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Modified Failure Rates for Safety Instrumented Systems based on Operational Experience from the Oil and Gas Industry

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Problem description

A significant amount of operational data associated with safety instrument systems (SISs) has been collected by the oil and gas facilities on the Norwegian continental shelf. Data collection is required by several regulators and safety standards. Such data are generated from failure notifications and work orders in the maintenance system. Review of operational data indicates that groups of similar equipment can experience different failure rates even under nearly identical operational environment. Specific inventory- and operational parameters (e.g. properties of equipment, maintenance practices, applied technology etc.) may result in those difference on reliability performance. It is of high interests to identify and analyze the parameters and would be found relevant relationships between the parameters and failure data (e.g. failure causes, failure modes or detection methods).

Preface

This master thesis documents the master project executed spring 2017 and is the final step in graduating with MSc degree from Norwegian University of Science and Technology (NTNU). The project has been performed in collaboration with SINTEF and STATOIL. The work is accomplished under the supervision of Prof. Mary Ann Lundteigen at the Department of Mechanical and Industrial Engineering. It is assumed that the readers have basic knowledge within the field of reliability, preferably related to safety instrumented systems in the oil and gas industry.

I would like to express my deep and heartfelt appreciation to main supervisor, Prof. Mary Ann Lundteigen, for giving me tremendous time, continuous encourage, sincere advice and great patience to review my work. During regular meeting with her, I have gained new knowledge and skills in project research and academic writing. I am also very grateful to my co-supervisors, Stein Hauge and Solfrid Håbrekke at SINTEF Safety Department, for their support and guidance, inspiring discussions and comments on the project thesis. I would also like to give special thanks to my co-supervisors, Bjørnar Berg and Espen Sørensen at Statoil, for providing access to relevant data and patient explanations concerning technical details throughout the project. Without their help and guidance, I wouldn't have completed this master thesis.

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Summary

In the oil and gas industry, SISs are designed to ensure production safety and reduce risk of major accidents. SISs should be demonstrated the fulfillment of specified safety requirement by appropriate reliability analysis with particular interest on the types of faults and how often they occur for various SIS equipment. Such operational data provides a basis for reliability quantification for each safety instrumented function (SIF), which is needed to demonstrate that safety integrity level (SIL) has been achieved. Review of operational data indicates that similar equipment can experience different failure rates, even it installed in similar environments. This variation on reliability performance can be explained by inventory- and operational parameters.

The main objective of the thesis is to propose an approach to identify the most important parameters based on data analysis, and suggest their relative influence on reliability performance of installed equipment. The result can be used to modify failure rates if significant parameters are identified. Modified failure rates enables the reliability analyst to more precisely quantify the reliability performance in SIL follow-up phases and predict the variations of reliability performance for new facilities, where changes in inventory- and operational conditions can be forecasted.

Statistical methods for analyzing inventory- and operational parameters are employed in the project, where shutdown valves have been considered in particular. The data analysis results illustrate the strong relationships between reliability performance and some parameters of the shutdown valves, e.g. sizes, leakage requirement and flow medium. Failure analysis is also performed to explain and verify the results. Modified failure rates of the shutdown valves for a new facility are established as an example in this thesis.

In short, the thesis proposes an approach to identify important parameters for reliability performance and modify failure rates based on operational data from the oil and gas industry. The work identifies a number of challenges and limitations in the approach and suggests considerable further work.

Contents

Abbreviations

ANOVA	–	Analysis of variance
COX	–	Proportion hazards model
DD	–	Dangerous detected
DU	–	Dangerous undetected
DOP	–	Delayed operation
ESD	–	Emergency shutdown valve
FMECA	–	Failure mode effects and diagnostic analysis
FTC	–	Fail to close
FTO	–	Fail to open
GLM	–	Generalized linear model
LCP	–	Leakage in closed position
MTTF	–	Mean time to failure
NOG	–	Norwegian oil and gas
OREDA	–	Offshore reliability data
PFD	–	Probability of failure on demand
PDS	–	Reliability of SIS
PSD	–	Process shutdown valve
PSA	–	Petroleum safety authority
PST	–	Partial stroke testing
SIL	–	Safety integrity level
SIS	–	Safety instrumented system
SIF	–	Safety instrumented function

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1 Introduction

1.1 Background

Within the oil and gas industry, SISs are designed to ensure production safety and reduce risk by implementing SIFs [1]. Each SIF should be demonstrated the fulfilment of SIL requirements by appropriate reliability analysis with interest on the types of faults and how often they occur for various SIS equipment. Such operational data are desired to be collected as input to reliability quantification of SISs during the whole life of SISs. A specific procedure for calculating failure rates and changing test intervals has been proposed by SINTEF [2]. Data collection also provides a basis for making decision on risk control, optimization maintenance and saving cost. It can be used to predict failure rates during design of new facilities, having data and experience with the similar equipment to be installed.

Data collection is required by several regulators and safety standards. It is required by the Norwegian Petroleum Safety Authority (PSA) to monitor the performance of barriers during the whole life of facilities (ref. Management Regulations, section 5 and section 19). The recent updated IEC 61511 has highlighted the requirements concerning the quality of reliability data. The data should be credible, traceable, documented and justified. ISO 20815 emphasizes the systematic collection and treatment of operational experience, which is considered as a mean for improvement of production and safety critical equipment [3]. NOG 070 also proposes that operational data could be used as a basis for reliability calculation based on historic field experience [4].

A significant amount of operational SIS data have been collected by the oil and gas facilities on the Norwegian continental shelf. Review established operational data illustrates that similar or same equipment may experience different failure rates even under comparable operational environments [5]. This variation on reliability performance may be explained by various parameters. Those parameters refer to inventory parameters and operational parameters that impact on the equipment's reliability performance, e.g. sizes for shutdown valves, measuring principle for level transmitters etc.

The focus of this master thesis is hence to propose an approach to identify significant parameters and investigate influence of inventory- and operational parameters on reliability performance and modify failure rates based on the analysis result. Modified failure rates are defined as more specific failure rates taking into account inventory- and operational parameters [5]. It is of interest to establish modified failure rates due to their application: 1) For providing more precise failure rates in follow-up SIS phase. 2) For predicting reliability performance for a group of equipment at a new facilities, where the equipment experience similar environmental and operational conditions as the existing facilities.

1.2 Objectives

The main objective of the thesis is to propose an approach to modify failure rates, including 1) identifying critical parameters that impact on reliability performance and investigating relationship between the parameters and reliability performance; 2) modifying failure rates for a specific group of equipment based on parameter analysis and failure analysis.

The main objectives will be achieved through addressing the following questions:

- Which group of equipment should be selected and what are criteria to identify the equipment?
- What are the most relevant parameters that can explain varying reliability performance? Is the equipment likely to be sensitive to those parameters?
- Which method is efficient to analyze the impact from inventory- and operational parameters on reliability performance?
- How to modify failure rates in relation to important inventory- and operational parameters?

1.3 Assumptions

The assumptions within the approach have a significant impact on validity and reliability of the conclusion. It is thus required to make reasonable assumptions. The following assumptions are made in this master project:

- Uncertainties due to inadequate information and data will be disregarded.
- The thesis focuses on DU failures of shutdown valves, covering various failure modes.
- Failure data used in this thesis have been collected by SINTEF.

- All the items have been put into service at time $t = 0$, and failure time is supposed to be stochastic independent and identically distributed.
- Failures occurred in burn-in phase have been removed because those failures are often related to start-up and installations issues and many of them are typical systematic faults.

1.4 Approach

The approach used in the thesis include the following steps:

- Identify equipment and parameters. Based on review of existing failure data, select one specific equipment group and identify parameters of equipment.
- Data collection. Collect information of equipment from one or more facilities and connect equipment parameters with failure records and maintenance records.
- Data analysis. Select appropriate approach to identify critical parameters that impact reliability performance significantly.
- Estimate failure rates. Based on updated failure rates categorize equipment groups according to significant parameters and modify failure rates for a new facility.

1.5 Structure of the thesis

- Chapter 1: Describe background, objectives, approach, as well as assumptions for this master thesis.
- Chapter 2: Review basic concepts and definitions with respect to failures and reliability estimation.
- Chapter 3: Elaborate statistical methods for analyzing data and modifying failure rates.
- Chapter 4: Present an approach to modify failure rates, study and select specific equipment and corresponding parameters.
- Chapter 5: Describe data analysis process and show the results of the analysis.
- Chapter 6: Elaborate an example of modifying failure rate based on failure analysis.
- Chapter 7: Concluding remarks and discussion, propose recommendations for further work.

2 Basic concepts and definitions

The objective of this chapter is to present main concepts and definitions related to failures, failure rates, reliability, inventory and operational parameters.

2.1 Failures

In IEC 60050-192, a failure is defined as *an event that results in a fault of the item* [6]. There are two main functions for SISs: 1) Ability to shut down or go to a safe state on demand. 2) Ability to enter or maintain safe state upon certain fault conditions. Failures associated with faults of SISs can be classified into four groups according to IEC 61508, IEC 61511 and NOROGs guideline 070:

- **Dangerous Detected** (DD): A failure which has the potential to put the component in a hazardous or fail-to-function state. This failure can be detected by self-test or online comparison of instruments.
- **Dangerous Undetected** (DU): A failure with potential to put component in a hazardous or fail-to-function state, but cannot be detected automatically or by self-test. Typically, it will be revealed during function test, random observation or upon real demand.
- **Safe Detected** (SD): A failure which does not have the potential to put the safety-related system in a hazardous or fail-to-function state and can be detected by automatically.
- **Safe Undetected** (SU): A failure which does not have the potential to put the component in hazardous or fail-to-function state and cannot be detected by test.

A similar classification has also been accepted by the PDS-method[1]. However, it should be noted that a given failure may be classified as either dangerous or safe depending on the intended application [7]. For example, loss of hydraulic supply to a valve actuator will be dangerous failure in an energize-to-trip application and safe failure in a de-energize-to-trip application. The focus of this master thesis is DU failure because they are the main contributors to unreliability for SISs.

[1] See also www.sintef.no/pds

2.2 Failure rates

Failure rate is defined in ISO 14224 as *conditional probability per unit of time that the item fails between* t *and* $t+dt$ *, provided that it has working over* $[0,t]$ [8]. It is used to reflect reliability performance and expresses numbers of failure per unit of time. There are different types of failure rates that apply for various situations:

- **Generic failure rates.** It derives from handbooks on the basis of operational experience, laboratory tests and expert judgements [5]. Examples of sources for generic failure rates are OREDA handbook, PDS handbook and EXIDA handbook. The generic failure rate indicates the average of the expected performance for the equipment under consideration, e.g. $\lambda_{DU} = 2.1 \times 10^{-6}$ per hour is a generic failure rate for emergency shutdown (ESD) valve in the PDS data handbook [7].
- **Operational failure rates**. It is based on companies own operational data sources (e.g. maintenance system) and thereby represent real failure data from operation. This data can be used to generate an average performance of equipment for a single or several facilities [5].
- **Modified failure rates**. It is defined as more specific failure rates taking into account inventory- and operational parameters [5]. For example, modified failure rates of ESD valves may be a result of breaking down the failures into various groups according to the sizes of ESD valves: small-sized (e.g. diameter < 1 inch), medium-sized (e.g. diameter 1-3 inch) and large-sized (e.g. diameter > 3 inch).
- **Manufacturer failure rates.** They are provided by manufactures for some specific products, based on failure reports, analyses and laboratory testing or a combination of these. Manufacture failure rates are more suitable for comparing performance among different products and less suited for predicting reliability of system [5].

Figure 1 illustrates the relationships between the four types of failure rates and their application. Generic failure rates are based on a large amount of operational experience from several facilities and for comparable equipment. They are often utilized in early project phases due to immature design and limited information about the selected equipment [4]. Operational failure rates come from one specific facilities, related with groups of equipment data (e.g. identification, character of equipment) and corresponding failure data (e.g. number of failures, operational time, failure modes etc.). Manufacture failure rates focus on groups of equipment from a specific vendor. They are widely used for comparison and selection of equipment during procurement. Modified failure rates take into consideration equipment characteristics as well as operational and environmental data (e.g. location, operational condition, special environment etc.). It can mainly be applied for SIL follow-up and estimate failure rates for new facilities or modify equipment by comparing conditions with the exciting facilities.

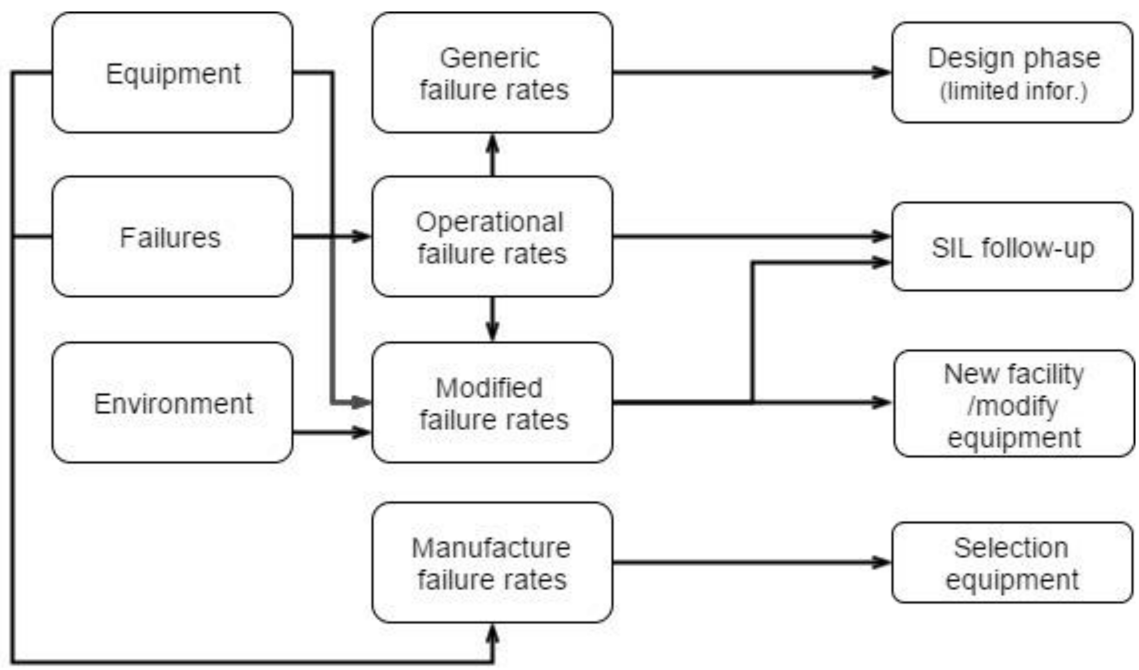


Figure 1 Relationships between failure rates and relevant applications

2.3 Reliability terminology

The following other concepts will be mentioned in this thesis:

- **Failure mode**: A failure mode is a manner in which failure occurs and may be related with the function lost [6].
- **Failure cause**: is a set of circumstances that leads to failure. A failure cause may originate during specification, design, manufacture, installation, operation or maintenance etc. [6]
- **Failure effect**: refers to consequence of a failure within or beyond the boundary of the failed item [6].
- **Failure mechanism**: is a process that leads to failure that may be physical, chemical, logical or a combination [6].
- **Aggregated operational time**: refers to aggregated time in operation for all components within an equipment group [8].
- **Detection method**: are ways to detect in which failures for a component or safety system are revealed [1].
- **Testing interval** (τ): expresses the time between function testing of a component or system [7].
- **Self-testing**: is a build-in test for assessing internal system status, which may occur on start-up and/or throughout operation [6].
- **Function test**: refers to a periodic test performed to detect dangerous hidden failures in a SIS so that, if necessary, a repair can restore the system to an 'as new' condition [1].
- **Partial stroke test (PST)**: is a testing method to reveal fail to close or fail to open for a valve by moving the valve without fully closing or open the valve [1].
- **Leakage test**: is a testing used to detect internal leak of the process fluid [1].
- **Probability of failure on demand** (PFD). is the average probability that a SIS is unable to perform its safety function upon demand [9]:

$$PFD_{avg} = \frac{1}{\tau}\int_0^{\tau} PFD(t)dt \approx \lambda_{DU} \cdot \tau / 2 \qquad (2.1)$$

2.4 Term of parameters

Parameters are referred to equipment attributes and operational environment that may impact on reliability performance, covering:

- **Inventory parameters** includes identification data (e.g. facility, location, tag number, equipment character), characteristics data (such as type, size) and operational data (e.g. operating time).
- **Operational parameters** includes environmental characteristics (e.g. pressure, temperature) and operation condition (e.g. flow medium).

This master thesis will more focus on the inventory parameters and operational conditions due to insufficient information for environment, e.g. the pressure within ESD and process shutdown (PSD) valves are not available in practice.

2.5 Reliability data in industries

Functional safety in various industries are different complying with relevant standards. SISs in the oil and gas industry focus on ability to shut down or isolate the production process to protect equipment under control (EUC) and return EUC to a safe state [1]. The main standards regarding SISs are IEC 61508 and IEC 61511. The main safety function for an aircraft is to keep the engines running and to maintain safe distance between aircraft by monitoring pressure from sensors and height from radar. Examples of applicable safety standards are US RTCA DO-1788, US RTCA-254 etc. SISs in the nuclear industry are mainly used to ensure cooling of the core and monitor earthquake activities according to standards IEC 61513 and IEC 61238.

A number of handbooks are available in different industries: oil and gas (e.g. OREDA and PDS), military (e.g. MIL-HDBK-217), aviation (e.g. guideline A120-17A and FAA regulations) and nuclear power plant (e.g. EIReDA, IAEA-TECDOC-1804 and T-book) etc. There are different motivations for providing various reliability data dossiers in the different industries. In the oil and gas industry, handbooks mainly focus on data for SIS elements. OREDA presents failure rates in relation to specified failure modes and mechanical equipment, including mean failure rates among the installations, lower and upper failure rates which mean 90% of the variation between the multiple samples [10]. SINTEF PDS handbook provides average failure rates containing DU failures, DD failures and safe failures [7]. In the aviation industry, obligation of collecting data lays on the continuing airworthiness of aircrafts according to the EASA regulation[2]. For the nuclear industry, reliability data in handbooks are mainly related to the components in safety-related systems, e.g. reactors, sites or reactor types [11].

Failure rates in various handbooks are computed by using different techniques and methods. In MIL-HDBK-217, failure rates are given by analytical functions which depend on parameters, e.g. temperature, voltage or electrical intensity [12]. The reliability data in EIReDA covers description of the equipment (e.g. identification, technical characteristics) and event recorded data (e.g. size of the samples, reliability parameters, accumulated time, number of failures) [13]. T-book's data based on critical failures includes probability of failures on demand, failure rates in standby, failure rates during operation and mean active repair time [14].

Several methods to estimate and predict the failure rates are available in various industry. The most common methods have been categorized into three groups for generic failure rates, operational failure rates and physics-of-failure rates, as shown in Figure 2. A method proposed by Brissand, is to estimate failure rates by comparing factors under generic conditions and factors under specific conditions for a specific plant [15]. Methods proposed by Brissand and themethod in MIL-HDBK-217F are based on generic failure rates. Vatn also suggested a procedure to estimate failure rate by predicting the effect of risk reducing measures [16]. This method and the method in Telcordia SR332 are related to operational failure rates. There are other physics-of-failure methods to modify failure rates are based on physics-of- failure parameters and acceleration models.

[2] Information of aviation industry comes from Professor Bjørn Axel Gran in institute form department of production and quality in NTNU.

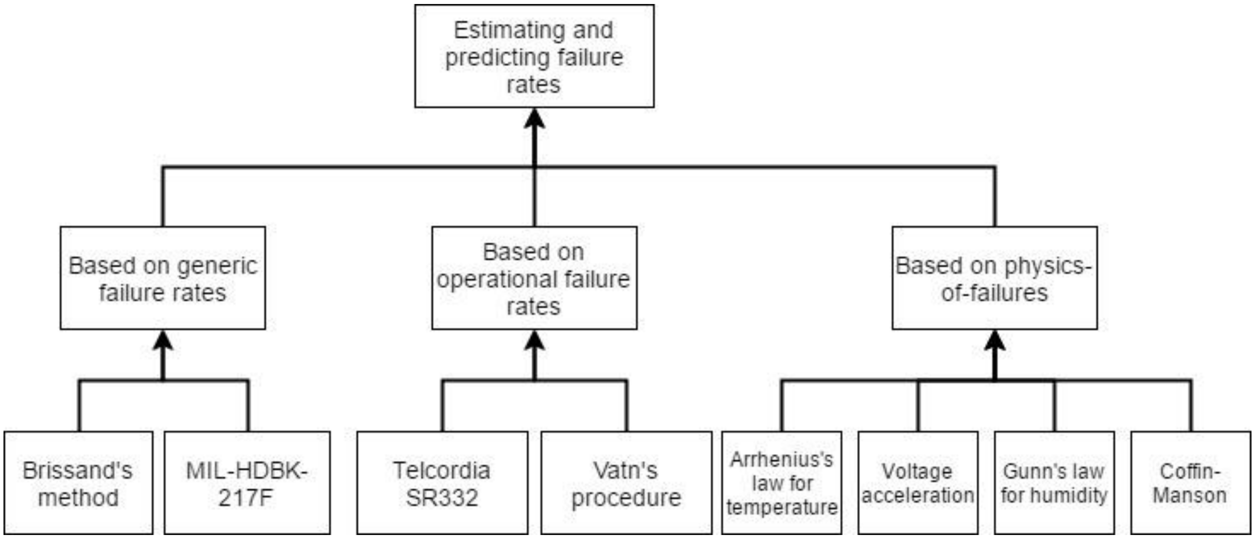


Figure 2 Methods for estimating and predicting failure rates in various industry

2.5.1 Based on generic failure rates

One example to modify failure rates based on generic failure rate is a method in MIL-HDBK-217F. It provides constant failure rate estimates for electronic equipment as well as the Part stress methods to account for influencing factors [1]. The method uses the part failure rate models where influencing factors covariant its effect and importance to the basic failure rate. Various coefficients should be determined by expert judgement. The general expression of the model is shown below:

$$\lambda_P = \lambda_b \cdot \lambda_1 \cdot \lambda_2 \cdot \lambda_3 ... \lambda_m \tag{2.2}$$

Where, $\pi_1 \pi_2 \pi_3 \cdots \pi_m$ are the influencing coefficients, e.g. temperature, application, power rating, electrical stress, contact construction, quality and operating environmental factors.

2.5.2 Based on operational failure rates

Telcordia SR332 is also regarded as a method to predict failure rate. It is called reliability prediction procedure for electronic equipment. Telcordia SR332 uses MIL-HDBK-217 as a starting point and predicts failure rates based on field experience [12]. There are three ways to predict a failure rate: 1) generic failure rate defined by the standard; 2) supplement the first method with real data that obtain from testing; 3) supplement the first method with real data that obtain from identical items under the same environmental conditions, identical items under different conditions or the field item are similar but not identical conditions. This method enable field data to incorporate into prediction in order to obtain more accurate results.

2.5.3 Based on physics-of-failure life cycle.

This kind of methods require comprehensive knowledge of the thermal, mechanical, electrical and chemical life cycle environment as well as process leading to failures in the field [17]. Many appropriate acceleration models are applied to predict failure rates, e.g. Arrhenius's law for temperature, Voltage acceleration, Gunn's law for humidity, Coffin-Manson based law for thermal cycling fatigue etc.

3 Statistical methods for data analysis

This chapter presents some statistical methods to analyze inventory- and operational parameters that significantly impact on the reliability performance as well as a method to modify failure rates based on operational data.

3.1 Overview of methods

Statistical methods for data analysis in this project involves three main steps, as shown in Figure 3, parameters analysis, equipment classification and modify failure rates. The aim of first step is to analyze parameters by using various methods, e.g. analysis of variance (ANOVA), generalized linear model (GLM) and proportion hazards model (COX model). The second step is armed at categorizing equipment into groups in accordance with significant inventory- and operational parameters. Modifying failure rates is the next step for generic failure rates or operational failure rates. Generic failure rates are derived from data from a range of facilities, while operational failure rate is regarded as a specific failure rate. The methods in step 1 and step 3 will be described in detail in the following sections.

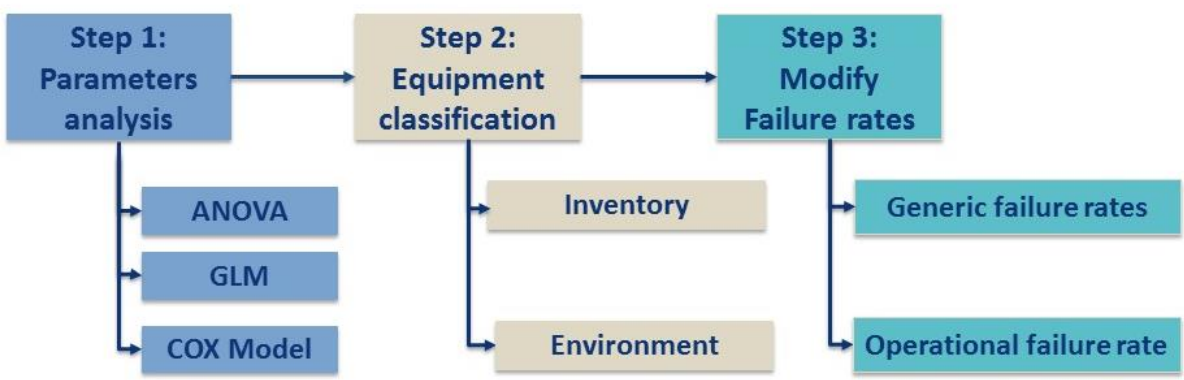


Figure 3 Overview of statistical methods in data analysis

3.2 Parameter analysis

A number of the different methods can be implemented to analyze inventory- and operational parameters. To retain validity and reliability of the analysis results, it is vital to determine an appropriate method that depends on characteristics of the data. The flowchart in Figure 4 illustrates the selection process.

There are two kinds of most commonly used estimation methods: Non-parametric estimation and parametric estimation. Nonparametric estimation makes no assumptions about the probability distribution of the variables. Kruskal-Wallis test and Friedman test are two nonparametric estimations that are equivalent to the parametric method ANOVA. Kruskal-Wallis test is used to test on the equality of median. Friedman test can also be employed to test on medians from three or more samples [18]. Those nonparametric tests are utilized to compare samples (e.g. failure time in this thesis) and demonstrate whether the samples originate from the same distribution.

Non-parametric estimation accommodate many conditions that parametric estimation do not handle, including non-normal distribution of samples, small sample sizes, ordered variables and outliers. In most cases, the choice between parametric and nonparametric estimation ultimately comes down to sample size and whether the center of the data's distribution is better reflected by the mean or the median [18]. However, it seems to be difficult to make accurate quantitative statements from non-parametric estimations. The results of nonparametric analyses are more likely to be intuitive. The master thesis thus focus on parametric estimation. Parametric estimation focuses on the parameters, e.g. mean and the standard deviation and makes various assumptions about the data.

Parametric estimation starts from failure time analysis. Considering an item (e.g. a valve) that is put into operation at t=0, failure times refers to the time from t=0 to the time in hours when the item doesn't function. It differs from the mean time to failures, i.e. the mean time between consecutive occurrences of failures. The aim of failure time analysis is to estimate the distribution of failure time. When the observation time is a specific period, not from the start of operation, GLM based on binomial distribution of failures should be considered. If failure time is supposed to be normally distributed, it is possible to perform ANOVA to analyze parameters. When distribution is known to be one of exponential family, e.g. binomial distribution or passion distribution, GLM model can be to analyze inventory and operational parameters. In the case of

Non-exponential family distribution, COX model is a method to assess simultaneous effect of parameters on reliability performance without consideration of distribution of failures. In this master thesis, ANOVA, GLM model and COX model will be preferable methods to analyze inventory- and operational parameters.

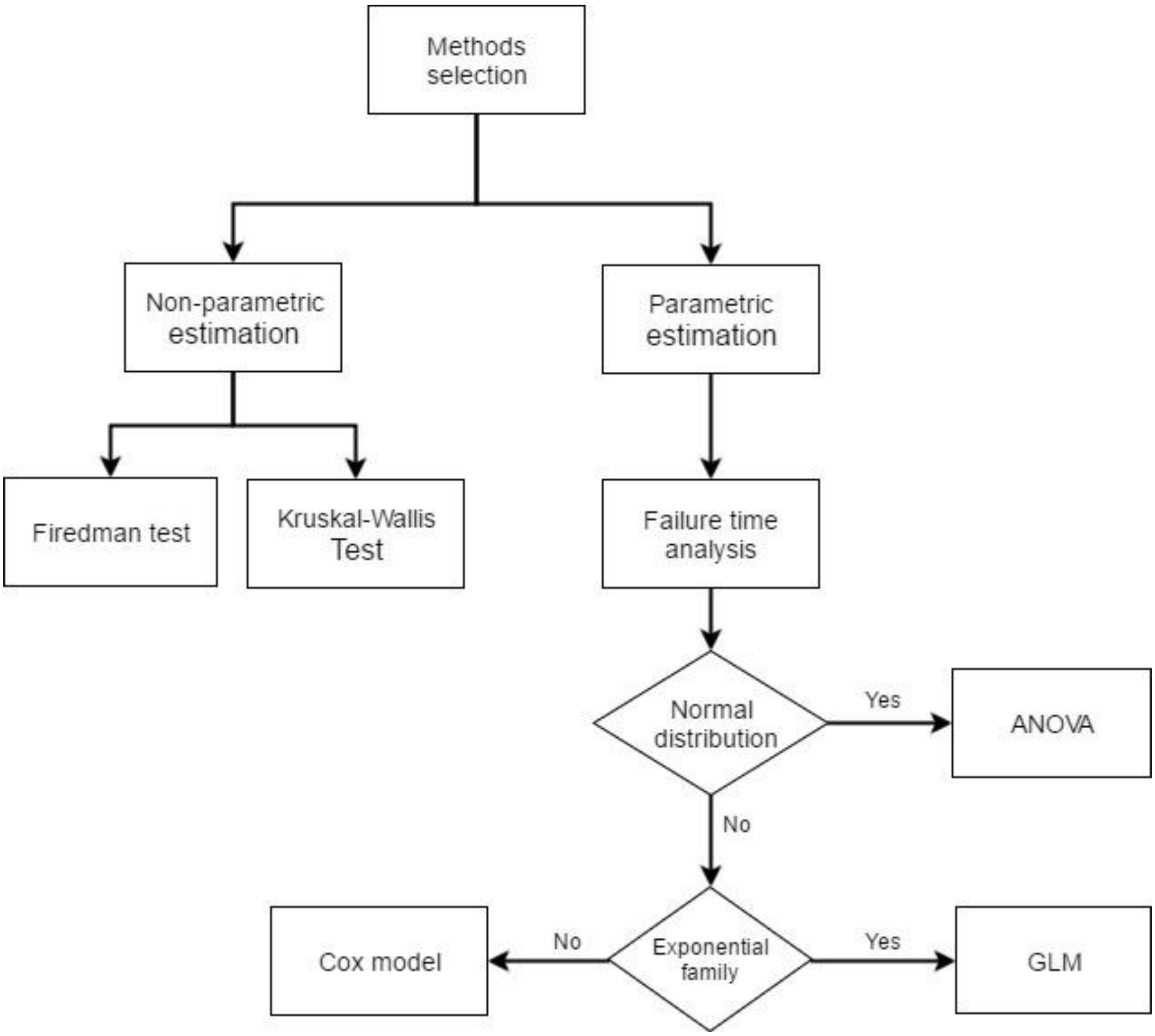


Figure 4 Flowchart of selection methods for parameter analysis

ANOVA, GLM model and COX model based on various distribution assumptions and different criteria, as shown in Table 1. Methods selection should take into account the failures distribution. That is the reason why we will perform failure time analysis as a basis of parameter analysis.

Table 1 Summary of parameter analysis

Methods	Distributions	Criteria	Estimations	Formula
ANOVA	Normal distribution	Failure time	Least squares estimation	$T = \sum b_{ik} x_{ik}$
GLM	Exponential family (Binomial)	Failure probability	Maximum Likelihood Estimation(MLE)	$\log(\frac{p}{1-p}) = \sum b_{ik} x_{ik}$
COX	Free-distribution	Failure rates/ hazard ratio	Partial likelihood	$\lambda_k = \exp(\sum \beta_{ik} x_{ik})$

ANOVA is widely used in reliability assessment because it is efficient in comparing the influences of several factors (inventory- and operational parameters). Nevertheless, it can only be applied for normal distribution of samples. In case that failures is normally distributed and have equal standard deviation, then ANOVA can be performed to analyze parameters.

In GLM models, it is assumed that the response variables is exponentially distributed. Then linear regression relationship between the response variables and the explanatory variables can be analyzed. In this instance, failure is supposed to be binomially distributed since the response failure can be regarded as discrete variables ('success' as 1 and 'failure' as 0). GLM model enables us to predict failure probability and analyze parameters that significantly influence failure probability.

It is unnecessary for COX models to make any assumption about the shape of the underlying distribution of failures. However, it is required to check some assumptions by statistical test, which will be introduced later.

Figure 5 illustrates different input and output in those models. Inputs of the models are related to inventory- and operational parameters as well as failure data (e.g. failure time, failure rates). Outputs in the models are used to check whether there is statistical significance (P-value) and estimated impact on reliability performance for each parameter (e.g. F value for ANOVA, exponential coefficient for GLM model and failure rates for COX model). The following sections will introduce those models in detail.

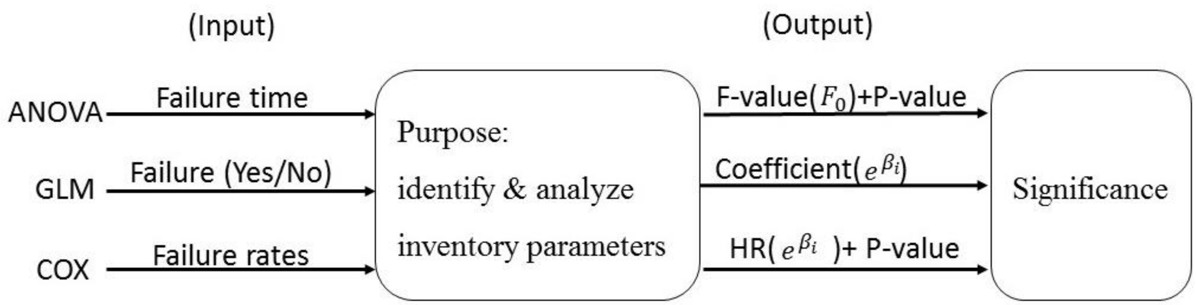


Figure 5 Statistical methods of input and output

3.2.1 ANOVA

ANOVA is a term used for comparing means of groups of observations where the groups are defined by the levels of factors [19]. It is performed to analyze contributions of specific factors (e.g. inventory- and operational parameters, such as size) to the total variability [20]. Based on least square estimation, an important consideration in this method is to analyze the differences between levels (categories, e.g. large-sized, medium-sized and small-sized) and within levels (e.g. in large-sized groups). Here, take one factor with n levels and k observed groups as an example. The total variation can be calculated as [20]:

$$SS_T = SS_E + SS_P = \sum_{i=1}^{n}\sum_{j=1}^{k}(y_{ij} - \overline{y_{i\cdot}})^2 + k\sum_{i=1}^{n}(y_{i\cdot} - \overline{y_{\cdot\cdot}})^2 \qquad (3.1)$$

Where SS_T is the total variation, SS_E is the variation at the same level and SS_P is the variation from different levels. y_{ij} is a response variable for the observation j at level i, implying the outputs measured in the tests. The term response variable is referred to measurements that are free to vary in response to other variables called explanatory variables [19]. $\overline{y_{i\cdot}}$ is the average value of response variable at level i and can be calculated as: $\overline{y_{i\cdot}} = \frac{\sum_{j=1}^{k} y_{ij}}{k}$. $\overline{y_{\cdot\cdot}}$ is the average value of all the response variables and can be expressed as: $\overline{y}_{..} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{k} y_{ij}}{N}$ ($N = k \times n$). Then analytical results are shown in Table 2.

Table 2 ANOVA result table for one-factor

Source	SS	DF	MS	F_0
Factor	SS_P	n-1	$MS_P = SS_P / n-1$	MS_P / MS_E
Variation	SS_E	N-n	$MS_E = SS_E / N-n$	
Total	SS_T	N-1		

Where, degree of freedom (DF) means the minimum number of comparisons necessary to draw a conclusion [20]. MS denotes the variation of the mean responses. If $F_0 > F_{\alpha,n-1,N-n}$, the factor is statistically influential on the response variables at $\alpha\%$ (e.g. 95%) significance level. $F_{\alpha,n-1,N-n}$ can be found in the F-distribution table.

3.2.2 GLM model

The aim of GLM is to describe the statistical relationships between response variable $Y_1,...Y_N$ and explanatory variables $x_1, x_2,...x_k$ by estimating the corresponding parameters $\beta_1, \beta_2,...\beta_k$ [21]. An explanatory variable is a type of independent variable that can affect response variables, which may be fixed by the experimental design.

GLM are mostly based on maximum likelihood estimation and allows for regression modeling when response variables are distributed as one of the members of the exponential family. The observational model is given by [21]:

$$y_i = \beta_0 + \beta_1 x_{i1} + ... + \beta_{ik} x_{ik} \tag{3.2}$$

$$y_i = g(\mu_i), \mu_i = E(Y_i) \tag{3.3}$$

Where g is a differentiable function called the link function [19]. A link function dependents on the distribution from exponential family is defined in

Table **3**:

Table 3 Link function for various exponential family members[21]

Distribution	Link functions	Models
Normal	$\mu_i = \beta_0 + \beta_1 x_{i1} + ... + \beta_{ik} x_{ik}$ (identity)	$\mu_i = \beta_0 + \beta_1 x_{i1} + ... + \beta_{ik} x_{ik}$
Poisson	$\ln(\mu_i) = \beta_0 + \beta_1 x_{i1} + ... + \beta_{ik} x_{ik}$ (log)	$\mu_i = \exp(\beta_0 + \beta_1 x_{i1} + ... + \beta_{ik} x_{ik})$
Binomial	$\ln(\frac{\mu_i}{1-\mu_i}) = \beta_0 + \beta_1 x_{i1} + ... + \beta_{ik} x_{ik}$ (logit)	$\mu_i = \frac{\exp(\beta_0 + \beta_1 x_{i1} + ... + \beta_{ik} x_{ik})}{1+\exp(\beta_0 + \beta_1 x_{i1} + ... + \beta_{ik} x_{ik}}$
Exponential	$1/\mu_i = \beta_0 + \beta_1 x_{i1} + ... + \beta_{ik} x_{ik}$ (reciprocal)	$\mu_i = 1/\exp(\beta_0 + \beta_1 x_{i1} + ... + \beta_{ik} x_{ik})$

It is decided to introduce a logit GLM model concerning binomial distribution in this master thesis. The main reason is that the observation time needn't cover the whole lifetime of item and only two possible outcomes should be considered (e.g. the response variables are measured on a binary scale, failure or not). Let $Y_i \sim Binomial(n_i, p_i)$ expresses response variables with failure probability p_i, implying likelihood for an item will fail at a given time. If $E(Y_i / n_i) = p_i$ and $\mathrm{var}(Y_i / n_i) = \frac{1}{n_i} p_i (1-p_i)$, then GLM model is given as:

$$\log(\frac{p_i}{1-p_i}) = \beta_{i0} + \beta_{i1} x_{i1} + ... + \beta_{ik} x_{ik} \tag{3.4}$$

Formula of failure probability is calculated as:

$$p_i = \frac{\exp(\beta_{i0} + \beta_{i1} x_{i1} + ... + \beta_{ik} x_{ik})}{1+\exp(\beta_{i0} + \beta_{i1} x_{i1} + ... + \beta_{ik} x_{ik})} \tag{3.5}$$

In order to interpret the meaning of β_i for each parameter, the next step is:

$$\frac{\partial(P_i)}{\partial(x_{ij})} = \frac{\partial(\frac{\varphi_i}{1+\varphi_i})}{\partial(x_{ij})} = \frac{\varphi_i}{(1+\varphi_i)^2} \exp(\beta_{ij}) \tag{3.6}$$

Where φ_i denotes $\exp(\beta_{i0} + \beta_{i1} x_{i1} + ... + \beta_{ik} x_{ik})$. It is concluded that failure probability is related with $\exp(\beta_{ij})$ and significant parameters can be found by comparing estimation of coefficient β_i.

3.2.3 COX Model

COX model is a survival model related to event hazards (e.g. failure rates) associated with time. It is possible to estimate the effect of parameters without any consideration of the distribution to response variables (e.g. failures). COX models can be used to modeling not only discrete (e.g. categorical variables) but also numeric.

Let $X_i = \{X_{i1}, X_{i2} ...... X_{ip}\}$ be the realized values of the covariates (e.g. inventory and operational parameters) and β is a column vector consisting of the coefficients. The hazard (i.e. failure in this case) function is formed as [22]:

$$h(t, X_i) = h_0(t)\exp(\beta X_i) \tag{3.7}$$

$$h(t) / h_0(t) = e^{(\beta_1 X_1 + \beta_2 X_2 ... + \beta_p X_p)} \tag{3.8}$$

Where $h_0(t)$ is called baseline hazard rate (i.e. failure rate), dependent only on time. The ratio of any two hazard rates are constant:

$$\frac{h(t, X^*)}{h(t, X)} = \frac{h_0(t)\exp(\sum_{i=1}^{p} \hat{\beta}_i X^*)}{h_0(t)\exp(\sum_{i=1}^{p} \hat{\beta}_i X)} = \exp(\sum_{i=1}^{p} \hat{\beta}_i (X^* - X)) \tag{3.9}$$

It implies that the ratio is independent of time t and the covariates (e.g. inventory- and operational parameters) may have a multiplicative effect on the hazard rates (failure rates) [23]. Even though the baseline hazard is unspecified, coefficients of the COX model can still be estimated through maximization of partial likelihood [24]. The conditional probability of a failure at time t_i and partial likelihood function are calculated as follows:

$$\Pr(t_i) = \frac{\exp(\beta X_i)}{\sum_{j \in R(t_i)} \exp(\beta X_j)} \ , \ L(\beta) = \prod_{i=1}^{k} \left[\frac{\exp(\beta X_i)}{\sum_{j \in R(t_i)} \exp(\beta X_j)} \right]^{\partial_i} \tag{3.10}$$

Where $R(t_i)$ denotes the number of cases that are at risk of failures at time t_i. ∂_i defines to be 0 if the item is censored (i.e. no failure within censoring time) and 1 if the item is uncensored (i.e. failure occurs within censoring time).

To interpret the meaning of β_i, it is suppose that we increase X_i by 1 while other covariate values are same, the relative change of failure hazard can be calculated as:

$$\frac{h(t, X_{new})}{h(t, X)} = \frac{h_0(t)\exp(\beta_1 X_1 + \beta_2 X_2 ... + \beta_i(X_i + 1) + ... + \beta_k X_k)}{h_0(t)\exp(\beta_1 X_1 + \beta_2 X_2 ... + \beta_i X_i ... + \beta_k X_k)} = \exp(\beta_i) \tag{3.11}$$

If $\exp(\beta_i) e^{\beta_i}$ are called hazard ratio (HR, in this case, it could be regarded as failure rates), it is concluded that "HR >1" indicates the failure rates will increase and vice versa. By comparing the value of HR, it can be found some significant parameters that impact on reliability performance.

3.3 Estimated failure rates

The purpose of estimating failure rates is to change failure rates based on operational experienced data, covering both generic failure rates and operational failure rates, as shown in Figure 6. Generic failure rates can be modified by categorizing failure rates into various subcategories, e.g. inventory and operational parameters. For operational failure rates, updating failure rates is related to real numbers of experienced failures in a specific period. Based on updated failure rates, modifying failure rates rely on more detailed analysis methods, e.g. Failure Mode Effects and Diagnostic Analysis (FMECA), failure analysis, Bayesian estimation. Methods to modify operational failure rates will be introduced in detail.

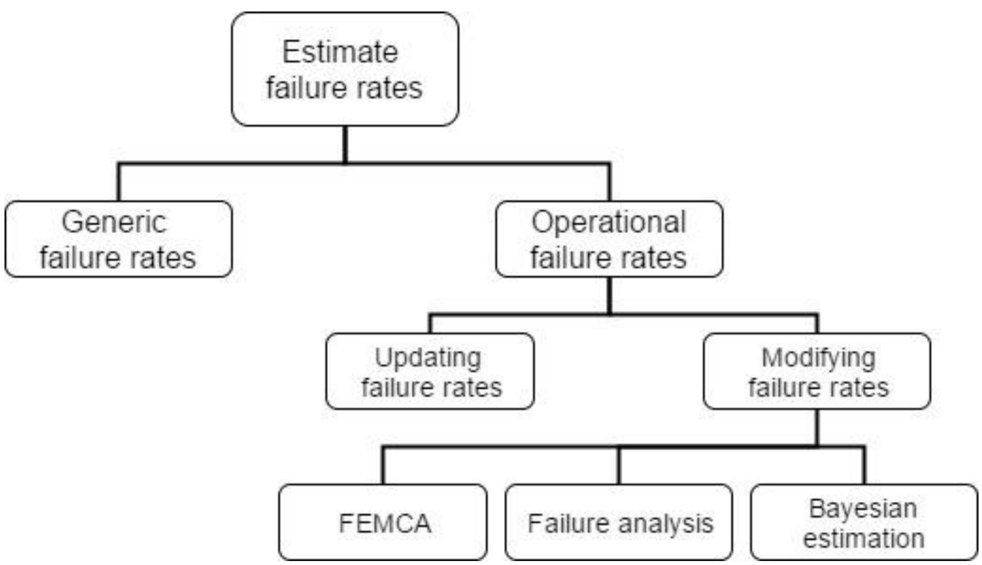


Figure 6 Estimation of generic failure rates and operational failure rates

3.3.1 Updated failure rates

The main intention of updating failure rates is to verify that the experienced failures are acceptable as intended or not. The calculation of failure rates based on the field experienced data is [4]:

$$\hat{\lambda}_{DU} = \frac{Number\ of\ \ failures}{Aggregated\ time\ in\ service} = \frac{x}{n \cdot t} \tag{3.12}$$

Where, x is the number of observed DU failures during observation period. *n* denotes number of components and t represents observation time. It is established 90% confidence interval for $\hat{\lambda}_{DU}$:

$$\left(\frac{1}{2t_n} Z_{0.95,2x}, \frac{1}{2t_n} Z_{0.05,2(x+1)} \right) \tag{3.13}$$

SINTEF report points out that it is possible to use operational data instead of generic data from handbooks under sufficient data [2]. Sufficient data imply a significant amount of available data with the high number of installed units based several years of operation [2]. Specific requirements concerning the volume of operating experience reference is made to the requirements for field experience as suggested in IEC 61508, e.g. 100000 operating hours and at least one year of service history [4]. However, it is not easy to distinguish sufficient data and insufficient data about failures. In practice, when having observed a few failures, for example 0 or 1 failures during operation, it will be recognized as insufficient data.

If the operational data is insufficient, it is difficult to solely use operational data due to statistical confidence problem. In this case, it will be necessary to combine the operational data with the a priori estimate of the failure rates:

$$\beta = \frac{\lambda_{DU}}{(\lambda_{DU-CE} - \lambda_{DU})^2}, \alpha = \beta \cdot \lambda_{DU} \tag{3.14}$$

Then updated failure rate based on operational experience combined with a prior failure rate, is estimated as:

$$\ddot{\lambda}_{DU} = \frac{\alpha + x}{\beta + t_n} \tag{3.15}$$

λ_{DU-CE} denotes conservative estimate of the failure rate and can be determined as:

$$\lambda_{DU-CE} = Max\left\{\text{user specified value, } 2\lambda_{DU}, 5\times10^{-7}\right\} \tag{3.16}$$

3.3.2 Modified failure rates

This section presents a method used to modify failure rates for a new facility or modified a new equipment with comparable environmental conditions, maintenance and operational procedures as a current facility [5].

Based on the result from performance analysis, the failure rates (i.e. generic failure rates or operational failure rates) can be divided into n groups:

$$\hat{\lambda}_{DU} = \lambda_1 + \lambda_2 + \ldots + \lambda_n \tag{3.17}$$

$$\lambda_i = \omega_i \cdot \hat{\lambda}_{DU} \tag{3.18}$$

The values of ω_i represents the impact on the reliability performance from parameter i and can be determined by expert judgement. The weight for each parameter should be normalized, and can be expressed as:

$$1 = \sum_{i=1}^{n} \omega_i \tag{3.19}$$

It is supposed that parameter i have m subcategories, then failure rates of parameter i can be divided:

$$\lambda_i = \lambda_{i1} + \lambda_{i2} + \ldots + \lambda_{ij} \tag{3.20}$$

$$\lambda_{ij} = \theta_{ij} \cdot \lambda_i \tag{3.21}$$

θ_{ij} is the fraction of DU failures for subcategory j among all DU failures for parameter i:

$$\theta_{ij} = \frac{No.of\ DU\ failures_{i,j}}{\sum_{j=1}^{m} No.of\ DU\ failures_{i,j}} \tag{3.22}$$

Then, by comparing existing parameter conditions and new parameter conditions, the modified failure rates can be calculated as:

$$\overset{*}{\lambda}_{DU} = \overset{*}{\lambda}_1 + \overset{*}{\lambda}_2 + \ldots + \overset{*}{\lambda}_n \qquad (3.23)$$

$$\overset{*}{\lambda}_i = \lambda_{ij} \cdot \sigma_{ij} \qquad (3.24)$$

Where σ_{ij} denotes the score of influence from subcategory j of parameter I, which is determined by judging of change between existing condition and new condition (e.g. inventory conditions). The assumptions of score are:

1) If the influence on reliability performance is supposed to be in a medium state, then $\sigma_{ij} = 1$
2) If the influence on reliability performance is supposed to be in a more suitable state, then $\sigma_{ij} < 1$
3) If the influence on reliability performance is supposed to be in a less suitable state, then $\sigma_{ij} > 1$

The weights ω_i is related to importance of influence on reliability performance from the each inventory- and operational parameters. The weight σ_{ij} is an estimated value for inventory and operational parameters by comparing conditions of the existing facilities and the new facility. The weight for each subcategory θ_{ij} generates from the statistical results of DU failures. Those estimated or experienced weights are critical to the results of modified failure rates.

4 Approach for modifying failure rates

This chapter gives an overview introduction for the approach to modify failure rates and elaborates how to identify equipment and inventory- and operational parameters.

4.1 Overview of approach

A necessary prerequisite for establishing modified generic failure rates is to evaluate the following two important questions: 1) Are the equipment likely to be sensitive to specific inventory- and operational parameters; 2) Can it be supported by operational experience or data? An approach for modifying failure rates involving six steps is suggested, as illustrated in Figure 7:

- **Step 1**: Identify equipment group based on the criteria of criticality, sufficiency, sensitivity and significance.
- **Step 2**: Identify the most relevant parameters that can explain variation in reliability according to the criteria of relevance, complexity, availability and repeatability.
- **Step 3**: Collect inventory data and operational environmental information.
- **Step 4**: Select available methods to analyze parameters and perform data analysis.
- **Step 5**: Check significance. It is also important to emphasize statistically, if there is no significance, it should be return to identify other equipment and/or parameters.
- **Step 6**: Modify failure rates for generic failure rates or operational failure rates.

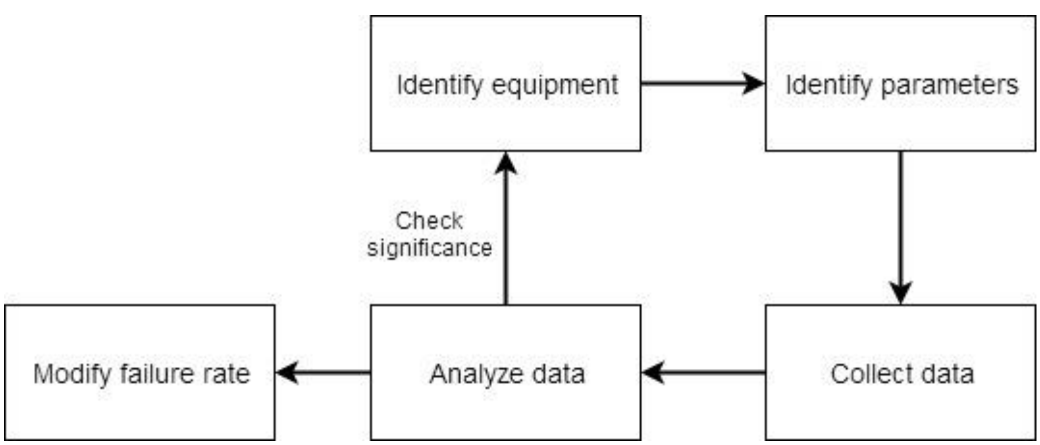


Figure 7 Approach to modify failure rates

4.2 Identify equipment

Based on review of operational data from several facilities, it is showed that reliability performance within a group of equipment can be quite different even in the same environment [6]. But not all types of equipment have variations in reliability performance. Some equipment are likely to demonstrate similar failure rates between different facilities, e.g. fire dampers. The priority of the data analysis is given to identify which groups of equipment in SISs are expected to have significant variations. It is necessary to review SIL requirement as the first step, e.g. safety analysis report (SAS) and safety requirement specification (SRS). It is also desirable to set up common criteria to evaluate and select equipment. Four criteria for identifying equipment are important:

- Criticality. Is the equipment critical for SISs with huge contributions to the PFD?
- Sufficiency. Is there enough information about the equipment and are there sufficient amount of operational data?
- Significance. Is there large variation for this type of equipment at different facilities?
- Sensitivity. Are the equipment sensitive to specific parameters?

It is decided to focus on ESD/PSD valves in this project on the basis of the criteria above. Data for shutdown valves are adequate and they are critical for the safety system. They are the major contributors to probability of failure on demand (PFD, as shown an example in Figure 8 [4]. It is a part of the process section on an offshore oil and gas production installation. In case of an emergency situation, e.g. the event of a failure in process control system, PSD and ESD valves will stop process or isolate equipment to prevent major accidents.

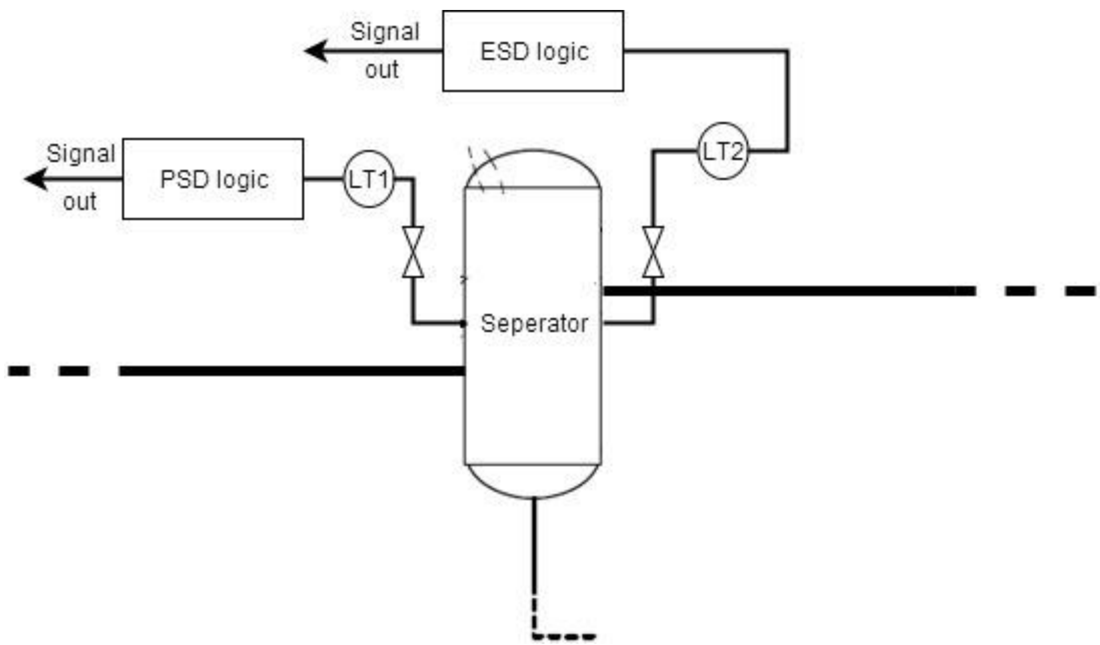


Figure 8 Example of shutdown valves in the safety system

If only the PSD function is considered in the calculation of PFD. Basically, a PSD function consists of sensors, a logic solvers and final element. Reliability Block Diagram (RBD) for PSD function, is illustrated in Figure 9.

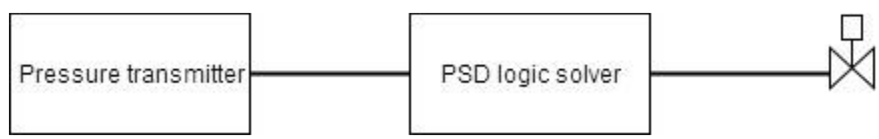


Figure 9 RBD for the PSD function

The PFD for PSD valve is 9.2×10^{-3} accounting for 67.6% of total PFD, as indicated in Table 4, which is a dominate contributor of PFD compared to the other components in the SIF.

Table 4 An example of PFD calculation results for the PSD functions

Component	Voting	Failure rate (per hour)	PFD for component	% of total
Transmitter	1oo1	0.3×10^{-6}	1.3×10^{-3}	9.6%
PSD logic	1oo1	0.7×10^{-6}	3.1×10^{-3}	22.8%
PSD valve	1oo1	2.1×10^{-6}	9.2×10^{-3}	67.6%
Total			1.4×10^{-2}	

Note: λ_{DU} generate from SINTEF PDS handbook[7], $\tau = 8760$ hours

4.3 Identify parameters

It is vital to determine the range and degree of collected data[11]. In this case, it is desirable to decide how many parameters and which parameters involved. Selection of inventory- and operational parameters should be taken into account four criteria:

- Relevance. Do those inventory- and operational parameters impact on reliability performance?
- Complexity. What is the degree of complexity for this parameter?
- Availability. Is it possible to collect and analyze the parameters?
- Repeatability. Which failure have actually occurred in the past? Did it occur again?

It is required to investigate the mechanism of the shutdown valves. Both ESD and PSD valves can isolate related process segments in case of emergency or abnormal operating conditions and thereby limit the flow within the valves. The boundary of a valve includes valves (e.g. bonnet, closure member, flange, seals, seat rings, stem and valve body etc.), actuator (e.g. actuating device, case, gear, piston etc.), control system and monitoring (e.g. control unit, cabling boxes, instrument, monitoring, internal power supply etc.), as showed in Figure 10 [10].

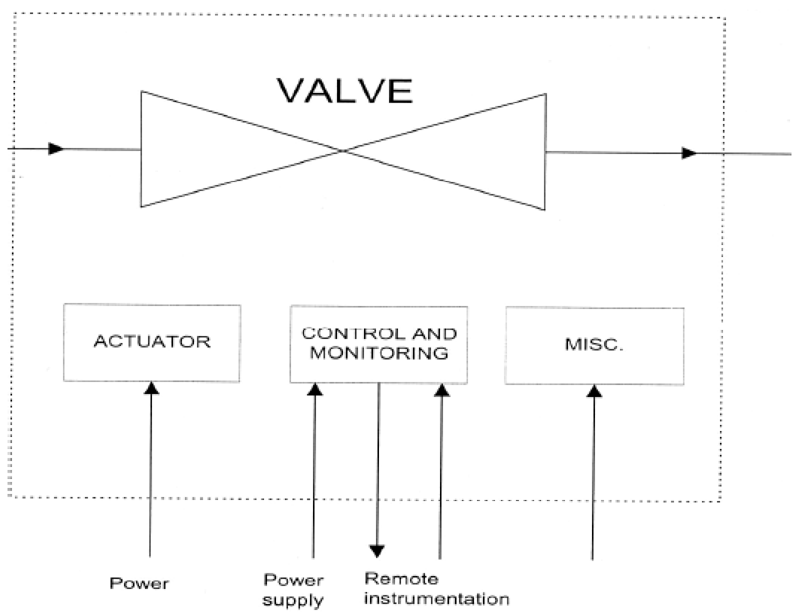


Figure 10 Boundary of shutdown valves

Selected parameters in terms of inventory equipment and operational/environmental conditions for ESD/PSD valves are showed in Table 5.

Table 5 Identify parameters for shutdown valves

Inventory information	Environment/Operational condition
Functional location (Tag number) Type Size Actuator principle Required response time	Area/location Flow medium Special environment area Date put into service

Functional location is a tag number used to identify equipment's physical location. Each location has an identical logical location number within a system and are vital to determine the identity of equipment. The groups of functional location are defined as main equipment, piping, electrical field equipment, automation field equipment and telecom field equipment.

There are three main types shutdown valves: Ball, Butterfly and Gate. All valves are designed to control pressure and flow based on various principles, function and structures. It is important to know each type of valve's characteristics and peculiarities, e.g. poor methanol resistance in O-rings and deposits that can prevent seat movement are challenges for ball valves. Precipitation and abrasion are typical problems for gate valves. A butterfly valve will usually produce turbulence flow that gives higher pressure and erosion to the valve at a small opening. Figure 11 shows an example of a line with a gate valve and a ball valve [25].

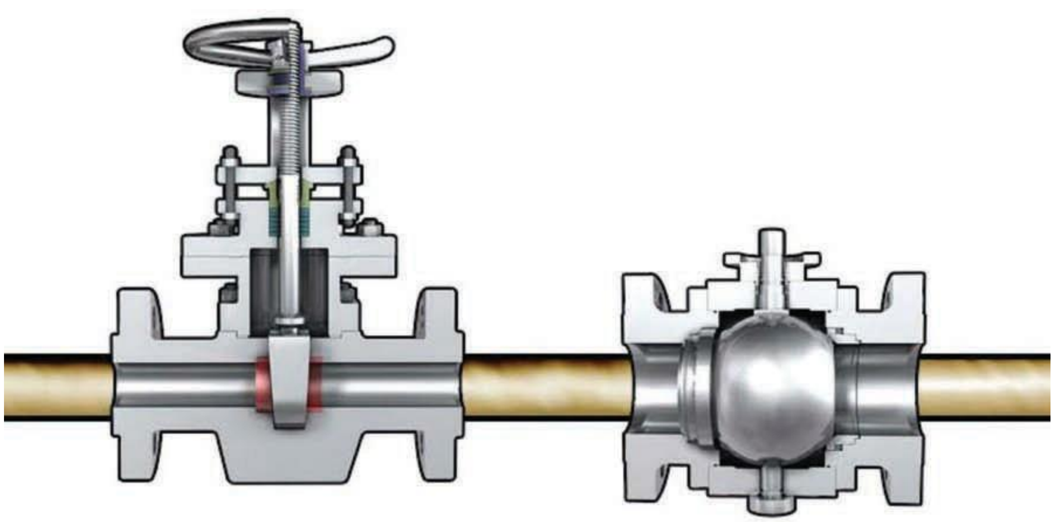


Figure 11 Example of ball valve and gate valve

Size of the valves affects maximum permitted working pressure, e.g. a 40 mm stem on a $4^{''}$ gate valve at 120 bar must be closed, while a $8^{''}$ valve has a differential pressure of 60 bar [25]. The surface area of a 10 inch valve is about 100 mm^2 and the area of a circular surface is calculated by the radius squared multiplied by Pi [25]: $10^{''} = 100mm^2 = \pi \cdot (\frac{11.3mm}{2})^2$. It is assumed that the pressure area for a $10^{''}$ ball valve is 50000 mm^2. Given a force of 500000N, then the pressure across the ball valve is 100 bar (100 bar = 10 N/ mm^2 = 1 kg).

In this project, size of valves are classified into three groups: small-sized, middle-sized and large-sized (in some cases, there is another group for extreme large-sized valves). Small-sized valves are characterized by small diameters with extreme high pressure, e.g. less than 1 inch. They differ from the other valves due to their particular structure and functions. However, those valves are usually not main contributors of total failures and risk. They may not cause to major accident. For example, a the valves with 1/2 inch diameter for the chemical injection system are regarded as small-sized valves. It is a water-based valve that will not lead to fire or explosion. Middle-sized valves refer to diameter of valves from 1 to 3 inch and large-sized valves are more than 3 inch.

Flow medium is a considerable parameter for valves since a valve is highly affected by the fluid flowing through it. Various fluid or gas result in erosion, corrosion, cavitation on the surface, degradation of seals and clogging by particles and deposits. The medium within ESD and PSD valves may be hydrocarbon liquid, gas, multiphase, chemical (e.g. Mono Ethylene Glycol (MEG), Triethylene Glycol (TEG) etc.), produced water, fresh water and sea water. Flow medium in the methanol injection system is consisting of 90% MEG and 10% water. The flow medium within gas compression and re-injection system is Hydrocarbon liquid (HC). For riser and well system, the flow medium is likely to be mixture of hydrocarbon, H_2O and sand.

Most safety valves use single principle actuators (i.e. spring return), can be divided into three groups: hydraulic, pneumatic or electrical. They supply different power to move or control valves. Hydraulic and pneumatic actuators should be able to operate the valve safely at the lowest instrument pressure, but not damaging the valve if it is operated at maximum instrument pressure [25].

Other inventory- and operational parameters, e.g. required response time, location and date put into service, provide also valuable information. Required response time is a measure of how long a valve is being opened or closed once it starts moving. Area/location describes the area where equipment installed, e.g. outside, inside or subsea. Date put into service explains when a valve starts to supply the service. Special environment conditions are referred to some particular situation, e.g. exposed to salt or ice. Detail information of main inventory and operational parameters, is listed in Table 6.

Table 6 Description of inventory and operational parameters

Parameters	Subcategories	Descriptions
Type	Ball	Control flow through it by rotating a perforated and pivoting ball, poor methanol resistance in O-rings and deposits.
	Gate	Open and close by lifting or putting a gate out/down of the path of the fluid. Precipitation and abrasion are typical problems.
	Butterfly	Regulating or isolating flow by a damper. It produces turbulence flow at a small opening that gives higher pressure drop and erosion
Size	Small-sized	Less than 1 inch
	Medium-sized	Between 1 and 3 inch
	Large-sized	Larger than 3 inch, (Extreme large more than 18 inch)
Flow medium	HC liquid	Oil and condensate hydrocarbon liquid
	Diesel	Diesel fuel in fare water system and power system etc.
	Chemical	Chemical medium in chemical injection system e.g. H_2S, Oxygen and some in methanol injection system e.g. 90% MEG with 10% water
	Multiphase	Mixture of different flow medium, e.g. mixture of hydrocarbon, water and sand
	Water	Fresh water with normal temperature and produced water with high temperature
	Sea water	Used for fire water system and is characterized by salt
	Gas	HC gas or HC vapor in gas compression and re-injection system, gas treatment system, gas export and metering system, heating medium system etc.
Actuator	Hydraulic	Using hydraulic power to move or control valves
	Pneumatic	Converts energy formed by vacuum or compressed air at high pressure into linear or rotary motion
	Electrical	Powered by a motor converts electrical energy into mechanical moving

5 Data analysis

The aim of this chapter is to use the statistical methods that was introduced in chapter 3 for parameters analysis, based on the collected data from two facilities within the Norwegian oil and gas industry. The present chapter is broken down into three main parts. The first part introduces the data collection process and describes the data sets, then five potential parameters are specified in this case. The second part elaborates the modeling process and defining variables in the models. The last part describes the result of two models GLM model and COX model, then validates the models is performed to check goodness of fit of models and data.

5.1 Data collection

A systematic and efficient way to collect data can improve completeness and large population of data [11]. Figure 12 illustrates the data-collection process in this thesis:

- Map resource for data-collection and review all the available data.
- Extract the relevant data and interpret data.
- Assess the quality of data. It is desirable to obtain all wanted events and exclude errors.
- Perform data analysis. If more data is required, it will return to extracting data.

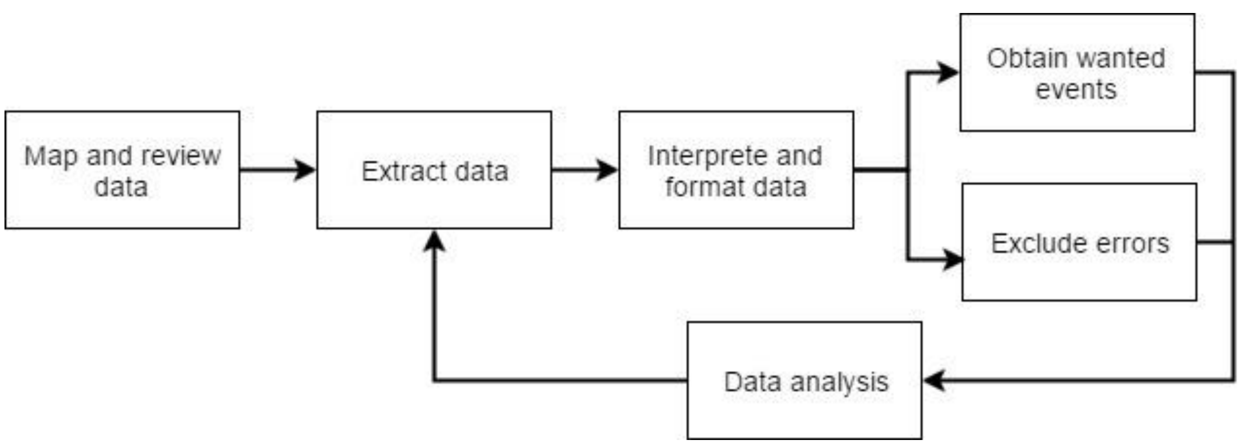


Figure 12 Data collection process

In this project, the data stems from two facilities within oil and gas industry in Norway and is mostly recorded in two information management systems: Systems, Applications & Products (SAP) and Technical Information and Documentation System (STID). SAP is an enterprise resource planning (ERP) system that enables the facility to run the business processed, ranging from accounting, sales, production, human resource, payment, maintenance and operation in an integrated environment. STID is used to control and manage documentations in the companies, covering operation, marketing, technology, project management and IT support etc.

Data collection can be performed by sorting key words (e.g. functional location, failure notifications and equipment number etc.). All the technical and equipment information are coded by a common coding system in SAP and STID. It enables us to ensure standardized classification and translation of the data. Additional manual effort is also required in data collection, e.g. reviewing corresponding documents, such as safety requirements specification (SRS), process and instrumentation diagrams (P&IDs), maintenance and operational report etc. In some cases, it is desirable to communicate with SAP experts and maintenance personnel to acquire reliable information. Despite various techniques could be employed in data collection, data for some inventory- and operational parameters turn out to be insufficient in practice, e.g. date put into service, operational temperature and pressure within a valve.

Collected data for this master project covers failure data sets, inventory data sets as well as maintenance data sets. Besides sortable categorical data, the data sets contain detailed comments with written text, e.g. description of characters of valves providing information about types and sizes of the valves. In total, the data sets through operational reviews have 589 ESD and PSD valves and 161 DU failures, and aggregated operational time is 3.2×10^{7} hours. Data analysis concerns both ESD and PSD valves for two facilities by ensuring the sample size is large enough. Modification of operational failure rates is based on the data from one specific facility.

Failure data sets comprise information in relation with failure time, failure mode, failure causes, failure consequence etc. In the PDS project of SINTEF, operational reviews of safety critical equipment on several facilities have been performed. The purpose of the data reviews have been to verify the performance of SIL and determine whether the functional test intervals should be adjusted [26]. Failure analysis with consideration of detection methods, failure causes and failure modes have been carried out in the specialization project [27]. Therefore, this master project will not review failure records, unless it is relevant to look into details during the data analysis. Inventory data sets are related to equipment data and environmental information that has been introduced in the previous chapter. Maintenance data sets include function test, leakage test and partial stroke test and test intervals etc.

5.2 Data sets

The quality of data set is highlighted for data analysis. There is always the possibility that the data sets from the facilities' system contain wrong data. So it is necessary to assess the quality of data sets and clean it before the data analysis. It is found that seven DU failures for one facility are regarded as one failure owing to the same design problem and high temperature. Another seven DU failures are removed from the dataset because of high-frequency problem on hydraulic system in the first two years. It is unable to find any relevant inventory information for one DU failure, which result in dropping from the data sets.

Being subjected to acquire insufficient information, available inventory- and operational parameters that are regarded as explanatory variables in the data analysis are: Type, Size, Flow medium, Actuator principle and Leakage requirement. Each parameter could be split into several subcategories, as shown in Figure 13. The main types of valves are ball, gate and butterfly valve. Sizes of the valves can be divided into three groups: Small, Medium and Large. Actuator principle refers to hydraulic, pneumatic and electric actuator. Flow medium within the valves may involve hydraulic liquid, gas, chemical, mixture, diesel and water etc. For maintenance parameter, we consider only one parameter: Leakage requirement. Having a leakage requirement does not essentially influence any degradation mechanism in the valves. The main reason for being a potential parameter, however, is that the valve with leakage requirement may be more vulnerable to failures that related to LCP failure mode. The same type of valve may have different DU failure rate, depending on whether the valve has been assigned leakage requirement or not. More detailed information of the five parameters has been described in the previous chapter.

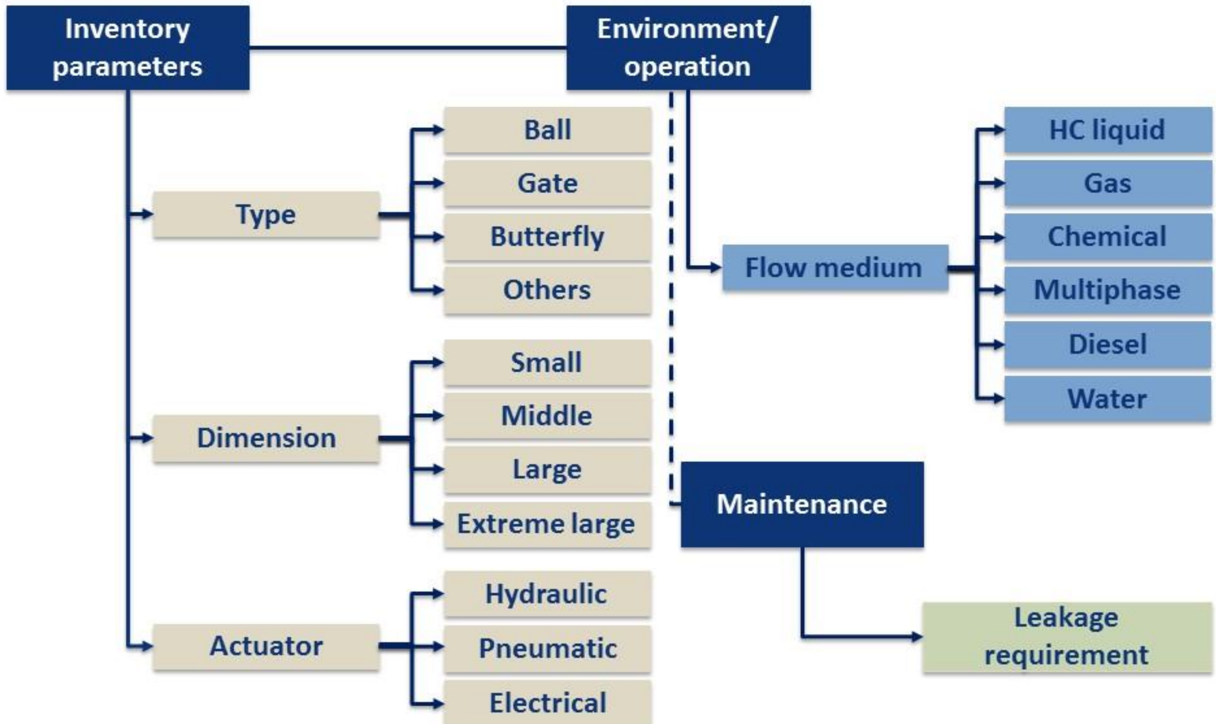


Figure 13 Inventory- and operational parameters for this case study

Censoring time is introduced to terminate observation, implying it prevents observing the full life time of the valves even though the valves have not failed. Censoring time expresses the hours between the dates put into the service until the end of observation. One facility has been installed and operated from 2005, while another one has been operated from 2007. As illustrated in Figure 14, censoring time for two facilities are defined as 11 years ($t_{s1} = 96456$ hours, 12/31/2005 to 12/31/2016) and 7 years ($t_{s2} = 72312$ hours, 10/01/2007 to 12/31/2015). The observation has to be terminated if a valve fails or the censoring times arrive at t_{s1} / t_{s2}.

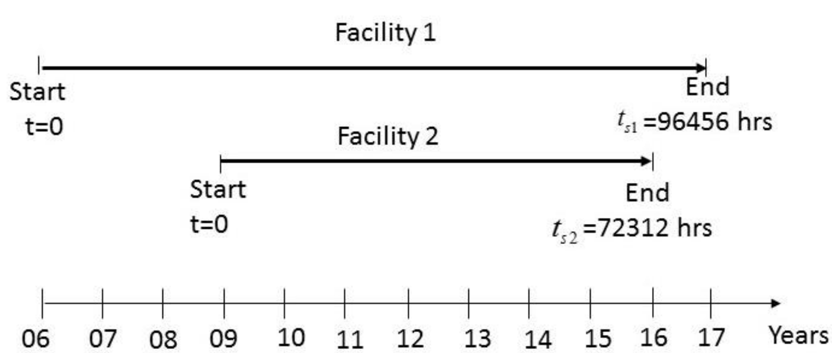


Figure 14 Operational time for two facilities

Table 7 illustrates an example of a dataset used in data analysis for the shutdown valves at two facilities. For instance, No. 1 valve has never failed in observation period, while No. 4 valve failed after time = 624 hours.

Table 7 An example of dataset used in data analysis

No.	Failure Time (hours)	Censoring	Type	Dimension	Flow Medium	Actuator	Leakage requirement
1	96456	0	BALL	Large	HC Liquid	Hydraulic	YES
2	96456	0	BALL	Medium	Others	Hydraulic	YES
3	96456	0	BALL	Large	Others	Hydraulic	NO
4	624	1	BALL	Large	Others	Hydraulic	NO
5	96456	0	BALL	Medium	Gas	Hydraulic	YES
6	96456	0	BALL	Medium	Gas	Hydraulic	YES
7	96456	0	BALL	Small	Gas	Hydraulic	YES
8	96456	0	BALL	Medium	Gas	Hydraulic	YES
9	96456	0	BALL	Small	Gas	Hydraulic	YES
10	96456	0	BALL	Medium	HC liquid	Hydraulic	YES
11	96456	0	BALL	Medium	Gas	Hydraulic	NO
12	96456	0	BALL	Medium	Gas	Hydraulic	NO
13	46056	1	BALL	Medium	Gas	Hydraulic	NO
14	34920	1	BALL	Medium	Gas	Hydraulic	NO
15	89448	1	BALL	Medium	Others	Pneumatic	NO
16	48360	1	BALL	Large	Gas	Hydraulic	NO
17	21264	1	BALL	Large	Gas	Hydraulic	NO
18	39384	1	GATE	Medium	Others	Hydraulic	YES
19	96456	0	BALL	Medium	Others	Pneumatic	NO
…	…	…	…	…	…	…	…
589	72312	0	Others	Medium	Others	Hydraulic	NO

Note: 1) "1" -failed and "0" - censoring.
2) "Yes" –with leakage requirement and "NO" – without leakage requirement

5.3 Regression modeling

The analysis of failure times is used as a basis for obtaining the failure distribution. Considering an item (e.g. a valve) that is put into operation at t=0, failure time refers to the time from t=0 to the time in hours when the item doesn't function. It differs from the mean time to failures, i.e. the mean time between consecutive occurrences of failures. Failures time of the ESD and PSD valves for two facilities are shown in Figure 15. There was in total 161 DU failures (36 DU failures for ESD valves and 125 DU failures for PSD valves).

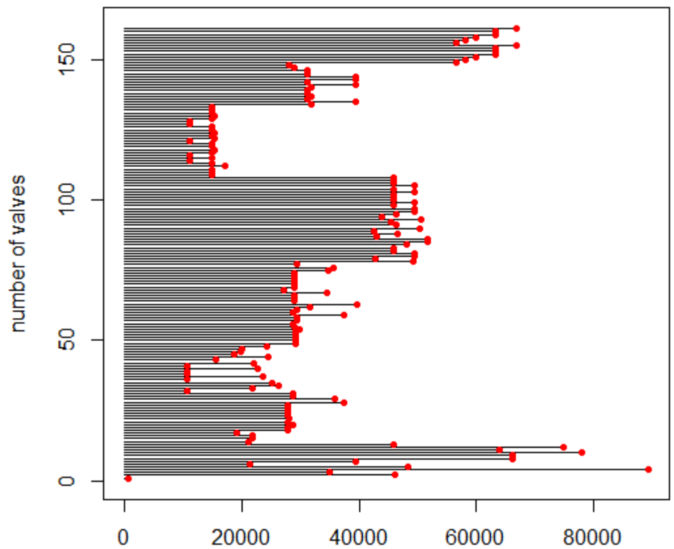


Figure 15 Failure time for ESD and PSD valves

It is desirable to determine which distribution of failure time fits the best by comparing how closely the plot points lie to the best-fit lines of a probability plot. Anderson-Darling (AD) is used to measure how well the data follow a particular distribution and compare the goodness of fit of several distribution. Four distributions are considered in this case: Weibull, Lognormal, Exponential and Normal distribution. As shown in Figure 16, AD value for the four distributions are near to 2167 (far from 0). That may be due to a greater number of censors in this case (428 censors and 161 failures).

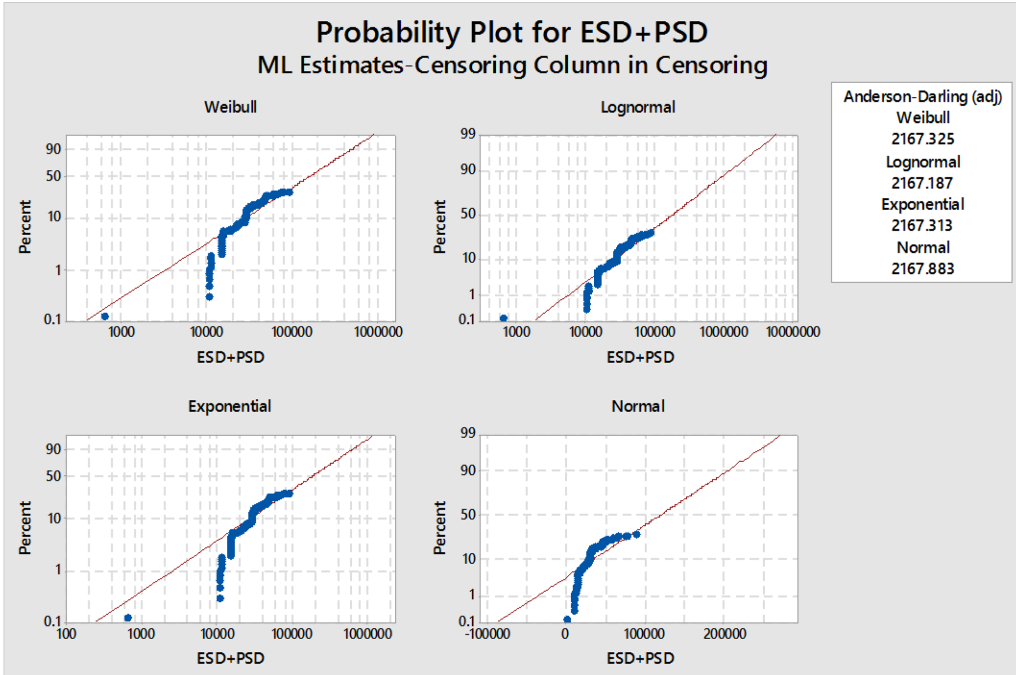


Figure 16 Probability of failure time for ESD and PSD valves

Any conclusion of failure distribution cannot be obtained from failure time analysis. In spite of that, two models have been suggested: 1) GLM model, based on binomial distribution, considering only whether a valve has failed or not during observation period in this method, rather than the whole lifetime of valves. 2) COX model. The advantage of the COX models is free of any assumption about the shape of underlying distribution [28]. The goal of model selection is to find an appropriate model that fits well data and can be used as a basis for inference and prediction. Poor model will lead to uncertainty and invalidity of the data analysis. The main reason for using GLM model and COX model is to avoid selecting inappropriate model, regardless of unknown distribution of failures.

Analysis models have been set up with consideration of the types of variables because the results of analysis is dependent on appropriate variables. A variable is not only something measured, but also something to be manipulated and controlled. Failure probability, i.e. likelihood of an item will fail at time t, is regarded as response variables in GLM models. Failure rates are treated as response variables in COX models. Both GLM and COX model allow to use categorical variables (names or labels, e.g. small, medium and large) and numerical variables (measurable quantity, e.g. 18' inch of a valve). For the categorical models, the result is estimated for each subcategories of explanatory variable, e.g. coefficient represents parameter small-sized at subcategories level. For numerical model, explanatory variables are expressed at category level, e.g. coefficient represents for parameter size.

In this instance, each potential inventory- and operational parameters for categorical variables are split into two or three levels taking into account computing complexity and limited data. As shown in Table 8, Ball, Gate and Others are regarded as three groups of the valves. "Other" includes Butterfly valves and unknown type of valves. Sizes of the valves are divided into three groups, i.e. S (0-1"), M (1"-3") and L (>3"). Actuator includes hydraulic and pneumatic two groups. "Other" for flow medium covers diesel, chemical, water and sea water, multiphase and unknown. Leakage requirement represents a dichotomous variable categorized as either "Yes" or "No".

Table 8 Summary of parameters classification

Type	Size	Medium	Actuator	Leakage requirement
Ball	L	HC liquid	Hydraulic	Yes
Others	M	Others	Pneumatic	No
Gate	S	Gate		

Numerical variables are given value in the same range (-1, 1). The similar range will reduce the impact from given value of the parameters (e.g. Ball = 1, Gate = -1 and others = 0). Table 9 illustrates the given value of inventory- and operational parameters.

Table 9 Summary of parameters with numerical variables

Type		Size		Medium		Actuator		Leakage requirement	
Ball	1	L	1	HC liquid	1	Hydraulic	1	Yes	1
Others	0	M	0	Others	0	Pneumatic	-1	No	-1
Gate	-1	S	-1	Gas	-1				

COX model can be specified as follows:

$$Failure\,rate\left(Time,\ Failure\right) = \beta_1 \cdot Type + \beta_2 \cdot Size + \beta_3 \cdot Flow\,medium + \beta_4 \cdot Actuator + \beta_5 \cdot Leakage$$

GLM model can be specified as follows:

$$Failure\ propability(Failure) = \beta_1 \cdot Type + \beta_2 \cdot Size + \beta_3 \cdot Flow\,medium + \beta_4 \cdot Actuator + \beta_5 \cdot Leakage$$

Where β_i denotes the estimated coefficient for each inventory- and operational parameter (explanatory variable), "Failure" means failure = 1 and censor = 0.

5.4 Analysis results

The feasible models in this project have been determined to be implemented in software R (codes in Appendix D). R program is a free software for statistical computing and graphics. The following sections will take COX model with categorical variables, COX model with numeric variables and GLM model with numerical variables as examples.

5.4.1 COX model

The results of data analysis in COX model with categorical variables are shown in Table 10. The results can mainly be interpreted by P-value, coefficient (i.e. estimated Beta β_i) and hazard risk (HR, i.e. failure rate, exponential coefficients). More detailed information for other models can be checked in Appendix C.

Table 10 Results for COX model with categorical variables

Explanatory variable	Beta(β_i)	HR	P-value	Low .95	Upper .95
Type Gate	0.27	1.31	0.17	0.89	1.94
Type Other	0.50	1.65	0.16	0.81	3.35
Size Medium	-1.25	0.29	1.32×10^{-8}	0.19	0.44
Size Small	-2.20	0.11	1.62×10^{-3}	0.03	0.44
Medium HC	-2.60	0.07	9.35×10^{-6}	0.02	0.23
Medium Other	-0.87	0.41	8.77×10^{-5}	0.27	0.65
Actuator Pneumatic	1.39	4.01	0.07	0.92	17.57
Leakage No	-1.30	0.27	2.11×10^{-3}	0.12	0.63
Leakage Yes	0.46	1.59	0.02	1.07	2.35
Likelihood ratio test = 171.1 on 9 df, p=0					
Wald test = 122.3 on 9 df, p=0					
Score (logrank) test = 160.8 on 9 df, p=0					

P-value (i.e. probability value) evaluates statistical significance of each variable. It should be noted that statistical significance is not the same as importance. Statistical significance is a likelihood to demonstrate difference between groups for variables caused by systematic samples other than by chance. A small P-value (e.g. $P<0.05$) enables us to determine reject null hypothesis (i.e. there is no effect from this variable on reliability performance) and gives the evidence for supporting statistical significance of the variable. In this case, there are three explanatory variables that have high statistical significance: Size (small and medium-sized), Flow medium (HC liquid and others) and leakage requirement (No or Yes).

The HR indicates if a variable is more likely to be related to changes in reliability performance. It can also be interpreted as multiplicative effects on the failure rates. It have been discussed in the chapter 3. If X_i increase by 1 while other covariate values remain constant, e.g. holding other variables being constant, $\exp(\beta_{23}) = 0.11$ means that being a small-size of valve will reduce 89% failure on average compared with other sizes of valves. $\exp(\beta_{51}) = 1.588$ indicates that leakage requirement for a valve increases the failure rates by 58% compared to other valves without leakage requirement. Some estimation for variables are not illustrated in the tables. The reason for may be that the model return coefficients based on a base level won't be shown in the tables.

The likelihood-ratio test, Wald test and score logrank test describe statistical significance of the COX model. The less represents the better statistical significant in general. In this case, '9 df' denotes proposed degree of freedom and P-values is in close 0. It implies that the H_0 hypothesis (i.e. there is no impact on reliability performance from the explanatory variables) is soundly rejected. Considered at a global level, it can be concluded that there is statistical significance in this model.

It also gives upper and lower 95% confidence interval for the failure rate. For example, the estimate range of 95% bound for Small-sized is from 0.03 to 0.44. The predicted failure probability at any given point time can be obtained by survival probability in R program. Survival probability will decrease while failure probability increase.

Figure 17 illustrates the estimated survival function for the ESD and PSD valves. The broken lines show a point-wise 95% confidence envelope around the survival function.

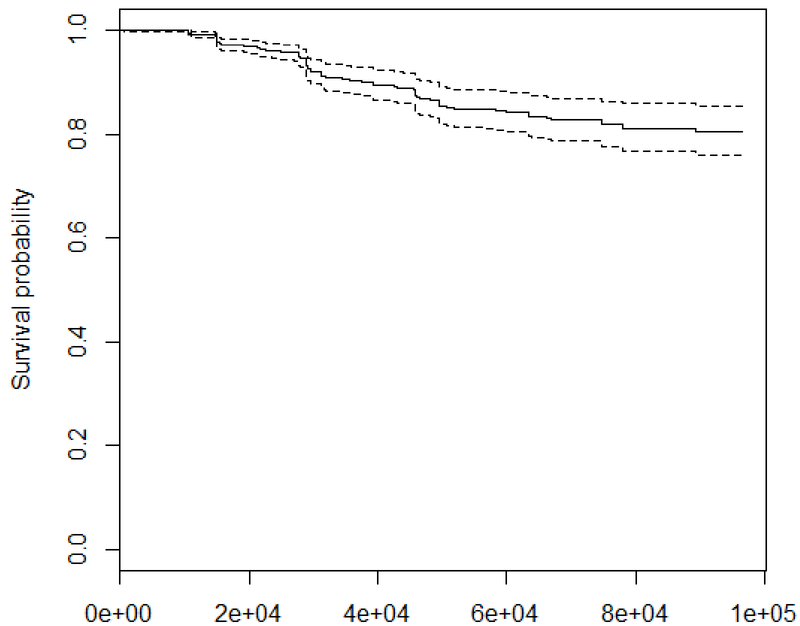


Figure 17 Estimated survival function in the COX mode (Time in hours)

The presence of correlation and interaction of the variables has important implication for the interpretation of statistical models and results. Hence, to develop the analysis models, statistical independence and autocorrelation of the explanatory variables should be checked [28]. For example, required response time of the valves often follow a linear regression with the sizes of the valves: $Response\,time = 2'' \cdot Diameter + 2''$ (for the control system). When the size of valves is included in the analysis models, the required response time is not regarded as an explanatory variable. Interaction of the explanatory variables in COX model can be checked in R, e.g. the size and flow medium. It indicate that the interactions should not be included in this case. The detail results of analysis by this model are not shown here due to page limitation.

Some explanatory variables may be excluded in the models due to statistical insignificance by command ‘step ()’ in R, e.g. type and actuator principle. It appears that they are not sensitive enough to distinguish subcategories. Therefore, the model could be developed by eliminating the two parameters:

$$Failure\,rates\left(Time,\ Failure\right) = \beta_1 \cdot Size + \beta_2 \cdot Flow\,medium + \beta_3 \cdot Leakage$$

The value of likelihood ratio test decreases to 165.3, as shown in Table 11, has reduced 5.8 with a loss of 3 degrees of freedom. It is reasonable to remove the parameters actuator and type from the model.

Table 11 Results for developed COX model with categorical variables

Explanatory variable	Beta	HR	P-value	Low .95	Upper .95
Size Medium	-1.32	0.27	6.15×10^{-10}	0.17	0.40
Size Small	-1.81	0.16	2.10×10^{-3}	0.05	0.52
Medium HC	-2.54	0.08	1.42×10^{-5}	0.03	0.25
Medium Others	-0.72	0.48	4.32×10^{-4}	0.32	0.73
Leakage NO	-1.10	0.33	4.47×10^{-3}	0.16	0.71
Leakage Yes	0.52	1.68	3.49×10^{-3}	1.19	2.38

Likelihood ratio test = 165.3 on 6 df, p=0
Wald test = 116.7 on 6 df, p=0
Score (logrank) test = 148.7 on 6 df, p=0

It is also desirable to check and verify the results obtained in the COX models with numerical variables. The results are listed in Table 12. Size, medium and leakage requirement could be considered as significant inventory- and operational parameters taking into account impact on failure rates.

Table 12 Results for COX model with numeric variables

	coef	exp(coef)	z	Pr(>|z|)	lower .95	upper .95
Size	1.24	3.45	6.61	0.00	2.39	4.99
Medium	-0.95	0.39	-5.91	0.00	0.28	0.53
Leakage	0.35	1.41	4.12	0.00	1.20	1.67

Rsquare= 0.226 (max possible= 0.966)
Likelihood ratio test = 151.2 on 3 df, p=0

Moreover, to show the interaction of variables on reliability performance, Figure 18 is used to illustrate survival probability with consideration of two of three explanatory variables. The large-sized valves with leakage requirement and large-sized valves with gas have the lowest survival probability.

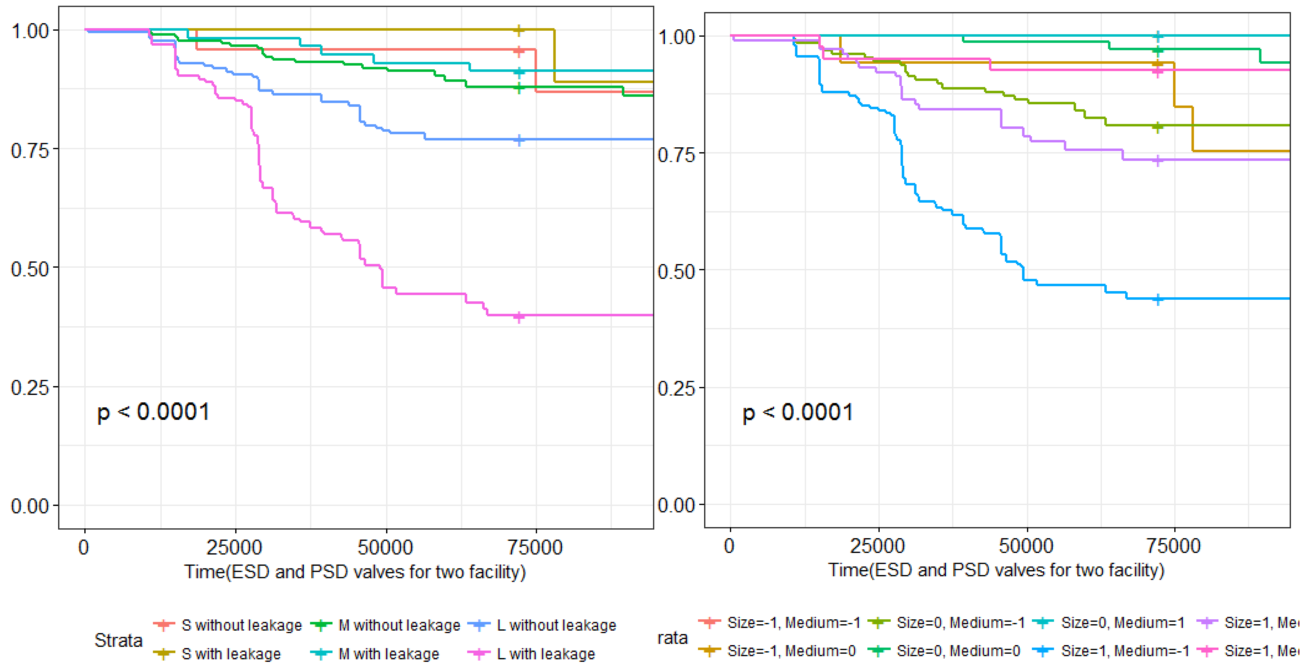
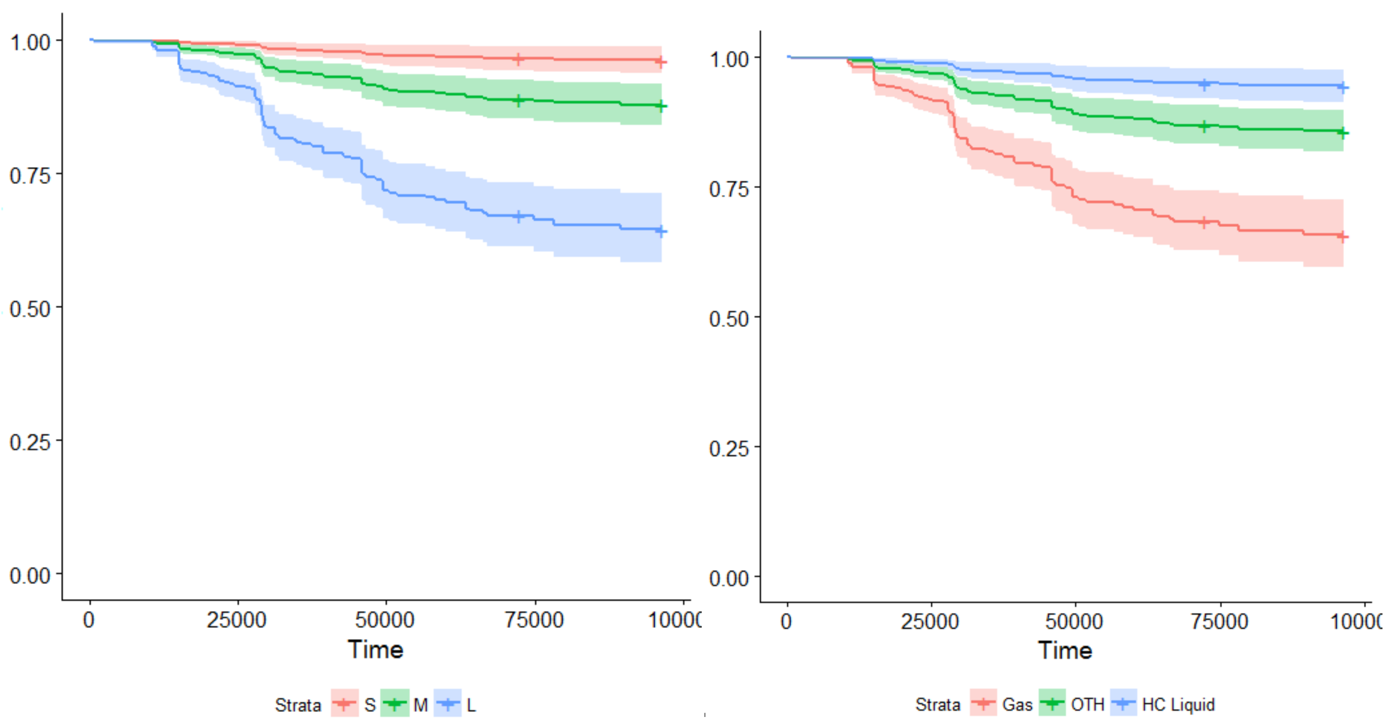


Figure 18 Estimated survival function for size and leakage requirement

Further, it is also possible to investigate the influence from numerical variables by check how estimation depended upon the value of a numeric variables. Figure 19 displays survival functions of sizes, flow medium and leakage requirement. It appears each variables significantly distinguish between subcategories when other variables are fixed to the average values, implying that those explanatory variables are independent upon the numeric values in the model.



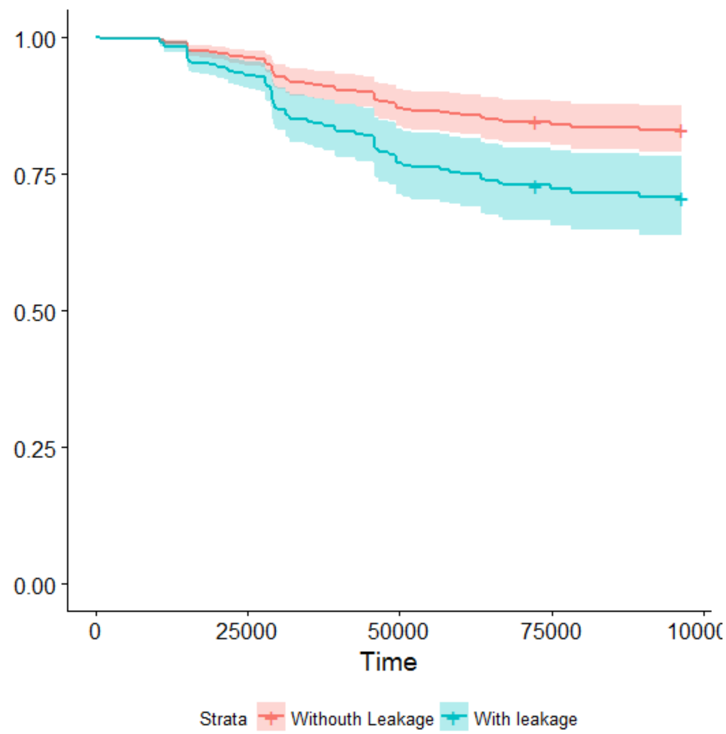


Figure 19 Estimated survival function with constant value

5.4.2 GLM model

The estimated results of the GLM model based on binomial distribution are displayed in Table 13. The results can mainly be interpreted by P-value, akaike information criterion (AIC) and coefficient (i.e. estimated Beta).

Table 13 Results for GLM model with numerical variables

Explanatory variable	Beta	Exp(Beta)	Standard error	Z-value	P-value
(Intercept)	-1.72	0.18	0.37	-4.67	2.99×10^{-6}
Type	-0.31	0.73	0.14	-2.16	0.03
Size	1.43	4.18	0.23	6.22	4.97×10^{-10}
Medium	-1.27	0.28	0.20	-6.24	4.29×10^{-10}
Actuator	-0.65	0.52	0.37	-1.77	0.08
Leakage requirement	0.38	1.46	0.11	3.33	0.86×10^{-3}

Null deviance: 690.96 on 588 degrees of freedom
Residual deviance: 539.74 on 583 degrees of freedom
AIC: 551.74

In this case, P values of explanatory variables for size, medium and leakage requirement, i.e. 1.43, -1.27 and 0.38 respectively, indicate that the three explanatory variables have high statistical significance. In addition, Exp(Beta) represents the impact from each inventory- and operational parameter on the reliability performance. The intercept, often labeled as a constant, is supposed to be the mean value of failure probability when all the explanatory variables are equal to 0. Z value is a ratio of each regression coefficient divided its standard error.

The null deviance shows how well the response variable is predicted by a model that include only intercept, whereas the residual deviance is related to a model includes the explanatory variables. For instance, null deviance is 690.96 on 588 degrees of freedom. The deviance decreases to 539.74 on 583 degrees of freedom. It implies that the deviance has reduced 151.22 with a loss of 5 degrees of freedom, a significant reduction in deviance. AIC is equal to 551 provides a value for assessing the quality of the model through comparison of related models. Its intent is to prevent us from including irrelevant variables.

Interactions between leakage requirement and size is involved in the developed GLM model, then the value of AIC decrease from 551.74 to 543.67, as illustrated in Table 14. It implies that the interaction should be taken into account in the model. The developed GLM model is:

$$Failure\ probability\left(Failure\right) = \beta_1 \cdot Size + \beta_2 \cdot Flow medium + \beta_3 \cdot Size : Flow medium$$

Size and interaction between Size and Leakage requirement are important for failure rates in this case. It can be also interpreted that Size and Leakage requirement have significant influence on reliability performance.

Table 14 Results for developed GLM model with numerical variables

Explanatory variable	Beta	Exp(Beta)	Standard error	Z-value	P-value
(Intercept)	-2.54	0.08	0.22	-11.33	2.00×10^{-16}
Size	1.57	4.81	0.21	7.34	2.08×10^{-13}
Medium	-1.09	0.34	0.18	-5.86	4.52×10^{-9}
Size: Leakage	0.66	1.93	0.13	5.15	2.63×10^{-7}

Null deviance: 690.96 on 588 degrees of freedom
Residual deviance: 535.67 on 585 degrees of freedom
AIC: 543.67

5.5 Model validation

When conducting any data analysis, it is important to evaluate how well the model fits the data and that the data meet the assumption of the model [24]. As a standard linear model, the assumptions that support the GLM should be checked. The validation methods for GLMs is used for Gaussian linear models. However, some adaption are necessary and depending on the type of GLM, which will not be discussed here. More information about the methods can be found in the book: Extending the linear model with R [29].

The focus of this thesis is to introduce the validation for COX models. Although the COX model has the assumption of distribution free failure times, there are still some essential assumptions: the variables are independent; the regression coefficients β_i is constant over time, which is also called proportional hazards (PH) assumption; the link function is exponential; linear combination of the explanatory variable [30]. The model validation is employed to examine goodness-of-fit of the models and data.

The data analysis using models produces a set of residuals. A residual represents the difference between the data and the model and are essential to explore the adequacy of the model [29]. It is of specific use in our context because some residuals can be used in more powerful ways to examine goodness-of-fit. As indicated in Figure 20, five residual Cox-Snell residual, Schoenfeld residual, deviance, martingale residuals and influential observation, can split into two main categories: Those used to validate the goodness-of-fit for the model (Cox-Snell, Schoenfeld and martingale residual) and those for data (influential/Score residual and deviance).

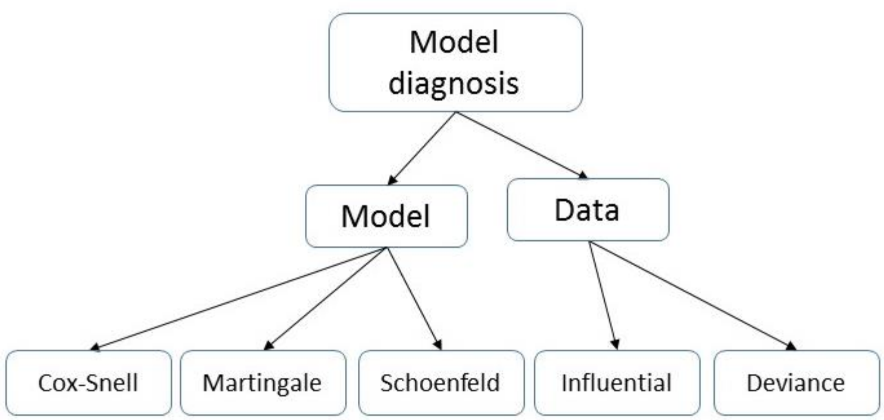


Figure 20 COX model validation process

Cox-Snell residuals are performed to examine the overall fit of a model. If the model fits, then the residuals should be distributed exponentially [24]. Martingale residual can be viewed as the difference between the observed number of death items and the expected numbers based on the fitted model. Schoenfeld residual are based on the contribution to the derivative of the log partial likelihood. If the Schoenfeld residual exhibits randomly, then this gives the evidence that the explanatory variables' effect is not changing by time [24]. It can be used to check PH assumption in the models. Score residuals (i.e. influential residual) is a measure for difference influences on explanatory variables' coefficients from various observations. The influence is the impact of a single data point on the fit of a model [24]. Deviance residual is a basic way to check potential outliers that are observation points are distant from other observations.

Which residuals should be used lies on the purpose of validation, e.g. when we concern proportional hazards (PH) assumption in the model, scaled Schoenfeld residuals vs time could be employed to test and graphical diagnostic. Some examples of residuals (i.e. Cox-Snell, Schoenfeld and score residuals) for the developed COX model with three categorical explanatory variables (i.e. Size, Flow medium and Leakage requirement) are given in the following section. Not all residuals will be applicable in this case.

5.5.1 Cox-Snell residuals

Cox-Snell residual is a kind of residual for checking overall goodness-of-fit of COX model. If the model fit well, the plot should have a 45-degree slope. Shown in Figure 21 is the exponential probability plot of Cox-Snell residuals, which confirms the adequacy of the fitted model.

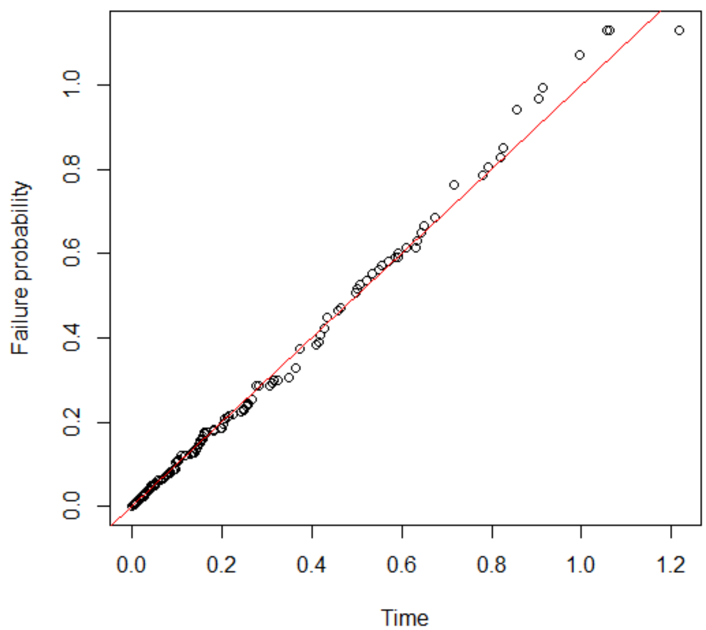


Figure 21 Checking goodness of fit for COX model

5.5.2 Scaled Scheoenfeld residuals

Statistical tests for the PH assumptions called Scale Scheoenfeld residuals, by using command 'cox.zaph()' in R. It computes at a test for each explanatory variables along with a global test for the model as a whole. Plotting scaled Schoenfeld residuals against time for each parameters in the model is shown in Figure 22, interpreting the graphs by smoothing. It is expected the slope of Schoenfeld residuals vs time should be not changing with time. In this case, it seems to be no obvious trend in the plots, implying that the PH assumptions appears to be supported for the explanatory variables: Size, Medium and Leakage requirement.

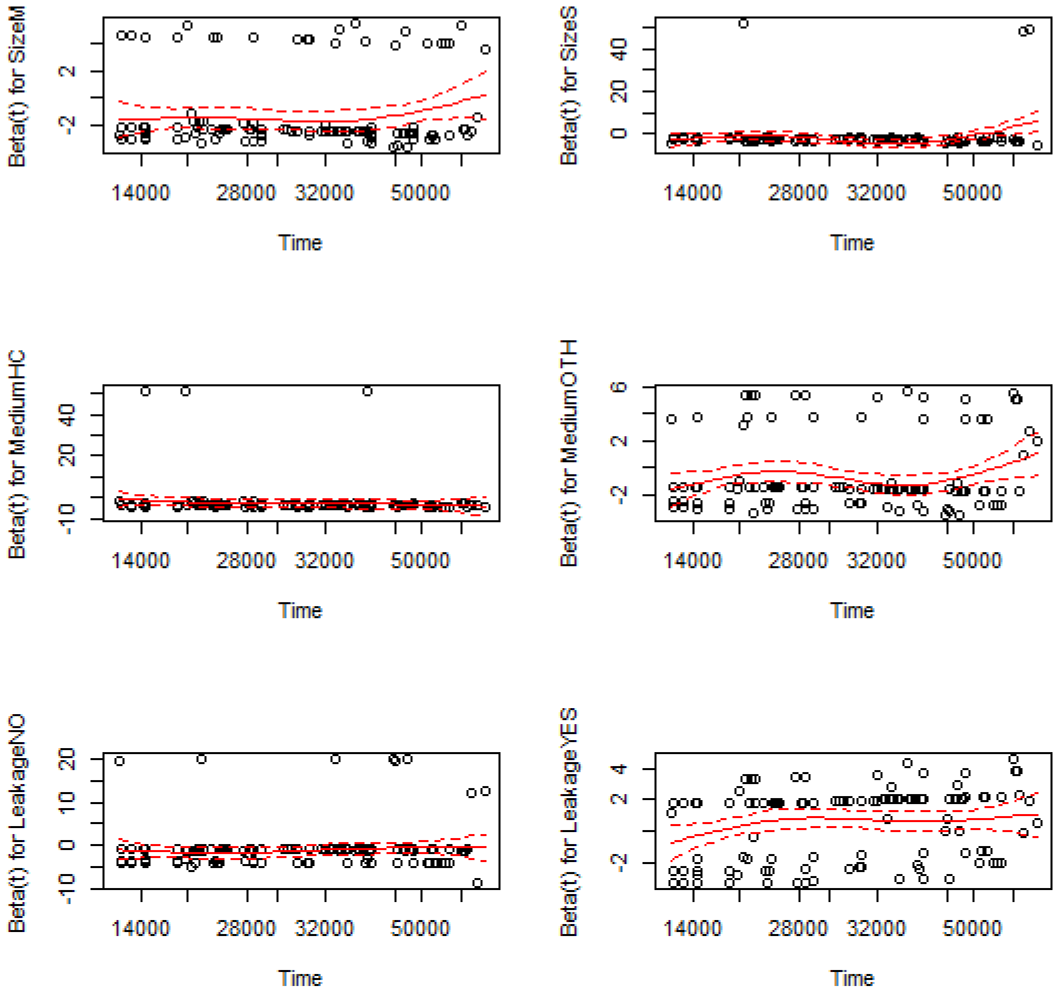


Figure 22 Plots of scaled Schoenfeld residuals against time

5.5.3 Scaled score residuals

Scaled score residual (i.e. influential residual) can be used to identify influential observations by estimating changes on coefficients. “Dfbeta” is a measure of estimated changes in the coefficients divided by their standard errors. In this case, scaled score residuals appear in Figure 23. It suggests that none of the observation is dramatically influential, although some of the residual value are large.

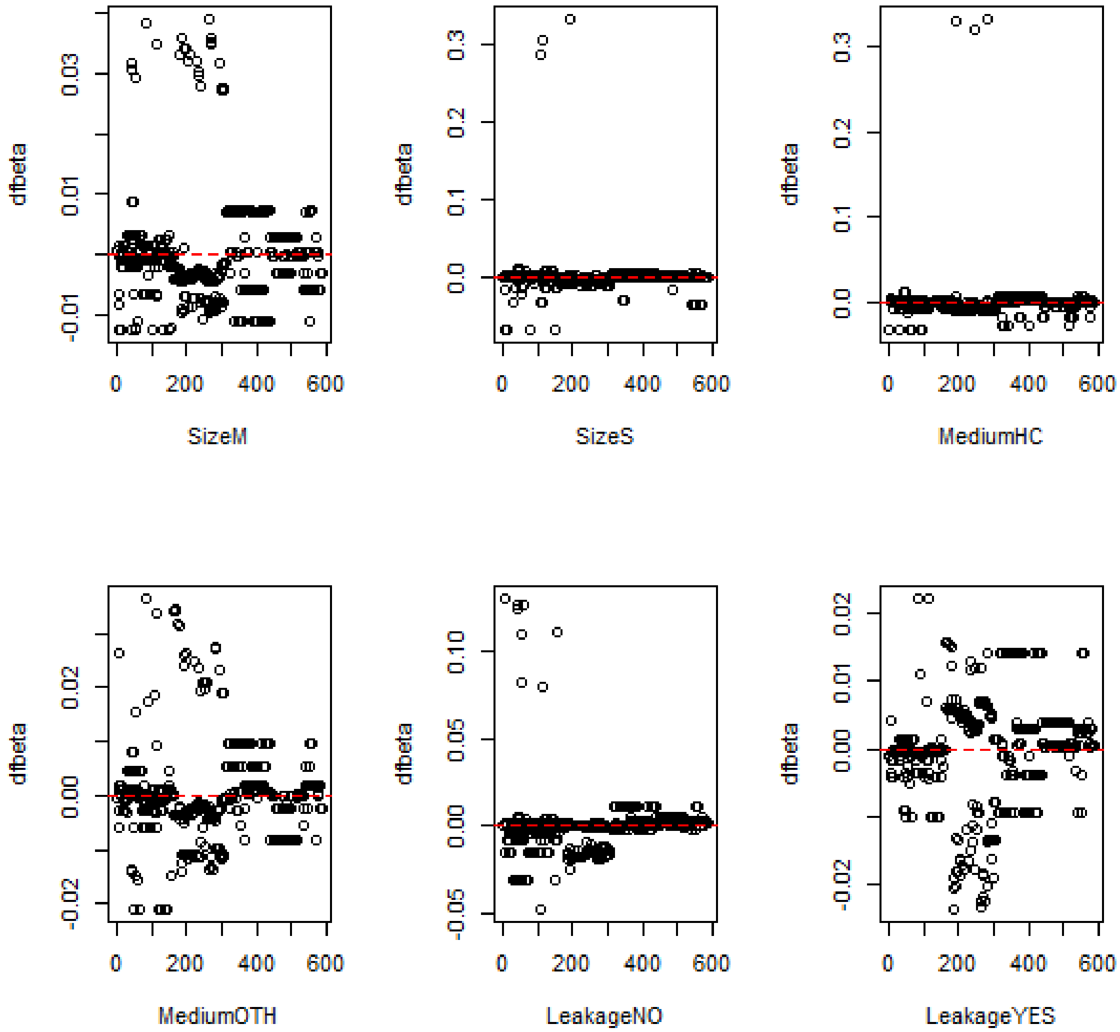


Figure 23 Plots of scaled score residuals

Summing up the above, it can be concluded that the developed COX model with categorical variables adequately describes the data in general. Cox-Snell residuals, Scaled Scheoenfeld residuals and scaled score residual, provide evidence that support goodness of fit for the model and the corresponding data.

Hence, it is concluded that the following parameters are significant for establishing modified failure rates for shut down valves:

- Size of valve is one of significant parameters for reliability performance (i.e. failure rates). Large size could be regarded as a negative influencing factor so that increased size will increase failure probability for a shutdown valve.
- Leakage requirement is a contributor to failures since it is associated with increasing failure probability. Valves with leakage requirement may be more vulnerable to the failures compared to the valves without leakage requirement.
- Valves with HC liquid medium will have lower failure probability compared to valves with gas.

6 Estimate failure rates

This chapter performs the failure analysis that is the basis for estimating DU failure rates. The analysis results in COX model and GLM model in the previous chapter are: 1) Larger size increase failure probability for an ESD or PSD valve; 2) Leakage requirement is a contributor to failures since it is associated with increasing failure probability; 3) Valves with HC liquid medium have lower failure probability compared to valves with others. In order to explain and verify those result, the failure analysis will be performed for acquiring more detail information about failures (e.g. failure modes, detection methods, failure causes) and investigating correlation between failures and parameters. This chapter also presents an example of modifying failure rates for a new facility that has similar environmental and operational conditions with the existing facilities, considering the influence of inventory- and operational parameters on reliability performance.

6.1 Failure analysis

Failure analysis is a process for examining the causes and mechanism of failures [31]. The focus of failure analysis is on DU failures for the ESD and PSD valves at the two facilities. The failure analysis is employed to investigate not only the failure causes but also the relationship between DU failures rates and inventory data. It enables us to obtain more detailed information of DU failures, failure rates associated with inventory- and operational parameters. Then it could be determined significant parameters that impact on reliability performance and modify failure rates for a new device or new facility.

DU failures can be classified into various groups with respect to failures (e.g. failure modes, detection methods and failure causes) and inventory- and operational parameters (e.g. type, size, flow medium of the valves). In the following section, the focus is on the three inventory- and operational parameters: size, flow medium and leakage requirement, because they are considered as significant inventory- and operational parameters from the data analysis in chapter 6.

DU failure modes for shutdown valves are mainly divided into delayed operation (DOP), fail to close on demand (FTC), and leakage in closed position (LCP). DOP refers to failures where the valves cannot be closed within the required closing time. FTC represents a situation where the valve will not fully close and may be caused by e.g. a broken spring, blocked return line for the hydraulic fluid or too high friction [1]. LCP is associated with a situation where fluid leaks through the closed valve and is often generated from corrosion or erosion on the gate or seat [1]. FTO are normally not dangerous failures for shut down valves since most shut down valve shall close upon demand. However, there are some valves that shall open upon demand and hence, FTO is also regarded as a failure mode in this thesis.

Detection methods for shut down valves are classified into the following subcategories: Function test, demand, random observation, partial stroke test and leakage testing. Function test is performed manually at predefined time intervals to verify the equipment functionality. Demand presents random events where the SIF with the equipment was needed, which implies that failures could be revealed during a planned or unplanned shutdown event. Random observation refers to a situation where operators or maintenance crew detect failures incidentally, such as an operator that may detect a hydraulic leak that would have caused the valve to close too slow. Partial stroke testing for a valve is a confirmed partially test of the valve's ability to perform its safety function by moving the valve without fully closing the valve [32]. Leakage testing is used to detect a too high internal leak rate through the valve.

The causes of DU failures may be associated with design, fabrication and installation, operation and maintenance as well as internal and external environment. Design is a common reason for failures of ESD and PSD valves, e.g. a valve actuator designed with insufficient tension so that failures will reoccur unless improving the actuator design. An example of an installation failure may be caused by incorrect installation. Operational failures are related to service and maintenance errors for the equipment, e.g. that a valve has not been sufficiently lubricated during preventive maintenance. External or internal environment are also important factors that impact on reliability performance, e.g. DU failures caused by excessive icing or sand production.

The following section will present and discuss results of DU failures classification in accordance with the three critical inventory- and operational parameters.

6.1.1 Size

Table 15 displays a large number of large-sized valves with DOP failure mode. By reviewing those DU failures, it is known that the failures often occur at one facility and mainly caused by similar hydraulic problems. The problems are in relation with their control systems, rather than the valves. In total 31 DU failures are linked to hydraulic problems and should be removed from our DU failure analysis in order to obtain more reasonable results.

Table 15 DU failure distribution for sizes and failure modes

Size \ Mode	DOP	FTC	FTO	LCP	Total
Large	114	13	1	3	131
Medium	9	16	-	2	27
Small	-	3	-	-	3
Total	123	32	1	5	161

Then the updated distribution of DU failures is illustrated at Table 16. The table shows that 78% of DU failures are related to Large-sized valves and the DOP failure mode accounts for over 83% of DU failures for Large-sized. FTC failures tend to occur within the Medium-sized group. DU failures of Small-sized valves account for only 1% of total DU failures. It seems therefore that a Large-sized valve and medium-sized valves have higher failure probability than Small-sized valve. That is the same results as the results from the data analysis introduced before.

Table 16 Updated DU failure distribution for sizes and failure modes

Size \ Mode	DOP	FTC	FTO	LCP	Total
Large	85	13	1	3	102
Medium	9	14	-	2	25
Small	-	3	-	-	3
Total	94	30	1	5	130

As showed in Table 17, DU failures of Large-sized valves and medium-sized valves are mainly detected by function test and demands. PST is used to reveal 14 DU failures for large-sized valves with gas medium. But they have been excluded from the dataset due to hydraulic problems that have been explained previously.

Table 17 DU failure distribution for sizes and detection methods

Method / Size	Demand	Function test	Leakage testing	Partial stroke test	Random observation	Total
Large	46	52	1	-	3	102
Medium	8	11	-	-	6	25
Small	-	1	-	-	2	3
Total	54	64	1	-	11	130

It is difficult to spot a clear correlation between failure causes and the sizes of valves due to a large number of failures with unknown causes in this case, as shown in Table 18.

Table 18 DU failure distribution for sizes and failure causes

Cause / Size	Design	Environment	Fabrication /installation	Management	Operation /maintenance	Unknown	Total
Large	3	12	2	1	4	80	102
Medium	2	9	1	-	1	12	25
Small	-	-	-	-	1	2	3
Total	5	21	3	1	6	94	130

6.1.2 Flow medium

The majority of DU failures occurs for the valves with gas medium, illustrated in Table 19, which is a bit of surprise consider that gas is a clean medium. DOP failure mode accounts for 76% of total. Those DU failures stem from one facility with a large number of DOP failures (123 DU failures in total). Only 3 DU failures are related to HC liquid, which can be used to explain why medium HC liquid has less impact on failure rates compared to gas.

Table 19 DU failure distribution for flow medium and failure modes

Mode / Medium	DOP	FTC	FTO	LCP	Total
Gas	75	19	1	4	99
HC	2	1	-	-	3
Others	17	10	-	1	28
Total	94	30	1	5	130

Table 20 shows the distribution of flow medium associated with ESD and PSD valves, considering valves at the two the facility as one data set. More detail statistical result about inventory- and operational parameters could be found on Appendix A. There are 268 valves with gas medium, accounting for 63% of total. 257 valves that are regarded as large-sized valves (i.e. 60% of the total). The major portion of the valves are the valves with gas medium or the large-sized valves. That may be one reason that medium gas and large-sizes have significant influence on failure rates.

Table 20 Distribution of the valves for flow medium and sizes of valves

Medium	No. of valves	Percentage	Size	No. of valves	Percentage
Gas	268	63%	Large	257	60%
HC	51	12%	Medium	154	36%
Others	108	25%	Small	16	4%

6.1.3 Leakage requirement

Leakage requirement is regarded as a significant inventory- and operational parameters as well. LCP failures mode should be the most dominate failure mode among the valves failures for the valves with leakage requirement. Leakage requirement is in relation to specified maximum internal leakage rate that is relevant to define the failure model LCP. However, there is no obvious evidence to support this assumption by the fact that only 5 DU failures is related to LCP failure mode, as shown in Table 21. Therefore, when modifying failure rates, leakage requirement will not be regarded as an inventory- and operational parameter that significantly impact on reliability performance.

Table 21 DU failure distribution for leakage requirement and failure modes

Mode / Leakage	DOP	FTC	FTO	LCP	Total
NO	38	19	1	3	61
YES	56	11	-	2	69
Total	94	30	1	5	130

6.2 Modifying failure rates

A method for modifying failure rates was suggested in chapter 3. Here, a specific example will be given to show how to modify failure rates based on operational experience taking into account inventory- and operational parameters. A company intends to install a new facility with comparable environmental and operational conditions corresponding to an existing the facility. There are two important inventory- and operational parameters for the ESD and PSD valves from the data analysis: size and flow medium, as we discussed previously. Four steps will be presented in detail in the following section.

Step 1: Update failure rates based on operational data

The objective of this step is to collect operational data for updating failure rates. It is a basis for modifying failure rates. The number of DU failures, aggregated operational time and failure rates of ESD and PSD valves for a facility are shown in Table 22. Updated failure rates for ESD and PSD valves is $\hat{\lambda}_{DU} = 8.9\times10^{-7}$) that is lower than generic failure rates from the PDS handbook ($\lambda_{DU} = 2.1\times10^{-6}$). The master project work covers categorizing failure data as well as inventory- and operational parameters (See Appendix B) for this specific facility.

Table 22 Summary of DU failures, operational time and failure rates

	No. of DU failures	Aggregated operational Time(hours)	Failure rates
ESD & PSD	13	1.5×10^{7}	8.9×10^{-7}

Step 2: Determine the two parameters weights, i.e. sizes and medium.

In order to divide updated failure rates $\hat{\lambda}_{DU}$ into groups of parameters, the weights of two parameters should be determined by expert judgement. For example, the weight of size is assigned as the value of 0.6, while the weight of flow medium is 0.4. The distribution of weights is shown in Table 23.

Step 3: Determine the subcategories weights for each parameter

We must determine the weights of subcategories corresponding DU failures. The weights θ_{ij} is calculated by the fraction of DU failures for subcategory j among all DU failures for parameter i, for example, the weight of small-sized is 15.4% (e.g. $\theta_{small-sized} = \frac{2}{2+5+6}$). Then we can obtain failure rates to subcategories for each parameter. For instance, the failure rate to small-sized of the valves is estimated as: $\lambda_{small-sized} = \omega_{size} \cdot \theta_{small-sized} \cdot \hat{\lambda}_{DU} = 0.6\times15.4\%\times8.9\times10^{-7} = 8.2\times10^{-8}$

Table 23 Parameter weights and failure rates for subcategories

Parameter	Weight of parameter (ω_i)	Subcategory	No. of DU failures	Weight of subcategory (θ_{ij})	λ_{ij}
Size	0.6	Small-sized	2	15.4%	8.2×10^{-8}
		Medium-sized	5	38.5%	2.0×10^{-7}
		Large-sized	6	46.1%	2.5×10^{-7}
Medium	0.4	Gas	5	38.5%	1.4×10^{-7}
		HC Liquid	0	-	-
		Others	8	61.5%	2.2×10^{-7}
Total					8.9×10^{-7}

Step 4: Determine score of influence of subcategory j of parameter i

By comparing inventory conditions (e.g. the distribution of inventory- and operational parameters) with existing facility and new facility, correction factors of subcategory σ_{ij} could be determined by expert judgement. The value of the correction factors regarding influence on reliability performance for each subcategories, can obtain from Table 24.

Table 24 Explanation of the correction factors based on expert judgement

σ_{ij}	Explanation
0.1	The subcategory j to the parameter i is expected to eliminate the failure rates for new facility compared to the existing facility with the similar conditions and it should be demonstrated significant impact on reliability performance through analysis parameters.
0.5	The subcategory j to the parameter i is expected to have a significant effort on decrease failure for new facility compared to the existing facility with the similar conditions.
1.0	No specific effect indicate that anything is changed for the failure rates
1.5	Failure rate will not considered changed for the new facility with respect to this subcategory j
3	The situation is significantly worse for new facility with respect to this subcategory j

As shown in Table 25, the conditions of the parameters rely on the distribution of subcategories for size and process medium.

Table 25 Comparison of the distribution for subcategories

Parameter	Existing facility	Distribution	New facility	Distribution	σ_{ij}	λ_{ij}^{*}
Size	Small-sized	12%	Small-sized	10%	1	8.2×10^{-8}
	Medium-sized	48%	Medium-sized	30%	1	2.0×10^{-7}
	Large-sized	40%	Large-sized	60%	1.5	3.7×10^{-7}
Flow medium	Gas	17%	Gas	30%	0.5	0.7×10^{-7}
	HC Liquid	35%	HC Liquid	35%	1	-
	Others	48%	Others	35%	1	2.2×10^{-7}
Total						9.5×10^{-7}

Where σ_{ij} illustrates the impact on failure rates by comparing the distribution subcategories for new facility and existing facility. It can be based on several experts and engineering knowledge and judgment by identifying the values for each subcategory. Modified failure rate are: $\lambda_{DU}^{*} = 9.5\times10^{-7}$ for ESD and PSD valves at new facility.

7 Discussions and Conclusions

This chapter is divided into three parts: 1) Summary the main contributions and results for the master project; 2) Discussion of challenges and limitations in the approach; 3) Proposed recommendations for further work.

7.1 Conclusions

Inventory- and operational parameters traditionally have often been skipped in reliability assessment. The main contribution of this thesis have been to suggest an approach to establish modified failure rates for safety critical equipment taking into account important inventory and operational parameters that significantly impact on reliability performance. The contributions are decomposed into three parts:

- An approach has been proposed for establishing modified failure rates, including identification of equipment and parameters, data collection, data analysis and modifying failure rates.
- Methods and analytical models have been employed to identify and analyze significant parameters.
- A method has been proposed to modify failure rates for a new facility, where it is foreseen that inventory and operational parameters may effect reliability performance.

The results of the thesis is that three important parameters have significant influence on reliability performance: size, flow medium and leakage requirement. Large-sized valves are more prone to fail compared with others, implying that increased size can increase the failure probability for shutdown valves. Valves located in pipelines with HC liquid will have lower failure probability compared to valves with other flow medium. It appears that valves with leakage requirement have higher failure rates than valves without leakage requirement. The reason for that may be that the valves with leakage requirements are required more complex maintenance procedures, high frequency to check and more strict acceptance criteria. Having large-sized, HC liquid or leakage requirements for shutdown valves do not essentially influence any degradation mechanism of the valves. It seems that the valves with large-sized, gas medium and leakage requirements may be more vulnerable to failures.

7.2 Discussions

Although the data from two facilities is not sufficient to obtain strong and uniform results, the more important is that the thesis offers an effective and practical approach to establish modified failure rates for safety critical equipment. The approach and the methods in this thesis is applicable during updating handbooks and design phases. They can be used for identifying important inventory- and operational parameters when updating failure data of the handbooks. They are also enable designers to pay more attention on the significant parameters in order to reduce the failure risk. When it is desired to decide size of a shutdown valve, for example, smaller-sized in a reasonable and acceptable range is better for reliability performance. Efforts in this thesis have also been made to elaborate statistical methods to identify and analyze the parameters for explaining variations of reliability performance in detail. It enables us to improve safe systems concerning significant inventory- and operational parameters during SISs design phases. Modified failure rates can be used to better predict the variations when it is foreseen that facilities' specific conditions. It provides more efficient data support on reliability performance prediction that apply for decision-making on risk control and management.

On a global level, the main objectives of the thesis have been realized. The various use of the term regarding reliability assessment and statistical methods are investigated and summarized in chapter 2 and 3. In chapter 4, the approach for modifying failure rates has been proposed and elaborated. It was decided to focus on shutdown valves and suggested the relevant selection criteria; Five potential parameters that impact on reliability performance are specified: size, flow medium, leakage requirement, type and actuator principle; statistical methods to analyze the parameters has employed in chapter 5; An example for modifying failure rates of the shutdown valves at a new facility is presented in chapter 6.

Despite having achieving the objectives, there are some challenges and limitations in the thesis related to the approach to modify failure rates, methods of data analysis and the quality of data as well as data-collection. Challenges in the approach arises from identification of equipment and parameters, derivation of categories, values of variables and subjective judgement. This thesis is delimited to shutdown valves based on data from two facilities. The variations of reliability performance have been revealed by size and flow medium in this case. It should be noted that the results may not be applicable for other facilities. When splitting up the parameters, a challenge is how to categorize the data. In this case, inventory- and operational parameters are divided into two or three categories in order to reduce complexity of calculation. However, in practice such classification can be further developed to more categories. The values used in the quantification of variables in the modes will also impact on result, which is defined as parameter uncertainty. Moreover, determining the weights of the parameters relies on subjective judgment form expert, which will have effect on credibility of the approach. The limitations of the approach may have many causes, such as the lack of knowledge, variation of the operational data and human factors etc.

The results of data analysis are dependent on applied methods and models. A poor model will lead to uncertainty and invalidity of the data analysis. The focus of this thesis is parameter estimations. The difference between parameter estimation and non-parameter estimation should be checked by several techniques and methods, but not covered in this thesis. The main reason for using COX and GLM model, is that they make no assumption about the underlying failure distributions and can be used for discrete variables, regardless of the distribution of failures. It will reduce inappropriateness from selection of models. However, the two models are linear regression models, without consideration of complex interaction and time-dependent variables. In addition, one shutdown valve had many failures due to design problem have been removed in the data analysis. That may potentially be a considerable contributor to failures.

The choice of methods and models is strongly dependent on the assumptions made in the approach. COX models rely on the assumption that the ratio between the failure rates is constant over time. The validation of the model is thus important and have been performed in R. A set of residuals, i.e. statistical tests, have been used to check assumptions of the models and goodness-of-fit of models. GLM model is based on the assumption that the failures are binomially distributed. The whole lifetime of the equipment (e.g. the time from the point put into service to the end of life) is not required in this model. It is difficult to conclude which method is more appropriate without specific situation. In this case, it is seemed that COX models perform more reasonably and applicably compared to GLM models since the assumptions and the models fit well the data. More specific statistical tests are desired to evaluate the two models.

When evaluating data based on field experience, two issues should be considered: the scale of collected data (e.g. the number of equipment) and the quality of collected data (e.g. the completeness of data). It is challenging to derive sufficient statistical significance and obtain uniform results from a dataset consisting of in total 161 failures for two facilities. The results of data analysis emphasize that equipment like shutdown valves are relatively few in numbers. In addition, a number of factors may lower the quality of data, e.g. human errors (e.g. editing/typing errors), technical problems (e.g. limited scope and scale of searching) and changes of information systems (e.g. different classification of failure modes). Failure notifications and equipment information are mainly registered by first line operation and maintenance personnel. They do not always fill in all relevant information concerning equipment and failures, e.g. time put into service, replacement information etc. Insufficient failure notifications will reduce the accuracy of failure analysis, e.g. unknown failure causes. The main uncertainty of data stems from misunderstand, time or cost constraints or lack of resource and support etc. More efforts on improving quality and completeness of data are expected. Some relevant recommendations for data collection, are shown in Table 26.

Table 26 Challenges and recommendations to data collection

Current situation and challenges	Recommendations
Insufficient inventory data in the systems	Improve the quality of SAP reports with respect to inventory and environmental parameters, e.g. time put into service, replacement information, pressure, and temperature etc.
Incomplete data recorded in the systems	Training for data- collection should be given to the first line operation and maintenance personnel. Detailed introduction about registering data will help to improve completeness of the data. Review and correcting records should be carried out regularly.
No documentation of how to perform data search in the systems	Prepare a brief introduction to search inventory and environmental data from the systems
Different code system and classification, e.g. failure modes, detection methods.	Check the difference in code system and reexamine classification of failure and detection methods. It is also necessary to discuss the content of the notification with operators in order to obtain as correct information as possible.
Inconsistent data forms from various manufacturers	Uniform data-collection formats with the same requirements for various manufacturers

7.3 Further work

Shutdown valves act as the examples in this master thesis. The further research activities could focus on collecting more data for other groups of safety critical equipment, e.g. level transmitters, fire and gas detectors, smoke detectors, pressure safety valves etc. It is desirable to identify and analyze relevant parameters and compare the difference between equipment groups. It will also be necessary to consider a larger sample of equipment based on data from several facilities to obtain sufficient statistical confidence. Some suggestions to improve the quality of data during data collection have been discussed in the previous section. More detailed recommendations to enhance the quality of data collection should be proposed after communication with the operators and maintenance personnel.

It is possible to develop the analytical methods to identify significant parameters with more complex and dynamic models. It should be noted that it will be more relevant to perform specific facility analysis for some types of equipment, such as smoke detectors, where the number of tags on one facility is often large.

In this master thesis, the application of modified failure rates is given for a new facility when estimating failure rates with comparable conditions as an existing facility. The approach to modify failure rates can also enable to update the data for safety critical equipment in the handbooks, e.g. PDS handbook, taking into account inventory- and operational parameters. Other applications of modified failure rates could be considered and discussed in further work, e.g. maintenance optimization etc.

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Appendix A Statistics for two facilities

The aim of this project report is to analyze various inventory- and operational parameters as well as DU failure data, and to provide a basis for identifying critical parameters that impact on the reliability performance of the valves. It focuses on data analysis for ESD and PSD valves based on operational experience from two facility within the oil and gas industry.

A.1 DU failures

We take into account DU failures for those two facilities. Detailed information of DU failures and corresponding operational time are shown in Table 27. Failure rates for two facilities are higher than generic failure rates from handbook, i.e. 2.1×10^{-6} per hour.

Table 27 Summary of failure rates information for two facilities

	DU failures	Aggregated Operational time	Lambda
ESD	44	8.1×10^{6}	5.5×10^{-6}
PSD	131	2.4×10^{7}	5.4×10^{-6}
ESD & PSD	175	3.2×10^{7}	5.4×10^{-6}

A.2 Type

The distribution of types for ESD and PSD valves is shown in the following table and figures. As seen, there are more Ball valves and Butterfly valves for PSD than for ESD valves.

Table 28 Types of the valves for two facilities

	Ball	Gate	Butterfly	Others
ESD	71	57	2	-
PSD	355	62	29	13
ESD+PSD	426	119	31	13

A.3 Size

Table 29 displays the distribution of the sizes of the ESD and PSD. The ESD and PSD valves are split into four groups according to their size: Small (0-1"), Medium (1"-3"), Large (3"-18") and Extreme large (>18"). It is shown that there are more large-sized valves for PSD than ESD.

Table 29 Sizes of the valves for two facilities

	Small	Medium	Large	Extreme large
ESD	18	30	54	27
PSD	18	196	171	70
ESD+PSD	36	226	225	97

A.4 Flow medium

It is found that gas is regarded as primary flow medium both for PSD than ESD. More detail information is shown in Table 30.

Table 30 Flow medium of the valves for two facilities

	ESD	PSD	ESD+PSD
Chemical	28	68	96
Diesel	-	8	8
Gas	63	261	324
HC liquid	21	57	78
Multiphase	2	23	25
Sea water	-	9	9
Water	16	33	49

A.5 Actuator principle

The distribution of actuator principles for ESD and PSD valves is illustrated in Table 31. The primary part of the ESD and PSD valves use hydraulic actuators.

Table 31 Actuator principles of the valves for two facilities

Actuator	Hydraulic	Pneumatic	Total
ESD	120	10	130
PSD	446	13	459
Total	566	23	589

A.6 Leakage requirements

Table 32 shows the difference leakage requirement between with ESD and PSD valves. The most of ESD valves (80% of total ESD valves) have leakage requirement, whereas only 26% of PSD valves require leakage test.

Table 32 The valves with leakage requirement for two facilities

Leakage requirement	ESD	PSD	ESD+PSD
Number	104	119	223
Percentage	80%	26%	38%

Appendix B Statistics for one facility

This project report focuses on data analysis for ESD and PSD valves based on operational experience from one facility within the oil and gas industry. The aim of the project report is to analyze DU failures associated with various inventory- and operational parameters, and to identify critical parameters that impact on the reliability performance of the valves.

B.1 DU failures

In this report, only DU failures are taken into account since they will prevent the execution of safety-critical functions as long as they are not detected and revealed. Detailed information of DU failures is shown in the following tables and figures.

Table 33 Summary of DU failure, operational time and failure rates for one facility

	DU failures	Operational time	Lambda
ESD	6	$5.0 \cdot 10^{6}$	$1.2 \cdot 10^{-6}$
PSD	7	$9.7 \cdot 10^{6}$	$7.2 \cdot 10^{-7}$
ESD & PSD	13	$1.5 \cdot 10^{7}$	$8.7 \cdot 10^{-7}$

It is beneficial to understand and analyze failures by classifying DU failures into various groups with respect to failure modes, failure mechanism and failure causes. In this report, DU failure modes are mainly divided into DOP, FTC and LCP. Detection methods are classified into the following subcategories: Function test, demand, random observation, and leakage testing. The causes of DU failures are associated with design, fabrication and installation, operation and maintenance as well as internal and external environment. Detailed information with respect to failure modes, detection methods and failure causes related to DU failures of ESD and PSD valves is listed in Table 34 and Table 35.

Table 34 DU failure modes and detection methods for one facility

Failure modes	Demand	Function test	Random observation	Total
FTC	1	8	4	13
LCP	1	-	3	4
FTO	-	1	1	2
Total	2	9	8	19

Table 35 DU failure modes and failure causes for one facility

Failure mode	Design	Environment	Fabrication /installation	Operation /maintenance	Unknown	Total
FTC	8	1	2	1	1	13
LCP	2	-	-	1	1	4
FTO	-	1	1	-	-	2
Total	10	2	3	2	2	19

B.2 Types

The distribution of types for ESD and PSD valves is shown in the following table:

Table 36 Types for ESD and PSD valves for one facility

Component	Ball	Gate	Butterfly
ESD	35	23	0
PSD	73	26	5
ESD+PSD	108	49	5

B.3 Sizes

The ESD and PSD valves are split into four groups according to their size: S (0-1"), M (1"-3"), L (3"-18") and XL (>18"), as shown in Table 37.

Table 37 Sizes for ESD and PSD valves for one facility

Component	Small	Medium	Large	Extreme Large
ESD	14	26	18	0
PSD	6	51	46	1
ESD+PSD	20	77	64	1

B.4 Flow medium

ESD and PSD valves are exposed to different process medium including hydrocarbon liquid, gas, multiphase, chemical (e.g. Mono Ethylene Glycol (MEG), Triethylene Glycol (TEG)), produced water, fresh water and sea water etc. The distribution of flow medium for ESD and PSD valve is illustrated below:

Table 38 Flow medium for ESD and PSD valves for one facility

Component	ESD	PSD	ESD+PSD
Chemical	15	8	23
Diesel	-	8	8
Gas	10	46	56
HC liquid	15	12	27
Multiphase	2	23	25
Sea water	-	3	3
Water	16	4	20

The medium through PSD valves are more likely to be gas and multiphase mixture compared to the medium in ESD valves.

B.5 Leakage requirement

Information concerning internal leakage requirements is illustrated in Table 39. As seen, a relatively higher portion of ESD valves has an associated internal leakage requirement as compared to PSD valves.

Table 39 Leakage requirement for ESD and PSD valves for one facility

Leakage requirement	ESD	PSD	ESD+PSD
Number	45	14	59
%	78%	13%	36%

Appendix C Data analysis in R

C.1 COX model with categorical variables

coxph(formula = Surv(Time, Failure) ~ Type + Size + Medium + Actuator + Leakage, data = ESD.PSD), n= 589, number of events= 161

	coef	exp(coef)	se(coef)	z	Pr(>|z|)	
Type Gate	0.27	1.31	0.20	1.37	0.17	
Type Other	0.50	1.65	0.36	1.39	0.16	
Size Medium	-1.25	0.29	0.22	-5.68	0.00	***
Size Small	-2.20	0.11	0.70	-3.15	0.00	**
Medium HC	-2.60	0.07	0.59	-4.43	0.00	***
Medium Other	-0.88	0.42	0.22	-3.92	0.00	***
Actuator Pneumatic	1.39	4.01	0.75	1.84	0.07	.
Leakage NO	-1.30	0.27	0.42	-3.08	0.00	**
Leakage YES	0.46	1.59	0.20	2.32	0.02	*
Significant codes:	0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					

	exp(coef)	exp(-coef)	lower .95	upper .95
Type Gate	1.31	0.76	0.89	1.94
Type Other	1.65	0.61	0.81	3.35
Size Medium	0.29	3.51	0.19	0.44
Size Small	0.11	9.00	0.03	0.44
Medium HC	0.07	13.49	0.02	0.23
Medium Other	0.42	2.40	0.27	0.65
Actuator Pneumatic	4.01	0.25	0.92	17.57
Leakage NO	0.27	3.66	0.12	0.63
Leakage YES	1.59	0.63	1.07	2.35

Concordance= 0.776 (se = 0.023)
Rsquare= 0.252 (max possible= 0.966)
Likelihood ratio test = 171.1 on 9 df, p=0
Wald test = 122.3 on 9 df, p=0
Score (logrank) test = 160.8 on 9 df, p=0

C.2 Developed COX model with categorical variables

coxph(formula = Surv(Time, Failure) ~ Size + Medium + Leakage, data = ESD.PSD2C)
n= 589, number of events= 161

	coef	exp(coef)	se(coef)	z	Pr(>|z|)	
Size Medium	-1.33	0.27	0.21	-6.19	0.00	***
Size Small	-1.81	0.16	0.59	-3.08	0.00	**
Medium HC	-2.54	0.08	0.59	-4.34	0.00	***
Medium Others	-0.72	0.48	0.21	-3.52	0.00	***
Leakage NO	-1.10	0.33	0.39	-2.84	0.00	**
Leakage YES	0.52	1.68	0.18	2.92	0.00	**

	exp(coef)	exp(-coef)	lower .95	upper .95
Size Medium	0.27	3.77	0.17	0.40
Size Small	0.16	6.08	0.05	0.52
Medium HC	0.08	12.70	0.03	0.25
Medium Others	0.48	2.06	0.32	0.73
Leakage NO	0.33	2.99	0.16	0.71
Leakage YES	1.68	0.60	1.19	2.38

Concordance= 0.777 (se = 0.023)
Rsquare= 0.245 (max possible= 0.966)
Likelihood ratio test = 165.3 on 6 df, p=0
Wald test = 116.7 on 6 df, p=0
Score (logrank) test = 148.7 on 6 df, p=0

Significant codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

C.3 COX model with numerical variables

coxph(formula = Surv(Time, Failure) ~ Size + Medium + Leakage, data = a)
n= 589, number of events= 161

	coef	exp(coef)	se(coef)	z	Pr(>|z|)	
Size	1.24	3.45	0.19	6.61	0.00	***
Medium	-0.95	0.39	0.16	-5.91	0.00	***
Leakage	0.35	1.41	0.08	4.12	0.00	***

	exp(coef)	exp(-coef)	lower .95	upper .95
Size	3.45	0.29	2.39	4.99
Medium	0.39	2.59	0.28	0.53
Leakage	1.41	0.71	1.20	1.67

Rsquare= 0.226 (max possible= 0.966)
Likelihood ratio test = 151.2 on 3 df, p=0
Wald test = 118.2 on 3 df, p=0
Score (logrank) test = 140.8 on 3 df, p=0

Significant codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

C.4 GLM model with numerical variables

glm(formula = Failure ~ Type + Size + Medium + Actuator + Leakage, family = binomial(link = logit), data = w)

Deviance	Residuals:			
Min	1Q	Median	3Q	Max
-1.6285	-0.6892	-0.442	0.7856	2.9963

	Estimate	Std. Error	z valu	e Pr(>|z|	)
(Intercept)	-1.72	0.37	-4.67	0.00	***
Type	-0.31	0.14	-2.16	0.03	*
Size	1.43	0.23	6.22	0.00	***
Medium	-1.27	0.20	-6.24	0.00	***
Actuator	-0.65	0.37	-1.77	0.08	.
Leakage	0.38	0.11	3.33	0.00	***

Null deviance: 690.96 on 588 degrees of freedom
Residual deviance: 539.74 on 583 degrees of freedom
AIC: 551.74
Number of Fisher Scoring iterations: 5

C.5 Developed GLM model with numerical variables

Glm (formula = Failure ~ Size + Medium + Leakage : Size, family = binomial(link = logit), data = w)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.52	-0.65	-0.39	0.87	3.09

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-2.54	0.22	-11.33	< 2e-16	***
Size	1.57	0.21	7.34	0.00	***
Medium	-1.09	0.19	-5.86	0.00	***
Size : Leakage	0.66	0.13	5.15	0.00	***

Null deviance: 690.96 on 588 degrees of freedom
Residual deviance: 535.67 on 585 degrees of freedom
AIC: 543.67
Number of Fisher Scoring iterations: 5

C.6 GLM model with categorical variables

Glm (formula = Failure ~ Type + Size + Medium + Actuator + Leakage, family = binomial(link = logit), data = ESD.PSD2G)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.64	-0.69	-0.36	0.78	2.78

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-0.17	0.22	-0.76	0.45	
Type Gate	0.67	0.31	2.17	0.03	*
Type Others	0.69	0.45	1.53	0.13	
Size Medium	-1.45	0.26	-5.63	0.00	***
Size Small	-2.51	0.78	-3.22	0.00	**
Medium HC	-3.06	0.62	-4.92	0.00	***
Medium Others	-1.15	0.28	-4.11	0.00	***
Actuator Pneumatic	1.92	0.89	2.16	0.03	*
Leakage NO	-1.37	0.45	-3.02	0.00	**
Leakage YES	0.54	0.26	2.08	0.04	*

Null deviance: 690.96 on 588 degrees of freedom
Residual deviance: 525.11 on 579 degrees of freedom
AIC: 545.11
Number of Fisher Scoring iterations: 6

Appendix D Code in R

```
##Plot of failure time
A<-read.table ("ESD Time to failure.txt", header=TRUE); A
nr<-130
plot(c(0,0),c(1,1),type="l", ylim=c(0,nr+1), xlim=c(0,max(A$Time[1:nr])+10),
xlab ="Time to failure", ylab ="nr")
for (i in 1: nr) lines(c (0, A$Time[i]), c(i,i))
for (i in 1: nr) {
if (A$Time[i]! =72312 & A$Time[i]! =96456)
points (A$Time[i], i, col = "red", pch=20)}

## COX model with categorical variables for ESD&PSD valves at two facilities
ESD.PSD<-read.table ("ESD+PSD for two.txt", header=TRUE)
library (survival)
args (coxph)
cox.cate<-coxph ( Surv (Time, Failure)~Type + Size + Medium + Actuator +
Leakage, data=ESD.PSD)
summary (cox.cate)
cox.new<-coxph ( Surv ( Time, Failure)~ Size + Medium + Leakage, data=ESD.PSD)
summary (cox.new)
cox.new1<-coxph ( Surv ( Time, Failure) ~ Size + Medium + Leakage+ Size:
Medium, data=ESD.PSD)
summary (cox.new1)

## Plot failure probability for COX model with categorical variables
plot (survfit (cox.cate), xlab="Time", ylab="Survival probability")
plot (survfit(cox.new), col = 'red', xlab="Time for new model", ylab="Survival
probability")

## COX with numerical variables for ESD and PSD valves at two facilities
a<-read.table ("ESD+PSD 1 for two.txt", header=TRUE)
library (survival)
args (coxph)
cox.no<-coxph (Surv (Time, Failure) ~Type + Size + Medium + Actuator +
Leakage, data=a)
summary (cox.no)
cox.no.new<-coxph (Surv (Time, Failure) ~ Size + Medium + Leakage, data=a)
summary (cox.no.new)


## Plot size and leakage requirement for COX model with numerical variables
library ("survminer")
require ("survival")
E.P2<- survfit (Surv (Time, Failure)~Size + Leakage, data=a)
Ggsurvplot (E.P2,pval = TRUE, xlab="Time(ESD and PSD valves for two
facility)", legend = "bottom", legend.labs=c("S without leakage", "S with
leakage", "M without leakage", "M with leakage", "L without leakage", "L with
leakage"), ggtheme = theme_bw(),xlim = c(0, 90000))

##Plot size and flow medium for COX model with numerical variables
library ("survminer")
require ("survival")
```

```
E.P2<- survfit (Surv (Time, Failure) ~Size + Medium, data=a)
ggsurvplot (E.P2, pval = TRUE, xlab="Time (ESD and PSD valves for two
facility)", legend = "bottom", ggtheme = theme_bw (), xlim = c(0, 90000))

#Validate estimated coefficient of sizes depends upon covariate value
cox.size<-with(a,data.frame(Size=c(-1,0,1), Type=rep(mean(Type),3),
Medium=rep(mean(Medium),3), Actuator=rep(mean(Actuator),3),
Leakage=rep(mean(Leakage),3)))
b<-survfit (cox.no, newdata=cox.size)
library ("survminer")
require ("survival")
ggsurvplot (b, pval = TRUE, conf.int=TRUE, lty=c (1, 2, 3), legend = "bottom",
legend.labs=c ("S","M","L"))

#Validate estimated coefficient of flow medium depends upon covariate value
cox.medium<-with(a,data.frame(Medium=c(-1,0,1), Type=rep(mean(Type),3),
Size=rep(mean(Size),3), Actuator=rep(mean(Actuator),3),
Leakage=rep(mean(Leakage),3)))
c<-survfit (cox.no, newdata=cox.medium)
library ("survminer")
require ("survival")
ggsurvplot (c, pval = TRUE, conf.int=TRUE, lty=c (1, 2, 3), legend = "bottom",
legend.labs=c ("Gas","OTH","HC Liquid"))

# Validate estimated coefficient of leakage requirement depends upon covariate
value
cox.lk<-with(a,data.frame(Leakage=c(-1,1), Type=rep(mean(Type),2),
Medium=rep(mean(Medium),2), Actuator=rep(mean(Actuator),2),
Size=rep(mean(Size),2)))
d<-survfit (cox.no, newdata=cox.lk)
library ("survminer")
require ("survival")
ggsurvplot (d, pval = TRUE, conf.int=TRUE, lty=c (1, 2,3), legend = "bottom",
legend.labs=c("Without Leakage", "With leakage"))


## COX validation or diagnosis
#Plot Cox-snell residuals
cox.snell<-ESD.PSD$Failure-resid (cox.new)
sv <- survfit (Surv (cox.snell, ESD.PSD$Failure) ~1)
plot (sv$time, -log(sv$surv), ylab="Failure probability", xlab="Time")
abline (0, 1,col = 'red', lty = 1)
title (main="Cumulative Hazards of Cox-Snell Residuals", sub ="Checking
goodness of fit for Cox models")

# Plot scale schoenfeld residuals
Par (mfrow=c (3, 2))
Plot (cox.zph (cox.new), col = 'red')

# Plot influential observations
dfbeta<-residuals (cox.new, type="dfbeta")
par (mfrow=c (2, 3))
for (j in 1:6){
plot (dfbeta[, j], xlab=names (coef (cox.new))[j], ylab="dfbeta")
abline (h=0, col = 'red', lty=2)}
```

```
# Plot Score residuals
score<-residuals(cox.new, type="score")
par (mfrow=c(2,3))
for (j in 1:6){
Plot (score[,j],xlab=names(coef(cox.new))[j],ylab="score")
Abline (h=0,col = 'red', lty=2)}


# Plot Martingale residuals
par (mfrow=c(2,3))
scatter.smooth (ESD.PSD$Size, resid(cox.new, type = "martingale"))
abline (h=0,col = 'red', lty=2)
scatter.smooth (ESD.PSD$Medium, resid(cox.new, type = "martingale"))
abline (h=0,col = 'red', lty=2)
scatter.smooth (ESD.PSD$Leakage, resid(cox.new, type = "martingale"))
abline (h=0,col = 'red', lty=2)

#Plot deviance (outliers)
plot (resid (cox.new, type = "deviance"), xlab="No. of valves",
ylab="Deviance")
abline (h=0,col = 'red', lty=2)


## GLM model with numerical variables for ESD and PSD valves at two facilities
w<-read.table("ESD+PSD for two.txt",header=TRUE)
glm.ESDPSD<-
glm(Failure~Type+Size+Medium+Actuator+Leakage,family=binomial(link=logit),
data=w)
summary(glm.ESDPSD)
glm.no<-step (glm.ESDPSD)
summary(glm.no)
glm.new<-glm(Failure~Size+Medium+Leakage, family=binomial(link=logit), data=w)
summary(glm.new)
glm.new1<-glm(Failure~Size+Medium+Leakage:Size, family=binomial(link=logit),
data=w)
summary(glm.new1)


## Validation and diagnosis for GLM model
par(mfrow=c(2,2))
plot(glm.new1)
deviance(glm.new1)
pchisq(535.67,585)
pchisq(690.96,588)
sum(residuals(glm.new1,type="pearson")^2)
```