway.

Goulter, I. and Kanzemi, A. (1988). Spatial and Temporal Groupings of Water Mains Pipe Breakage in Winnipeg. *Canadian Journal of Civil Engineering*, **5**, pp. 91-97.

Goulter, I., Davidsen, J. and Jacobs, P. (1993). Predicting Water-Main Breakage Rates. *Journal of Water Resources Planning and Management-Asce*, **119**, pp. 419-436.

Gukild, I. (1978). *Undersøkelse av korrosjonsskade på vannledningsnett i Trondheim kommune*. SINTEF, Trondheim.

Gustafson, J.M. and Clancy, D.V. (1999a). Modeling the occurrence of breaks in cast iron water mains using methods of survival analysis. In: *Proceedings of annual conference of AWWA*, Chicago, Illinois, 20 – 24 June 1999.

Gustafson, J.M. and Clancy, D.V. (1999b). Using Monte Carlo simulation to develop economic decision criteria for the replacement of cast iron water mains. In: *Proceedings of annual conference of AWWA*, Chicago, Illinois, 20 – 24 June 1999.

Halhal, D., Walters, G.A., Ouazar, D. and Savic, D.A. (1997). Water Network Rehabilitation with a Structured Messy Genetic Algorithm. *Journal of Water Resources Planning and Management*, ASCE, **123**, No. 3, May/June, pp. 137-146.

Hansen, G.K. and Vatn, J. (1999). *Verktøy for pålitelighetsevaluering av vannledningsnett*. STF38 A99422, SINTEF, Trondheim.

Hansen, G.K. and Vatn, J. (2000). Combining hydrostatic and reliability models for water distribution networks. To appear in: *Proceedings of Foresight and Precaution Conference*, 15th - 17th May 2000, Edinburgh, Scotland, UK.

Herz, R. (1996). Ageing processes and rehabilitation needs of drinking water distribution networks. *Journal of Water Supply Research and Technology-Aqua*, **45**, pp. 221-231.

Herz, R. (1997). Rehabilitation of water mains and sewers. In: *Water-Saving Strategies in Urban Renewal- European Approaches, European Academy of the Urban Environment*, pp.105-14.

Herz, R. (1998). Exploring rehabilitation needs and strategies for drinking water distribution networks. In: *Proceedings of the first IWSA/AISE International Conferance on Master Plans for Water Utilities*, Jun 17-18 1998, Prague.

Høyland, A. and Rausand, M. (1994). *System Reliability Theory: Models and Statistical Methods*. John Wiley & Sons, Inc, New York.

ISO/TR 11295 International Standard. *Techniques for rehabilitation of pipeline systems by the use of plastic pipes and fittings*. International Standards Organization.

ISO/DIS 15686-1. Draft International Standard. *Buildings- Service life planning- Part 1: General principles*. International Standards Organization.

Kaara, A.F. (1984). *A decision support model for the investment planning of the reconstruction and rehabilitation of mature water distribution systems*. PhD thesis, MIT, Cambridge, MA.

Kalbfleisch, J. and Prentice, R.L. (1980). *The Statistical Analysis of Failure Time Data*. John Wiley and Sons, New York.

Kelly D. and O'Day, D. (1982). Organizing and analyzing leak and break data for making replacement decisions. *Journal AWWA*, November, **74**(11), pp. 589-594.

Kim, J.H. (1992). *Optimal rehabilitation/replacement for water ditrsibution systems*. PhD thesis, University of Texas, Austin.

Klein, J. and Moeschberger, M. (1997). *Survival analysis: Techniques for Censored and Truncated data*. Springer, New York.

Kleiner, Y. (1997). *Water Distribution Network rehabilitation, Selection and Scheduling of Pipe rehabilitation Alternatives*. PhD thesis, University of Toronto.

Kleiner, Y., Adams, B.J. and Rogers, J.S. (1998a). Long-term planning methodology for water distribution system rehabilitation. *Water Resources Research*, **34**, pp.2039-2051.

Kleiner, Y., Adams, B.J. and Rogers, J.S. (1998b). Selection and scheduling of rehabilitation alternatives for water distribution systems. *Water Resources Research*, **34**, pp. 2053-2061.

Kleiner, Y. and Rajani, B. (1999). Using limited data to assess future needs. *Journal of Water Supply Research and Technology-Aqua*, **91**, July, No. 7, pp. 47-61.

Kumar, D. and Klefsjö, B. (1994). Proportional hazards model - a review. *Reliability Engineering & System Safety*, **44**, pp.177-188.

Lawless, J.F. (1987). Regression methods for Poisson process data. *Journal of American Statistical Association*, **82**, pp. 808-815.

Lawless, J.F. and Thiagrarajah, K. (1996). A point-process model incorporating renewals and time trends, with application to repairable systems. *Technometrics*, **38**,pp. 131-138.

Le Gat, Y. (1998). *Etude statistique des defaillances des canalisations du resau d'irrigation de la societe du canal de Provance*. Cemagref, Bordeaux.

Le Gat, Y. (1999). Forecasting Pipe Failures in Drinking Water Network Using Stochastic Processes Models - Respective Relevance of Renewal and Poisson Processes. In: *Proceedings of the 13th EJSW,* 8 September – 12 September, Dresden University of Technology. ISBN: 3-86005-238-1.

Lei, J. (1997). Statistical approach for describing lifetimes of water mains - Case Trondheim Municpality. STF22 A97320, SINTEF, Trondheim.

Lei, J. and Sægrov, S. (1998). Statistical approach for describing lifetimes of water mains. *Water Science and Technology*, **38**, No. 6, 1998, pp. 209-217.

Li, D. and Haimes, Y. (1992). Optimal Maintenance- Related Decision-Making for Deteriorating Water Distribution-Systems 1. Semi-markovian model for a water main. *Water Resources Research*, **28**, pp. 1053-1061.

Lindqvist, B. (1997). Statistical Modeling and Analysis of Repairable Systems. In: *Proceedings of 1st International Conference on Mathematical Methods in Reliability*, September 16-19, Bucharest, Romania.

Lidström, V. (1996). *Diagnos av avloppsledningars kondition*. Institutionen för teknisk vattenresurslära, Lunds tekniska högskola, Lunds universitet.

Madiec, H., Botzung, P., Bremond, B. and Eisenbeis, P. (1997). Implementation of a probability model for renewal of drinking water networks. *Water Supply*, **14**, (3/4), pp. 347-351.

Malandain, J., Le Gauffre, P. and Miramond, M. (1998). Organising a Decison Support System for Infrastructure Maintenance: Application to Water Supply Systems. In: *Proceedings of 1st International Conference on new Information technologies for decision Making in Civil Engineering*, Oct 11-1998, Montreal, pp. 1013-1025.

Malandain, J., Le Gauffre, P. and Miramond, M. (1999). Modeling the aging of water infrastructure. In: *Proceedings of the 13th EJSW,* 8 September – 12 September, Dresden University of Technology. ISBN: 3-86005-238-1.

Malandain, J. (1999). *Modélisation de l'état de santé des réseaux de distribution d'eau pour l'organisation de la maintenance. Etude du patrimoine de l'agglomération de Lyon.* Thèse de Doctorat n° 99 ISAL 0040 de l'Institut National des Sciences Appliquées de Lyon, Laboratoire URGC / Hydrologie Urbaine, 206 p.

Miljøverndepartementet (1988). *Vannforsyning Kommunal hovedplan, Veileder i målstyring av kommunens planlegging, utbygging og drift*. T-711, ISBN 82-7234-715-5.

Morris, R.E. (1967). Principal Causes and Remedies of Water Main Breaks. *Journal AWWA*, pp. 782-798.

Mosevoll, G. (1994). Vedlikehold og fornyelse av VA- ledninger: Modeller for tilstands-prognose / Funksjonskrav til informasjonsystemer. Dr.ing avhandling, Institutt for Vassbygging, Norges Tekniske Høgskole, Universitetet i Trondheim.

NS-EN 752-1. Norwegian Standard. *Drain and sewer systems outside buildings. Part 1: Generalities and definitions*. Norwegian Standards Association (NSF).

Prentice, R., Williams, B. and Peterson A. (1981). On the regression analysis of multivariate failure time data. *Biometrika*, **68**, (2), pp. 373-379.

Press, W., Teukolsky, S., Vetterling, W. and Flannery, B. (1992). *Numerical Recipes in FORTRAN- The art of Scientific Computing*. Cambridge University Press, Cambrige.

Preston, N., Melbourne, P., Eimermacher, M., Hadzilacos, T. and Kalidromitis, V. (1999). UtilNets: A Water Mains Rehabilitation Decision Support System. In: *Proceeding of NO-DIG 1999*, North American Society of Trenchless Technology, Orlando May 1999.

Quimpo, R.G. and Shamsi, U.M. (1991). Reliability-Based Distribution-System Maintenance. *Journal of Water Resources Planning and Management-ASCE*, **117**, No. 3, May-June, pp. 321-339.

Quimpo, R.G. (1996). Measures of Water Distribution System Reliability. In: *Proceedings of Risk Based Decision Making in Water Resources*, October 8-13, 1995, Santa Barbara, California.

Rausand, M. and Reinertsen, R. (1996). Failure mechanisms and life models. *International Journal of Reliability, Quality and Safety Engineering*, **3**, No. 3, pp. 137-152.

Ræstad, C. (1995). Nordic Experiences with water pipeline systems. *3rd International Conference, Sector C- Pipe materials and handling*, CEOCOR Praha ’95, October 11th-13th 1995.

Røstum, J. (1997). The concept of business risk used for rehabilitation of water networks. In: *Proceedings of the 10th EJSW at Tautra. "Deterioration of Built Environment: Buildings, Roads and Water Systems"*, Norwegian University of Science and Technology, IVB-report B2-1997-2, ISBN 82-7598-040-2, pp. 67-75.

Røstum, J., Dören, L. and Schilling, W. (1997). *Proceedings of the 10th EJSW at Tautra. "Deterioration of Built Environment: Buildings, Roads and Water Systems"*, Norwegian University of Science and Technology, IVB-report B2-1997-2, ISBN 82-7598-040-2.

Samset, O. (1988). *Reliability Estimation Based on Operating History if Repairable Systems*. Diploma thesis, Division of Mathematical Sciences, Norwegian Institute of Technology, Trondheim.

SAS (1994). *User's Guide*. Version 6, Cary, NC, USA, SAS Institute Inc.

Schneiter, C.R., Haimes, Y.Y., Li, D. and Lambert, J.H. (1996). Capacity reliability of water distribution networks and optimum rehabilitation decision making. *Water Resources Research*, **32**, pp. 2271-2278.

Shamir, U. and Howard, D.D. (1979). An Analytic Approach to Scheduling Pipe Replacement, *Journal AWWA*, May, **71**, pp. 248-258.

Smith, E.P. (1994). *An Optimal replacement- Design Model for a Reliable Water Distribution Network System*. PhD thesis, Virginia Polytechnic Institute and State University.

Stacha, J.H. (1978). Criteria for Pipeline Replacement. *Journal AWWA*, May, **70**, pp. 256-258.

Sundahl, A.C. (1996). *Diagnos av vattenledningars kondition*. Report 3200, Institutionen för teknisk vattenresurslära, Lunds tekniska högskola, Lunds universitet.

Sundahl, A.C. (1997). Geographical analysis of water main breaks in the city of Malmö, Sweden. *Journal of Water Supply Research and Technology-Aqua*, **46**(1), pp. 40-47.

SYSTAT (1997). *New Statistic*. Chicago, USA, SPSS Inc.

Sægrov, S., Melo Baptista, J.F., Conroy, P., Herz, R.K., LeGauffre, P., Moss, G., Oddevald, J.E., Rajani, B. and Schiatti, M. (1999). Rehabilitation of water networks: Survey of research needs and on-going efforts. *Journal of Urban Water* (submitted).

Trujillo, R.A. (1995). *Bedarfsprognose und Strategieentwicklung für die Rehabilitation stätischer Wasserrohrnetze.* Institut für Städtbau und Landesplanung, Universität Karsruhe.

UtilNets (1997). *Reliability-Based Decision Support System for the Maintenance Management of the Underground Network of Utilities*. (Final technical report), Computer Technology Institute.

Vagnerini, R. (1996). *Studio dell'affidabilita du una rete di distribuzione idrica cittadina il caso di Reggio Emilia. Analisi e proposte metodologiche*. PhD thesis, Universita degli Studi di Firenze.

Vatn, J. (1993). *OREDA Data Analysis Guidelines*. report STF75 F93024, SINTEF Sikkerhet og pålitelighet, Trondheim.

Vatn, J. and Tveit, O.A. (1997). Modellering av pålitelighet i drikkevannsforsyningen. STF38 A96446, ISBN 82-595-9638-5, SINTEF Sikkerhet og pålitelighet, Trondheim.

Wagner, J.M., Shamir, U. and Marks, D.H. (1988a). Water Distribution Reliability: Analytical Methods. *Journal of Water Resources Planning and Management*, May, **114**, pp. 253-275.

Wagner, J.M., Shamir, U. and Marks, D.H. (1988b). Water Distribution Reliability: Simulation Method. *Journal of Water Resources Planning and Management*, May, **114**, pp. 276-294.

Walski, T.M. and Pelliccia, A. (1982). Economic Analysis of Water Main Breaks. *Journal of Water Resources Planning and Management*, **74**, pp.140-147.

Walski, T. (1987). *Water supply system rehabilitation*. American Society of Civil Engineers.

Walski, T. (1993). Water Distribution Valve Topology for Reliability-Analysis. *Reliability Engineering & System Safety*, **42**, pp. 21-27.

Wengström, T.R. (1993a). *Comparative analysis of pipe break rates: a literature review*. Institutionen för vattenförsörjnings- och avloppsteknik, Chalmers tekniska högskola.

Wengström, T.R. (1993b). *Drinking water pipe breakage records : a tool for evaluating pipe and system reliability*. Institutionen för vattenförsörjnings- och avloppsteknik, Chalmers tekniska högskola.

Woodburn, J., Lansey, E. and Mays, L.W. (1987). Models for the optimal rehabilitation and replacement of water distribution system components. In: *Proceedings of ASCE 1987 National Conference on Hydraulic Engineering*, Virginia.

WRc (1998). *Using mains break data to predict future rehabilitation requirements*. Contract no.: 11359-0, WRc, Swindon.

Wu, S.J., Yoon, J.H. and Quimpo, R.G. (1993). Capacity-Weighted Water Distribution-System Reliability. Reliability Engineering & System Safety, **42**, pp.39-46.

Description of WINROC: A program for estimation of NHPP parameters

The program WINROC for estimating the parameters in the NHPP ("Power law" model), is programmed in FORTRAN by Jørn Vatn at SINTEF, Industrial Management, Safety and Reliability as a part of the project.

The program require the following input file format (Tabulator separated text file):

No. of pipes (p)
No. of failures (f)
No. of covariates (c)
*
Name $Covariate_1$
Name $Covariate_2$
…
Name $Covariate_{\#}$

a_i	b_i	$Pipe_i$	*	$Covariate_{i1}$	$Covariate_{i2}$	$Covariate_{i\,c}$	Inventory data
a_j	b_j	$Pipe_j$	*	$Covariate_{j1}$	$Covariate_{j2}$	$Covariate_{j\,c}$	
…							
a_p	b_p	$Pipe_p$	*	$Covariate_{p1}$	$Covariate_{p2}$	$Covariate_{p\,c}$	

T_1	$Pipe_i$	Failure data
T_2	$Pipe_I$	
…		
T_f	$Pipe_p$	

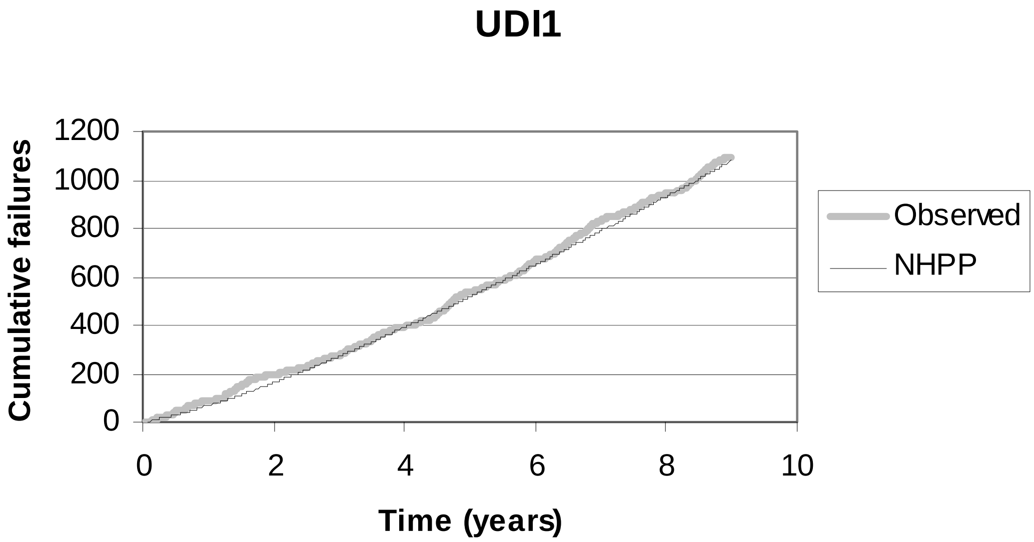
Where * is an option for stratification and (a_i,b_i) represents the time window where $pipe_i$ is observed.

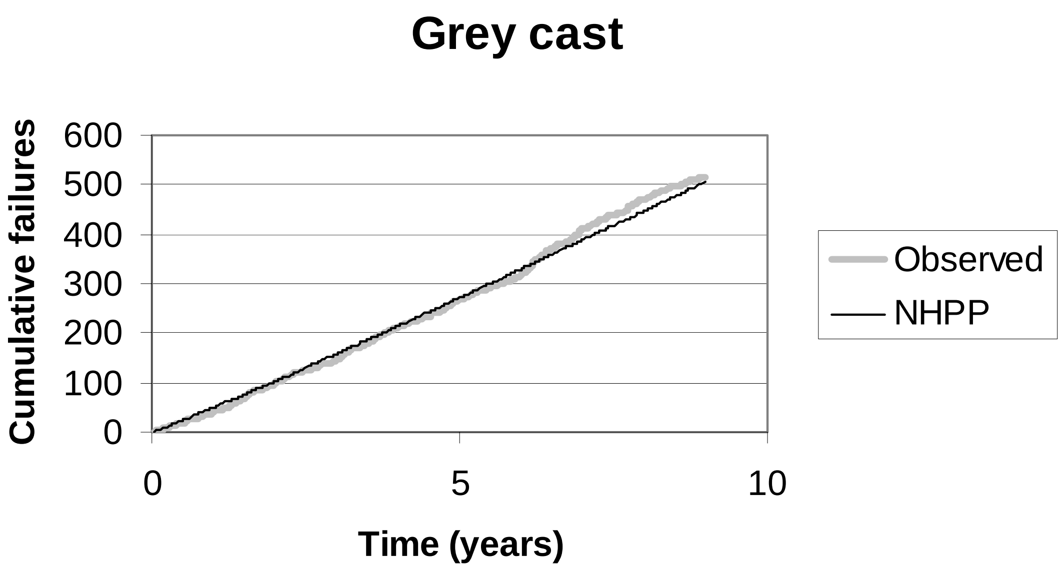
The program is executed by typing *winroc def* in DOS mode. The output file is automatically generated by the program. The user designates the name of the output file in a definition file (def). The output file includes:

- descriptive statistics for the input file
- estimated values for the parameters
- cumulative plots
- predicted failures for the observed period

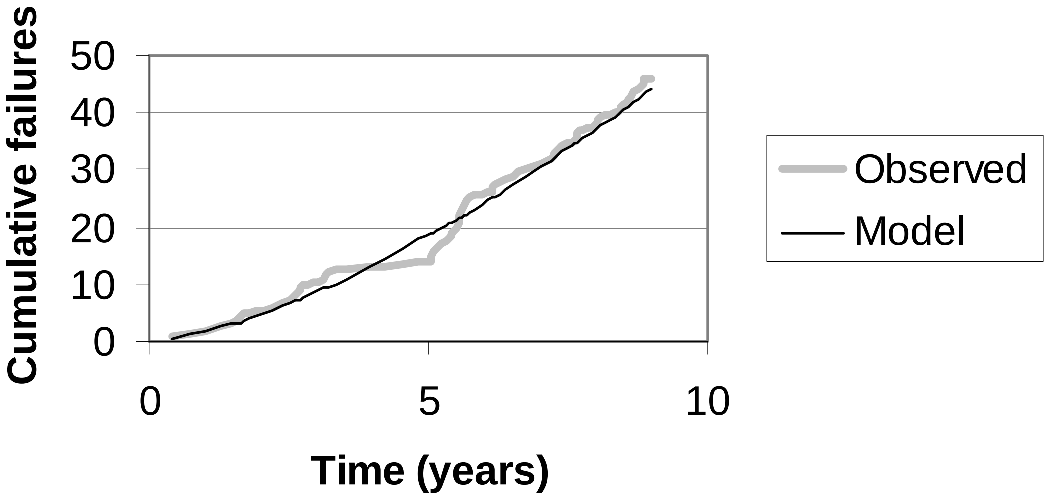
Cumulative plots for NHPP for the period 1988-1996

In the following plots the observed cumulative failures are compared to the predicted failures (NHPP) for each of the groups UDI1, Grey cast, UDI2 and PDI. The comparison is carried out for the period 1988-1996 (nine years).

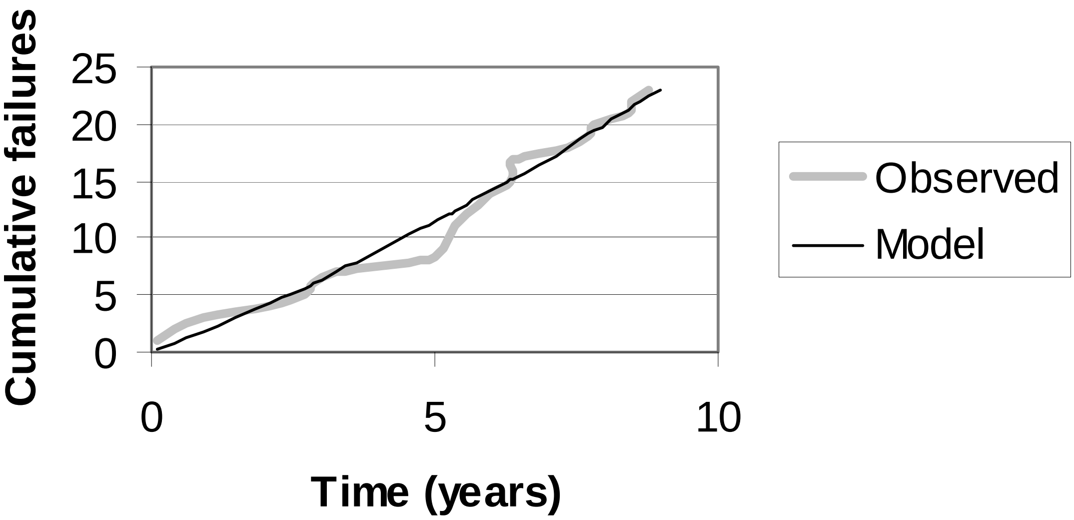




UDI2

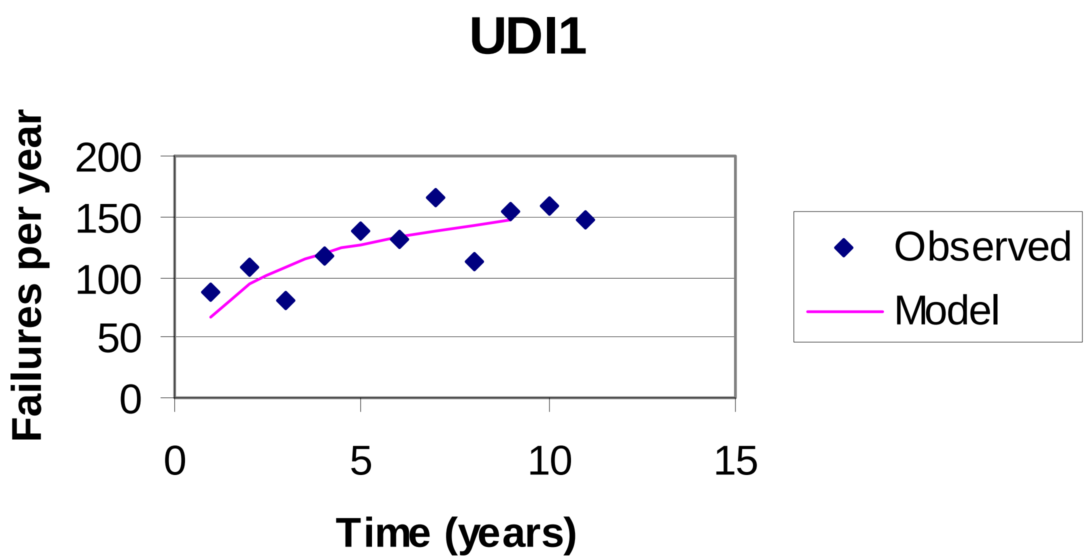

Cumulative failures
50
40
30
20
10
0
0
5
10
Time (years)
Observed
Model

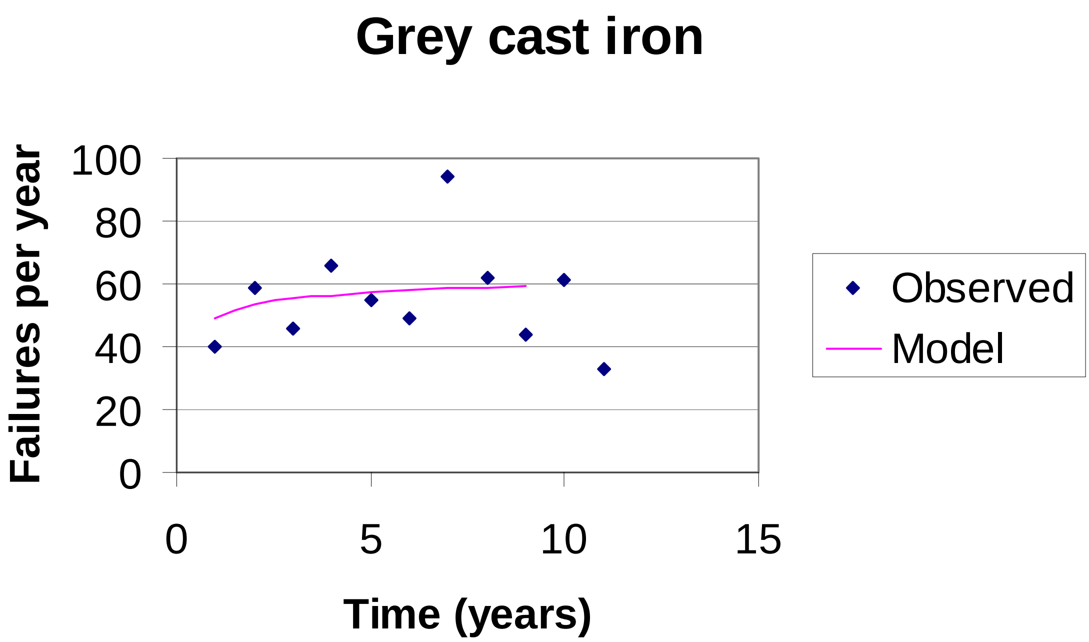
PDI

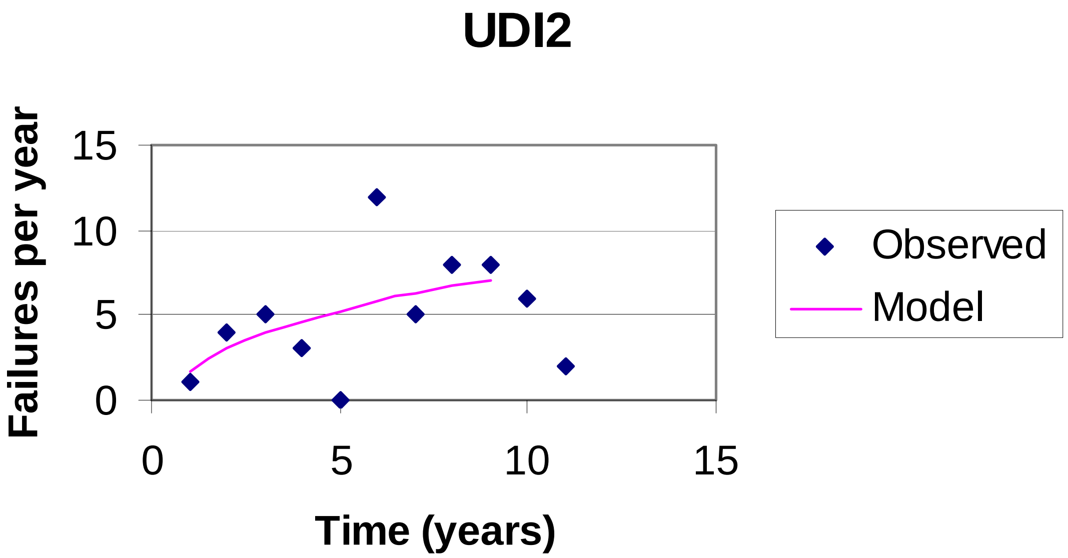

Cumulative failures
25
20
15
10
5
0
0
5
10
Time (years)
Observed
Model

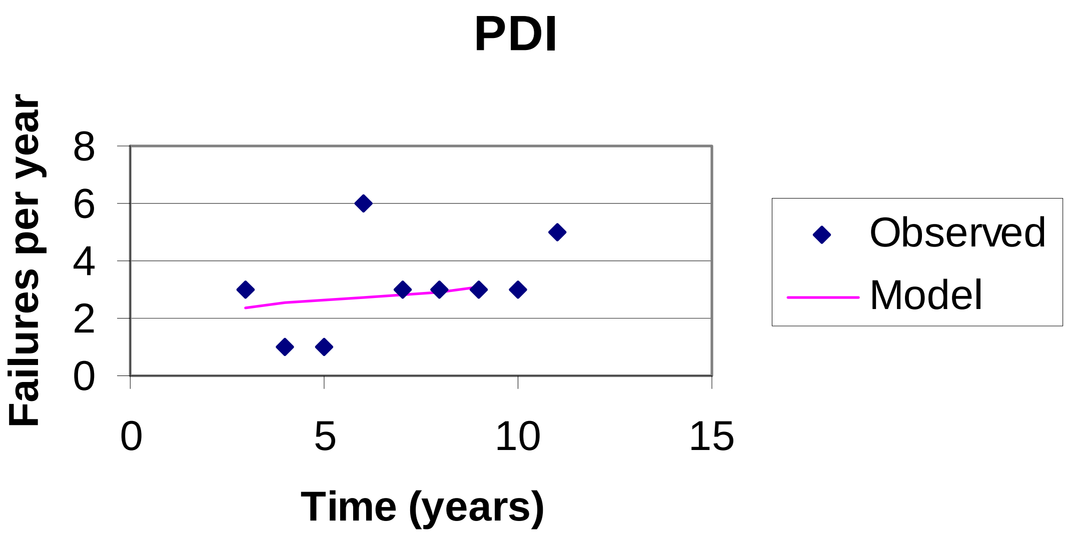
Annual plots NHPP

In the following annual plots for the groups UDI1, Grey cast, UDI2 and PDI are shown. The annual plots show the observed number of failures and the predicted number of failures for each year from 1988 to 1996 (nine years). The observed number of failures for the two following years 1997 and 1998 are also shown.



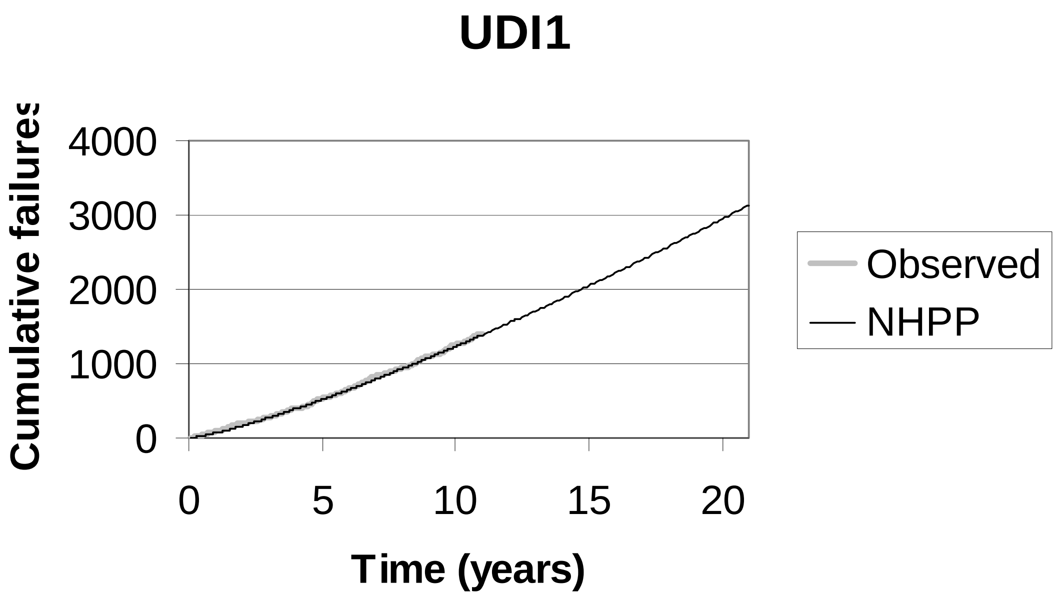


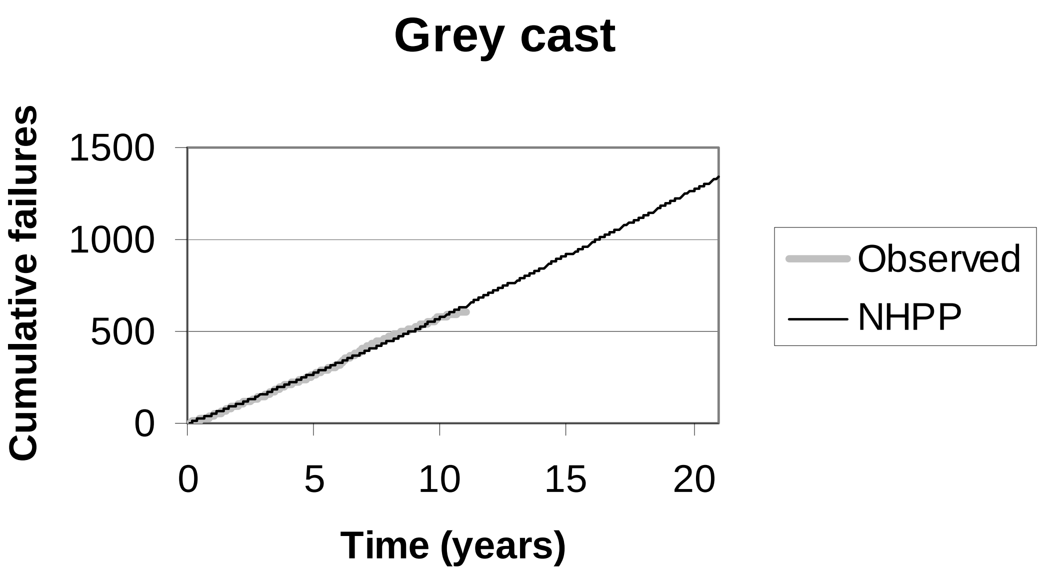

UDI2
Failures per year
15
10
5
0
0
5
10
15
Time (years)
Observed
Model

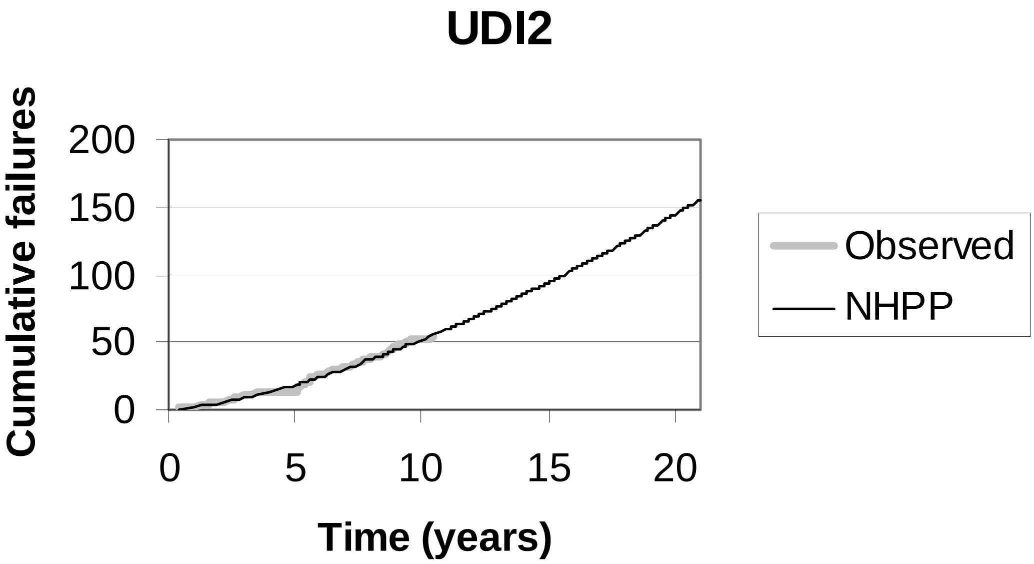

PDI
Failures per year
8
6
4
2
0
0
5
10
15
Time (years)
Observed
Model

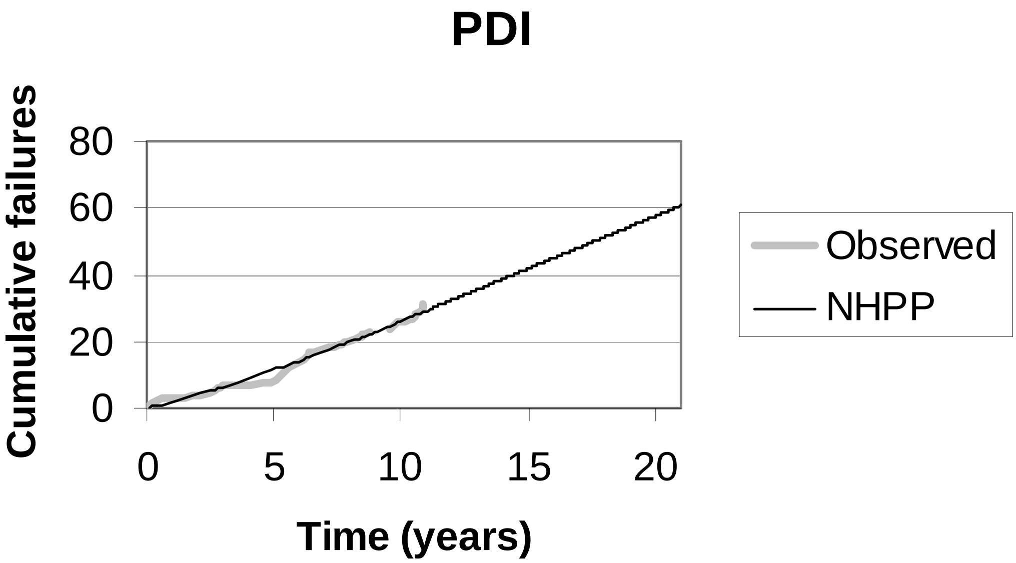
Calibration, verification and prediction with NHPP

In the following cumulative plots for the period of calibration, verification and prediction for the groups UDI1, Grey cast, UDI2 and PDI are shown. The calibration period is from 1988-1996 (nine years) and the verification period is from 1997-1998 (two years). Cumulative failures are predicted for an additional ten years.






UDI2
Cumulative failures
200
150
100
50
0
0
5
10
15
20
Time (years)
Observed
NHPP


PDI
Cumulative failures
80
60
40
20
0
0
5
10
15
20
Time (years)
Observed
NHPP

Coding system in Gemini VA

The following table shows the coding system used in Gemini VA for *pipe material*, *soil condition* and *failures*. For more information about codes used in Gemini VA see Lei (1997).

Pipe material	**Norwegian terms**	**Corresponding English terms**
AAS	Asbest-sement	Asbestos- cement
AIF	Tunnel i fjell	Tunnel in rock
AKT	Teglstein kanal	Brick channel
BAD	Dob. arm. f. NS 3028	Double reinforcement , Norwegian Standard
BAE	Enk. arm. f. NS 3028	Single reinforcement , standard
BAF	Arm. falsrør eggform	Reinforcement fold pipe egg-shaped
BAM	Arm. falsrør NS 462	Reinforcement fold pipe
BAN	Arm. falsrør NS 3026	Reinforcement fold pipe
BMN	Bet. muffer. NS 461	Concrete socket
BMT	Bet. muffer. NS 3027	Concrete socket
BMU	Betong mufferør	Concrete socket pipe
BON	Bonna rør	Concrete pipe type “Bonna”
BUF	Uarm. falsrør	Fold pipe
GUP	Glassfib. arm. ume.	Glass fibre reinforcement
LER	Leirrør	Vitrified clay
MCU	Kopper	Copper
MGA	Galvanisert stål	Galvanised steel
MSK	Stål-korrugert(Armco	Steel groove
MST	Stål	Steel
PEH	Polyet. høy dens.	High density polyethylene
PEL	Polyet. lav dens.	Low density polyethylene
PRE	Premo rør	PREMO pipe
PVC	Polyvinylklorid	PVC
RAB	Bet. inj.rehab,akryl	Concrete injected rehabilitation, akryl
REB	Bet. rehab m/Epoxy	Concrete pipe rehab. with epoxy lining
RES	Stj. rehab m/Epoxy	Iron pipe rehab. with epoxy lining
RGA	Galvrør rehab m/PE	Galvanised pipe rehab. with PE
RGB	Bet. rehab m/GUP	Concrete rehab. With GUP
RHS	Stj. rehab m/PEH	Iron rehab. with PEH
RPE	Bet. rehab m/PE50	Concrete rehab. With PE50
RTI	Bet. rehab m/Tube-in	Concrete rehab. With Tube-in
SEN	Sentabrør	Concrete asbestos pipe
SJA	Stj.dukt.innv.mørtel	Ductile iron, cement morter inside

SJB	Stj.du.innv.utv.bet.	Ductile iron , cement morter outside
SJC	Stj.du.innv.utv.sink	Ductile iron, zinc coating inside/outside
SJD	Stj.du.innv.utv.poly	Ductile iron PE coating outside
SJG	Stj. - grått	Cast iron
SJK	Stj. – duktilt	Ductile iron

Soil condition		
FJ	Fjell	Rock
LE	Leire	Clay
MO	Morene	Moraine
NN	Ukjent	Unknown
OM	Oppfylte masser	Backfill
SG	Sand / Grus	Sand/gravel

Failure code		
DAN	Annet	Misc. repair problems
DBR	Brudd/lekkasje	Pipe burst/ leakage
DST	Tilstopping	Blockage
K03	Kval.vurd: Svært Dårlig	Quality assessment: very bad
QA3	Tilstand: Dårlig	Condition: bad
QA4	Tilstand: Meget dårlig	Condition: very bad
QA5	Tilstand: Ubrukelig	Condition: can not be used further
R61	Reparasjon/vedlikehold le	Repair/ maintenance pipe
R72	Rehabilitering ledning	Rehabilitation of pipe
R76	Utskifting ledning	Exchange of pipe
U31	Inspeksjon/tilsyn	Inspection/ checking
U32	TV-undersøking	Internal examination by TV camera
U33	Lekkasjesøking	Leakage detection
U41	Rensk/spyling	Cleaning/ flushing
U61	Reperasjon/vedlikehold le	Repair/ maintenance pipe
U62	Reperasjon/vedlikehold ku	Repair/ maintenance manhole
U64	Reperasjon/vedlikehold ve	Repair/ maintenance valve
U71	Rehabilitering	Rehabilitation
U72	Rehab. ledning (mer enn	Rehabilitation pipe (more than
U75	Utskifting/omlegging	Exchange/ new items
U76	Utskifting/omleggin ledni	Exchange/ new pipe
U79	Utskifting/omleggin vent/	Exchange/ new valve
B01	Sprukket rør på langs	Pipe cracked/burst horizontal
B02	Sprukket rør på tvers	Pipe cracked/burst vertical
B03	Utsprunget flak	Section of pipe wall is missing
B04	Hull p.g.a. tæring	Hole due to corrosion

B05	Slitasje innvendig i rør	Inside wear of pipe
B06	Tetning skadet	Damaged joint seal
B07	Utglidd rør	Joint separation
B08	Utglidd bend	Joint separation at a bend
B09	Anboringsarmatur skadet	Damage to private connection tapping
B10	Hydrant skadet	Fire hydrant damaged
B11	Stoppventil skadet	Damaged valve
B12	Annet	Misc.
B13	Tilstopping inne i lednin	Blockage inside pipe
H01	For å forebygge driftsfor	Preventative maintenance activity
SAN	Annen følgeskade	Other damages which follow a break
SBV	Brudd i vannforsyning	Water supply interrupted
SOB	Oversvømmelse/vannskade -	Flooding/ damage due to water
SOU	Oversvømmelse/vannskade-o	Flooding/ damage due to water-o
SOV	Oversvømmelse/vannskade -	Flooding/ damage due to water
SSB	Spillvannsutslipp	Sewage discharge
SVA	Helt stengt/trafikk hoved	Main road fully closed to traffic
SVB	Delvis stengt/trafikk hov	Main road partly closed to traffic
SVC	Helt stengt/trafikk mindr	Side roads fully closed to traffic
SVD	Delvis stengt/trafikk min	Side roads partly closed to traffic
T01	Fjellgrøft	Trench in rock
T02	Jordgrøft	Trench in soil
T03	Fjell/jordgrøft	Combined soil/ rock trench
T04	Grunnvannstand over ledni	Ground water level above pipe
T11	Setninger	Settling of ground/ pipes etc.
T12	Stor jordlast	Heavy load from soil
T13	Stor trafikklast	Heavy load from traffic
T14	Skolinger	Concrete/wood supports under pipe
T15	Utvasking/utgraving	Soil washed out by water
T16	Frost/tele	Frost / movement of soil due to frost
T17	Graving nær ledning	Digging close to pipe
T18	Trykkstøt	Water hammer
T22	Vann fra slamavskiller/se	Water from sludge separation tank
T31	Rust innvendig	Internal corrosion
T32	Rustknoller innvendig	Internal corrosion products
T33	Rust utvendig - brun farg	External corrosion - brown colour
T34	Rust utvendig - svart far	External corrosion - black colour
T35	Tæring innvendig i topp rør	Internal corrosion top of pipe
T36	Tæring innvendig i bunn rør	Internal corrosion bottom of pipe
T37	Slitasje innvendig	Internal wear
T38	T‘ring utvendig på rør	External tear pipe
T39	T‘ring på gummipakning	Tear of rubber sealing
T41	Knust/sprukket rør	Demolished/ cracked pipe
T42	Sammenpresset rør	Pipe inflated

T43	Rør sprukket i skjøt	Pipe cracked in joint
T43	Rør sprukket i skjøt	Pipe cracked in joint
T44	Åpne/forskjøvne skjøter	Open/ out of line joints
T45	Forskjøvet pakning	Rubber sealing in wrong position
T51	Innvendig begroing	Internal growth (biofilm)
T62	Innstikkende rør	Connected pipes inside outer wall
T64	Avleiring, sand/slam	Deposits, sand/ sludge
T72	Motfall	Slope of pipe in wrong direction
T81	Sterkt regn	Heavy rain
T82	Sterk snøsmelting	Heavy snowmelt
T84	Lekkasje avløp ut	Leakage sewage out
T85	Sterk tapping, vann	Heavy water consumption
T86	Lekkasje, vann	Leakage, drinking water
T94	Dårlig anleggsarbeid	Bad construction work
T96	Annet	Other things
T97	Ukjent	Unknown

List of publications

Røstum, J. (1997). The concept of business risk used for rehabilitation of water networks. In: *Proceedings of the 10th EJSW at Tautra. "Deterioration of Built Environment: Buildings, Roads and Water Systems"*, J.Røstum, L. Dören and W. Schilling (ed.), Norwegian University of Science and Technology, IVB-report B2-1997-2, ISBN 82-7598-040-2, pp.67-75.

Schilling, W., Røstum, J. and Sægrov, S. (1998). Fornyelsesstrategier for VA-nett. Scandinavian Society of Trenchless Technology, Årsmøte og Konferanse, Oslo, 18-19 Mars.

Røstum, J. (1998). Fornyelsesstrategi for vannledningsnett- tilstandsutvikling. VAR forskningsdagene 1998, NTNU. Tapir forlag, Trondheim, ISBN: 82-519-1347-0, pp. 39-44.

Eisenbeis, P., Røstum, J. and Le Gat, Y. (1999). Statistical Models for Assessing the Technical State of Water Networks - Some European Experiences. In: *Proceedings of annual conference of AWWA*, Chicago, Illinois, 20 – 24 June 1999.

Røstum, J., Baur, R., Sægrov, S., Hörold, S. and Schilling, W. (1999), Predictive service-life models for urban water infrastructure management. In: *Proceedings of 8th International Conference on Urban Storm Drainage*, Sydney, Australia, 30 August - 3 September, ISBN 0 85825 718 1, pp. 594-601.

Røstum, J. Schilling, W. (1999). Predictive service life models for water network management. In: *Proceedings of the 13th EJSW*, 8 September – 12 September, Dresden University of Technology, ISBN: 3-86005-238-1.

Røstum, J. and Schilling, W. (1999). Predictive service life models for water network management", in: Proceedings of 17th International Congress NO-DIG '99, 11- 13 October, Budapest, Hungary, published by Hamburg Messe- und Congress GmbH, St.Petersberger Strasse 1, 20355 Hamburg, Germany, pp. 249 - 258.

Røstum, J., Vatn, J. and Schilling, W. (2000). Modelling pipe breaks in water distribution networks as a Non Homogeneous Poisson Process (NHPP). International Water Association IWA World Congress PARIS 2000 (accepted as Poster presentation).