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## **Toolbox for Statistical Analysis of Load and Strength in Vehicle Engineering**

Master's thesis in Applied Mechanics

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MASTER'S THESIS IN APPLIED MECHANICS

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CHALMERS UNIVERSITY OF TECHNOLOGY  
Göteborg, Sweden 2018

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## ABSTRACT

In the fatigue reliability assessment of the automotive industry there is a need for capturing and accounting for the variation in customer load measurements. This is what the variation mode and effect analysis(VMEA) aims to do, but there is no easy and systematical way of using it and there is little information on the methods robustness in the face of random variations. This thesis is implementing the VMEA method, that has been modified for the vehicle industry, by using the programming language Python, thus creating a VMEA toolbox and then testing it on customer load and component strength data, provided by Volvo Group Trucks Technology. To test the robustness of the VMEA method a parameter study and a sensitivity study are performed. In the parameter study the four different input parameters, which are prone to change between cases, are tested. The parameter study is performed in order to provide a framework for how each input parameter affects the end results for the VMEA method. The aim of the sensitivity study is to test the robustness with regard to fewer customer measurements. The first part of the sensitivity study consists of strategically removing customer load data in order to determine both the amount of data and which data is needed to receive reasonable results. In other words, to determine how the variation of magnitudes, of the customer loads, affects the VMEA results. The second part of the sensitivity study consisted of randomly removing different amount of customer load data multiple times. From the results of this thesis it is observed that VMEA is reliable and a robust method for doing fatigue reliability assessments in the automotive industry, on a component level. When it comes to the four input parameters, it can be concluded that the VMEA method is robust when using reasonable estimations of input parameters. For the sensitivity study, VMEA shows robustness when missing customer data and only at a few points have a striking deviation, but even then provides conservative results. Overall, the conclusion is that the variation has the largest impact on the safety factors and thus it is of great importance to capture it as good as possible in the full scale test. Finally, it is safe to say that VMEA is a good way of doing fatigue reliability assessments as it is taking into account all statistical uncertainties and variations when doing so. Additionally it provides the option of adding uncertainties for which there exists no rigorous statistical data ones and providing established safety factors.

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# Nomenclature

|                    |                                                                                           |
|--------------------|-------------------------------------------------------------------------------------------|
| $\alpha$           | Proportional material constant                                                            |
| $\bar{\xi}_L$      | Averages of the numbers representing spectrum types for customer load                     |
| $\bar{\xi}_S$      | Averages of the numbers representing spectrum types for component strength                |
| $\beta$            | Wöhler exponent                                                                           |
| $\delta_L$         | Sum of uncertainties for the customer loads                                               |
| $\delta_S$         | Sum of uncertainties for the component strengths                                          |
| $\delta_\beta$     | Sum of uncertainties for the Wöhler exponent                                              |
| $\eta_L$           | Driven distance, $T$ , divided by target distance, $T_d$                                  |
| $\gamma$           | Cornell reliability index                                                                 |
| $\gamma_p$         | Cornell reliability index                                                                 |
| $\Lambda(t)$       | Load                                                                                      |
| $\phi$             | Total safety factor                                                                       |
| $\phi_d$           | Extra deterministic safety factor                                                         |
| $\phi_s$           | Extra statistical safety factor                                                           |
| $\sum$             | Strength                                                                                  |
| $\tau$             | Total uncertainty                                                                         |
| $\tilde{\alpha}_e$ | Logarithmic mean value of the equivalent strength                                         |
| $\tilde{N}$        | Geometric average of the fatigue life                                                     |
| $\tilde{n}_T$      | Target life in fatigue cycles                                                             |
| $\xi$              | Spectrum type measure                                                                     |
| $D$                | Damage sum                                                                                |
| $d$                | Pseudo damage                                                                             |
| <i>FOSM</i>        | First Order Second Moment                                                                 |
| <i>GUI</i>         | Graphical User Interface                                                                  |
| $L_i$              | Sum over all counted amplitudes for customer loads measurement                            |
| $L_{eq}$           | Equivalent load for one customer load measurement                                         |
| $M$                | Number of applied loads                                                                   |
| $m_L$              | Logarithmic mean value of the equivalent loads                                            |
| $m_S$              | Logarithmic mean value of the equivalent strength                                         |
| <i>MSC</i>         | MacNeal-Schwendler Corporation                                                            |
| $N$                | Number of cycles                                                                          |
| $n$                | Number of measurements                                                                    |
| $n_e$              | Cyclic endurance limit                                                                    |
| $S_d$              | Extra safety distance                                                                     |
| $S_i$              | Sum over all counted amplitudes for component strength                                    |
| $S_k$              | Sum over all counted amplitudes for component strength measurement                        |
| $s_L$              | Standard deviation of the logarithmic transformation of the equivalent customer loads     |
| $s_\alpha$         | Standard deviation of the logarithmic transformation of the equivalent component strength |
| $T$                | Driven distance                                                                           |

|             |                                    |
|-------------|------------------------------------|
| $t$         | Strength                           |
| $T_d$       | Target distance                    |
| $T_t$       | Target time of usage               |
| $t_{0.025}$ | Strength                           |
| $VCC$       | Volvo Cars Corporation             |
| $VGTT$      | Volvo Group Truck Technologies     |
| $VMEA$      | Variation Mode and Effect Analysis |

# CONTENTS

|                                                                                        |           |
|----------------------------------------------------------------------------------------|-----------|
| <b>Abstract</b>                                                                        | <b>i</b>  |
| <b>Acknowledgements</b>                                                                | <b>ii</b> |
| <b>Contents</b>                                                                        | <b>v</b>  |
| <b>1 Introduction</b>                                                                  | <b>1</b>  |
| 1.1 Background . . . . .                                                               | 1         |
| 1.2 Problem formulation . . . . .                                                      | 2         |
| 1.3 Project aim and objectives . . . . .                                               | 2         |
| 1.4 Scope of work and limitations . . . . .                                            | 2         |
| 1.5 Previous work . . . . .                                                            | 3         |
| <b>2 Theory</b>                                                                        | <b>4</b>  |
| 2.1 Reliability and Fatigue . . . . .                                                  | 4         |
| 2.1.1 The Reliability Problem . . . . .                                                | 4         |
| 2.1.2 Fatigue Life Prediction for Variable Amplitude . . . . .                         | 4         |
| 2.2 Developing Robust Product design using VMEA . . . . .                              | 5         |
| 2.2.1 Probabilistic VMEA . . . . .                                                     | 5         |
| 2.3 Probabilistic VMEA for the reliability problem . . . . .                           | 6         |
| 2.3.1 Uncertainty in the Measuring of Loads . . . . .                                  | 6         |
| 2.3.2 Uncertainty in the Measuring of Strength . . . . .                               | 7         |
| 2.3.3 The Uncertainty Due to the Estimated Exponent $\beta$ . . . . .                  | 8         |
| 2.3.4 Predictive Safety Index . . . . .                                                | 9         |
| 2.3.5 Including additional safety factor . . . . .                                     | 9         |
| <b>3 The VMEA toolbox</b>                                                              | <b>10</b> |
| <b>4 Methodology</b>                                                                   | <b>15</b> |
| 4.1 Parameter Study . . . . .                                                          | 15        |
| 4.1.1 Reference Analysis . . . . .                                                     | 15        |
| 4.1.2 The Wöhler exponent $\beta$ . . . . .                                            | 16        |
| 4.1.3 The cyclic endurance limit $n_e$ . . . . .                                       | 16        |
| 4.1.4 The target life $T_d$ . . . . .                                                  | 17        |
| 4.1.5 Added uncertainties . . . . .                                                    | 17        |
| 4.2 Sensitivity study . . . . .                                                        | 18        |
| 4.2.1 Strategically decreasing amount of customer load measurements . . . . .          | 19        |
| 4.2.2 Randomly decreasing amount of customer load measurements . . . . .               | 21        |
| <b>5 Results and Analysis</b>                                                          | <b>22</b> |
| 5.1 Reference analysis results . . . . .                                               | 22        |
| 5.2 Parameter study . . . . .                                                          | 23        |
| 5.2.1 Wöhler exponent, $\beta$ , results . . . . .                                     | 23        |
| 5.2.2 The cyclic endurance limit, $n_e$ , results . . . . .                            | 27        |
| 5.2.3 The target life, $T_d$ , results . . . . .                                       | 27        |
| 5.2.4 Added uncertainties, results . . . . .                                           | 30        |
| 5.3 Sensitivity study . . . . .                                                        | 32        |
| 5.3.1 Strategically decreasing amount of customer load measurements, results . . . . . | 32        |
| 5.3.2 Randomly decreasing amount of customer load measurements, results . . . . .      | 36        |
| <b>6 Discussion</b>                                                                    | <b>38</b> |
| <b>7 Conclusions</b>                                                                   | <b>39</b> |



# List of Figures

|      |                                                                                                                                                                             |    |
|------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----|
| 1.1  | Probability density distributions of costumer service loads, test track loads and structural strength.                                                                      | 1  |
| 3.1  | Toolbox software flowchart.                                                                                                                                                 | 10 |
| 3.2  | Choose type of file and add necessary values                                                                                                                                | 11 |
| 3.3  | Visualization of the last uploaded signal                                                                                                                                   | 11 |
| 3.4  | Estimation of the Wöhler exponent using curve fitting                                                                                                                       | 12 |
| 3.5  | Probability density for load/strength                                                                                                                                       | 13 |
| 3.6  | Excel sheet for the VMEA results                                                                                                                                            | 14 |
| 5.1  | Varying Wöhler exponent vs. Extra safety distance, $S_d$                                                                                                                    | 23 |
| 5.2  | Varying Wöhler exponent vs. Extra deterministic safety factor, $\phi_d$                                                                                                     | 23 |
| 5.3  | Varying Wöhler exponent vs. Total uncertainty, $\tau$                                                                                                                       | 24 |
| 5.4  | Varying Wöhler exponent vs. Extra statistical safety factor, $\phi_s$                                                                                                       | 24 |
| 5.5  | Varying Wöhler exponent vs. Total safety factor, $\phi$                                                                                                                     | 25 |
| 5.6  | Figures for the equivalent customer load and the equivalent component strength vs. the varying Wöhler exponent                                                              | 25 |
| 5.7  | Varying Wöhler exponent vs. Cornell Reliability index, $\gamma$                                                                                                             | 26 |
| 5.8  | Figures for both the mean of the logarithmic equivalent customer load and component strength vs. varying cyclic endurance limit                                             | 27 |
| 5.9  | Figures for the Extra safety distance and the Extra deterministic safety factor vs. varying Target life, $T_d$                                                              | 27 |
| 5.10 | Varying target distance vs. Extra statistical safety factor, $\phi_s$                                                                                                       | 28 |
| 5.11 | Varying target distance vs. Total safety factor, $\phi$                                                                                                                     | 28 |
| 5.12 | Varying target distance vs. $m_L$ (Mean of the logarithmic equivalent load)                                                                                                 | 29 |
| 5.13 | Varying target distance vs. Cornell reliability index, $\gamma$                                                                                                             | 29 |
| 5.14 | Figures for $\gamma$ , $S_d$ vs. varying extra added uncertainty                                                                                                            | 30 |
| 5.15 | Figures for $\phi_d$ , $\phi_s$ vs. varying extra added uncertainty                                                                                                         | 30 |
| 5.16 | Varying extra added uncertainty vs. Total safety factor, $\phi$                                                                                                             | 31 |
| 5.17 | Behaviour of the extra safety distance, $S_d$ , and the extra deterministic safety factor, $\phi_d$ , for different amount of loads when removing loads from each group     | 32 |
| 5.18 | Behaviour of the total uncertainty, $\tau$ , and the extra statistical safety factor, $\phi_s$ , for different amount of loads when removing loads from each group          | 32 |
| 5.19 | Behaviour of the total safety factor, $\phi$ , for different amount of loads when removing loads from each group                                                            | 33 |
| 5.20 | Behaviour of the Cornell reliability index, $\gamma$ , for different amount of loads when removing loads from each group                                                    | 33 |
| 5.21 | Cornell reliability index, when taking out one measurement out of each group, compared to taking out 3 measurements from the middle group                                   | 34 |
| 5.22 | Cornell reliability index, when only using the highest and lowest customer load measurement, compared to only keeping two customer load measurements that are in the middle | 35 |
| 5.23 | Behaviour of the extra safety distance, $S_d$ , and the extra deterministic safety factor, $\phi_d$ , for different amount of loads when removing loads from each group     | 36 |
| 5.24 | Behaviour of the extra statistical safety factor, $\phi_s$ , and the total uncertainty, $\tau$ , for different amount of loads when removing loads from each group          | 36 |
| 5.25 | Behaviour of the total safety factor, $\phi$ , when randomly removing customer load measurements from the population                                                        | 37 |
| 5.26 | Behaviour of the total safety factor, $\gamma$ , when randomly removing customer load measurements from the population                                                      | 37 |



# 1 Introduction

The project ahead is a master thesis and an effort by two students at the Applied Mechanics Master's Programme at Chalmers University of Technology in Gothenburg, Sweden for MSC Software Corporation (MSC), Volvo Cars Corporation (VCC) and Volvo Group Trucks Technology (VGTT), all situated in Gothenburg, Sweden.

The following chapter is an introduction to the project in terms of describing background, problem formulation, objectives and scope of work and limitations.

## 1.1 Background

It is known that some vehicles never leave the city, some are almost always on the highway and some are only used on construction sites. A similar type of variation exists among how the drivers are utilizing the vehicle. Nevertheless, it is safe to say that during a complete lifetime, no vehicle has identical operating environment. This indicates that every vehicle has a unique and unpredictable load history and that there is an overall service load variation. A similar variation also exists in terms of component strength due to manufacturing, material defects and so on. These variations are uncertainties that affect the overall vehicle durability and are shared by all components.

For companies such as VCC and VGTT, knowledge about fatigue and the risk of failure is crucial. Some components are more critical than others and thus for some, the risk of failure has to be negligible, for some a small risk is acceptable and for others a moderate risk is acceptable. In this sort of fatigue assessment it is noted that mechanical fatigue is a highly empirical science with large uncertainties. All uncertainties need to be accounted for but some affect the durability more than others. The variation in material strength and other material related uncertainties are usually small due to extensive material processing knowledge, while the variation in load is highly unpredictable and differs significantly between customer types. It is therefore necessary to give a reliability to the fatigue assessment. The most common approach is by the implementation of test track loads, that are constructed as bad-case scenarios, in order to make sure that all customer types are captured in the load variation. The result from the test track loads are then used to calculate the dimensions for the different components. The overall distribution situation with customer service loads, structural strength and the test track load is called the reliability problem and is visualized in Figure 1.1.

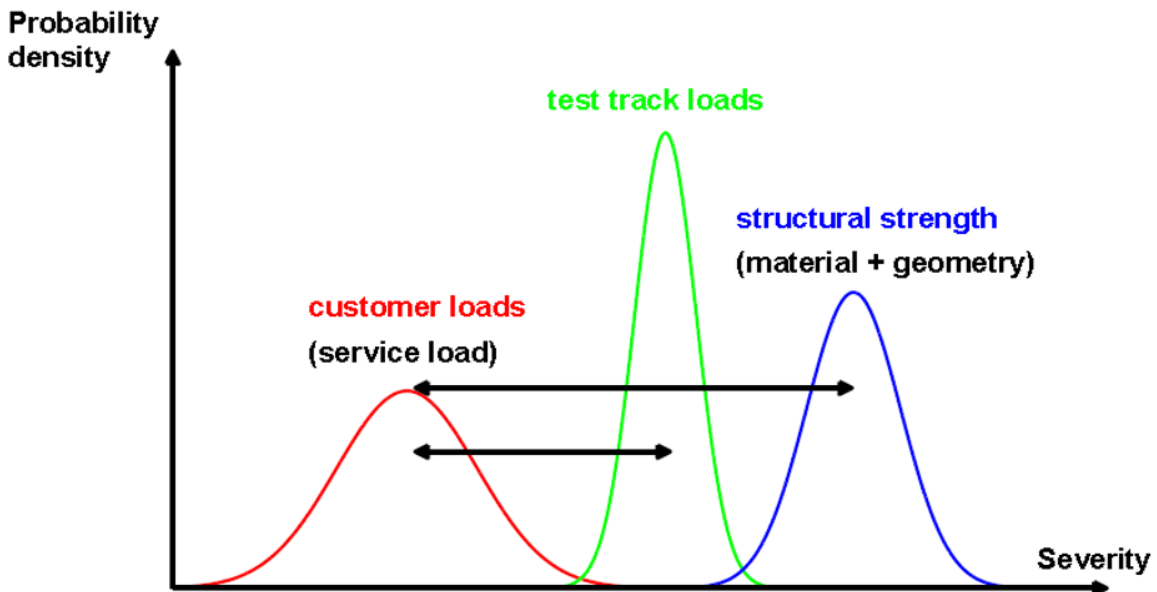


Figure 1.1: *Probability density distributions of costumer service loads, test track loads and structural strength.*

The test track loads do not represent the service loads and engineers at VGTT are studying a statistical approach based on full scale tests. They have performed tests on their trucks in different customer type environments and collected data for the service load variation around the world. The statistical approach is a first order second moment (FOSM), and is the probabilistic version of Variation Mode and Effect Analysis (VMEA). The VMEA approach takes the quantitative measures of failure causes into account, which assesses the uncertainties in all areas including the service loads and the component structural strength. Additionally, it allows proper safety factors to be established with regard to the required service life, where the overall goal is to avoid over-sizing and give a sense of reliability in the fatigue assessment [4].

## 1.2 Problem formulation

At the moment, the automotive industry has not developed an effective working procedure with the implemented probabilistic VMEA to their fatigue and robustness assessment. It is therefore of industry interest to develop a tool that in a systematic way, from collected test data captures the variations in both the service loads and the structural strength, statistically accounts for all uncertainties and provides the wanted reliability in the fatigue assessment in form of safety factors.

## 1.3 Project aim and objectives

The specific aim of this project is to develop the asked for tool in form of a software with a graphical user interface (GUI), implement test data for a specific component provided by VGTT, give a reliability safety factor to the fatigue assessment and study both the created software's validity and the VMEA method itself through a parameter study and a data sensitivity study.

Within the main problem statement, the following objectives are identified:

- Implement probabilistic VMEA to the fatigue assessment of the automotive industry.
- Create the software that runs the fatigue assessment including the probabilistic VMEA approach using the programming language Python.
- Perform a fatigue and failure analysis of a specific component and present quantities of interest in form of a report and plots.
- Perform a sensitivity study of the input service load measurements and a parametric study of influential input fatigue parameters.

## 1.4 Scope of work and limitations

The master thesis is approximately 20 weeks of work, which gives 30 ECTS credits and started January 22nd 2018, hence the main limitation is the time frame. Other limitations are identified as:

- No physical tests are performed, input data is provided by VGTT and therefore current VGTT customer definitions are used.
- The software is industry specific and not applicable in all areas.
- A complete analysis is only performed on one specific component.

## 1.5 Previous work

Studies where statistical methods have been applied in order to assess fatigue problems in the industry, have been done before in various ways. In particular, VMEA, has been put forward to use for fatigue assessments in order to compensate for the lack of data that is usually connected with work in fatigue problems.

The more traditional way to predict the fatigue life for a component is to use material properties from constant amplitude tests together with the Palmgren-Miner rule [1]. In [1] a similar estimation is being done, but this time using a variable amplitude test instead of constant amplitude test. This is being driven by the fact that validation tests have shown that the procedure with constant amplitude gives poor results[1]. However, no statistical method is being applied and uncertainties are not accounted for [1].

Applying the statistical method VMEA has been done in a number of studies in different ways. In [5] the VMEA method has been outlined and its practical usefulness has been thoroughly described for some engineering problems. Particularly interesting is the use of VMEA as a fatigue assessment tool by combining it with the Palmgren-Miner method and rainflow counting algorithm [5]. In [2] VMEA has been used to study the fatigue life of a jet engine component with the goal to find a safety margin that takes prediction uncertainties into account. In order to do this, possible uncertainty sources have been identified and assessed in order to calculate total uncertainty of the life prediction of the component[2].

In [7] a study has been done where the statistical approach has been focused on the critical product function. In other words, making a component design so that it is insensitive to unforeseen variations in loads [7]. Doing this is referred to as a robust design and uses three steps, identification of variation, design experiments to find robust solutions, and statistically based estimations of safety margins [7]. To achieve this, [7] has used a top-down analysis using VMEA on the product characteristics and analyzing how sensitive these characteristics are to variation.

More information can be found in the Reference section, about the studies used in the literature study of this project. All of them do not necessarily have much focus on VMEA, but they do give a good overview of fatigue life analysis, and different methods to approach the reliability problem.

## 2 Theory

In this chapter the theory used in this Master Thesis is presented.

### 2.1 Reliability and Fatigue

An overall goal of vehicle design is to make robust and reliable products which meet the demands of the customers [3]. Reliability can be regarded as avoidance of failure [7]. Failure can have different reasons and come in multiple forms. In some cases, a component can break leading to no or just reduced functionality. It can be due to fatigue, perhaps the costumer is misusing the product or simply the product does not live up to customer expectation which from their point of view is also a failure [7]. For the automotive industry however, the main reason for component failure is fatigue [3]. It is also known that mechanical fatigue in general is more often than not, a highly empirical science with large uncertainties [5]. The most important uncertainty is due to random variation and the other to account for is lack of knowledge, where both uncertainties can have endless of sources depending on application area [7]. It is therefor of importance to, besides estimate the lifetime of a component, investigate and take into account possible variation and its influence on the life prediction itself [3]. It is also of interest to be aware of the uncertainties due to lack of knowledge, to give a sense of reliability to the fatigue assessment [7].

#### 2.1.1 The Reliability Problem

As mentioned, the most important uncertainty is random variation. The two variation quantities that have the largest influence on component life are primarily the load that the component is exposed to and the components structural strength [3].

Variation in component strength will, for instance, be from material scatter, material defects, supplier variation and manufacturing tolerances [8]. However, the manufacturing process is to some extend well known and predictable in terms of percentages of errors, tolerances and so on. This enables the variation in component strength from batch-to-batch and even unit-to-unit to be estimated[7].

Variation in the subjected load will come from, the fact that all vehicles will be exposed to different types of environments and utilized by different drivers. For a single vehicle the load-time history can be seen as a random process. It is of interest to evaluate the population containing the individual vehicle when continuing with reliability assessment[7].

These two variations, their distribution and the relation between them is called the reliability problem or the load-strength model and is illustrated in Figure 1.1. The problem can, for avoided failure, be defined as follows.

$$\sum > \Lambda(t) \quad \text{for} \quad t < T_t \quad (2.1)$$

Where the strength,  $\sum$ , is modelled as a fixed value and the load,  $\Lambda(t)$ , is modelled as a varying value that represents the sum of the damage and the parameter  $T_t$  is the target time of usage. Additionally, the risk of failure may be assessed with a reliability index  $\gamma$ , which is defined as a function of the distribution of the strength and the final load measures,  $\gamma = f(\sum, \Lambda(T_t))$ . The reliability index will be used for comparisons in terms of a measure of the distance between the two distributions, thus the distance to the failure mode [8].

#### 2.1.2 Fatigue Life Prediction for Variable Amplitude

In traditional fatigue assessment for variable amplitude, material properties from constant amplitude tests are used together with the Palmgren-Miner hypothesis of cumulative damage as below:

$$D = \sum_i \frac{n_i}{N_i} = \sum_i \frac{n_i}{\alpha S_i^{-\beta}} \approx \sum_i \frac{n_i}{\hat{\alpha} \hat{S}_i^{-\hat{\beta}}} = \frac{1}{\hat{\alpha}} \sum_i n_i \hat{S}_i^{\hat{\beta}} \quad (2.2)$$

Failure or fatigue limit is here predicted when the damage sum,  $D$ , is equal to one and  $n_i$  is the number of cycles of the amplitude  $S_i$ , which are obtained with cycle counting with for instance the Rain-Flow-Count algorithm. Material parameters  $\alpha$  and  $\beta$  are estimated from the Basquin relation below:

$$N = \alpha S^{-\beta} \quad [1] \quad (2.3)$$

Finally,  $\hat{\alpha}$ ,  $\hat{\beta}$  are the material parameters resulting estimates for specific R-ratio, according to  $R = S_{min}/S_{max}$  [1].

It is of interest, when comparing the severity of different loads, to have the pseudo damage be as independent of the material model as possible [9]. Therefore, using the definition for the pseudo damage number, also known as duty value, as the sum is preferable [8]. The equation for the duty value can be seen in Eq. 2.4

$$d = \sum_i S_i^\beta \quad (2.4)$$

In Eq. 2.4 the proportional constant,  $\alpha$ , is left out, because it is irrelevant when comparing the severity of different loads, and one is left with only  $\beta$  [8].

However, validation test have shown that this results in poor predictions and an overall criticism towards the Palmgren-Miner hypotheses. On the other hand, alternative methods are demanding in the form of computational resources and detailed knowledge about crack geometry, crack growth laws, and so on. There is a proposed method in [1], which is based on improving the test part of the fatigue assessment. In other words, instead of constant amplitude test the proposal is to perform multiple tests with a load spectra scaled to different levels. This results in a method based on real service tests but with use of the simple Palmgren-Miner hypothesis [1]. The proposed method assesses fatigue evaluation but does not account for uncertainties. Without identifying and quantifying uncertainties in the method, there is no measure for the accuracy of the fatigue assessment and perhaps most importantly the method does not give any sense of reliability. The proposal is however a basis for introducing more complete methods.

## 2.2 Developing Robust Product design using VMEA

In order to take uncertainty into account in the engineering design process, tools are used for rational handling of influential sources and for quantitative measures of the uncertainties of fatigue life, component strength or malfunction [8]. In order to produce robust engineering designs of components, the concept VMEA has been introduced as an extension of the previously used Failure Mode and Effects Analysis (FMEA) [8]. The FMEA is a systematic way to identify failure possibilities based on engineering experience, while VMEA has added mathematical statistics and actual quantities of uncertainties. The VMEA concept has been categorized in three different levels of complexity, namely basic VMEA, enhanced VMEA and probabilistic VMEA [7] [4], where probabilistic VMEA is of main interest for this project. The probabilistic VMEA corresponds to a FOSM reliability method in structural dynamics [8]. The main objective for using VMEA is to find a proper safety factor or reliability index to the previously defined reliability problem [8]. More specifically for this thesis VMEA will be used to quantify model uncertainties of the fatigue phenomenon, as the knowledge about its influential variables is low [8].

### 2.2.1 Probabilistic VMEA

The probabilistic VMEA is for the late design phases, when more knowledge about the component is available it suits when predicting fatigue life and when determining safety factors is of interest [4]. What makes probabilistic VMEA different from enhanced VMEA is the fact that in probabilistic VMEA a model for prediction is being used, which includes statistical uncertainties, model uncertainties and random variation [4]. Scatter cannot be avoided but is handled by using safety factors. Model uncertainties and random variation can be decreased by gathering more data or build better models [4]. The main goal of the probabilistic VMEA is to quantify the most important uncertainties, and assess the magnitude of the uncertainties by using standard deviations [4]. The probabilistic VMEA is, as mentioned, a FOSM method, where first order refers to the linearization of the target function, and second moment refers to the fact that only the means and variances are used [4]. The end result of a probabilistic VMEA is a safety factor or a reliability index, derived from the total uncertainty, which for the reliability problem is used as a measure of the distance to the failure mode [4]. Probabilistic VMEA can also aid in choosing additional safety factors for the component design.

## 2.3 Probabilistic VMEA for the reliability problem

In the following sections, the probabilistic VMEA is implemented to the reliability problem and the overall fatigue assessment. Uncertainties in fatigue calculations, random loads and scatter are identified and described with detailed equations. Additionally the implementation ends up with the safety distance to failure and the overall reliability index for the fatigue assessment.

### 2.3.1 Uncertainty in the Measuring of Loads

Usually one of the biggest uncertainties, when designing a new product, is the customer load, i.e. the engineers do not have a full picture of how their customers use the product[8]. In order to gather information about the customer, load tests and measurements are being done in various ways[8]. In the automotive industry measurements are being done either on a test track, that is supposed to represent how the customers use the vehicle, or the measurements are being done while the customers use the vehicle[8]. The limitations of doing tests on a track is that the results might be biased, i.e. the test track only represents an extreme customer load or an estimated mean variance of the customer load[8]. To do tests where the vehicle is used by the customer produces better data than a test track, but it is more expensive[8]. By combining data from real life measurements and from track measurements, it is possible to calculate an equivalent load with a reliability index[8]. To do this the customer population, where the measurements are done, must be properly divided in different groups of users before calculating the reliability index[8]. The reason for this is so that the reliability index refers to a specific group of users in order to be optimized and eventually optimize the safety factors needed[8].

To calculate a viable reliability index for the customer load uncertainty, one will need a mean value and the standard deviation for each sample[8]. To achieve this an equivalent load,  $L_{eq}$ , will first be calculated by using the measurement data as:

$$L_{eq} = \left( \frac{\eta_L}{n_e} \sum_{i=1}^M L_i^\beta \right)^{\frac{1}{\beta}} \quad (2.5)$$

where  $\eta_L = \frac{T_d}{T}$  and  $L_i$  is the sum over all counted amplitudes for the driven distance  $T$ , and  $T_d$  is the target life by means of driving distance,  $M$  are the number of applied loads,  $\beta$  is assumed to be a material or component variable,  $n_e$  is a cycle number e.g.  $10^6$  cycles [8]. With the equivalent load it is possible to find the mean and the standard deviation of the logarithmic transformation of the population:

$$m_L = \frac{1}{n} \sum_{i=1}^n \ln(L_{eq,i}) \quad (2.6) \quad s_L = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (\ln(L_{eq,i}) - m_L)^2} \quad (2.7)$$

With a small number of fatigue test samples,  $n$ , there will be an uncertainty in the standard deviation and the uncertainty measure must be adjusted assuming a normal distribution for the logarithmic property,[8], and using:

$$\delta_{L,1} = s_L \frac{t_{0.025,n-1}}{2} \sqrt{1 + \frac{1}{n}} \quad [8] \quad (2.8)$$

where the parameter  $t_{0.025,n-1}$  depends on the amount of measurements that are used. The different values can be seen in Table 2.1.

| n           | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 18  | 30  | $\infty$ |
|-------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|----------|
| $t_{0.025}$ | 4.3 | 3.2 | 2.8 | 2.6 | 2.4 | 2.4 | 2.3 | 2.3 | 2.2 | 2.2 | 2.1 | 2.0 | 1.96     |

Table 2.1: Values for the student-t,  $t_{0.025,n-1}$ , dependent on the number of measurements [8].

A small number of samples is just one uncertainty, if more types of uncertainties can be identified they can also be added in the calculations of the mean and standard deviation of the consumer loads by using:

$$\delta_L = \sqrt{\delta_{L,1}^2 + \delta_{L,2}^2 + \delta_{L,3}^2 \dots} \quad [8] \quad (2.9)$$

where each  $\delta_{L,i}$  is an estimated uncertainty[8].

### 2.3.2 Uncertainty in the Measuring of Strength

The uncertainty, in the measuring of strength, is possible to calculate in a similar way as the uncertainty in the measuring of loads[8]. Similar to the calculations of the uncertainty of loads, the equivalent strength,  $\tilde{\alpha}_e$  is defined as:

$$\tilde{\alpha}_e = \left( \frac{1}{n_e} \sum_{i=1}^M S_i^\beta \right)^{\frac{1}{\beta}} \quad (2.10)$$

The random property is the summarized damage to failure, with a known spectrum and a constant  $n_e$ [8]. The life is assumed to be log-normally distributed, and with this assumption the mean value and standard deviation of the equivalent strength can be calculated:

$$m_S = \frac{1}{n} \sum_{i=1}^n \ln(\tilde{\alpha}_{e,i}) \quad (2.11) \quad S_\alpha = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (\ln(\tilde{\alpha}_{e,i}) - m_S)^2} \quad (2.12)$$

When an estimation of the standard deviation has been calculated, it can be used to calculate an uncertainty for the reliability index[8]. A prediction interval of 95% will be used for future assessment of the strength and it is assumed that the logarithm of the strength is normally distributed[8]. A prediction interval can now be calculated using the student-t distribution:

$$m_s \pm s_\alpha \cdot t_{0.025, n-1} \cdot \sqrt{1 + \frac{1}{n}} \quad (2.13)$$

In this case the t-value is used to compensate for the uncertainty in the standard deviation and the  $\frac{1}{n}$  term in Eq. 2.13 takes the uncertainty of the mean value  $m_s$  into account[8]. When number of tests is increasing towards infinity the t-value approaches the value 2. With this the actual uncertainty component for the reliability index can be defined:

$$\delta_{S,1} = \frac{s_\alpha \cdot t_{0.025, n-1}}{2} \cdot \sqrt{1 + \frac{1}{n}} \quad (2.14)$$

which can be seen as a measure for the standard deviation of the predicted equivalent strength.

This uncertainty measure includes the uncertainty in estimated mean and the variance estimate, it also includes the scatter of the specimens[8]. The uncertainty due to  $\beta$ , previously mentioned, has an effect on both strength and load and will be added separately. The influence of the  $\beta$ -uncertainty on the standard deviation will be neglected[8].

When comparing strength with the load, there may be additional error sources and variations involved, such as model errors, error because the tested specimen comes from a single supplier while in the future several suppliers might be used[8]. Variation is an uncertainty source that is difficult to quantify[8]. By experience a good guess of its influence (if other information is not available) is 10% and since the equations use logarithms the contribution to the standard deviation will be  $\delta_{S,2} = 10$ .

Identifying and quantifying uncertainty sources properly will increase the confidence one can have in the estimations[8]. One example of other possible uncertainty sources is lack of equivalence between laboratory reference tests and the service situation[8]. Other examples are multiaxiality, residual stresses, multidimensional loads, environment or mean values [8]. Uncertainties can be reduced and balanced to the cost of the additional work if more effort is put into test design and the use of components or structures instead of material specimens[8].

Another uncertainty is the damage accumulation theory including the Basquin equation and equation of equivalent load, which will both add to the uncertainty of the predicted life[8]. Just like the other uncertainties, these can be estimated by experience, literature data and specially designed tests, which will add more percentage variation components [8]. Doing laboratory tests with load spectra similar to customer load spectra will reduce the model uncertainties at the cost of more advanced tests[8].

The total uncertainty measure of strength, can simply be calculated by summarizing all the uncertainty that contains variances of log strength:

$$\delta_S^2 = \sum_{i=1}^p \delta_{S,i}^2 \quad (2.15)$$

Because of the quadratic summation, which puts emphasis on the largest uncertainty, in practice all uncertainties that are less than 20% of the largest uncertainties can be neglected[8].

### 2.3.3 The Uncertainty Due to the Estimated Exponent $\beta$

An important parameter in the load-strength interaction in fatigue cases is the Wöhler exponent  $\beta$  [3][8]. In the industry it is usually used as a fixed value depending on what is known about the component [3]. For example, for welded components a value of  $\beta = 3$ , for poorly defined components a value of  $\beta = 5$  and for high strength components with smooth surface a value of  $\beta = 8$  [3]. These values can be seen as rules of thumb, but one must consider the fact that they also contain uncertainties. By using experience and historical data it is possible to define the uncertainties in the  $\beta$ -exponent, for example, a welded component may have an uncertainty between 2.5 to 3.5 on the  $\beta$ -exponent [3]. Better estimates of the uncertainty of the  $\beta$ -exponent can be achieved by doing tests and then do a statistical analysis on the test results [3]. It can be shown in [3], that the sensitivity coefficient with the respect to  $\beta$  is:

$$c_\beta = \frac{\partial(\ln(S_{eq}) - \ln(L_{eq}))}{\partial\beta} = \frac{1}{\beta} \left( \frac{1}{\beta} \ln \frac{\tilde{n}_T}{\tilde{N}} + \xi_S - \bar{\xi}_L \right) \quad (2.16)$$

where  $\tilde{n}_T$  is the target life in fatigue cycles,  $\tilde{N}$  is the geometric average of the fatigue life of a reference specimens, and  $\bar{\xi}_L$ ,  $\xi_S$  are the averages of the numbers representing spectrum types [3]. The sensitivity of the  $\beta$ -exponent is dependent on the differences between the spectrum type numbers for the reference test and for usage [3].

The spectrum type measure  $\xi$  can be calculated by using the spectrum of the load amplitudes in the function:

$$\xi = \frac{\sum S_k^\beta \ln(S_k)}{\sum S_k^\beta} - \frac{1}{\beta} \ln \left( \frac{1}{M} \sum S_k^\beta \right) \quad (2.17)$$

The spectrum type measure has the property that it is equal to zero for a constant amplitude and it is scale invariant [8].

In order to calculate the uncertainty for the Wöhler exponent,  $\beta$ , the standard deviation must first be calculated, which is done with Eq. 2.18 below:

$$S_\beta = S_l \sqrt{\frac{1}{\sum_{i=1}^n (a_i - \bar{a})^2}} \quad [8] \quad (2.18) \quad a_i = \left\{ \frac{\sum S_k^\beta \ln(S_k)}{\sum S_k^\beta} \right\}_i \quad [8] \quad (2.19)$$

where,  $S_l$ , is the standard deviation for the number of cycles for the strength tests, and,  $n$ , is the number of strength tests [8]. The standard deviation is adjusted with the student-t distribution because of the uncertainty in the estimation of  $S_l$  [8]. The calculation with the student-t distribution is done with Eq. 2.20 below:

$$S'_\beta = S_\beta \frac{t_{0.975, n-1}}{t_{0.975, \infty}} \quad [8] \quad (2.20)$$

To calculate the uncertainty for the estimation of the Wöhler exponent,  $\beta$ , both the adjusted standard deviation,  $S'_\beta$ , and the sensitivity coefficient,  $c_\beta$  are used according to Eq. 2.21 below:

$$\delta_\beta = c_\beta \cdot S'_\beta \quad [8] \quad (2.21)$$

### 2.3.4 Predictive Safety Index

The equivalent loads and strengths,  $m_L$  and  $m_S$  respectively, and the reliability indices previously presented can now be used to form a reliability index based only on expected values, variances of scatter and uncertainty components[8]. To do this the Cornell reliability index will be used, which is based on the difference between strength and load[8]. More precisely for this thesis the logarithmic form of the Cornell reliability index will be used:

$$\gamma_{log} = \frac{\mu_{log\Sigma} - \mu_{log\Lambda}}{\sqrt{\sigma_{log\Sigma}^2 + \sigma_{log\Lambda}^2}} \quad (2.22)$$

The logarithmic form is used because of the linear behaviour of the fatigue phenomenon on the logarithmic scale [8]. Because of the logarithmic transformation of the variables the nonlinearities are small compared to the overall approximation level[8].

Mixing together the load and strength uncertainties,  $m_L$  and  $m_S$  respectively, the estimated values for each uncertainty source and using them in the logarithmic form of the Cornell reliability index gives the following formula for calculating a predictive safety index for fatigue:

$$\gamma_p = \frac{m_S - m_L}{\sqrt{\delta_S^2 + \delta_L^2 + \delta_\beta^2}} \quad [8] \quad (2.23)$$

The advantage of the predictive safety index is that it is related to the scatter and uncertainty sources involved[8]. It is possible to calculate theoretical probabilities of failure, by placing distributional model assumptions on the predictive reliability index[8]. The predictive reliability index may be interpreted as a percentile in the normal distribution, if the mean values are normally distributed[8]. This makes it possible to calculate the probability of failure[8]. However, in order to use the percentile interpretation as true failure frequencies, it is necessary for the tails of the distribution to follow the assumed mode, which is rarely the case for small probabilities[8]. Because of this the percentile interpretation should only be used as comparisons between different solutions or as a starting point for deciding a target value for the index[8].

### 2.3.5 Including additional safety factor

The additional safety factor can be seen as a mixture of probabilistic interpretation and a deterministic safety distance [8]. To include the extra safety distance, Eq. 2.23 is rewritten as:

$$m_S - m_L > S_d + 2\tau, \quad \tau = \sqrt{\delta_S^2 + \delta_L^2 + \delta_\beta^2} \quad (2.24)$$

Now the safety target consists of two terms, namely  $S_d$  and  $2\tau$ . The total uncertainty,  $\tau$  is multiplied by 2 in order to correspond to an approximate 95% prediction interval [8]. The approximate 95% prediction interval is based on the assumption that there is an approximate normal distribution of the differences between measurements[8].

The first term,  $S_d$  on the right hand side, in Eq. 2.24, is interpreted as a deterministic extra safety distance to the failure mode[8]. The  $S_d$  and  $2\tau$  terms can be formulated in terms of safety factors[8]. The reformulation of the terms,  $S_d$  and  $2\tau$  gives the total safety factor,  $\phi$  as::

$$\phi = \phi_d \cdot \phi_s, \quad \phi_d = e^{S_d}, \phi_s = e^{2\tau} \quad (2.25)$$

### 3 The VMEA toolbox

The need for a systematical way of approaching the reliability problem and in order to perform the parameter and sensitivity studies efficiently, a toolbox implementing the VMEA method is necessary. The toolbox is created with Python programming and contains, implementation of VMEA theory, rainflow cycle counting, Palmgren-Miner damage accumulation and a curve fitting iteration. These parts are created as function files separately and the equations implemented have all been presented in the theory. Additionally, a GUI is programmed for easier usage of the toolbox where all the separate functions are connected. Since the toolbox is used for the upcoming studies and for future simpler usage of the toolbox, the following sections will thoroughly present the entire toolbox process. In figure 3.1, a flowchart of the toolbox is illustrated.

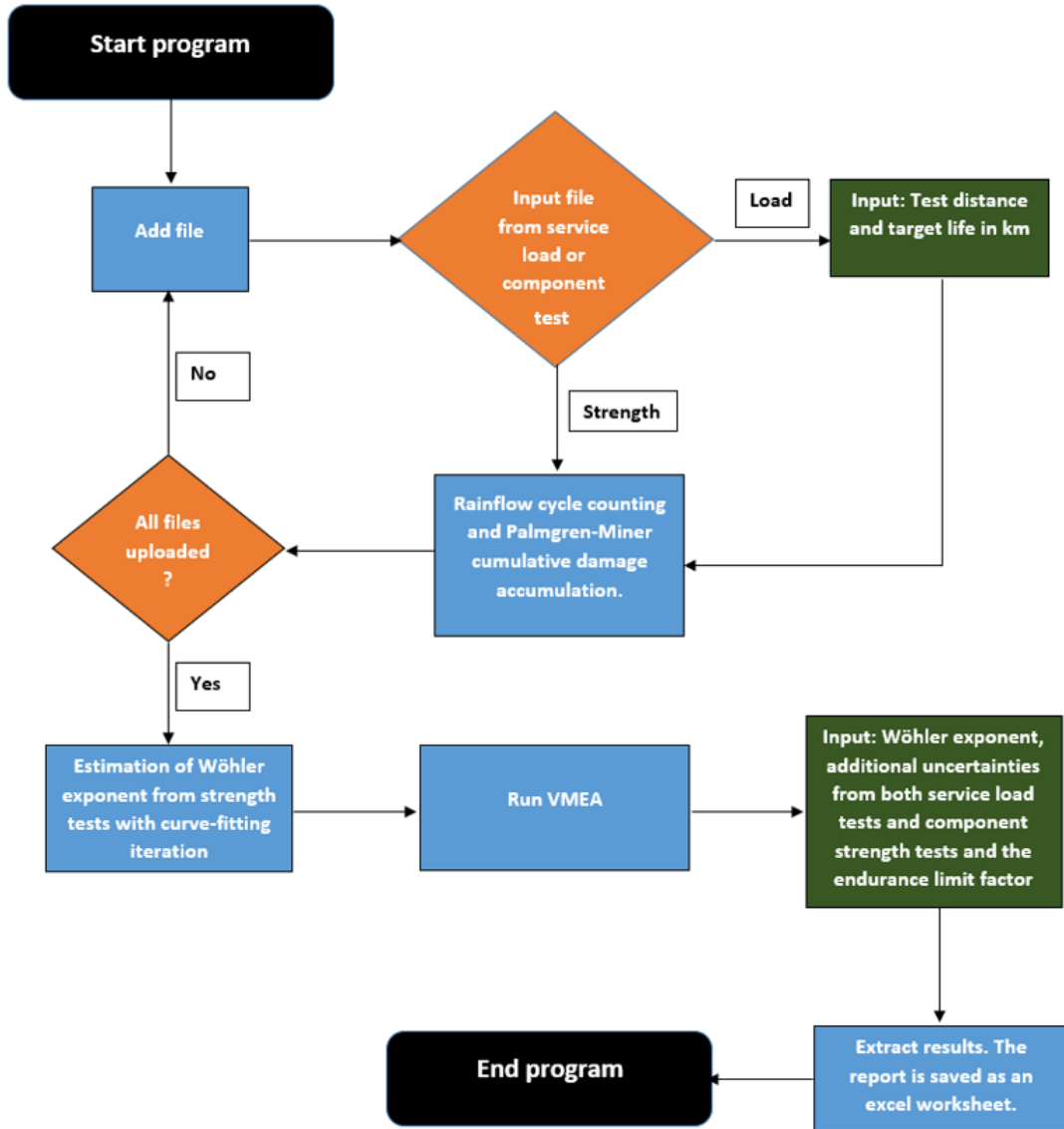


Figure 3.1: *Toolbox software flowchart.*

The flowchart is a simple manual to follow during the working procedure with the toolbox. For easier visualization an overview of the program GUI is illustrated in figure. The work procedure follows the the flowchart presented and the buttons are strategically placed from left to right. A step by step presentation of the work procedure within the program GUI follows.

- Step 1 (Add File/Plot Signal): Browse, upload, open, read the input file and choose whether it is a customer load input file or a component strength input file. If the input file is from customer load measurements insert the tested distance and target life both in kilometers, as can be seen in figure 3.2. The file needs to be a .csv (comma separated value) file and the function saves a complete data set of the input signal in terms of force against time in units measured by test operator. The input signal can be visualized in a plot with the button "Plot Signal". An example of a plot signal can be seen in figure 3.3.

Figure 3.2: Choose type of file and add necessary values

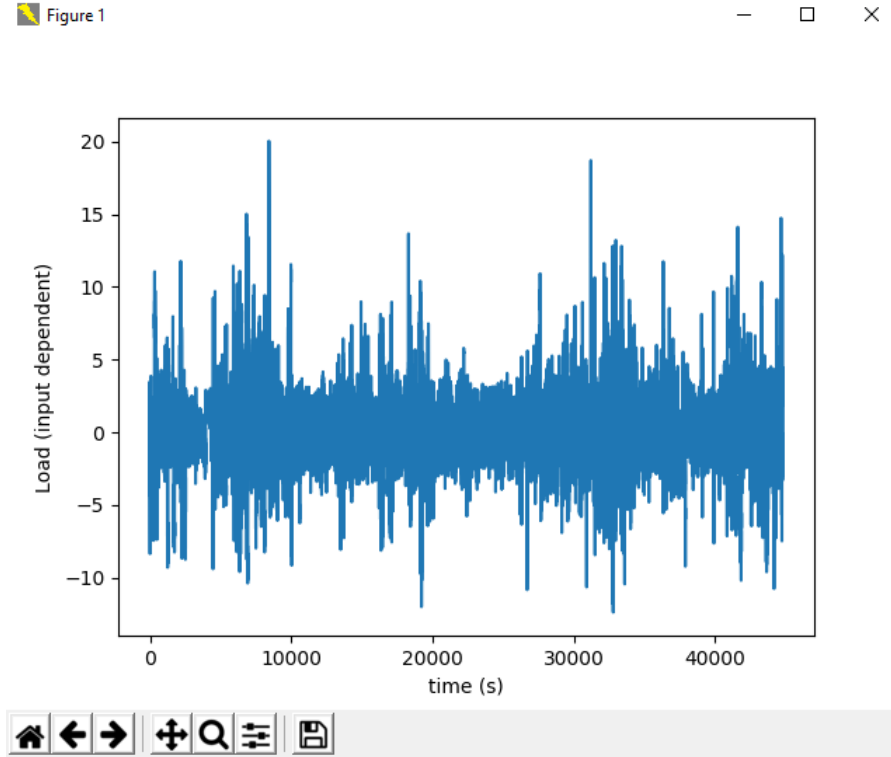
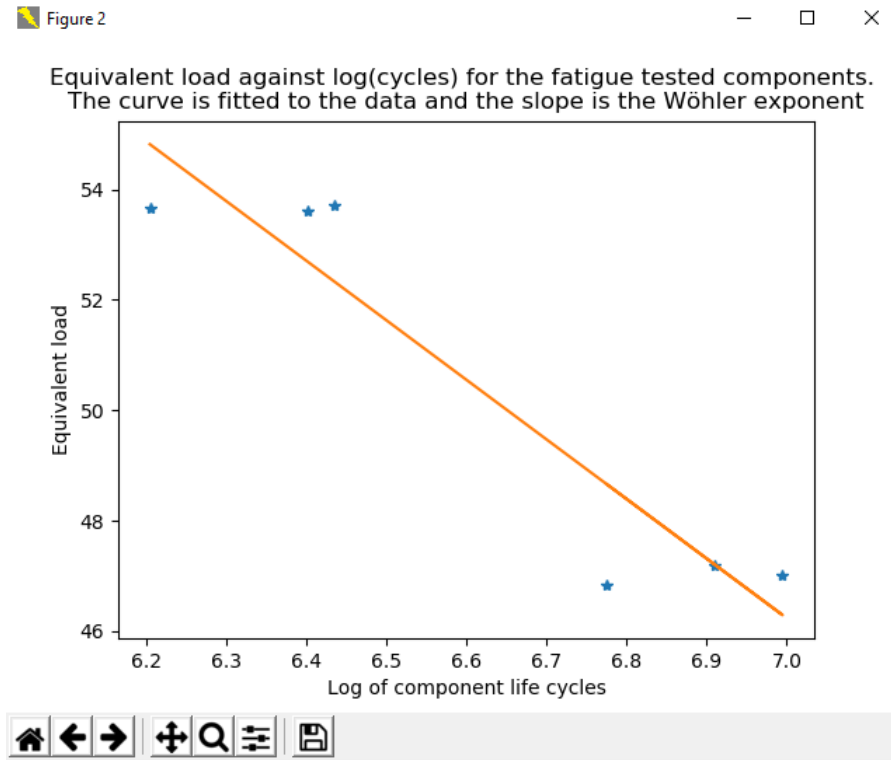


Figure 3.3: Visualization of the last uploaded signal

- Step 2 (Rainflow Cycle Counting): Consists of a function file that implements a Rainflow cycle counting algorithm, it is an existing package to python [6]. The input is the saved data set and the function will identify cycles, maximum, minimum and the cycle count. The identified cycles are used to calculate all load ranges. Additionally to this step, the Palmgren-Miner damage accumulation rule is implemented, hence it sums up all load ranges from identified cycles powered by the Wöhler exponent and returns a sum in form of a pseudo damage number, also known as duty value, according to,  $d = \sum_i S_i^\beta$  [8]. At this point the Wöhler exponent is unknown and therefore, for each file the pseudo damage number or duty value is calculated and stored for all realistically possible Wöhler exponents which are 3 to 15. Before proceeding from this step one should go back to step one and redo this procedure until all necessary files are uploaded.

- Step 3 (Estimate Wöhler Exponent): Makes use of the uploaded component strength files, importing both the duty values and the life to failure for each component strength test. The function calculates the equivalent strength and matches it against the life with a curve fitting algorithm. An iteration is designed including a regression analysis according to method of least squares, starting with the Wöhler exponent at  $\beta = 3$  and iterates to the Wöhler exponent with the smallest error. The returned Wöhler exponent will be a real number while for the upcoming steps one must specify an integer, the reason being that the duty values were only calculated for Wöhler exponents 3 to 15 and one of these must be used in the upcoming step. The result of a curve fitting can be seen in figure 3.4.



- Step 4 (Run VMEA): This step initiates with asking for necessary input parameters. These are the Wöhler exponent , in additional uncertainties from customer load measurements, additional uncertainties from component strength tests and the endurance limit  $n_e$ . With this information the function makes use of the duty values for the chosen Wöhler exponent and returns equivalent loads, equivalent strengths, total uncertainties and the various safety factors. At the end of this function a plot is presented which illustrates the distribution of both the customer load measurements and the components structural strength based on the probability density of their respective equivalent loads/strengths, as seen in figure 3.5.

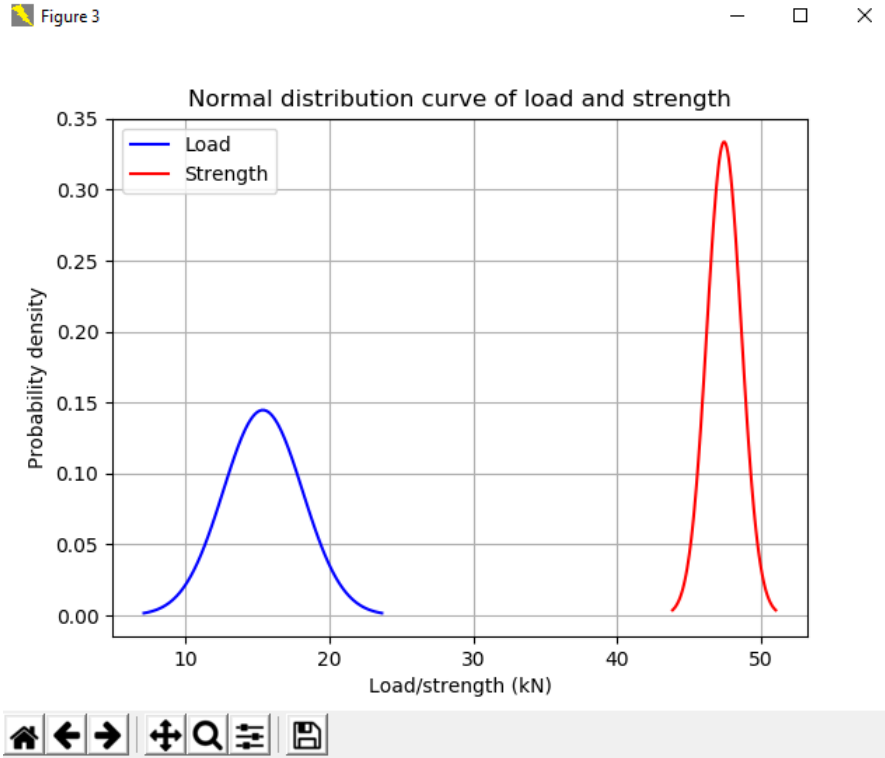


Figure 3.5: *Probability density for load/strength*

- Step 5 (Save Results): The final step is to save the results. The function allows you to save a result report as an .xlsx (Excel) file. The report presents the overall VMEA results of interest. This can be seen in figure 3.6

[illegible]

Figure 3.6: *Excel sheet for the VMEA results*

## 4 Methodology

In this chapter the methodology of both the parameter and sensitivity studies on VMEA as a reliability method will be described.

### 4.1 Parameter Study

When working with the created software some parameters are identified as user inputs. A parameter study is therefore prepared with the objective to analyze the effect that the user input parameters have on the final results. This enables all users to either proceed or cancel the analysis depending on the amount of information they have for the specific parameter. For a successful parameter study a reference case is necessary. The study is performed for one parameter at the time. The changes in results, when changing an input parameter, will be compared to the reference case.

The different input parameters that are studied include the Wöhler exponent  $\beta$ , the cyclic endurance limit  $n_e$ , the target life  $T_d$  and the additional uncertainties that can be added on top of the statistical ones.

#### 4.1.1 Reference Analysis

The reference analysis is performed on data provided by VGTT on a steering knuckle component. The data consists of measurements from 6 rig tests, also referred to as component strength tests and 13 field measurements, also referred to as customer load tests. The customer load tests were done by VGTT with sensors capturing load signals with the unit kilo newton [kN]. The component strength tests, also done by VGTT, were performed with the use of synthetic load inputs at two different load spectrum's that are based on measurements from a truck driven on a test track. The synthetic loads were used on 6 components of the same type in order to capture the variation in the components fatigue resistance. The synthetic load runs until the component fails whereby the synthetic load signals are saved. The input files from both customer load tests and component strength tests contain a data set of load versus time, hence are compatible to the created toolbox.

The customer loads were measured on the same type of vehicle driven at different road types around the world by different customers. In which operating environment the field measurements took place and for how long is presented in Table 4.1.

Table 4.1: Field measurement data

| Field           | Time [s] | Distance [km] |
|-----------------|----------|---------------|
| Bergen          | 13329    | 118           |
| South Brazil    | 109746   | 1790          |
| Dresden         | 23505    | 161           |
| Garbage         | 12299    | 66            |
| Göteborg        | 1495     | 17            |
| Middle Brazil   | 122658   | 2366          |
| Norway          | 63960    | 801           |
| Sand: long      | 21794    | 287           |
| Sand: short     | 9507     | 56            |
| Tank            | 7008     | 49            |
| Timber: 3 days  | 17272    | 73            |
| Timber: 5 days  | 69778    | 700           |
| Västra Götaland | 18664    | 321           |

Additionally, the user input parameters are provided from VGTT according to Table 4.2.

Table 4.2: Values for the input parameters that will be used as reference values.

| Parameter                    | Parameter value | Unit     |
|------------------------------|-----------------|----------|
| Wöhler exponent $\beta$      | 9               | [-]      |
| Cyclic endurance limit $n_e$ | 1 000 000       | [Cycles] |
| Target life $T_d$            | 1 000 000       | [km]     |
| Added uncertainties $\tau$   | 0               | [%]      |

The input files together with the input parameters are inserted into the created VMEA toolbox. The results from this analysis are from now on refereed to as the reference analysis.

#### 4.1.2 The Wöhler exponent $\beta$

The study on the  $\beta$ -parameter is done by running the toolbox once for each  $\beta$ -value and then saving the results. The other input parameters are kept constant according to the values in Table 4.2. The  $\beta$ -value is tested for values from  $\beta = 3$  to  $\beta = 15$  where  $\beta = 9$  is regarded as the reference value. The top value of  $\beta$  that is tested is much higher than the rule of thumb values, mentioned in chapter 1.3.1, in order the test the extreme ends of the possible  $\beta$ -values.

As mentioned in the presentation of the VMEA toolbox, it estimates a Wöhler exponent  $\beta$ , but it is still the user, of the VMEA toolbox, that chooses which Wöhler exponent to continue doing the calculations with. Therefor the parameter study on the  $\beta$ -parameter, to outline its effects on the end results, is important.

#### 4.1.3 The cyclic endurance limit $n_e$

The study on the  $n_e$ -parameter is done by running each  $n_e$ -value once. The values that are tested can be found in Table 4.3. The values are chosen in a way to ensure the changes that occur both over and under the reference value are captured. The cyclic endurance limit,  $n_e$ , is prone to change when the material changes [8]. This indicates that some knowledge of the material is important. The parameter study on the  $n_e$ -parameter is done to outline the  $n_e$ -parameters effect on the end result.

Table 4.3:  $n_e$ -values that will be tested in the parameter study.

| $n_e$ [Cycles]              |
|-----------------------------|
| 50 000                      |
| 100 000                     |
| 500 000                     |
| 900 000                     |
| 1 000 000 (Reference value) |
| 5 000 000                   |
| 10 000 000                  |

#### 4.1.4 The target life $T_d$

The target life of a component depends on the operating environment, in other words where it will be used. The areas where the customer loads were measured perhaps have a variety of target lives. It is important to take this into account when using the VMEA toolbox. However in this study, the  $T_d$ -parameter is changed for all measurements for each  $T_d$ -value once. The study on the  $T_d$ -parameter is done in order to outline the effect it has on the end result and the values that are tested can be found in Table 4.4.

Table 4.4:  $T_d$ -values that will be tested in the parameter study.

| $T_d$ [km]                  |
|-----------------------------|
| 100 000                     |
| 250 000                     |
| 500 000                     |
| 900 000                     |
| 1 000 000 (Reference value) |
| 1 500 000                   |
| 2 000 000                   |

#### 4.1.5 Added uncertainties

The VMEA toolbox, and the VMEA method, enable the user to add additional uncertainties on top of the already calculated statistical uncertainties. There are two types of additional uncertainties to add, additional uncertainties from customer load measurements and additional uncertainties from component strength tests. For the parameter study it is assumed that the considered uncertainty is identical in customer load measurements and strength component test. The added uncertainty comes from for example, the manufacturer or engineering experience in terms of percentages. These percentages cannot simply be added to the statistical ones as percentages. The uniform distribution assumption is therefor used and the percentage value is rewritten to decimal form and divided by the square root of three, according to the example,  $10\% \rightarrow \frac{0.1}{\sqrt{3}}$ , before adding them to the statistical uncertainties [8]. The parameter study aims to outline how much a variation of different percentages effects the end results. The parameter study will be done by using the values found in Table 4.5 one by one and saving the results for each.

Table 4.5:  $T_d$ -values that will be tested in the parameter study.

| Added uncertainty, $\tau$ |
|---------------------------|
| 0% (Reference value)      |
| 3%                        |
| 5%                        |
| 10%                       |
| 15%                       |
| 20%                       |
| 50%                       |

## 4.2 Sensitivity study

In this section the methodology and reasoning behind the sensitivity study is outlined. The aim of the sensitivity study is to analyze the robustness of the VMEA method, with regard to the amount of customer tests needed and which of these are more important than others for the end result. The entire population consists of the 13 customer load measurements from the reference analysis and are initially divided into different groups, depending on the magnitude of the measurements calculated equivalent load. The groups are divided into smooth, rough and very rough, and can be seen in Table 4.6, where the smooth group contains the lower end of the equivalent load spectrum and very rough contains the higher end of the equivalent load spectrum. As for the parameter study, all six strength tests are used all through the sensitivity study, since the amount is according to least recommended.

Table 4.6: Group divisions for the customer equivalent loads, based on the magnitude of the equivalent load.

| <b>Smooth</b>     | <b>Equivalent load [kN]</b> |
|-------------------|-----------------------------|
| Timber: 5 days    | 11.03                       |
| Tank              | 11.27                       |
| South Brazil      | 12.32                       |
| Middle Brazil     | 13.81                       |
| <b>Rough</b>      | <b>Equivalent load [kN]</b> |
| Garbage           | 14.40                       |
| Sand: long        | 15.07                       |
| Gothenburg        | 15.38                       |
| Timber: 3 days    | 15.79                       |
| Norway            | 15.91                       |
| <b>Very rough</b> | <b>Equivalent load [kN]</b> |
| Västra Götaland   | 17.54                       |
| Sand: short       | 17.90                       |
| Bergen            | 18.99                       |
| Dresden           | 20.44                       |

### 4.2.1 Strategically decreasing amount of customer load measurements

In this part of the sensitivity study, load measurement tests are taken out of the total population, seen in Table 4.6, strategically to identify patterns and importance of different measurements on the end result.

The first test aims at removing measurements from each group, keeping the spread. One load measurement is taken out of each group, seen in Table 4.6, leaving a total of 10 load measurements. The load measurements are kept can be seen in Table 4.7.

Table 4.7: The 10 load measurements that are kept after taking out 3 tests out of each group for the first time.

| <b>Smooth</b>     | <b>Equivalent load [kN]</b> |
|-------------------|-----------------------------|
| Tank              | 11.27                       |
| South Brazil      | 12.32                       |
| Middle Brazil     | 13.81                       |
| <b>Rough</b>      | <b>Equivalent load [kN]</b> |
| Garbage           | 14.36                       |
| Sand: long        | 15.07                       |
| Timber: 3 days    | 15.79                       |
| Norway            | 15.91                       |
| <b>Very rough</b> | <b>Equivalent load [kN]</b> |
| Västra Götaland   | 17.54                       |
| Sand: short       | 17.90                       |
| Bergen            | 18.99                       |

The identical procedure is done and thus another load measurement taken out of each group from the remaining population, seen in Table 4.7, leaving a total of 7 load measurements. The load measurements that are kept can be seen in Table 4.8 below.

Table 4.8: The 7 load measurements that are kept after taking out 3 load measurements out of each group for the second time

| <b>Smooth</b>     | <b>Equivalent load [kN]</b> |
|-------------------|-----------------------------|
| South Brazil      | 12.32                       |
| Middle Brazil     | 13.81                       |
| <b>Rough</b>      | <b>Equivalent load [kN]</b> |
| Garbage           | 14.40                       |
| Timber: 3 days    | 15.79                       |
| Norway            | 15.91                       |
| <b>Very rough</b> | <b>Equivalent load [kN]</b> |
| Västra Götaland   | 17.54                       |
| Sand: short       | 17.90                       |

For the second test all the load measurements previously taken out are returned and the entire population restored. Three load measurements, but this time only from the Rough-group are removed, seen in Table 4.6, leaving a total of 10 load measurements. This removes a big part of the middle spectra and thus, with more values at the respective ends, guarantees a variation. The load measurements that are kept can be seen in Table 4.9 below.

Table 4.9: The 10 load measurements that are kept after taking out 3 tests out of the Rough-group.

| <b>Smooth</b>     | <b>Equivalent load [kN]</b> |
|-------------------|-----------------------------|
| Timber: 5 days    | 11.03                       |
| Tank              | 11.27                       |
| South Brazil      | 12.32                       |
| Middle Brazil     | 13.81                       |
| <b>Rough</b>      | <b>Equivalent load [kN]</b> |
| Sand: long        | 15.07                       |
| Timber: 3 days    | 15.79                       |
| <b>Very rough</b> | <b>Equivalent load [kN]</b> |
| Västra Götaland   | 17.54                       |
| Sand: short       | 17.90                       |
| Bergen            | 18.99                       |
| Dresden           | 20.44                       |

The two following tests are considered extreme cases. As before the entire population is restored, whereby all load measurements except for two from the Rough-group are removed, seen in Table 4.6. The load measurements that are kept can be seen in Table 4.10.

Table 4.10: The 2 load measurements kept from the Rough-group.

| <b>Rough</b> | <b>Equivalent load [kN]</b> |
|--------------|-----------------------------|
| Sand: long   | 15.07                       |
| Gothenburg   | 15.38                       |

The final one as mentioned, is an extreme case but at the opposite end. Here all load measurements except for two, the one with the lowest equivalent load and the one with highest equivalent load are removed. The load measurements that are kept can be seen in Table 4.11.

Table 4.11: Group divisions for the customer equivalent loads, based on the magnitude of the equivalent load.

| <b>Smooth</b>     | <b>Equivalent load [kN]</b> |
|-------------------|-----------------------------|
| Timber: 5 days    | 11.03                       |
| <b>Very rough</b> | <b>Equivalent load [kN]</b> |
| Dresden           | 20.44                       |

### 4.2.2 Randomly decreasing amount of customer load measurements

In this part of the sensitivity study, load measurements are randomly taken out of the full population. If customers are not specified by the severity of their operating environment, the overall sensitivity to fewer measurements becomes of interest. The population of load measurement can be seen in Table 4.12.

Table 4.12: The population of load measurement.

| Tests           | Equivalent load [kN] |
|-----------------|----------------------|
| Timber: 5 days  | 11.03                |
| Tank            | 11.27                |
| South Brazil    | 12.32                |
| Middle Brazil   | 13.81                |
| Garbage         | 14.40                |
| Sand: long      | 15.07                |
| Gothenburg      | 15.38                |
| Timber: 3 days  | 15.79                |
| Norway          | 15.91                |
| Västra Götaland | 17.54                |
| Sand: short     | 17.90                |
| Bergen          | 18.99                |
| Dresden         | 20.44                |

As mentioned, the selection of which load measurements to take out is from a pure random process. The amount of randomly taken out load measurements is varying.

For the first iteration of the randomized sampling, three load measurements are randomly selected and the VMEA toolbox is used on the remaining 10 load measurements. The same procedure is replicated two more times, three tests in total, to ensure the validity of results. The second test is identical to the previous except that five load measurements are randomly selected three times. For the third iteration of the randomized sampling, eight load measurements are randomly selected and the VMEA toolbox is used on the remaining 5 load measurements. This randomized selection is being iterated twice.

## 5 Results and Analysis

In this chapter, all results are presented. Additionally, for each specific result a short analysis and discussion is held.

### 5.1 Reference analysis results

In Table 5.1 the results from the reference analysis can be observed. These results are a VMEA analysis, with the use of the VMEA toolbox, of VGTTs provided files and data. They are considered as the "correct" values and are the results that the rest of the studies are compared to.

Table 5.1: VMEA results on the reference case, where all the customer load measurements and strengths tests were used.

| <b>Uncertainty Evaluation</b>               |                    |
|---------------------------------------------|--------------------|
| Total strength uncertainty                  | 0.036768 [-]       |
| Total load uncertainty                      | 0.222091 [-]       |
| Total Wöhler exponent uncertainty           | 0.014828 [-]       |
| Total uncertainty                           | 0.225602 [-]       |
| <b>Reliability Evaluation</b>               |                    |
| Load, $m_L$                                 | 2.71 [log(kN)]     |
| Strength, $m_S$                             | 3.858672 [log(kN)] |
| Cornell Reliability Index, $\gamma$         | 5.064544 [-]       |
| Extra Safety Distance, $S_d$                | 0.691368 [-]       |
| Extra Deterministic Safety Factor, $\phi_d$ | 1.996445 [-]       |
| Extra Statistical Safety Factor $\phi_s$    | 1.570202 [-]       |
| Total Safety Factor, $\phi$                 | 3.134822 [-]       |

## 5.2 Parameter study

In this section the results from the parameter study are presented separately for each of the studied parameters.

### 5.2.1 Wöhler exponent, $\beta$ , results

In Figure 5.1, the behaviour of the extra safety distance  $S_d$ , when changing the Wöhler exponent  $\beta$ , is shown. It is observed that  $S_d$  quickly stabilizes when the Wöhler exponent is increased. For example, from Wöhler exponent,  $\beta = 8$  to  $\beta = 10$ , with regard that  $\beta = 9$  is the estimated one, the extra safety distance changes by barely 4%.

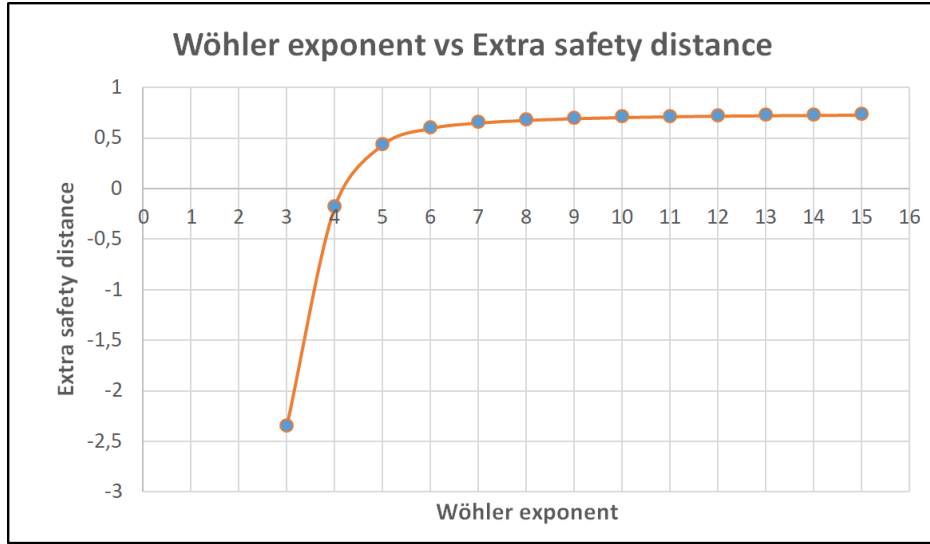


Figure 5.1: Varying Wöhler exponent vs. Extra safety distance,  $S_d$

In Figure 5.2, the behaviour of the extra deterministic safety factor,  $\phi_d$ , is shown. Since  $\phi_d$  is calculated using the natural logarithm of  $S_d$  according to,  $\phi_d = e^{S_d}$ , Eq.2.25, it stands to reason that it is showing a similar behaviour.

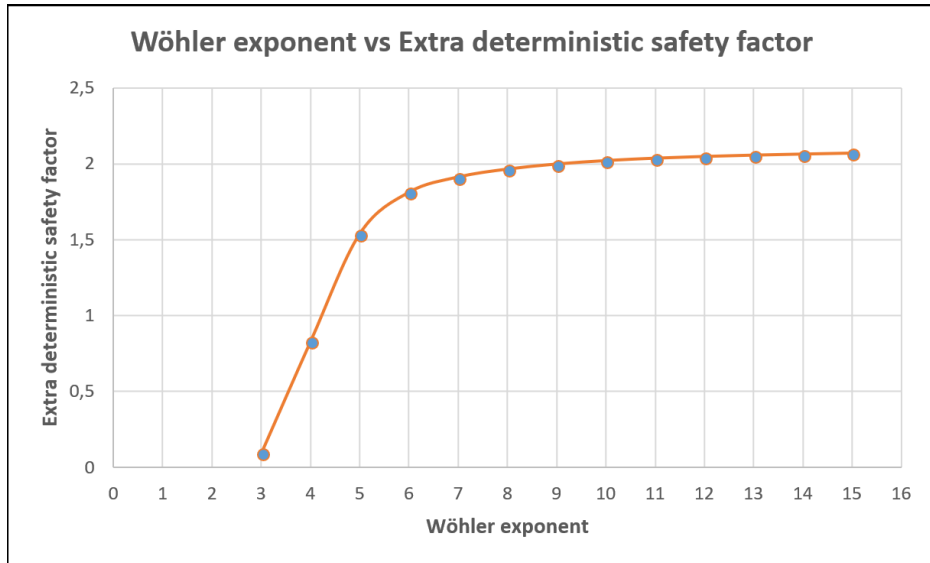


Figure 5.2: Varying Wöhler exponent vs. Extra deterministic safety factor,  $\phi_d$

In Figure 5.3, the behaviour of the total uncertainty,  $\tau$ , is shown. Just like the behaviour for the extra safety distance, the  $\tau$ -parameter quickly stabilizes as it approaches the estimated Wöhler exponent  $\beta = 9$ . The difference as expected, is that the total uncertainty,  $\tau$ , decreases.

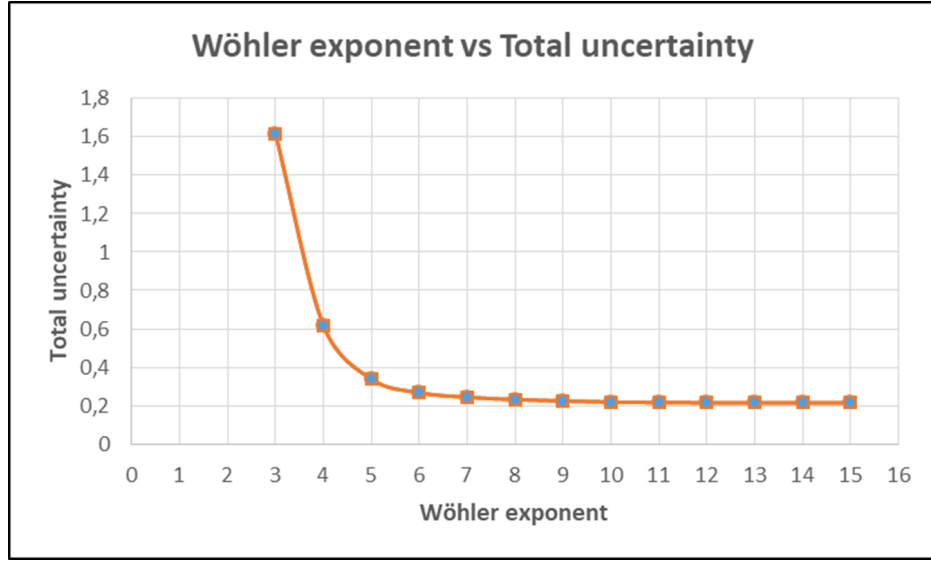


Figure 5.3: *Varying Wöhler exponent vs. Total uncertainty,  $\tau$*

In figure 5.4, the behaviour of the extra statistical safety factor,  $\phi_s$ , is observed. The extra statistical safety factor is calculated according to,  $\phi_s = e^\tau$ , Eq.2.25, and thus has similar behaviour as the total uncertainties.

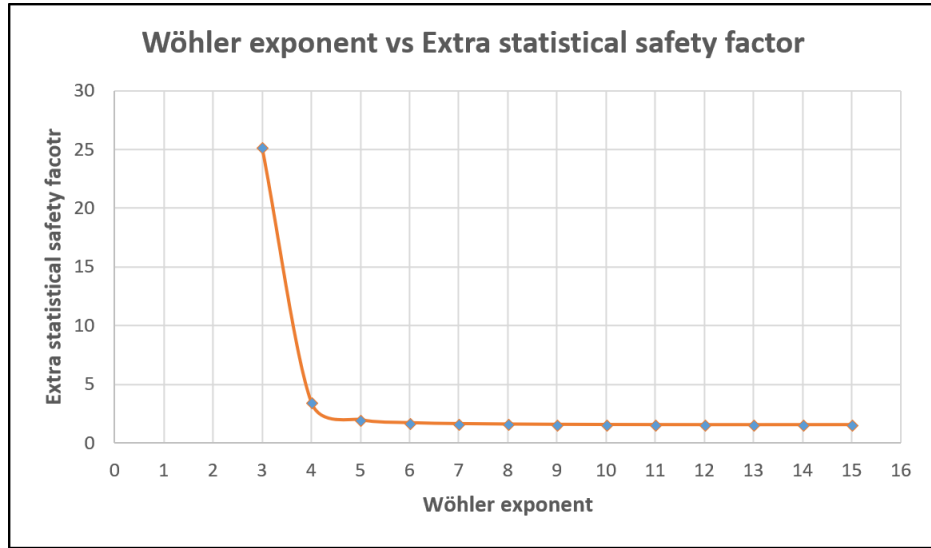


Figure 5.4: *Varying Wöhler exponent vs. Extra statistical safety factor,  $\phi_s$*

The behaviour of the total safety factor,  $\phi$ , is presented in figure 5.5. The total safety factor is simply the extra deterministic safety factor multiplied with the extra statistical safety factor,  $\phi = \phi_d \cdot \phi_s$ , see Eq.2.25. As the rest, it is observed that it converges quickly to a value close to the one of  $\beta = 9$ .

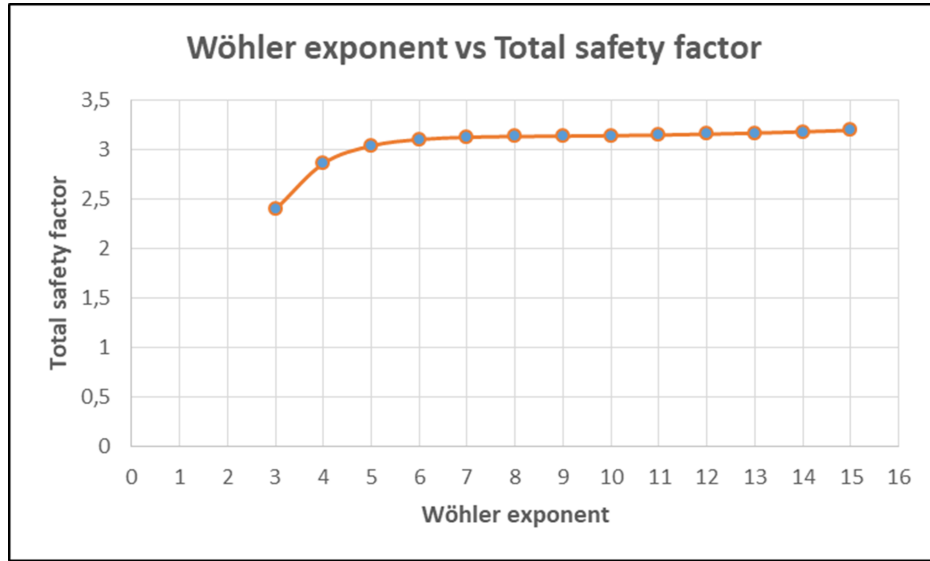
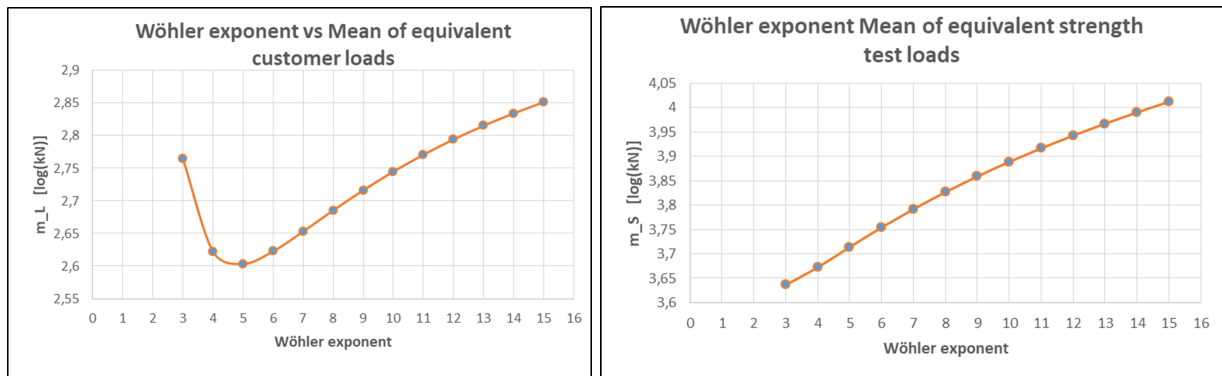


Figure 5.5: Varying Wöhler exponent vs. Total safety factor,  $\phi$

In figure 5.6, the behaviour of the  $m_S$  and  $m_L$ -parameter, with a varying Wöhler exponent, is shown. It is observed that the behaviour of the  $m_S$  and  $m_L$ -parameters has a substantial difference in behaviour from  $\beta = 3$  and  $\beta = 5$ . However, once again when the  $\beta$ -value is closing in on the reference value,  $\beta = 9$ , the behaviour stabilizes and both the  $m_S$  and  $m_L$ -parameter shows stable increase of similar degree. It is observed that both  $m_S$  and  $m_L$  are increasing when the Wöhler exponent is increasing. However, since they are both increasing in a similar fashion, this is of no concern, since in the VMEA method for calculating the safety factors the difference between  $m_L$  and  $m_S$  is what is important.



(a) Varying Wöhler exponent vs.  $m_L$  (Average equivalent customer load)

(b) Varying Wöhler exponent vs.  $m_S$  (Average equivalent component strength)

Figure 5.6: Figures for the equivalent customer load and the equivalent component strength vs. the varying Wöhler exponent

In figure 5.7, the behaviour of the Cornell reliability index,  $\gamma$ , is shown. It is, as for the other safety factors, observed that the  $\gamma$ -parameter has rapid changes at first but is stabilizing as it is closing in on  $\beta = 9$ .

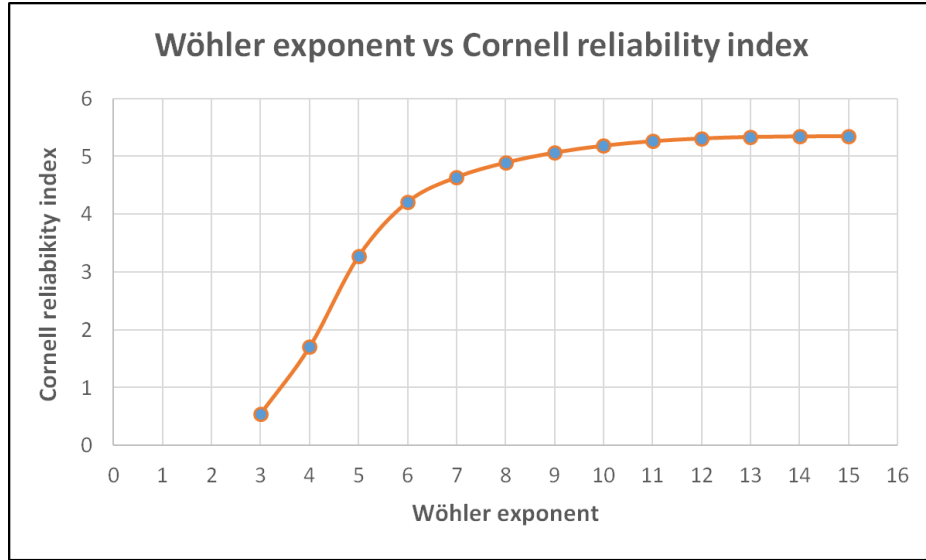
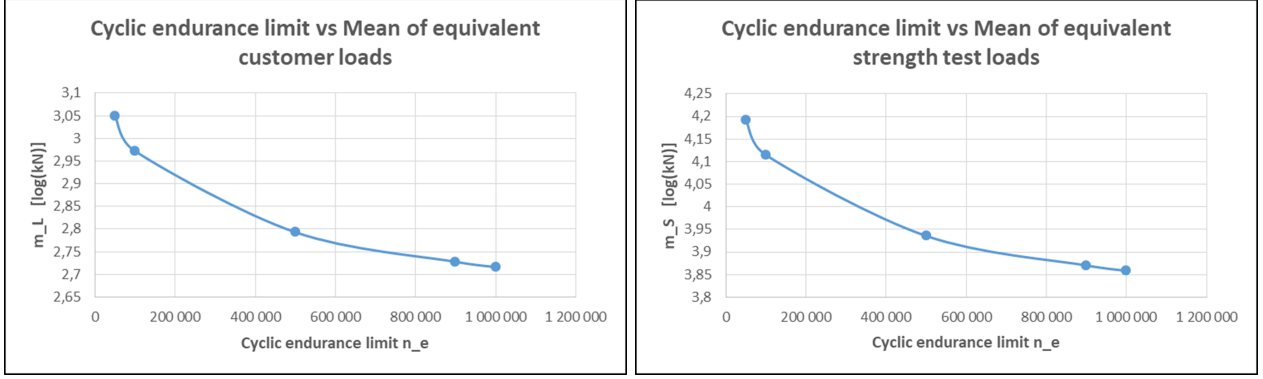


Figure 5.7: *Varying Wöhler exponent vs. Cornell Reliability index,  $\gamma$*

The overall results for varying Wöhler exponent,  $\beta$ , show that a small deviation,  $\pm 2$ , from the estimated  $\beta$  has a small effect on the Cornell reliability index. It should be observed that there is a rapid development, either increase or decrease for the  $\beta$  values 3 to 6 whereby the development pace decreases drastically. Putting effort into having a high precision estimation of the Wöhler exponent is not beneficial since the Cornell reliability index does not change that much when close to the estimated value.

### 5.2.2 The cyclic endurance limit, $n_e$ , results

In figure 5.8, the behaviour of the  $m_S$  and  $m_L$ -parameter, with a varying cyclic endurance limit, is shown. Both the  $m_S$  and  $m_L$ -parameter show a very similar behaviour. Observing, the equations for the equivalent load and strength respectively, Eq.2.5 and Eq.2.10, the behaviours are expected since the  $n_e$ -parameter is a common denominator. For the same reason and regarding the fact that all safety factors are based on the difference between  $m_S$  and  $m_L$ , the safety factors are not affected by the cyclic endurance limit,  $n_e$ , at all.



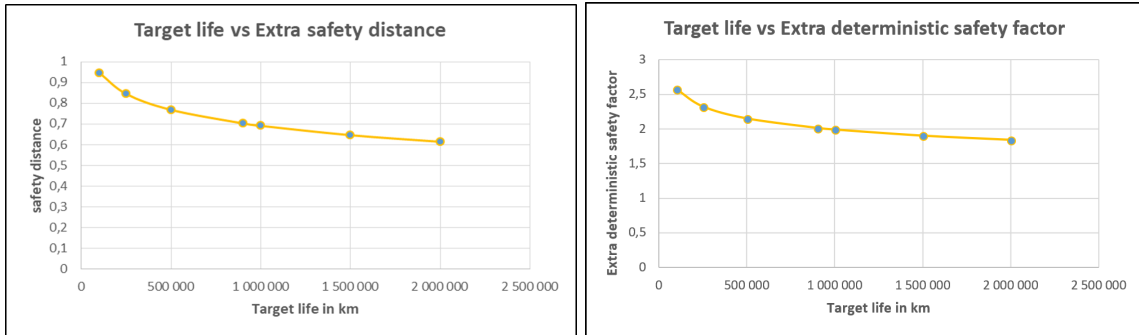
(a) Varying cyclic endurance limit vs.  $m_L$   
(Mean of the logarithmic equivalent load)

(b) Varying cyclic endurance limit vs.  $m_L$   
(Mean of the logarithmic equivalent strength)

Figure 5.8: Figures for both the mean of the logarithmic equivalent customer load and component strength vs. varying cyclic endurance limit

### 5.2.3 The target life, $T_d$ , results

In figure 5.9, the behaviour of the extra safety distance,  $S_d$ , and the extra deterministic safety factor  $\phi_d$ , with a varying target life, is shown. It is observed that both show a similar behaviour when the target life is increased. Since the  $\phi_d$  is calculated from  $S_d$ , according to Eq.2.25, it stands to reason that they are behaving similarly.



(a) Varying target distance vs. Extra safety distance,  $S_d$

(b) Varying target distance vs. Extra deterministic safety factor,  $\phi_d$

Figure 5.9: Figures for the Extra safety distance and the Extra deterministic safety factor vs. varying Target life,  $T_d$

In figure 5.10, the extra statistical safety factor,  $\phi_s$ , behaviour against varying target lives,  $T_d$ , is presented. Since the target life only affects the fatigue goal of the equivalent customer loads and thus has no statistical affect, the constant behaviour is as expected.

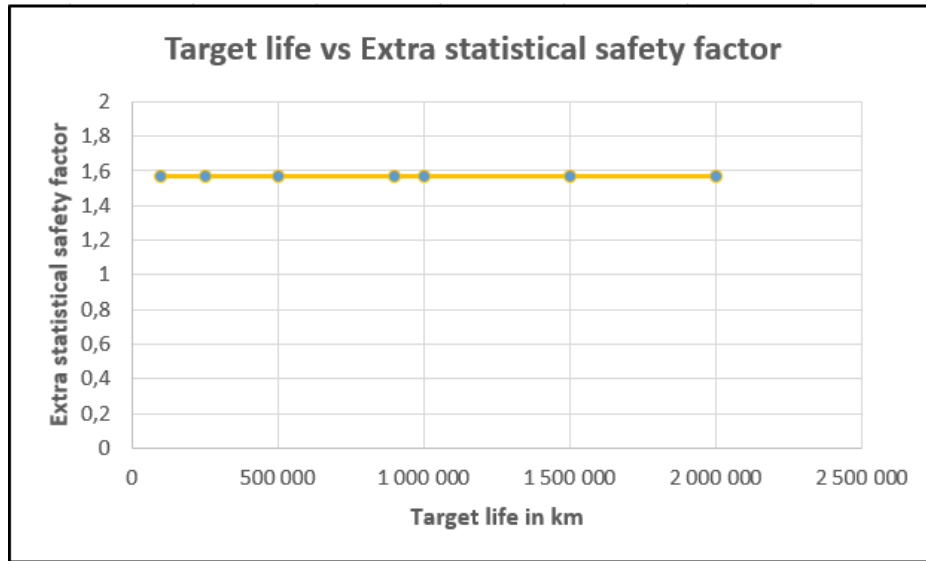


Figure 5.10: Varying target distance vs. Extra statistical safety factor,  $\phi_s$

In figure 5.11, the behaviour of the total safety factor,  $\phi$ , with a varying target life, is shown. As mentioned, the extra statistical safety factor is not affected by the varying target life, thus when calculating the total safety factor, according to Eq.2.25, only the  $\phi_d$ -parameter has any effect on  $\phi$ . This explains why  $\phi_d$  behaves in a similar way as  $\phi$  and the results are as expected.

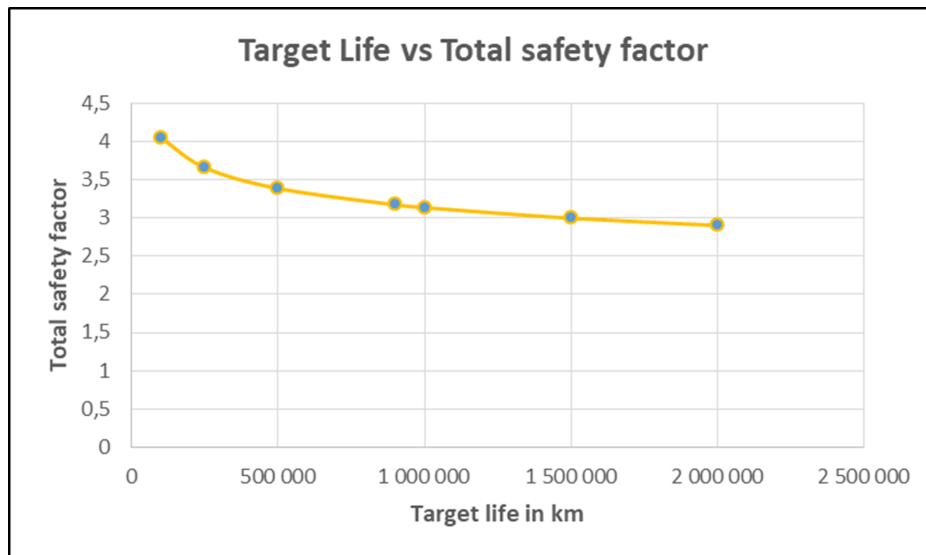


Figure 5.11: Varying target distance vs. Total safety factor,  $\phi$

In figure 5.12, the behaviour of the mean of the logarithmic equivalent customer load,  $m_L$ , with a varying target life, is shown. According to, Eq.2.5, it stands to reason that the  $m_L$ -parameter is increasing with an increase in target life. Though it is observed that the  $m_L$ -parameter does not have a linear relationship to the target life.

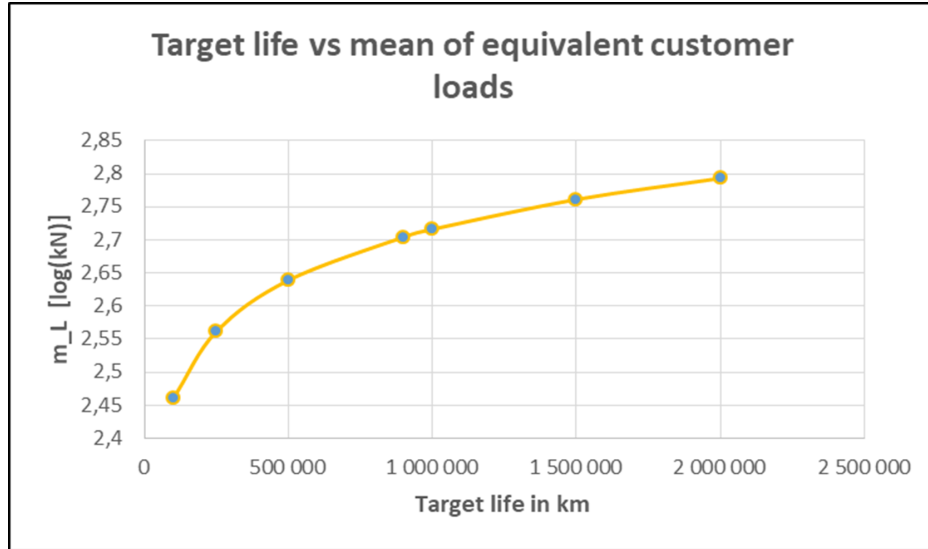


Figure 5.12: Varying target distance vs.  $m_L$  (Mean of the logarithmic equivalent load)

In figure 5.13, the behaviour of the Cornell reliability index,  $\gamma$ , with a varying target life, is shown. It is observed that the Cornell reliability index decreases as the target life is increased. It stands to reason that the reliability that a component will last 2 000 000 km is less than it lasting 1 000 000 km.

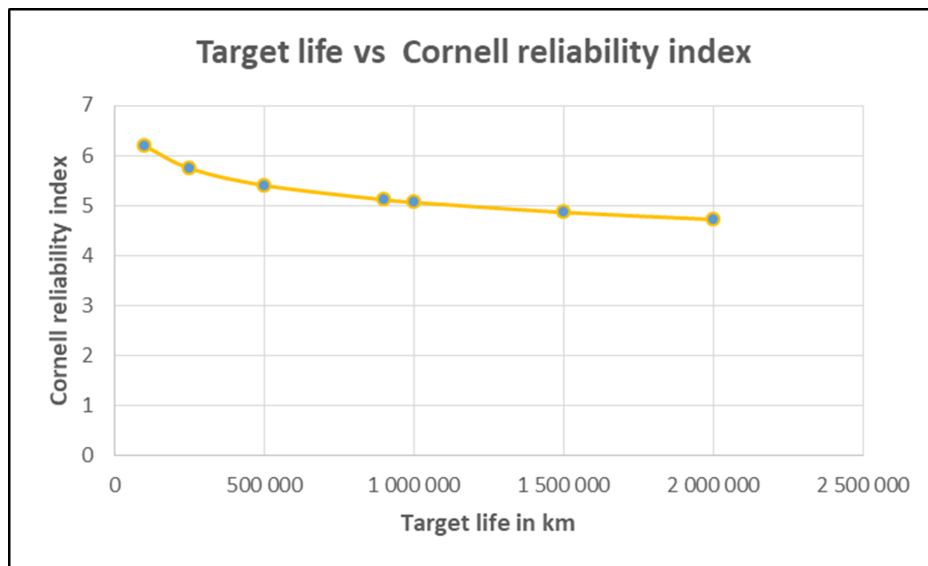
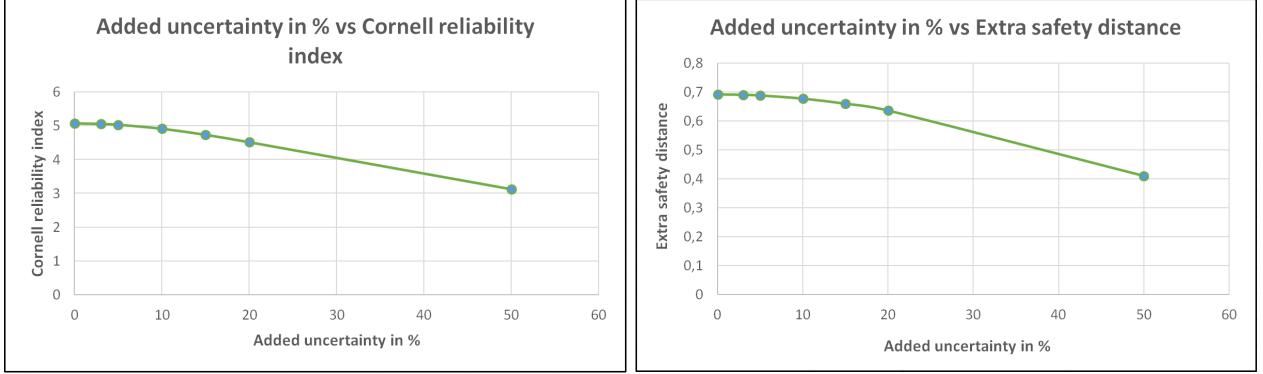


Figure 5.13: Varying target distance vs. Cornell reliability index,  $\gamma$

The overall result from varying target life, show that it has no effect on the statistical uncertainties.

### 5.2.4 Added uncertainties, results

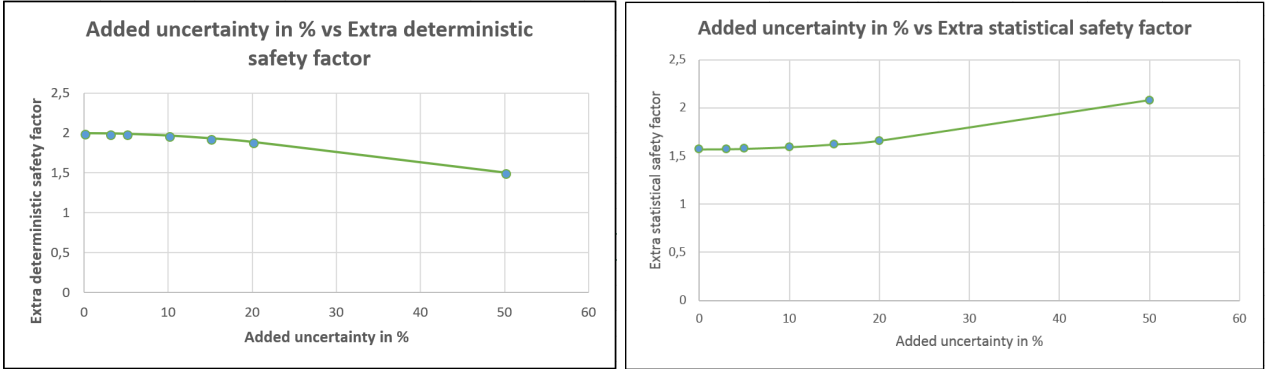
In figure 5.14, the behaviour of the Cornell reliability index,  $\gamma$ , and the extra safety distance,  $S_d$ , with a varying added uncertainty, is shown. It is observed and reasonable that the reliability index and the safety distance are decreasing when additional uncertainties are introduced. It is also observed that the decrease of the values for  $\gamma$  and  $S_d$  is non-linear. In figure 5.15, the behaviour of the extra deterministic safety factor,  $\phi_d$ , and the extra



(a) Varying extra added uncertainty vs. Cornell reliability index,  $\gamma$  (b) Varying extra added uncertainty vs. extra safety distance,  $S_d$

Figure 5.14: Figures for  $\gamma$ ,  $S_d$  vs. varying extra added uncertainty

statistical safety factor,  $\phi_s$ , with a varying added uncertainty, is shown. As expected from adding uncertainties, it is observed that  $\phi_d$  and  $\phi_s$ , increases and decreases respectively.



(a) Varying extra added uncertainty vs. extra deterministic safety factor,  $\phi_d$  (b) Varying extra added uncertainty vs. extra statistical safety factor,  $\phi_s$

Figure 5.15: Figures for  $\phi_d$ ,  $\phi_s$  vs. varying extra added uncertainty

In figure 5.16, the total safety factor,  $\phi$ , with varying added uncertainty,  $\tau$ , is shown. It is observed that  $\phi$  does not react at all to the additional uncertainties. Since  $\phi_d$  and  $\phi_s$  are used for calculating  $\phi$ , in Eq. 2.25, it is known that they cancel each other out. Since  $\phi$  does not react at all, it shows that  $\phi_d$  and  $\phi_s$  have an exactly opposite reaction to the additional uncertainties.

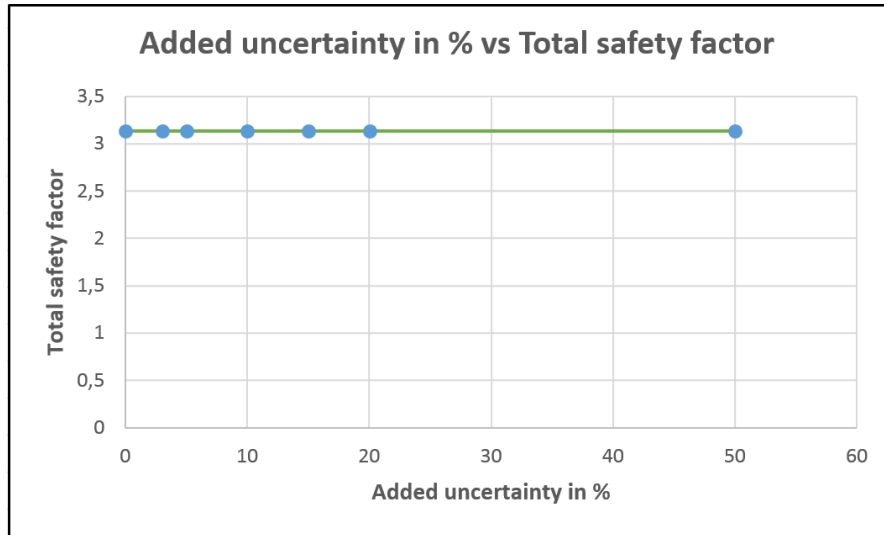


Figure 5.16: *Varying extra added uncertainty vs. Total safety factor,  $\phi$*

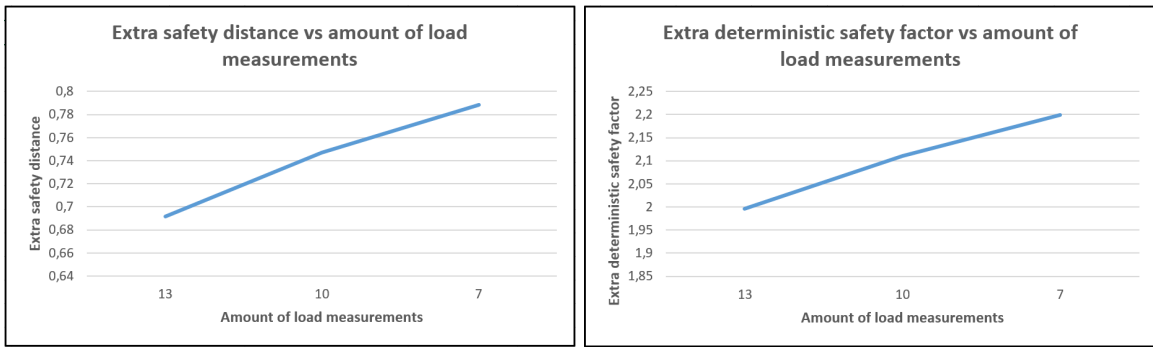
The overall result from adding uncertainties, indicate that the choice of safety factor is important and perhaps even considering all in the reliability assessment. The general reasons for the behaviour is adding uncertainties actually increases the statistical safety factor since it accounts for more uncertainties then the standard procedure.

## 5.3 Sensitivity study

In this section the results from the sensitivity study are presented for each study in the same order as the methodology.

### 5.3.1 Strategically decreasing amount of customer load measurements, results

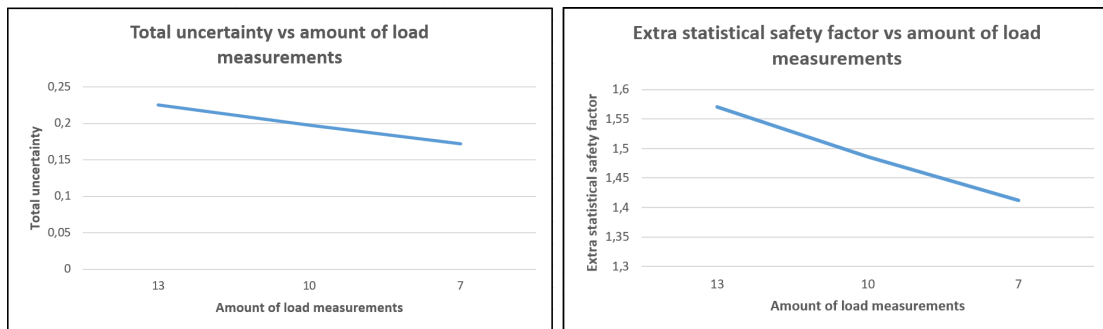
In figure 5.17, the behaviour of the extra safety distance,  $S_d$ , and the extra deterministic safety factor  $\phi_d$ , when removing one from each severity group, is presented. It is observed that both  $S_d$  and  $\phi_d$  are showing a very similar behaviour and that they are both increasing even though the number of customer measurements is decreasing which is unexpected. However, this is due to the spread of the customer loads, being more and more narrow when removing customer measurements from each group of measurements. The variation is the basis of the method and removing measurements at the tails of the variation makes a greater impact than the statistical uncertainty of fewer measurements. This is in particularly important when dealing with a population of 13 in total.



(a) Behaviour of the extra safety distance,  $S_d$ , for different amount of loads when removing loads from each group  
 (b) Behaviour of the extra deterministic safety factor,  $\phi_d$ , for different amount of loads when removing loads from each group

Figure 5.17: Behaviour of the extra safety distance,  $S_d$ , and the extra deterministic safety factor,  $\phi_d$ , for different amount of loads when removing loads from each group

In figure 5.18b, the behaviour of the extra statistical safety factor,  $\phi_s$ , for the same study, is shown. It is observed that  $\phi_s$  has a rapid decrease when removing customer measurements from each group of measurements. After observing the results from the deterministic safety factor and distance this stands to reason. Additionally, the statistical uncertainty decreases and therefore the statistical safety factor is decreasing. The calculation for  $\phi_s$  is done by using  $\tau$ , presented in figure 5.18a, indicating it is reasonable that both are decreasing.



(a) Behaviour of the total uncertainty,  $\tau$ , for different amount of loads when removing loads from each group  
 (b) Behaviour of the extra statistical safety factor,  $\phi_s$ , for different amount of loads when removing loads from each group

Figure 5.18: Behaviour of the total uncertainty,  $\tau$ , and the extra statistical safety factor,  $\phi_s$ , for different amount of loads when removing loads from each group

In figure 5.19 the behaviour of the total safety factor,  $\phi$ , is shown. To calculate  $\phi$ , Eq. 2.25 is used, where both the extra deterministic safety factor,  $\phi_d$ , and the extra statistical safety factor,  $\phi_s$ , are included. It is observed that  $\phi$  is decreasing when removing customer measurements from each group of measurements. It is observed that the rapid decrease of  $\phi_s$ , from figure 5.18b, is enough to compensate for the increase of  $\phi_d$ , from figure 5.17b. This is reasonable since, fewer measurements and the more narrow spread of customer loads should provide a decreased certainty. It should be observed that the scale on the y-axis is very narrow and the decrease not big.

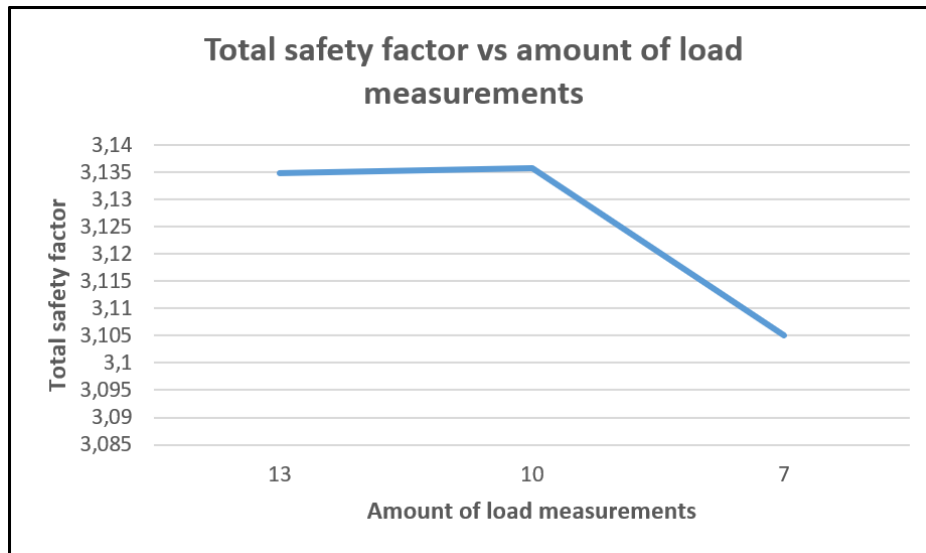


Figure 5.19: Behaviour of the total safety factor,  $\phi$ , for different amount of loads when removing loads from each group

In figure 5.20, the behaviour of the Cornell reliability index,  $\gamma$ , is shown. As for the deterministic safety factor and distance, the same observation is made, mainly that  $\gamma$  is increasing even though there are fewer customer load measurements. This is now reasonable and expected for the same explanation as above.

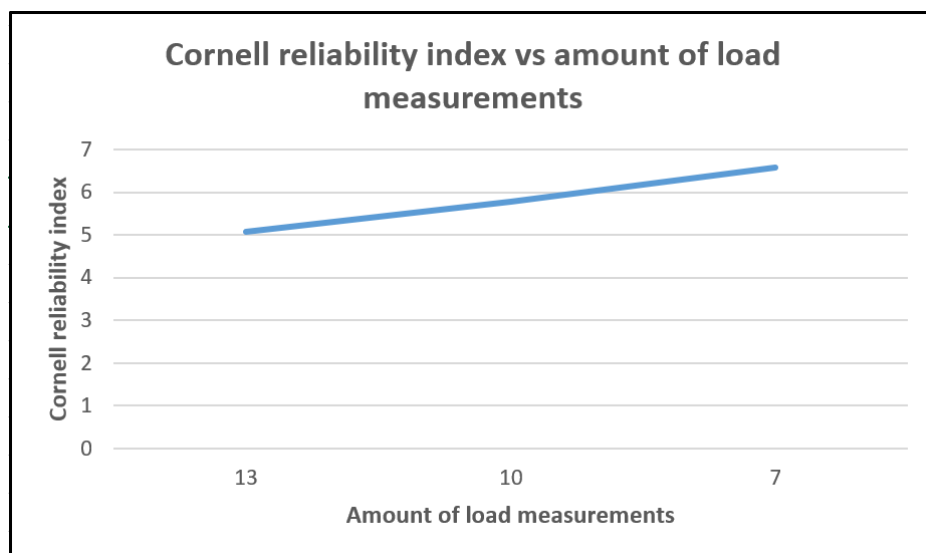


Figure 5.20: Behaviour of the Cornell reliability index,  $\gamma$ , for different amount of loads when removing loads from each group

For the second study, the value for the Cornell reliability index, when removing three customer measurements from the Rough-group (middle), is compared with the value for the Cornell reliability index when taking out one customer measurement out of each group, thus to the first study. The result is presented in figure 5.21. It is observed that the development of the Cornell reliability index is going in separate directions, depending on how customer measurements have been removed. The Cornell reliability index, when removing customer measurements from the Rough-group decreases while it increases for removing one from each group. As explained before, the variation is the main influence and by keeping the values at the tails of the distribution you get more accurate results. The decrease for the second study show that the variation is accounted for but due to removing customer load measurements from the middle there is an overall larger uncertainty and the Cornell reliability index decreases.

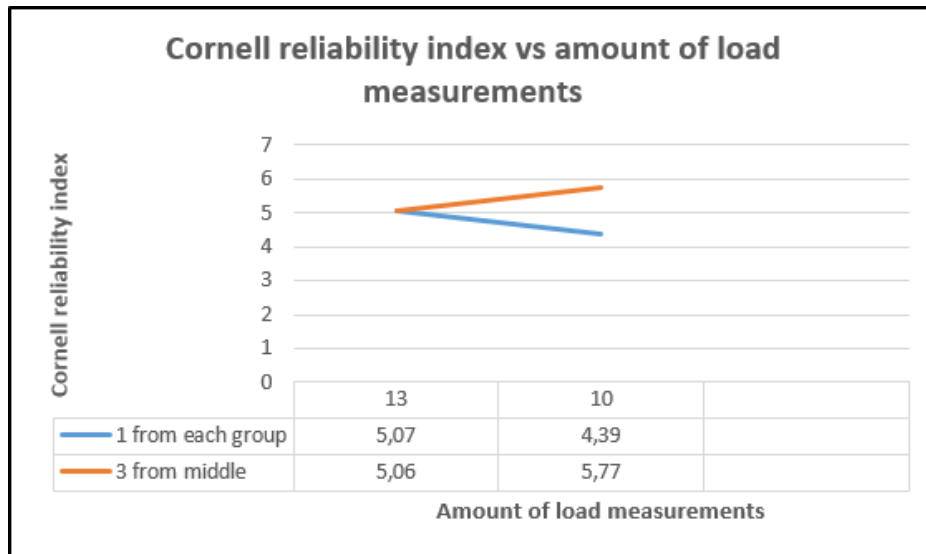


Figure 5.21: *Cornell reliability index, when taking out one measurement out of each group, compared to taking out 3 measurements from the middle group*

In this extreme study, presented in figure 5.22, a comparison is shown between, keeping only the highest and lowest customer load measurement and keeping only two values from the middle. As the previous result have shown, these confirm that the variation has the largest influence on the safety factors. It is in other words observed that, only customer loads from the middle provide a high Cornell reliability index, due to the spread being extremely narrow. On the other hand, only keeping the highest and lowest customer load provides a low Cornell reliability index, due to the variation being high.

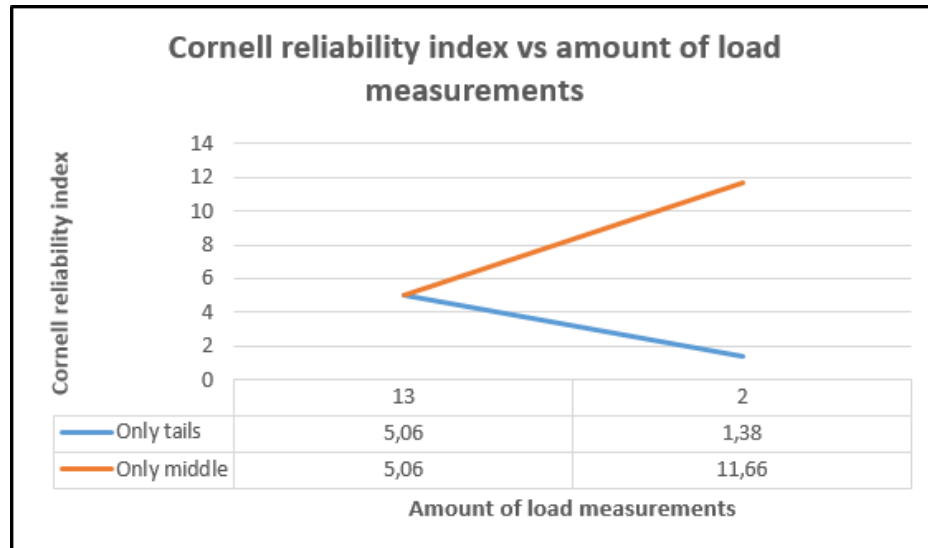
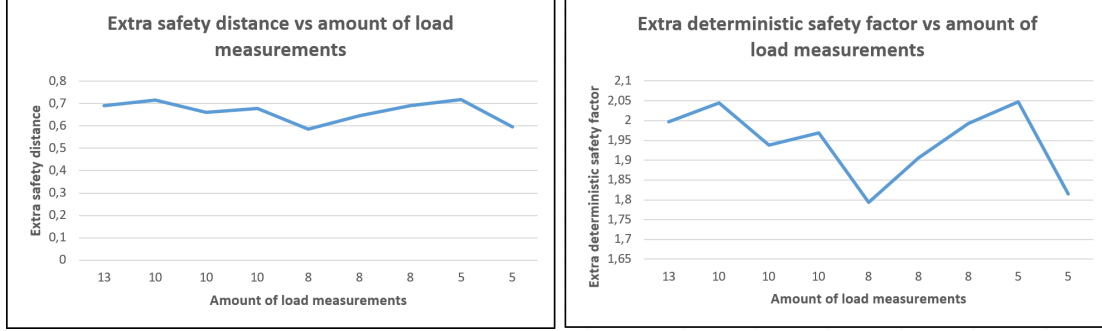


Figure 5.22: *Cornell reliability index, when only using the highest and lowest customer load measurement, compared to only keeping two customer load measurements that are in the middle*

### 5.3.2 Randomly decreasing amount of customer load measurements, results

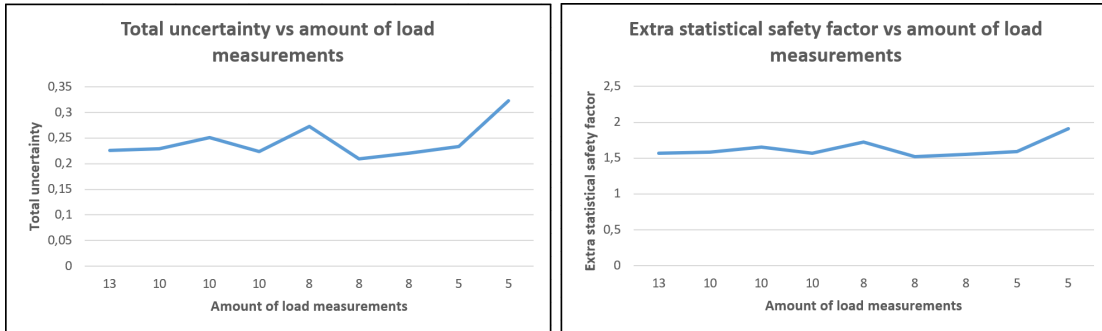
The randomly decreasing amount of customer load measurements study consisted of removing three measurements three times, five measurements three times, eight measurements twice and in the result the entire development is presented. In figure 5.23, the behaviour of the extra safety distance,  $S_d$  and the extra deterministic safety factor,  $\phi_d$ , is shown. In figure 5.23b, it is observed that the behaviour of  $\phi_d$  is having a volatile behaviour but is favoring a decrease rather than an increase. As the amount of customer measurements, randomly removed, increases the results behaviour is increasingly volatile.



(a) Behaviour of the extra safety distance,  $S_d$ , when randomly removing customer load measurements from the population (b) Behaviour of the extra deterministic safety factor,  $\phi_d$ , when randomly removing customer load measurements from the population

Figure 5.23: Behaviour of the extra safety distance,  $S_d$ , and the extra deterministic safety factor,  $\phi_d$ , for different amount of loads when removing loads from each group

In Figure 5.24, the behaviour of the total uncertainty,  $\tau$  and the extra statistical safety factor,  $\phi_s$ , is shown. It is observed that the behaviour of  $\phi_s$  is to a certain degree stable and contained when randomly removing customer measurements. Even by the end when eight customer measurements are randomly removed at a time,  $\phi_s$  is close to its original value. However, this does not indicate how many measurements that are sufficient since the statistical uncertainties are calculated based on the measurements left.



(a) Behaviour of the total uncertainty,  $\tau$ , for different amount of loads when removing loads from each group (b) Behaviour of the extra statistical safety factor,  $\phi_s$ , when randomly removing customer load measurements from the population

Figure 5.24: Behaviour of the extra statistical safety factor,  $\phi_s$ , and the total uncertainty,  $\tau$ , for different amount of loads when removing loads from each group

In Figure 5.25, the behaviour of the total safety factor,  $\phi$ , is shown. It is observed that when randomly removing three customer measurements, the results for  $\phi$  have a low variation from its original value but randomly removing more than three customer measurements the behaviour of  $\phi$  is becoming volatile. Since  $\phi$  is calculated using  $\phi_d$  and  $\phi_s$ , using Eq. 2.25, it is observed that the volatility of  $\phi_d$  is the determining factor for the behaviour of  $\phi$ . These results are expected since the total population is as small as 13 and removing five equals removing around 40%.

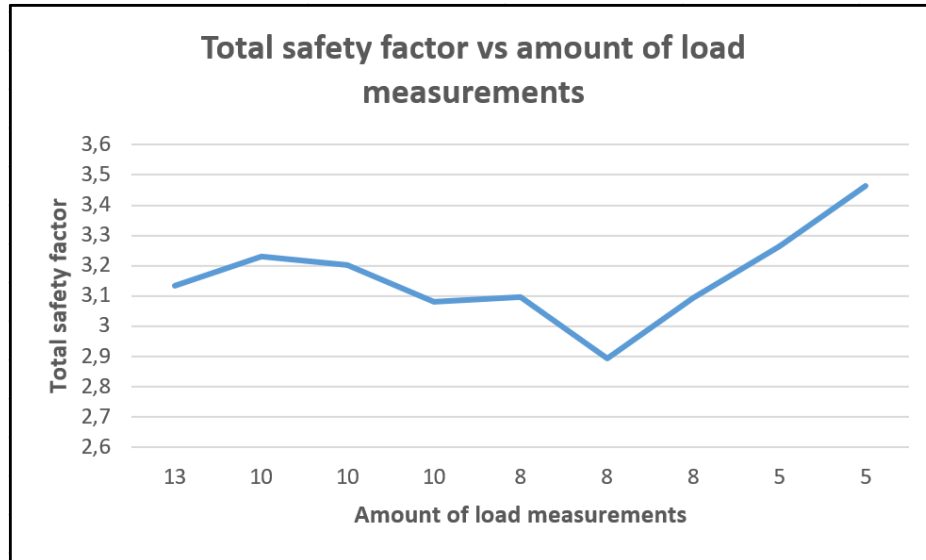


Figure 5.25: Behaviour of the total safety factor,  $\phi$ , when randomly removing customer load measurements from the population

In Figure 5.26, the behaviour of the Cornell reliability index,  $\gamma$ , is shown. The results for  $\gamma$  are stable, and the two most deviating points are when more than 3 customer measurements are randomly removed. But even then, for the most part,  $\gamma$  is close to its original value. It is observed that even when  $\gamma$  is strongly deviating from its original value it is decreasing, hence providing conservative results.

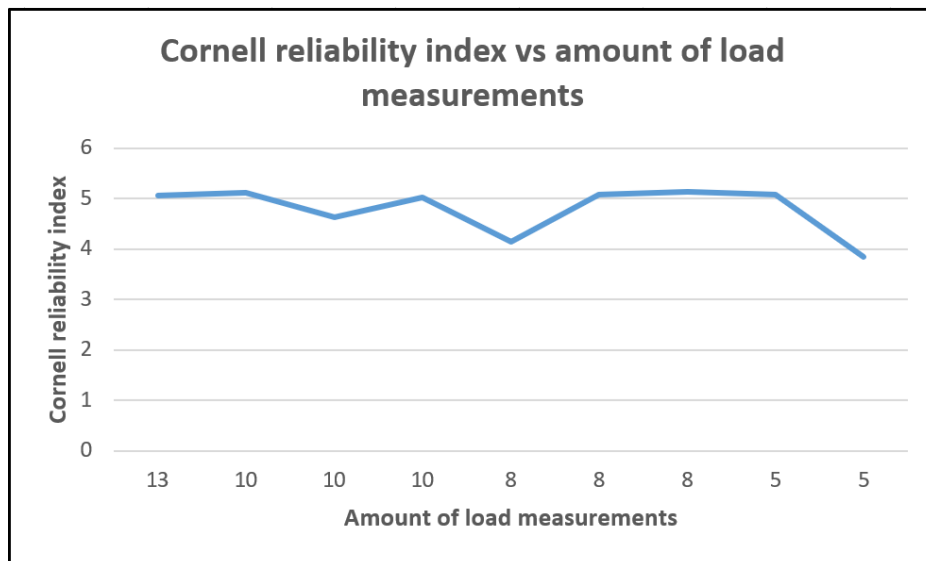


Figure 5.26: Behaviour of the total safety factor,  $\gamma$ , when randomly removing customer load measurements from the population

## 6 Discussion

Probabilistic VMEA is a statistical method which has been implemented to the fatigue reliability assessment, for the automotive industry on component level. A systematical implementation of the VMEA method is of interest for the automotive industry. At the moment, the extent of how much this implementation of the VMEA has been tested in practice, is low. One main purpose for this master thesis project was to create a first iteration of a software with a GUI, where the VMEA method is implemented. The goal with the VMEA toolbox was to provide a simple and systematical way for the vehicle industry to use VMEA in their reliability assessment. The other main purpose was to test the VMEA method and provide information about the reliability and robustness of the method is. In order to study this, two studies were performed. First, a parameter study was carried out where effects on the results were studied when changing identified toolbox input parameters. In the second study a sensitivity analysis was performed, where a different amount of customer load measurements were randomly removed from the data population.

The VMEA toolbox flowchart shows that the VMEA method has successfully been implemented to be used in a rather simple and systematical way.

The results from the parameter study, indicated that the VMEA method is rather robust to changes in terms of the input parameters identified in the working procedure. The Wöhler exponent quickly converged when the specific parameter tested approaches its most reasonable value in other words the value from the reference analysis. The rest of the parameters, the target life, the cyclic endurance limit and the additional uncertainties are somewhat diffuse and perhaps the user cannot be sure of the actual value. However, all the results show that the VMEA method is robust to estimations and even though the safety factors are affected, the behaviour is within reasonable percentages.

For the sensitivity results, the main observation was that the variation has a greater influence on the safety factors than the statistical uncertainty from removing measurements. This was observed since the strategical removal of customer load measurements showed that the measurements that are at the tails of the distribution are the ones with the greatest influence. Removing these, thus narrowing down distribution, gave an increase to the safety factor, even though the uncertainties due to fewer measurements increased. It can therefor be recommended, when doing full scale tests that the best but most importantly the worst operating environments have been captured. If the variation is successfully captured, amount of tests in the middle of the distribution can be decreased.

Additionally, it was observed that when more than three customer measurements from the initial population were removed, the deviation of the results started to rapidly increase. Though, even when there was a lot of deviation, from the values from the reference analysis, the results were conservative. When looking at the Cornell reliability index, where all the calculations are embedded, it did not have strong deviation from its original value, the reference analysis, and when deviating was providing matching or conservative results. Since the total population consists of 13 customer load, one cannot say whether randomly removing load measurements will always give conservative results. What can be said however, is that the VMEA method in general is not sensitive to removing a couple of measurements when the total population is 13. Once again, the results show that if the variation is captured properly in similar fatigue reliability assessment to this one, the amount of measurements can easily be decreased.

This master thesis was limited by both time and in total population of customer load measurements. To conclude the results observed in this project and increase the possibility of using VMEA in fatigue reliability assessments, more studies are needed. A first step would be a similar study with the total population of load measurements doubled. For future work, the VMEA methods reliability in facing uncertainties and variation, in terms of different types of components and also between types of vehicles, should be tested.

A possible use of VMEA is to use simulations to produce synthetic component strength signals, instead of physical tests, in the fatigue reliability assessment. A study of how one may go about using simulations instead of physical tests, in the development of a product, will broaden the area of where VMEA is usable and make it available to more potential users. VMEA in this thesis is only applicable on a component level with signals from a single channel output. The next step is to investigate how VMEA should be modified in order to be able to do fatigue reliability assessments on a system level with multiple channel outputs.

## 7 Conclusions

To reach the main objectives of the project, the probabilistic version of the VMEA method was implemented into a usable software with a GUI, thus creating the VMEA toolbox. Additionally, tests of the importance of the four input parameters, that are chosen by the user were done. Additionally, tests of how robust the VMEA method is when introducing fewer measurements, both strategically and randomly removing measurements, were carried out.

- Based on the results in this thesis, VMEA is a reliable and a robust way to do fatigue reliability assessments, for the automotive industry.
- The VMEA toolbox is a systematical way of carrying out a VMEA analysis on measurement data from a component from a vehicle.
- The variation has the largest impact on the safety factors and thus it is of great importance to capture it as good as possible.
- If the spread of the customer load measurement is captured, then the VMEA method is not sensitive to a reasonable amount of fewer measurements, while still being able to provide reasonable results.
- It can be concluded that the VMEA method is robust when using reasonable estimations of input parameters.

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