Chapter 1

Problem Statement

1 Introduction

There will always be a need for maintenance on mechanical systems and components because of friction and wear. It is however not always as simplistic as "if it breaks, repair it" and in recent years the need for scientific maintenance has increased tremendously. Reasons for this could be the increased sophistication of production equipment, the need for a high return on an investment and the high cost of maintenance.

The objective of an organization's maintenance activities should be to support the production process with maximal levels of availability, reliability, operability and safety at acceptable cost. If this objective is pursued the results will be clearly evident in the form of increased production capacity and thus company profit. As high profit is the reason for the existence of production concerns, maintenance should be regarded in a very serious way.

Various maintenance models exist to act as guidelines for an effective maintenance function. One such model called 'The Maintenance Cycle' is proposed by Coetzee[22] and act as a good overview of the total complicated maintenance function. See Figure 1.1. on the next page.

The maintenance cycle is divided into two orbits namely: (1) The outer cycle which represents the managerial processes in the maintenance organization; and (2) The inner cycle which involves the operational and technical processes. In this dissertation we will focus on maintenance strategy setting, one of the components in the inner cycle.

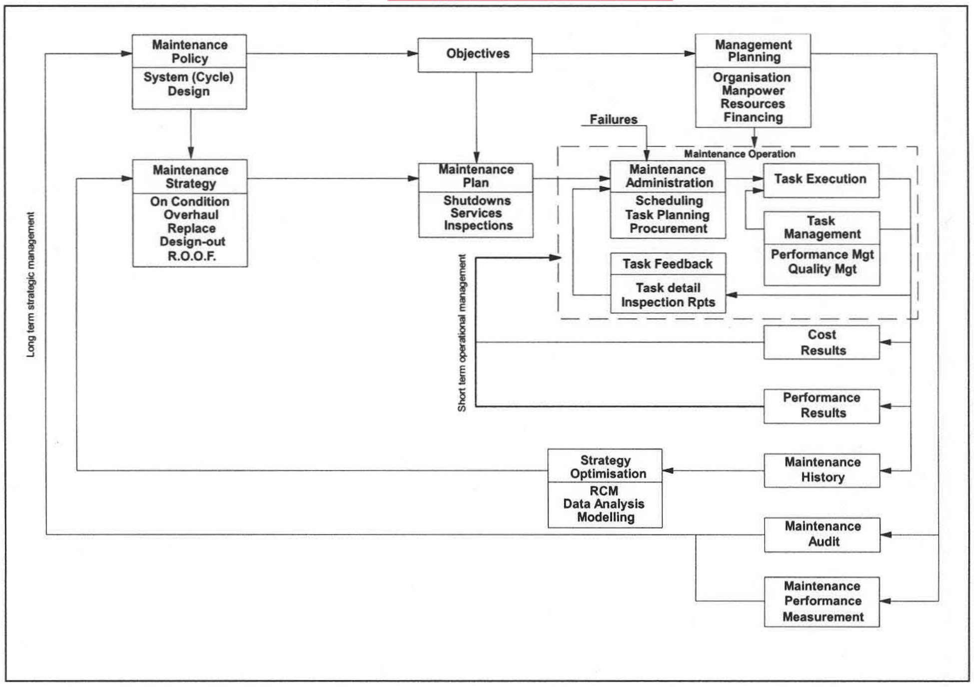

Figure 1.1.: *The Maintenance Cycle (taken from Coetzee[22])*

Several maintenance strategies are identified and are illustrated in the diagram in Figure 1.2. below. This dissertation is on an advanced type of preventive maintenance strategy which combines scheduled renewal on the use based maintenance branch and condition monitoring, specifically vibration monitoring, on the predictive maintenance branch. Scheduled renewal is defined as the complete renewal of a system or component due to replacement or complete overhaul. Only scenarios where complete renewal of a system or component takes place after failure are considered in this dissertation. Since this type of scenario is usually (not always) associated with components and not systems there will only be referred to components in the text when renewal situations are discussed.

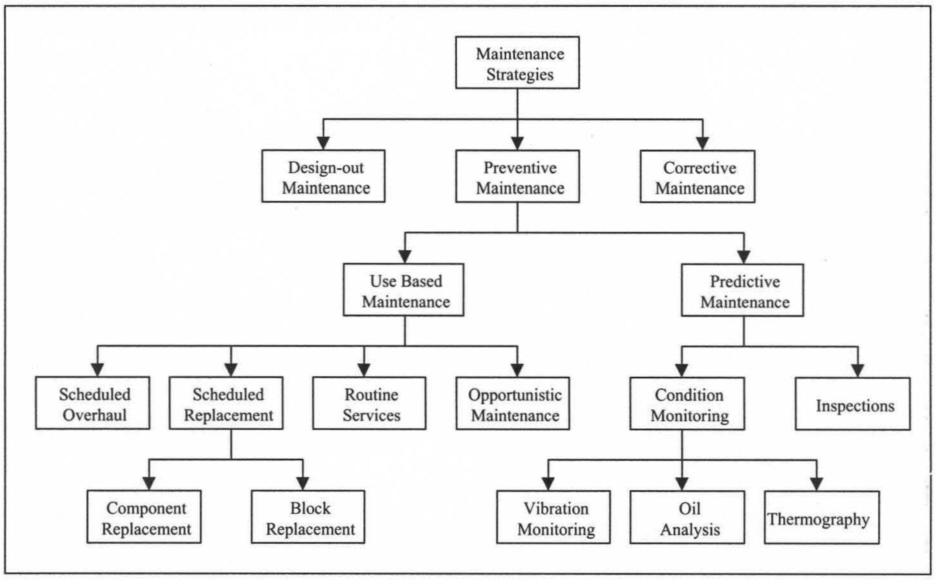

Figure 1.2: *Maintenance Strategies (adapted from Coetzee[22])*

Although the science of scheduled renewal, i.e. determining the optimal economic service life of a component before renewing it, and the technological marvel of vibration monitoring seem to be very close in the maintenance strategy tree, it is not nearly the case. A statistical approach is usually followed to calculate the optimal time for use based preventive renewal from time failure data while a methodology based on previous experience in the form of empirical rules and benchmarks are used to predict optimal renewal times with vibration monitoring.

Both mentioned strategies are well established in practice and have proven themselves in many different situations although some disadvantages and deficiencies are experienced. It is believed that if a single scientific preventive maintenance strategy setting technique can be found that is able to overcome the current shortcomings and incorporate both techniques' advantages, much improved maintenance renewal decisions will be the result. This is the main goal of this dissertation.

The goal of preventive maintenance strategy setting is always to minimize the total life cycle cost of a component, i.e. to determine the optimal economical renewal instant for a component and not necessarily to predict the time to failure of the component. This fact influences the approach of this research project immensely.

In chapter 1 the two strategies are introduced in enough detail to be able to understand the objectives for the research project. After this discussion it would also be possible to identify and describe the most promising and logical research route that will lead to the achievement of the objectives.

2 Use Based Preventive Renewal

Use based preventive renewal is all about determining the optimal economic instant to replace a component preventively. This optimal instant could be measured in any use parameter for instance running hours, tonnage handled or production throughput. Running hours (also called working age or time) is most often used. Failure data of identical components in the past is used to estimate optimal preventive renewal of future components. This strategy is only a feasible possibility if failure data of a specific component is available.

2.1 Failure Data

Since time is usually used to describe a component's age this discussion will be on *time failure data* but the same principles apply for any other use parameter. Different types of time failure data are identified, i.e. time failure data sets with different inherent characteristics. This fact is very important since different analysis techniques are used for every type of data set. Classification of data set types is a field on its own and details regarding the topic are beyond the scope of this dissertation, but logical steps that are taken in the process of classification are mentioned briefly. These steps are discussed with the aid of the flow diagram in Figure 2.1. on the next page.

STEP (i): *Order T_i's (times to failure) chronologically*

Before the classification process starts, the failure times should be sorted in its original chronological order of occurrence. This has to be done to discern trends in the data.

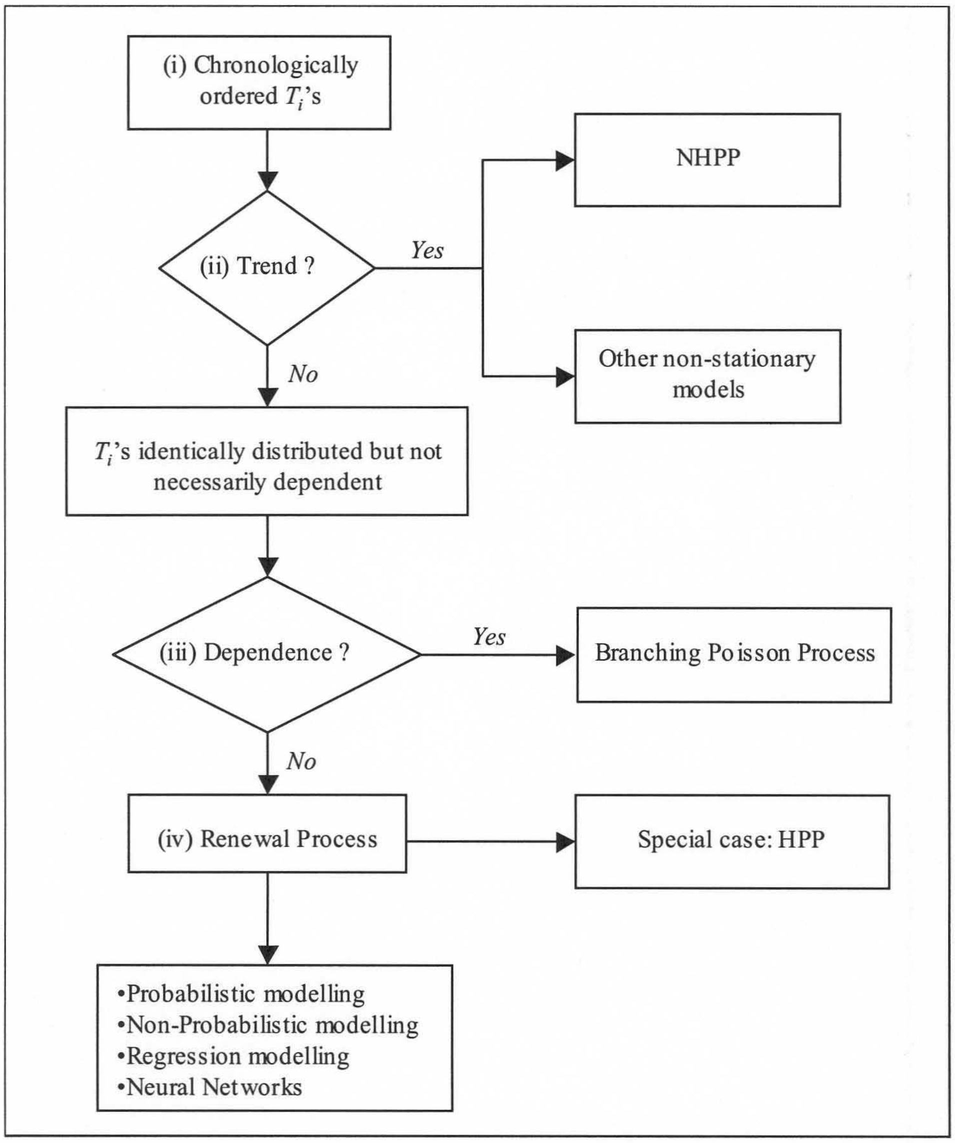

Figure 2.1: *Diagram to aid with classification of data (Adapted from Ascher and Feingold[15])*

STEP (ii): *Test for a trend in data*

A number of techniques exist to recognize trends in data. Graphical techniques include (a) plotting cumulative failures versus cumulative time on linear paper; (b) estimating average failure rate in successive time periods; and (c) Duane plots.

Mathematical techniques proposed by Laplace (1773), Bartholomew (1955), Bates (1955), Boswell (1966), Cox and Lewis (1966) and Boswell and Brunk (1969) are typically used to determine the existence of trends. Note that these techniques do not all apply for every possible scenario and that certain techniques are only applicable to certain situations.

If a trend is found in a data set, the data set can be modeled by non-stationary models like the Non-Homogeneous Poison Process or models based on a sequence of independent but not identically distributed random variables. If not, it implies that the data is identically distributed, but no conclusion can be made about the dependence of the data and therefore step (iii) has to be evaluated.

STEP (iii): *Test for dependence*

Although very important, this step is often neglected. Ascher and Feingold[15] suggest three reasons for this:

(a) The need for a large number of times to failure or T_i's.
(b) The complexities involved in implementing and interpreting these tests.
(c) An almost complete lack of understanding of the need to perform this type of test.

The most straightforward way of testing for dependency of successive T_i's, is by means of the sample correlation coefficient of lag j, called C_j. (Lag j refers to the correlation between T_i and T_{i+j}, $i=1,2,...,m-j$, $1<i+j<m$ where m is the total number of observed T_i's).

If the data turns out to be dependent, a Branching Poison Process is suitable to represent it. This type of data set is encountered in situations where primary failures has a positive probability of triggering one or more subsidiary failures. An example will be where a primary failure causes one or more secondary failures which are not detected until after the system is put back into operation. Another example is where repair to a system is not done properly and the system fails again after repair because of the same undetected problem.

It might be argued that subsidiary failures are not true functional system failures and should not be dealt with in the same way as with true functional failures. In practice however, subsidiary failures will also cause a system to be out of operation and it must thus be seen as true functional failures.

STEP (iv): *Renewal process*

If the diagram leads to step (iv), the data is independent and identically distributed (i.i.d.) and is generated by a renewal process. Because it is independent and identically distributed we can infer that a previous failure of a system, sub-system or component do not influence the variation of the future life of the system, sub-system or component and consecutive failures arise from the same failure distribution.

A renewal process that generates i.i.d. data is defined as a non-terminating sequence of independent and identically distributed non-negative variables $T_1, T_2, \ldots, T_n$ which with probability one, are not all zero. In this case the typical variable is time to failure and it is usually the time to failure of sub-systems or components. Failure data of sub-systems or components is in general more likely to be part of a renewal process than the failure data of systems, although this is not a rule.

In practice a renewal process is also referred to as an "As-Good-As-New" scenario. If a component fails, it is replaced or completely overhauled and the component is as-good-as-new again. As stated earlier will this dissertation be limited to the event of complete renewal. This type of data is analyzed with methods referred to as renewal theory which comprises probabilistic, non-probabilistic or regression models.

2.2 Incomplete Observations or Censored Data

Up to this point it was assumed that time failure data was compiled from observed times to failure of a specific component. This is not always true and it could be that observations were incomplete. Incomplete observations are frequently encountered in data sets. An observation that is only known to have occurred before a certain time, within a certain interval of time or after a certain time is called a censored observation. These cases are called left-censored, interval censored or right-censored observations respectively. Censored observations contain valuable information and have to be included in failure time models.

Two distinct types of right-censoring are identified. The first type, Type I, occurs when n components are put on test for a fixed time c and at the end of time c a number of components are still operational. In this case it is known that for the failed items indexed by i, $T_i \le c$ and for the components still operational indexed by j, $T_j > c$. A different type of right-censoring occurs where observation ceases after a pre-specified number of failures. This is called Type II-censoring and the right-censored time (or times in the case where all items were not started up on the same time) is (are) not known before observation starts.

Only Type I right-censored observations (also called suspensions) are considered in this research project. The terminology will remain the same for the remainder of the text as before, i.e. time failure data or failure times refers to both failures and suspensions.

2.3 Renewal Theory

Renewal theory comprises of estimating component reliability from recorded failure times of replaced components and calculating the renewal time which minimize the total average life cycle cost of future components. Four important reliability concepts are defined in renewal theory to form the base of reliability modelling approaches used on i.i.d. data:

(i) The *failure density*, *f*, which is the probability of component failure at a specific instant.

(ii) The *cumulative failure density*, *F*, or the *unreliability function* which gives the probability of component failure up to a certain instant.

(iii) The *reliability function*, *R*, which gives the probability of component success up to a certain instant.

(iv) The *instantaneous failure rate*, *force of mortality* or *hazard rate*, *h*. This function gives the probability of component failure in a short interval $(t, t+\Delta t]$ provided that the component is still operational at time t.

Three different mathematical approaches suitable to approximate the reliability functions are identified: (1) A probabilistic modelling approach; (2) A non-probabilistic modelling approach; or (3) A regression modelling approach. A fourth approach used to estimate the reliability of a component, part of a renewal process, is the utilization of neural networks. Neural networks do not strive to estimate the reliability functions but build dynamic models with observed data suitable to predict future events.

The four approaches are introduced below without concentrating too much on the underlying mathematics whereafter comments will be made about optimal renewal instant calculation.

2.3.1 Probabilistic Modelling Approach

Probabilistic modelling approaches are primarily based on the fact that failure times generated by a specific renewal process all arise from the same underlying distribution. Estimation of this underlying distribution or failure density function plays an important role in this type of approach. Another characteristic of probabilistic modelling is that only time (or any other use parameter) is used to represent the reliability functions and no concomitant information concerning failures is included. With these facts stated it is possible to define the formal reliability functions for this approach in terms of recorded failure times T_i and continuous time t.

2.3.1.1 Probability Density Function (PDF)

The probability density function, $f(t)$, denotes the positive probability of a failure T occurring within an interval dt. In probabilistic notation it can be expressed as $f(t)dt = P\{t \le T \le t + dt\}$ with $f(t) \ge 0$ for all t and the probability of all outcomes $\int_{t=0}^{\infty} f(t)dt = 1$.

2.3.1.2 Cumulative Probability Density Function (Unreliability function)

$F(t)$ is the cumulative probability of failures or the probability of component failure as a function of time, i.e. $F(t) = P\{T \le t\}$ or $F(t) = \int_{t=0}^{t} f(t)dt$.

2.3.1.3 Reliability Function (Survivor function)

This function, $R(t)$, represents the probability of component success and is closely related to the unreliability function. In probabilistic terms is $R(t) = P\{T \ge t\}$ or $R(t) = 1 - F(t)$.

2.3.1.4 Hazard Rate (Instantaneous Rate of Failure)

The hazard rate, *h(t)*, is the most important and most valuable reliability function and because of its importance it is introduced in some detail. For this purpose we first define conditional probability. Suppose that one event, say *X*, is dependent on a second event, *Y*. We define the conditional probability of event *X*, given event *Y* as $P\{X|Y\}$. From the third axiom of probability is:

$$P\{X \cap Y\} = P\{X \mid Y\}P\{Y\} \tag{2.1.}$$

In equation (2.1.), $X \cap Y$ denotes both *X* and *Y* take place. This imply the probability that both *X* and *Y* occur is the probability that *Y* occurs multiplied by the conditional probability that *X* occurs, given the occurrence of *Y*. Equation (2.1.) can be written as the definition of conditional probability:

$$P\{X \mid Y\} = \frac{P\{X \cap Y\}}{P\{Y\}} \tag{2.2.}$$

For further discussion on conditional probability, see Lewis[17].

Let *h(t)dt* be the probability that the system will be in the failed state at some time $T < t + dt$, given that it has not yet failed at $T = t$. From the definition of conditional probability we have:

$$h(t)dt = P\{T < t + \Delta t \mid T > t\} = \frac{P\{(T > t) \cap (T < t + \Delta t)\}}{P\{T > t\}} \tag{2.3.}$$

The numerator on the right-hand side of (2.3.) is an alternative expression for the probability density function, i.e.:

$$P\{(T > t) \cap (T < t + dt)\} \equiv P\{t < T < t + dt\} = f(t)dt \tag{2.4.}$$

Combining equations (2.3.) and (2.4.) then yields:

$$h(t) = \frac{f(t)}{R(t)} \tag{2.5.}$$

For an increasing hazard rate a component has an increasing probability to fail and use based preventive renewal will be a definite option to consider, although costs will have the final say. Preventive renewal will only be used if the total cost of a failure is considerably higher than the total cost of preventive actions. If equation (2.5.) yields a constant hazard rate, the component is said to have a random shock failure pattern because the risk of failure of the component remains the same throughout the component's life. Corrective renewal will be the first option to consider for this case, i.e. repair only on failure. Corrective renewal will also most probably be used for a component with a decreasing hazard rate, since the probability of component failure becomes less as time progresses. It should be kept in mind however that condition based preventive renewal, like vibration monitoring, could be used for any shape of the hazard rate. Clearly the hazard rate has enormous value.

It is important to note that the reliability functions as defined above for the probabilistic approach are all related and if one of the functions is determined any other function can be derived.

2.3.1.5 Estimation Methods

There are several appropriate techniques that can be used to estimate the reliability functions. These techniques are discussed below.

- Parametric distributions. A continuous parametric distribution can be fitted to the data, usually to represent the failure density function. The Weibull distribution is often used for this purpose but exponential, normal, hyper-exponential or log-normal distributions are used in certain cases as well. See Coetzee[22].
- Techniques based on partial distributional knowledge. Certain properties of a data set can often be assumed before analysis, for instance an increasing hazard rate, because of observed physical properties of the component which generated the data set. This allows for slightly simplified techniques to fit parametric distributions on a data set. Ascher and Feingold[15] describe these simplifications briefly with references.
- Hazard plotting. This graphical procedure can be used to fit an appropriate hazard rate to data without any analytical techniques. It is performed on distribution specific paper, usually Weibull probability paper, is fast and easy to use and is often taught to semi-skilled analysts in the industry. See Nelson[16].
- Bayes's methods or Bayesion theory. Bayesian statistical inference is based on a subjective viewpoint of probability. This subjective viewpoint is often referred to as the "degree of believe" in the

behavior of a certain parameter, which is considered as a random variable. The subjective viewpoint is captured by a specified *prior distribution* based on prior knowledge about a parameter. This prior distribution is then updated with the aid of Bayes's theorem to a *posterior distribution* after new observation of the parameter of interest. See Hines and Montgomery[26].

- Multivariate models. This type of modelling is used more at a system level than at a simple component level. It is assumed that the components in the system as well as the system itself behave according to a renewal process and that more than one type of failure is associated with the system. Examples are a system of components in parallel where a number of components have to fail before system failure or components in series where failure of any component causes system failure. The reliability functions for this type of modelling are similar to those outlined above except that it is expressed in terms of the joint probabilities of different occurrences of failure. See Crowder et. al.[27].

All of the above mentioned techniques have the ability to accommodate incomplete observations or suspensions by allowing for it in parameter estimation procedures like the maximum likelihood method.

2.3.2 Non-probabilistic Modelling Approach

Non-probabilistic models or natural reliability estimators are the direct statistical analog of the probabilistic models described in the previous section. Natural reliability estimators represent the reliability functions in a discrete manner based on observed failure times and do not recognize the existence of an underlying distribution as a primary assumption. As is the case with the probabilistic approach, the non-probabilistic approach only models the primary use parameter, thereby excluding concomitant information on failures. A brief introduction to the reliability functions in their non-probabilistic forms is given below.

2.3.2.1 Failure Density Function

To estimate the failure density function in a discrete manner is not non-probabilistic in the true sense of the word since we are estimating the underlying distribution of a data set. It is listed here however because no probabilities are predicted with the discrete function but probabilities are simply reproduced in retrospect.

$$f(t) = \frac{\frac{\Delta n}{N}}{\Delta t} = \frac{1}{N}\frac{\Delta n}{\Delta t} \qquad (2.6.)$$

In (2.6.) Δn denotes the number of failures in the interval $[t,t+\Delta t]$, N the total number of failure observations and Δt an appropriate time length.

2.3.2.2 Reliability and Unreliability Functions

If no incomplete observations are present in the data, the reliability or unreliability function can be estimated with:

$$R(t) = 1 - F(t) = 1 - \frac{\text{Number of failures up to time } t}{N} \qquad (2.7.)$$

This function was generalized by Kaplan and Meier[25] to handle censored observations.

2.3.2.3 Hazard Rate

Without making an assumption on the underlying distribution in the data, the hazard rate can be obtained by:

$$h(t) = \frac{1}{n(t)}\frac{\Delta n}{\Delta t} \qquad (2.8.)$$

n(t) is the population surviving up to time *t*.

Non-probabilistic estimators act as very useful guidelines on the form of the reliability functions before having to decide on a continuous distribution to fit to the data if a probabilistic approach is going to be used.

2.3.3 Regression Modelling Approach

Regression modelling of failure data can be seen as a hybrid between the previous two approaches but it has enough unique features to be recognized as a solitary third approach to renewal data modelling. Two clear properties define the regression modelling approach:

(a) Regression models do not use the existence of an underlying failure distribution as primary assumption but immediately recognize the being of the survivor function or hazard rate, similar to non-probabilistic models.
(b) Not only is the primary use parameter modeled by regression models but also concomitant information surrounding failures or covariates.

Regression models found in the literature are introduced below according to the date of first introduction without mathematical details.

2.3.3.1 Accelerated Failure Time Models (AFTM) - 1966

Accelerated failure time models or accelerated life models strive to estimate the survivor function of a component as a function of its *accelerated* life. The accelerated life is a modified use parameter for a component that is determined by the influence of covariates on the original use parameter. Covariates accelerate (or decelerate) the predicted arrival of failures, thereby allowing for the effects of circumstantial influences surrounding failures.

2.3.3.2 Proportional Hazards Models (PHM) - 1972

For proportional hazards models, the hazard rate is of primary concern. The hazard rate is determined by a baseline hazard rate which is a function of time only and a functional term dependent on time and covariates which acts multiplicatively on the baseline hazard rate. The multiplicative effect of the covariates on the baseline hazard rate implies that the ratio of the hazard rates of any two items observed at any time t associated with two different covariate sets will be a constant with respect to time and proportional to each other.

2.3.3.3 Prentice Williams Peterson Model (PWP model) - 1981

This model is a major elaboration of the PHM and although very little research has been done on this model it is considered to have enormous potential. It is suitable to model data sets generated by both renewal processes and repairable systems and allows for the effects of covariates on the failure process. It also takes scenarios into account where more than one failure have occurred on a specific unit and it is possible to stratify data, i.e. group data based on influential differences.

2.3.3.4 Proportional Odds Models (POM) - 1983

The odds of a failure occurring is defined as the ratio between the unreliability function and the reliability function. For this model, a value φ is introduced as the ratio between the odds of a failure occurring estimated when considering the influence of covariates and the odds of a failure occurring estimated without considering covariates. The model assumes that the covariates has a diminishing effect on a component as time increases, i.e. $\varphi \to 1|_{t\to\infty}$.

2.3.3.5 Additive Hazards Models (AHM) - 1990

For additive hazards models the hazard rate is also of primary interest as in the case of PHM. This time the hazard rate is constructed as the sum of a baseline hazard rate which is a function of time only and a functional term dependent on time and covariates. The direct analogue of this model could also be used in repairable systems to model *failure rate* in an additive manner.

2.3.4 Neural Networks

Neural networks have a large appeal to many researchers due to their great closeness to the structure of the brain, a characteristic not shared by other modelling techniques. In an analogy to the brain, an entity made up of interconnected neurons, neural networks are made up of interconnected processing elements called units, which respond in parallel to a set of input signals given to each. The unit is the equivalent of its brain counterpart, the neuron.

A neural network consists of four main parts:

1. Processing units, where each processing unit has a certain activation level at any point in time.
2. Weighted interconnections between the various processing units which determine how the activation of one unit leads to input for another unit.
3. An activation rule which acts on the set of input signals at a unit to

produce a new output signal, or activation.

4. Optionally, a learning rule that specifies how to adjust the weights for a given input/output pair.

Recently attempts were made to apply neural networks in the reliability modelling field[28,29,30]. Failure data with covariates were used as processing units to estimate or teach the neural network and additional data was then used as inputs to predict future outputs. The results were compared to the predictions of proportional hazards models and accelerated failure models and proved to be very promising.

Neural networks are not considered to be an "official" renewal modelling approach by failure data analysts because very little research has been done on its application in reliability modelling up to date. It is listed here however because of its enormous future potential. No further reference to neural networks will be made in this dissertation.

2.4 Optimal Use Based Preventive Renewal Decision Models

As stated in the introduction the aim for optimal decision making in renewal theory is not to predict the exact time to failure of a component but to minimize the total life cycle cost of a component. This is done with the aid of the described reliability functions estimated by single variable techniques or regression models.

Two very important quantities in optimal decision making are the cost of unexpected replacement or failure of a component, C_f, and the cost of preventive replacement C_p. It is normally much more expensive to deal with an unexpected failure than it is to renew preventively. A balance has to be obtained between the risk of having to spend C_f and the advantage in the cost difference between C_f and C_p without wasting useful remaining life of a component. The optimum economic preventive renewal time will be at this balance point.

A similar argument to the one above can be followed if availability of a component is more important than cost. Only this time the downtime due to unexpected failure, T_f, and the downtime due to preventive replacement, T_p, are weighed against each other to determine an optimum.

2.5 Concluding Remarks

Use based preventive renewal has established itself as a maintenance strategy with the ability to bring huge cost savings about if implemented correctly. This statement is supported by countless instances in the industry where use based preventive renewal is practised successfully.

When considering this preventive strategy it is important to note that it is extremely dependent on accurate failure data, which is often not easy to find in practice because of negligence in failure data recording processes. This requirement also implies that use based preventive renewal can only be applied after several failures of a component have occurred.

Renewal theory as outlined above is familiar to most reliability engineers, especially the probabilistic and non-probabilistic approaches. Regression modelling in renewal theory is still in its infant stage in the reliability world although there are no doubts about is potential. The probabilistic and non-probabilistic approaches have one prominent disadvantage in the fact that concomitant information is not included in models but this problem is being addressed in regression models.

3 Preventive Renewal Based on Vibration Monitoring Predictions

By analyzing the vibrational behavior of a component, an enormous amount of information about the component's condition can be learned. This fact has been proven over and over in the past and it has driven development on theoretical vibration analysis techniques up to a very high technological level. Neural networks, self organizing maps, fuzzy logic, time series analysis, coherence, frequency band energy methods, trending, correlation and many other techniques were developed for decision making in vibration monitoring or were applied to vibration monitoring as a result. Very little of this high level vibration technology is found in the industry however and often only absolute basic vibration techniques are used in condition monitoring programs.

An overview of techniques often used in preventive renewal based on vibration monitoring is presented in this section. The term "vibration monitoring" here, refers to the typical vibration monitoring practices found in the industry and not to the total complex field.

3.1 Methodology

Vibration monitoring is a condition monitoring maintenance strategy which relies almost entirely on the current condition of the component as determined by vibration parameters to make renewal decisions. Benchmarks or envelopes are specified for every measured vibration parameter and if a parameter or certain parameters exceed these specified levels, the component is renewed. Reliable benchmark levels are usually specified by the component's manufacturer although experience could optimize these levels to a certain extent. Graphical aids like vibration severity charts and waterfall plots are often used to assist the vibration monitoring person in making renewal decisions.

3.2 Vibration Parameters

In most cases only time domain vibration parameters are measured to evaluate the condition of a component. These include peak signal values, RMS values, Crest factors and Kurtosis. Frequency domain analyses commonly found are power spectral density analysis, cepstrum and high-frequency resonance techniques.

3.3 Shortcomings of Preventive Renewal Based on Vibration Monitoring

A number of shortcomings that have an influence of this research project are outlined below.

3.3.1 Lack of Comparative Means Between Current Vibration Condition and Past Vibration Behavior

Very often in practice only short term changes in vibration levels are considered to estimate component reliability, i.e. only the vibrations measured during a specific component's life time are used to predict useful remaining life. This is usually done with the aid of waterfall plots where different vibration levels are presented in a user-friendly, graphical manner such that it is easy to recognize trends in vibration behavior.

No verified or established means exist to consider long term vibration behavior in reliability estimations. Long term vibration behavior refers to vibration histories recorded from similar components that have failed under equivalent conditions in the past. Long term vibration behavior of components certainly holds extremely valuable information in terms of current component reliability since vibration conditions during a component's life tend to repeat itself in subsequent components.

The lack of a scientific technique with which long term vibration information can be incorporated in present component reliability estimation is considered to be a shortcoming of preventive renewal based on vibration monitoring.

3.3.2 Significance of Vibration Parameters

Numerous vibration parameters are usually measured and evaluated when monitoring the condition of a component as discussed in (3.2.). In very few cases all of the measured parameters are significant in the failure process and often renewal decisions are made based on the level of a parameter totally insignificant in the failure process.

Up to date, it is impossible to identify vital parameters in the failure process if only the current vibration behavior is considered. This is a second major deficiency of vibration monitoring.

3.3.3 Calculation of Optimal Renewal Instant

Vibration monitoring is definitely not perfect as a predictive preventive maintenance strategy. A perfect predictive preventive maintenance strategy would be able to determine the exact length of a component's remaining life. No such method exists. Unexpected failures of components still do occur regardless of the fact that the vibration levels are monitored and unexpected failures are normally very expensive relative to preventive replacements. Thus, renewal decisions based on vibration monitoring do not bring into account the risk of an expensive unexpected failure or the possibility of loss of useful remaining life due to premature renewal.

3.3.4 Lack of Commitment towards Vibration Monitoring

In general there was found during this research project that there is a lack of commitment towards vibration monitoring in the industry. In many cases expensive vibration monitoring equipment is used as the flagship of the maintenance department although inspections are done very irregularly and not recorded properly. Often the information supplied by vibration monitoring is totally disregarded when a decision has to be made and experience or intuition is relied on. Even if vibration information is considered, the final decision is frequently left to the discretion of the vibration technician.

It does not matter how technologically advanced vibration monitoring is, if it is not practiced correctly meaningful results are impossible to obtain. This is a maintenance management issue and will not be addressed in the dissertation but this shortcoming could obviously have a huge effect on results from this dissertation.

4 Integrating Use Based Preventive Renewal and Vibration Monitoring

There is very little doubt as to the enormous economical advantages that preventive renewal have in maintenance engineering, whether the renewal instant is determined by use based statistics from the past or present condition monitoring (including vibration) information. The discussion above supports this statement but also identifies shortcomings in current practices where these approaches are used. A method with the ability to integrate the principles of use based preventive renewal and renewal based on vibration monitoring could potentially overcome the mentioned shortcomings while encompassing all the advantages of both approaches. Successful identification and implementation of such a method is the objective for this dissertation. The formal research objectives are:

(i) Combining used based preventive renewal principles and preventive renewal based on vibration monitoring to make more appropriate renewal decisions than with either one of the mentioned techniques alone.

(ii) Verifying the theory used to achieve (i) with data obtained from the industry.

The route to the objective certainly runs through use based regression models with measured vibration parameters as covariates. From the discussion above it should be evident that no other logical route exist to approach the problem since the probabilistic and non-probabilistic approaches are lacking to handle covariates and almost no research has been done on neural networks in reliability. The research area will thus immediately be narrowed down to the above-mentioned route. The strategy to be followed to the objectives is outlined below.

4.1 Literature Study

A thorough literature study has to be done on regression models suitable to model failure data generated by a renewal process to become acquainted with existing techniques and models. The aim with the literature study is not to go into the details of the various models but rather to become aware of the abilities of the different techniques.

4.2 Identification of Most Suitable Model

After an appropriate literature survey it would be possible to identify the model most suitable to integrate used based preventive renewal and preventive renewal based on vibration monitoring. This means that all the advantages and disadvantages of the various models considered in the literature study will have to be balanced to determine the best model.

4.3 Thorough Study on Chosen Model

To be able to implement the chosen model successfully an in-depth study on the mathematics of the chosen model will be done. This study will range from the original proposal of the model to optimal decision making, using the model.

4.4 Practical Evaluation of the Model

For this research project to have worth in the reliability modelling world, the theoretical results will have to be evaluated in practice. Data recorded in industrial situation will thus be collected and modeled to prove the success of this dissertation.