Reliability Study and Maintenance Decision Making of Wheel Temperature Detectors

by

Azadeh Marghoub Shadkar

A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

in

Engineering Management

Department of Mechanical Engineering
University of Alberta

Abstract

In 2011, Canadian Pacific (CP) Railway decided to replace the visual No.1 Air Brake test with a new Automated Train Brake Effectiveness (ATBE) for condition monitoring of rail cars through both physical inspection and measurements by fixed track-side Wheel Temperature Detectors (WTD). To make the most effective use of technology for operational and maintenance decision-making, the new technology should be shown to be reliable, with outputs that are understandable and interpreted accurately. The present work uses the WTD temperature readings along with records of sensor system failures to develop a method for detecting wheels prone to failure. A set of detector data was checked against neighbouring detectors to improve the classification of a fault with a wheel through multiple measurements and to determine whether there may be a fault with the detector. Studying one train passing consecutive detectors yields useful information about the health of the brakes at each axle of the set of rail cars. Thus, three neighbouring detectors were selected for comparative assessment. Five neighbouring detectors were also selected, but there was no significant databases were employed and the reliability of detectors was modeled. The best fit to the failure distributions was the normal. Mean-time-between failure (MTBF) for all detectors was calculated to be 2.7 years. For an individual detector the MTBF was about three months. But, for winter operations, the MTBF was found to be only 1.8 months. Several recommendations for follow-up analysis work are offered, with suggestions for industrial implementations that should improve overall WTD system reliability.

Acknowledgement

I wish to express my gratitude to Dr. Michael Lipsett, my supervisor, for providing me with the opportunity to do my Master's. I am grateful for his continuous support, guidance and encouragement throughout my program at the University of Alberta. I am thankful that he empowered me during difficult times and made me believe I could complete this goal. I would like to offer my deep appreciation to Dr. Michael Hendry, my co-supervisor for his time, invaluable guidance and support; he was always ready to offer any kind of support for the progress of the project.

I would like to thank Dr. Derek Martin and the Canadian Rail Research Laboratory (CaRRL) for funding and giving me the chance to participate in this research. I would also like to thank Transport Canada and Canadian Pacific; and special thanks to Michelle Jamieson, Ereena Baig and Abe Aronian for facilitating access to datasets and always being ready with data support.

I am appreciative to my friend Roya Vaghar Anzabi for her support and for sharing her knowledge and expertise; and to my other true friends who stood by me in the toughest days of my life, I will never forget their kindness.

Lastly, I want to express my love and gratitude to my dearest who were always there for me no matter what: my mother for dreaming big for me, my father for believing in me and my brother for motivating me. You are the reason of my existence; without you, none of this would be possible.

Table of Contents page

List of Tables page

List of Figures page

Chapter 1. Introduction

1.1. Background and motivation

The motivation for the present work comes from a decision made by Canadian Pacific (CP) in September 2011 to apply the Automated Train Brake Effectiveness (ATBE) process by using Wheel Temperature Detectors (WTDs) to more effectively and reliably monitor the condition of air brakes and to improve overall train safety. The ATBE process, which consisted of automated temperature data reading, gathering, processing and reporting the detector output allowed CP to obtain an exemption from Transport Canada's (TC) regulated No.1 air brake test on the British Columbia Coal train fleet, "providing the trains receive a valid and successful ATBE test" (Aronian, Jamieson, 2014). In addition to adopting new technology and processes, to make the most effective use of technology and make the most accurate and effective decisions, it should be demonstrated that new technology is reliable enough and can function as desired under the specified conditions. There is very little time between WTD detection and component failure. For the detectors to be useful, it is necessary to understand and accurately interpret their output. For this to happen, approaches need to be developed to best use the detectors. Determining whether the detectors are functioning properly through their reading values is the first and most common data used by the industry to understand the condition of the moving train. This is of great value as it will also help to prevent undesired train stoppage which results from false failure detection and costs approximately \$4000 -\$5000 each time (Bracket, Peter, Personal interview, 2014)

For the railroad industry, Wheel Temperature is an indication of the effectiveness and functionality of the railcar air brake. Therefore, wheel temperature detectors are strategically positioned alongside the track, and sensors are used to measure the temperature of passing wheels to detect and diagnose air brake problems or failures.

Some point out that "Blocked brakes and overheated axles are among the main immediate causes of hazards in railway operations" (Achuthan and Keerthana, 2014, p.6). Improper function of the air brake can lead not only to the failure of the air brake, but can also damage the wheels. Blocked brakes can overheat wheel rims, which leads to breakage of the wheel disc, formation of wheel flat and, in extreme cases, fire or derailment. This is not just a safety issue, it is an economic issue as well; replacing damaged wheels and brake legs is often costly.

In addition to using a technically reliable and efficient detection system and understanding the outputs, it is important to improve the practices involved in maintaining detection systems to achieve a higher level of reliability, especially in Canada's harsh and changing weather conditions. Unplanned failures and thus unplanned stoppages for repair and maintenance are costly events that make up a significant portion of operating costs. Hence, preventive maintenance is considered an effective strategy for lowering system failures, increasing reliability and consequently decreasing maintenance costs (Barabady and Kumar, 2008).

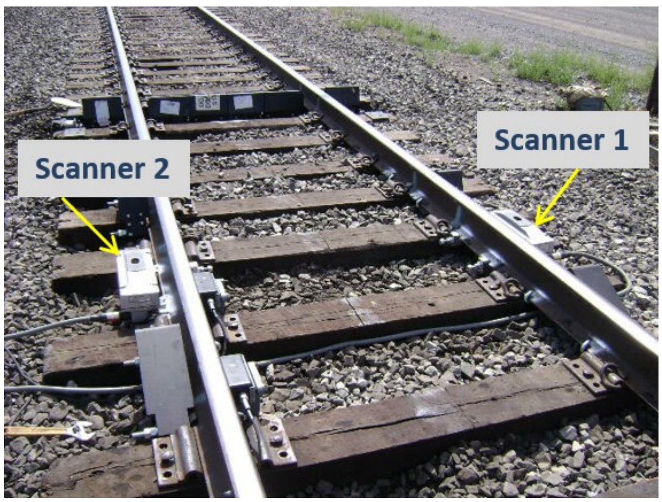


Figure 1-1: Servo style hot wheel detector

(Public Domain Dedication)

A reliable detection system also can be a useful tool in the hands of maintenance staff. Identifying which wheels have the potential to fail can reduce the time required for train inspection when the train reaches its destination or is stopped for maintenance. Effective maintenance also requires precise and proper information.

It is not helpful to gather huge amounts of data on a daily basis during the operation of the WTDs without being able to accurately understand and interpret the information. Data is used extensively for effective decision making, but when the data is incorrect or incorrectly integrated, the decision-making process becomes needlessly complicated (Karim, 2008). An abundance of data may unnecessarily complicate the task of transforming data into information that can support maintenance action (Berggren, 2010). In contrast, the lack of proper and complete data recording and management leads to the company's dependence on the expertise and knowledge of its personnel, which may prove harmful in the long term (Morant, 2014). In this regard, data management needs to be improved by collecting more accurate data, knowing what parameters to measure and accessing related information. Although maintenance techniques and data-based decision-making processes have improved over the years, further study and analysis is required of the most crucial data corresponding to the needs of the industry. In summary, there is significant need for a reliable system to detect mechanical functioning and practices involved in operating and maintaining train braking systems.

1.2. Research Problem

This work aims to reduce the potential for derailment and to enhance railway safety. The present work intends to study the failures of WTD and to demonstrate that the ATBE test/WTD system is a reliable replacement for the air brake No.1 test and to improve the system reliability by improving maintenance. Other objectives are to develop/propose an exploratory data analysis approach to more effectively use the data and achieve higher reliability in interpreting the data collected by the detectors.

This study explores the area of improvements in data management related to maintenance tickets and exhibits the ways in which a complete and accurate data recording can be used to determine maintenance practices.

1.3. Project objectives

The overall objective of this project is to investigate the wealth of data collected as a result of the installation of wayside detectors and to use the data to improve the diagnosis of wheels prone to failure. Because it offers a new perspective and new data analysis tools, it also provides an opportunity to revisit mechanical reliability issues involved in monitoring the condition of train air brakes in cold weather in Canada.

There are five thesis objectives:

1. To conduct a failure causes analysis and failure modes analysis of the available Wheel Temperature Detectors (WTD) failure data to understand the conditions under which the WTDs fail, and the associated failure rates;
2. To correlate a specific failure/event of a WTD recorded in the maintenance database to its temperature readings on the day of failure so as to determine whether the failure/event shows itself on the readings and measurements of the WTDs;
3. To assess the data quality of WTD measurements by comparing the data recorded by multiple sequential detectors, which requires the development of methods for the analysis sequential WTD data to detect anomalies and identify axles that may be prone to failure on a particular train;
4. To model the reliability to obtain the failure pattern, degree of reliability in the specified time period, and Mean Time Between Failures (MTBF), because applying MTBFs allows for improved maintenance planning and scheduling; and
5. To provide recommendations to improve data collection and management to facilitate monitoring the status and condition of the WTDs and increase accuracy of the reliability-related analyses.

The research methodology scheme is shown in Figure 1-2:

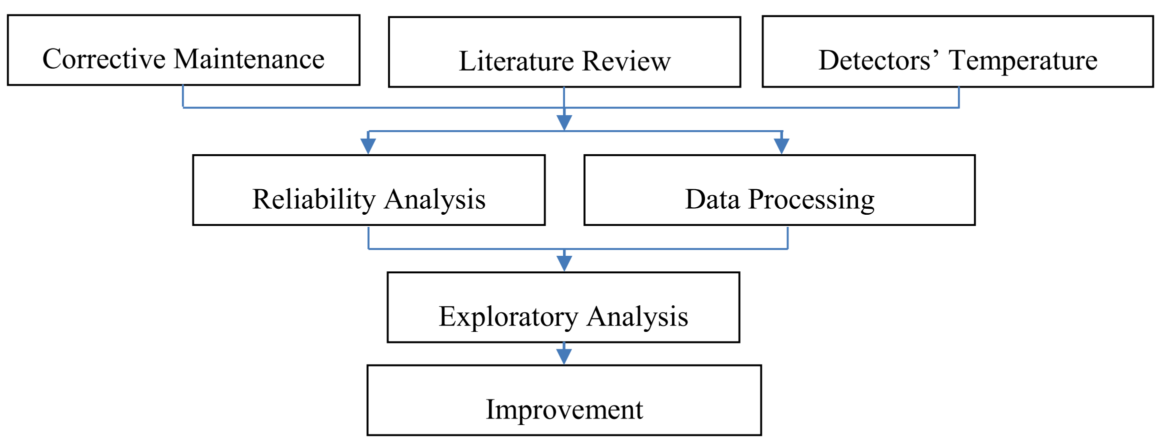


Figure 1-2: Research methodology

1.4. Thesis organization

This thesis consists of six chapters, including this introductory chapter. Chapter 2 presents a review of the literature and concepts relevant to the reliability of WTDs, including reliability theory and its possible application in maintenance, failure mode and effect analysis. The chapter also includes a description of the current condition monitoring system, maintenance practices used by railways, and a functional description of the detectors. Chapter 3 presents the data sets being applied to assess the trustworthiness of WTD measurements and to model the reliability in this study. Chapter 4 describes the most important failure modes for WTD along with a trustworthiness assessment of WTD measurements, anomaly detection and the identification of wheels that have the potential to fail. Chapter 5 models the reliability of the detectors and obtains the associated parameters using their time-to-fail data. It also defines, calculates, and presents the mean time between failures to improve maintenance planning and scheduling. Chapter 6 outlines the results, summarizes the conclusions and provides recommendations for implementing a new program in industry. It also provides recommendations for future studies.

Chapter 2. Literature Review

This literature review looks at three main areas. One area is the condition monitoring equipment used in railways, especially wheel temperature detection (WTD) systems. The second includes exploratory data analysis techniques and the concept of system reliability, and how both can be helpful in improving the maintenance-related practices that ultimately lead to a more reliable system. The last area of focus is Canadian Pacific (CP) documentation and research in the field of reliability and maintenance management of railways. This was helpful when considering areas where improvement could result in better maintenance planning.

Sources for the literature review were scientific publications databases, including but not limited to ProQuest, Scopus, Google Scholar and various types of documents such as papers, articles, books, theses, standards, technical manuals and reports. In the initial stage of the research, literature related to decision-making, maintenance practices in industry, statistical analysis, and reliability was reviewed along with CP regulations and company documents.

This chapter looks into the concept of reliability, some reliability-related statistical subjects, and current condition monitoring techniques and equipment used by railways. It also looks at failure trends, decision-making and maintenance strategies.

2.1. Condition Monitoring

Condition monitoring is monitoring the condition of a system in order to identify a failure or fault before it is developed (Martin K.F, 1994). Condition monitoring is typically applied to systems with a trend to failure. Condition monitoring makes it possible to pre-diagnose a failure and thus is one of the main elements of predictive maintenance. One of the main condition monitoring methods is “infrared thermography,” which is how WTD works.

2.1.1. Wayside Inspection System (WIS)

Many different types of automatic and mechanical systems have evolved or been developed for condition monitoring. One of the systems that railways use to monitor the condition of in-service trains is a Wayside Detection System, which uses interrogating sensors placed along the sides of tracks to detect specific faults on rolling stock (Palo et al., 2013, p. 658). Hot wheels, hot bearings, a wheel slide, and wheel impact are some of the defects that can damage trains and threaten their safe operation. By using wayside detectors, railways have significantly decreased these hazards and risks (Figure 2-6) (Barke and Chiu, 2005). The number and distance between the detectors may vary depending on the traffic in the area where the train is operating.

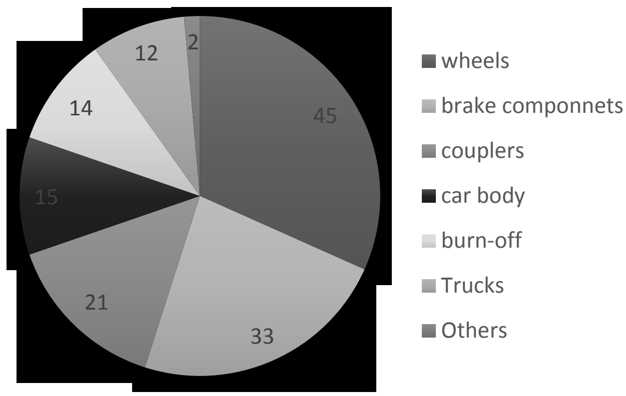


Figure 2-1: Number of derailments with their causes prevented by using wayside detectors (Barke and Chiu, 2005)

Different types of wayside detectors are available. Some are reviewed in bellow:

1. Hot Bearing Detectors

Bearing failure can be a serious hazard. A seized bearing can cut the axle and cause a derailment, which has substantial consequences in terms of interrupting the operation of the train and increasing the railway cost. When a bearing is close to failure it gets very hot (Barke and Chiu, 2005). When hot box detectors sense the heat emitted by the bearing, they set off an alarm.

2. Wheel Temperature Detectors

Unreleased brakes increase the temperature of the wheels. The rise in temperature itself can cause changes in the structure of the wheel material. If the brake binding causes the wheels to become completely stuck, the wheels slide over the rail, which can cause them to skid or flatten or experience other irregularities and safety issues. Hot wheel detectors work on the same principal as hot box detectors; they detect the temperature of the wheels on a running train, identify those with abnormal temperatures, and raise an alarm to notify the train crew to act.

3. Dragging Equipment Detectors

Dragging equipment is detected mechanically. The detectors that perform this function are composed of paddles mounted in the rail to check the undercarriage of a running train. When the dragging object hits the paddles, the detectors sense the motion and report the problem. (Barke and Chiu, 2005)

4. Wheel Impact Load Detectors (WILD)

WILD consist of strain gauges fixed to the track. "The strain gauges quantify the force applied to the rail through a mathematical relationship between the applied load and the deflection of the foot of the rail." These impact forces affect the health and condition of the rail car wheel and need to be monitored. (Stratman et al., 2007)

5. Weigh in motion (WIM)

WIM detectors basically work like WILD, and are applied by railways to check the axles' load and identify an overloaded train.

6. Acoustic Bearing Detectors

Acoustic bearing detectors record the acoustic signature of each bearing by means of track-side located microphones, and detect axle bearing defects of a passing train. Depending on the geometry of the defect, "the contact between [the] bearing defect and internal components causes a 'ringing' of the body of the bearing" (Barke and Chiu, 2005) and produces vibrations.

2.2. Wheel Temperature Detection

As discussed briefly in the Wayside Detectors section, WTDs are positioned wayside and use thermal sensors to detect wheels with abnormal temperatures, which is a sign of airbrake binding. The system works in conjunction with axle counting devices and can identify the wheels at risk. When installed on the points at which that airbrake needs to be applied (i.e., at the bottom of a downward slope), WTDs can detect cold wheels that could be a sign of an ineffective airbrake. Hot wheel detectors should be able to function in harsh environments exposed to such conditions as sun, cold, rain, snow, and wind. Detector spacing depends on each railroad's preference and local conditions, but 20-30 (1 mile=1.6 km) miles is a typical interval. WTDs provide the most current information on the condition of train wheels and air brake performance (Chong et. al., 2010). This enables railways to alert railroad staff of probable air brake failures and to take proactive action before failures occur. The following explanation of WTDs is based on the literature review, the system manual, and the site visit at the CP yard in Golden, BC.

The main components of the system are trackside equipment, scanners, a transducer and transducer cables, radio and antenna, power supply, cable, temperature sensors, standby battery, and snow blowers.

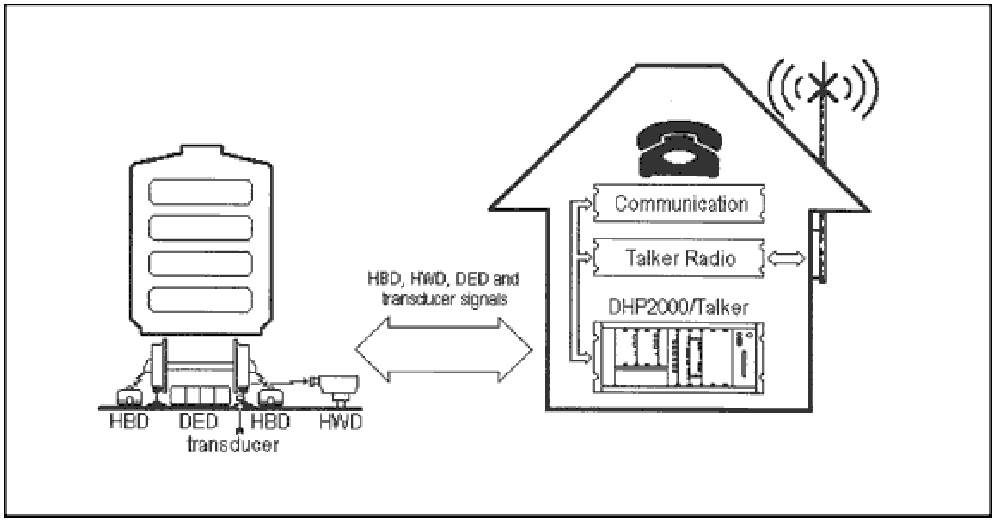


Figure 2-2: Typical WIS configuration
(Railway Investigation Report, 1999)

The scanner targets the wheel plate near the thread, about 2 ½ inches above the rail. It measures the wheel heat, using the temperature of the bottom of the car as reference. Set at an angle, the scanner is capable of scanning the wheels on the near and far rail (Railway Investigation Report, 1999) When a train arrives at an hot box detector (HBD) site, the scanner shutter opens and the scanner references the bottom of the car or truck side frames as "base ambient" before reading the next wheel. "The [wheel] temperature detectors] infrared scanner can be focused directly on the wheel's surface. Since the required information is obtained by "looking at" only a small part of each car, a method is required to know when the wheels are in the scanners' view. This method is called "gating" the heat signal. In gating, electromagnetic devices called transducers are used to detect the presence of the car's wheels. The transducers are electromagnetic devices that can detect a moving mass of metal. When wheels are in view of the sensing device (as determined by the transducers), heat samples are taken to determine the temperature of the wheels" (CN Wayside Inspection System Manual, 1995). As each wheel passes through the gating transducers, the scanner reads the wheel heat relative to the side frame of the bottom of the car or truck. After the train has passed the detection site, all measurements are sent to the central data center where they are processed and compared to the other axle's temperature. If there are any abnormalities, the train crew will be notified. The process of data acquisition, data processing, alarm generation and transition takes around 10 minutes.

2.3. Current Practices in use by Canadian Pacific

The No.1 airbrake test that was addressed in Chapter 1 is the main air brake test that Canadian railways uses to inspect the condition of the train airbrakes. The person conducting the test evaluates the air pipe integrity based on decrease in pressure, determines whether the brake parameters are within the identified limits, and visually inspects. The actuation and release of airbrake on each railcar. The test normally takes around 60 to 90 minutes. In addition in being time-consuming, the process is prone to human error, especially in harsh winter weather. Railways plan to rely more on technology-based inspection systems such as WTDs, so they need to make sure that these systems are functioning reliably and are providing sound measurements of wheel temperatures. Furthermore, train stops are costly for the railways companies, so the number of unnecessary stops must be reduced. CP thresholds for a hot wheel used to be 200 ^{o}F, a temperature that is relatively common for train wheels. As a result, trains had to stop frequently. Ultimately, the threshold was raised to 600 ^{o} F. Now two sites have a threshold of 200 ^{o} F, showing the significance of detecting the real hot wheels. In 2004, CP introduced an internal "Equipment Health Monitoring System (EHMS), in which the detector's data are collected, evaluated, and reported to the maintenance facilities and train crew (Aronian et al., 2012).

Currently, CP is using a number of tools to highlight the outliers in the temperature readings, including looking at the temperature reading trends of the detectors on a train base. An abnormal spike or drop could signify a detector failure. Also, the individual wheel temperature on each rail car is plotted. These temperatures tend to fit to a normal distribution, so 99.7% of the temperature readings lie within three standard deviations of the mean. Applying this empirical rule to the train temperature distribution makes it possible to identify the outliers. To determine the ineffectiveness of the airbrake on a wheel, the wheel temperature should be an outlier and should exceed a preset threshold. A wheel will be categorized as a hot wheel if its temperature is above a given limit and at least 3σ above the train mean wheel temperature (Aronian et al., 2012). CP also has its own general operating instructions (GOI) for WTDs that need to be considered by the train crew. When an alarm message is reported, railway staff consider GOI and timetable instructions in order to decide on the proper course of action. Based on the conditions, the train can be stopped immediately and inspected, or the inspection can take place after the train stops at the designated location. GOI also provide the train crew with guidance on other issues, including how to avoid the prolonged application of a brake while passing a detection site, the speed limit of the train while entering those sites, and when to use the radio system (not while passing over the detectors). Sections 13, 14, and 15 of the Signals and Communication Requirements provide rules for installing, testing, maintaining, and inspecting the WTDs, and alarm levels and other system settings. (Canadian Pacific Red Book, 2010). Based on these requirements, the inspection and test intervals for the WTD system vary from three months to one year. The inspection covers the physical condition, operation and function, and related components.

2.4. Data Management and Decision Making

During the literature review, significant emphasis was placed on effective data management. In a modern society, information and data are the main components of any organization. Data collection is used for financial, legal, safety, standardization and reliability purposes. The data need to be processed and studied to be a basis for a decision. The amount and quality of the data are important factors. Excessive data recording and storage can make it impossible to extract correct information, and cause inadequate results or complicate the decision-making process. Data overload should be avoided. It is important to know the parameters that need to be measured to identify which data are worth recording. In order to make an accurate and effective decision, data collection and data management need to be done in an effective manner.

Another important factor for decision-making is information. A sufficient amount of information is needed; too little cannot reduce the risks associated with decision-making (Newell et. al., 2007), while too much makes the decision-making process more difficult (Gelle and Karhu, 2003). Better decisions will be made when “recent, relevant and reliable” information is provided

(Emblemsvåg, 2005) and presented efficiently to the decision-makers. When determining how much information is needed, considerations include time and money constraints and the tendency to process the information, as well as other external and internal factors. Other important factors influencing decision-making are human judgment and intuition. In many real-time cases, decisions are made based on the decision-maker's experience, judgment, and feelings rather than facts and information. This leads to errors. Studies show that these errors arise due to a lack of relevant data. The likelihood of such errors confirms the importance of collecting and managing in such a way that the right information and data will be available and accessible when needed. Depending on the need and purpose of the company and the data collection itself, two type of analysis can be performed:

Qualitative Analysis: Data are gathered from interviews and meetings. The useful information is extracted and conclusions made based on the data pattern and other findings.

Quantitative analysis: Data is collected and evaluated using statistical methods. The statistical analysis can be carried out either by considering the average values to evaluate the performance or by considering the population of data to predict a trend.

Maintenance data are amongst the data sets that are widely used in different industries. Collecting, analyzing, and managing maintenance data and recorded failure events can provide industries with solutions to improve performance. Although maintenance techniques have evolved, there are still issues in terms of knowing and understanding what information is required. Efficient maintenance requires precise and reliable information and appropriate knowledge provisioning. Managing the vast amount of information needed to perform maintenance practices can be challenging. The lack of proper data collection, management and maintenance support information can lead to improper failure identification as well as the "No Fault Found" phenomena which results in more time spent on maintenance activities and lower system availability (Söderholm, 2007). To summarize, it is necessary to develop an effective method of data collection and a database containing the required and complete information. (Morant, 2014)

2.5. Analysis required for mechanical reliability function

2.5.1. Failure Modes and Effects Analysis

Failure mode and effect analysis (FMEA) was developed in 1950 by US army reliability engineers. It was then widely adapted by other industries such as aerospace and automotive (Teng and Ho, 1996). FMEA is often the first step in reliability analysis. Conducting FMEA yields information about the system and makes it possible to assess failure causes, modes and their impact on the operation of the system. This is useful in identifying possible areas of improvement, which eventually leads to opportunities to enhance a system's safety and operation (Morant, 2014). The impact of a failure on a system is one of the main reasons to conduct maintenance activities, so the outcome of FMEA can also be used to schedule maintenance and inspection activities. Some of the important terms related to FMEA are:

Functional Failures: This term describes the failed states when a system is not able to function in a way that the user desires and finds acceptable. Functional failures need to be identified in order to make failure management possible (Moubray, 1997).

Failure modes: Failure modes are the ways that a failure can occur.

Failure Effects: Failure effects address what happens as a result of a failure, the effects that the failure has on operation and production, how it affects safety and the environment and, in general, what are the consequences (Moubray, 1997).

Failure rate: This refers to the number of failures per operation time that a system, equipment or a component is functioning. The failure rate varies during the lifetime of a system. It is divided into three periods: burn-in, useful-life and wear-out (Rausand and Høyland, 2004).

Failure pattern: Failures can be related to age. The failure pattern illustrates the pattern rate at which a system or equipment depreciates during its lifespan. The following figure depicts the different failure patterns:

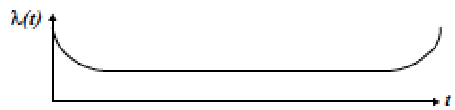
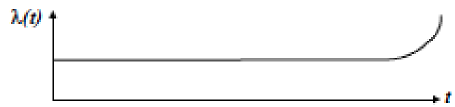
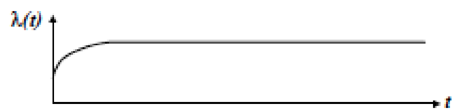
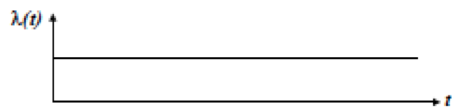
	**Pattern A – Bathtub:** Infant mortality, then a constant or increasing failure rate, followed by a distinct wear-out zone *Example*: overhauled reciprocating engine
	**Pattern B – Traditional Wear-out:** Constant or slowly increasing failure rate followed by a distinct wear-out zone *Example*: reciprocating engine, pump impeller
	**Pattern C – Gradual Rise with no Distinctive Wear-out Zone:** Gradually increasing failure rate, but no distinct wear-out zone *Example*: gas turbine
	**Pattern D – Initial Increase with a Leveling off:** Low failure rate initially, then a rapid increase to a constant failure probability *Example*: complex equipment under high stress with test runs after manufacture or restoration such as hydraulic systems
	**Pattern E – Random Failure:** Constant failure rate in all operating periods *Example*: roller/ball bearings
	**Pattern F – Infant Mortality:** High infant mortality followed by a constant or slowly rising failure rate *Example*: electronic components

Figure 2-3: Failure rate pattern
(Moubray, 1997)

Historical data, technical specifications of the system, manuals, operating condition and system failure rates are some of the factors that can help when conducting a failure mode and effects analysis (Awan, 2014), which has two phases:

1. Potential failure modes and their effects are identified.
2. The rank of the failure modes is specified according to the severity and probability of the occurrence (Sharma et al., 2005, Teng and Ho, 1996).

2.5.2. Reliability Analysis

Reliability is defined as the probability that a product will not fail within a defined period of time under given functional and environmental conditions (Bertsche, 2008). The concept of system reliability grew more significant after World War II when reliability was used to evaluate the operational safety of aircraft engines (Rausand and Høyland, 2004).

Understanding the nature of a problem is the primary step towards solving it. Failing to understand can lead to errors. Reliability analysis can be applied as a systematic tool for understanding the system from the perspective of failure, function and safety, and thus clarifying how to improve it. Furthermore, reliability analysis defines aspects of design or practice that are important to the continuity of operation and/or present high risks that require more attention.

A reliability assessment indicates and validates that the system is capable of fulfilling its reliability and safety requirements. Design optimization is the act of having an optimal design for safety and operation regularity. Maintenance planning is necessary to determine the best possible maintenance and inspection strategies. Modification support verifies that modifications are in line with the safety and reliability requirements. Modification support can be considered one of the main applications of reliability analysis (Hansen and Aarø, 1997). There are three main elements to system reliability: hardware, software (processes) and people (Rausand and Høyland, 2004). This thesis primarily deals with hardware reliability but it also addresses improvements in the reliability of processes through the effective use of collected data. The hardware reliability is modeled through actuarial information. Reliability modeling involves the following six steps: (Vaghar Anzabi and Lipsett, 2011)

Data collection: the operating life of the system of interest is calculated.

Data collection: the system's operating life is calculated.

Failure probability function estimation: histogram plot of time-to-failure data is used to select a distribution.

1. Fitting the distribution: a distribution is fitted to the data set.
2. Parameter estimation: a statistical method is used to estimate the parameters related to the model.
3. Goodness-of-fit test (GOF): the selected distribution's fit to the data set is evaluated.

4. Reliability function: if the selected distribution is not rejected by the test, the reliability function will be obtained.

Studies have looked at reliability analysis and assessments in various fields. In one test, an automatic laser-based wheel profile monitoring system (WPMS) was installed to monitor a wagon wheel's condition. The system recorded reliability and the accuracy of measurements, which showed that during the winter, there were more failures. This led to a recommendation to increase system reliability during winter months (Lin et al., 2015). Analyses were done on reliability and the failure mechanisms of the components under thermal mechanical loading and a determination was made regarding their operational life under high temperatures. The reliability functions for different temperatures were modeled applying the Reliasoft platform. The Weibull distribution was selected (Pulido, 2012). The failure of haul truck tires was studied and common failure modes were defined. Also the failure modes of interest for improved condition monitoring were identified. The failure time of the tires was collected from laboratory tests and applied for modeling the reliability to determine the probability of failures. Lifetime distribution was used for reliability assessment and it was found that the failure probability follows a

3P-Weibull distribution (Vaghar Anzabi and Lipsett, 2011). To obtain more information about a natural-gas pressure-regulating installation, the operability, reliability and availability of the installation was studied. The available corrective maintenance data were applied to acquire failure rates. Reliasoft was the software used for plotting reliability against the time (Gerbec, 2010). The reliability and the maintenance efficiency of the mining equipment were stated as the factors that impact equipment performance. The failure and repair data for subsystems and components of a crushing plant at a mine in Iran were collected from different sources and applied to model and calculate the reliability within specified time intervals using Reliasoft Weibull software. The components with low reliability were determined to allocate effort and resources to improve overall reliability. It was indicated that reliability assessment is useful in deciding maintenance intervals, and subsequently preventive maintenance intervals were defined for achieving a desired level of reliability (Barabady and Kumar, 2008). The reliability of open pit mining equipment was analysed as one the methods to mitigate the effect of failures on equipment. The factors affecting reliability were studied. Common techniques for reliability modeling such as failure mode effects and criticality analysis (FMECA), Pareto analysis, statistical analysis and reliability growth were explained with the examples. In statistical analysis, the reliability distribution and associated parameters were presented. Additionally, some of the required reliability and maintenance data were stated, including "the failed equipment," "the time of failure," "the time of repair," and "duration of the repair." It was shown that although there is a capturing data system, the quality of collected data is poor. It was indicated that implementing reliability methods can assist in enhanced maintenance practices (Hall and Daneshmend, 2003). Reliability study of safety systems (Bodsberg and Hokstad, 1997) and heat detector systems (Leinum, 1992) were also studied. Researchers investigated reliability in different fields and studies that have been done in the area of condition monitoring of the different detectors in use by railways (Stratman et al., 2007; Hajibabaia et al., 2012). But these do not focus on WTDs and modeling their reliability. Besides, one should bear in mind that there are substantial differences among the particular WTDs and the case-specific data on the system failures, so this study reports the result of a case study.

To explain and discuss reliability, it is necessary to know some of the terms that are the basis of Reliability. In the subsequent part of this chapter, some definitions and terms that are commonly used in reliability analysis are explained briefly:

- **Random Variables**

Reliability analysis generally deals with quantitative or qualitative measures. Random variables are used to denote these measures (Canavos, 1984). In the case of quantitative measures, the random variable would be time-to-failure, which can take on any value from 0 to infinity, which makes it a continuous random variable.

- **Probability Density Function and Cumulative Distribution Function**

In reliability, the two most important statistical functions are the probability density function (pdf) and cumulative distribution function (cdf). Other reliability-related parameters can be obtained using these two closely related functions.

The pdf and cdf describe the probability distribution of a random variable. The pdf is denoted as $f(x)$ and the cdf as F(x) (Mendenhall et al., 2003).

Figs. 2-1 and 2-2 illustrate, respectively, a pdf and its relationship with the cdf:

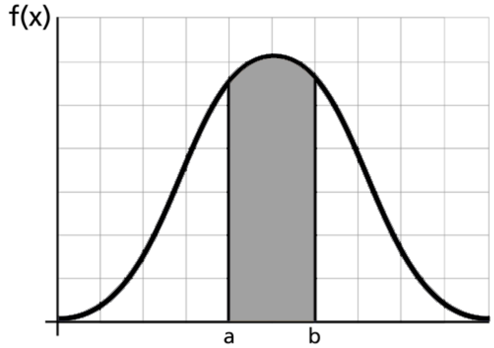


Figure 2-4: A probability density function
(Reliasoft. User's guide)

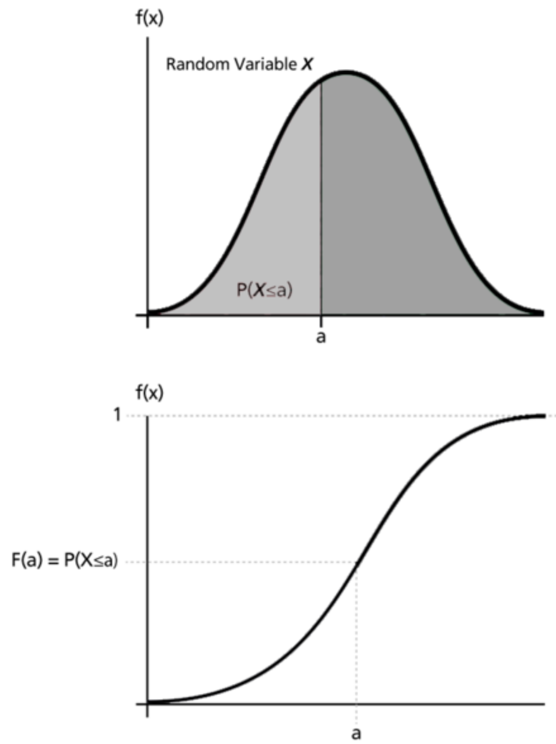


Figure 2-5: The pdf-cdf relationship
(Reliasoft. User's guide)

For a continuous random variable X, the pdf function is defined as:

$$P(a \leq X \ \leq b) = \int_{a}^{b} f(x)dx \qquad \text{Equation 2-1}$$

Where a and b can be any two numbers with a =< b.

As shown in Figure 2-2, the area under the curve from a to b is the probability that X takes a value between a and b. “The pdf represents the relative frequency of failure times as a function of time.” (Phoha and Thomas, 2006)

The cumulative distribution function (cdf), is shown as F(x) and is described as:

$$F(x) = P(X \le x) = \int_0^x f(s)ds \qquad \text{Equation 2-2}$$

Where X is a random variable and x is a number.

Cumulative values of the pdf are presented by cdf. This means that a value on the cdf curve is equal to the area to the left of that value under the pdf curve. In reliability, cdf, also known as “unreliability,” gives the probability that an item or system will fail before the time t (Phoha and Thomas, 2006).

The relationship between pdf and cdf can be shown as follows:

$$F(x) = \int_0^x f(s)ds \qquad \text{Equation 2-3}$$

Or

$$f(x) = \frac{d\,(F(x))}{dx} \qquad \text{Equation 2-4}$$

The area under the pdf curve up to a point of x is the cdf.

- **Reliability Function**

The reliability function is one of the most important in reliability analysis. It provides the probability that a system or component can function as planned and for a certain period of time (Ebeling, 2010). Figure 2-3 illustrates this:

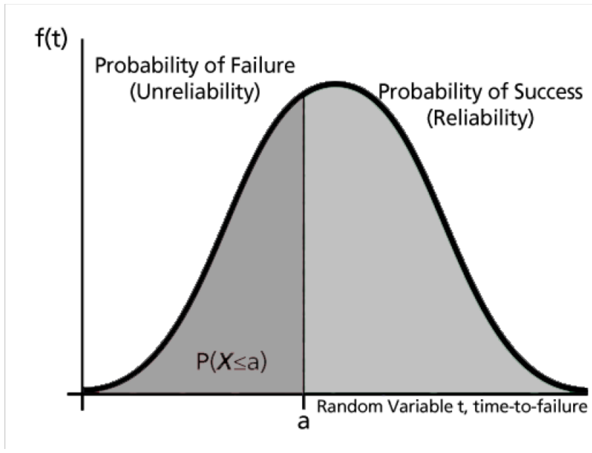


Figure 2-6: Unreliability vs Reliability
(Reliasoft. User's guide)

Mathematically, Equation 2-5 can be used to derive the reliability function.

$$F(x) = \int_0^x f(s)ds \qquad \text{Equation 2-5}$$

This equation gives us the probability of unreliability. It needs to be subtracted from 1 to obtain the reliability function.

The following equation demonstrates the relationships between unreliability and reliability, using Q(t) for unreliability and R(t) with reliability:

$$Q\,(t) + R(t) = 1 \qquad \text{Equation 2-6}$$

$$R(t) = 1 - Q(t) \qquad \text{Equation 2-7}$$

$$R(t) = 1 - \int_0^t f(s)ds \qquad \text{Equation 2-8}$$

$$R(t) = \int_t^\infty f(s)ds \qquad \text{Equation 2-9}$$

This equation is equal to:

$$f(t) = -\frac{d(R(t))}{dt}$$ Equation 2-10

- **Failure Rate Function**

Failure rate is the number of failures per time and describes a system's failure trend. This could be very useful for planning maintenance and allocating resources (Finkelstein, 2008). The failure rate function is defined by:

$$\lambda\,(t) = \frac{f(t)}{R(t)}$$ Equation 2-11

- **Mean Time to Fail (MTTF)**

The mean time to fail (MTTF) or mean life is a measure of the average time that a system or component has operated before a failure. The MTTF is an indicator of reliability performance. Mathematically it is defined as:

$$\bar{T} = m = \int_0^{\infty} t.f(t)dt$$ Equation 2-12

- **Mean Time between Failure (MTBF)**

"Mean Time between Failure (MTBF) is a basic measure of a system's reliability" (Torell et al., 2004). MTBF is similar to MTTF. Both terms are often wrongly used. The difference is that MTTF is used for systems that are not repairable while MTBF is used for systems that are. MTBF can be calculated by the following equation:

$$MTBF\,(t) = \frac{t}{N(t)}$$ Equation 2-13

t: sum of the operating times

N(t): the number of failures in time interval of t

A more reliable system has a higher MTBF. MTTF and MTBF can be used to determine inspection and maintenance schedules.

- **Lifetime Distributions**

Lifetime distributions are applied widely in reliability modeling (Vaghar and Lipsett, 2011). The pdf mathematically describes the distribution. Other reliability indexes such as failure rate and mean time can be derived from the pdf. When minimum data requirements are met, any distribution can be deployed to model the fit, analyze the data, and represent the behaviors. There are many distributions but some tend to better represent most of the life data and pattern failure of many of the mechanical and electrical systems, thus earning the name, "Lifetime Distributions." Weibull that can be used in different forms (one-parameter, two-parameter, and three-parameter) as well as normal and lognormal distributions are examples of lifetime distributions. Many distributions are available in literature; in this section, some are briefly reviewed with respect to reliability.

Normal Distribution:

Normal distribution has been shown to be the most important and the widely used continuous probability distribution for many reliability and life data analyses (Canavos, 1984). One of the characteristics of this distribution is that it is symmetric and bell-shaped, meaning that the distribution of the population about the mean is even. The pdf of a normal distribution is defined in Equation 2-14:

$$f(x) = \frac{1}{\sigma(2\pi)^{\frac{1}{2}}} \exp[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2] \qquad \text{Equation 2-14}$$

μ: the mean and location parameter, and

σ: the standard deviation and scale parameter

Lognormal Distribution

Lognormal distribution also has widespread applications. It fits the random variables if their lognormal values are distributed normally (Crow and Shimizu, 1988). Lognormal distribution works better with fatigue-stress failures.

The pdf of a lognormal distribution is given by:

Equation 2-15

$$f(x) = \left\{\frac{1}{\sigma x(2\pi)^{1/2}} \exp\left[-\frac{1}{2}\left(\frac{\ln x - \mu}{\sigma}\right)^2\right]\right\} \quad for\ (x\ \geq 0)$$

Exponential Distribution

Exponential distribution is mathematically simple. It applies in the modeling of units or systems with a constant failure rate.

The two-parameter exponential probability density function is given in Equation 2-16:

Equation 2-16

$$f(t) = \lambda \exp(-\lambda(t-\gamma))$$

Where:

t: operating time

λ: constant failure rate

1/λ: mean time between failures, or to fail

γ: location parameter

Gamma distribution:

Gamma distribution is versatile and fits well to most data sets. It can be used extensively in various areas (Canavos, 1984). When used in the context of reliability testing, it marks out the likelihood of partial failures.

The probability distribution function is given in Equation 2-4.

Equation 2-17

$$f(x) = \frac{\lambda}{\Gamma(a)}(\lambda x)^{a-1} \exp(-\lambda x) \quad (for\ x \geq 0)$$

Where:

a: shape parameter

λ: scale parameter

and Γ(a) is the gamma function and is defined as follows:

$$\Gamma(a) = \int_0^{\infty} x^{\,a-1} \exp(-x)\, dx$$ Equation 2-18

Weibull Distribution

The Weibull distribution is used widely in reliability analysis. A very useful characteristic that makes it versatile is that based on the value of the shape parameter (β), it can be fitted to a variety of life data. It can model constant and inconstant failure rates (Canavos, 1984).

The pdf of this distribution is:

$$f(t) = \frac{\beta}{\eta^{\beta}} t^{\beta-1} exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \quad (for\ t \geq 0)$$ Equation 2-19

β: Shape parameter

η: Scale parameter

- **Parameter Estimation**

To fit a distribution to the life data, the parameters of the lifetime distribution need to be estimated to achieve the closest fit to the data. In reliability analysis, there are two methods of parameter estimation: maximum likelihood estimation (MLE) and rank regression. Rank regression is divided into two forms: regression on x (RRX) and regression on y (RRY). The method chosen for analysis is determined based on the size of the data set. In most cases, the rank regression method works better with small data sets, whereas MLE works better with a larger ones. Large is usually defined as a data set with a sample size greater than 30. RRX works better than RRY with small sample sizes (ReliaSoft. User's guide).

- **Goodness-of-Fit Tests**

When performing a reliability analysis, the model's fit must be evaluated after a distribution model is fitted to a data set. Various statistical tools can be used to assess the fit of a distribution. Some of these tests are described below:

- **Probability Plotting**

This method visually assesses the fit of the distribution model. It can be used when the rank regression parameter estimation method is applied. It is not an accurate indicator when the maximum likelihood method is used. If a straight line is achieved when the probability is plotted, it can be inferred that the distribution fits the data well.

- **Correlation coefficient**

This method is also used when rank regression is applied. The correlation coefficient is shown by ρ and is an index of how well the probability line fits the data. A correlation coefficient can take on any value between +1 to -1. The closer the value is to +1 or -1, the better the fit of the distribution. A value equal to +1 or -1 is the perfect fit, but with a different slope. A value equal to 0 means that the data are randomly distributed (Fenton, Norman, and Martin Neil, 2012).

- **Likelihood Value**

The likelihood value (L) is a measure used to evaluate the fit of a distribution when the MLE is used as a parameter estimation method. The values that L can take are not limited to a range and can be any number, so it is not possible to decide on the fit of a distribution based only on the L value. This value can be used for comparative assessment between the fit of multiple distributions.

- **Chi-Squared Test**

This test should be used for large sample sizes, those with a minimum of 25 to 35 samples. If the calculated chi-squared statistic value (W) is less than the critical parameter (χ^2) for all values of a significant level (α), the hypothesis regarding the distributional form is accepted.

- **Modified Kolmogorov-Smirnov (KS) Test**

Another test that is used in reliability modeling is the Modified Kolmogorov-Smirnov (KS) Test. The standard KS test is applied to check the fit of a continuous distribution when the parameters are known, but in life-data analysis, in most cases the parameters are unknown so another type of KS test is applied, a modified KS test. The modified KS test can be used for small sample sizes. .In general it is more powerful than the chi-squared test. It compares the cumulative distribution functions of two data sets.

The test is based on the maximum absolute difference between the observed probability (Q_i) and predicted probability ($\hat{Q}_i$) for a data set that contains N observations (i.e., failure times) (Kececioglu, 2002).

$$D = \max\left|\hat{Q}_i - Q_i\right| \qquad 1 < i < N$$

The test takes the probability that the calculated D for the sample data set is less than the D_{max}. A lower probability value, close to 0, is desired as it shows that there is not a significant difference between the data set and the fitted distribution. The KS test calculates a P-value based on the maximum absolute difference between the two cumulative distribution functions and sample sizes.

- **P-Value:**

P-Value, a number between 0 and 1, is a statistical measure that determines a result's statistical plausibility. A larger P-value indicates that the groups of data were sampled from similar distributions (du Prel et al., 2009).

2.6. Maintenance strategies and models

Maintenance is defined as the combination of technical, managerial, and supervision actions to sustain a system in, or bring it back to a state in which it will be capable of functioning as required (Morant, 2013). A main target of maintenance is to increase reliability and availability by minimizing a system's outage time (Morant, 2014). Decreasing the amount of time spent on maintenance will decrease a system's downtime. It was after the 1980's that more attention was paid to maintenance departments and improving maintenance practices. Prior to that, bringing a system or equipment back to running was enough to qualify a maintenance department as satisfactory. In order to increase availability and decrease downtime, different maintenance strategies can be selected and used (Khan and Haddara, 2003). Defining objectives is the basic step for selecting a maintenance strategy. Nowadays, complicated systems demand highly complex and costly maintenance strategies (Morant, 2014). Maintenance strategies are affected by internal factors such as the nature of the industry, type and criticality of the system, operational safety and availability, cost effectiveness of the practice and external factors like weather conditions. Different maintenance strategies are addressed in the next section.

2.6.1. Maintenance Strategies

Maintenance is categorized into corrective or preventive. In corrective maintenance, after a failure has occurred and a fault recognized, maintenance is done to put the system back to function.

Preventive maintenance is carried out routinely and at pre-determined intervals to lower the probability of failure or degradation of a system (Morant, 2013) Condition-based and predetermined maintenance are strategies that fall under this category. Corrective maintenance can be deferred or immediate. The figure below is the schema of these approaches:

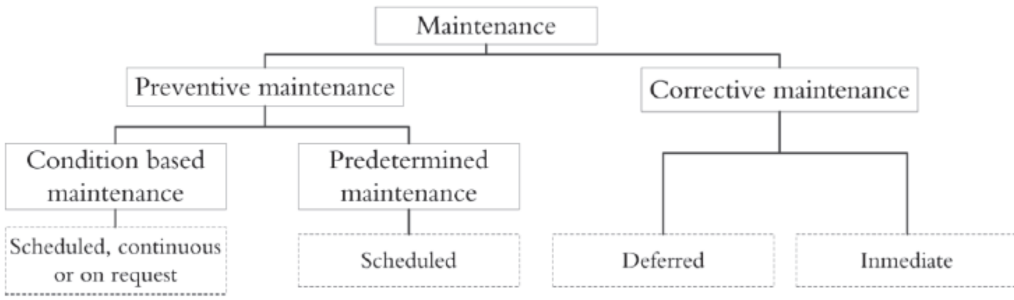


Figure 2-7: A schema of different approaches of maintenance
(Morant, 2014). Adopted from EN 13306, (2010))

Using same basis and logic as above, the following section categorizes maintenance strategies into two main groups: reactive and proactive. However, it goes deeper and splits the maintenance strategies into smaller and more detailed groups (Swanson, 2001).

Reactive Maintenance

Reactive maintenance is performed when the system has faced a failure. The purpose of reactive maintenance is to bring the system back to operation by means of temporary repair or replacement (Swanson, 2001)

Proactive Maintenance

This strategy is generally used for more critical systems and equipment and relies on condition monitoring and regular maintenance, before conducting failure-of-fault maintenance (Swanson, 2001). Proactive maintenance is divided into two categories: preventive and predictive.

Preventive maintenance

In this strategy, maintenance activities like cleaning, lubricating, and replacement are performed depending the time at which the equipment or system is in service. Preventative maintenance may decrease the chance of failure and increase the life of the system, but at the same time it disturbs the system's regular operation (Swanson, 2001). It can be adopted for failures with minor consequences. However, for those with major consequences, predictive maintenance is preferred.

Predictive maintenance

Condition monitoring and condition-based maintenance are the two activities involved in predictive maintenance. Condition monitoring uses the physical condition of the system, such as temperature and vibration, as a symptom of failure. Condition-based maintenance involves maintenance based on observed maintenance triggers (Swanson, 2001). Three key elements are involved in condition-based maintenance: data acquisition about the system's health, processing of the acquired data, and decision-making regarding maintenance actions (Morant, 2014).

Shutdown Maintenance

The system, equipment, or plant are shut down while maintenance activities are performed and completed (Awan, 2014).

Risk-based maintenance

Reducing the overall risk is the purpose of the risk-based maintenance (RBM). The RBM approach offered by Khan and Haddara (Khan and Haddara, 2003) consists of three segments: risk estimation, risk evaluation and maintenance planning. All contributing events to a failure are identified along with their consequences, which can correlate to the probability and frequency of the occurrence. The value of the risk associated with the failure is calculated. The risks are then compared to their acceptance criteria and rejected or accepted. Maintenance is planned using a reverse fault-tree analysis to get to the desired failure probability. The maintenance plan needs to be verified against the acceptable level of risk.

Reliability-Centered maintenance

The maintenance environment has changed over the years, transitioning from interval-based to reliability-centered maintenance. RCM can use the elements of other maintenance strategies in addition to modifications in design and operating practices to optimize maintenance periods

(Awan, 2014). RCM can be employed to develop new maintenance strategies to reduce corrective maintenance and advance maintenance performance (Morant, 2014). "RCM focuses on the application of FMEA for a technically and economically feasible, simple, and precise, easily understood, executed and controlled maintenance strategy" (Moubray, 1997). RCM has brought a new outlook to maintenance, and has resulted in a decrease of 40 to 70% in maintenance work (Moubray, 1997). Research shows that for the most part, RCM has been successfully applied to various systems in different industries: "Its application on wheel sets and rolling stock has been also demonstrated" (Poddar, 2014; Rezvanizaniani et al., 2008). As mentioned earlier, based on the decision criteria one of the maintenance strategies can be selected by the company's maintenance department. In some cases, the maintenance department decides to outsource a part or all of the maintenance tasks. Outsourcing helps to reduce "operational cost and capital investment" but has its own risks that need to be considered strategically (Awan, 2014). Some of the risk areas that can be addressed deal with losing control over the parameters affecting maintenance, such as cost, condition of the assets, safety, and core competence (Morant, 2014).

2.6.2. Maintenance Models

In addition to strategies, different maintenance models are addressed in the literature. The models can be theory-based or data-driven. Theory-based models are either statistical or physical (Morant, 2014). Statistical models use historical time-to-fail to estimate the reliability based on the distribution of the failure records. Physical models use mathematical models to describe the physics of the system failure. Both require several assumptions. Data-driven models derive models based on real historical data and collected condition-monitoring data. A large amount of data is required to obtain an accurate and valid model. It would be of great value to have a hybrid model combining theory-based and data-driven models that can consider the physics of failure with operational conditions.

Chapter 3. Presentation of Data

3.1. Corridor of study

The corridor of study for this project was a BC coal loop, which is a fully operative line for coal trains that connects the coal mines in southeast British Columbia (BC) to export terminals on the west coast of British Columbia (Aronian, Jamieson, 2014). There are seven subdivisions in this area, with 40 WTD sites placed approximately every 25 miles. The region is considered mountainous, and as many brake applications occur in the mountain grades, this region was selected for the study. Figure 3-1 shows the BC coal loop map; the BC coal route is highlighted in blue and the detector sites are shown in red.

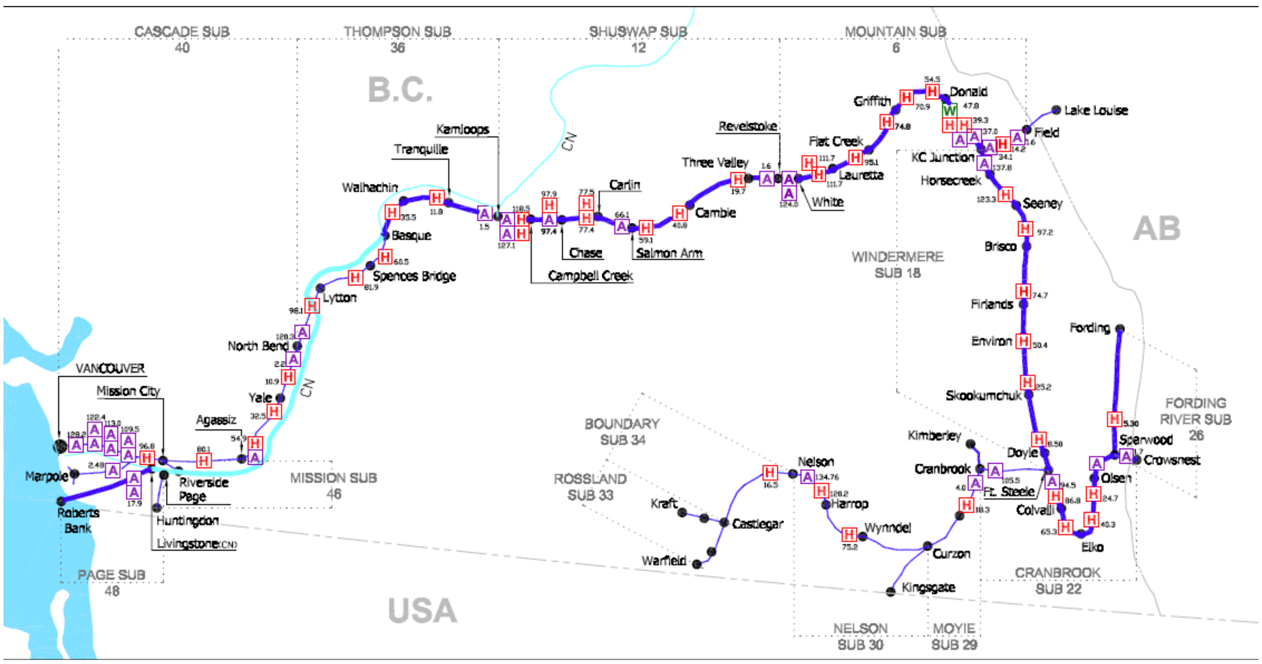


Figure 3-1: BC coal loop map and the location of the detectors
(Jamieson, Michelle, Personal communication, 2013)

The subdivisions that the detectors are installed in are as follows: Cascade, Cranbrook, Fording River, Mountain, Shuswap, Thompson and Windermere. Each of the detectors is located at a milepost. The mileposts are used as an ID for each detector in this study. Mileposts increase numerically from East to West. The detectors under study are listed in the following table:

No.	Detector	No.	Detector
1	Cascade 10.9	21	Shuswap 40.8
2	Cascade 32.5	22	Shuswap 59.1
3	Cascade 54.9	23	Shuswap 77.4
4	Cascade 80.1	24	Shuswap 77.5
5	Cascade 96.8	25	Shuswap 90
6	Cranbrook 24.7	26	Shuswap 97.9
7	Cranbrook 40.3	27	Shuswap 118.5
8	Cranbrook 65.3	28	Thompson 11.8
9	Cranbrook 86.8	29	Thompson 35.5
10	Fording River 5.3	30	Thompson 44.3
11	Mountain 14.2	31	Thompson 60.5
12	Mountain 30.2	32	Thompson 81.9
13	Mountain 39.3	33	Thompson 98.1
14	Mountain 44.9	34	Windermere 8.5
15	Mountain 54.5	35	Windermere 25.2
16	Mountain 70.9	36	Windermere 50.4
17	Mountain 74.8	37	Windermere 54.7
18	Mountain 95.1	38	Windermere 97.2
19	Mountain 111.7	39	Windermere 113.4
20	Shuswap 19.7	40	Windermere 123.3

Table 3-1: 40 detectors under study

3.2. Available data sets related to WTDs

Two sets of data were applied in this study to analyze the system. The first one is the maintenance records of the above-mentioned 40 WTDs over the five-year period from 2009 to 2013 and the second is the raw temperature readings of the same WTDs over the same period of time.

3.2.1. Maintenance Records of WTDs

Maintenance record files contain data related to the events/failures that have occurred to the WTDs and are recorded in the maintenance tickets, including outage time, ticket number, the date and time of ticket issuance, the subdivision and mileage where the failed detector was located, the reported problem, the cause and sub-cause of the failure, the action taken, and, in some cases, the failed components and subcomponents. A part of a maintenance record file is captured in Figure 3-2.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Outage T	Ticket Numbe	Opened Time	Type	U	Region	Subdivisio	Milea	Equipm	Equipment Description	Reported Problem	Cause	Sub Cause	Action Taken
4	282	CP2009-01-03-(	1/3/09	S&C	0	Pacific	Mountain	70.9	HBD	SDM HBD (250-439-9542	RTC reports the last 2 trains got a system not work	Unknown	Trouble Cleared	Inspected/Tested
12	114	CP2009-01-03-(	1/3/09	S&C	0	Pacific	Cascade	96.8	HBD	604 462 0875**EW	Scanner 96.8 south track reported itself not worki	Environmental	Snow/Ice/Frost	Removed Obstruction
17	134	CP2009-01-04-(	1/4/09	S&C	0	Pacific	Shuswap	59.1	HBD	250 832 2232	RTC reports that the last train got not working mes	Environmental	Snow/Ice/Frost	Removed Obstruction
23	0	CP2009-01-04-(	1/4/09	S&C	0	Pacific	Shuswap	77.5	HBD	250 835 8636	RTC reports that the last train got not working mes	Unknown	Trouble Cleared	Inspected/Tested
27	41	CP2009-01-04-1	1/4/09	S&C	0	Pacific	Cascade	32.5	HBD	604 869 2743	RTC reports 32.5 reported itself not working. Secc	Environmental	Snow/Ice/Frost	Removed Obstruction
28	84	CP2009-01-04-1	1/4/09	S&C	0	Pacific	Cascade	54.9	HBD	604 796 3015	System not working message for the last several tr	Environmental	Snow/Ice/Frost	Removed Obstruction
29	73	CP2009-01-04-1	1/4/09	S&C	0	Pacific	Cascade	96.8	HBD	604 462 0875**EW	RTC reports HBD on N and S tracks at 96.8 report	Environmental	Snow/Ice/Frost	Removed Obstruction
30	1	CP2009-01-05-(	1/5/09	S&C	0	Pacific	Cascade	10.9	HBD	604-863-2405 via RF link	HBD has reported its self not working.	Unknown	Trouble Cleared	Inspected/Tested
31	140	CP2009-01-05-(	1/5/09	S&C	0	Pacific	Shuswap	77.4	HBD	250 835 8661	RTC has reported tha thte scanner at 77.5 south t	Environmental	Snow/Ice/Frost	Removed Obstruction
32	341	CP2009-01-05-(	1/5/09	S&C	0	Pacific	Shuswap	59.1	HBD	250 832 2232	RTC has reported that the scanner at 59.1 has rep	Environmental	Snow/Ice/Frost	Removed Obstruction
33	30	CP2009-01-05-(	1/5/09	S&C	0	Pacific	Shuswap	19.7	HBD	250 837 4643	RTC has reported that the HBD at 19.7 has reporte	Environmental	Snow/Ice/Frost	Removed Obstruction
34	107	CP2009-01-05-(	1/5/09	S&C	0	Pacific	Shuswap	40.8	HBD	250 836 3343	HBD has reported its self not working for the last tw	Environmental	Snow/Ice/Frost	Removed Obstruction
35	3	CP2009-01-05-(	1/5/09	S&C	0	Pacific	Cascade	54.9	HBD	604 796 3015	Scanner reported itself not working.	Environmental	Snow/Ice/Frost	Inspected/Tested
37	142	CP2009-01-05-(	1/5/09	S&C	0	Pacific	Cascade	10.9	HBD	604-863-2405 via RF link	RTC reports that the scanner never gave a post tr	Power Company	B.C. Hydro	Outside Party Handled
40	133	CP2009-01-05-(	1/5/09	S&C	0	Pacific	Mountain	95.1	HBD	250-433-6538 (Cell)	RTC reported scanner reported it self not working	Environmental	Snow/Ice/Frost	Removed Obstruction
49	120	CP2009-01-06-(	1/6/09	S&C	0	Pacific	Mountain	14.2	HBD	250 344 5095	RTC reports the HBD at mile 14.2 has given a incoi	Unknown	Undetermined	Inspected/Tested
51	56	CP2009-01-06-(	1/6/09	S&C	0	Pacific	Mountain	95.1	HBD	250-433-6538 (Cell)	RTC reports scanner reported itself not working fo	Environmental	Snow/Ice/Frost	Removed Obstruction
56	46	CP2009-01-06-(	1/6/09	S&C	0	Pacific	Shuswap	40.8	HBD	250 836 3343 To 250 832	RTC advises the HBD's aren't working	Environmental	Snow/Ice/Frost	Removed Obstruction
57	113	CP2009-01-06-(	1/6/09	S&C	0	Pacific	Shuswap	19.7	HBD	250 837 4643	RTC reports the HBD isn't working	Environmental	Snow/Ice/Frost	Removed Obstruction
58	154	CP2009-01-06-(	1/6/09	S&C	0	Pacific	Mountain	95.1	HBD	250-433-6538 (Cell)	RTC reports the HBD at mile 95.1 has reported itse	Environmental	Snow/Ice/Frost	Removed Obstruction
59	102	CP2009-01-07-(	1/7/09	S&C	0	Pacific	Mountain	54.5	HBD	250-430-7173 (Cell)	RTC reports HBD at mile 54.5 has reported itself n	Environmental	Snow/Ice/Frost	Removed Obstruction
67	59	CP2009-01-08-(	1/8/09	S&C	0	Pacific	Mountain	95.1	HBD	250-433-6538 (Cell)	HBD has been intermittently working for trains pas	Environmental	Snow/Ice/Frost	Removed Obstruction
68	0	CP2009-01-08-(	1/8/09	S&C	0	Pacific	Mountain	70.9	HBD	SDM HBD (250-439-9542	Scanner is being working intermittently during the	Environmental	Snow/Ice/Frost	Removed Obstruction
69	121	CP2009-01-08-(	1/8/09	S&C	0	Pacific	Mountain	111.7	HBD	250-433-6539 (Cell)	RTC has reported that the scanner is intermittentl	Environmental	Snow/Ice/Frost	Removed Obstruction
93	94	CP2009-01-10-C	1/10/09	S&C	0	Pacific	Shuswap	19.7	HBD	250 837 4643	RTC reports HBD at mile 19.7 has reported itself nc	S&C	Maintenance	Inspected/Tested
95	79	CP2009-01-10-C	1/10/09	S&C	0	Pacific	Shuswap	40.8	HBD	250 836 3343	RTC reports HBD at mile 40.8 has reported itself n	S&C	Maintenance	Inspected/Tested
96	158	CP2009-01-11-0	1/11/09	S&C	0	Pacific	Mountain	54.5	HBD	250-430-7173 (Cell)	RTC reports the HBD at mile 54.5 has reported itse	Environmental	Snow/Ice/Frost	Removed Obstruction
98	0	CP2009-01-11-0	1/11/09	S&C	0	Pacific	Mountain	14.2	HBD	250 344 5095	Last train got two Post train messages from the sa	Unknown	Trouble Cleared	Inspected/Tested
99	58	CP2009-01-11-0	1/11/09	S&C	0	Pacific	Mountain	95.1	HBD	250-433-6538 (Cell)	RTC reporting every second train get a Not Workir	Environmental	Snow/Ice/Frost	Removed Obstruction
115	120	CP2009-01-13-C	1/13/09	S&C	0	Pacific	Mountain	95.1	HBD	250-433-6538 (Cell)	RTC has reported that the HBD has randomly hit tl	Transportation	Train Operations/Train Cr	Inspected/Tested
116	1	CP2009-01-14-C	1/14/09	S&C	0	Pacific	Cranbrook	40.3	HBD	250 423 3930	RTC reports last 4 trains at HBD 40.3 reported itse	Transportation	Train Operations/Train Cr	Reboot/Reset
144	0	CP2009-01-17-C	1/17/09	S&C	0	Pacific	Cranbrook	40.3	HBD	250 423 3930	Crew reported to RTC that train was going over the	Unknown	Undetermined	Inspected/Tested
148	1	CP2009-01-17-C	1/17/09	S&C	0	Pacific	Thompson	11.8	HBD	**E 250-318-3935 (Cell m	RTC reports the last westbound train got a system	Unknown	Undetermined	Inspected/Tested
164	198	CP2009-01-19-C	1/19/09	S&C	0	Pacific	Mountain	70.9	HBD	SDM HBD (250-439-9542	RTC reports the HBD at mile 70.9 on MacDonald t	S&C	Maintenance	Repaired/Replaced
[illegible]	24	CP2009-01-21-C	1/21/09	S&C	0	Pacific	Thompson	44.3	HBD	250-318-2554 (Cell model	RTC reported last train went over scanner did not	Unknown	Trouble Cleared	Inspected/Tested
185	218	CP2009-01-23-(	1/23/09	S&C	1	Pacific	Cranbrook	40.3	HBD	250 423 3930	RTC reports the HBD 40.3 is giving a Hot Box alarr	S&C	Maintenance	Repaired/Replaced
187	60	CP2009-01-23-(	1/23/09	S&C	0	Pacific	Thompson	35.5	HBD	250-318-0793 (Cell mode	RTC reports the HBD 35.5 gave a system not work	Unknown	Trouble Cleared	Inspected/Tested
191	28	CP2009-01-23-(	1/23/09	S&C	0	Pacific	Thompson	11.8	HBD	**E 250-318-3935 (Cell m	HBD reported not working.	Unknown	Trouble Cleared	Inspected/Tested
196	268	CP2009-01-25-(	1/25/09	S&C	0	Pacific	Mountain	111.7	HBD	250-433-6539 (Cell)	RTC has reported that the the lst train by 111.7 rece	S&C	Maintenance	Reboot/Reset

Figure 3-2: A sample part of the maintenance record file

The below chart shows an incident related to a detector and was extracted from the main file and shown as an example:

Outage time	198 min
Ticket number	CP2009-01-19-074
Opened Time	1-19-09
Type	S&C
Subdivision	Mountain
Mileage	70.9
Equipment	HBD
Reported Problem	RTC reports the HBD at mile 70.9 on MacDonald track has reported itself not working for the last two trains
Cause	S&C
Sub Cause	Maintenance
Action Taken	Repaired/Replaced
Component	Trackside Equipment
Sub Component	Lid Cover

Table 3-2: Some of recorded fields in a maintenance record file

The maintenance records data were used for identifying the failures, failure modes and failure causes of the WTDs as well as modeling the reliability.

3.2.1.1. ***Limitations of WTD maintenance data***

Analyses were done using the corrective maintenance records that were available in the CPR maintenance department database. The data set is accepted as it is; the data are manually entered and are prone to error, For instance, if corrective maintenance has been done during an inspection but it is not recorded, then this maintenance activity is not considered in the analysis. In this way, there may be data quality issues that cannot be verified. In the present work, databases were separate. There was no access to the data set regarding the operating and maintenance history of the air brakes, which made relationships amongst air brake conditions, WTD readings, and maintenance records impossible to verify with complete confidence (This data quality issue is not unique to railroads). The exact times of failures were also not captured in the maintenance tickets and that resulted in some uncertainty. The installation date of the detectors was not recorded in the CP maintenance record database, so a particular time period that the system was in operation before a failure occurs was unknown. To model the reliability, the time period the system was in operation before the failures occurred is needed. In order to solve the lack of information and to obtain more accurate results, the first failure of each detector was assumed to be the time the system was put in operation. The time between each successive failure was calculated. The summation of the time between the first failure and each consequent failure and the cumulative mean time between failures gives us a good estimation of the operating hours of the detectors before failure. The calculated time-to-fail was used for reliability modeling and analysis.

3.2.2. Temperature readings of WTDs

CP maintains a database of raw data of temperature readings of the detectors. This dataset was another source of data being used in this study. WTDs raw temperature readings from 2009 to 2013 were made available by CP for the analysis. A portion of raw data has been shown as a sample in Figure 3-3**.**

```
001ID520202011800C50040-
00382508374643.SHUSWAP........................................11C4
002SD34B46464505BA04806141442C01C0578288C143C145002580258160C73
003TD5444A90F09010D0E28031F1001C00002006D00001A1D000000000E101012B2B6042E
03A9042603B101002412E2
004GD5001C001C001C001C001C00000000000000000000000048704890002FFF8000200
042000000003D118F
005ADCE110E0E00005000111800400200171200400400060F014007000913004002000B11
00400700121400885200172100410000D0B004007000D12014007000C14004102000C140
04002000808006C970002070037070000A13019007000D270037020011120076970002A75
006ADC2101B1A00380000070E019007000D19003802000E07008297001415003700001206
015E07000A16003802000813006292001717003700000D0B015E0700101A003702000C0D0
05E970004050037070005040015E07000B0A003707000B0D005B970028CB
```

Figure 3-3: Portion of sample raw data

The dataset is a compact and structured transmitted train data which is conveyed on a private line. The data is transmitted in several "text" lines. Each of these lines contains different types of data related to the train, such as "SD" (Site Data), "TD" (Train Data), "AD" (Axle Data), and "HD" (Hot Wheel Data). To transfer more volume of data the data is converted to Hex. The TD line and HD line are the ones that were most used in the analysis. Due to the confidential nature of the data set, more explanation in this regard is not possible.

- ***Limitations of WTD temperature readings***

Identifying a train was not possible by using the data captured by the WTD records, which made monitoring and comparing a specific train's (and its wheels) temperature readings over the neighboring detectors for anomaly detection more complicated. This process is used in this study for anomaly detection and CPR has now modified the recording of data with metadata with their new detection system, which includes train ID and other relevant information.

3.3. Processing of raw WTD data

The 5-year raw data of the detectors' reading was decoded based on the document provided by CP railway using the Matlab software (The code is available in Appendix A). The reference document for decoding the transmitted data is confidential and therefore explanation of the content is not possible.

The mileage of installation of each of the WTDs, which is mentioned in the name of each of the reading's files, was used as an ID for each of the WTDs. The extracted data from this database was used in a trustworthiness assessment of the WTDs' wheel temperature measurements.

The parameters that were applied are listed below:

-Name of the detector

-Train data including:

Train Arrival Year, Month, Day, Hour and minute, Train Direction, Axle count, Train length, Train Speed in and out, Ambient temperature

-Hot wheel data including:

Temperature of the wheels in Fahrenheit from scanner 1 and 2 per each axle of the train

The wheel temperatures from both scanners were plotted for each axle. A very brief part of the analysis is presented here as sample. The average of the wheel temperatures was also calculated and shown on the plots.

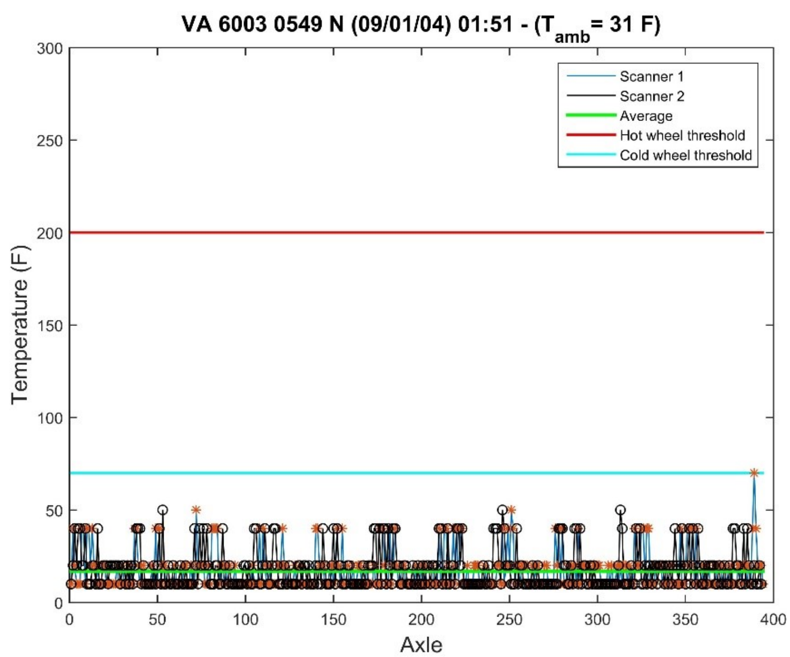


Figure 3-4: Wheel temperature per axle from both scanners

Also, the wheel temperatures from each of the scanners were plotted separately:

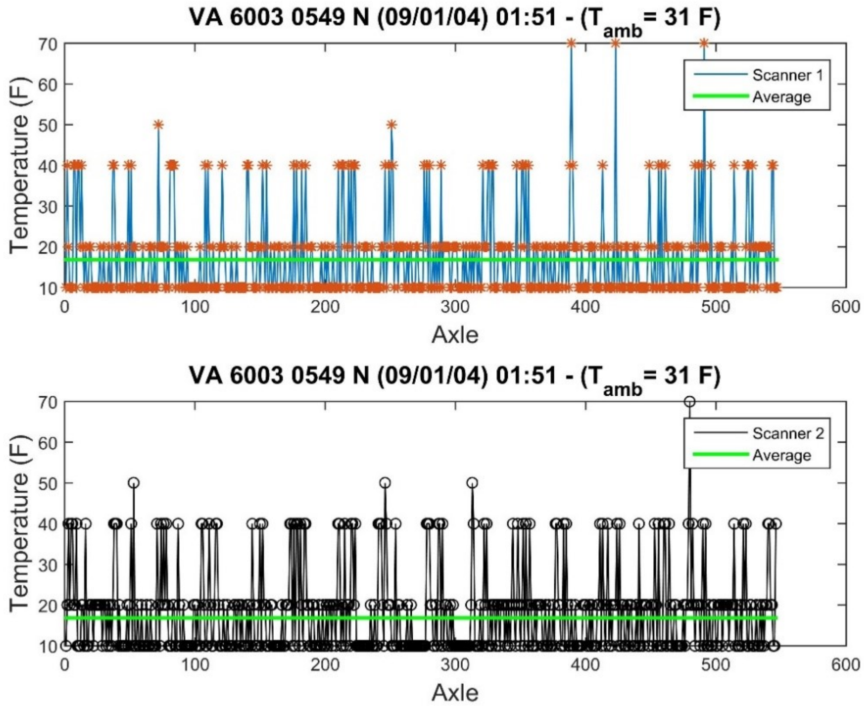


Figure 3-5: Wheel temperature per Axle from scanner 1 and scanner 2

The plots are used for trend analysis and anomaly detection analysis that are carried out in the next chapters.

Chapter 4. Data Trustworthiness Assessment

In this chapter failure events recorded in maintenance records have been analyzed to identify common failure modes and failure causes of wheel temperature detectors (WTDs). A WTD field dataset has also been used to analyze the dependability of these systems. Correlations between maintenance records and failures have been performed to see if the effect of WTD failures can be observed in temperature readings. Considering that one detector in passing by trains gives us an understanding about the condition and health of the detectors and that one train passing by consecutive detectors yields useful information about the health of railcars, to determine if a recorded failure relates to a detector or a train wheel, we carried out trend analysis and applied some basic statistical analysis to WTD outputs. An approach was presented to predict potential detector and railcar component failures by better understanding and interpreting the output of wheel temperature the readings of one detector in trains passing by, and the comparison of three, consecutive detectors in a path of one moving train have been analyzed. The analysis has been done for two cases: one for the detector installed on flat a area and one for the detector installed on a sloping area. The same analysis of following a train over three neighboring detectors has been implemented over five neighboring detectors to compare the classification accuracy.

4.1. Failure Analysis of WTDs

An accurate failure analysis would result in effective preventive measures that would decrease the probability and reduce the impact of failures (Morant et al., 2014). A variety of methods exist for investigating failure conditions and analysis. In this study, failures are identified and analyzed based on the historical failure data available in the corrective maintenance database. Knowing the definition of failure is critical for carrying out the analysis. In this study, failure is defined based on the outage time or downtime of the detectors mentioned in the maintenance records. Outage time refers to the time, in minutes, between “open” and “resolved” states, when the incident is reported/opened and when the detector is back in service and has been confirmed to be working as intended.

Figure 4-1: Schematic of outage time

Excluding "Null" findings and downtimes of "0," "1," "2" and "3" minutes from the data recorded in the maintenance records file, the number of failures for each detector is shown in the following table:

No.	Detector	Number of Failures	No.	Detector	Number of Failures
1	Cascade 10.9	70	21	Shuswap 40.8	85
2	Cascade 32.5	56	22	Shuswap 59.1	26
3	Cascade 54.9	45	23	Shuswap 77.4	45
4	Cascade 80.1	59	24	Shuswap 77.5	71
5	Cascade 96.8	62	25	Shuswap 90	9
6	Cranbrook 24.7	36	26	Shuswap 97.9	57
7	Cranbrook 40.3	39	27	Shuswap 118.5	63
8	Cranbrook 65.3	21	28	Thompson 11.8	83
9	Cranbrook 86.8	19	29	Thompson 35.5	30
10	Fording River 5.3	26	30	Thompson 44.3	52
11	Mountain 14.2	77	31	Thompson 60.5	45
12	Mountain 30.2	3	32	Thompson 81.9	30
13	Mountain 39.3	76	33	Thompson 98.1	60
14	Mountain 44.9	33	34	Windermere 8.5	17
15	Mountain 54.5	76	35	Windermere 25.2	22
16	Mountain 70.9	199	36	Windermere 50.4	22
17	Mountain 74.8	114	37	Windermere 54.7	16
18	Mountain 95.1	248	38	Windermere 97.2	21
19	Mountain 111.7	106	39	Windermere 113.4	9
20	Shuswap 19.7	96	40	Windermere 123.3	30

Table 4-1: Number of failures for the detectors in the corridor of study

Table 4-2 shows the number of the detector failures in each subdivision vs. the number of the trains that passed by each subdivision.

No.	Subdivision	Number of failures	Number of passed trains	% of failures to passed trains
1	Cascade	292	211,423	0.14%
2	Cranbrook	116	59,879	0.19%
3	Fording River	26	7,957	0.33%
4	Mountain	933	226,501.00	0.41%
5	Shuswap	452	285,225	0.16%
6	Thompson	300	184,478	0.16%
7	Windermere	137	96,628	0.14%

Table 4-2: Number of failures to the number of passed trains

The Mountain subdivision has the highest number of failures.

Detector failure modes include "system not working," "scanner not working," "no reporting to trains," and "wrong axle counts reporting." Each failure is a portion of all possible causes. Fig. 4-2 shows the cause of failures and the percentage related to detection systems The most commonly recorded failure causes are "unknown," "signal and communication" (S&C) and "environmental." Other recorded causes include "transportation and power company" (infrastructure failures) and "M/W" (maintenance work failures).

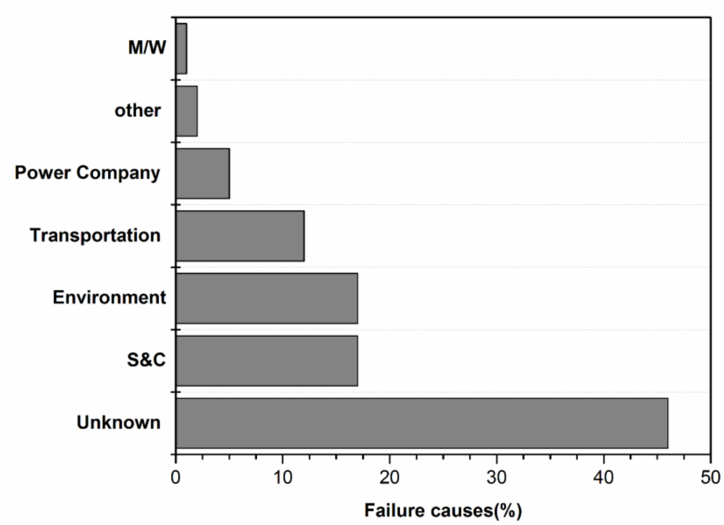


Figure 4-2: Histogram of failure causes of detectors

There are a number of reasons for "unknown" failure, among them an incomplete understanding of the root causes of failure in complex systems, as well as not being equipped with the appropriate "means of diagnosing the system condition" (Morant, 2014). Identifying failures in electronic-based systems is complicated, which could be also a reason for the high number of "unknown" failures. Having a more complete knowledge of systems and maintenance tasks can be very helpful. The high percentage of environmental-caused failures can be related to harsh weather conditions during the winter. The following chart confirms this.

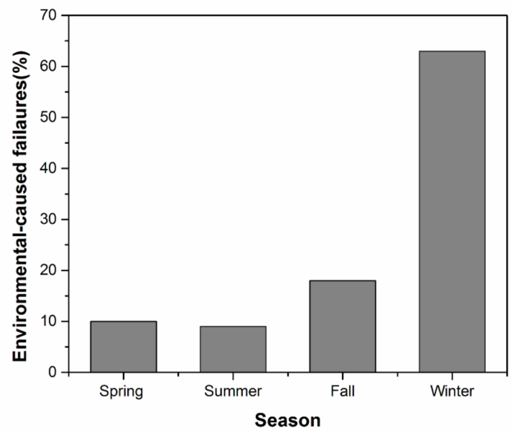


Figure 4-3: Detector failures caused by environmental problems

Environmental conditions affect system operations by interrupting normal functioning and causing random failures, which the specific causes and failure modes are not easy to identify.

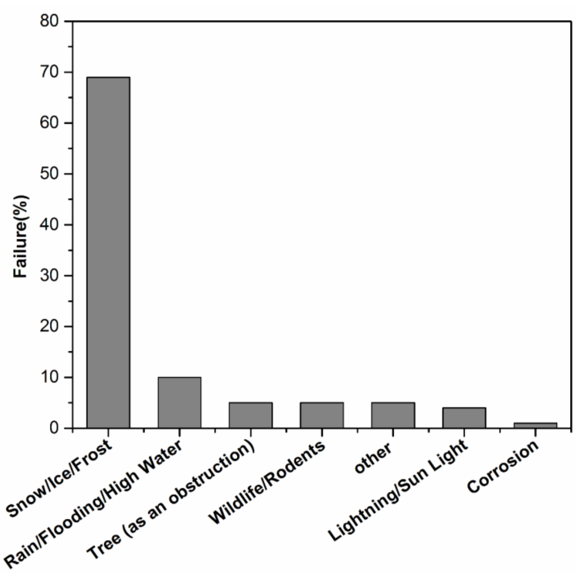


Figure 4-4: Detector failure sub-causes during winter

Fig. 4-5 shows that the components with the most failures are “scanners,” “transducers,” the “lid” and the “transducer clamp.” This has led us to focus on improving these components by more routine inspections, regular replacement and calibration, and decreasing the intervals between these established practices.

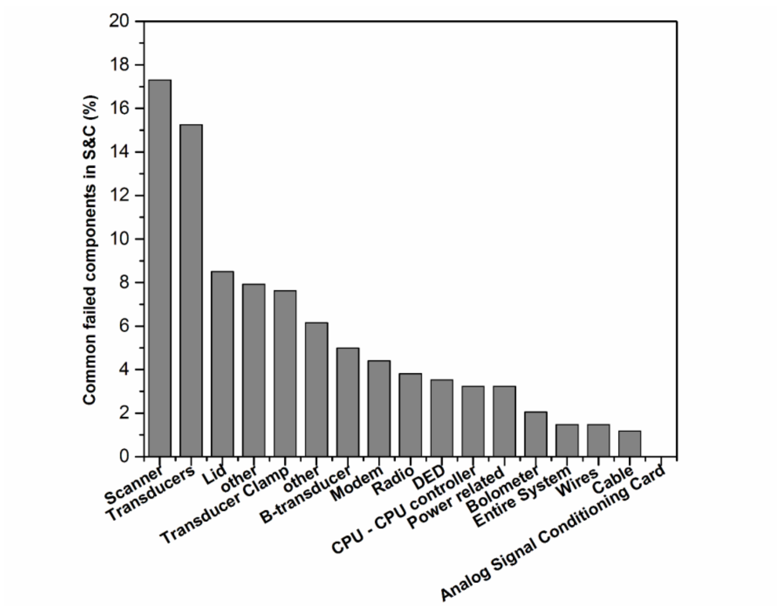


Figure 4-5: Most common failed components for WTD systems.
Note: “Other” is the sum of rare failed components (< %1)

4.2. Event Correlation

This part of the analysis was carried out to better understand and interpret the output of the detectors’ temperature readings and detecting anomalies; the question here is whether a failure of a WTD shows itself in its temperature readings. A specific detector was recorded in the maintenance tickets. An attempt was made to correlate the detector’s data with the temperature readings/measurements on the day the failure occurred.

For instance, according to the maintenance record files, a maintenance ticket was issued for Cascade 54.9 on 2009-01-04 at 9:09:00 pm. Cascade had a downtime of 84 minutes. However, the exact time of failure is not identified in the records so in order to perform the event correlation, the data files of all the trains that passed Cascade 54.9 on 2009-01-04 was extracted from the database. The wheel temperatures versus wheels were plotted to determine whether any abnormal plot could be seen and related to the recorded failure. Brake shoes apply the same force on both wheels on both sides of the train, so we expected close measurements from both scanners 1 and 2 for each wheel. The readings of scanners 1 and 2 were plotted separately. The y-axis indicates the temperature read by the detector for each axle shown on the x-axis. The average of the readings is also shown.

The following figures illustrate the results for two of the trains. The plots for all the trains that passed Cascade 54.9 on 2009-01-04 can be found in Appendix B.

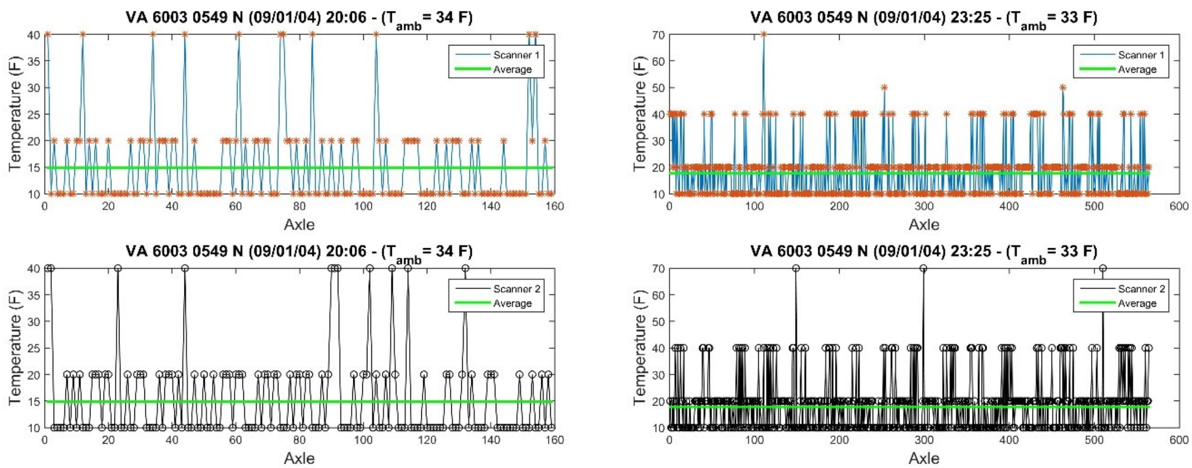


Figure 4-6: The wheel temperature per axles for trains passed by Cascade 54.9 on 2009-01-04 at 20:06 and 23:25

The exact time of failure is not recorded. The maintenance ticket was issued at 9:09:00 pm, so it can be assumed that the failure occurred sometime before 9:00 pm. It is difficult to point to a specific plot as the output of the failed detector's reading. The plot appears to be normal and does not reflect the failure of the system. The validity of the data is still doubtful, as is its accuracy. Correlating the records of failure to the temperature-axle readings was not conclusive. More comparative assessments and studies are needed to determine which events or observations do not conform to an expected pattern and can be related to the abnormal data. The need for more information led us to use the data along with some basic statistics such as mean and standard deviation calculations of the population.

4.3. Anomaly detection based on WTD readings

This step of the study involves performing a basic statistical analysis on available data related to the WTD readings in order to improve the use of the collected data and provide a better understanding of the detectors' outputs.

The standard deviation and error percentage of each of the three detectors gives information on the health of the detection system. These numbers help to determine whether the detector readings are reliable enough to be acted upon. For the dataset examined, when the standard deviation and error percentage of the first or last detector in a set is higher than the other two, it is recommended to look at the readings of the detectors to its left and right. The following are the criteria used to classify a wheel with the potential to fail: mean and standard deviation values higher than 10°C (50°F), along with a determination that a particular wheel in the sequence has two out of three detector measurements higher than 15.5°C (60°F). Each analysis has been done on a particular detector. The average and STD of the temperature read by the detector in the passing trains has been studied for several days before and after the day of the recorded failure. The average of the readings was not very indicative. However, in most cases, the higher STD was observed on the day of the failure. The following figure shows the STD of the wheel temperature readings for all trains that passed a detector on a specific day.

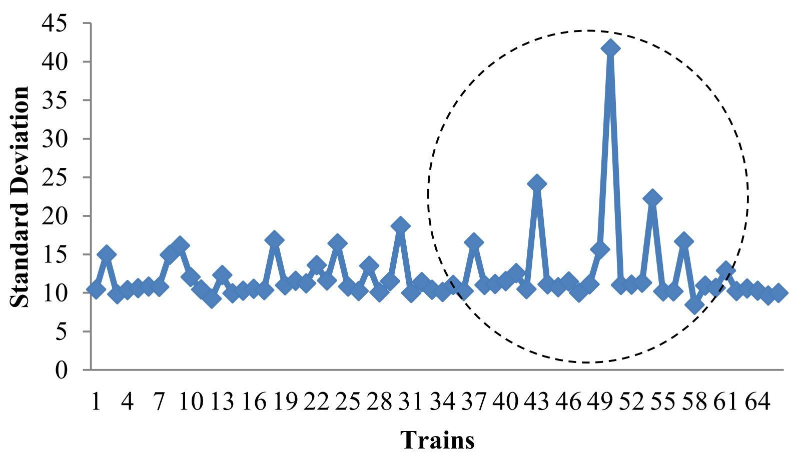


Figure 4-7: STD for one detector for different trains

To obtain a better sense of what was going on with the system and passing railcars, a recommendation was made to look at three consecutive detectors on a route of one specific train that had same number of axles, cars and locomotives. Reports from a single detector may not really be definitive indicators of failure of the detectors or railcar components. But a detector report — in comparison and in combination with other information — can help to determine the nature of an anomaly. Observing one detector and passing trains leads to understanding about the condition and health of the detectors themselves. Examining the data from one detector and comparing the average and standard deviation of the temperatures for a set of readings on a train data sequence yields insight about the health of the detection system. Additionally, by observing multiple neighbouring valid detectors, it is possible to compare the condition of a set of railcars' individual axles. This method helps to identify individual wheels that are either hot or cold relative to the other wheels, which, if repeated, indicates an inoperable brake. Three neighboring detectors need to be selected. The detectors' mileage is used as a form of identification (ID). In this way, the sequence of installation is recognized. Since there is no train ID available in the WTD data sets, one characteristic of the train, such as train length or axle counts, should be considered to identify a train. The challenge to this approach of train identification is slack action. Depending on the physical territory (track grade, curves) and train operation (braking, non-braking) over an HBD site, the train length can vary considerably – a train going up a hill stretches out, a train coming down the hill bunches up. Train length alone cannot be used as train ID. The next option for train identification is total number of axles. The parameters for identifying a train were length, direction, date and time of trip, and total number of axles.

Based on the train direction, the next detector that the train passes on its route will be identified. Figure 4-8 shows the schematic arrangements of the detectors.

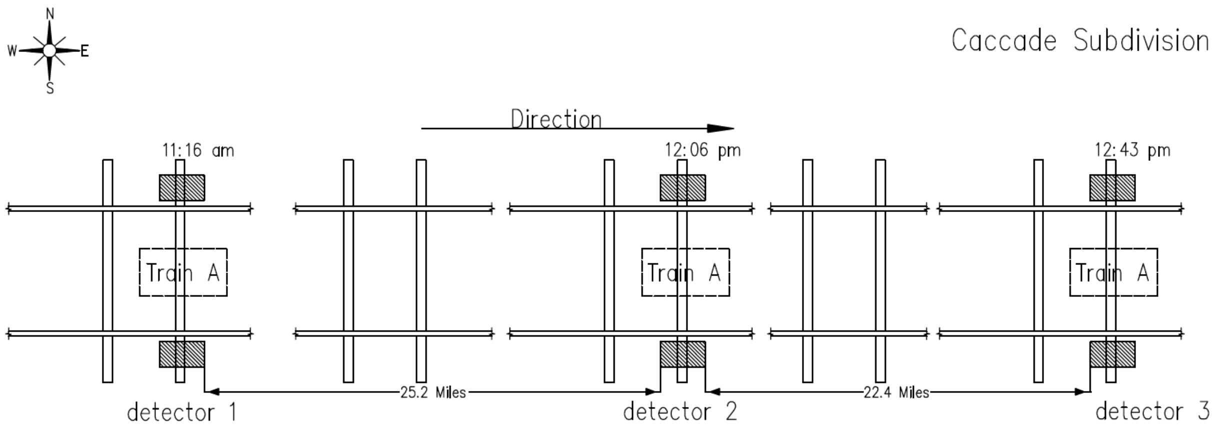


Figure 4-8: Arrangements of three subsequent detectors in the Cascade subdivision

The figure below plots the temperature per axle for an identified train that has passed the three subsequent detectors:

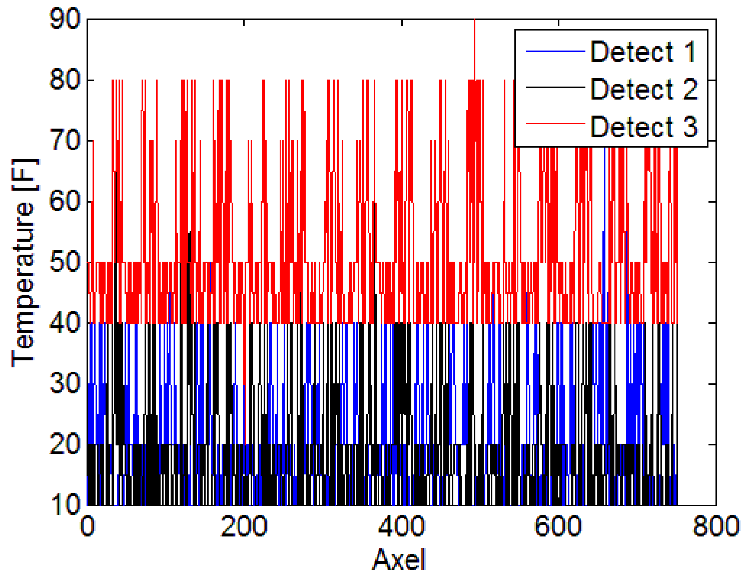


Figure 4-9: Wheel temperatures per axels for detectors 1, 2, and 3

The readings in this plot from detectors 1 and 2 are closer to each other than they are to detector 3. This can come be attributed to the geographical differences on the installation points of these detectors. Detector #3 has a slight slope, which means that the required air breaking will increase the temperature of all of the wheels. These detectors are at a great distance from each other. Although selecting one train on one specific day reduces the variables that could affect the train's condition, the distance between the detectors still allows for the possibility that the wheel condition will change. As the air brake is applied to the all of the wheels on one car, ideally it is expected that detector scanners 1 and 2 on the wheel set on a particular car will have roughly the same temperature. Scanner 1 and Scanner 2 are independent and therefore calibrated independently. To ensure an accurate assessment of the condition of each axle and wheel, only the readings from Scanner 1 have been taken out for the first 50 wheels of the train. These readings have been plotted over the three subsequent detectors, as shown in Figure 4-10:

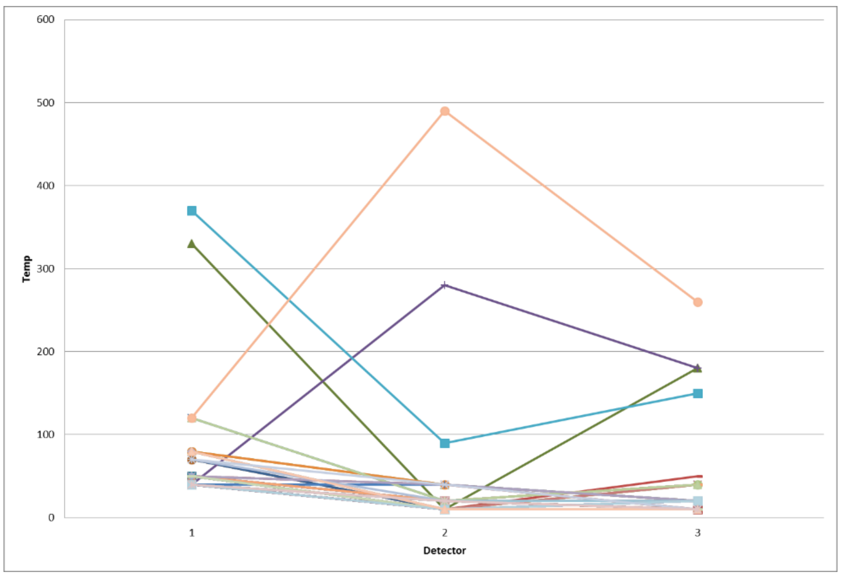


Figure 4-10: First 50 wheel temperatures per axels for detectors 1, 2, and 3

There are a couple of spikes on the plot which show some kind of abnormality. A trend can be seen on the bottom part of the plot for detectors that contain a majority of the readings. This indicates that each detector is functioning properly because they all have the same measurements for most of the wheels. The standard deviation on each wheel for all three detectors can be used as an indicator to determine wheels with the potential of failure, as the plot in Figure 4-11 shows.

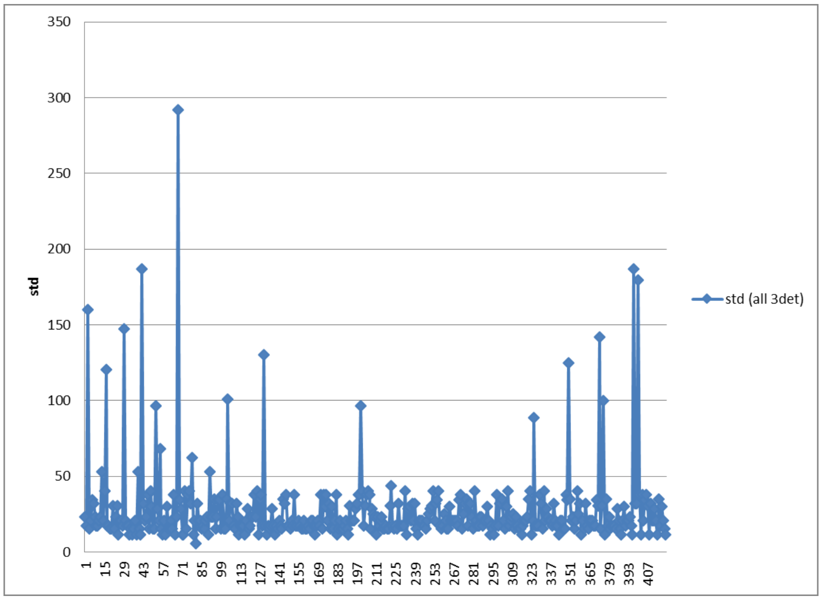


Figure 4-11: STD for each wheel that passed the three detectors

The other indicator considered is the error percentage of the detectors, which is calculated below and shown in Fig. 4-12 for the three detectors:

Equation 4-1

$$Error\ Percentage = (T_i - T_{ave})/T_{ave} \times 100$$

Where, T_i and T_{ave} are wheel temperatures and the average of the wheel temperature respectively. This plot basically shows the detector with more variance in its temperature readings than the others.

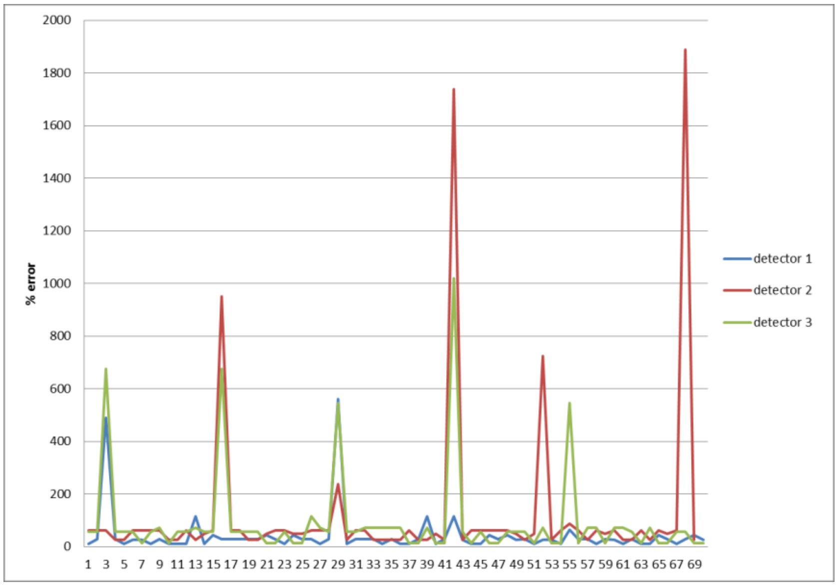


Figure 4-12: Error percentage of detectors 1, 2, and 3 per wheel

The same analysis has been carried out for the same detectors with other trains passing by on the same day. A check of reproducibility of sensor consistency helps to reduce the effect of external variables such as ambient temperature and weather conditions. It is also assumed that the trains' loads are constant, and their speed when entering HBD sites is limited to a threshold and can therefore be assumed to be constant as well. It is possible, of course, to use the axle count to dilate or compress the time sequence to a normalized length. As seen in Figure 4-11, the standard deviation of temperatures for all three detectors is generally under 50. There are a couple of higher values (primarily in trains 1 or 3), but interpreting based only on STD does not seem to be accurate. There could be cases with high temperature values and hot wheels, such that the wheels are prone to failure, but the data has little variance, causing the STD to be low. To gain a more precise analysis, the following two criteria were considered: the average temperature of wheels in all three detectors and the readings of two out of three detectors with values greater than 50. These thresholds are set based on the trend seen in the plots of the current analysis and apt to vary due to changes in the seasons and the location of the detectors. The data points with all the three criteria are shown in Figure 4-13.

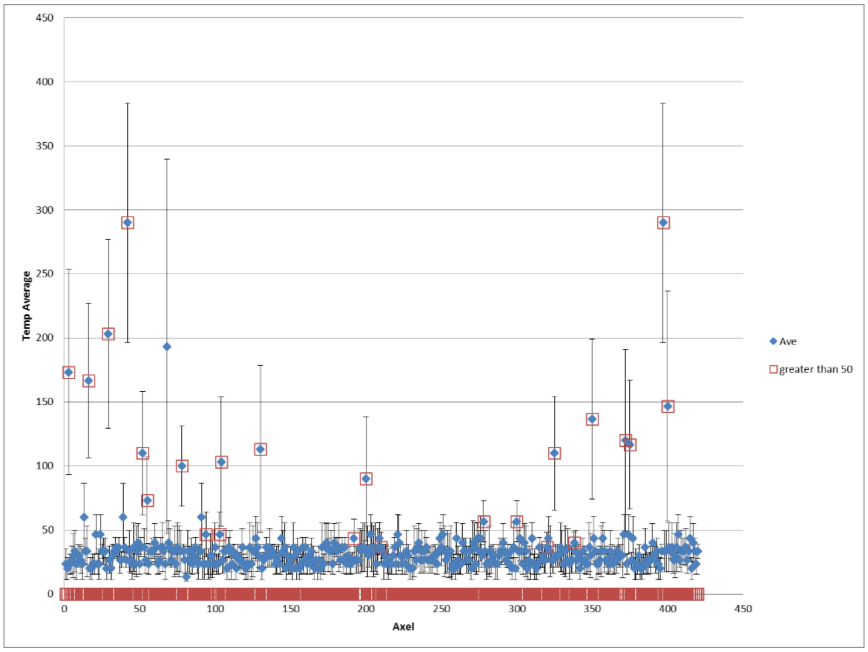


Figure 4-13: Data points with STD, average, and two out of three values greater than 50

Considering all three criteria together will lead us to a situation that can be related to a set of good measurements on bad wheels. A fault classification means that certain wheels require prompt attention. This diagnosis is based on the logic that such high values for some points are not expected when the other values are well within one range, showing that the detectors are functioning as desired and the high read temperature is related to damaged or hot wheels. Based on this logic, the wheels categorized as potential failures on each train are shown in the following table:

	Data points meeting all three criteria (wheels with potential to fail)
Train 1	3,16,29, 42, 52, 55, 78,104,130,200,325,350,372,375,397,400
Train 2	None
Train 3	158, 171,197,223,275
Train 4	None
Train 5	None

Table 4-3: Wheels with potential failures

The STD and error percentage of each of these detectors provide information on the health of the detection system. Based on these numbers, it is possible to determine whether the readings of the detector are reliable enough to be acted upon. The results of the analysis are summarized in the following table:

	Detector 1		Detector 2		Detector 3	
	STD	Ave Error %	STD	Ave Error %	STD	Ave Error %
Train 1	27	56	54	80	26.24	27
Train 2	10	38	10	42	14.40	22
Train 3	14	44	19	47	23.45	74
Train 4	11	39	10	40.	18.03	66
Train 5	10	34	10	47	18.82	73

Table 4-4: Summary of the STDs and average error percentage of detectors 1, 2, and 3

The analysis has been done on the Cascade subdivision, which has relatively flat tracks. In order to verify the analysis and compare the results with an elevated subdivision, the analysis has been repeated on the Mountain subdivision. Three subsequent detectors were selected:

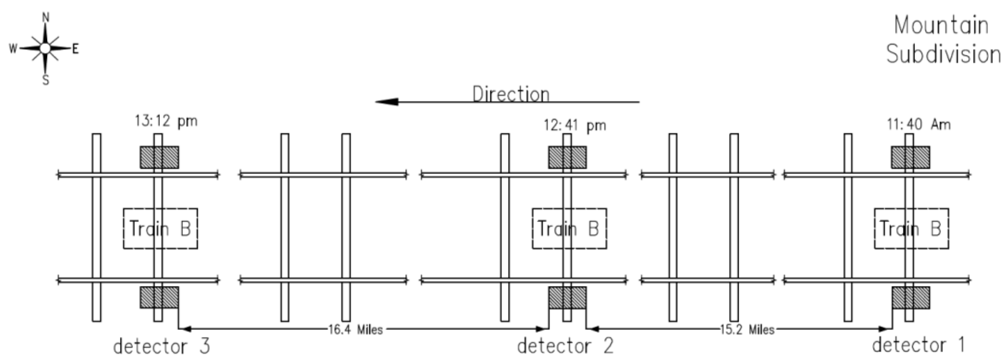


Figure 4-14: Schematic of three subsequent detectors in the Mountain subdivision

As the first step, the temperature of the first 50 wheels are plotted:

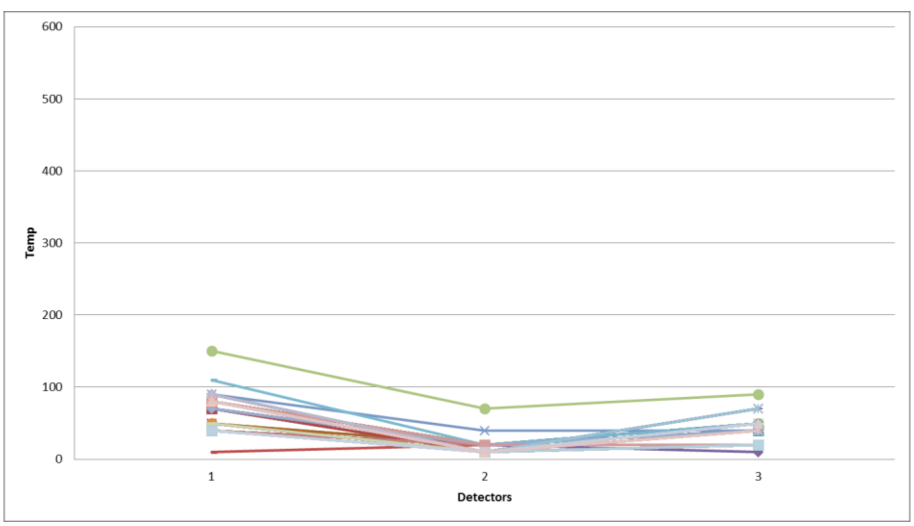


Figure 4-15: The first 50 wheel temperatures per axels for detectors 1, 2, and 3 in the Mountain Subdivision

The readings of all three are relatively close. A point with a high difference is not detected. This shows that all three detectors are sensing roughly the same temperatures, which is an indication that the wheels are functioning properly. The distance between these three detectors is less than the distances considered in the Cascade subdivision, so there are fewer external factors to affect their temperature readings. The second plot to look at is the average of temperatures over the three consecutive detectors for each wheel.

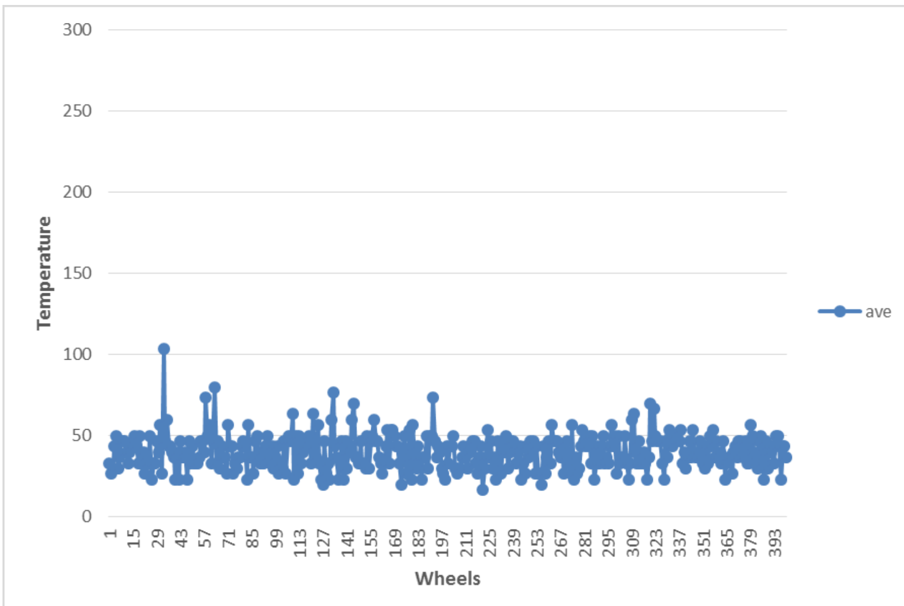


Figure 4-16: Average of temperatures over the three consecutive detectors

The plot shows that the average wheel s temperature is less than 10°C (50°F). The points that are higher than 10°C (50°F) should be considered more closely, as this implies that one or more wheels surpassed the average temperature. Setting 10°C (50°F) as a threshold for the average, the following plot depicts the points that contain higher values:

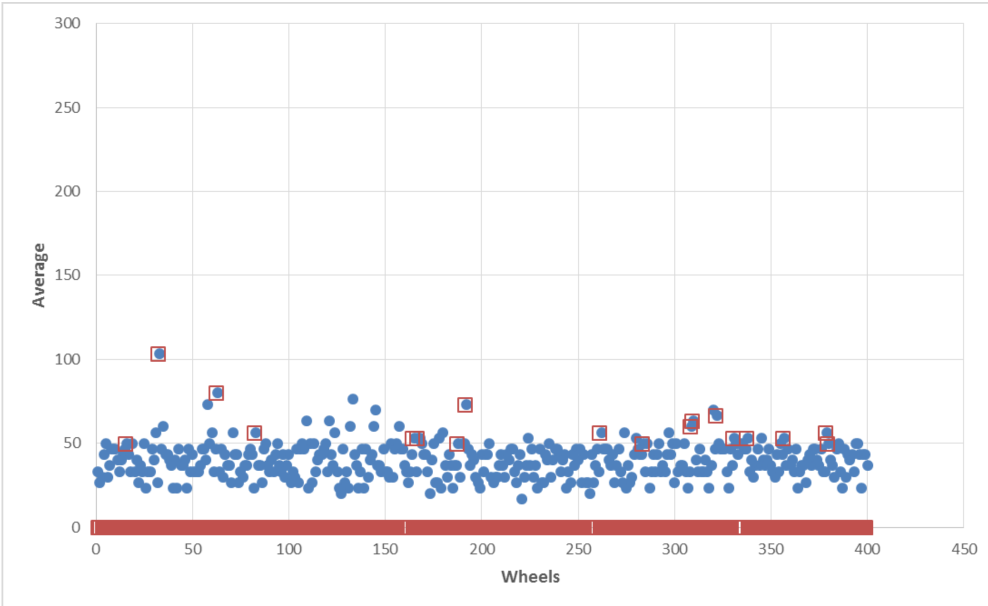


Figure 4-17: The average points higher than 10̊ C (50̊ F)

The standard deviation of the wheels over the three detectors is another indicator, as shown in the next plot:

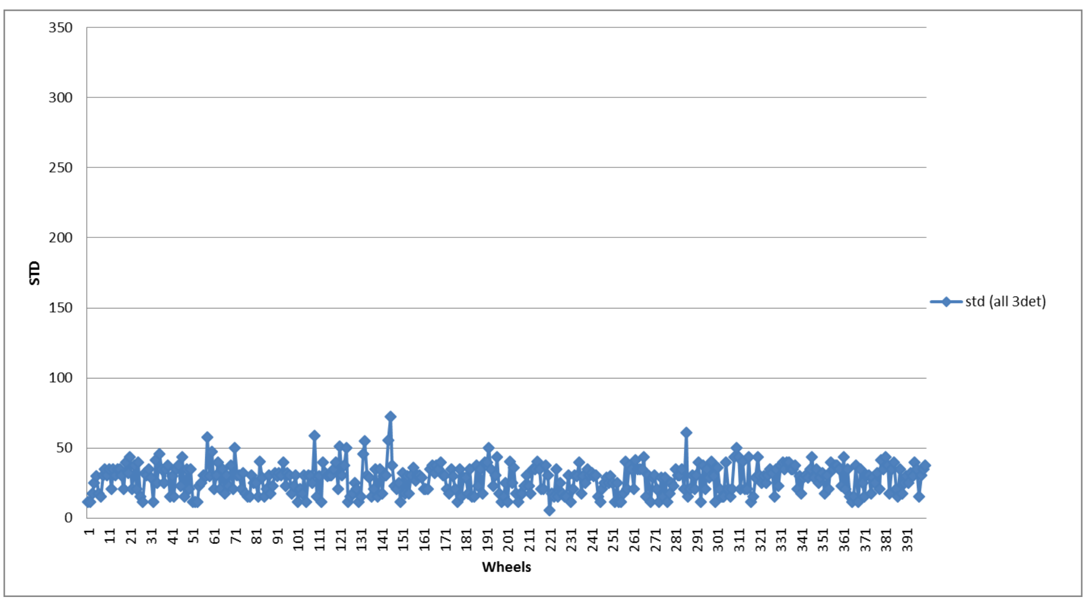


Figure 4-18: STD for each wheel that passed the three detectors

Again, a trend can be seen here. Most of the STD values are less than 10 °C (50 °F). The wheels that have a higher value need to be examined. The other indicator considered is the error percentage of the detectors (Figure 4-19). The plot depicts only the detectors that vary in temperature readings. To better see the trend, the error percentage of the detectors was plotted only for the first 70 wheels.

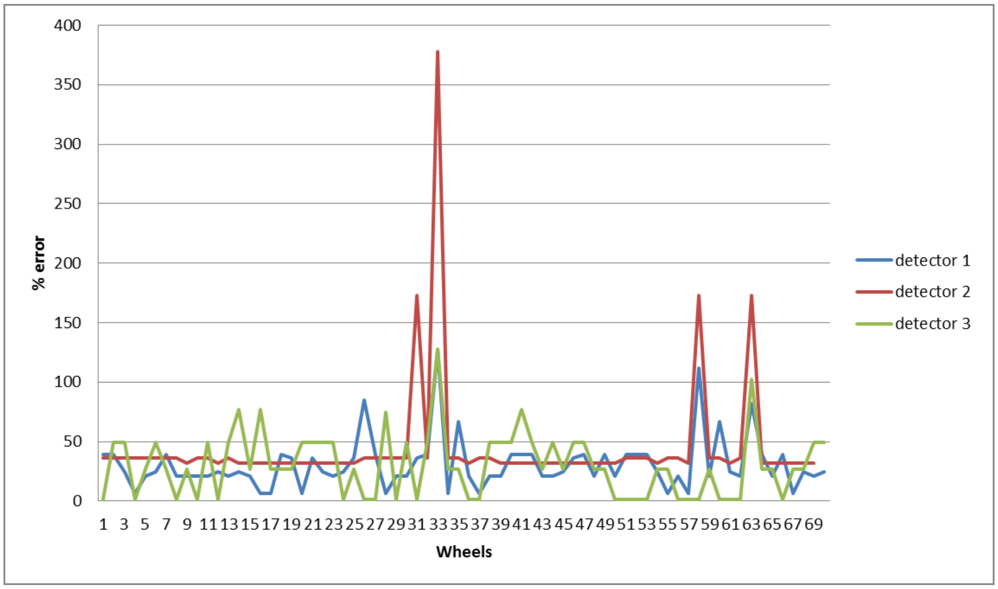


Figure 4-19: Error percentage of detectors 1, 2, and 3 per wheel

Detector 2 has the highest error percentage. The average of the error percentage for this detector is almost 39. This value is 28 and 32 for detectors 1 and 3 respectively.

Another criterion was added to the analysis. It followed the rationale used for the analysis in the Cascade subdivision to achieve higher accuracy in identifying the potential failed wheels by not relying only on the average or standard deviation, but by considering the readings of two detectors out of the three. The threshold for the temperature of the wheels is set to 15.5 °C (60 °F) based on the trend seen in the plot of temperature per axle. This threshold can be modified according to the preference and desire of the departments or people involved in establishing the decision-making criteria.

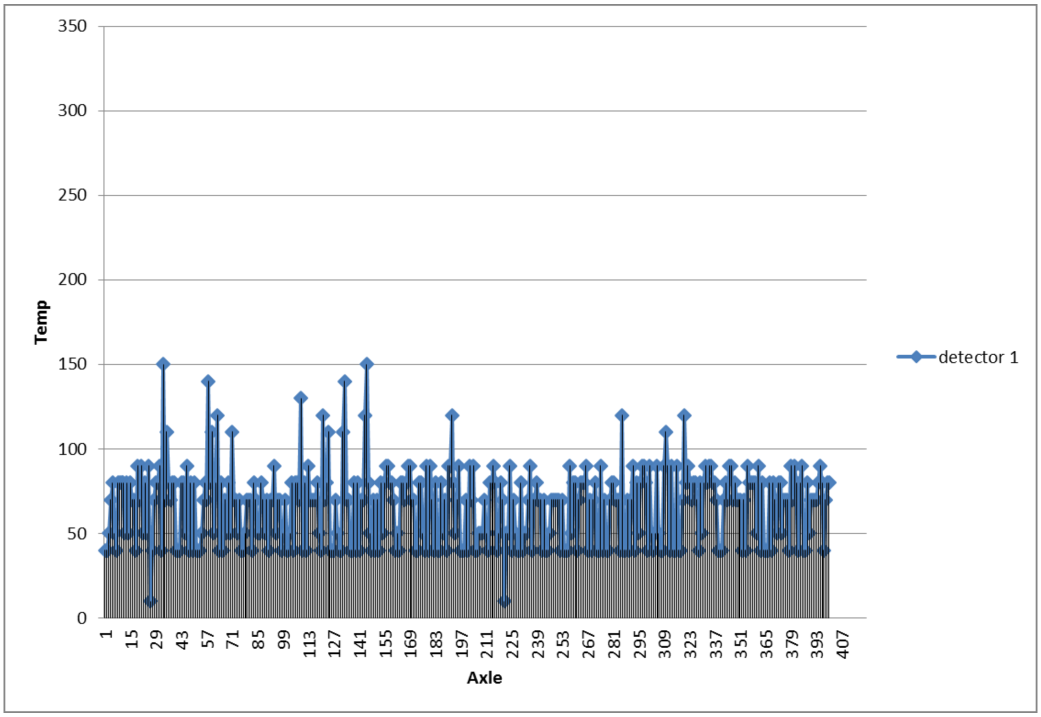


Figure 4-20: The temperature per axle

The criteria considered for the classification are the average and standard deviation values higher than 10°C (50°F) and the wheels that two out of the three detectors have sensed to be higher than 15.5°C (60°F). The data points with all three criteria are shown in Figure 4-21.

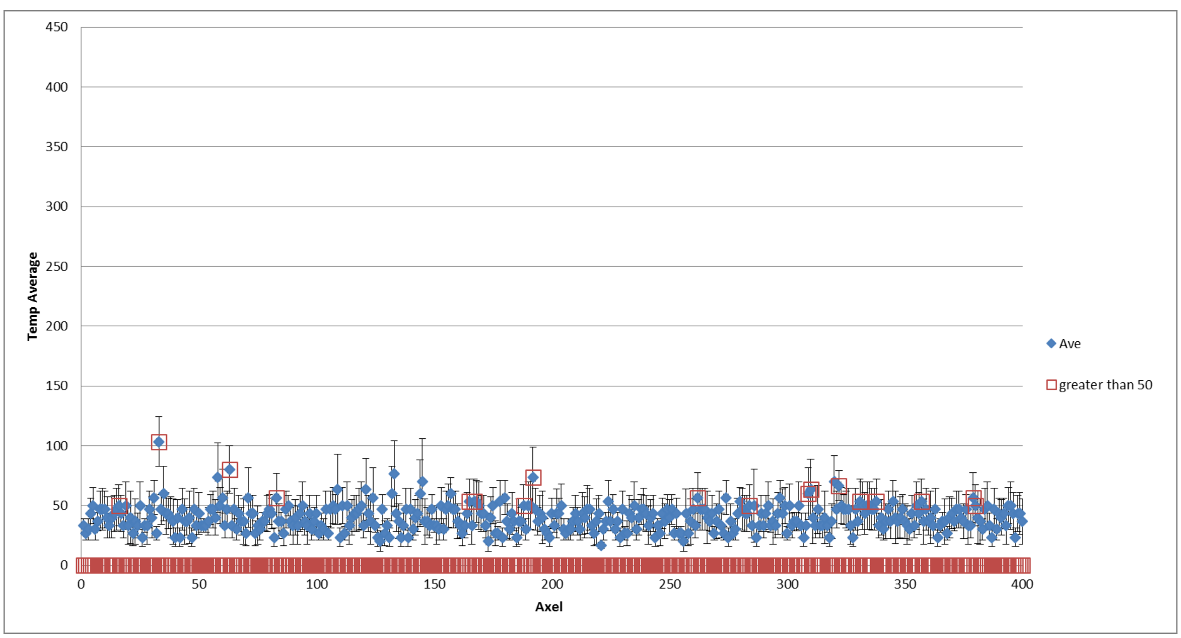


Figure 4-21: Data points with STD, average, and two out of three values greater than 50

According to the defined criteria, the wheels prone to failure are wheels 192 and 310. The proposed analysis is also applicable for the detectors that are installed in sloping areas. Since the analysis uses statistics to make a comparison between the three points, a change in the geographical location would not affect the results. The analysis is modifiable; based on the industry decision-makers' discretion, the thresholds can be modified to increase or lower sensitivity. Lowering the threshold will categorise more wheels as prone to failure.

Another section of data analysis includes comparing the classification accuracy by increasing from three to five the number of the detectors being studied. In this regard, two other detectors in the Cascade subdivision were considered for the study. The data regarding the train that passed the three detectors were considered and the analysis was performed. Looking back at Figure 4-8, one detector was added before Detector 1 and one after Detector 3.The heading direction is west to east. Fig. 4-22 schematically illustrates the arrangement of the five detectors:

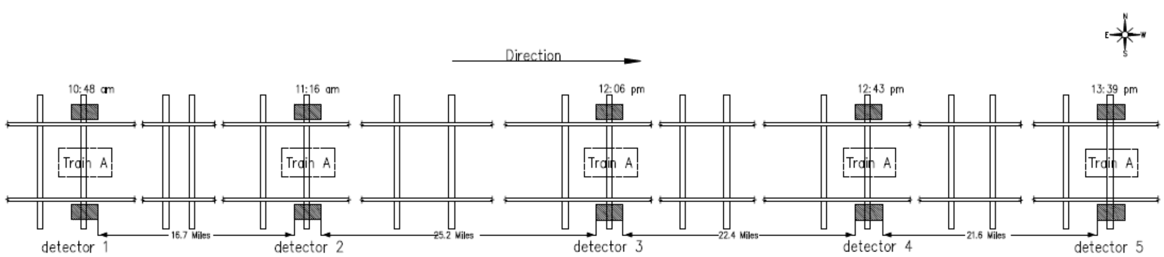


Figure 4-22: The arrangement of five subsequent detectors in the corridor of the study

Fig. 4-23 shows the temperature readings over the five detectors for the first 50 axles:

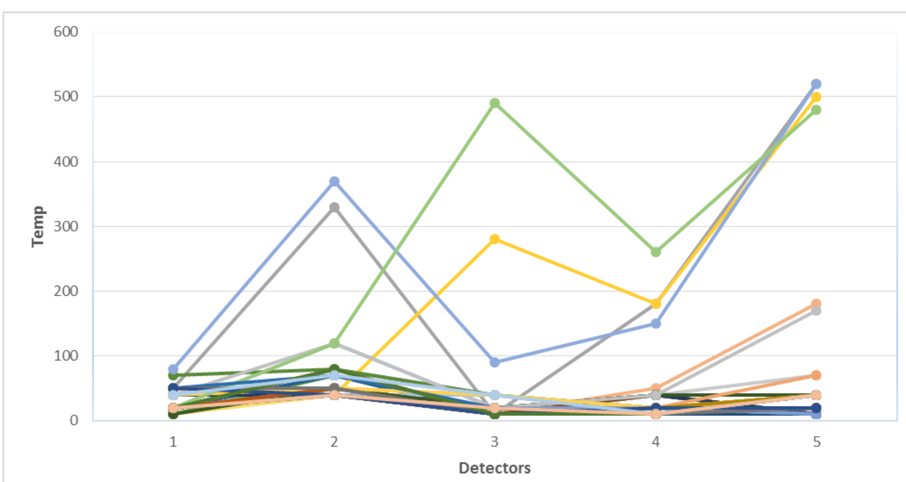


Figure 4-23: Wheel temperatures per axels over the five subsequent detectors

The readings with a value higher than 10°C (50°F) are specified in the following plot:

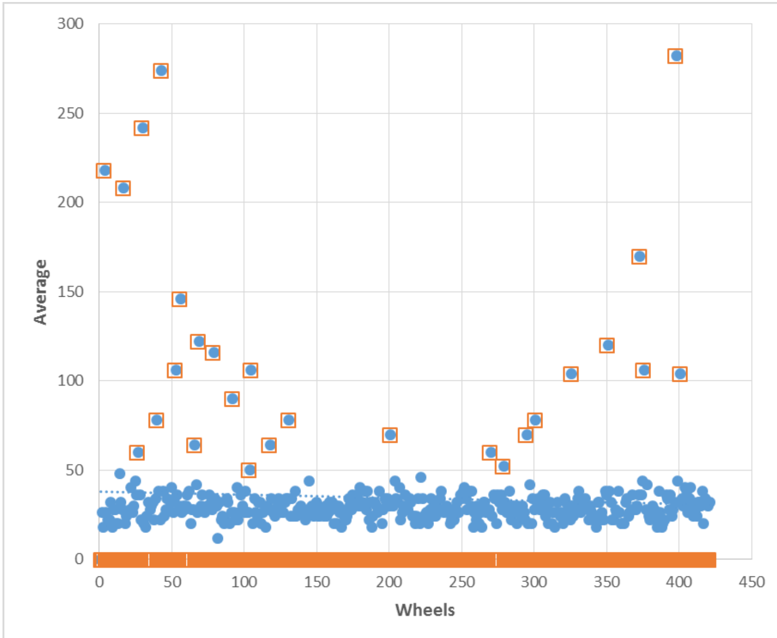


Figure 4-24: The average of the points higher than 10° C (50° F)

The standard deviation for each wheel passing by the five detectors:

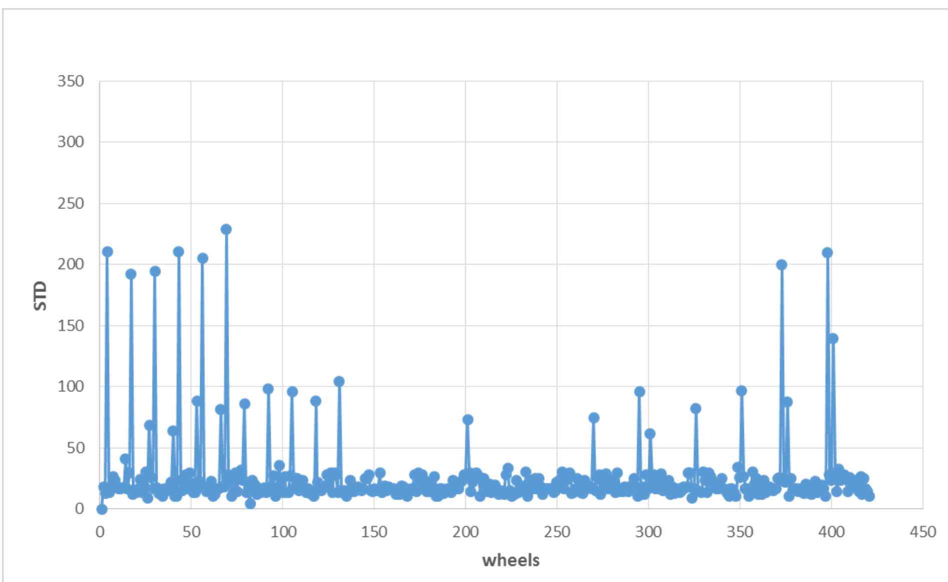


Figure 4-25: STD for each wheel that passed the five detectors

Standard deviation has low statistical significance for sample population of only three or five members in the set, but it does allow some comparison of the variability between using three detectors as opposed to five detectors to find anomalies in a sequence relating to whether an axle is giving an unusual reading. To identify the detectors that vary in their readings compared to the others, the error percentage for each of the five detectors was also calculated and plotted:

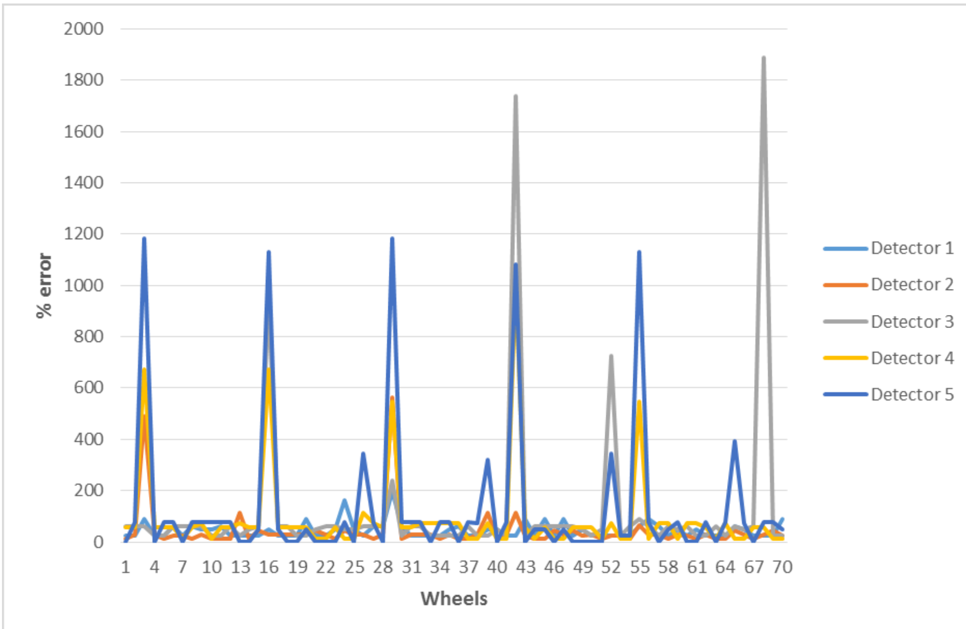


Figure 4-26: Error percentage of detectors 1, 2, 3, 4, and 5 per wheel

To accurately compare the data of three detectors and five detectors to find out which had the higher classification accuracy, the thresholds were constant for the analysis. For the third criterion, the readings of three detectors out of five were considered. Fig. 4-27 shows the data points with average and STD values more than 10°C (50°F) along with the data points that three out of the five detectors have detected with temperatures higher than 10°C (50°F).

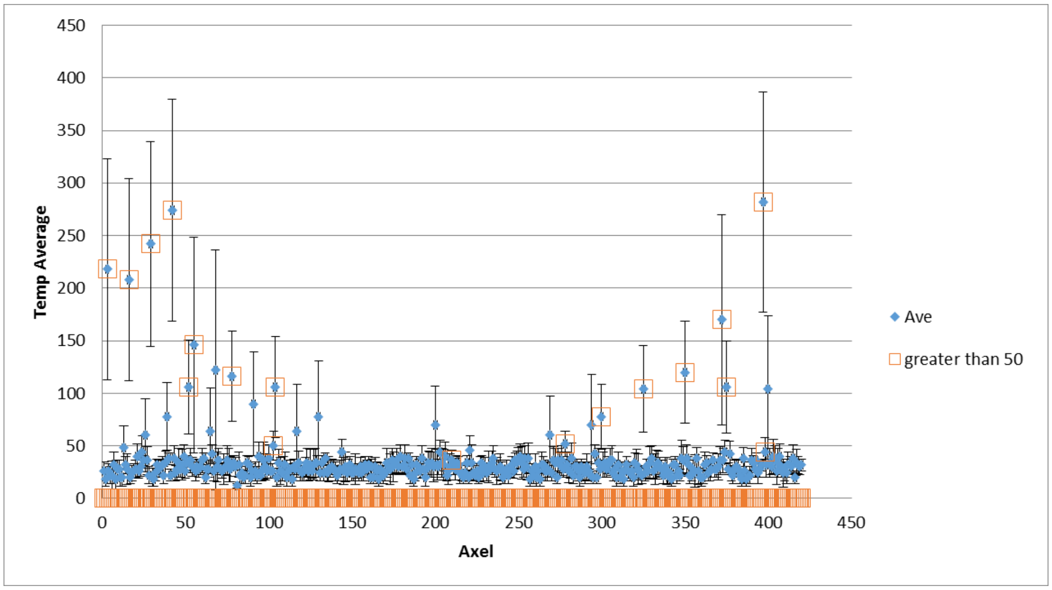


Figure 4-27: Data points with STD, average, and three out of five values greater than 50

Considering all three criteria together led us to a fault classification that identifies the wheels that have the potential to failure and require prompt attention. Those wheels are wheels 3, 16, 29, 42, 55, 68, 130, 372, 397, and 400. In the analysis in which three consecutive detectors were considered instead of five for the same train on the same day, a higher number of wheels was categorized as prone to failure. Those wheels are wheels 3, 16, 29, 42, 52, 55, 78, 104, 130, 200, 325, 350, 372, 375, 397, and 400.

4.4. Statistical Analysis on WTD readings

Trend analysis is one of the widely used techniques for detecting and analyzing anomalies. To analyze the trend, the probability distributions of the temperature reading data for each of the selected three detectors in both the Cascade and the Mountain subdivisions have been plotted in the following figures. Data files 1, 2, and 3 refer to detectors 1, 2, and 3.

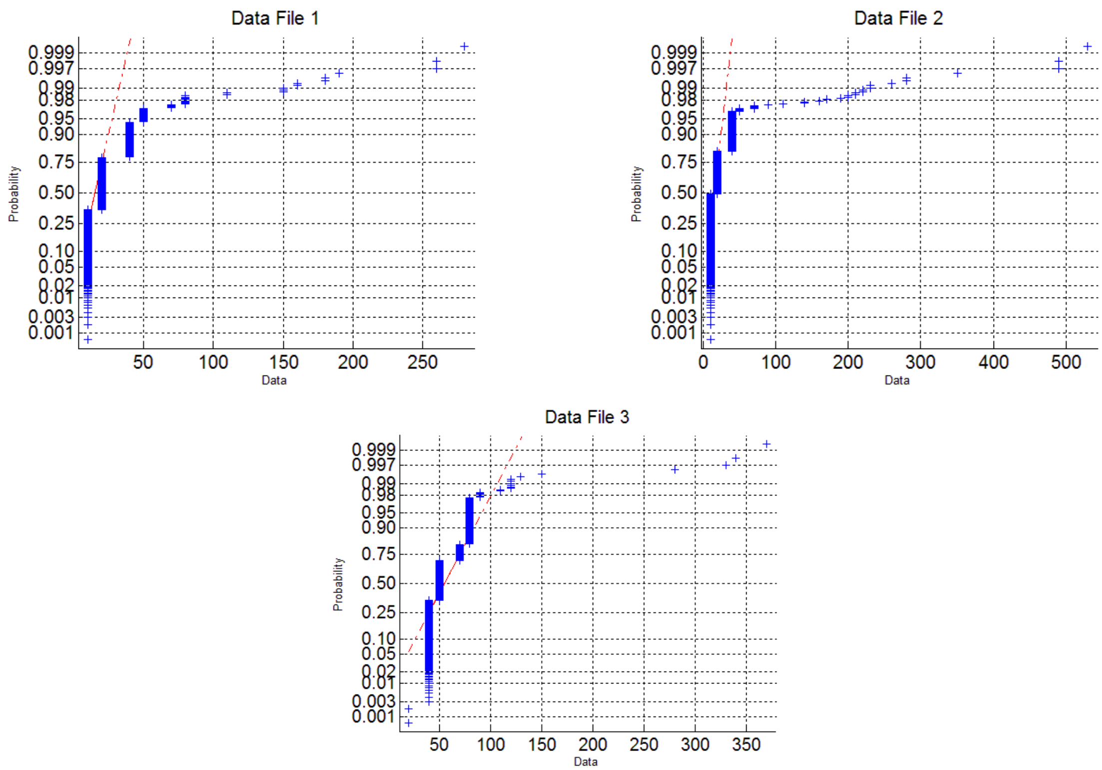


Figure 4-28: Probability distributions for detectors 1, 2, and 3 readings in Cascade subdivision

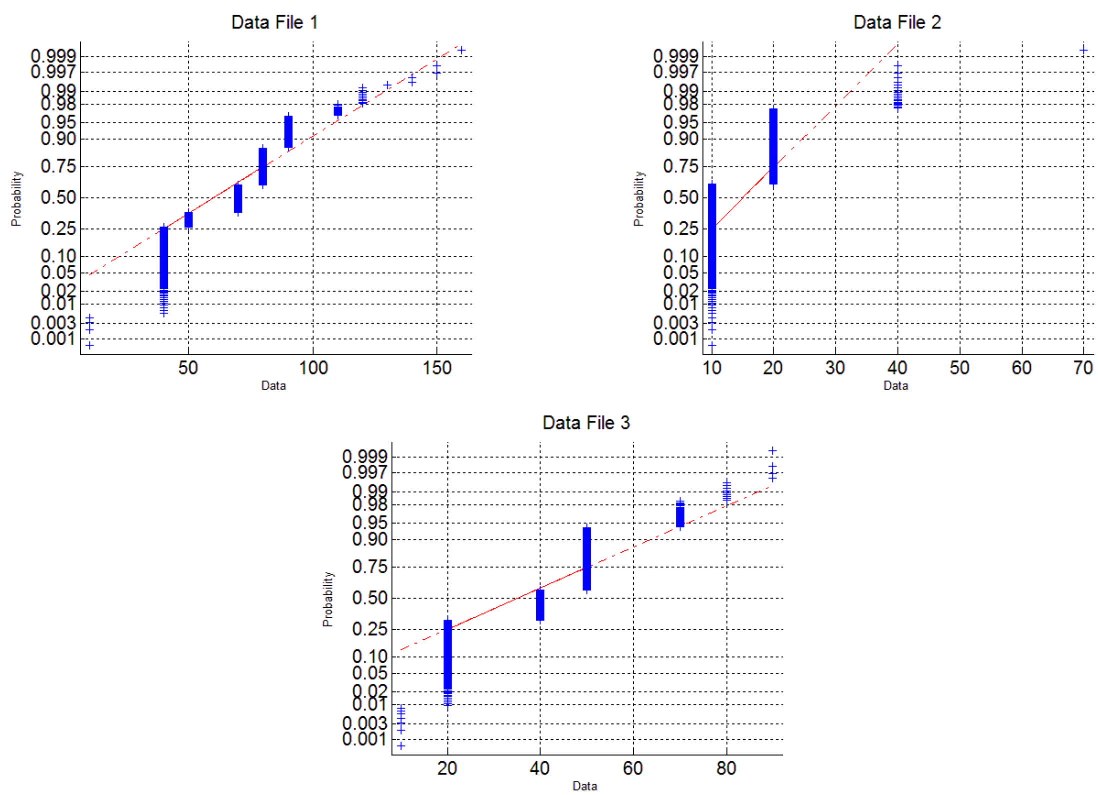
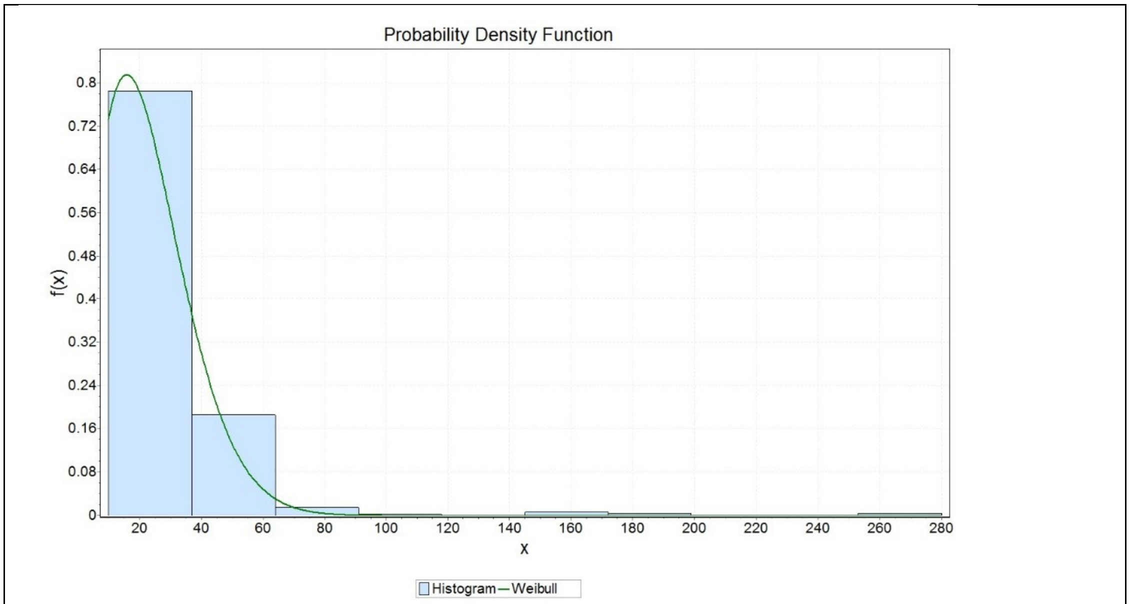


Figure 4-29: Probability distributions for detectors 1, 2, 3 readings in Mountain subdivision

The data are skewed, which adds a third statistical moment, and thus the normal distribution does not give the best fit for the data. The underlying cause of the skewness is unclear. The probability distribution for temperature readings of detectors 1, 2, and 3 in the Cascade subdivision are plotted. The maximum likelihood estimation (MLE) method has been used through distribution fitting software. The fitted distribution, the associated parameters, and the skewness and excess kurtosis are also shown for each detector.

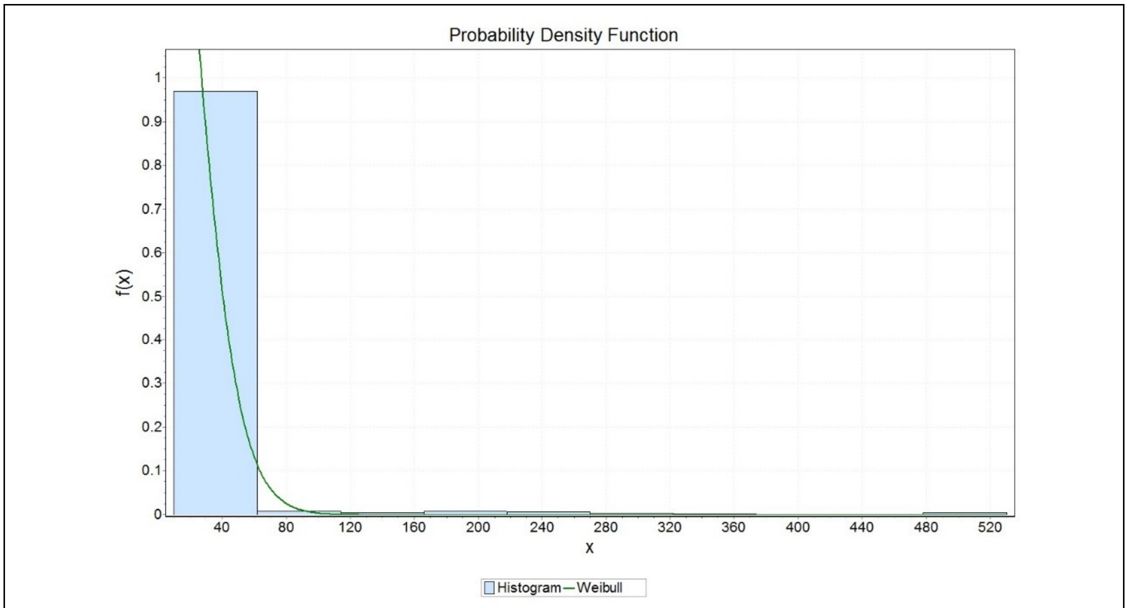
Cascade- Detector 1:



2P Weibull Sample Size: 840	Parameters	α=1.7315 β=26.136		
	Skewness	5.7262	Excess Kurtosis	44.848

Table 4-5:Probability distribution and the associated statistical parameters

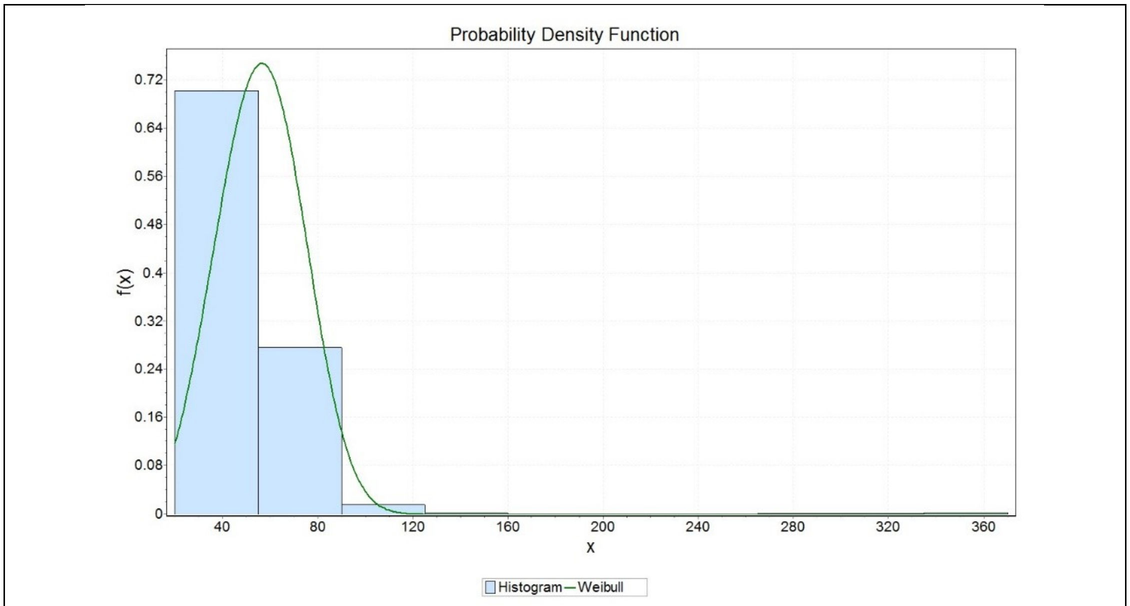
Cascade- Detector 2:



2P Weibull Sample Size: 840	Parameters	α=1.4332 β=25.143		
	Skewness	7.5564	Excess Kurtosis	69.433

Table 4-6: Probability distribution and the associated statistical parameters

Cascade- Detector 3:

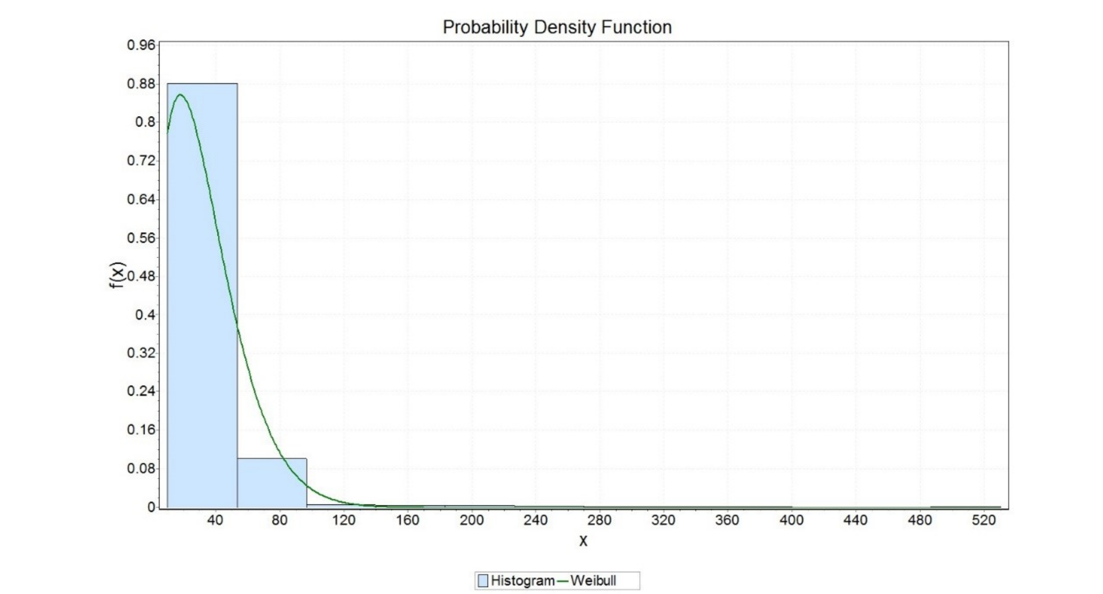


2P Weibull Sample Size: 840	Parameters	α=3.4531 β=62.384		
	Skewness	6.5872	Excess Kurtosis	68.803

Table 4-7: Probability distribution and the associated statistical parameters

The readings for all the detectors were merged together and the PDF was plotted.

Cascade- Detectors 1, 2, 3:

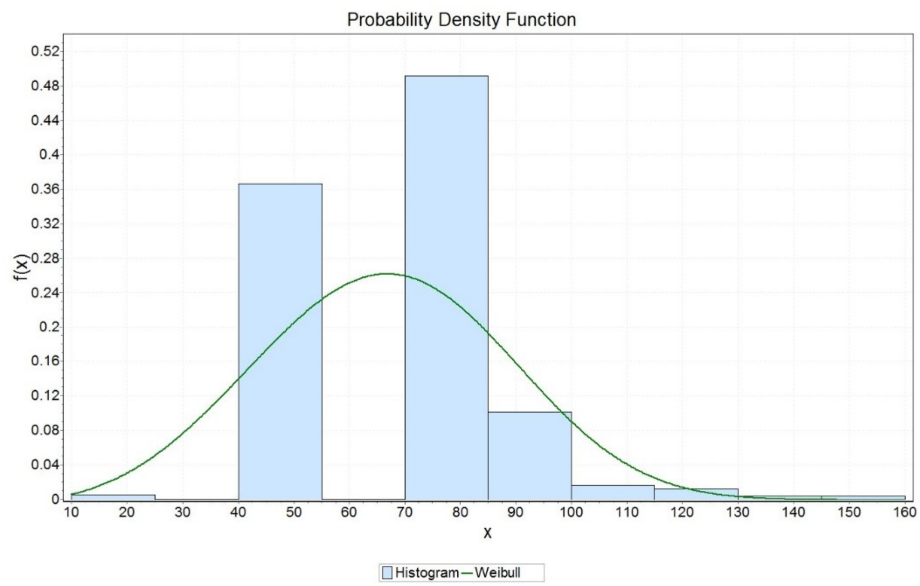


2P Weibull	Parameters	α=1.4945 β=37.651		
Sample Size: 2520	Skewness	5.6359	Excess Kurtosis	54.387

Table 4-8: Probability distribution and the associated statistical parameters

The best distribution is the two-parameter Weibull The average of the shape parameter (α) for the selected detectors in the Cascade subdivision is 1.55 and for the scale parameter (β) it is 29.64. Skewness is a measure of symmetry of a distribution and indicates whether a distribution tails off in one direction or another. A normal distribution has a skewness of zero. The distributions fitted to the temperature readings of the detectors in the Cascade subdivision are positively skewed, which indicates that the tail on the right side is longer than the one on the left side. Kurtosis measures the thickness of the tails of a distribution. Excess kurtosis is the remainder of the kurtosis value minus 3.0. A normal distribution has a kurtosis of zero. Positive kurtosis means that the distribution is more peaked and the tails of the distribution are thicker than those in a normal distribution. By contrast, negative values of kurtosis mean that the distribution is flatter in the middle and has thin tails. Compared to the kurtosis for a normal distribution, the kurtosis is huge for each of the detectors. The high kurtosis is problematic and suggests that there is a big clump of specific temperatures concentrated in a part of the distribution and that the distribution is too peaked to be normal (Acock, 2008). The distribution of the second detector is the one with the highest skewness and kurtosis. Based on the previous analysis in detecting the anomaly, this detector was the one with the highest error percentage. The same analysis has been done with the temperature readings of the selected detectors in the Mountain subdivision. The results are summarized in the following tables:

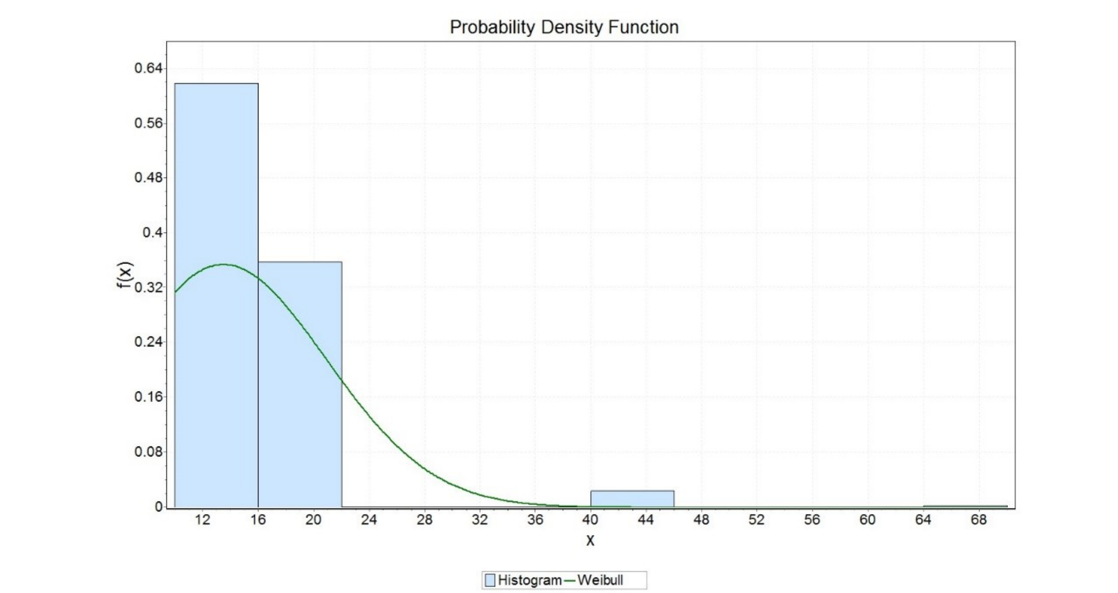
Mountain- Detector 1:



2P Weibull Sample Size: 800	Parameters	α=3.3509 β=74.228		
	Skewness	0.34498	Excess Kurtosis	0.55754

Table 4-9: Probability distribution and the associated statistical parameters

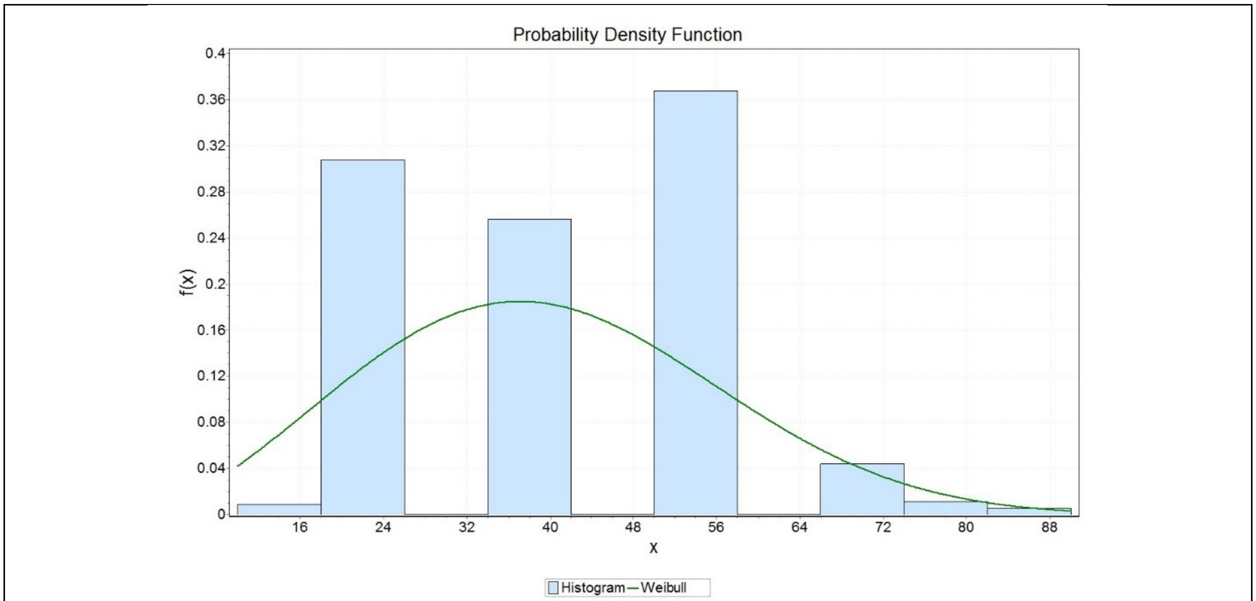
Mountain- Detector 2:



2P Weibull Sample Size: 800	Parameters	α=2.4334 β=16.769		
	Skewness	2.2644	Excess Kurtosis	9.6478

Table 4-10:Probability distribution and the associated statistical parameters

Mountain- Detector 3:

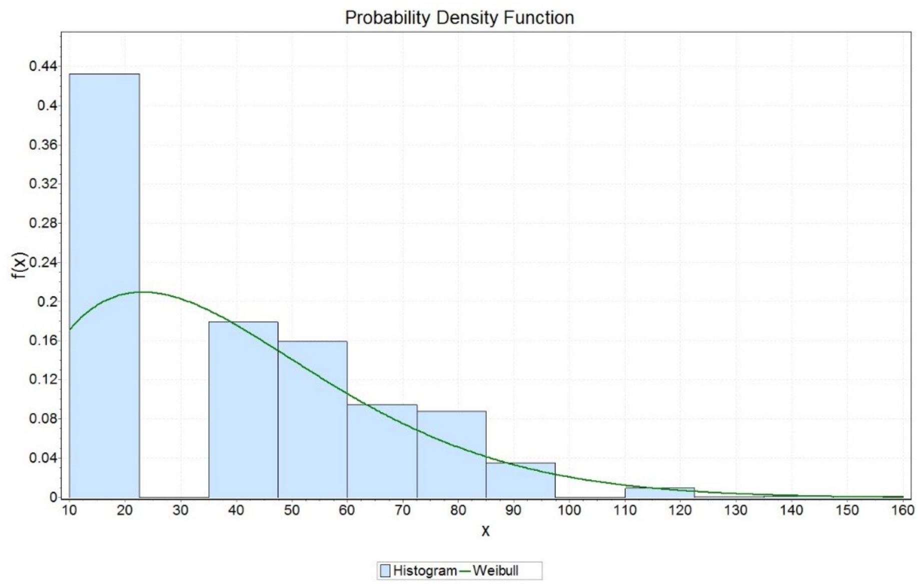


2P Weibull Sample Size: 800	Parameters	α=2.5823 β=44.838		
	Skewness	0.1959	Excess Kurtosis	-0.20211

Table 4-11: Probability distribution and the associated statistical parameters

And for the readings of the three detectors in the Mountain subdivision as one data set:

Mountain- Detectors 1, 2, 3:



2P Weibull Sample Size: 2400	Parameters	α=1.5543 β=44.914		
	Skewness	0.68461	Excess Kurtosis	-0.15011

Table 4-12: Probability distribution and the associated statistical parameters

The two-parameter Weibull is the distribution to use in this step as well. The average of the shape parameter (α) for the selected detectors in the Mountain subdivision is 2.19 and for the scale parameter (β) it is 35.50. The values of skewness and kurtosis are much lower than those in the Cascade subdivision, but still normal distribution cannot be the proper fit, because in this case the values are too low to be a normal distribution. The negative values for kurtosis are obtained in this step. That implies that the distribution is flatter and has thin tails, which means there are large variations within the dataset, leading to a situation in which the data is not concentrated around the mean.

The shape and scale of the two-parameter Weibull distribution for detector 2 in both subdivisions are not as well-formed as the others. Based on the previous analysis, these two detectors have a higher error percentage.

4.5. Conclusion

The assumption that reports from just one detector may not be indicative is valid. It is by combining the other reports that an abnormality can be identified. A number of tools and reports are used in industry, each with its own function depending on the information required. Looking at one detector in passing trains and comparing the average and STD on a train-base help us to understand the health of the detection system, while having multiple detectors in one window and looking at the STD and the average instead of solely at the data on a train base helps us to better understand and monitor the condition of the railcars. Identifying wheels prone to failure might reduce the time required to inspect the train wheels. Considering three consecutive detectors seems to be ideal for monitoring, as this method has identified more wheels prone to failure. It is also more practical; gathering the information related to a train passing by three detectors is more doable. In a case the possibility of an anomaly is found on the first or last of three detectors, the "three-detector window" can be shifted in a way that the suspicious detector (data points) stays in the middle of the data. Looking at the new detector before or after the significant data point leads to a better understanding of the detectors and the railcar condition. Even if the decision-makers find the classification accuracy of the five detectors higher, they can choose to deal with just three detectors and then adjust the setting on a case-by-case basis.

Fitting distribution to the temperature readings of the detectors shows that there is a large number of variables that are not measured, but that affect the wheel temperature. Variables can be external (such as weather conditions, including precipitation as well as temperature), and can affect brake performance and sensor sensitivity. Variables can be internal. The accuracy of the WTD system may be affected by an incipient fault. The brake system on the train may have a fault that affects the measured temperature of the wheels. Train operators may rely more or less on dynamic braking, which affects how much the brakes will heat. For our purposes, these processes are random, as they are unmeasured and there is no other information about how they work. At least one of these processes is not normally distributed. This apparent (or real) randomness makes predicting a pattern and trend more complicated (as there may be more than one random process involved). This means that there are underlying processes that can be found with further examination.

Chapter 5. System Reliability Analysis

In this chapter we will look behind the statistics to see how reliable wheel temperature detector (WTD) systems are. A statistically significant answer to this question would allow railway industries to confirm whether a system is sufficiently reliable. We are studying the detection system to ensure the railway industry that such systems are capable of performing their designed function through their estimated lifetime. Statistical modelling of failures is a common method for modelling reliability.One of the widely used methods to assess a system's reliability is reliability modeling based on lifetime distribution. This method uses a statistical distribution to predict the reliability function. The parameters obtained from fitting the distribution to the dataset can then be used to estimate, for a specific period, the probability of failure, failure rate, reliability, and mean time to fail. The collected failure data of the systems under study are used, and a lifetime distribution that best fits the data is selected. The parameters are estimated and plots are generated to examine the model's acceptability. If the test rejects the fitted distribution, the procedure should be repeated until an acceptable model is achieved. The following figure illustrates the technique:

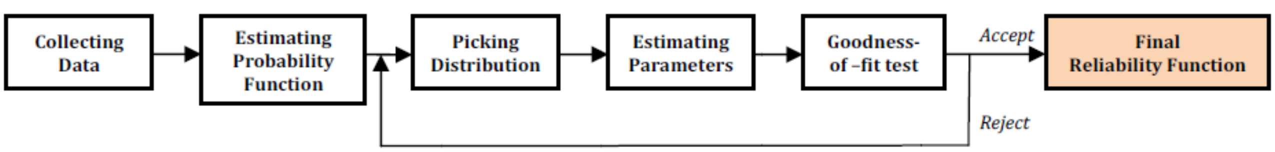


Figure 5-1: Finding Reliability Model Algorithm
(Vaghar and Lipsett, 2011)

One of the approaches for modelling reliability is based on the times-to-fail of the system. The time of failure that shows the amount of hours it takes for an operational unit to fail would lead us to accurately model the reliability. The time period that was considered for this research was five years, from 2009 to 2013. However, to obtain higher accuracy in reliability modeling and predicate the trend, all failure data available in the maintenance records between 2009 and 2014 were applied. In the maintenance database, the information related to the time of failure included date, time, and the outage time of the detectors. In maintenance terms, outage time is the impact of failure in WTDs. Thus, the date and time of the failures of the 40 detectors in the corridor being studied were considered as failure indicators of the detection system, as was the outage time mentioned in the file for the failed systems. Excluding the Null findings and failures that caused zero, one, two, and three minutes of outage times, the failure of the detectors was defined as any event that caused the detectors to be down for more than three minutes.

The time to fail for each detector in the study was used for the analysis. A measure of the system's reliability is the number of failures in a determined interval.

The number of failures for each detector extracted from the maintenance database is shown in the following table.

No.	Detector	Number of Failures	No.	Detector	Number of Failures
1	Cascade 10.9	70	21	Shuswap 40.8	85
2	Cascade 32.5	56	22	Shuswap 59.1	26
3	Cascade 54.9	45	23	Shuswap 77.4	45
4	Cascade 80.1	59	24	Shuswap 77.5	71
5	Cascade 96.8	62	25	Shuswap 90	9
6	Cranbrook 24.7	36	26	Shuswap 97.9	57
7	Cranbrook 40.3	39	27	Shuswap 118.5	63
8	Cranbrook 65.3	21	28	Thompson 11.8	83
9	Cranbrook 86.8	19	29	Thompson 35.5	30
10	Fording River 5.3	26	30	Thompson 44.3	52
11	Mountain 14.2	77	31	Thompson 60.5	45
12	Mountain 30.2	3	32	Thompson 81.9	30
13	Mountain 39.3	76	33	Thompson 98.1	60
14	Mountain 44.9	33	34	Windermere 8.5	17
15	Mountain 54.5	76	35	Windermere 25.2	22
16	Mountain 70.9	199	36	Windermere 50.4	22
17	Mountain 74.8	114	37	Windermere 54.7	16
18	Mountain 95.1	248	38	Windermere 97.2	21
19	Mountain 111.7	106	39	Windermere 113.4	9
20	Shuswap 19.7	96	40	Windermere 123.3	30

Table 5-1: Number of failures for the detectors in the corridor being study [Same as Table 4-1]

5.1. Reliability Modeling

The time-to-fail data were calculated and used to model reliability. The software used for the analysis was Reliasoft, Weibull ++9. The analysis method for modeling the reliability and estimating the parameters will change depending on the quantity and type of failure data, Maximum Likelihood Estimation (MLE) and Rank Regression are the two analysis methods. MLE is recommended in cases with a sufficient amount of data because it allows for more precise estimates with larger sample data sets. Rank Regression is preferred when the sample sizes are small (ReliaSoft. User's guide). In this analysis, wherever data points are more than 30, the MLE method is used. For smaller data (< 30 data points), the Rank Regression method is used.

Maximum Likelihood Estimation (MLE)

This analysis method estimates the parameters of the distribution by maximizing the "likelihood function," which is based on the probability density function (PDF). For instance, for a generic probability density function:

$$f(x;\ \theta_1, \theta_2, \cdots, \theta_k) \quad \text{Equation 5-1}$$

The likelihood function is defined as the product of the probability density functions:

$$L = \prod_{i=1}^{n} f\ (x_i\ ;\ \theta_1\ , \theta_2, \cdots, \theta_k) \quad \text{Equation 5-2}$$

Where:

x: data points (times to failure) and

$\theta_1\ , \theta_2, \cdots, \theta_k$: parameters to be estimated

The values for parameters will be estimated such that the highest value for Equation 5-2 is obtained (Brownlee, 1965).

Rank Regression Parameter Estimation

The Rank Regression method, also called the Least Squares method, plots and linearizes the unreliability function and then estimates the parameters through median ranks. In this method a straight line is fitted to the data points in a way that the sum of squares of the distance of the points to the line is minimized (Mendenhall et al., 2008). This minimization can be done on the x-axis (minimum horizontal distance) or y-axis (minimum vertical distance). This is shown in the figure below:

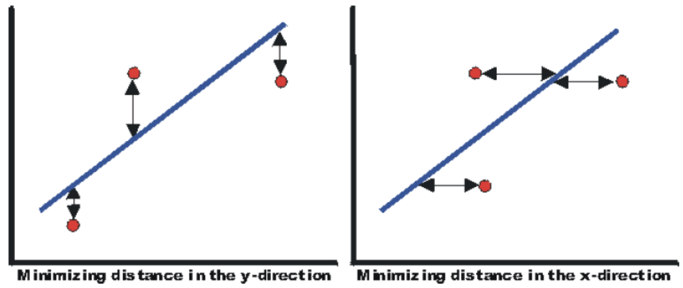


Figure 5-2: minimization on y- direction and x-direction
(ReliaSoft. User's guide)

The form of the straight line fitted to the data points is y=ax+b. The value of a and b need to be found such that "minimum value for the square of the distance of points from the line is achieved" (ReliaSoft. User's guide), which is the mathematical minimization of the following equation:

$$\sum_{i=1}^{N}(\hat{a} + \hat{b}y_i \; - \; x_i)^2 = \min(a, b)\sum_{i=1}^{N}(a + by_i \; - \; x_i)^2 \qquad \text{Equation 5-3}$$

Where:

$\hat{a}$ and $\hat{b}$ are the least squares estimates of a and b

Confidence Bounds and Ranking Method are the parameters that also need to be set for the analysis.

Confidence Bounds

One of the important concepts in reliability analysis is that of confidence bounds. Confidence bounds, also known as confidence intervals, are used to estimate accuracy. Life data analysis results depend on sample sizes, so there is uncertainty in the results. Confidence intervals quantify this uncertainty. Confidence bounds give us a range that we are confident includes the true value of the parameter (Brownlee, 1965). The larger sample data set makes it possible to obtain the "more confidence," resulting in the "narrower confidence bound". Generally, the confidence bound gets more dispersed when there is a higher probability of covering the quantity of interest. For instance, a "99% confidence interval is wider than 95% confidence interval. Commonly used confidence intervals are 95% and 99% (du Prel at al., 2009). Confidence intervals are either one-sided or two-sided. In Weibull ++9, there are two ways to calculate confidence intervals: the Fisher matrix method and the likelihood ratio method. The first is not conservative enough in a situation with a small sample size, but for large sample sizes, both methods work the same way. The Fisher matrix method is more widely used in statistical analyses.

Ranking Method

Ranking methods define the way the unreliability estimates are associated with the times-to-failure. There are two methods: the median rank method and the Kaplan-Meier method. "The failure order number and the cumulative binomial distribution" (Reliasoft. User's guide) are the bases for assigning the estimated unreliabilities in the median rank method. For the Kaplan-Meier, "the product of the surviving fractions" (ReliaSoft. User's guide) is the basis. Generally it is recommended to use the median rank method for unreliability estimation. Accordingly, in this study, the Fisher matrix and median rank methods were used, respectively, to calculate confidence intervals and estimate the unreliabilities.

The reliability analysis was conducted in two phases; in the first phase, the analysis was conducted based only on the software. In this phase, the life time distributions under the analysis were 1P-exponential, 2P-exponential, normal, lognormal, 2P-Weibull, 3P-Weibull, Gamma and Generalized gamma (G-Gamma). In the second phase, according to research needs and reliability modeling knowledge, a decision was made to analyze the two-parameter distributions. The results of these two phases were compared to see the difference, and the distributions were selected. Since there were not enough data points for the Mountain 30.2 detector, it was excluded from the analysis. The time-to-fail of the detectors was applied and the probability density function plots for all 39 detectors were achieved. The plots for one of the detectors is illustrated here as an example. The plots for all of the detectors are presented in Appendix C.

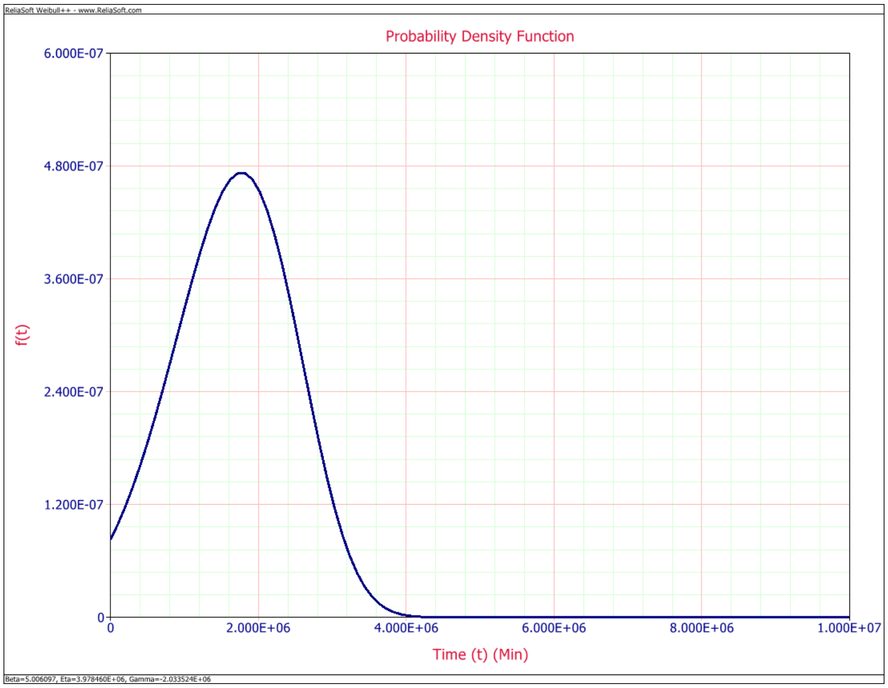


Figure 5-3: Estimated Probability Density Function for Cascade 32.5

The probability density functions provide a helpful means to visualize a failure's probability distribution. For any time interval on the x-axis, the probability of the occurrence of a failure is the area under the probability density curve over that interval (Wang, 2002). "The analysis of lifetime data leads to the estimation of parameters" (AC Cohen and BJ Whitten, 1988, p.14). The parameters define/control the shape, scale and location of the probability distribution function. The following table encompasses the fitted distributions to the failure data, the parameter estimation method, and with estimated parameters. The Maximum Likelihood Method (MLE) is the most commonly used method. However, since the MLE is not appropriate for small data sets, the Rang Regression Method (RRX) was used in couple of cases.

No.	Detector	Analysis Method	Fitted Distribution	Estimated Parameters
1	Cascade 10.9	MLE	G-Gamma	μ= 1892.35, σ= 0.013, λ=50.00
2	Cascade 32.5	MLE	3P-Weibull	β= 5.00, η= 3.98E+06, γ= -2.03E+06
3	Cascade 54.9	MLE	3P-Weibull	β= 1.18, η= 1.18E+06, γ= 217330.29
4	Cascade 80.1	MLE	G-Gamma	μ= 14.75, σ= 0.01, λ=50.00
5	Cascade 96.8	MLE	Normal	Mean= 1.51E+06, STD=926869.48
6	Cranbrook 24.7	MLE	2P-Weibull	β= 3.29, η= 1.99E+06
7	Cranbrook 40.3	MLE	G-Gamma	μ= 14.83, σ= 14.83, λ=50.00

No.	Detector	Analysis Method	Fitted Distribution	Estimated Parameters
8	Cranbrook 65.3	MLE	G-Gamma	μ= 14.83, σ= 0.02, λ=30.50
9	Cranbrook 86.8	RRX	Gamma	μ=13.38 , K=1.60
10	Fording River 5.3	RRX	G-Gamma	μ= 14.60, σ= 0.16, λ=3.74
11	Mountain 14.2	MLE	G-Gamma	μ= 14.69, σ= 0.15, λ=4.42
12	Mountain 39.3	MLE	3P-Weibull	β= 12.24, η= 5.44E+06, γ= 3.99E+069
13	Mountain 44.9	MLE	Normal	Mean= 700789.25, STD=405854.99
14	Mountain 54.5	MLE	G-Gamma	μ= 11.89, σ= 0.50, λ=3.21
15	Mountain 70.9	MLE	G-Gamma	μ= 14.38, σ= 0.35, λ=1.61
16	Mountain 74.8	MLE	Gamma	μ=13.02, k=3.01
17	Mountain 95.1	MLE	3P-Weibull	β= 2.99, η= 2.10E+06, γ= -547900
18	Mountain 111.7	MLE	2P-Weibull	β= 2.08, η= 1.55E+06
19	Shuswap 19.7	MLE	3P-Weibull	β= 2.78, η= 2.31E+06, γ= -478647.59
20	Shuswap 40.8	MLE	3P-Weibull	β= 6.67, η =4.15E+06, γ= -2.12E+06
21	Shuswap 59.1	MLE	G-Gamma	μ= 14.73, σ =0.10, λ=2.36
22	Shuswap 77.4	MLE	G-Gamma	μ= 14.76, σ= 0.01, λ=50
23	Shuswap 77.5	MLE	G-Gamma	μ= 14.67, σ= 0.01, λ=50
24	Shuswap 90	RRX	Normal	Mean=196481.61, STD=99822.57
25	Shuswap 97.9	MLE	G-Gamma	μ= 14.72, σ= 0.01, λ=50
26	Shuswap 118.5	MLE	G-Gamma	μ= 14.60, σ= 0.14, λ=4.03
27	Thompson 11.8	MLE	G-Gamma	μ= 14.69, σ= 0.17, λ=3.63
28	Thompson 35.5	MLE	G-Gamma	μ=14.56, σ=0.21, λ=1.87
29	Thompson 44.3	MLE	G-Gamma	μ=14.62, σ=0.24, λ= 2.38
30	Thompson 60.5	MLE	Normal	μ=1.21E+06, σ=708236.77
31	Thompson 81.9	MLE	G-Gamma	μ=14.55, σ=0.21, λ=3.84
32	Thompson 98.1	MLE	G-Gamma	μ=14.69, σ=0.13, λ=5.82
33	Windermere 8.5	RRX	G-Gamma	μ=14.44, σ=0.16, λ=1.95
34	Windermere 25.2	RRX	G-Gamma	μ=14.67, σ=0.08, λ=4.87
35	Windermere 50.4	RRX	G-Gamma	μ=14.20, σ=0.20, λ=2.14
36	Windermere 54.7	RRX	2P-Weibull	β=1.30 , η=1.42E+06
37	Windermere 97.2	RRX	3P-Weibull	β=1.81 , η =1.03E+06 , γ=379933.8
38	Windermere 113.4	RRX	2P-Exponential	Mean time=384530.89 , γ=319757
39	Windermere 123.3	MLE	Normal	Mean=1.60E+06 , STD=638490.712

Table 5-2: summary of the analysis for each of the detectors

In this step of the analysis, the times-to-failure of all the detectors in one subdivision were considered as one data set. As with the previous section, probability distribution functions (PDFs) are plotted. Fig. 5-4 shows the PDF for the mountain subdivision. The rest of the plots can be found in Appendix C.

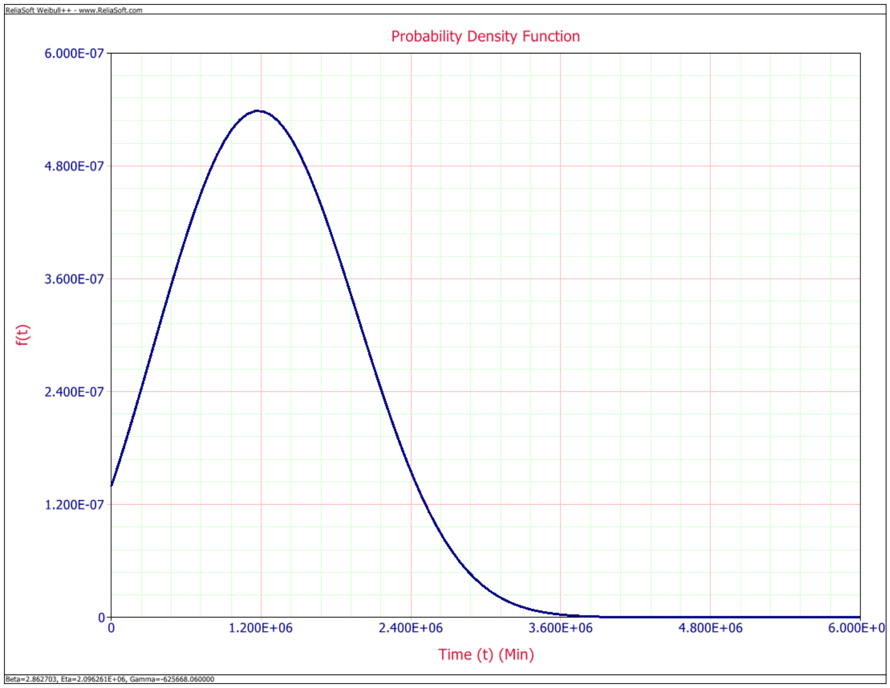


Figure 5-4: Estimated Probability Density Function of Mountain subdivision

As all the failures related to the detectors in a subdivision were consolidated, the number of sample data was adequate to apply the MLE method for all the subdivisions except for "Fording River," which has just one detector with 25 recorded failures.

The table below summarizes the results:

No.	Subdivision	Fitted Distribution	Estimated Parameters
1	Cascade	G-Gamma	μ= 14.85, σ= 0.018, λ=50.00
2	Cranbrook	G-Gamma	μ= 14.78, σ= 0.09, λ=7.93
3	Fording River	G-Gamma	μ= 14.60, σ= 0.16, λ=3.74
4	Mountain	3P-Weibull	β=2.86, η=2.10E+06, γ=-625668.06
5	Shuswap	Normal	μ=1.54E+06 , STD= 764593.18
6	Thompson	G-Gamma	β= 14.66, η= 0.20, γ= 3.65
7	Windermere	G-Gamma	β= 14.55, η= 0.22, γ= 3.35

Table 5-3: Fitted distribution and Estimated Parameters for each Subdivision

In general, after fitting a distribution to a dataset, it is necessary to measure the compatibility of the fitted model with the theoretical probability distribution function. There are statistical tools such as probability plotting, correlation coefficient, likelihood value (LKV) and goodness-of-fit tests (GOF) such as the chi-squared test and modified Kolmogorov-Smirnov (KS) test that help in assessing the fit of a distribution.

Weibull ++9 software uses statistical tests and ranks the distributions in terms of their fit to the data. The K-S (GOF), a normalized correlation coefficient (PLOT), and the LKV are the three tests that the software uses to rank the distributions. Based on the parameter estimation method, each of these tests will have a weight upon which the ranking is based. The assigned weights are as follows:

Weights for Rank Regression (RR)		Weights for Maximum Likelihood (MLE)	
Goodness-of-Fit	50%	Goodness-of-Fit	40%
Plot Fit	20%	Plot Fit	10%
Likelihood Ratio	30%	Likelihood Ratio	50%
	Total: 100%		Total: 100%

Table 5-4: The weights assigned to each test in Weibull ++9

The values obtained from using each test in conjunction with the weights are combined to make one value, DESV:

"DESV= (AVGOF Rank x AVGOF Weight) + (AVPLOT Rank x AVPLOT Weight) + (LKV Rank x LKV Weight)" (ReliaSoft. User's guide)

The distributions will be ranked according to the calculations. The one with the lowest DESV will be selected as the best fit. (ReliaSoft. User's guide)

So far, all the results presented above were based on the software ranking; all the distributions presented were ranked first. Various factors should be considered when selecting a distribution. In addition to goodness-of-fit test results, engineering knowledge is needed to interpret the results and select the appropriate life distribution for modeling the data set. The more parameters a distribution has, the more uncertain the estimates will be. Therefore, the analysis must be reviewed to determine whether it is feasible to choose a two-parameter distribution over a three-parameter distribution. In order to make such a comparison, the second phase of the analysis was implemented. As mentioned earlier, the goodness-of-fit results in the software use a modified KS test, since it is a powerful test that works with any sample size. For this analysis, the weights for the tests were modified so that the distributions were ranked only by the GOF results. The weight for the GOF test was set to 100 and the plot fit and likelihood ratio to zero. All three default tests available in the software were still calculated. However the distributions were ranked based on the GOF results. The P-Values were obtained and the distributions ranked based on the P-values.

Those with a larger P-Value were selected. To achieve higher accuracy, certainty, and practicality for the model, the two-parameter distributions were selected. The fitted distributions ranked first by the software were compared to the two-parameter distributions that were ranked first based on their P-value. The two-parameter distributions for this analysis were 2P-exponential, 2P-Weibull, lognormal, normal and gamma.

Table 5-5 summarizes the results of the goodness-of-fit tests.

No.	Detector	Software first Rank Fitted Distribution	P-Value	two-Parameter Distribution	P-Value
1	Cascade 10.9	G-Gamma	0.66	Normal	0.1218
2	Cascade 32.5	3P-Weibull	0.76	Normal	0.5231
3	Cascade 54.9	2P-Exponential	0.32	2P-Exponential	0.3270
4	Cascade 80.1	G-Gamma	0.76	Normal	0.3190
5	Cascade 96.8	Normal	0.1276	Normal	0.1276
6	Cranbrook 24.7	Normal	0.2320	Normal	0.2320
7	Cranbrook 40.3	G-Gamma	0.4275	Normal	0.3731
8	Cranbrook 65.3	3P-Weibull	0.9934	Normal	0.9927
9	Cranbrook 86.8	G-Gamma	1.0000	Gamma	1.0000
10	Fording River 5.3	G-Gamma	0.9851	Normal	0.5757
11	Mountain 14.2	G-Gamma	0.8490	Normal	0.8490
12	Mountain 30.2	Gamma	1.0000	2P-Exponential	1.0000
13	Mountain 39.3	3P-Weibull	0.4008	Normal	0.1273
14	Mountain 44.9	Gamma	0.1864	Gamma	0.1864
15	Mountain 54.5	G-Gamma	0.6660	Gamma	0.4180
16	Mountain 70.9	3P-Weibull	0.3690	2P-Weibull	0.1562
17	Mountain 74.8	Gamma	0.2820	Gamma	0.2820
18	Mountain 95.1	3P-Weibull	0.5212	Normal	0.4617
19	Mountain 111.7	2P-Weibull	0.0484	2P-Weibull	0.0484
20	Shuswap 19.7	Normal	0.3789	Normal	0.3789
21	Shuswap 40.8	3P-Weibull	0.0233	Normal	0.0025
22	Shuswap 59.1	G-Gamma	0.7271	Normal	0.1061
23	Shuswap 77.4	3P-Weibull	0.7695	Normal	0.6367
24	Shuswap 77.5	G-Gamma	0.8912	Normal	0.6437
25	Shuswap 90	Lognormal	0.9996	Lognormal	0.9996
26	Shuswap 97.9	G-Gamma	0.8436	2P-Weibull	0.5533
27	Shuswap 118.5	G-Gamma	0.0275	Normal	0.0272
28	Thompson 11.8	Normal	0.0461	Normal	0.0461
29	Thompson 35.5	G-Gamma	0.9173	Normal	0.5446
30	Thompson 44.3	G-Gamma	0.9946	Normal	0.8203
31	Thompson 60.5	Normal	0.9971	Normal	0.9971
32	Thompson 81.9	G-Gamma	0.4418	Normal	0.4129
33	Thompson 98.1	G-Gamma	0.5136	Normal	0.2438
34	Windermere 8.5	G-Gamma	1.0000	Normal	0.9674

No.	Detector	Software first Rank Fitted Distribution	P-Value	two-Parameter Distribution	P-Value
35	Windermere 25.2	G-Gamma	1.0000	2P-Weibull	0.7889
36	Windermere 50.4	G-Gamma	0.9984	Normal	0.7712
37	Windermere 54.7	2P-Weibull	0.9952	2P-Weibull	0.9952
38	Windermere 97.2	G-Gamma	0.9595	Gamma	0.9529
39	Windermere 113.4	G-Gamma	0.7283	2P-Exponential	0.7048
40	Windermere 123.3	Normal	0.9747	Normal	0.9698

Table 5-5: GOF results for three-parameter distributions vs. two-parameter distributions

For the purpose of practicality, the two-parameter distributions were considered. The PDF for Cascade 32.5 is shown here. The other PDFs are presented in Appendix C.

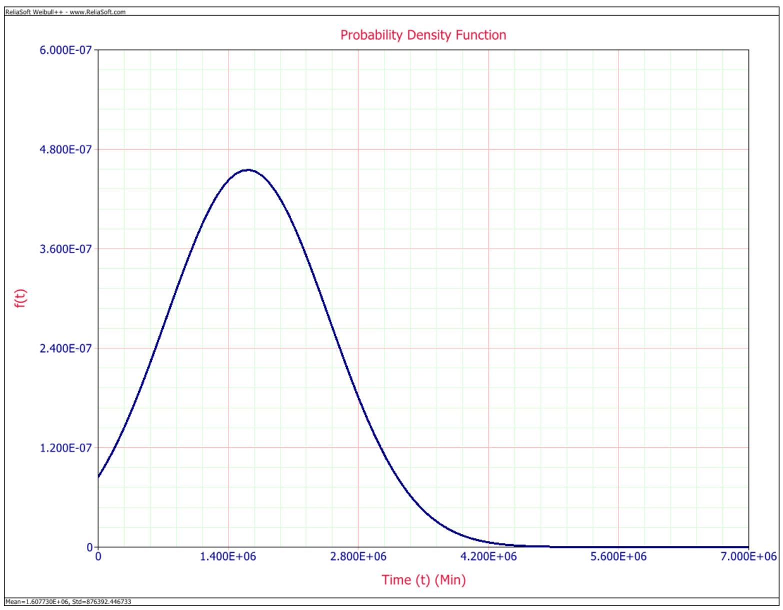


Figure 5-5: Estimated PDF for the 2-parameter distributions for Cascade 32.5

Normal distribution is the dominant two-parameter distribution for the detectors. It seems that this lifetime distribution can be selected to model the reliability and predict the trend of the detectors. For the 14 detectors with a different distribution, normal distribution is selected manually in the software to compare the GOF results and to see the difference in P-Values.

No.	Detector	Two-Parameter Distribution	P-Value	Normal Distribution P-Value
1	Cascade 54.9	2P-Exponential	0.3270	0.0174
2	Cranbrook 86.8	Gamma	1.0000	0.9645

No.	Detector	Two-Parameter Distribution	P-Value	Normal Distribution P-Value
3	Mountain 30.2	2P-Exponential	1.0000	1.0000
4	Mountain 44.9	Gamma	0.1864	0.1501
5	Mountain 54.5	Gamma	0.4180	0.0553
6	Mountain 70.9	2P-Weibull	0.1562	0.1482
7	Mountain 74.8	Gamma	0.2820	0.0164
8	Mountain 111.7	2P-Weibull	0.0484	0.0016
9	Shuswap 90	lognormal	0.9996	0.8976
10	Shuswap 97.9	2P-Weibull	0.5533	0.5271
11	Windermere 25.2	2P-Weibull	0.7889	0.7927
12	Windermere 54.7	2P-Weibull	0.9952	0.6951
13	Windermere 97.2	Gamma	0.9529	0.5580
14	Windermere 113.4	2P-Exponential	0.7048	0.2869

Table 5-6: Comparison of P-Values between normal & other two-parameter distributions

Except for the six detectors listed below, the difference in the result of the GOF test is not very different. This proves that normal distribution could be selected for modeling reliability. More in-depth study on the condition of Cascade 54.9, Mountain 54.5, Mountain 74.8, Mountain 111.7, Windermere 97.2, and Windermere 113.4 is required to interpret the inconsistency.

The finalized two-parameter fitted distributions along with the associated estimated parameters are shown in the table below. In order to prevent repetitive depiction, the table includes only the functions of the models that are not normal. For those with normal distribution, the model is defined by

$$f(t) = \frac{1}{\sigma\,(2\pi)^{1/2}}\, exp\,[-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2]$$

Equation 5-4

And the coefficients are stated in the table.

No.	Detector	Two-Parameter Distribution	P-Value	Estimated Parameters
1	Cascade 10.9	Normal	0.1218	μ =1.80E+06 , σ= 750260.66
2	Cascade 32.5	Normal	0.5231	μ = 1.61E+06, σ= 876392.44
3	Cascade 54.9	2P-Exponential	0.3270	$f(t) = \mu\, e^{-\mu(t-\gamma)}$ μ = 1.09E+06, γ= 239039
4	Cascade 80.1	Normal	0.3190	μ = 1.51E+06, σ= 746660.88
5	Cascade 96.8	Normal	0.1276	μ =1.51E+06, σ= 926869.48
6	Cranbrook 24.7	Normal	0.2320	μ =1.78E+06, σ= 641449.46
7	Cranbrook 40.3	Normal	0.3731	μ =1.84E+06, σ= 707654.63

8	Cranbrook 65.3	Normal	0.9927	μ =1.52E+06, σ=777069.04
9	Cranbrook 86.8	Normal	0.9645	μ =985163.49, σ=696449.24
10	Fording River 5.3	Normal	0.5757	μ =1.47E+06, σ=708845.85
11	Mountain 14.2	Normal	0.8490	μ =1.55E+06, σ=680470.92
12	Mountain 39.3	Normal	0.1273	μ = 1.24E+06, σ=486831.25
13	Mountain 44.9	Normal	0.1501	μ = 700789.25, σ=405854.99
14	Mountain 54.5	Gamma	0.4180	μ =11.26, k= 0.94
15	Mountain 70.9	Normal	0.1482	μ =1.40E+06, σ=624290.59
16	Mountain 74.8	Gamma	0.2820	μ =13.02, k=3.01
17	Mountain 95.1	Normal	0.4617	μ =1.33E+06, σ=668955.26
18	Mountain 111.7	2P-Weibull	0.0484	$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \exp(-(\frac{t}{\eta})^{\beta})$ β=2.08, η=1.55E+06
19	Shuswap 19.7	Normal	0.3789	μ = 1.57E+06, σ= 819386.84
20	Shuswap 40.8	Normal	0.0025	μ = 1.73E+06, σ= 767874.54
21	Shuswap 59.1	Normal	0.1061	μ = 2.06E+06, σ= 638682.49
22	Shuswap 77.4	Normal	0.6367	μ = 1.62E+06, σ= 620770.69
23	Shuswap 77.5	Normal	0.6437	μ = 1.20E+06, σ= 703775.16
24	Shuswap 90	Normal	0.8976	μ =196481.61, σ= 99822.57
25	Shuswap 97.9	Normal	0.5271	μ =1.47E+06, σ= 687847.01
26	Shuswap 118.5	Normal	0.0272	μ =1.61E+06 , σ= 668546.59
27	Thompson 11.8	Normal	0.0461	μ =1.74E+06, σ=710223.72
28	Thompson 35.5	Normal	0.5446	μ =1.72E+06, σ= 564411.35
29	Thompson 44.3	Normal	0.8203	μ =1.66E+06, σ= 678827.51
30	Thompson 60.5	Normal	0.9971	μ =1.21E+06 , σ= 708236.77
31	Thompson 81.9	Normal	0.4129	μ =1.36E+06 , σ= 736855.69
32	Thompson 98.1	Normal	0.2438	μ =1.43E+06, σ= 782413.91
33	Windermere 8.5	Normal	0.9674	μ =1.54E+06, σ= 512877.71
34	Windermere 25.2	Normal	0.7927	μ =1.77E+06, σ=550610.61
35	Windermere 50.4	Normal	0.7712	μ =1.13E+06, σ= 489756.76
36	Windermere 54.7	Normal	0.6951	μ =1.25E+06, σ=843421.32
37	Windermere 97.2	Gamma	0.9529	μ =12.51, k=4.76
38	Windermere 113.4	2P-Exponential	0.7048	$f(t) = \mu\, e^{-\mu(t-\gamma)}$ μ = 384530.89, γ= 319757
39	Windermere 123.3	Normal	0.9698	μ =1.60E+06, σ= 626453.69

Table 5-7: Final two-parameter fitted distributions and their estimated parameters

Now that the distributions are finalized and the parameters are calculated, a variety of plots and results can be obtained from the analysis. Two-sided confidence bounds for a 90% confidence level are considered. Figure 5-7 presents the plots of reliability over time and the plots of failure rate over time for Mountain 95.1. Appendix C shows the reliability vs. time and failure rate vs. time plots for all the detectors in the corridor of the study.

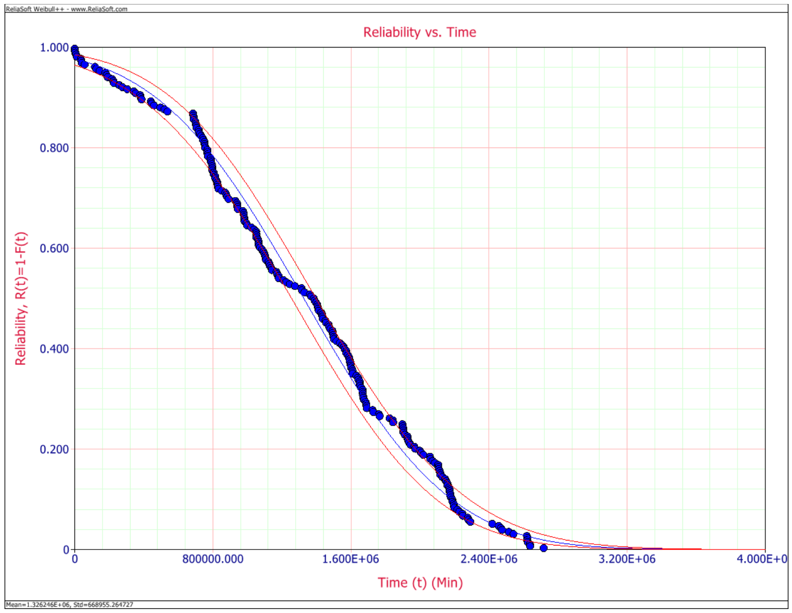


Figure 5-6: Reliability-time plot for Mountain 95.1

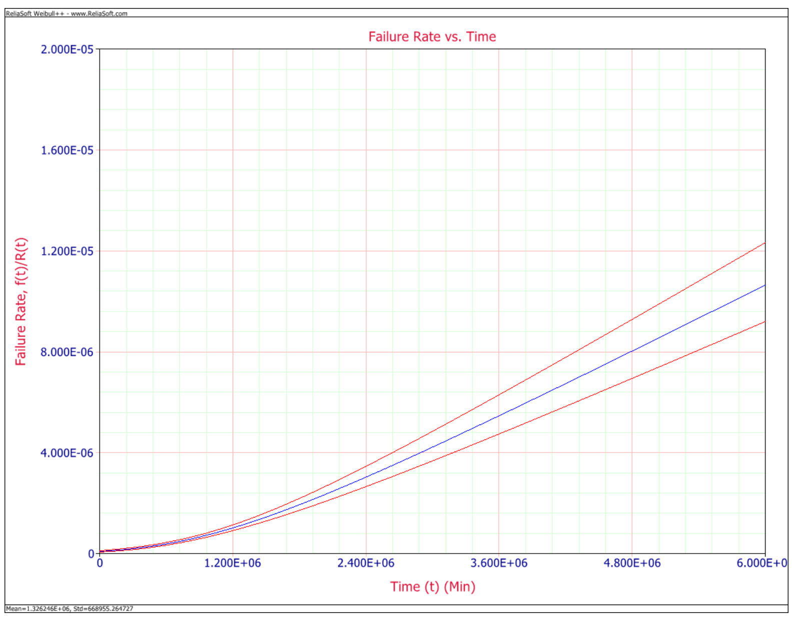


Figure 5-7: Failure rate-time plot for Mountain 95.1

Reliability plots and failure rate plots help in estimating the life characteristics of the WTDs. Another result that can be useful for industry is the degree of reliability of the WTDs. In this study, one year is the time span considered for calculating reliability. The results are summarized in the following table. The values are presented in percentages and demonstrate the probability that a WTD operates effectively for a specific time period. For Cascade 10.9 has a 95% chance of operating successfully after one year in use. Mountain 54.5 and Shuswap 90 have the least reliability degree after one year, while Shuswap 59.1 has the highest.

No.	Detector	Reliability (t=1 yr)	No.	Detector	Reliability (t=1 yr)
1	Cascade 10.9	96%	21	Shuswap 59.1	99%
2	Cascade 32.5	97%	22	Shuswap 77.4	96%
3	Cascade 54.9	82%	23	Shuswap 77.5	83%
4	Cascade 80.1	91%	24	Shuswap 90	0%
5	Cascade 96.8	95%	25	Shuswap 97.9	92%
6	Cranbrook 24.7	98%	26	Shuswap 118.5	95%
7	Cranbrook 40.3	97%	27	Thompson 11.8	96%
8	Cranbrook 65.3	90%	28	Thompson 35.5	98%
9	Cranbrook 86.8	75%	29	Thompson 44.3	95%
10	Fording River 5.3	91%	30	Thompson 60.5	83%
11	Mountain 14.2	93%	31	Thompson 81.9	87%
12	Mountain 39.3	93%	32	Thompson 98.1	88%
13	Mountain 44.9	67%	33	Windermere 8.5	98%
14	Mountain 54.5	0%	34	Windermere 25.2	98%
15	Mountain 70.9	92%	35	Windermere 50.4	89%
16	Mountain 74.8	89%	36	Windermere 54.7	81%
17	Mountain 95.1	88%	37	Windermere 97.2	94%
18	Mountain 111.7	90%	38	Windermere 113.4	68%
19	Shuswap 19.7	90%	39	Windermere 123.3	96%
20	Shuswap 40.8	94%			

Table 5-8: Estimated time of reliability for each of the detectors

To determine the difference between selecting a two-parameter distribution and the distributions selected by the software, the detectors in each subdivision need to be subjected to the comparative assessment that was done for the fitted distribution ranked first by the software and the two-parameter distribution. This part of the analysis works on any maintenance, inspection or operation practices on a subdivision-based rather than detector-based word missing here.

No.	Subdivision	Software first Rank Fitted Distribution	P-Value	Two-Parameter Distribution	P-Value
1	Cascade	G-Gamma	0.2705	Normal	0.0119
2	Cranbrook	G-Gamma	0.3134	Normal	0.0973
3	Fording River	G-Gamma	0.9851	Normal	0.5757
4	Mountain	3P-Weibull	0.0075	Normal	0.0053
5	Shuswap	Normal	0.0011	Normal	0.0011
6	Thompson	G-Gamma	0.1233	Normal	0.0066
7	Windermere	G-Gamma	0.8171	Normal	0.7938

Table 5-9: P-Value comparison between normal and other two-parameter distributions

Appendix C shows the PDFs of normal distributions fitted to the data set for each subdivision. Fig. 5-7 shows the PDF related to Cascade subdivision:

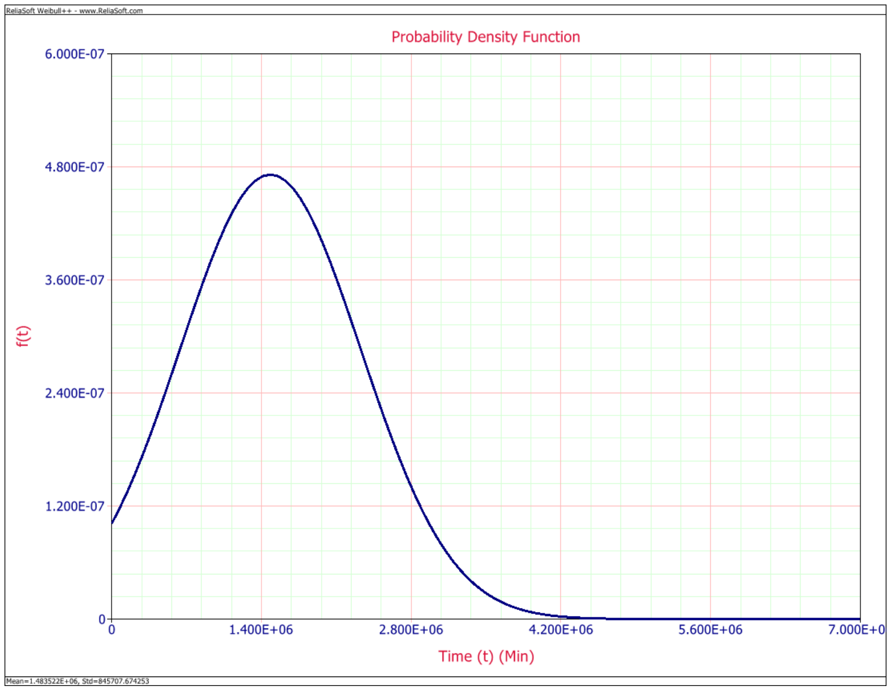


Figure 5-8: Probability density functions for Cascade subdivision

Taking into consideration the GOF test results, the normal distribution can be selected as the appropriate model. The reliability function for the detectors can then be defined by:

$$f(t) = \frac{1}{\sigma\ (2\pi)^{1/2}}\ exp\ [-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2\ ] \qquad \text{Equation 5-5}$$

Where the associated parameters, mean (μ) and standard deviation (σ), along with GOF results for each subdivision are shown in the following table:

No.	Subdivision	2-Parameter Distribution	P-Value	Estimated Parameters
1	Cascade	Normal	0.0119	μ=1.48E+06, σ=845707.67
2	Cranbrook	Normal	0.0973	μ=1.63E+06, σ= 751655.78
3	Fording River	Normal	0.5757	μ=1.47E+06, σ=708845.85
4	Mountain	Normal	0.0053	μ=1.24E+06, σ=719077.73
5	Shuswap	Normal	0.0011	μ=1.54E+06, σ=764593.18
6	Thompson	Normal	0.0066	μ=1.55E+06, σ=730971.49
7	Windermere	Normal	0.7938	μ=1.39E+06, σ=636503.64

Table 5-10: GOF results and the estimated parameters for each subdivision

Appendix C shows the plots of against time and failure rate against time to the data set for each subdivision. The plots for the Cascade and the Mountain subdivisions are as follows:

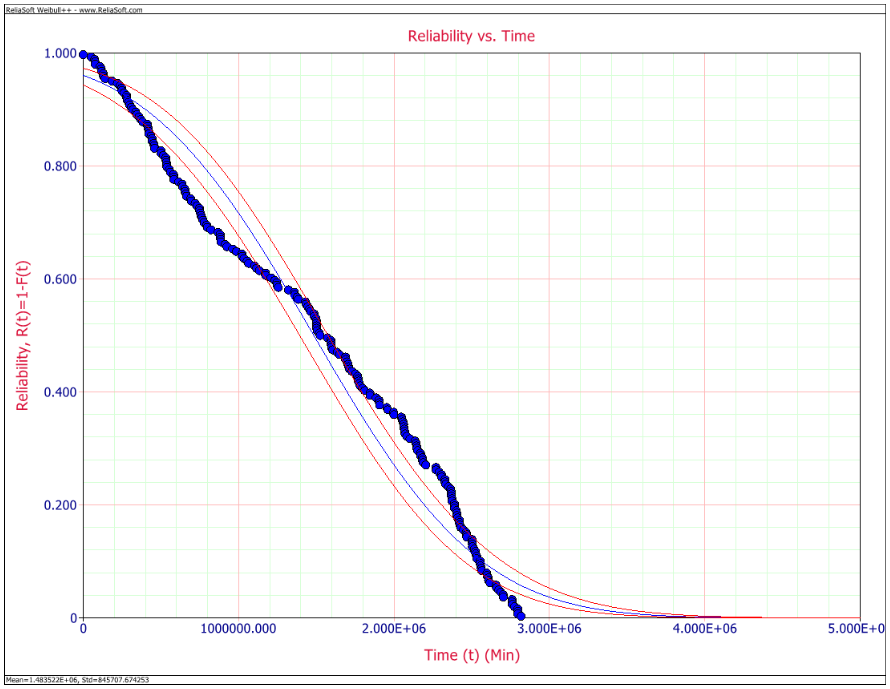


Figure 5-9: Reliability vs time for Cascade subdivision

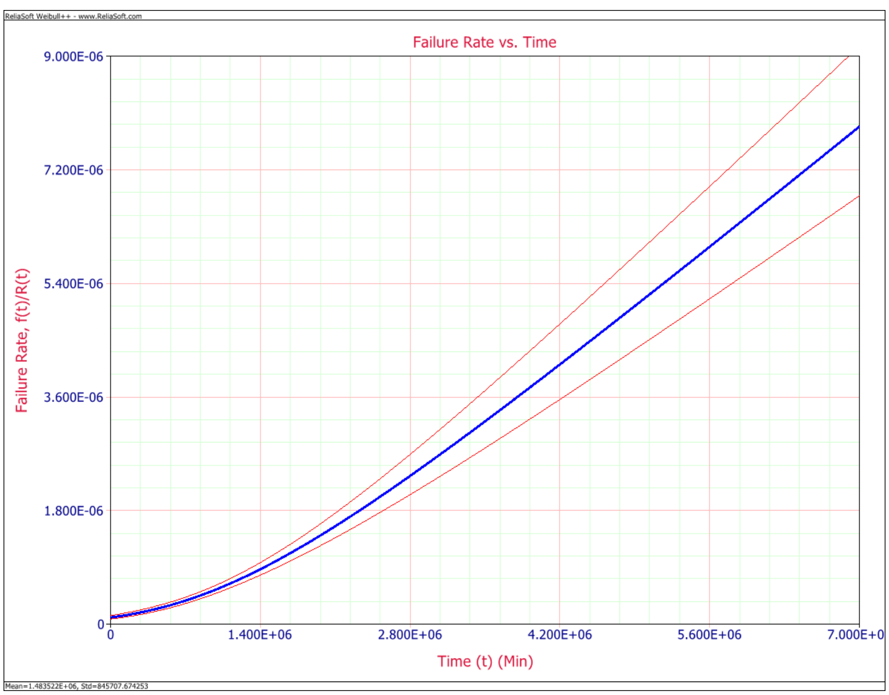


Figure 5-10: Failure rate vs time plots for Cascade subdivision

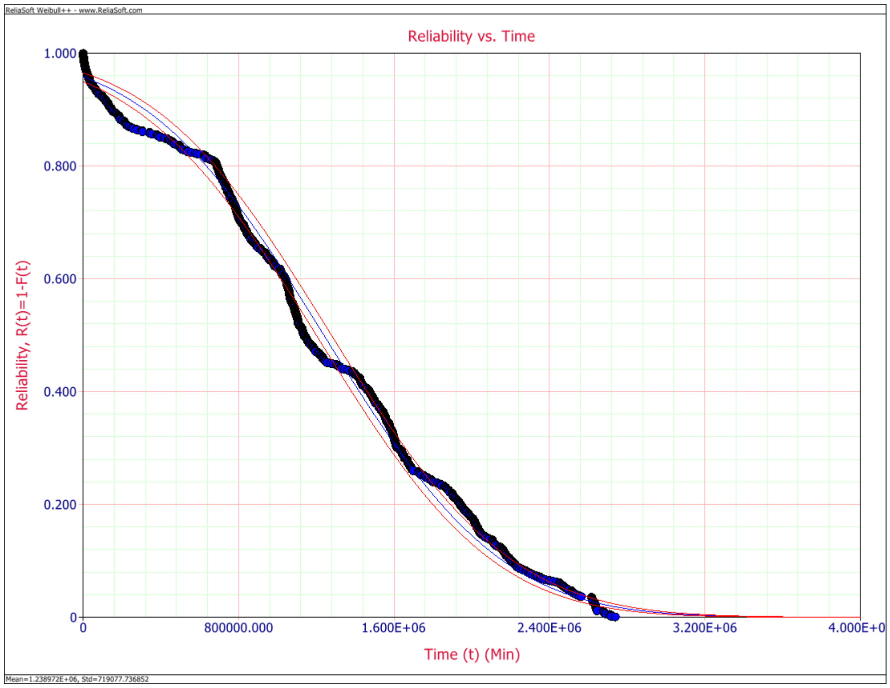


Figure 5-11: Reliability vs time for Mountain subdivision

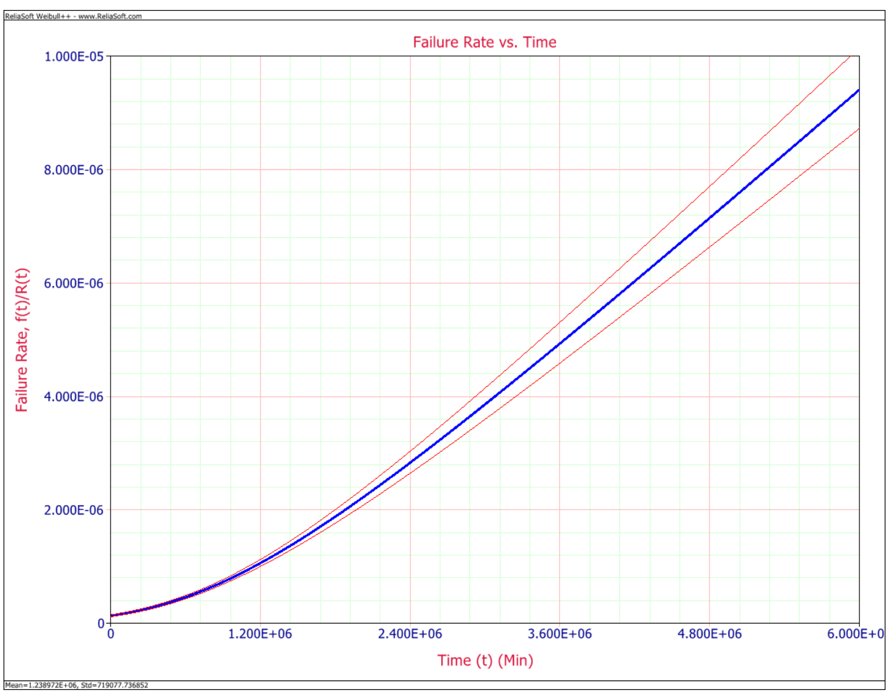


Figure 5-12: Failure rate vs time plots for Mountain subdivision

In this phase of the analysis, the times-to-failure of all the detectors are consolidated into one dataset and the pattern of probability function is as follows:

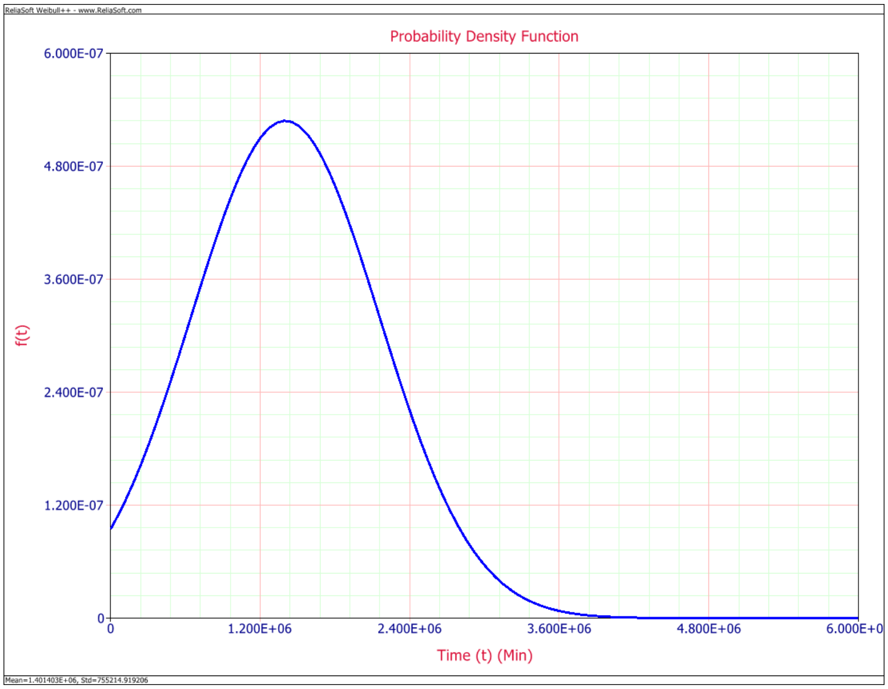


Figure 5-13: Estimated probability function for all failure data

A normal distribution seems to be the proper model for reliability and predicting failure. As this distribution is a two-parameter distribution, there is no need to make any comparative assessment and therefore it is selected as the final model.

$$R(t) = \frac{1}{\sigma\ (2\pi)^{1/2}}\ exp\ [-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2\ ] \qquad \text{Equation 5-6}$$

Where:

μ = 1.40E+06

σ = 755214.91

Fig. 5-10 shows the reliability versus time, which gives the probability of a detector's survival over time:

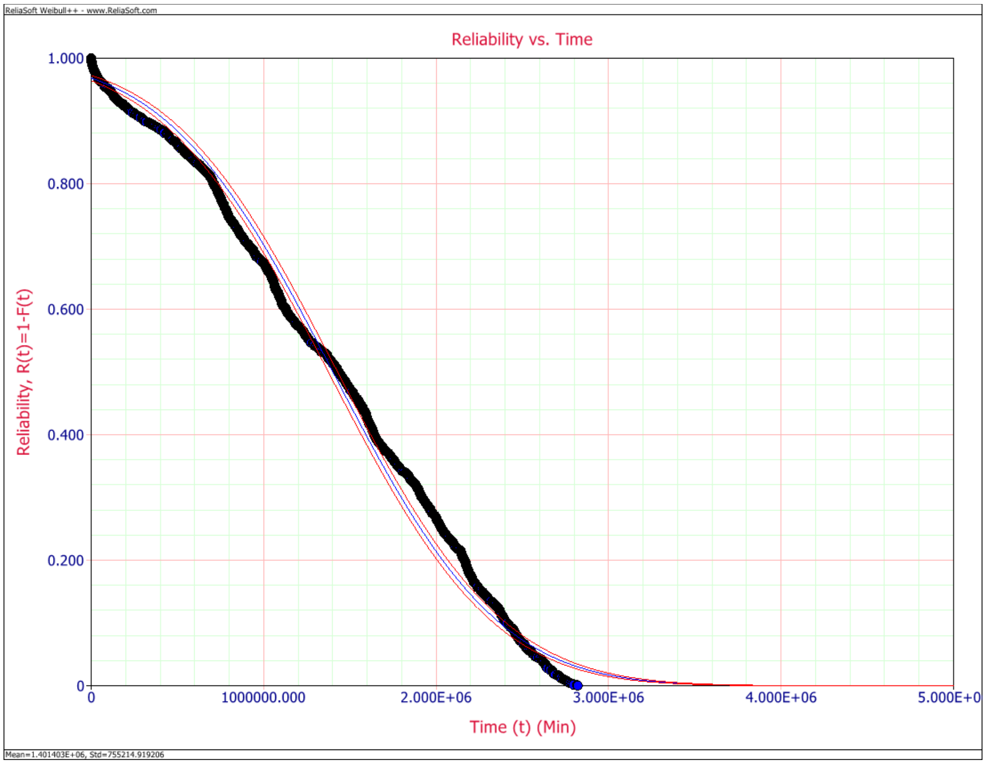


Figure 5-14: Reliability function for all the data

The next plot displays the failure rate versus time.

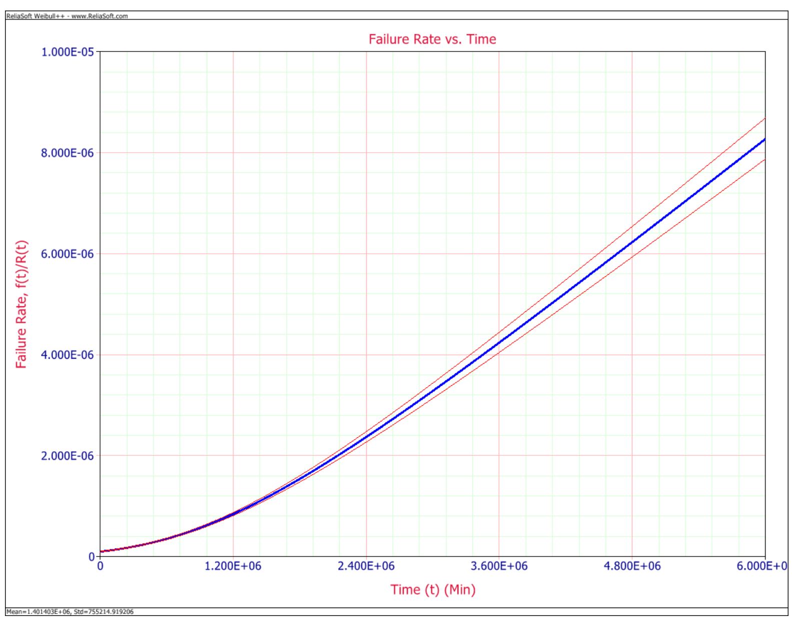


Figure 5-15: Failure rate vs time for all data

The following plots show the PDF, reliability, and failure rate for all the data together, along with the PDF, reliability and failure rate related to the detector with the least degree of reliability (Shuswap 90) and the one with the highest degree (Shuswap 59.1). These multiple plots on one graph provide a better view and comparison of the detectors' condition.

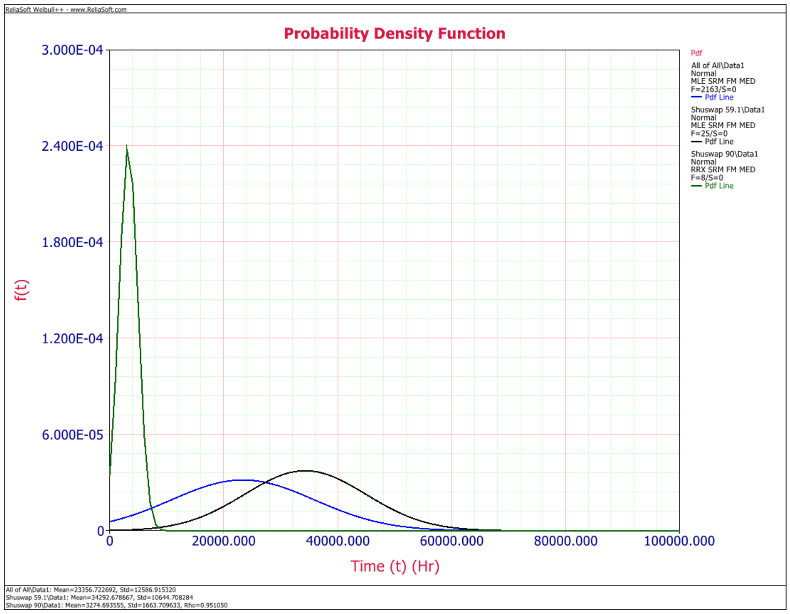


Figure 5-16: Overlay plot of PDF of all the detectors the detector with the maximum reliability, and the detector with the minimum reliability

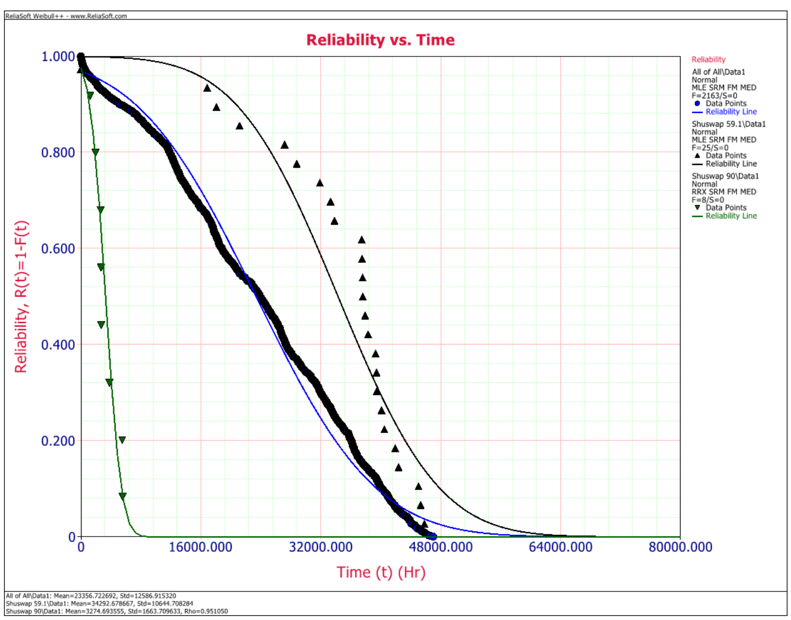


Figure 5-17: Overlay plot of reliability vs. time of all the detectors the detector with the maximum reliability and the detector with the minimum reliability

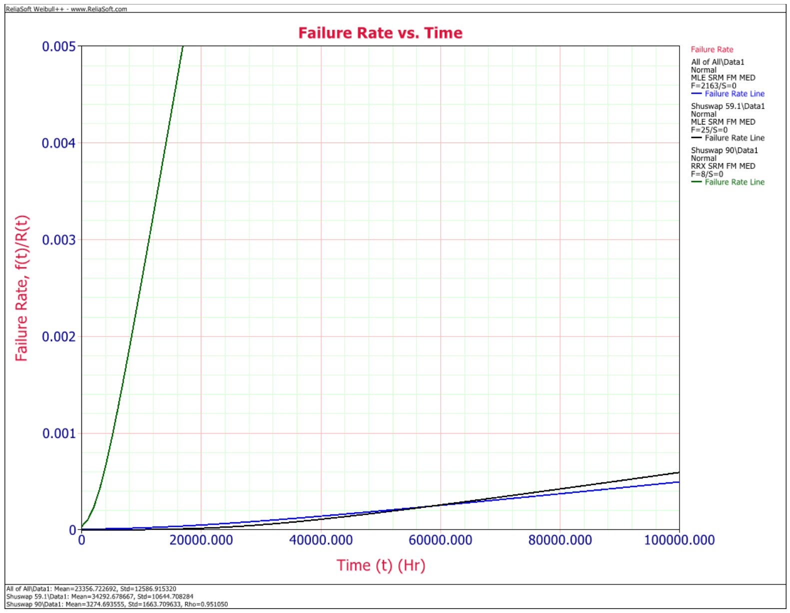


Figure 5-18: Overlay plot of failure rate vs. time of all the detectors the detector with the maximum reliability, and the detector with the minimum reliability

5.1.1. Winter Time Analysis

Chapter 4 showed that most detector failures occur during winter. The higher number of failures affects the reliability and functionality of the WTD systems. To analyze this effect, the reliability based on the failures that occurred during cold weather conditions is modeled. Figure 5-19, based on historical data from 1999 to 2012, shows typical weather at the Golden Airport weather station over the course of an average year (Weatherspark).

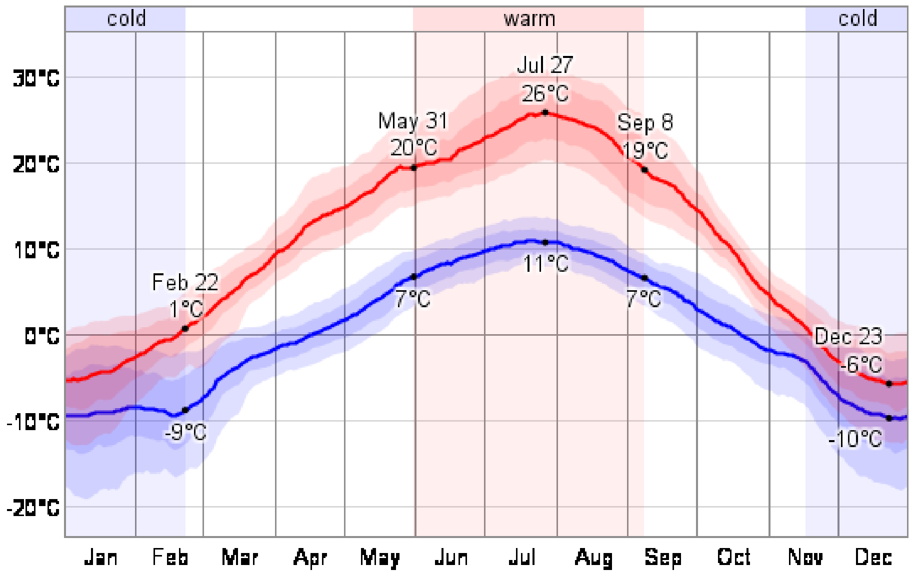


Figure 5-19: The daily average low (blue) and high (red) temperature at the Golden Airport weather station

The warm season is approximately from May 31 to September 8 with an average temperature above 20°C, and the cold season is from November 17 to February 22 with an average temperature of 1°C. In line with this trend, the months of November, December, January and February are cold months, and therefore the failures of all of the detectors for these months were considered for reliability analysis. The winter analysis needed to be done on a yearly basis. The failure data of all the detectors in each year from 2009 to 2013 were extracted from the data base. For example, when analyzing winter 2010, the failures that occurred in November and December 2009 were considered along with the failures that occurred in January and February 2010. Time-to-fail was calculated and the best distribution was fitted to the data. The PDFs of the winter failures are presented in an overlay plot (figure). The overlay plot shows the results of the failure data sets in winters 2010, 2011, 2012, and 2013 in one plot. The overlay plot shows the results of the multiple data sets in one plot. This allows us to compare the failure data of the different winters:

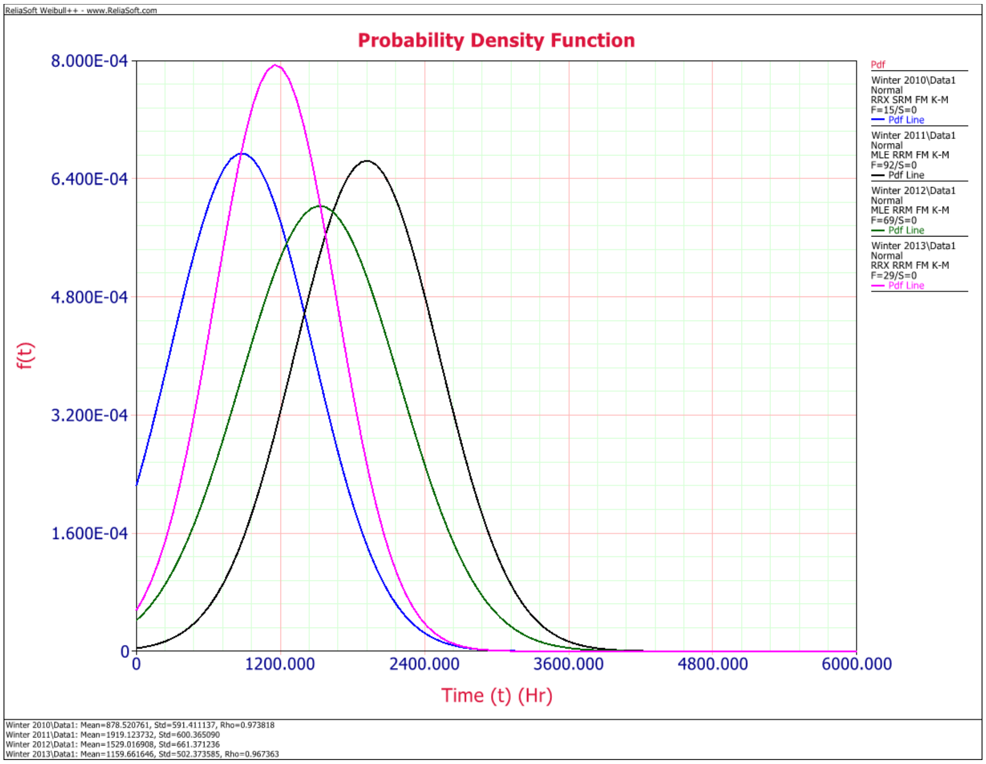


Figure 5-20: Overlay PDF plot of winters 2010, 2011, 2012, and 2013 failures

Normal distribution was the proper fit to all of the data sets.

$$f(t) = \frac{1}{\sigma(2\pi)^{1/2}} exp\,[-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2] \qquad \text{Equation 5-7}$$

The associated estimated parameters for the winter failures of each year are summarized as follows:

No.	Time Period	Estimated Parameters
1	Winter 2010	μ=52711.24, σ=35484.66
2	Winter 2011	μ=115147.42, σ=36021.90
3	Winter 2012	μ=91741.01, σ=39682.27
4	Winter 2013	μ=69579.69, σ=30142.41

Table 5-11: Summary of the estimated parameters of all the detectors in different winters

Fig. 5-15 shows the overlay plots of reliability time and failure rate time for winters 2010, 2011, 2012, and 2013.

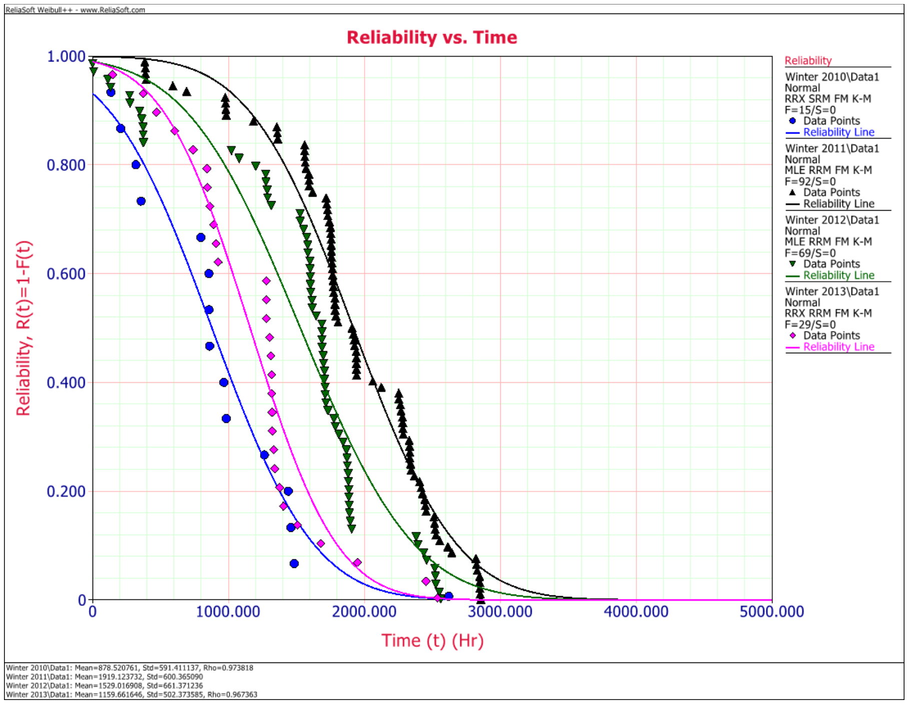


Figure 5-21: Reliability time for all the detectors' failures during winters 2010, 2011, 2012, and 2013

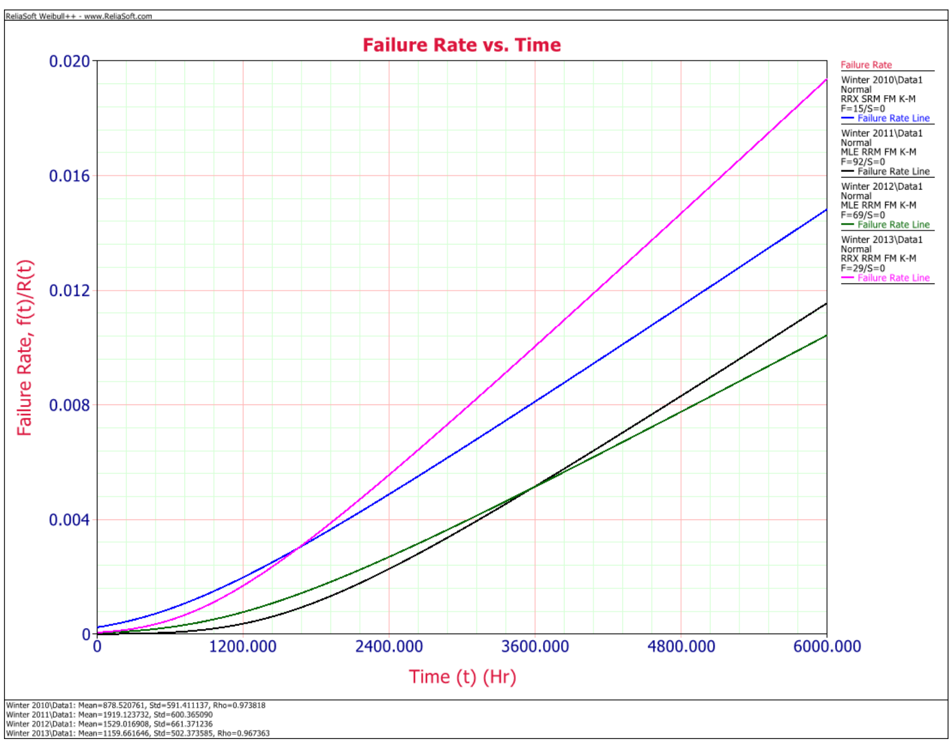


Figure 5-22: Failure rate time for all the detectors' failures during winters 2010, 2011, 2012, and 2013

A pattern and trend can be observed for the winter failures. Winter 2013 has the highest failure rate and winter 2012 has the lowest. When taking into consideration the weather trend and the average temperature during the winter months (Nov-Feb) of 2010, 2011, 2012, and 2013 (The weather network), the higher failure rate cannot be attributed only to the cold weather: clearly there were other factors that need to be identified.

5.2. Application in maintenance practices

One of the reasons for undertaking this research is to improve the maintenance of the wheel detection system by assessing the reliability of the detectors, and to increase their availability by reducing their failure rate and downtime through improvement in maintenance practices. Maintaining the detection systems involves different skills. Therefore, a number of different perspectives should be considered for improved efficiency in maintenance (Morant, 2014). The availability of the detection system can be improved by focusing maintenance at essential intervals (Awan, 2014). To achieve effective preventive maintenance, it is important to define the optimal intervals (Morant, 2014). This part of the study investigates the time between failures to show the potential for reduced outage time resulting from the implementation of a proactive maintenance cycle. The time between the failures provides industry decision-makers with better insight into the condition of the detectors, which will help in designing maintenance routines. Predicting the detectors' failures in advance and managing the scheduled maintenance and inspection based on that will increase reliability.

Other factors that should be considered for maintenance decision-making include the current maintenance plan, availability of the maintenance crew, and availability of spare parts. Case-specific information such as the report after each inspection and maintenance should also be taken into consideration (Awan, 2014).

MTBF is a statistic that is of great interest to the railway industry. The mean time between failures is applied in case the system can be repaired, restored, and put back into service. MTBF is the average time between the failures that does not take into account the outage time and time to repair; it measures only the time a system was operating. MTBF is calculated by the following equation:

$$MTBF(t) = \frac{t}{N(t)}$$ Equation 5-8

Where,

t: Cumulative operating time

N(t): Number of failures in time t

The following tables respectively encompass the calculated MTBF for each detector and subdivision. The unit of the reported MTBFs is in years.

No.	Detector	Mean Life (Yr)	No.	Detector	Mean Life (Yr)
1	Cascade 10.9	3.4	21	Shuswap 59.1	3.9
2	Cascade 32.5	3.0	22	Shuswap 77.4	3.0
3	Cascade 54.9	2.5	23	Shuswap 77.5	2.2
4	Cascade 80.1	2.8	24	Shuswap 90	0.3
5	Cascade 96.8	2.8	25	Shuswap 97.9	2.7
6	Cranbrook 24.7	3.4	26	Shuswap 118.5	3.0
7	Cranbrook 40.3	3.5	27	Thompson 11.8	3.3
8	Cranbrook 65.3	2.8	28	Thompson 35.5	3.2
9	Cranbrook 86.8	1.8	29	Thompson 44.3	3.1
10	Fording River 5.3	2.8	30	Thompson 60.5	2.3
11	Mountain 14.2	2.9	31	Thompson 81.9	2.5
12	Mountain 39.3	2.3	32	Thompson 98.1	2.7
13	Mountain 44.9	1.3	33	Windermere 8.5	2.9
14	Mountain 54.5	0.1	34	Windermere 25.2	3.3
15	Mountain 70.9	2.6	35	Windermere 50.4	2.1
16	Mountain 74.8	2.6	36	Windermere 54.7	2.3
17	Mountain 95.1	2.5	37	Windermere 97.2	2.4
18	Mountain 111.7	2.6	38	Windermere 113.4	1.3
19	Shuswap 19.7	2.9	39	Windermere 123.3	3.0
20	Shuswap 40.8	3.2			

Table 5-12: The mean time between failure for each detector

No.	Detector	Mean Life (Yr)
1	Cascade	2.8
2	Cranbrook	3.0
3	Fording River	2.8
4	Mountain	2.3
5	Shuswap	2.9
6	Thompson	2.9
7	Windermere	2.6

Table 5-13: The mean time between failure for each subdivision

When considering together, the detectors have an average failure time of 2.7 years.

Since the data meet the assumptions of normality, the mean time between failures is the same as the mean value and "the probability that a randomly selected value is above the mean equals 0.5" (Weinberg, and Abramowitz, 2008, p.205). This implies that 50% of the failures have occurred before 2.7 years, and that by scheduling maintenance or inspection intervals before this time period, 50% of the failures can be prevented while another 50% would be missed. The likelihood that a randomly designated value is lower than a particular score x is determined "by calculating the area under the normal distribution curve to the left" (Weinberg and Abramowitz, 2008, p. 205). Depending on the industry decision-maker's discretion and considering important factors such as cost and resources, it is possible to identify the percentage of failures that could be avoided. Using a z-score and standard normal distribution table (Appendix D), the area under the normal PDF curve was calculated. This shows what time period is required to avoid a certain percentage of the failures. The z-score is written as follows (Fitz-Gibbon et al., 1987):

$$Z = \frac{x - \mu}{\delta} \quad \sigma \neq 0 \qquad \text{Equation 5-9}$$

The mean and standard deviation values for all the detectors failure data are:

$\mu = 1.40E+06$

$\sigma = 755214.9192$

These values were put in the z-score formula and x was calculated for the assumed percentages. For the analysis, 25% and consequently 75% were considered as examples.

The schematics below depict the results:

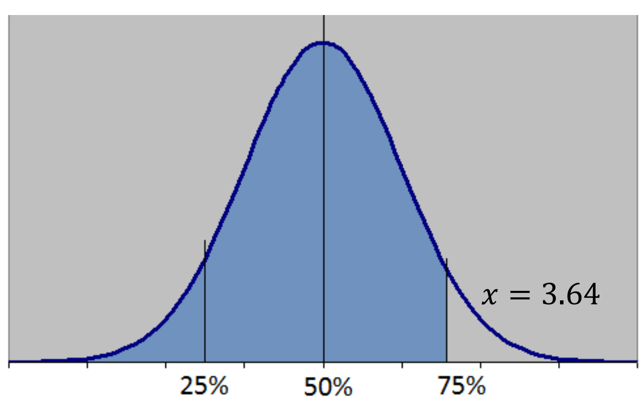


Figure 5-23: 75% of the failure population happens before x

The area under the curve (z-score) is drawn from the table and the value x which in our case study represents the time interval that there is a probability of occurrence of 75% of the failures, calculated as 3.64 (years) using Equation 5-9 and the values of mean and STD.

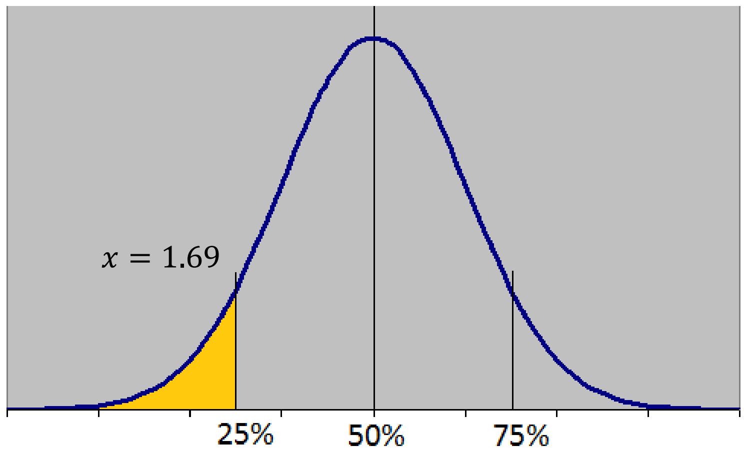


Figure 5-24: 25% of the failure population happens before x

Using the same method, the time interval that the probability of failure is 25% has been calculated as 1.69 years. This implies that for preventing 75% of the failures, the maintenance intervals should be set less than 1.69 years and if they are set to more than the mean value (2.7 years), it is probable that 75% of the failures are being missed.

The mean time between failures in winter time are also calculated and summarized in Table 5-14. As four months of the year are being considered as winter time, the MTBFs are reported in months.

Time period	MTBF (Mon)
Winter 2010	1.2
Winter 2011	2.6
Winter 2012	2.0
Winter 2013	1.5

Table 5-14: The mean time between failure for all the detectors in winter

5.3. Conclusion

Applying real-time failure data, the reliability functions and the associated parameters were obtained for each detector as well as each subdivision. In addition, by considering the failure data of all the detectors as one integrated data set, the related reliability function was achieved. Collecting more accurate data regarding the time of failure and the time of issue of the maintenance ticket, or at least having an estimation of how long it normally takes to issue a maintenance ticket can make reliability modeling more accurate.

Normal distribution was finalised as the best fit and as the function that can be used to predict the trend of failures and model reliability. But six out of 40 detectors did not fit the normal distribution. To determine why, a more in-depth study is required. Various factors can cause this inconsistency. Some are related to the detectors and the way they are maintained and repaired. For example, a skewing of data can be caused by variability in the time spent repairing the detectors, the stage at and duration over which the failures have occurred, and whether the failures have occurred late in the detectors' life-span or early. Some of the errors are related to data collection, and can be traced to the level of training and consistency of service of the people responsible for collecting and recording the data, and the technology used for this purpose. Some could be as a result of external random processes such as weather conditions. It could beneficial for the railways to interpret these results along with the failure data to investigate why the detectors do not fit into the normal distribution.

In order to improve the maintenance practices and be proactive rather than reactive, the maintenance and inspection intervals could be set by considering the MTBF. Applying the reliability models and the estimated parameters, the MTBF was calculated for each of the detectors and all of them together throughout the whole time period of the study (2009-2013) and in the winter times, which can be used to devise maintenance intervals. The time required for preventing 25% and 75% of the failures were also calculated and presented as examples to give an understanding about how the probability of failures is related to decreasing or increasing the maintenance intervals.

.

Chapter 6. Conclusions and Future Work

6.1. Conclusion

The results of this study are beneficial for improved interpreting of the measurements gathered by the wheel temperature detectors (WTDs) and understanding the failure pattern of the WTDs, both of which provide information on the status and conditions that influence the decision-making process concerning planning of maintenance activities.

This study showed that data collection alone is not sufficient; it is the methods and processes of extracting the right information and understanding the outputs that can improve the decision-making process. The reliability of the wheel temperature detectors was modeled, the degree of reliability showed that WTDs are relatively reliable systems. Reliability-based preventive maintenance intervals have also been suggested. The results being offered by this study—the reliability functions, failure rates, and the mean time between failures—are all important parameters that have been observed; tracking these reliability metrics provides an organization with tools that are helpful in the decision making process. Inspections at intervals shorter than the MTBF for each location and planned maintenance intervals shorter than the MTBF will likely reduce the impact of external factors such as weather conditions, thereby increasing the effectiveness of the operations (Xia et al., 2013).

Analyzing the maintenance data is known as part of the solution for improving system performance, but a well-structured database that contains accurate and complete data is essential, along with good contextual decision criteria related to the data. Currently, data are being collected by the maintenance department, so resources are being allocated and consumed merely for data collection. More accurate and effective data collection would increase the functionality and efficiency of the process. This entails a process of simple tasks, such as logging WTD system events in more detail, recording all observations that may be pertinent (even the ones that do not seem to be crucial), logging the decisions made in different situations, noting any case-specific information (such as the report prepared by inspectors), and documenting any modification made in the system.

6.2. Recommendations to Industry

Results of the analysis of the CP data base containing maintenance records indicate that some area-specific information logistics management could be improved. The below offers some suggestions for improvement:

1. Make the collected information and data more visible for better failure identification and consequently improve maintenance and inspections. The database should be structured in a way that allows a system's historical data to be available to check the inspections and maintenance that have been carried out over time;
2. Modify control management, i.e., record all the changes in a system such as replacing an old system with a new one, as well as the reasons for the changes;
3. Document procedures of the diagnostic and repair process, including explanations of how to proceed from identifying and reporting a failure to closing the work order; parameters that can be described in the corrective maintenance record file could include but not be limited to the following: the date the work order (WO) was opened, the WO notification date, on the way dates, corrective action start date, failure identification date, the date corrective action ended, the date the WO was closed, the response time, the repair time, the symptom of the failure, the cause of the failure, and the failure location (Morant, 2014);
4. Emphasize training of the maintenance workers to show them the importance of accurate data gathering and recording, and encourage them to complete all of the required information on each maintenance record file;
5. Structure the knowledge base of the company about maintenance changes in routines, procedures, and systems so that organizational learning has positive effects on maintenance improvement (Luxhøj et al., 1997), and encourage individual learning or problem solving programs in maintenance (Morant, 2014);
6. Establish correlations amongst the three systems of interest—Air brakes, WTD readings/detection process, and maintenance/inspection records—to determine relationships that could be applied in detecting and identifying failures more effectively;

7. Consider qualitative defenses against systematic failures as an additional activity in predicting the probability of random hardware failures; because systematic failure and software failure rates could not be quantified, they cannot be generally predicted;
8. Apply a knowledge management program to keep institutional knowledge of the WTD system and related maintenance actions; this is one way to lower the risk of dependency on the expertise of individuals;
9. Develop knowledge transfer among the stakeholders involved in the maintenance of the detection systems so that they all share knowledge and information for more holistic viewpoints and perceptions of what are best practices to improve performance;
10. Adopt railway-related standards and best practices that are successfully used in other jurisdictions, e.g., European railways;
11. Evaluate alternative inspection equipment such as handheld noncontact thermal sensors and other modern diagnostic tools.

These recommendations will only be effective where there is a corporate culture that values evidence-based decision making and retaining corporate knowledge. The importance and effect of each task involved in the maintenance plan, even the simplest ones, should be mentioned and accepted by all personnel.

6.3. Future work

The present work is part of the long-term goal of improving cost-effective and reliable rail operations through system knowledge and context-based decision making. Further work could be oriented towards the following:

1. Adopting a complete RCM program for the maintenance of the detection systems as well as other systems that are in use by railways;
2. Carrying out an economic analysis to see the feasibility of replacement of RCM for current maintenance practices;
3. Implementing a maintenance management system (MMS) with basic requirements such as a list of equipment that requires maintenance, maintenance instructions, daily and weekly schedules, and a preventive maintenance plan could be considered;

4. Conducting a feasibility study and cost-benefit analysis of upgrading the current system to an on-board monitoring system (or applying both systems in parallel);
5. Comparing the level of train stoppage reduction achieved by replacing the current procedures with new ones to check the capability and the potential of the new processes.

References

- A.Clifford Cohen, Betty Jones Whitten. *"Parameter Estimation in Reliability and Life Span Models"* Volume 96 of Statistics: A Series of Textbooks and Monographs , 1998.
- Achuthan, K.N., Keerthana, R., AUTOMATED AXLE/WHEEL HEAT MEASUREMENT, Proceedings of IRF International Conference, Bangalore, 2014, ISBN: 978-93-82702-68-9
- Acock, Alan C. *A gentle introduction to Stata*. Stata press, 2008.
- Aronian, Abe, Michelle Jamieson, "Update on Technology Driven Train Inspections at Canadian Pacific." 2014 Air Brake Association' conference, 2014.
- Aronian, Abe, Michelle Jamieson, and Kim Wachs. "Automated Train Brake Effectiveness (ATBE) Test Process at Canadian Pacific." 2012 Joint Rail Conference. American Society of Mechanical Engineers, 2012.
- Awan, Waqas Amir. *Waqas Amir Awan*. Diss. University of Alberta, 2014.
- B Newell, Benjamin R., David A. Lagnado, and David R. Shanks. *Straight choices: The psychology of decision making*. Psychology Press, 2007.
- Barabady, Javad, and Uday Kumar. "Reliability analysis of mining equipment: A case study of a crushing plant at Jajarm Bauxite Mine in Iran." *Reliability engineering & system safety* 93.4 (2008): 647-653.
- Barke, Derek, and W. K. Chiu. "Structural health monitoring in the railway industry: a review." *Structural Health Monitoring* 4.1 (2005): 81-93.
- Berggren, E. G. "Efficient track maintenance: methodology for combined analysis of condition data." *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit* 224.5 (2010): 353-360.

- Bernd Bertsche, *Reliability in automotive and mechanical engineering*, VDI-Buch, doi: 10.1007/978-3-540-34282-3_1, Springer – Verlag Berlin Heidelberg 2008

- Bodsberg, Lars, and Per Hokstad. "Transparent reliability model for fault-tolerant safety systems." *Reliability Engineering & System Safety* 55.1 (1997): 25-38.

- Bose, Ranjit. "Advanced analytics: opportunities and challenges." *Industrial Management & Data Systems* 109.2 (2009): 155-172.

- Brownlee, Kenneth Alexander, and Kenneth Alexander Brownlee. *Statistical theory and methodology in science and engineering*. Vol. 150. New York: Wiley, 1965.

- Canadian Nationals, Wayside Information System Technical Manual- May 1995

- Canadian Pacific , Red Book of S&C Requirements-Section 15 Hot Box Detector Testing After a Replacement, Repair, or Change, 2010

- Canadian Pacific Website. - www.cpr.ca

- Canavos, George C. *Applied probability and statistical methods*. Little, Brown, 1984.

- Chong, See Yenn, Jung-Ryul Lee, and Hye-Jin Shin. "A review of health and operation monitoring technologies for trains." *Smart Structures and Systems*6.9 (2010): 1079-1105.

- Crespo Márquez, A., et al. "The maintenance management framework: A practical view to maintenance management." *Journal of Quality in Maintenance Engineering* 15.2 (2009): 167-178.

- Crow, Edwin L., and Kunio Shimizu, eds. *lognormal distributions: Theory and applications*. Vol. 88. New York: M. Dekker, 1988.

- Du Prel, Jean-Baptist, et al. "Confidence interval or p-value?: part 4 of a series on evaluation of scientific publications." *Deutsches Ärzteblatt International* 106.19 (2009): 335-9.

- Ebeling, Charles E. *An introduction to reliability and maintainability engineering*. 2nd ed. Waveland Press, Inc., 2010.

- Emblemsvåg, Jan. "Business analytics: getting behind the numbers."*International Journal of Productivity and Performance Management* 54.1 (2005): 47-58.

- Fenton, Norman, and Martin Neil. *Risk assessment and decision analysis with Bayesian networks*. CRC Press, 2012

- Finkelstein, Maxim. *Failure rate modelling for reliability and risk*. Springer Science & Business Media, 2008.

- Fitz-Gibbon, Carol T., and Lynn Lyons Morris. *How to analyze data*. No. 8. Sage, 1987.

- Gelle, Esther, and Katja Karhu. "Information quality for strategic technology planning." *Industrial Management & Data Systems* 103.8 (2003): 633-643.

- Hajibabaia, H., et al. "Wayside defect detector data mining to predict potential WILD train stops." *Annual Conference and Exposition of the American Railway Engineering and Maintenance-of-Way Association (AREMA), Chicago, Illinois*. 2012.

- Hall, Robert A., and Laeeque K. Daneshmend. "Reliability modelling of surface mining equipment: data gathering and analysis methodologies."*International Journal of Surface Mining, Reclamation and Environment* 17.3 (2003): 139-155.

- Hansen, Geir Klingenberg, and Ragnar Aarø. "Reliability Quantification of Computer-Based Safety Systems. An Introduction to PDS." (1997): 1997.

- Jardine, Andrew KS, Daming Lin, and Dragan Banjevic. "A review on machinery diagnostics and prognostics implementing condition-based maintenance." *Mechanical systems and signal processing* 20.7 (2006): 1483-1510.

- Karim, R., (2008), *A Service-Oriented Approach to eMaintenance of Complex Technical Systems*, doctoral thesis, Luleå University of Technology, Luleå, Sweden.

- Kececioglu, Dimitri. “Relaibility and Life Testing Handbook Volume”, 2002.

- Khan, Faisal I., and Mahmoud M. Haddara. "Risk-based maintenance (RBM): a quantitative approach for maintenance/inspection scheduling and planning." *Journal of Loss Prevention in the Process Industries* 16.6 (2003): 561-573.

- Lagnebäck, Robert. Evaluation of wayside condition monitoring technologies for condition-based maintenance of railway vehicles. Luleå: Luleå University of Technology, 2007.

- Lavallé, Omer. "Canadian Pacific Railway". The Canadian Encyclopedia.Toronto: Historica Canada, 2008. Web. 7 Mar 2008.

- Leinum, Trygve. "Reliability of heat detector systems on an offshore production plant." *Reliability Engineering & System Safety* 36.1 (1992): 63-66.

- Lin, Jing, Julio Pulido, and Matthias Asplund. "Reliability analysis for preventive maintenance based on classical and Bayesian semi-parametric degradation approaches using locomotive wheel-sets as a case study."*Reliability Engineering & System Safety* 134 (2015): 143-156.

- Luxhøj, J.T., Riis, J.O. and Thorsteinsson, U., (1997), "Trends and Perspectives inIndustrial Maintenance Management", *Journal of Manufacturing Systems*, vol. 16, no.6, pp. 437-453

- Martin, K. F. "A review by discussion of condition monitoring and fault diagnosis in machine tools." *International Journal of Machine Tools and Manufacture* 34.4 (1994): 527-551.

- McGonigal Robert S., Defect detectors looking for trouble in all the right places, 2006, Trains Magazine, www. trn.trains.com

- Mendenhall, William, Robert Beaver, and Barbara Beaver. *Introduction to probability and statistics*. Cengage Learning, 2008.

- Morant, Amparo, et al. "Dependability improvement through configuration management, A study of railway signalling systems." *International Journal of COMADEM* (2013).
- Morant, Amparo, Per-Olof Larsson-Kråik, and Uday Kumar. "Data-driven model for maintenance decision support: A case study of railway signalling systems." *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit* (2014): 0954409714533680.
- Morant, Amparo. "Dependability and Maintenance Analysis of Railway Signalling Systems." (2014).
- Moubray, John. *Reliability centered maintenance*. Industrial Press, 1997
- Murthy, D. N. P., A. Atrens, and J. A. Eccleston. "Strategic maintenance management." *Journal of Quality in Maintenance Engineering* 8.4 (2002): 287-305.
- Palo, Mikael, et al. "Wheel/rail condition monitoring to support rolling stock maintenance actions." *Proceedings of 10th International Heavy Haul Association Conference*. 2013.
- Phoha, Shashi, and F. Thomas. "La Porta, Christopher Griffin, Sensor Network Operations." (2006)
- Poddar, Vivek, Reliability Centered Maintenance (RCM) and Ultrasonic Leakage Detection (ULD) as a maintenance and condition monitoring technique for freight rail airbrakes in cold weather conditions, University of Alberta, 2014.
- Pulido, Julio. "Reliability analysis for components under thermal mechanical loadings." *Reliability and Maintainability Symposium (RAMS), 2012 Proceedings-Annual*. IEEE, 2012.
- Railway Investigation Report R99T0031, http://www.tsb.gc.ca/, 1999
- Railway Investigation Report-R03T0080, http://www.tsb.gc.ca/, 2003.

- Rausand, Marvin, and Arnljot Høyland. *System reliability theory: models, statistical methods, and applications*. Vol. 396. John Wiley & Sons, 2004.
- ReliaSoft User's guide Weibull ++ version 6. USA: ReliaSoft Publishing; 2002
- Rezvanizaniani, S. M., et al. "Reliability Centered Maintenance for rolling stock: A case study in coaches' wheel sets of passenger trains of Iranian railway." *Industrial Engineering and Engineering Management, 2008. IEEM 2008. IEEE International Conference on*. IEEE, 2008.
- Schöbel, Andreas, Manfred Pisek, and Josef Karner. *Hot box detection systems as a part of automated train observation in Austria*. na, 2006.
- Sharma, Rajiv Kumar, Dinesh Kumar, and Pradeep Kumar. "Systematic failure mode effect analysis (FMEA) using fuzzy linguistic modelling."*International Journal of Quality & Reliability Management* 22.9 (2005): 986-1004.
- Söderholm, Peter. "A system view of the No Fault Found (NFF) phenomenon." *Reliability Engineering & System Safety* 92.1 (2007): 1-14.
- Stratman, Brant, Yongming Liu, and Sankaran Mahadevan. "Structural health monitoring of railroad wheels using wheel impact load detectors." *Journal of failure analysis and prevention* 7.3 (2007): 218-225.
- Swanson, Laura. "Linking maintenance strategies to performance."*International journal of production economics* 70.3 (2001): 237-244.
- Teng, Sheng-Hsien, and Shin-Yann Ho. "Failure mode and effects analysis: an integrated approach for product design and process control." *International Journal of Quality & Reliability Management* 13.5 (1996): 8-26.
- The Weather Network - US Coverage." *The Weather Network*. N.p., n.d. Web. 10 Apr. 2016.

- Torell, Wendy, and Victor Avelar. "Mean time between failure: Explanation and standards." *white paper* 78 (2004).

- Vaghar Anzabi, R., and M. G. Lipsett. "Reliability analysis & condition monitoring methods for off-road haul truck tires." Porccedings of the 24th Condition Monitoring and Diagnostic Engineering Management (COMADEM) Conference, May 30-June 1, Stavanger, Norway. 2011.

- Wang, John X. *What every engineer should know about decision making under uncertainty*. Vol. 37. CRC Press, 2002.

- Weatherspark-https://weatherspark.com/averages/28248/Golden-British-Columbia-Canada

- Weinberg, Sharon Lawner, and Sarah Knapp Abramowitz. *Statistics using SPSS: An integrative approach*. Cambridge University Press, 2008.

- Wikipedia, the free encyclopedia. This file is made available under the Creative Commons CC0 1.0 Universal Public Domain Dedication (https://creativecommons.org/publicdomain/zero/1.0/deed.en).

- Xia, Yuanni, et al. "Railway infrastructure disturbances and train operator performance: The role of weather." *Transportation research part D: transport and environment* 18 (2013): 97-102.

- Zoeteman, Arjen. "Life cycle cost analysis for managing rail infrastructure."*European journal of transport and infrastructure research EJTIR, 1 (4)*(2001).

Appendix A

Decoding raw temperature readings of the WTDs and extracting temperatures from scanners 1 and 2 of a detector, three or five neighbouring detectors with same axle count.

```
clc; close all; clear all;

Plot_OnOff = menu('Plot Option','Plot','Don''t Plot');
%%  Outut Key:
Data_file{1,1}='ID';
Data_file{1,2}='Original Filename';
Data_file{1,3}='Area';
Data_file{1,4}='Subdivision';
Data_file{1,5}='Milage';
Data_file{1,6}='Year';
Data_file{1,7}='Month';
Data_file{1,8}='Day';
Data_file{1,9}='Hour';
Data_file{1,10}='Min';
Data_file{1,11}='Length';
Data_file{1,12}='Direction';
Data_file{1,13}='Speed in';
Data_file{1,14}='Speed out';
Data_file{1,15}='Axle Count';
Data_file{1,16}='Loco Count';
Data_file{1,17}='Car Count';
Data_file{1,18}='Alarm Count';
Data_file{1,19}='Integrity Count';
Data_file{1,20}='Warn Count';
Data_file{1,21}='HW Data';
Data_file{1,22}='Amb Temp (F)';
Data_file{1,23}='Amb Temp (C)';
Data_file{1,24}='Temperature (Axles)';

%%
fileName=ls('*txt');    % List of files in Folder
```

```
%% Assembling the output Excel file
[a,b]=size(fileName);
for ii=1:a;
    datareader(ii,1) = textscan(fileName(ii,:), '%s','delimiter','\n');    %
import all the data from each datafile into a cell
    data_import{ii,1} = textread(fileName(ii,:), '%s','delimiter','\n');    %
import all the data from each datafile into a cell
end


for ii=1:length(datareader);
    dataFile{ii,1}=ii; % ID - Not in the files
    dataFile{ii,2} = datareader{ii,1}{1,1};
end


for ii=1:length(datareader);
    dataFile{ii,3} = dataFile{ii,2}(1:2); % Area
    dataFile{ii,4} = str2num(dataFile{ii,2}(4:7)); % Subdivision
    dataFile{ii,5} = str2num(dataFile{ii,2}(9:12))/10; % Milage
    dataFile{ii,6} = str2num(['20',dataFile{ii,2}(16:17)]); % Year
    dataFile{ii,7} = str2num(dataFile{ii,2}(18:19)); % Month
    dataFile{ii,8} = str2num(dataFile{ii,2}(20:21)); % Day
    dataFile{ii,9} = str2num(dataFile{ii,2}(23:24)); % Hour
    dataFile{ii,10} = str2num(dataFile{ii,2}(25:26)); % Min
    bb=(data_import{ii,1}(11,:));    % a dummy variable to compare each row's
ID (HD, HW, ...)
    dataFile{ii,11}=hex2dec([bb{1,1}(46:49)]); % Length
    dataFile{ii,12}=hex2dec([bb{1,1}(24:25)]); % Direction
    dataFile{ii,13}=hex2dec([bb{1,1}(26:27)]); % Speed in
    dataFile{ii,14}=hex2dec([bb{1,1}(28:29)]); % Speed out
    dataFile{ii,15}=hex2dec([bb{1,1}(30:33)]); % Axle Count
    dataFile{ii,16}=hex2dec([bb{1,1}(34:37)]); % Loco Count
    dataFile{ii,17}=hex2dec([bb{1,1}(38:41)]); % Car Count
    dataFile{ii,18}=hex2dec([bb{1,1}(50:53)]); % Alarm Count
    dataFile{ii,19}=hex2dec([bb{1,1}(54:55)]); % Integrity Count
    dataFile{ii,20}=hex2dec([bb{1,1}(56:57)]); % Warn Count
    dataFile{ii,21}=hex2dec([bb{1,1}(86:87)]); % HW Data
    dataFile{ii,22}=hex2dec([bb{1,1}(88:91)]); % Amb Temp (F)
```

```
    dataFile{ii,23}=(dataFile{ii,21}-32).*(5/9); % Amb Temp (C)
end

%% Hot Wheel:
str_idx=10; % Temp data starts from the 10th character in each line
[a,b]=size(fileName);

%% A loop to extract all files into one Matlab matrix:
for ii=1:a;  % Go through each and every file
    m=1;
    for jj=7:2:length(data_import{ii,1});   % 7:2:end
        bb=(data_import{ii,1}(jj,:));   % a dummy variable to compare each
row's ID (HD, HW, ...)
        if strcmp(bb{1,1}(4:5),'HD');  % Check if the row has the desired
data type
            n=2;
            for kk=str_idx:4:(length(bb{1,1}))-6
                temp_far{ii,1}(m,1)=hex2dec([bb{1,1}(8:9)]);  % Number of
Axles.
                temp_far{ii,1}(m,n)=hex2dec([bb{1,1}(kk:kk+3)]);  %
Extracting temp values (twice the number of axles (for Scan1 and Scan2))
                n=n+1;
            end
            clear dum_var %
            dum_var{ii}=temp_far{ii,1}(:,2:end);
            d=dum_var{ii}(:);
            dataFile{ii,24}=d(d~=0);    % Temperature
            m=m+1;
        end
    end
end

%%
for ii=1:a;  % Go through each and every file
    SS(ii)=length(temp_far{ii,1}(:,1));
end
%%
```

```
if length(unique(SS))~=1 ; % means there are detectors with different length
    for ii=1:a
        D1=temp_far{ii,1}(:);
        D2=D1(SS(ii)+1:end); % removing 16 or 17 from the begining of data
        D3=D2(1:2:end,:);
        D4=D2(2:2:end,:);
        Ave_temp(ii,1)= mean(D2);% Total data
        Ave_temp2(ii,1)= mean(D3);% Scanner 1
        Ave_temp3(ii,1)= mean(D3);% Scanner 2
        Standard(ii,1) = std(D2,0,1);
        clear D1 D2 D3 D4
    end
    Ave_temp=[Ave_temp, Standard];
    xlswrite('AveTemp',Ave_temp);
    xlswrite('AveTemp_Scan1',Ave_temp2);
    xlswrite('AveTemp_Scan2',Ave_temp3);
    Data_file(2:length(datareader)+1,:)=dataFile;
    xlswrite('DATA',Data_file);

    if Plot_OnOff==1
        for ii=1:a
            D1=temp_far{ii,1}(:);
            D2=D1(SS(ii)+1:end); % removing 16 or 17 from the begining of
data
            D3=D2(1:2:end,:);
            D4=D2(2:2:end,:);


            figure
            plot(D2,'b','LineWidth',1); hold on
            plot(Ave_temp(ii,1).*ones(size(D2)),'k','LineWidth',2)
            title(['Raw Data for Detect. ',num2str(ii)],'FontSize',15);
            xlabel('Axle','FontSize',15)
            ylabel('Temperature [F]','FontSize',15)
            legend('Data File','Average')
            set(gca,'fontsize',15)
            clear D1 D2 D3 D4
```

```
        end
    end

elseif length(unique(SS))==1
    %% Seperating temps
    for ii=1:a
        temp_exel3(:,ii)=temp_far{ii,1}(:);
    end
    temp_exel2=temp_exel3(length(temp_far{ii,1}(:,1))+1:end,:);
    temp_exel=reshape(temp_exel2((temp_exel2~=0)),[],3);
    temp_exel_Scan1=temp_exel(1:2:end,:);
    temp_exel_Scan2=temp_exel(2:2:end,:);

    %% Exporting Data to Excel
    Data_file(2:length(datareader)+1,:)=dataFile;
    xlswrite('DATA',Data_file);
    xlswrite('Temp',temp_exel);
    xlswrite('Temp_Scan1',temp_exel_Scan1);
    xlswrite('Temp_Scan2',temp_exel_Scan2);

    Nrows=[1,2,3];

    %% Plot Section
    if Plot_OnOff==1
        % Normal Probability Plot
        figure
        normplot(dataFile{Nrows(1),24});
        title('Data File 1','FontSize',15)
        set(gca,'fontsize',15)

        figure
        normplot(dataFile{Nrows(2),24});
        title('Data File 2','FontSize',15)
        set(gca,'fontsize',15)
```

```
        figure
        normplot(dataFile{Nrows(3),24});
        title('Data File 3','FontSize',15)
        set(gca,'fontsize',15)

        %% Data files Normalized w.r.t eachother
        figure

plot((dataFile{Nrows(1),24}./dataFile{Nrows(2),24}),'b','LineWidth',1); hold
on

plot((dataFile{Nrows(2),24}./dataFile{Nrows(2),24}),'k','LineWidth',1)

plot((dataFile{Nrows(3),24}./dataFile{Nrows(2),24}),'r','LineWidth',1)
        title('Data files Normalized w.r.t 2nd data file','FontSize',15)
        xlabel('Axle','FontSize',15)
        ylabel('Normalized Temperature','FontSize',15)
        legend('Detect 1','Detect 2','Detect 3')
        set(gca,'fontsize',15)

        %% Data files Normalized w.r.t eachother (Scanner 1)
        figure

plot((dataFile{Nrows(1),24}(1:2:end)./dataFile{Nrows(2),24}(1:2:end)),'b','Li
neWidth',1); hold on

plot((dataFile{Nrows(2),24}(1:2:end)./dataFile{Nrows(2),24}(1:2:end)),'k','Li
neWidth',1)

plot((dataFile{Nrows(3),24}(1:2:end)./dataFile{Nrows(2),24}(1:2:end)),'r','Li
neWidth',1)
        title('Data files Normalized w.r.t 2nd data file (Scanner
1)','FontSize',15)
        xlabel('Axle','FontSize',15)
        ylabel('Normalized Temperature','FontSize',15)
        legend('Detect 1','Detect 2','Detect 3')
        set(gca,'fontsize',15)

        %% Data files Normalized w.r.t eachother (Scanner 2)
```

```
        figure

plot((dataFile{Nrows(1),24}(2:2:end)./dataFile{Nrows(2),24}(2:2:end)),'b','Li
neWidth',1); hold on

plot((dataFile{Nrows(2),24}(2:2:end)./dataFile{Nrows(2),24}(2:2:end)),'k','Li
neWidth',1)

plot((dataFile{Nrows(3),24}(2:2:end)./dataFile{Nrows(2),24}(2:2:end)),'r','Li
neWidth',1)
        title('Data files Normalized w.r.t 2nd data file (Scanner
2)','FontSize',15)
        xlabel('Axle','FontSize',15)
        ylabel('Normalized Temperature','FontSize',15)
        legend('Detect 1','Detect 2','Detect 3')
        set(gca,'fontsize',15)

        %% Data Files
        figure
        plot((dataFile{Nrows(1),24}),'b','LineWidth',1); hold on
        plot((dataFile{Nrows(2),24}),'k','LineWidth',1)
        plot((dataFile{Nrows(3),24}),'r','LineWidth',1)
        title('Raw Data','FontSize',15)
        xlabel('Axle','FontSize',15)
        ylabel('Temperature [F]','FontSize',15)
        legend('Detect 1','Detect 2','Detect 3')
        set(gca,'fontsize',15)

        %% Data Files - mean value (Noise reduction) - First Term of Fourier
Series
        figure
        plot((dataFile{Nrows(1),24})-
(mean(dataFile{Nrows(1),24})),'b','LineWidth',1); hold on
        plot((dataFile{Nrows(2),24})-
(mean(dataFile{Nrows(2),24})),'k','LineWidth',1)
        plot((dataFile{Nrows(3),24})-
(mean(dataFile{Nrows(3),24})),'r','LineWidth',1)
        title('Filtered Data files','FontSize',15)
        xlabel('Axle','FontSize',15)
```

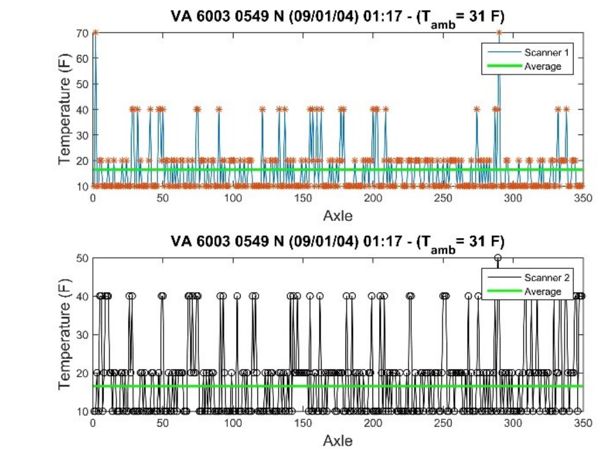
```
        ylabel('Temperature [F]','FontSize',15)
        legend('Detect 1','Detect 2','Detect 3')
        set(gca,'fontsize',15)

        %% Devided by their own mean value
        figure

plot((dataFile{Nrows(1),24})./(mean(dataFile{Nrows(1),24})),'b','LineWidth',1
); hold on

plot((dataFile{Nrows(2),24})./(mean(dataFile{Nrows(2),24})),'k','LineWidth',1
)

plot((dataFile{Nrows(3),24})./(mean(dataFile{Nrows(3),24})),'r','LineWidth',1
)
        title('Raw data/ Mean value','FontSize',15)
        xlabel('Axle')
        ylabel('Temperature [F]')
        legend('Detect 1','Detect 2','Detect 3')
        set(gca,'fontsize',15)

        %% Mean value of Data files
        figure
        bar([(mean(dataFile{Nrows(1),24})),
mean((dataFile{Nrows(2),24})),mean((dataFile{Nrows(3),24}))]);
        title('Mean value of Raw data','FontSize',15)
        xlabel('Detectors','FontSize',15)
        ylabel('Mean value of Temperature [F]','FontSize',15)
        set(gca,'fontsize',15)

        %
        figure
        plot((dataFile{Nrows(1),24}),'b','LineWidth',1);  hold on
        plot((dataFile{Nrows(2),24}),'k','LineWidth',1)
        title('','FontSize',15)
        xlabel('Axle','FontSize',15)
        ylabel('Temperature [F]','FontSize',15)
        set(gca,'fontsize',15)
```

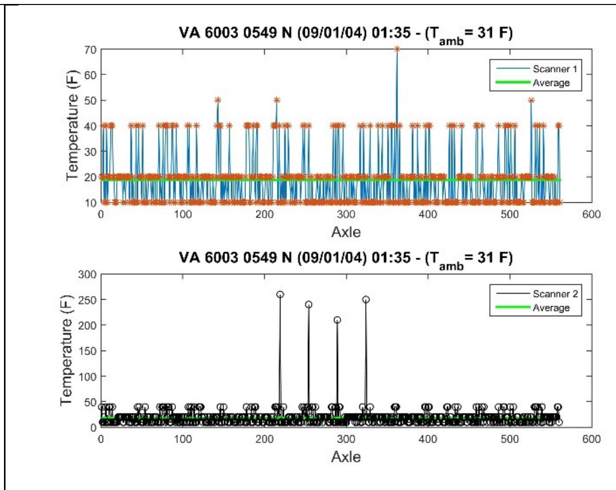
```
%% Max/Min for a specific Axle
[~,c]=max(dataFile{Nrows(1),24});
[~,c2]=max(dataFile{Nrows(2),24});
[~,c3]=max(dataFile{Nrows(3),24});

% Min for a specific Axle
[~,c4]=min(dataFile{Nrows(1),24});
[~,c5]=min(dataFile{Nrows(2),24});
[~,c6]=min(dataFile{Nrows(3),24});

figure
plot(Nrows, [(dataFile{Nrows(3),24}(c)),
(dataFile{Nrows(2),24}(c)),(dataFile{Nrows(1),24}(c))],'r','LineWidth',1);
hold on
plot(Nrows, [(dataFile{Nrows(3),24}(c4)),
(dataFile{Nrows(2),24}(c4)),(dataFile{Nrows(1),24}(c4))],'b','LineWidth',1);
plot(Nrows, [(dataFile{Nrows(3),24}(c)),
(dataFile{Nrows(2),24}(c)),(dataFile{Nrows(1),24}(c))],'rs','LineWidth',1);
hold on
plot(Nrows, [(dataFile{Nrows(3),24}(c4)),
(dataFile{Nrows(2),24}(c4)),(dataFile{Nrows(1),24}(c4))],'bs','LineWidth',1);
legend('Max','Min')
ylabel('Temperature [F]','FontSize',15), xlabel('Detector')
set(gca,'fontsize',15); grid on

% Variance
V1 = var(dataFile{Nrows(1),24});
V2 = var(dataFile{Nrows(2),24});
V3 = var(dataFile{Nrows(3),24});

figure
plot(V1,'b','LineWidth',1); hold on
plot(V2,'k','LineWidth',1); hold on
plot(V3,'r','LineWidth',1); hold on
title('Variance','FontSize',15)
xlabel('Detectors','FontSize',15)
```

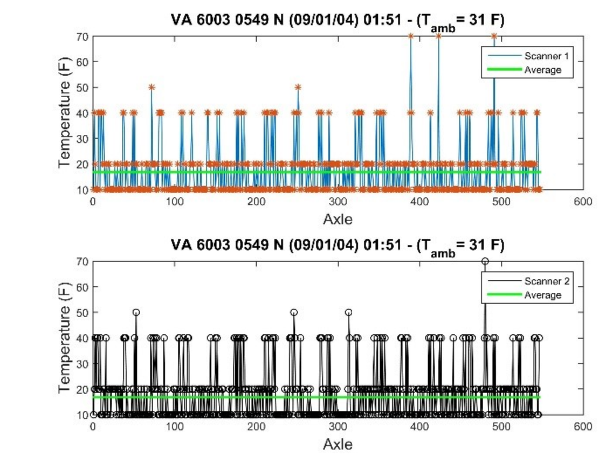
```
    ylabel('Mean value of Temperature [F]','FontSize',15)
    legend('Detect 1','Detect 2','Detect 3')
    set(gca,'fontsize',15)

    %% Standard Deviation
    s1 = std(dataFile{Nrows(1),24},0,1);
    s2 = std(dataFile{Nrows(2),24},0,1);
    s3 = std(dataFile{Nrows(3),24},0,1);

    figure
    plot(s1,'b','LineWidth',1); hold on
    plot(s2,'k','LineWidth',1); hold on
    plot(s3,'r','LineWidth',1); hold on
    title('Standard Deviation','FontSize',15)
    xlabel('Detectors','FontSize',15)
    ylabel('Mean value of Temperature [F]','FontSize',15)
    legend('Detect 1','Detect 2','Detect 3')
    set(gca,'fontsize',15)

    %% Histograms
    figure
    hist(dataFile{Nrows(1),24})
    set(gca,'fontsize',15)
    title('Detect 1','FontSize',15)

    figure
    hist(dataFile{Nrows(2),24})
    set(gca,'fontsize',15)
    title('Detect 2','FontSize',15)

    figure
    hist(dataFile{Nrows(3),24})
    set(gca,'fontsize',15)
    title('Detect 3','FontSize',15)
end
```

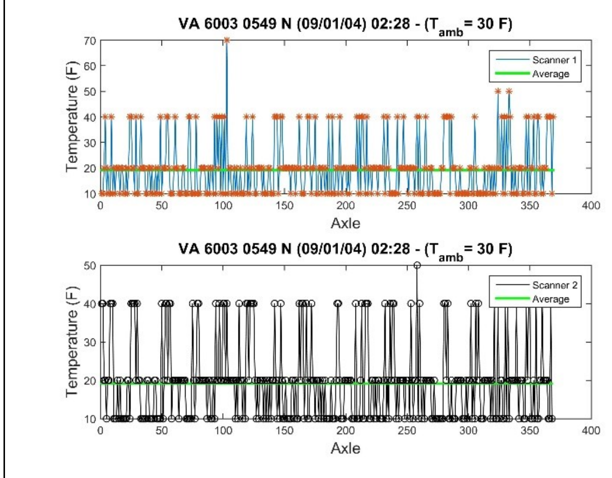
Appendix B

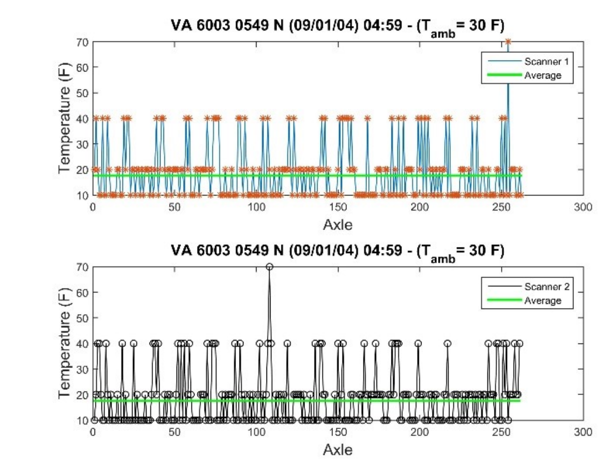
The temperature versus axle plots for all the trains passed Cascade 54.9 on 2009-01-04:

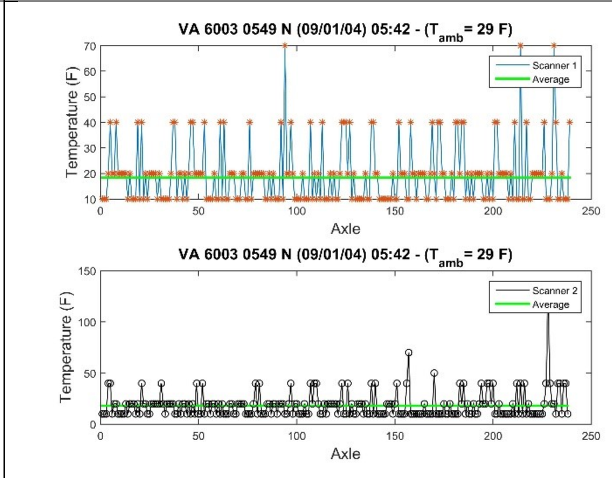


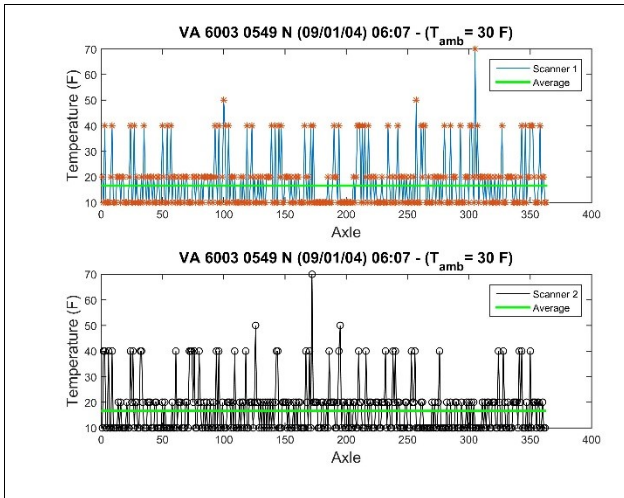


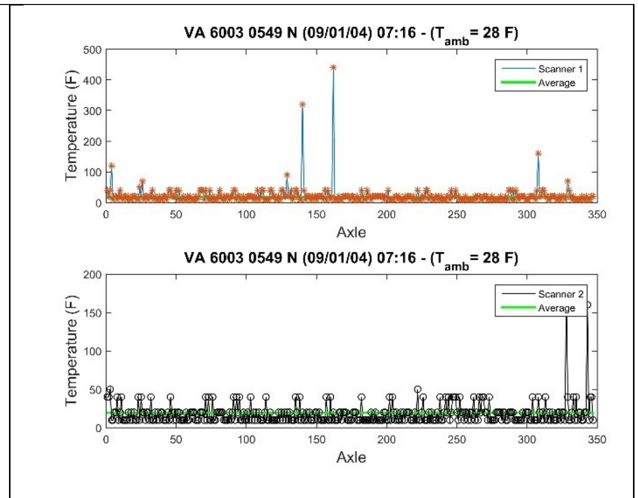


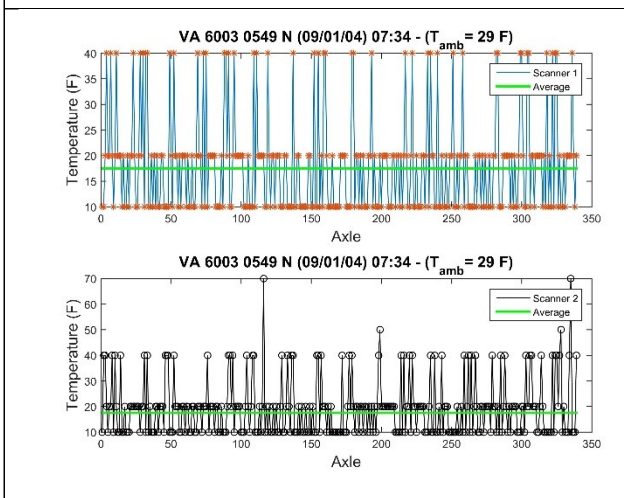


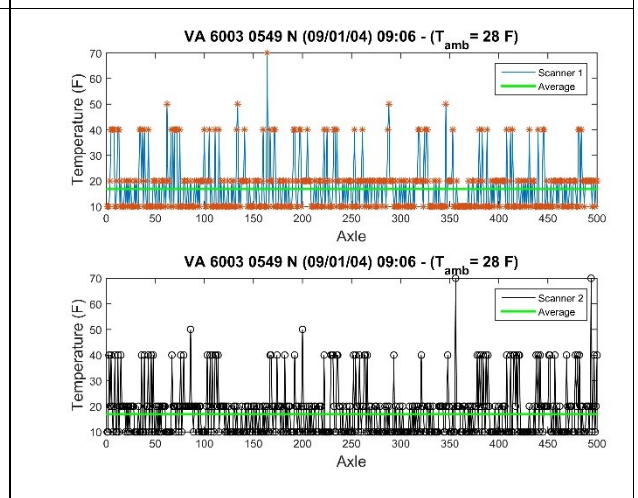


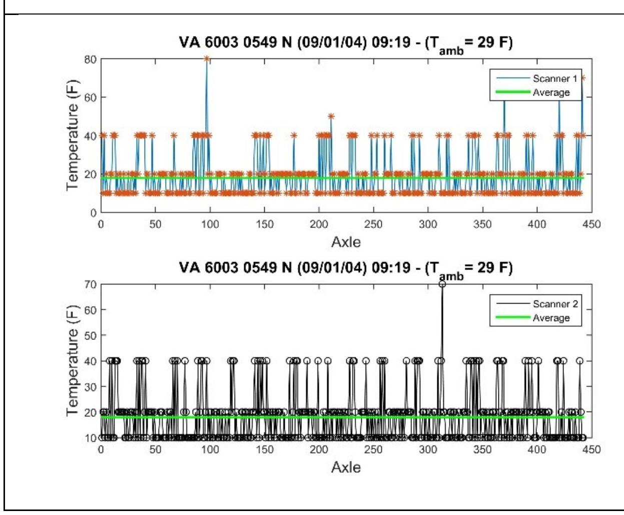


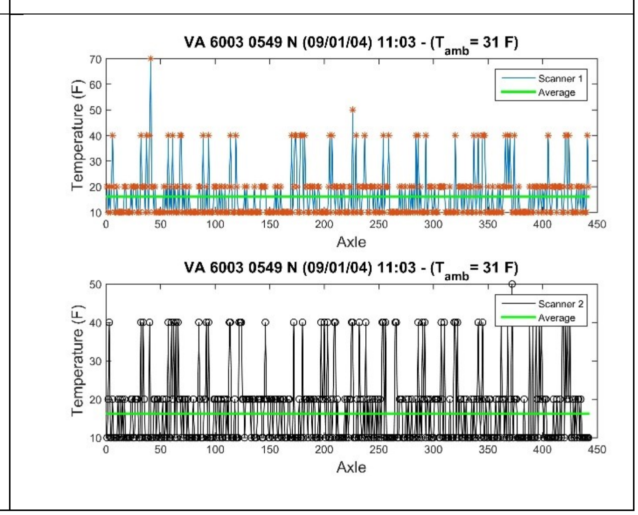

VA 6003 0549 N (09/01/04) 06:07 - (T amb = 30 F)
Temperature (F)
Axle
Scanner 1
Average
VA 6003 0549 N (09/01/04) 06:07 - (T amb = 30 F)
Scanner 2
Average

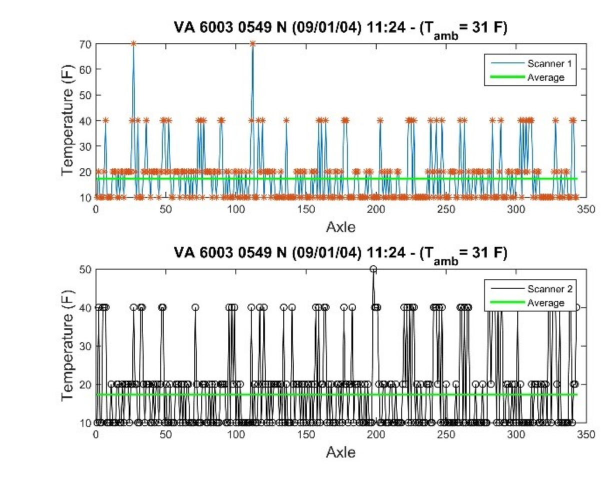

VA 6003 0549 N (09/01/04) 07:16 - (T amb = 28 F)
Temperature (F)
Axle
Scanner 1
Average
VA 6003 0549 N (09/01/04) 07:16 - (T amb = 28 F)
Scanner 2
Average

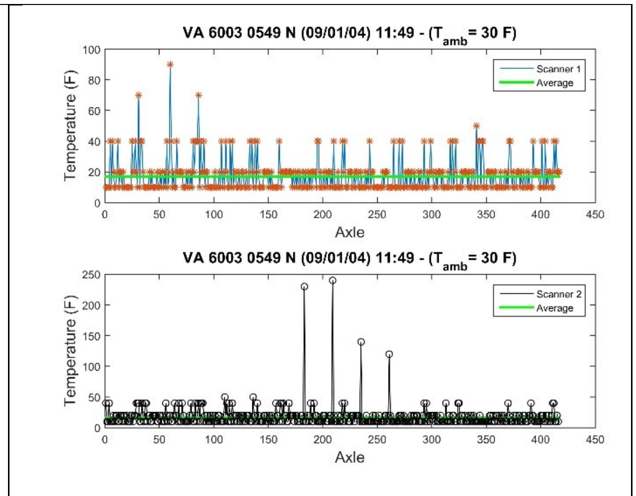

VA 6003 0549 N (09/01/04) 07:34 - (T amb = 29 F)
Temperature (F)
Axle
Scanner 1
Average
VA 6003 0549 N (09/01/04) 07:34 - (T amb = 29 F)
Scanner 2
Average

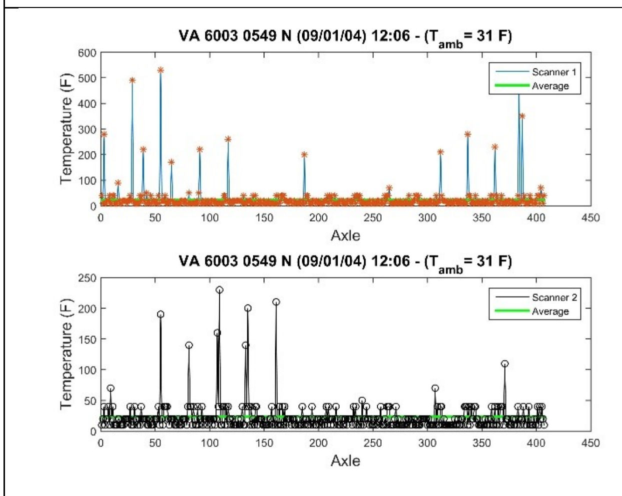

VA 6003 0549 N (09/01/04) 09:06 - (T amb = 28 F)
Temperature (F)
Axle
Scanner 1
Average
VA 6003 0549 N (09/01/04) 09:06 - (T amb = 28 F)
Scanner 2
Average

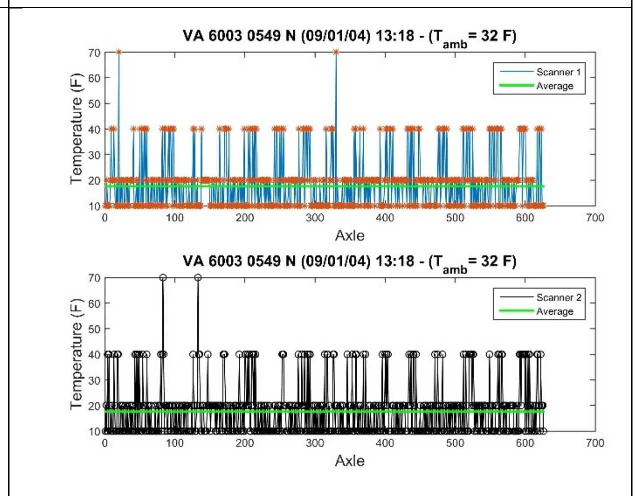

VA 6003 0549 N (09/01/04) 09:19 - (T amb = 29 F)
Temperature (F)
Axle
Scanner 1
Average
VA 6003 0549 N (09/01/04) 09:19 - (T amb = 29 F)
Scanner 2
Average

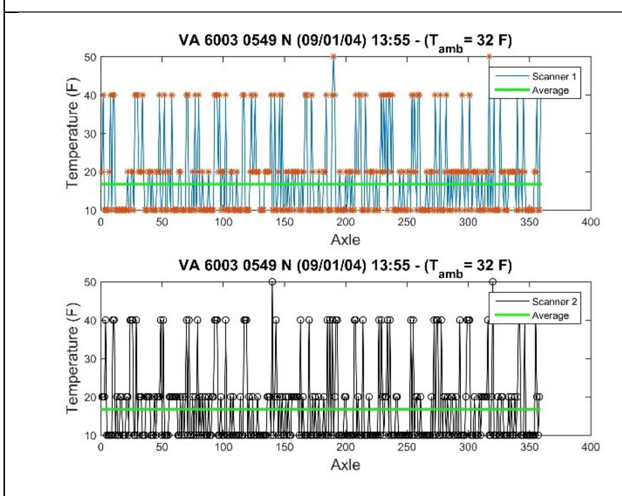

VA 6003 0549 N (09/01/04) 11:03 - (T amb = 31 F)
Temperature (F)
Axle
Scanner 1
Average
VA 6003 0549 N (09/01/04) 11:03 - (T amb = 31 F)
Scanner 2
Average

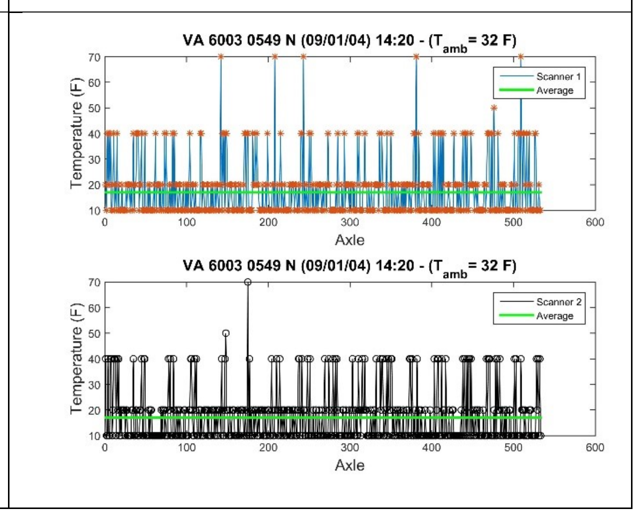

VA 6003 0549 N (09/01/04) 11:24 - (T_{amb} = 31 F)
Temperature (F)
Axle
Scanner 1
Average
VA 6003 0549 N (09/01/04) 11:24 - (T_{amb} = 31 F)
Temperature (F)
Axle
Scanner 2
Average


VA 6003 0549 N (09/01/04) 11:49 - (T_{amb} = 30 F)
Temperature (F)
Axle
Scanner 1
Average
VA 6003 0549 N (09/01/04) 11:49 - (T_{amb} = 30 F)
Temperature (F)
Axle
Scanner 2
Average


VA 6003 0549 N (09/01/04) 12:06 - (T_{amb} = 31 F)
Temperature (F)
Axle
Scanner 1
Average
VA 6003 0549 N (09/01/04) 12:06 - (T_{amb} = 31 F)
Temperature (F)
Axle
Scanner 2
Average


VA 6003 0549 N (09/01/04) 13:18 - (T_{amb} = 32 F)
Temperature (F)
Axle
Scanner 1
Average
VA 6003 0549 N (09/01/04) 13:18 - (T_{amb} = 32 F)
Temperature (F)
Axle
Scanner 2
Average


VA 6003 0549 N (09/01/04) 13:55 - (T_{amb} = 32 F)
Temperature (F)
Axle
Scanner 1
Average
VA 6003 0549 N (09/01/04) 13:55 - (T_{amb} = 32 F)
Temperature (F)
Axle
Scanner 2
Average


VA 6003 0549 N (09/01/04) 14:20 - (T_{amb} = 32 F)
Temperature (F)
Axle
Scanner 1
Average
VA 6003 0549 N (09/01/04) 14:20 - (T_{amb} = 32 F)
Temperature (F)
Axle
Scanner 2
Average

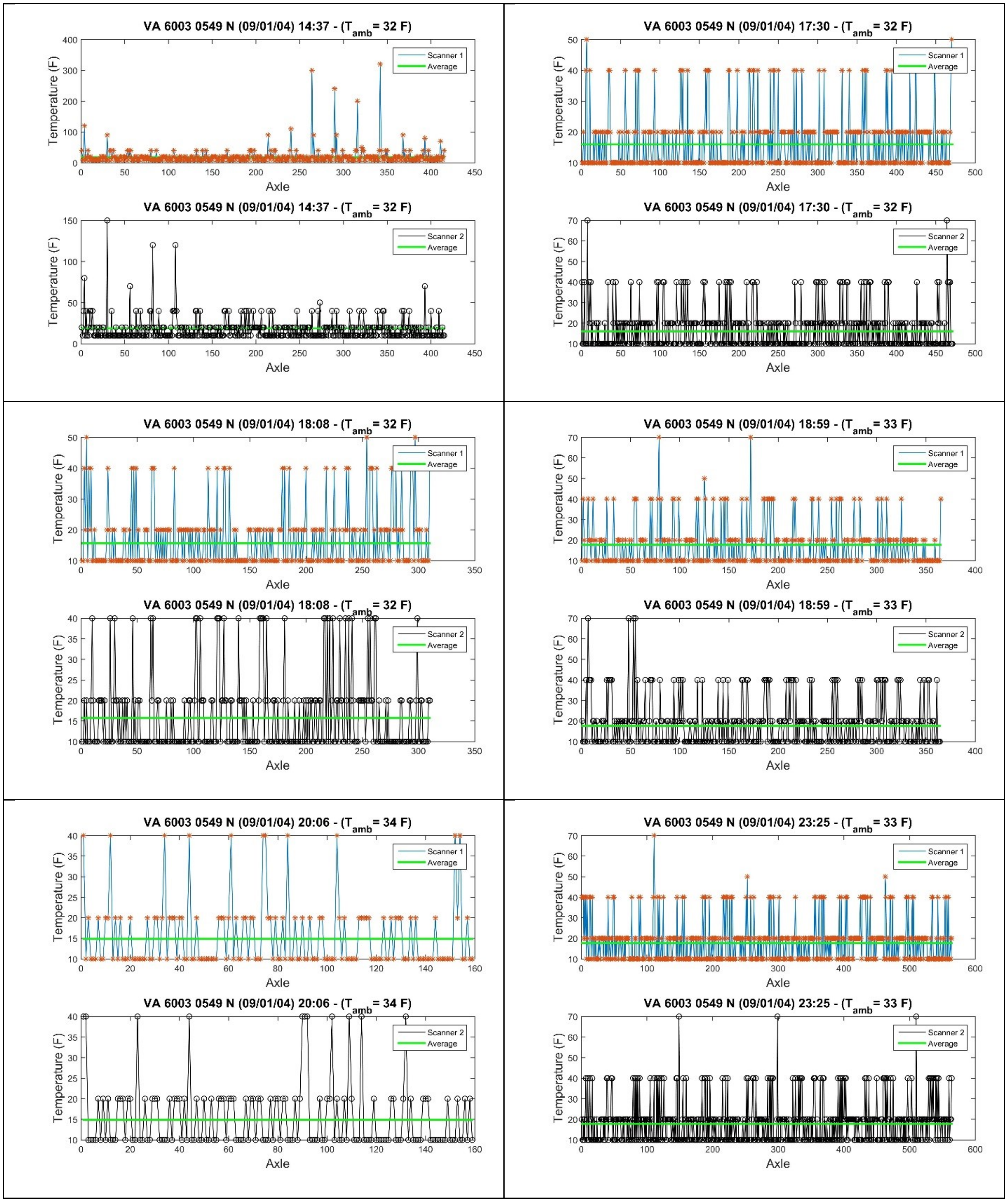
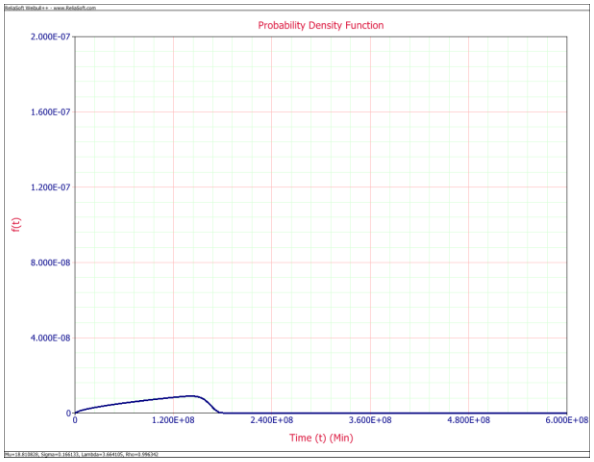


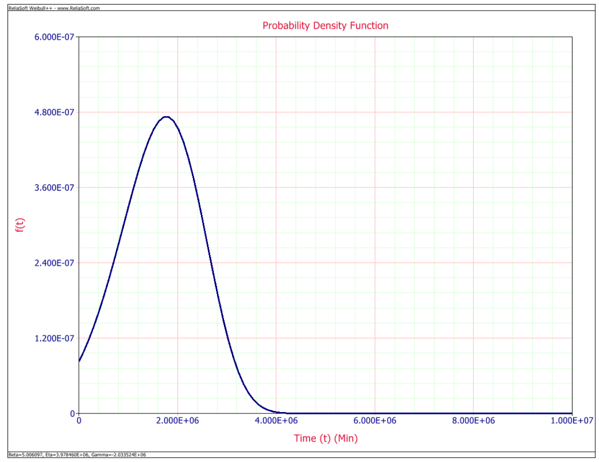
Figure a-1: Temperature-Axle plots for all the trains that passed Cascade 54.9 on 2009-01-04

Appendix C

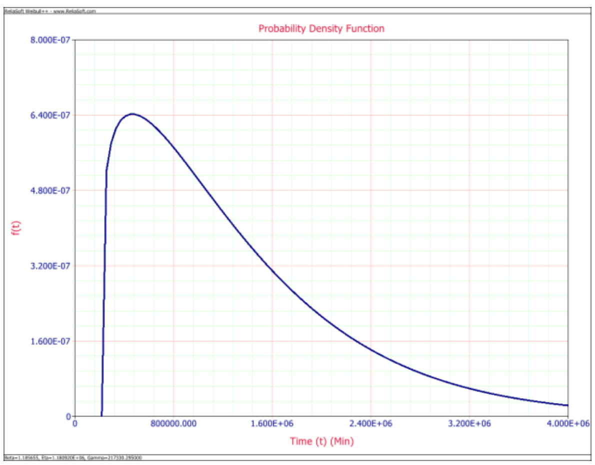
The Probability Distribution Functions (PDF) plots for the detectors based on the the software ranking:



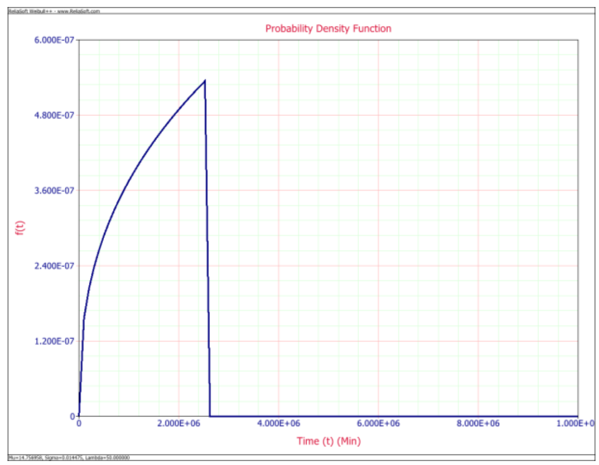
Cascade 10.9



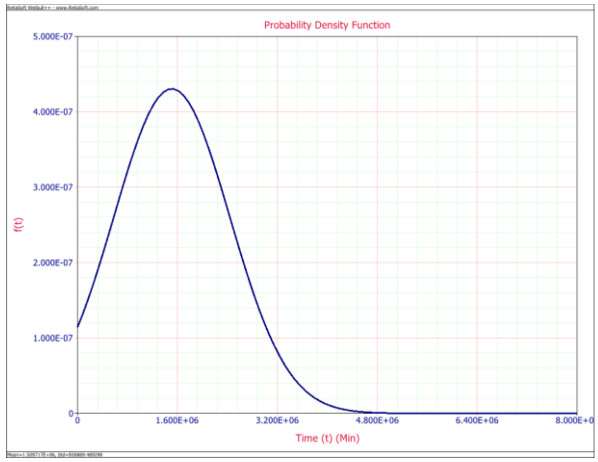
Cascade 32.5



Cascade 54.9

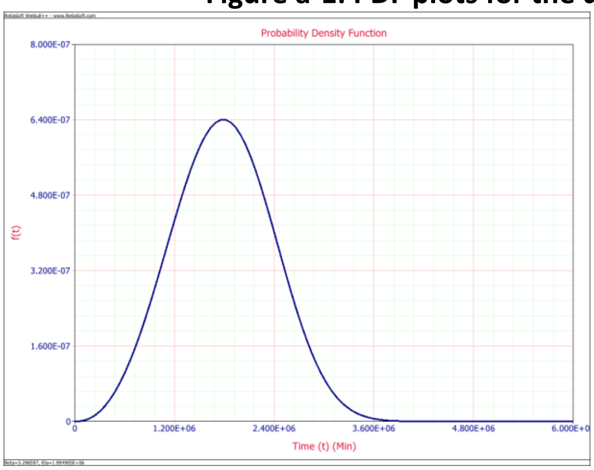


Cascade 80.1

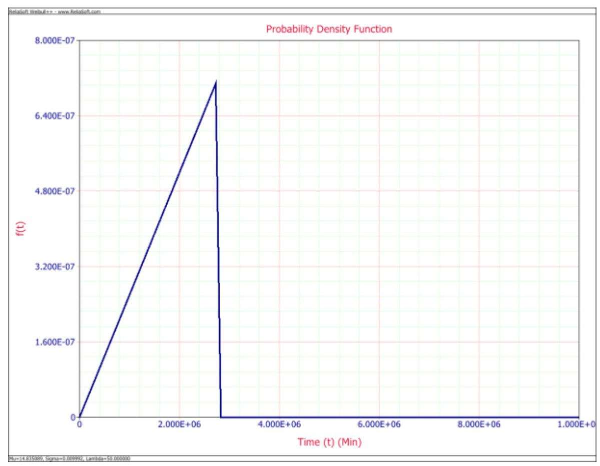


Cascade 96.8

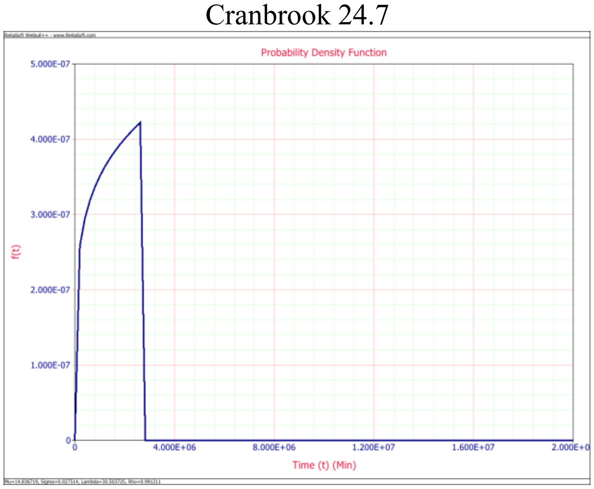
Figure a-1: PDF plots for the detectors in Cascade subdivision



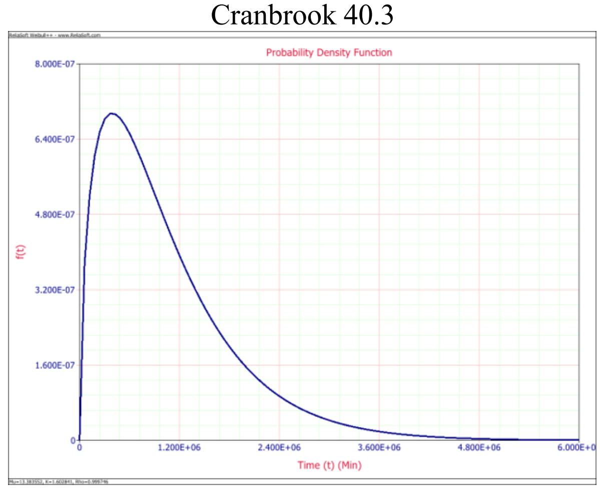
Cranbrook 24.7



Cranbrook 40.3



Cranbrook 65.3



Cranbrook 86.8

Figure a-2: PDF plots for the detectors in Cranbrook subdivision

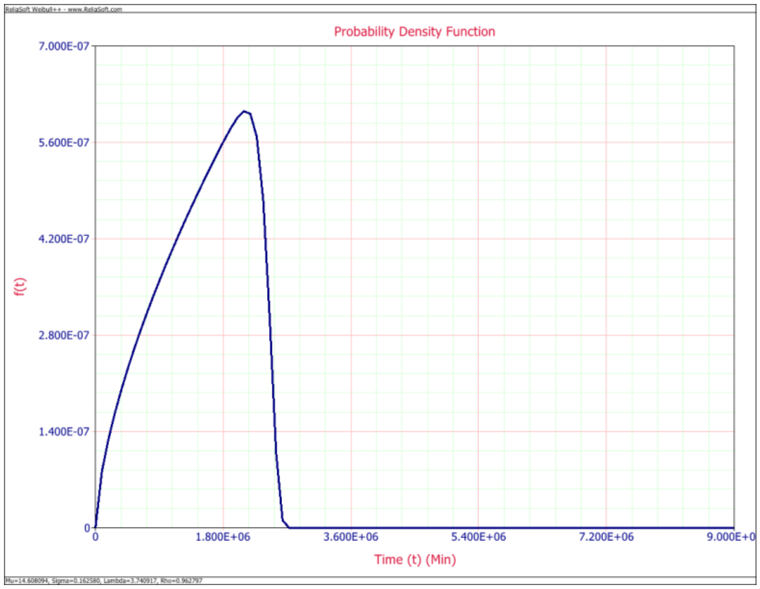
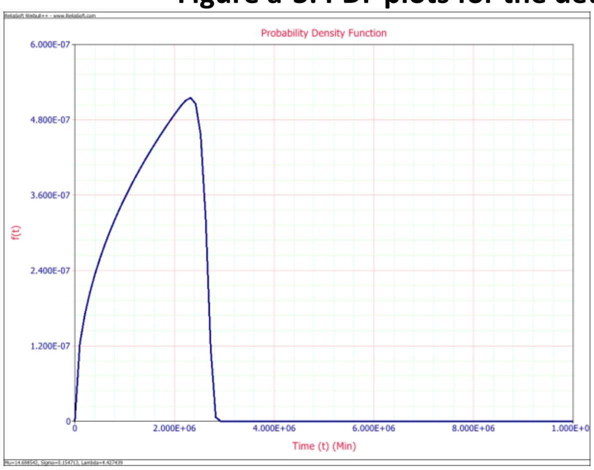
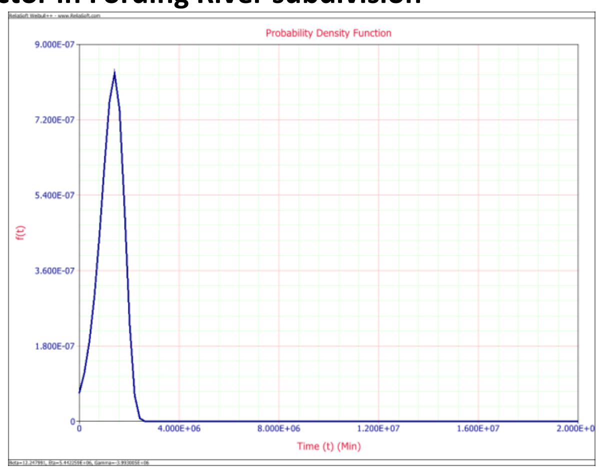


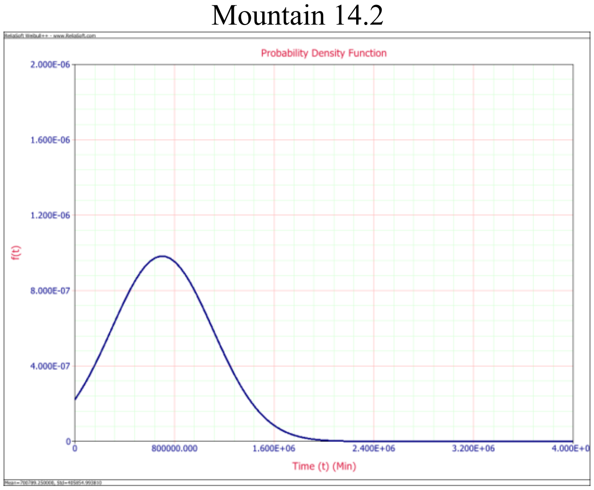
Figure a-3: PDF plots for the detector in Fording River subdivision

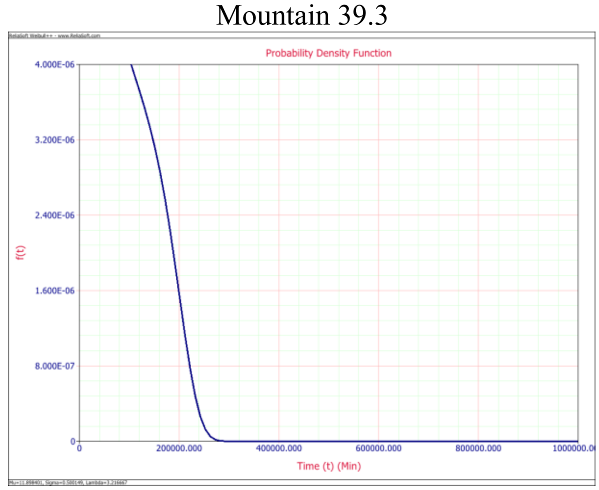


Mountain 14.2

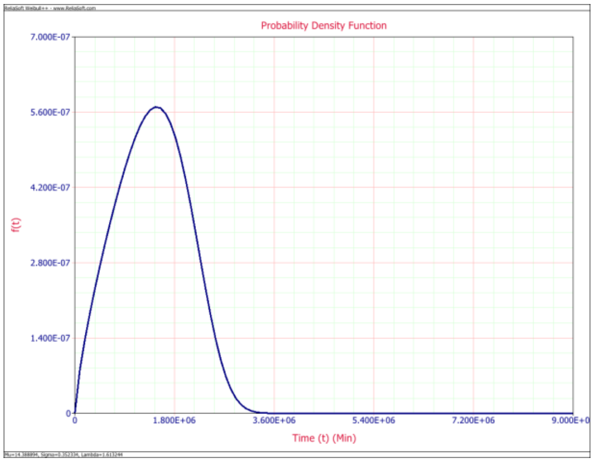


Mountain 39.3

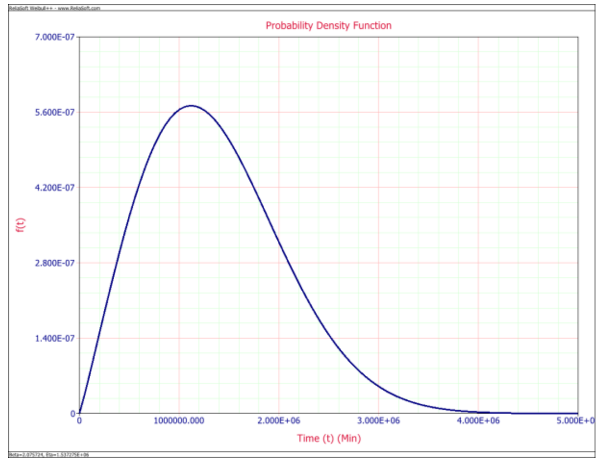




Mountain 44.9



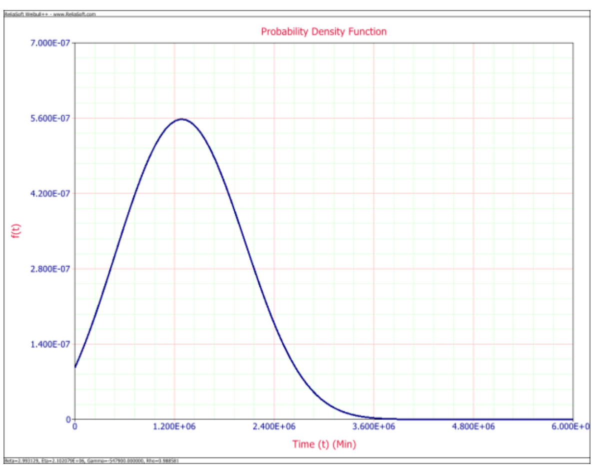
Mountain 54.5

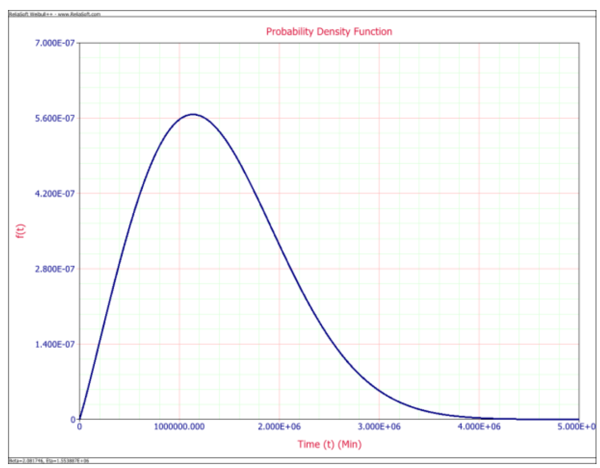


Mountain 70.9

Mountain 74.8

Figure a-4: PDF plots for the detector in Mountain subdivision

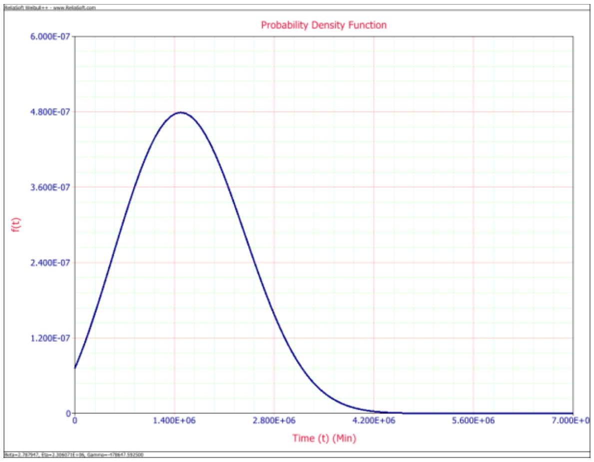




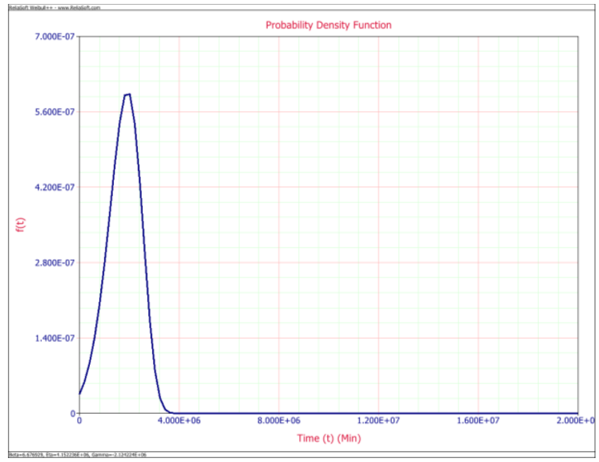
Mountain 95.1

Mountain 111.7

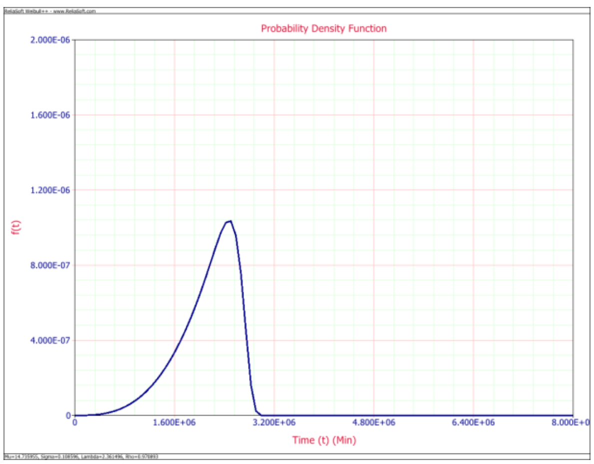
Figure a-4: PDF plots for the detector in Mountain subdivision



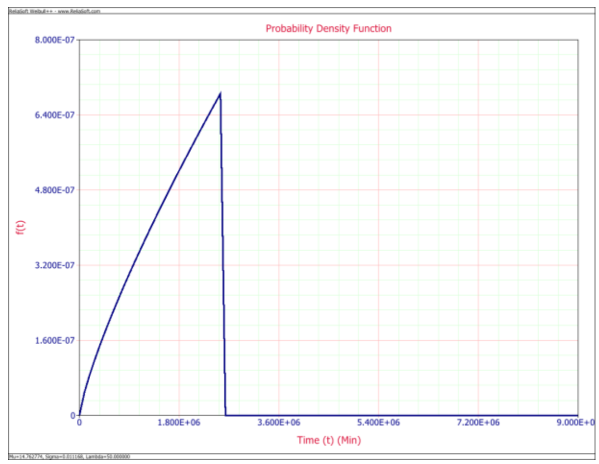
Shuswap 19.7



Shuswap 40.8

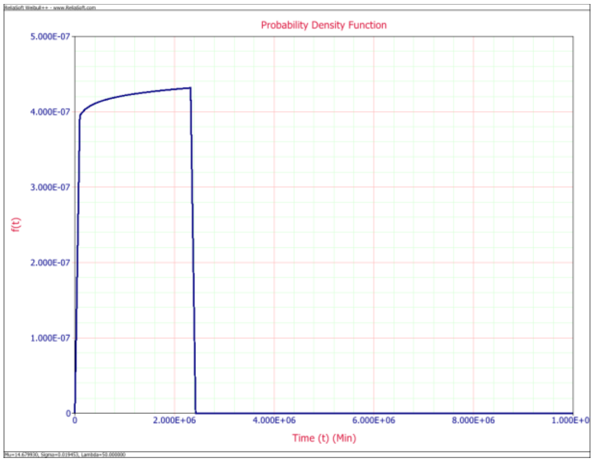


Shuswap 59.1

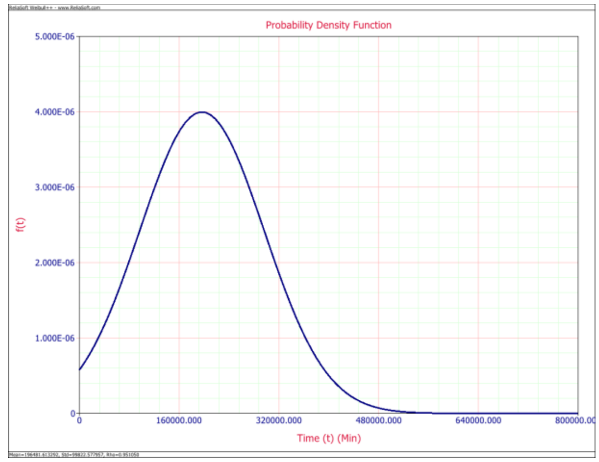


Shuswap 77.4

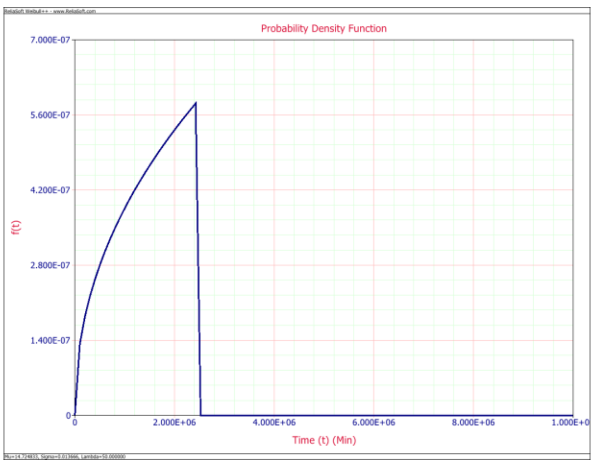
Figure a-5: PDF plots for the detector in Shuswap subdivision



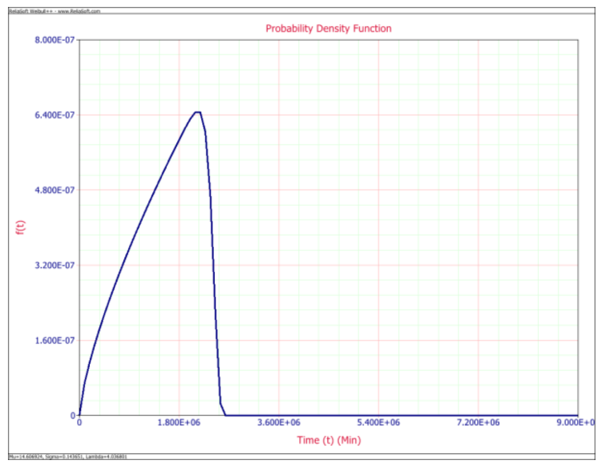
Shuswap 77.5



Shuswap 90

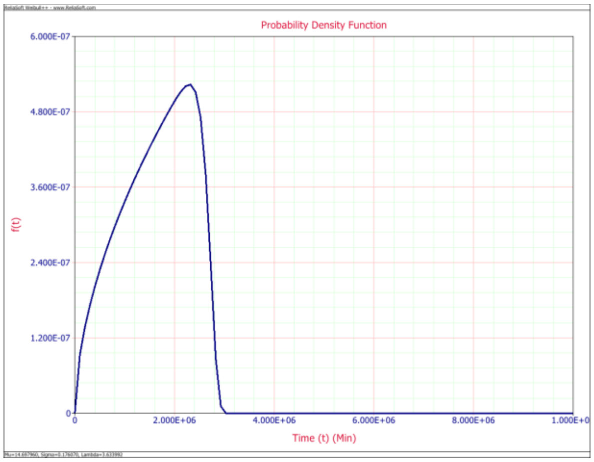


Shuswap 97.9

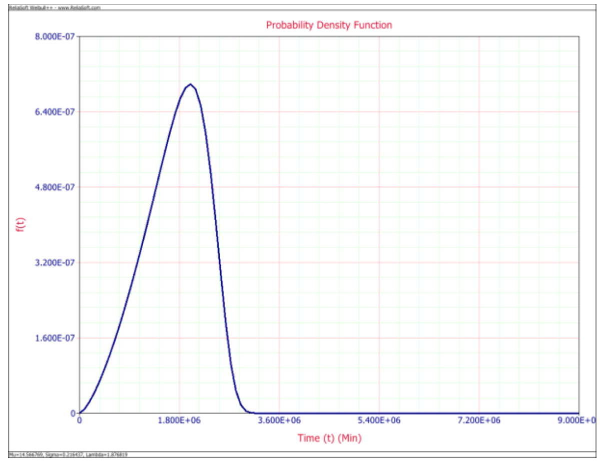


Shuswap 118.5

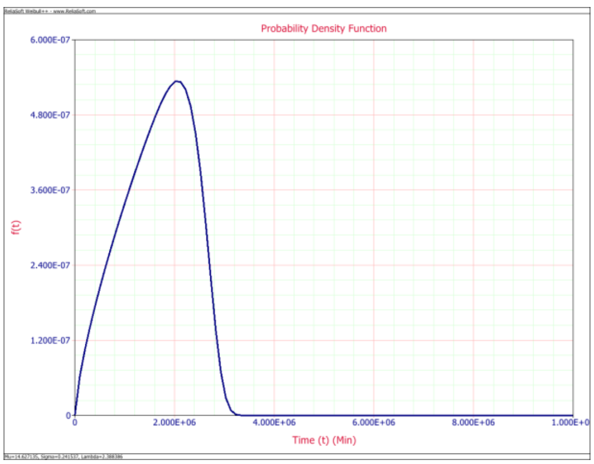
Figure a-5: PDF plots for the detector in Shuswap subdivision



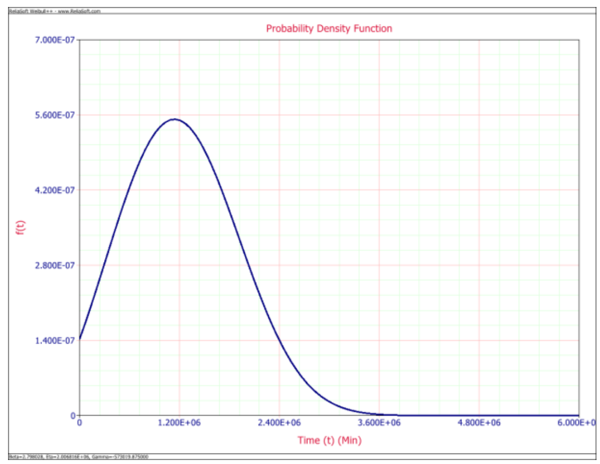
Thompson 11.8



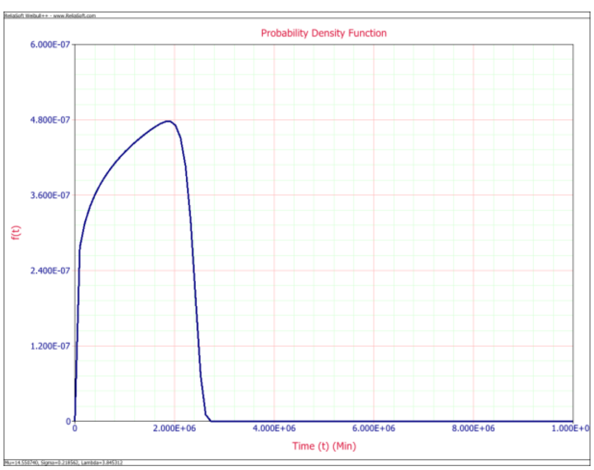
Thompson 35.5



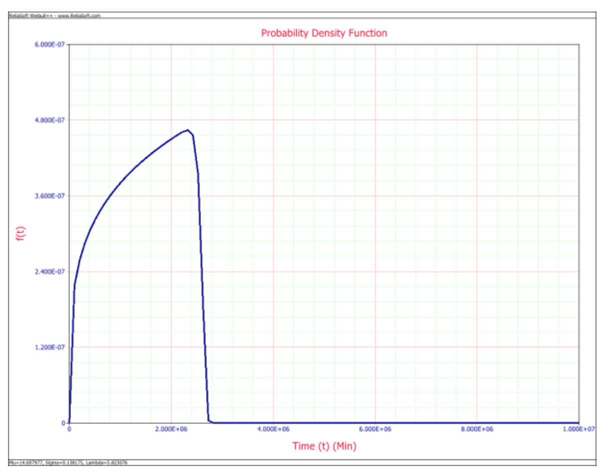
Thompson 44.3



Thompson 60.5

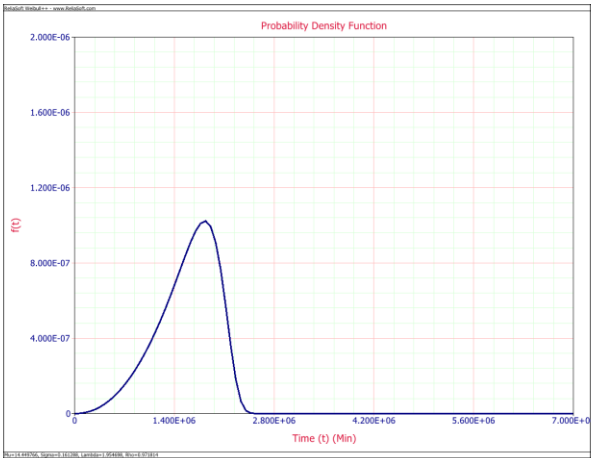


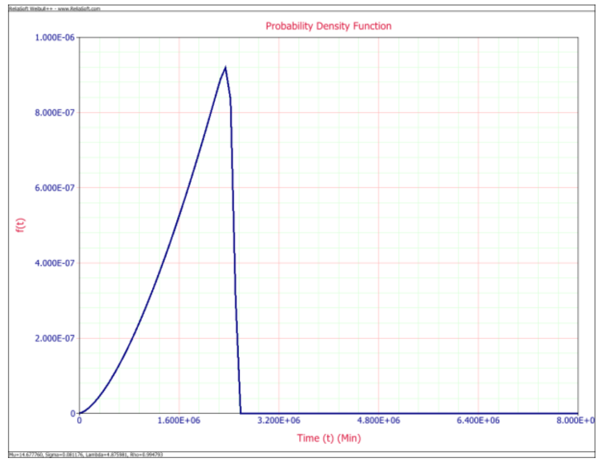
Thompson 81.9



Thompson 98.1

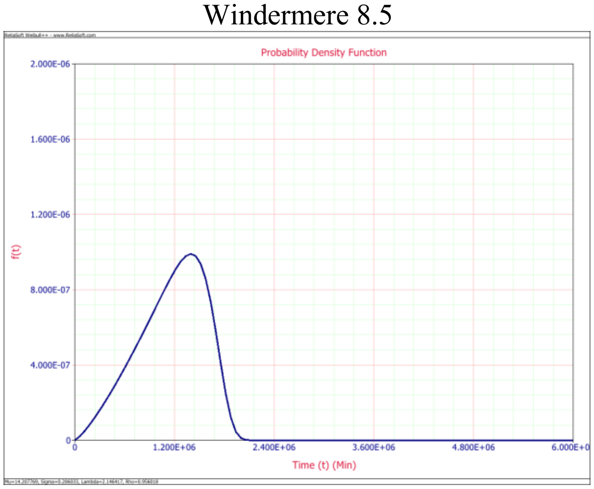
Figure a-6: PDF plots for the detector in Thompson subdivision

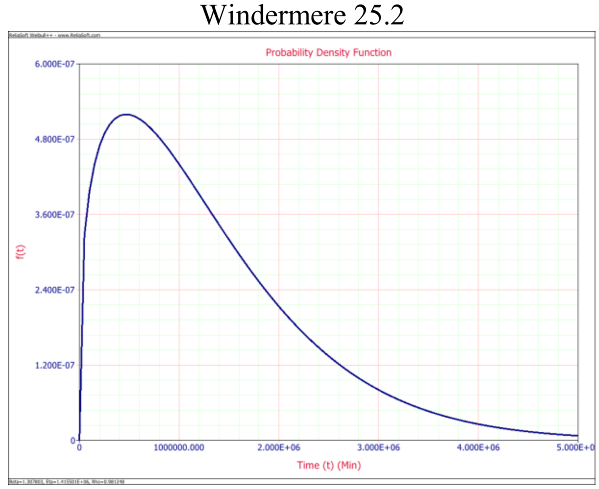




Windermere 8.5

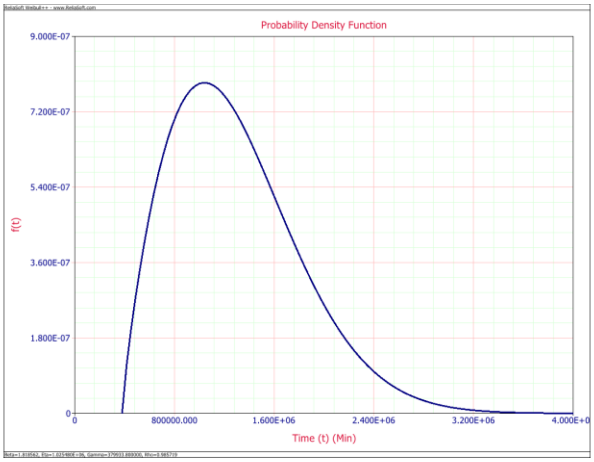
Windermere 25.2

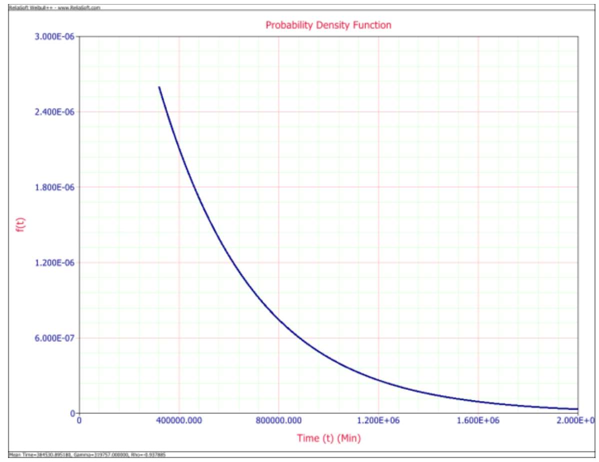




Windermere50.4

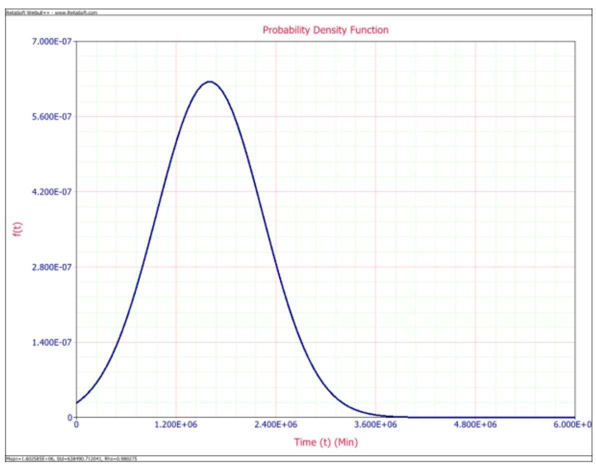
Windermere 54.7





Windermere 97.2 Windermere 113.4

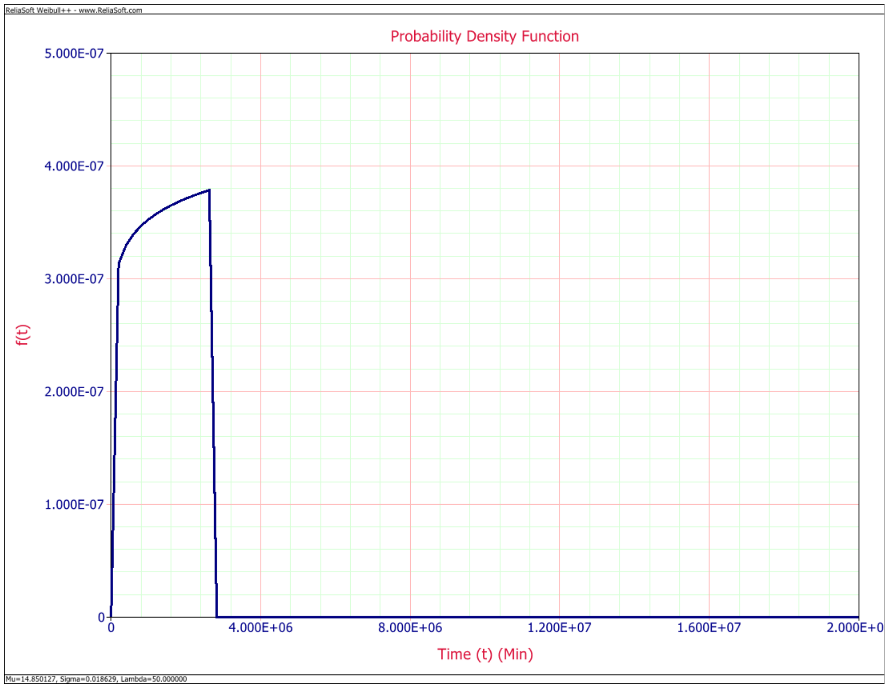
Figure a-7: PDF plots for the detector in Windermere subdivision



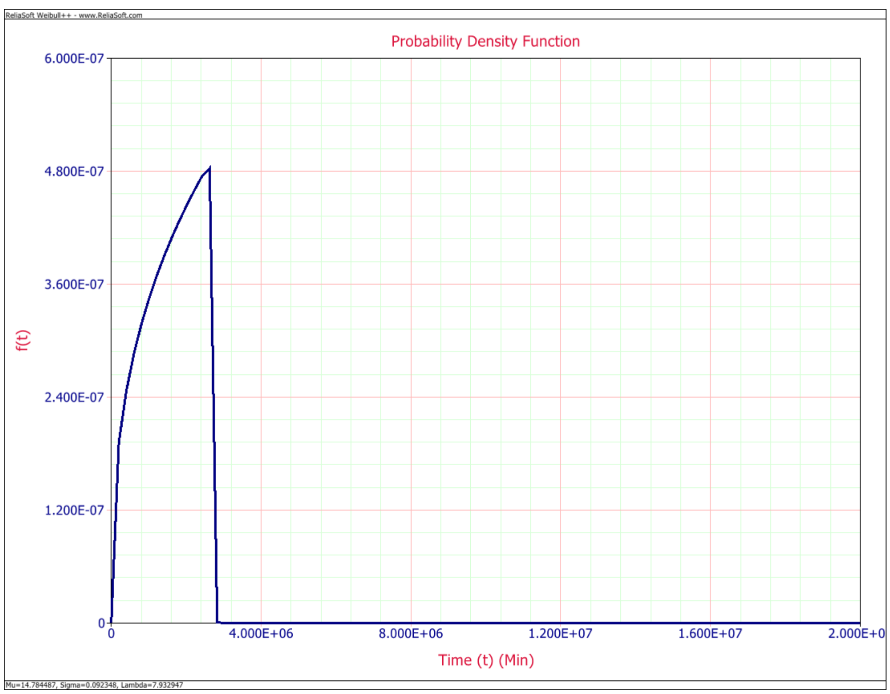
Windermere 123.3

Figure a-7: PDF plots for the detector in Windermere subdivision

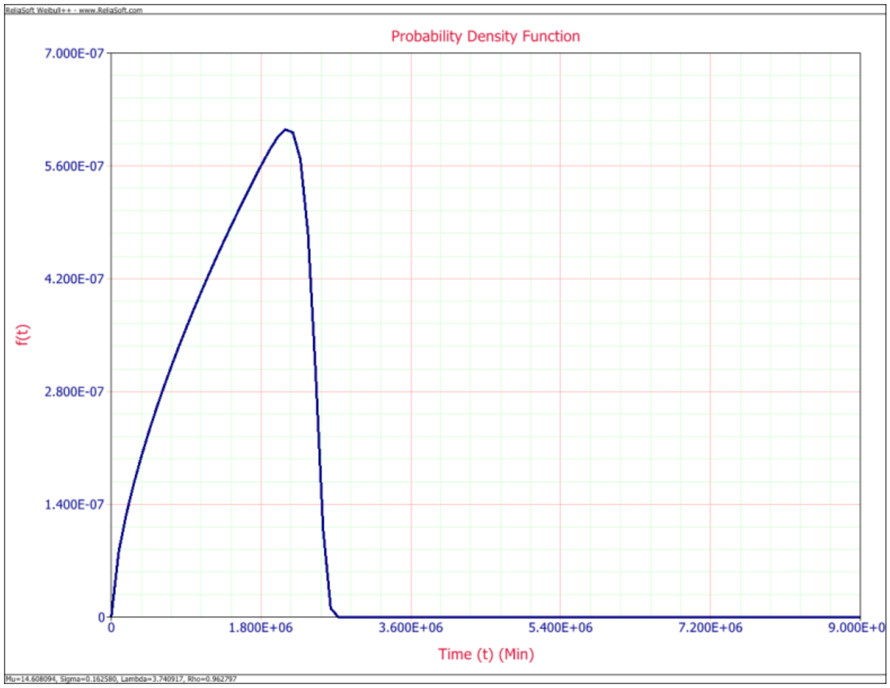
The PDF plots for distributions selected by software for each subdivision are plotted and depicted as follows:



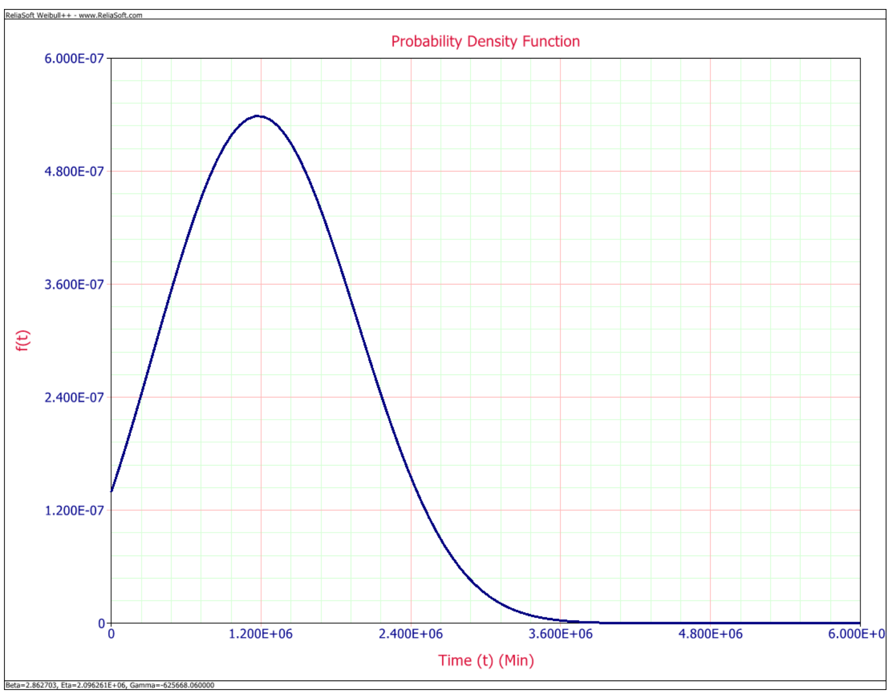
Cascade



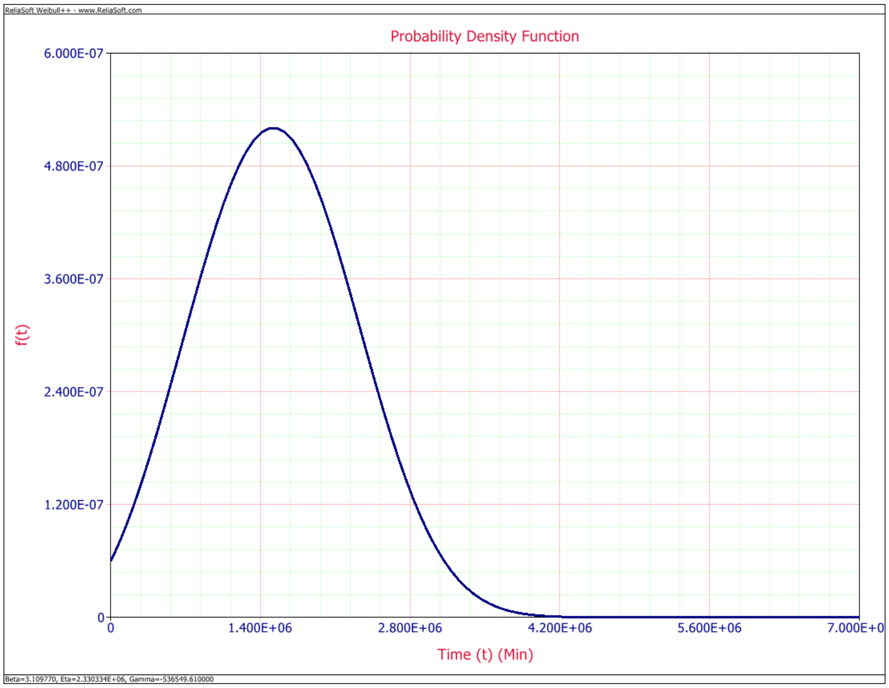
Cranbrook



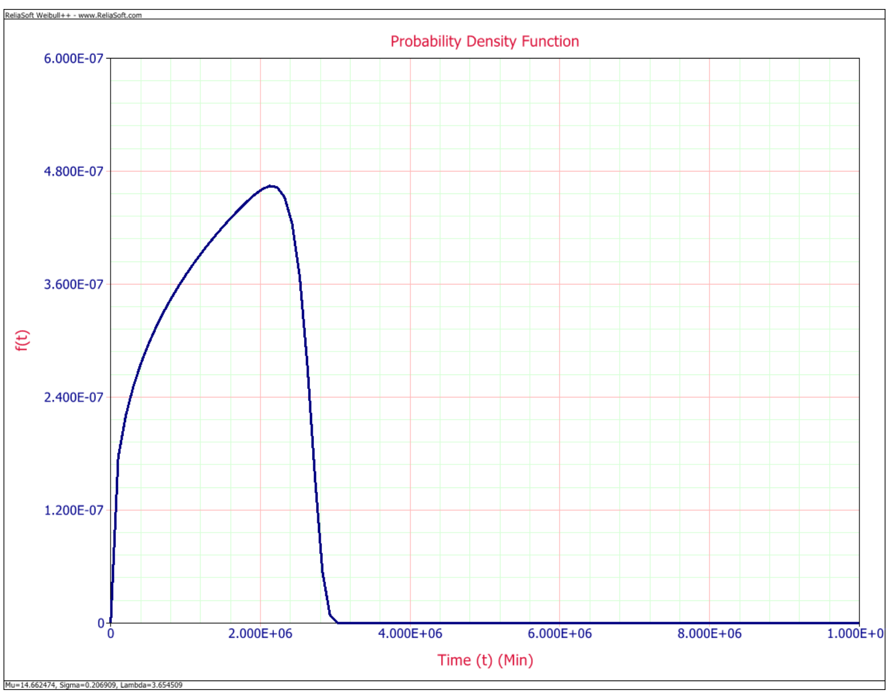
Fording River



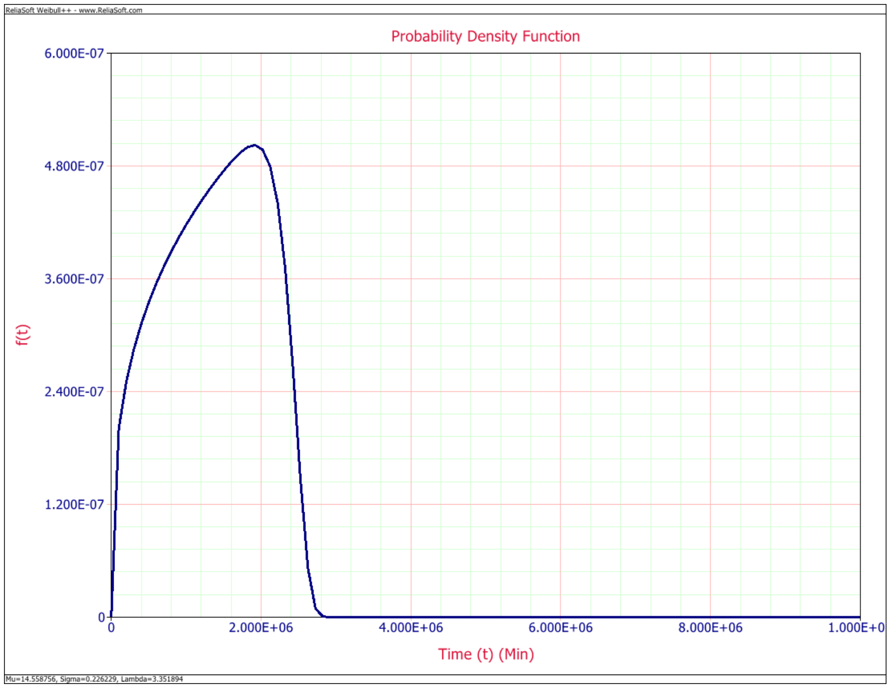
Mountain



Shuswap



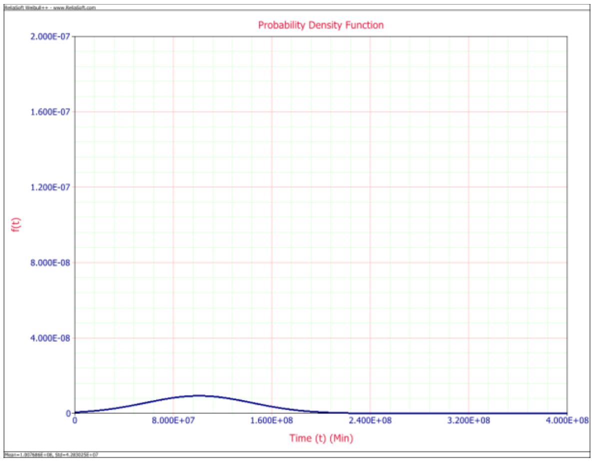
Thompson



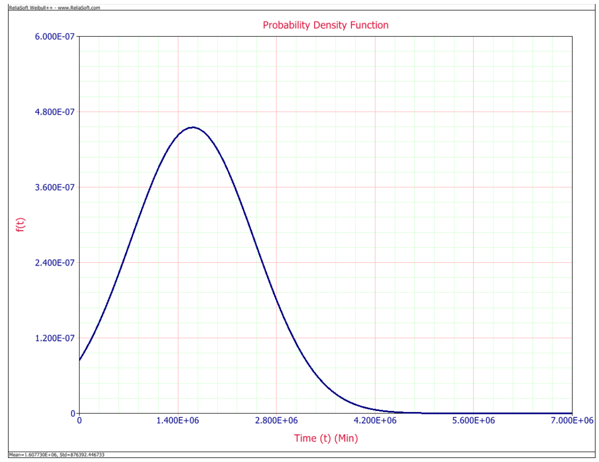
Windermere

Figure a-8: PDF plots for the detectors in each subdivision

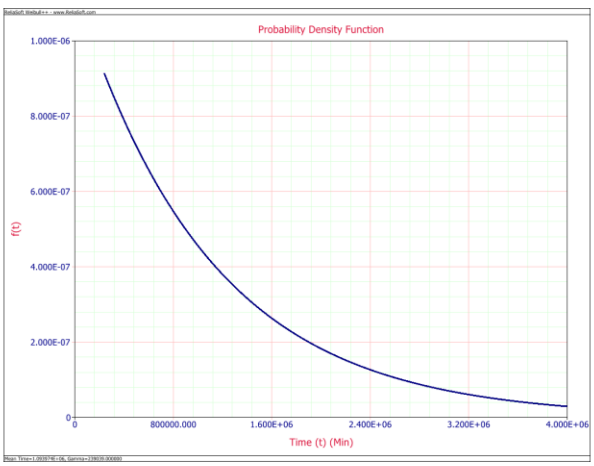
The PDFs for the 2-parameter distributions:



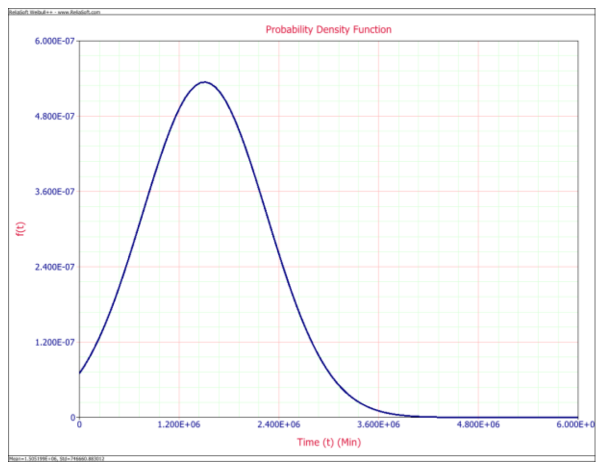
Cascade 10.9



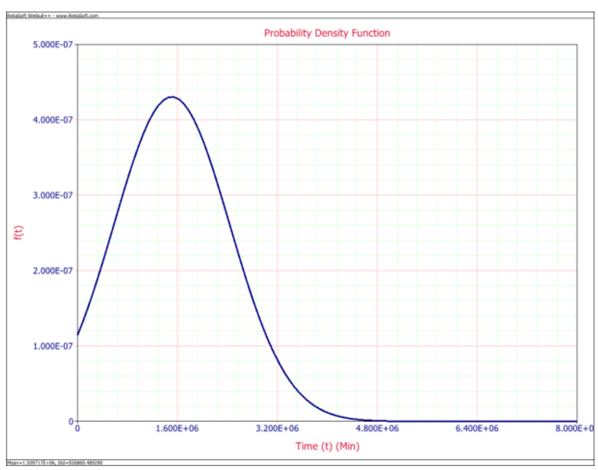
Cascade 32.5



Cascade 54.9

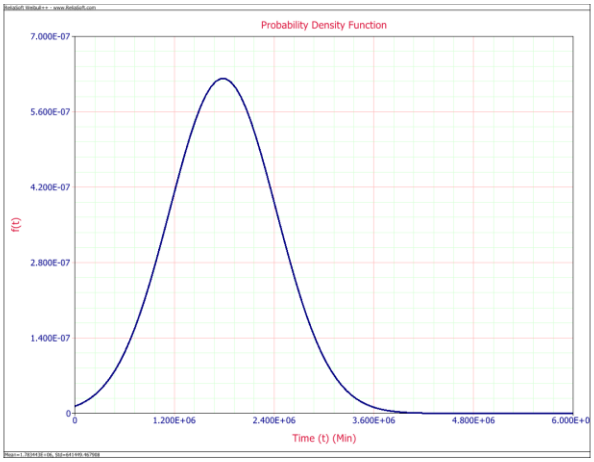


Cascade 80.1

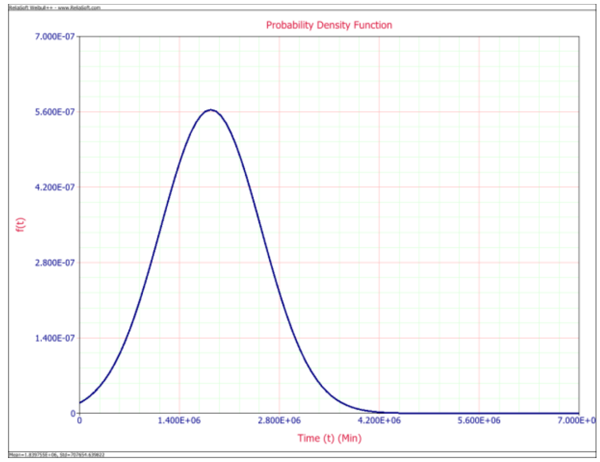


Cascade 96.8

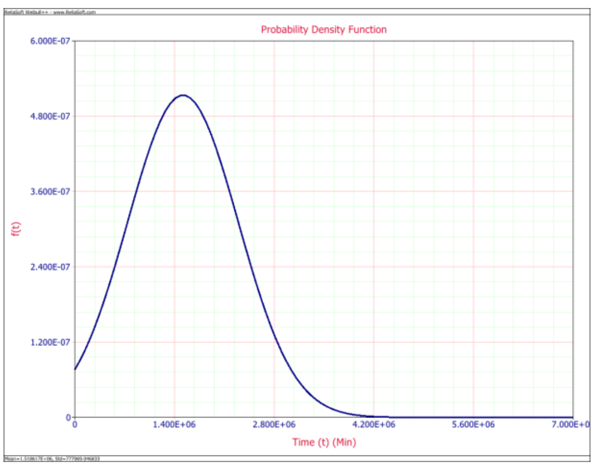
Figure a-9: PDF plots for the 2-parameter distribution for the detectors in Cascade subdivision



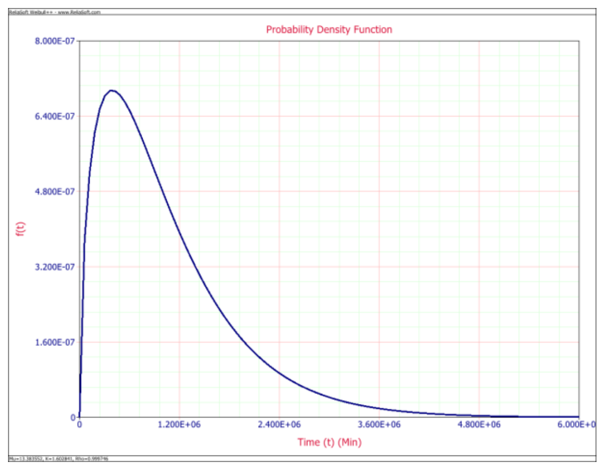
Cranbrook 24.7



Cranbrook 40.3



Cranbrook 65.3



Cranbrook 86.8

Figure a-10: PDF plots for the 2-parameter distribution for the detectors in Cranbrook subdivision

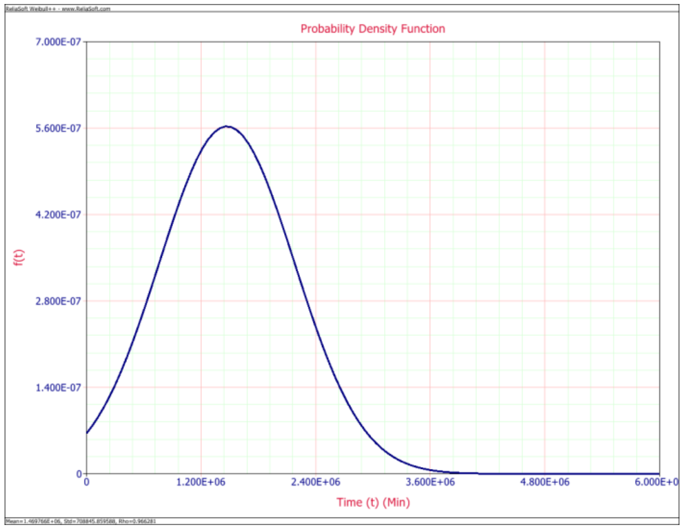
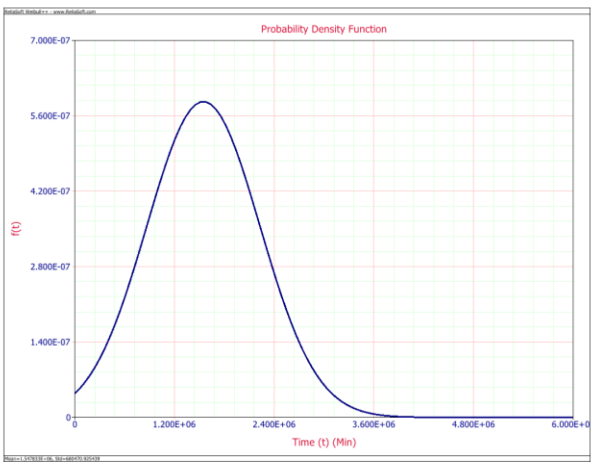
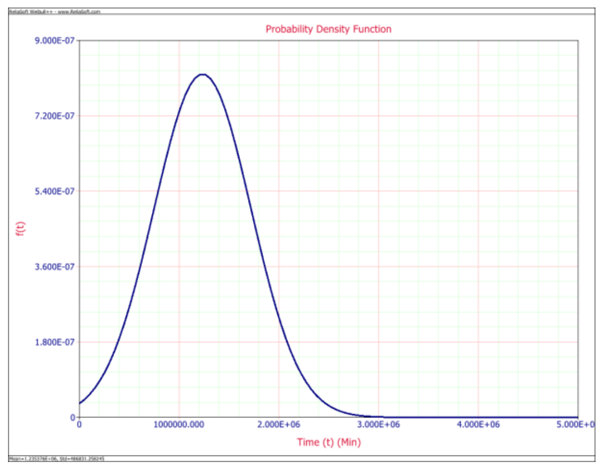


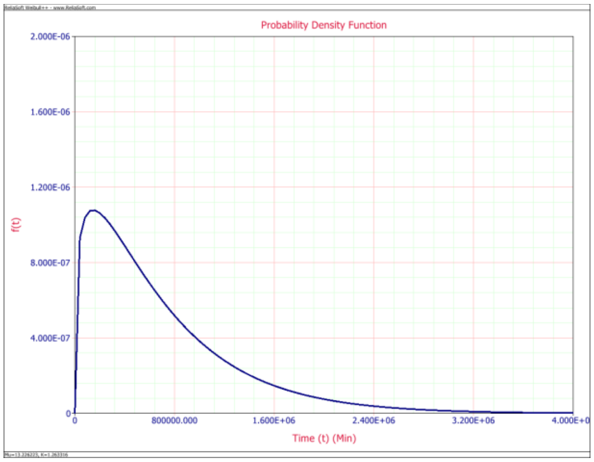
Figure a-11: PDF plot for the 2-parameter distribution for the detectors in Fording River



Mountain 14.2

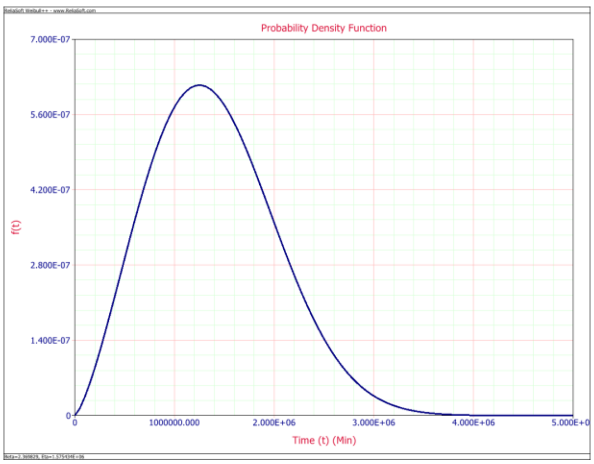


Mountain 39.3

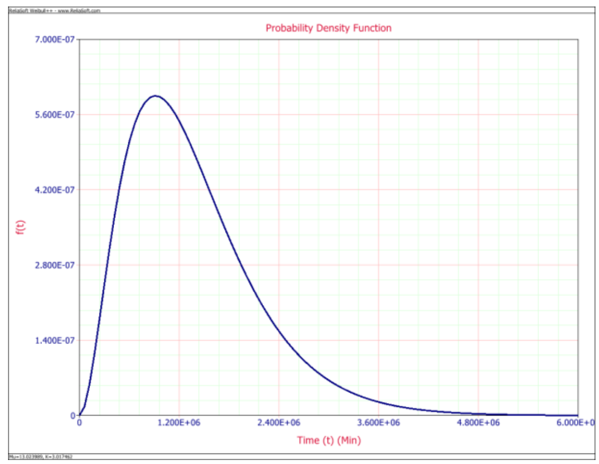


Mountain 44.9

Mountain 54.5

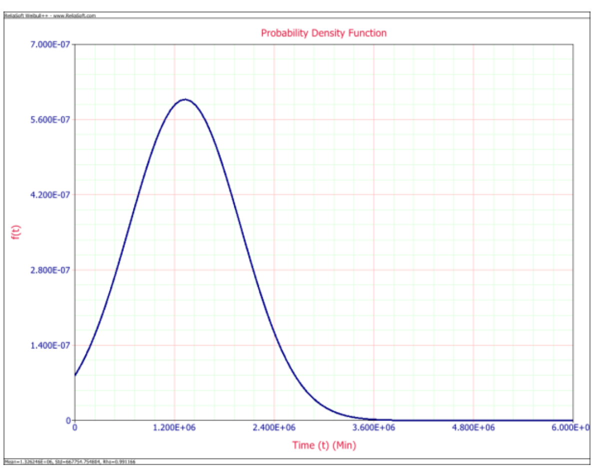


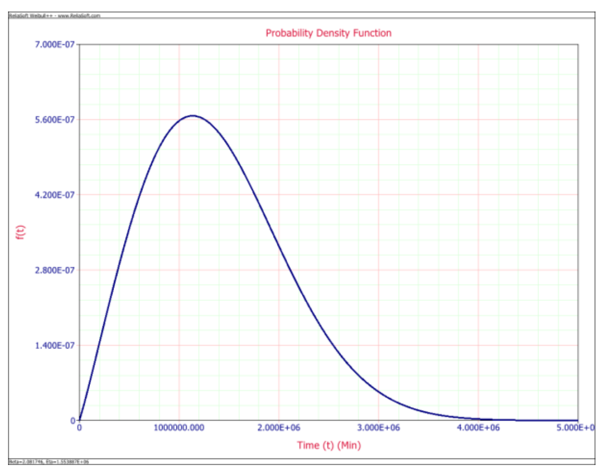
Mountain 70.9



Mountain 74.8

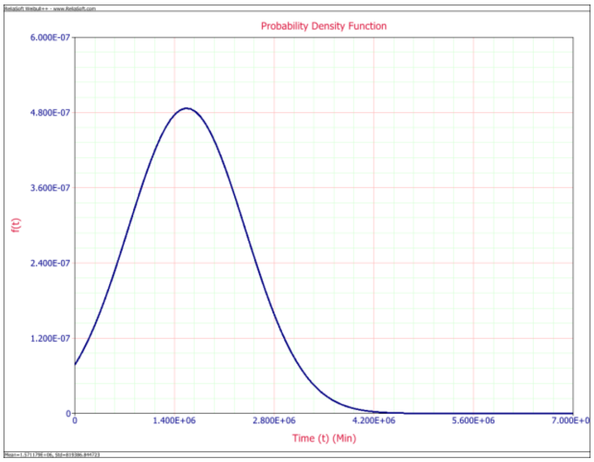
Figure a-12: PDF plot for the 2-parameter distribution for the detectors in Mountain Subdivision



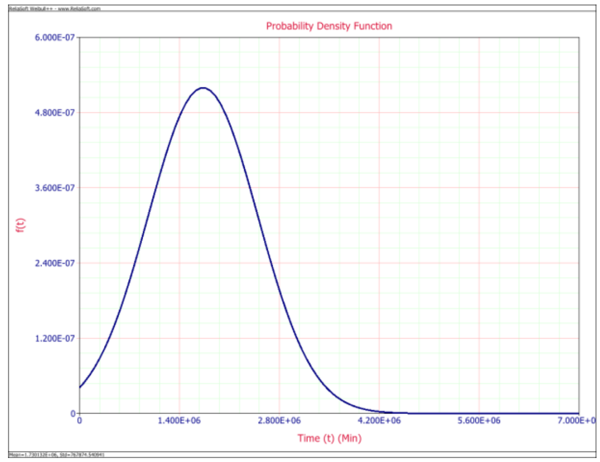


Mountain 95.1 Mountain 111.7

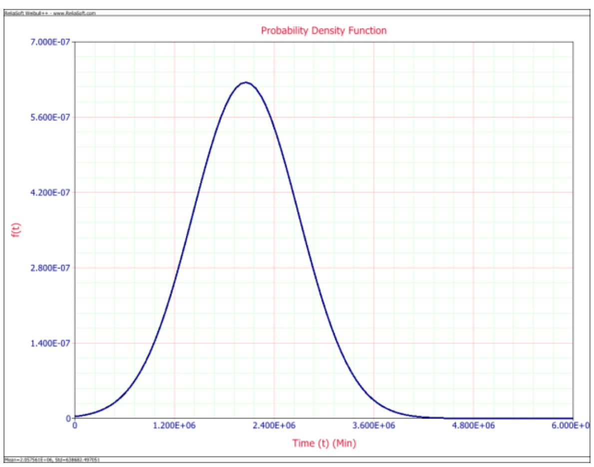
Figure a-12: PDF plot for the 2-parameter distribution for the detectors in Mountain Subdivision



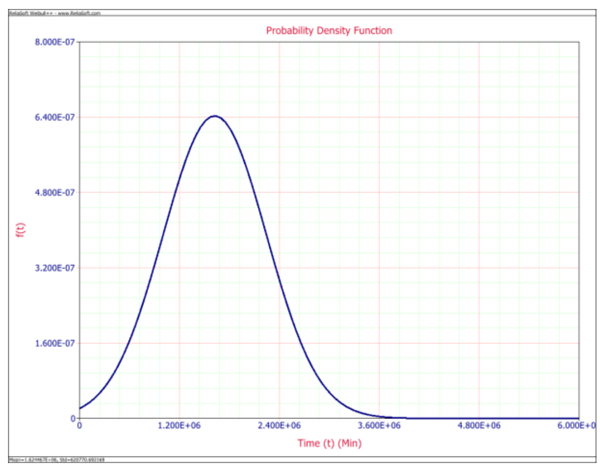
Shuswap 19.7



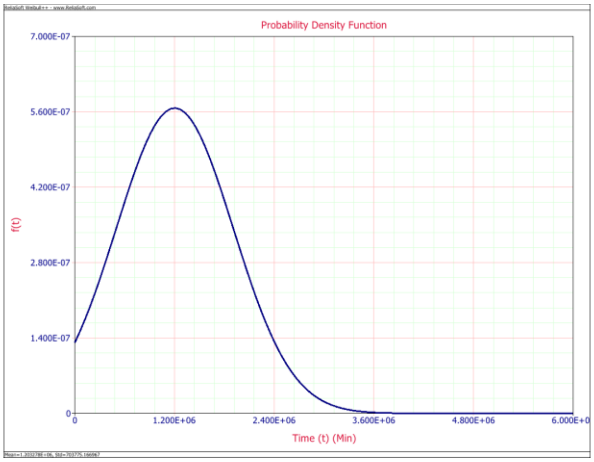
Shuswap 40.8



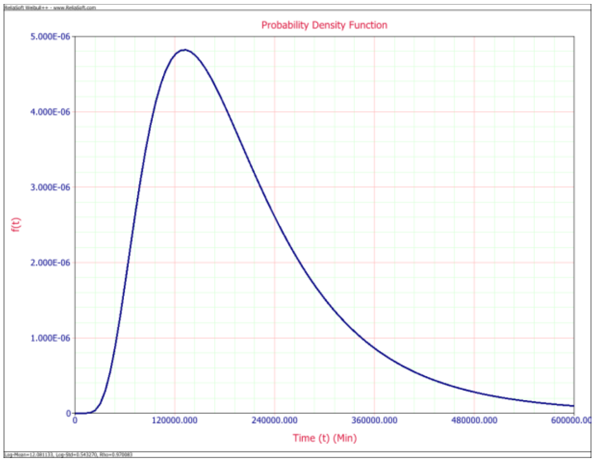
Shuswap 59.1



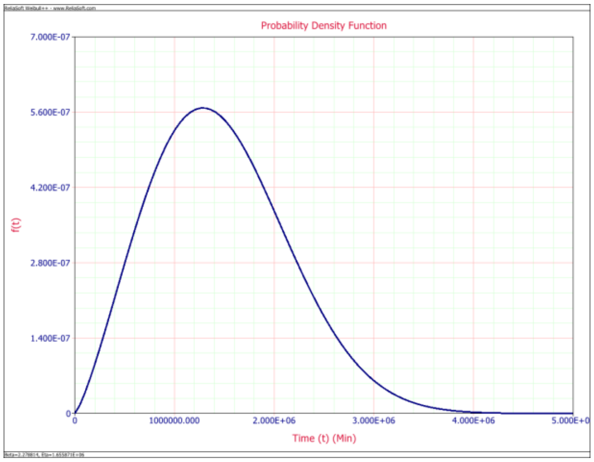
Shuswap 77.4



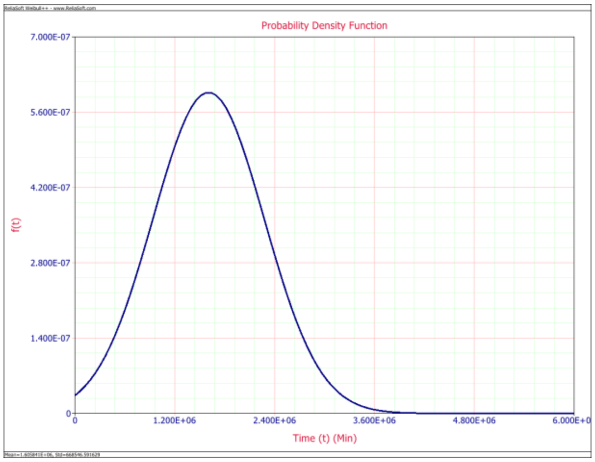
Shuswap 77.5



Shuswap 90

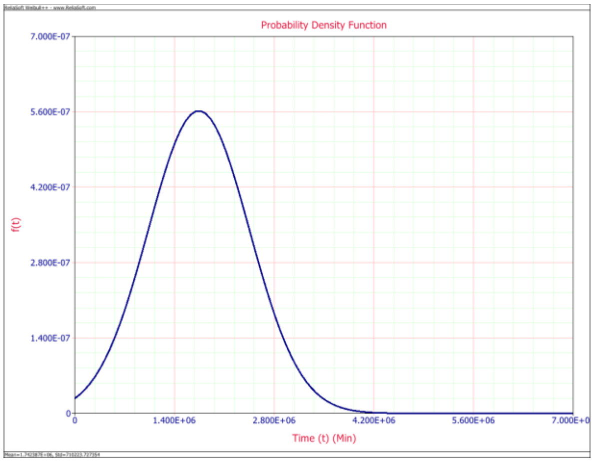


Shuswap 97.9

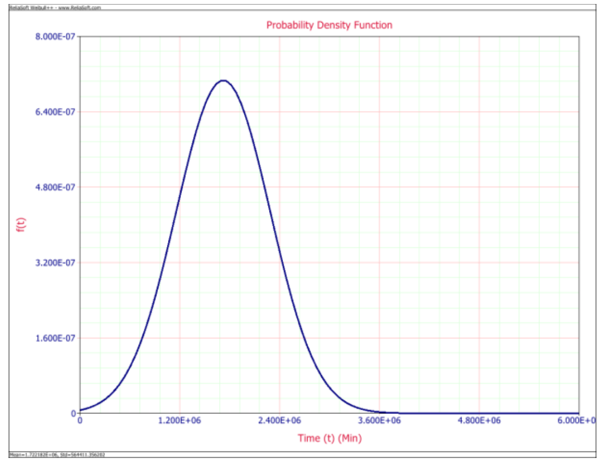


Shuswap 118.5

Figure a-13: PDF plot for the 2-parameter distribution for the detectors in Shuswap Subdivision

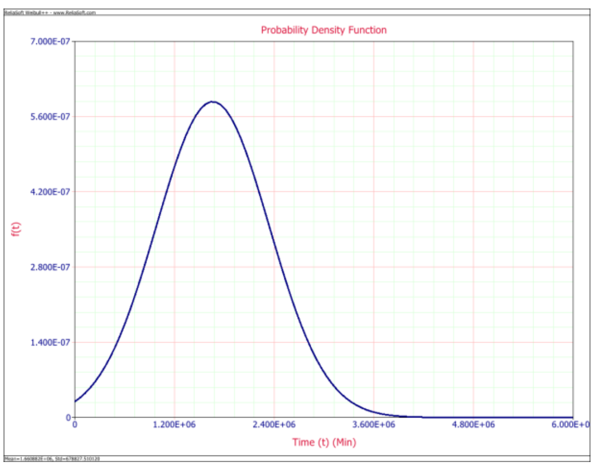


Thompson 11.8

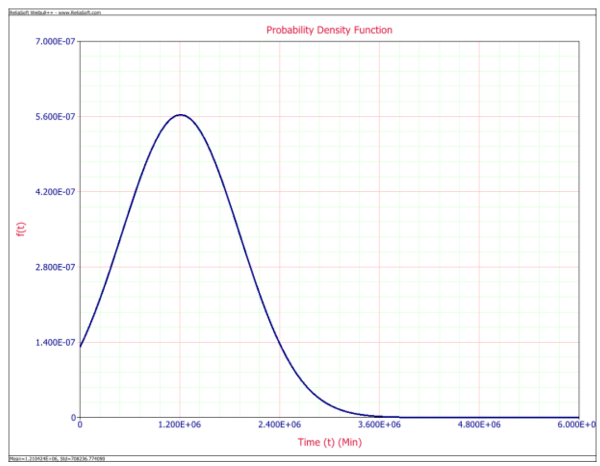


Thompson 35.5

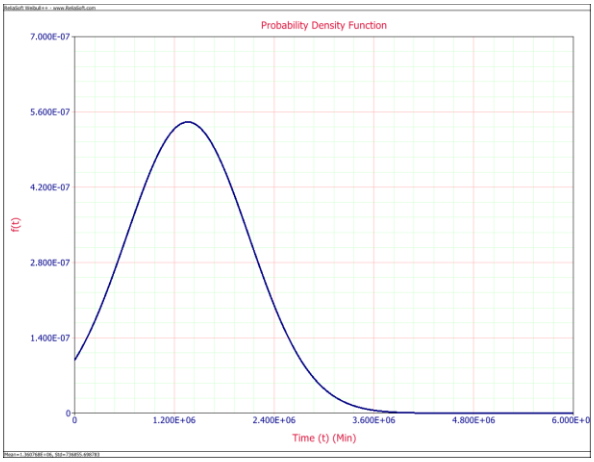
Figure a-14: PDF plot for the 2-parameter distribution for the detectors in Thompson Subdivision



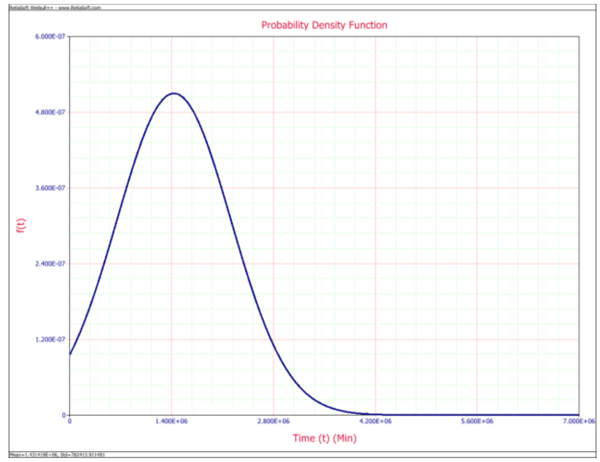
Thompson 44.3



Thompson 60.5

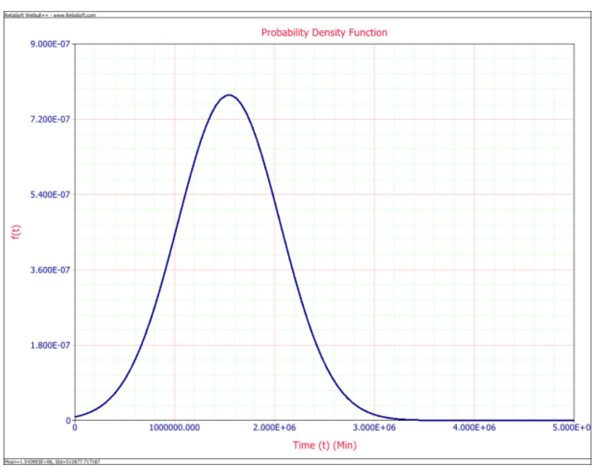


Thompson 81.9

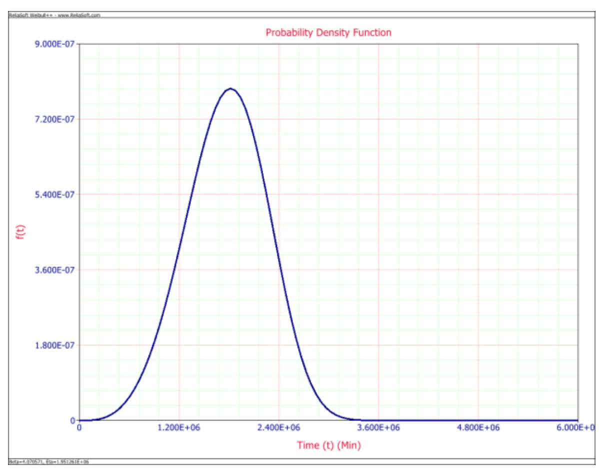


Thompson 98.1

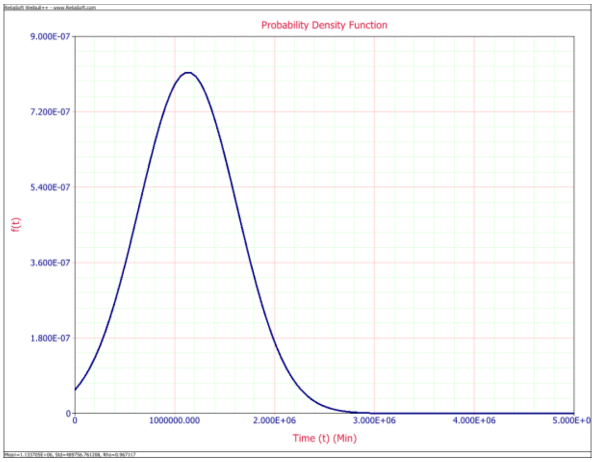
Figure a-15: PDF plot for the 2-parameter distribution for the detectors in Thompson Subdivision

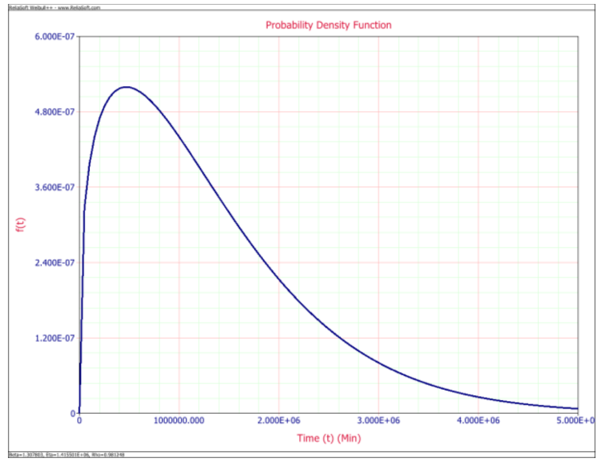


Windermere 8.5



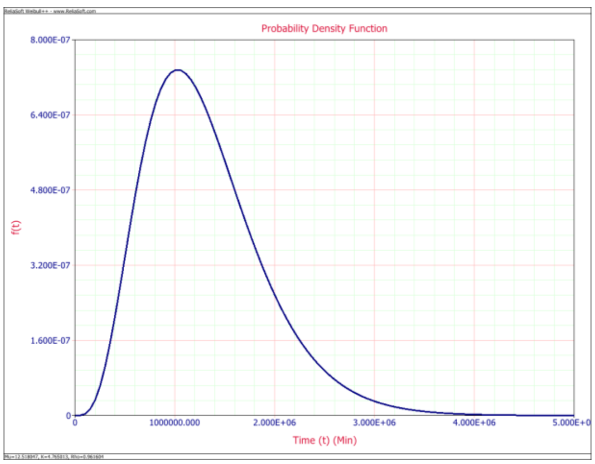
Windermere 25.2

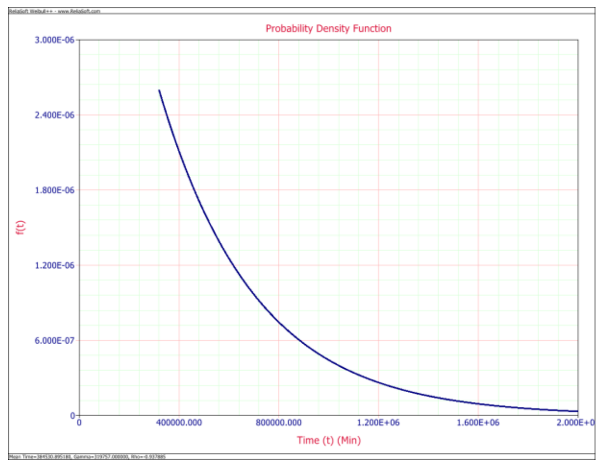




Windermere50.4

Windermere 54.7

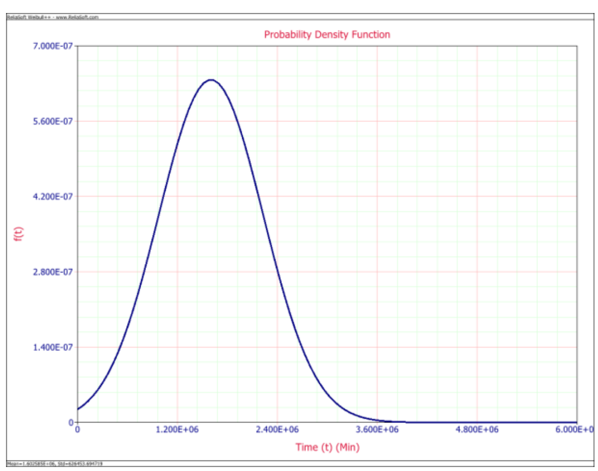




Windermere 97.2

Windermere 113.4

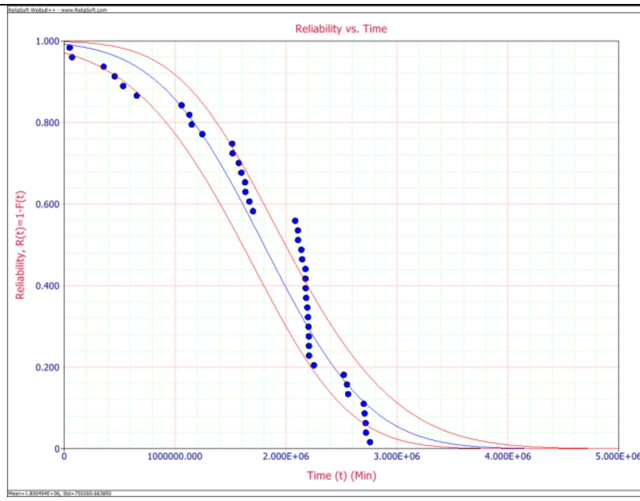
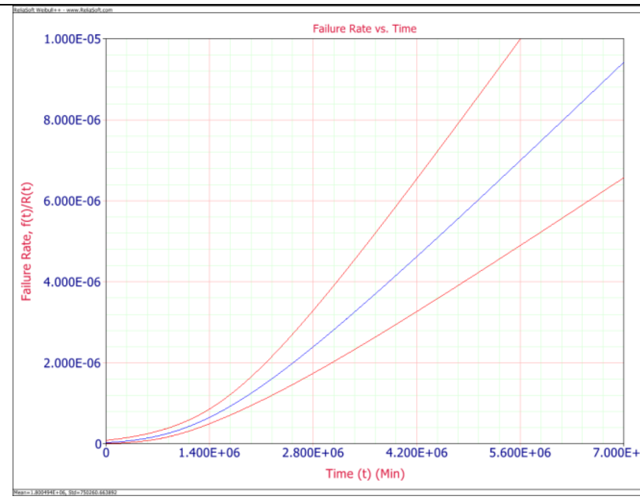
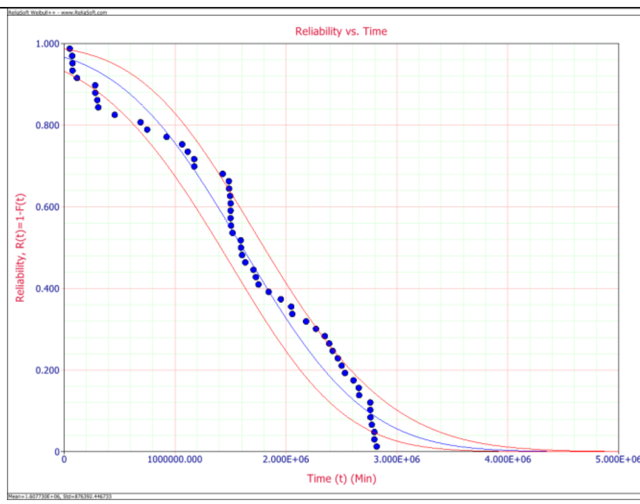
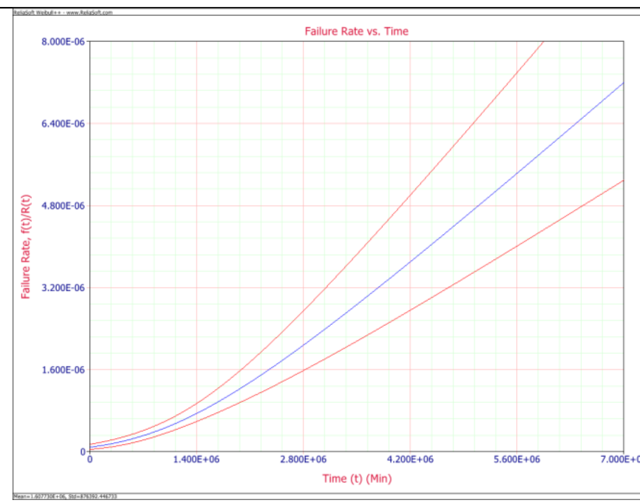
Figure a-16: PDF plot for the 2-parameter distribution for the detectors in Windermere Subdivision



Windermere 123.3

Figure a-16: PDF plot for the 2-parameter distribution for the detectors in Windermere Subdivision

The reliability versus time and failure rate versus time after finalization and selection of normal distribution are as follow:

Cascade 10.9		
Cascade 32.5		

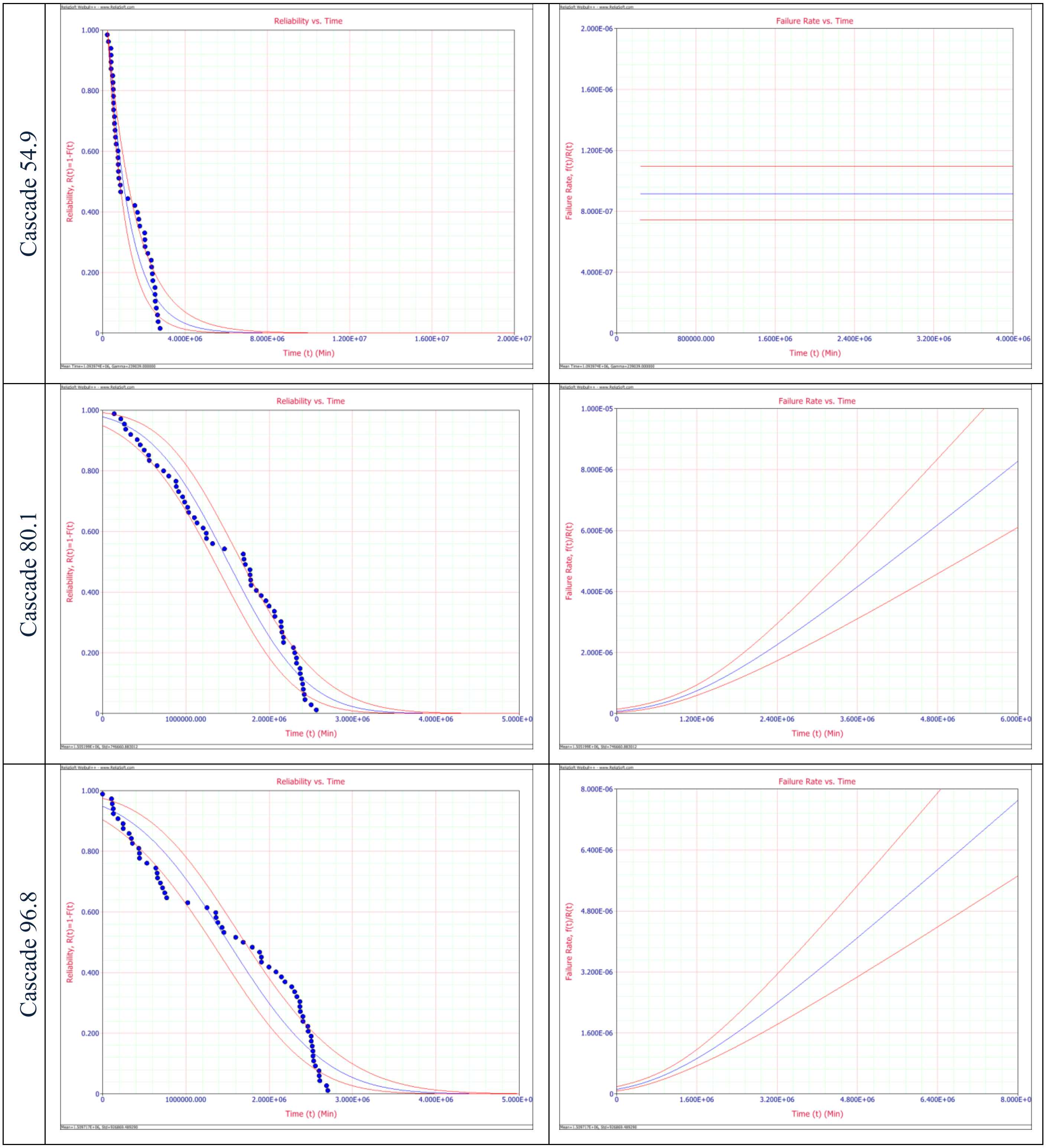
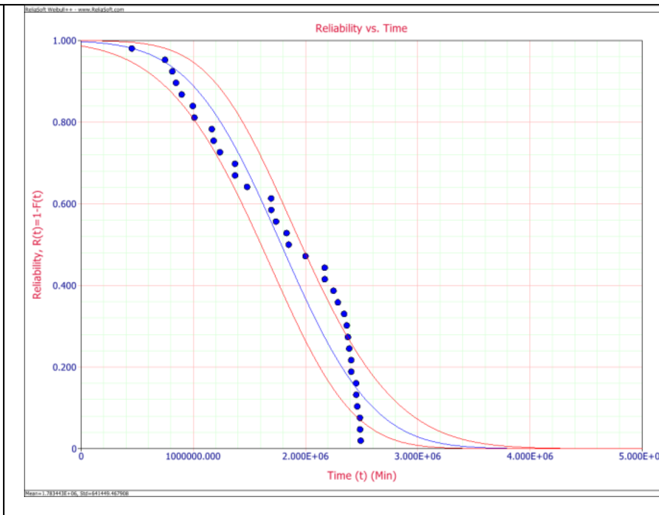
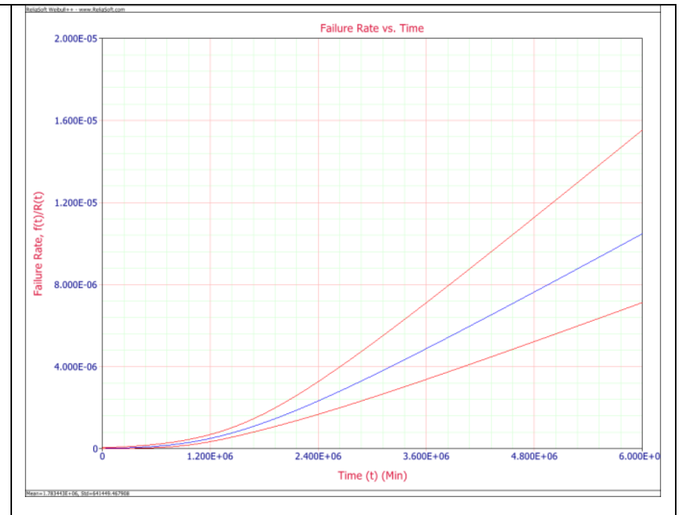


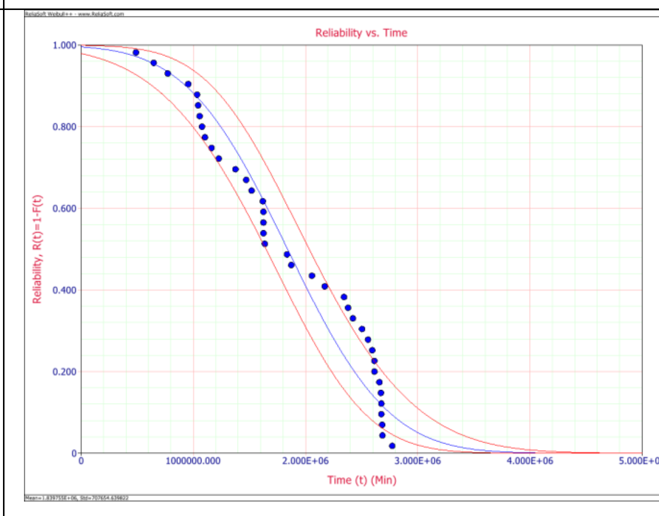
Figure a-17: Reliability-Time and Failure rate-time for the detectors in Cascade Subdivision

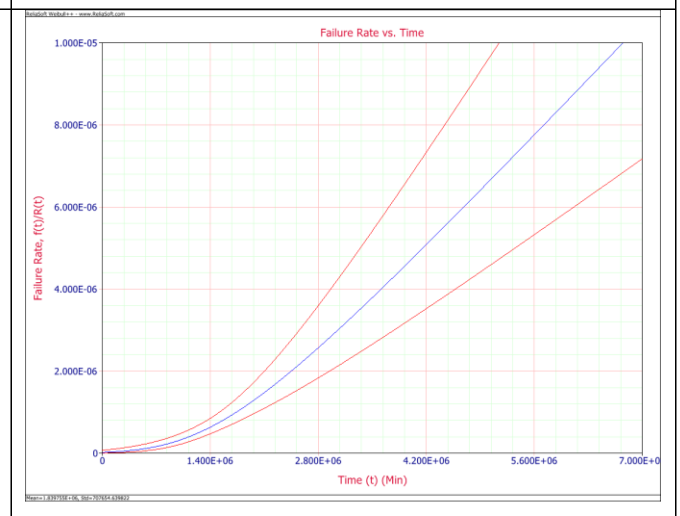
Cranbrook 24.7



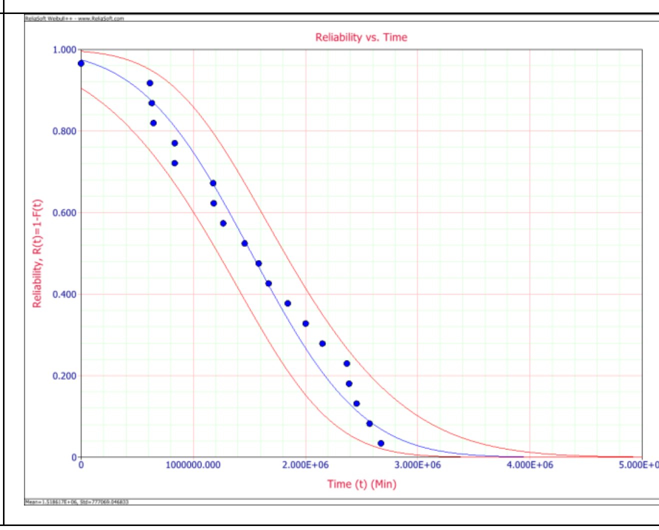


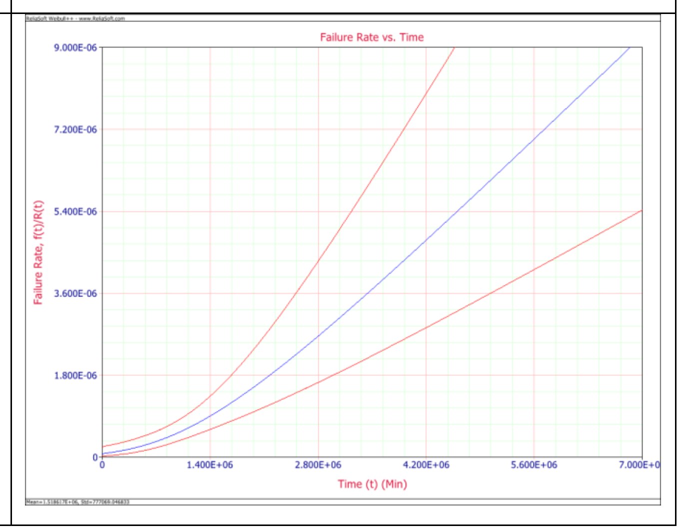
Cranbrook 40.3





Cranbrook 65.3





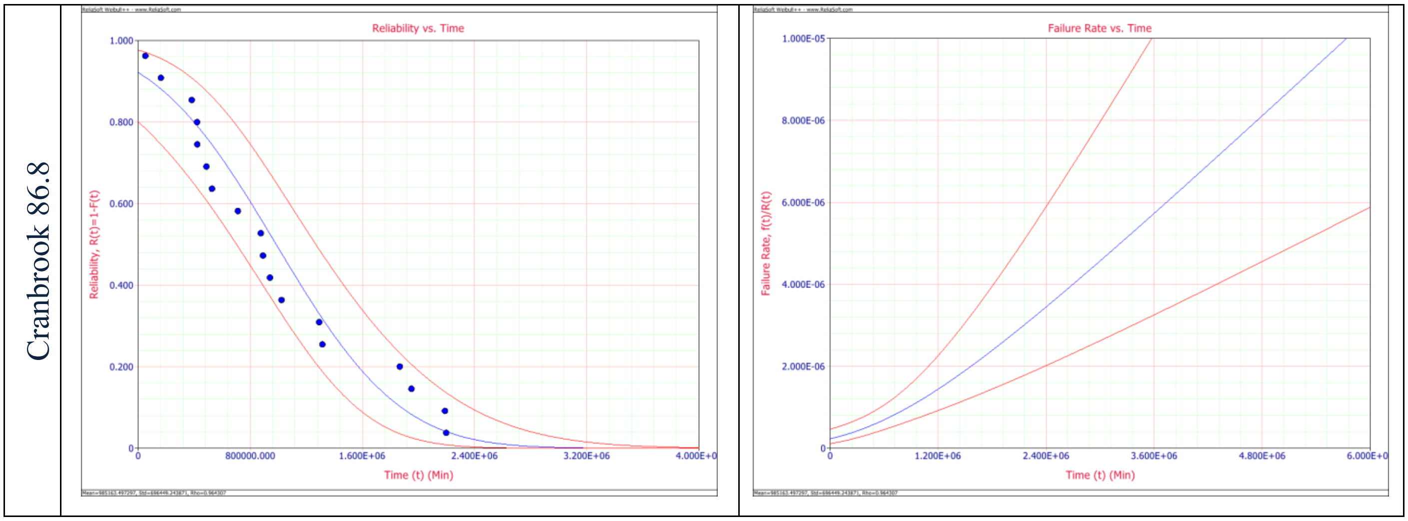


Figure a-18: Reliability-Time and Failure rate-time for the detectors in Cranbrook Subdivision

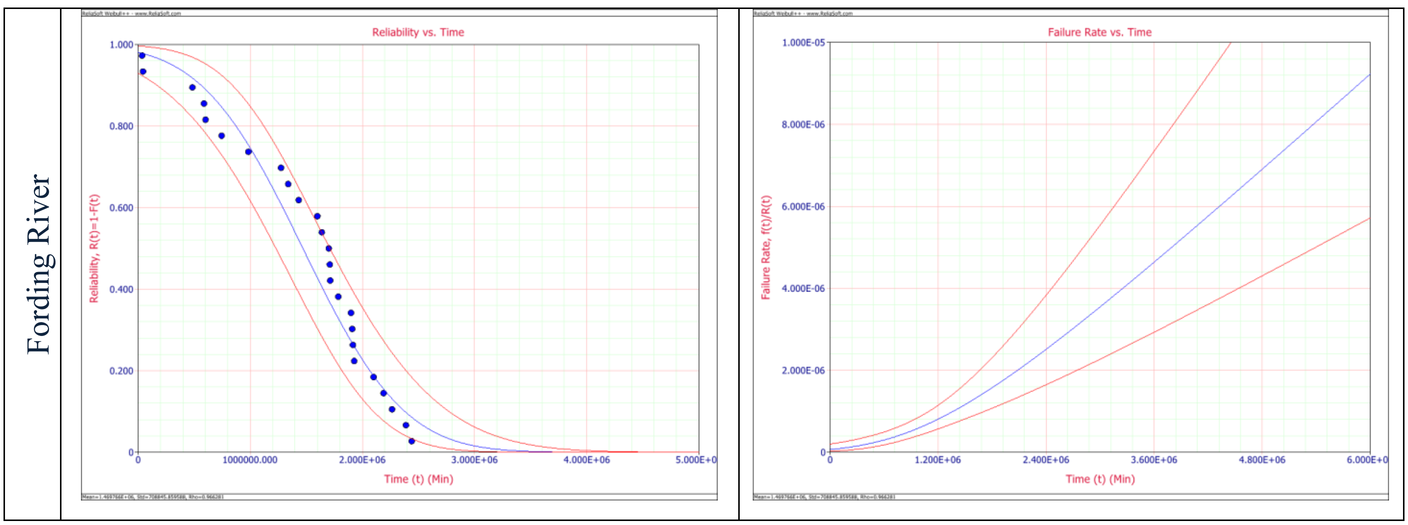
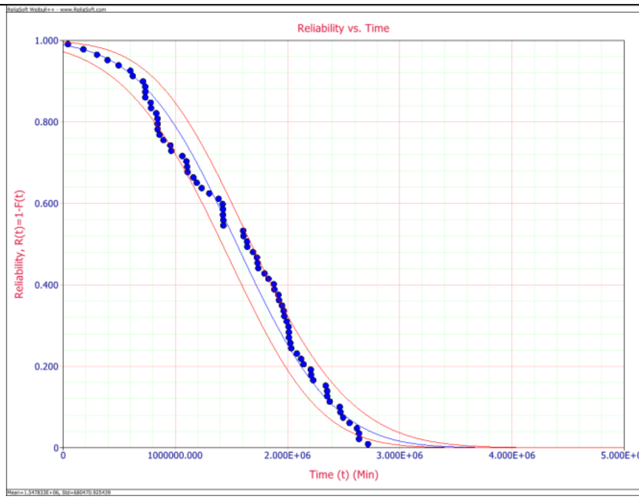
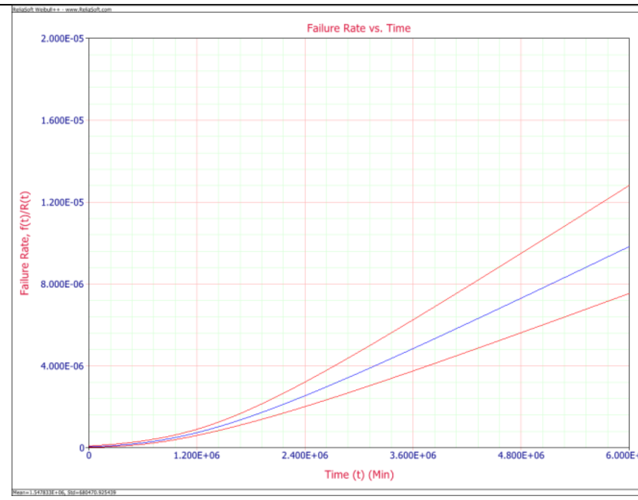


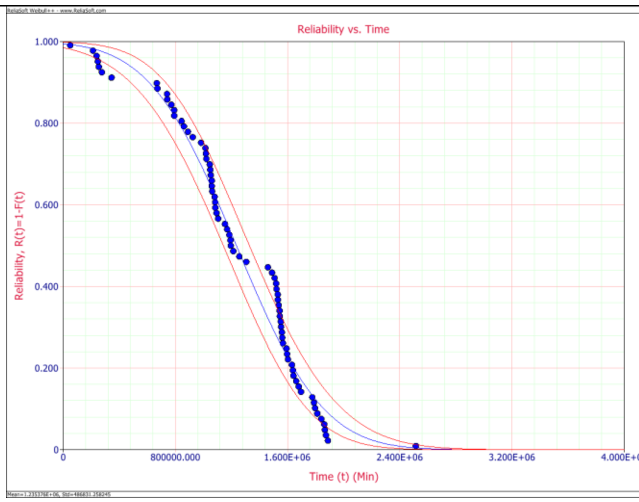
Figure a-19: Reliability-Time and Failure rate-time for the detectors in Fording River Subdivision

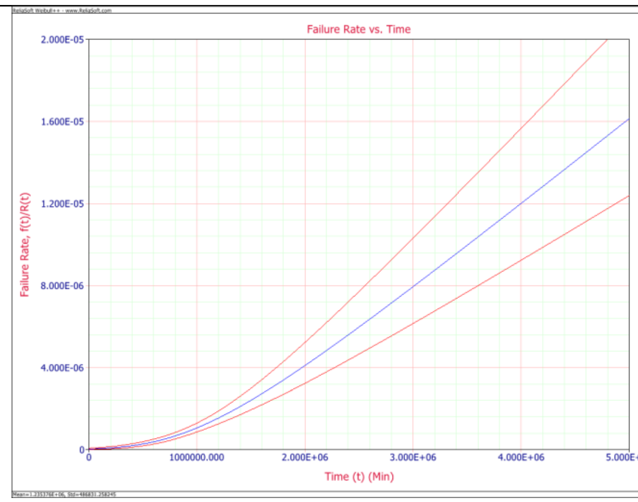
Mountain 14.2



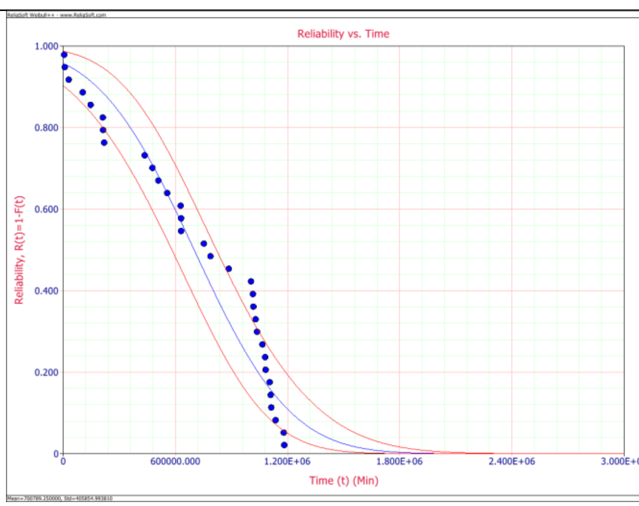


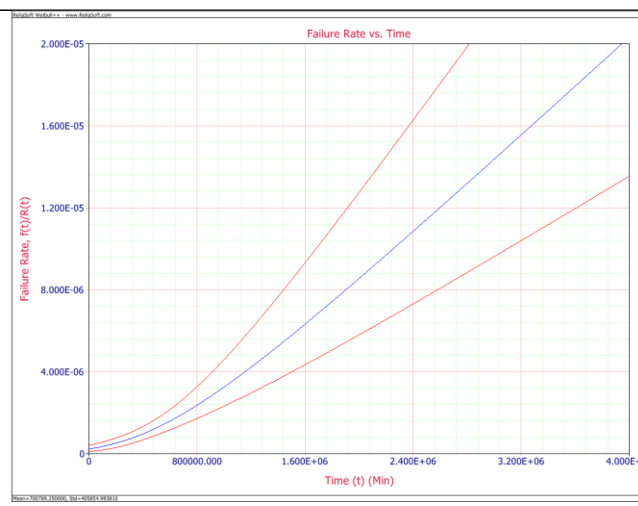
Mountain 39.3



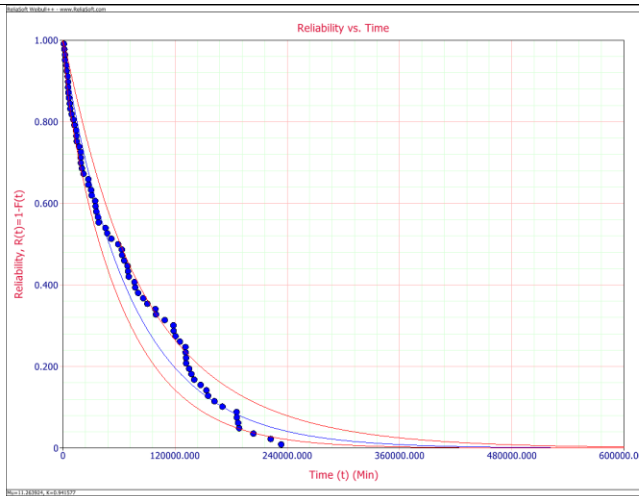


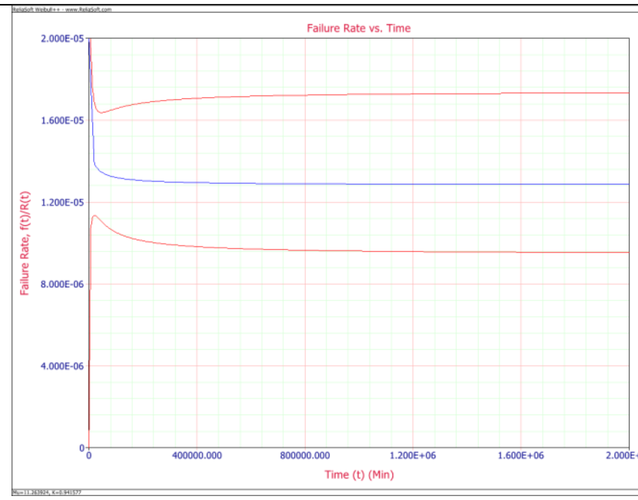
Mountain 44.9



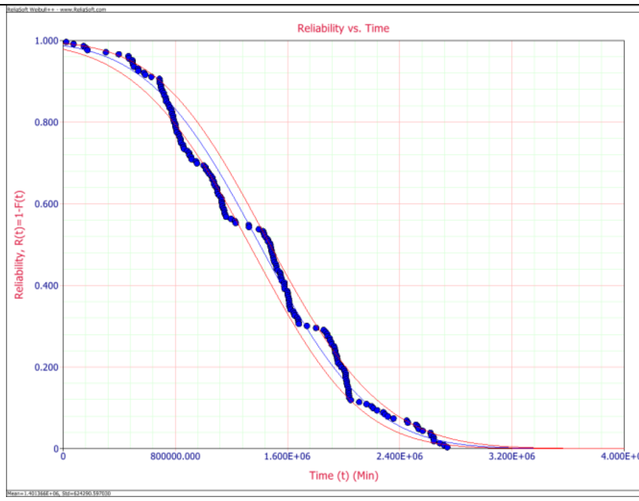


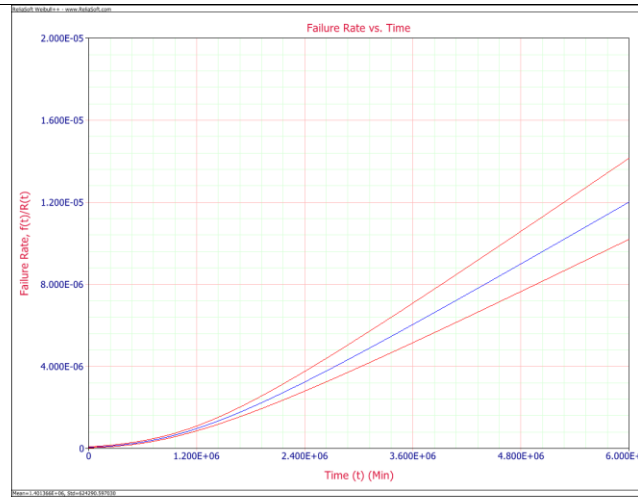
Mountain 54.5



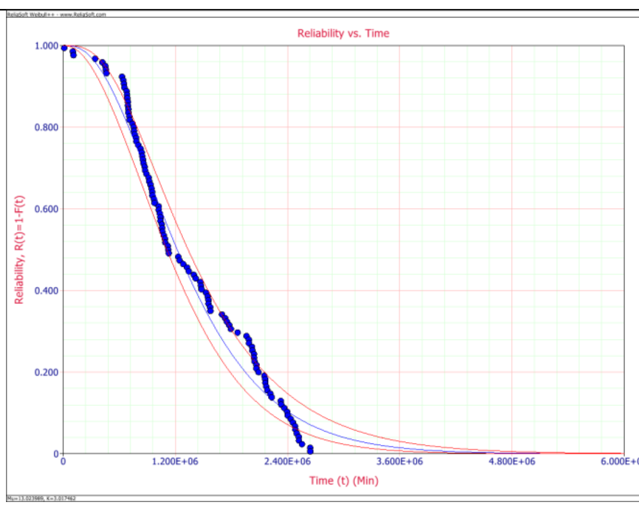


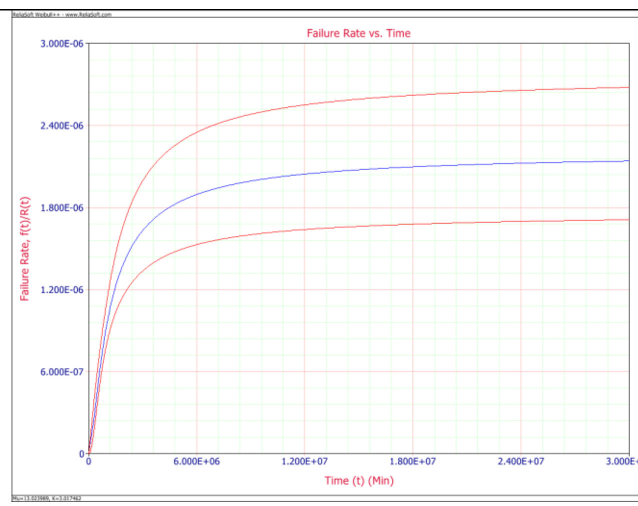
Mountain 70.9



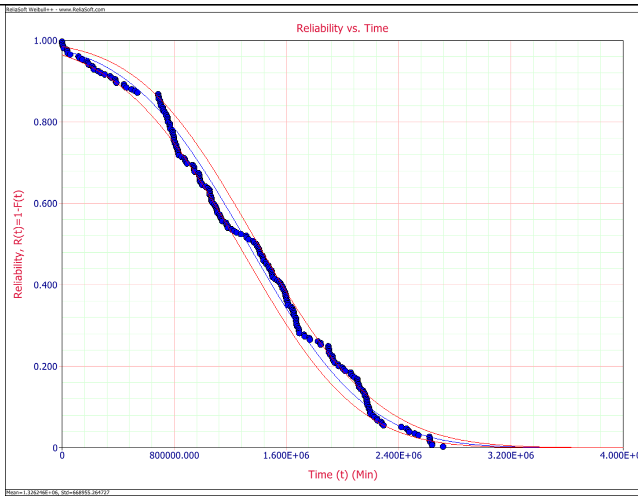


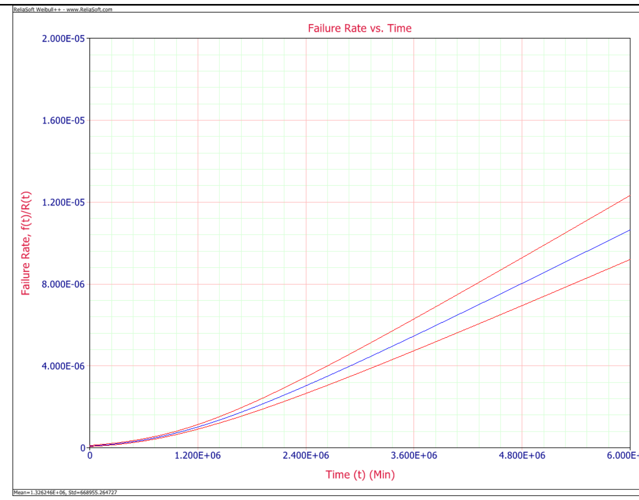
Mountain 74.8



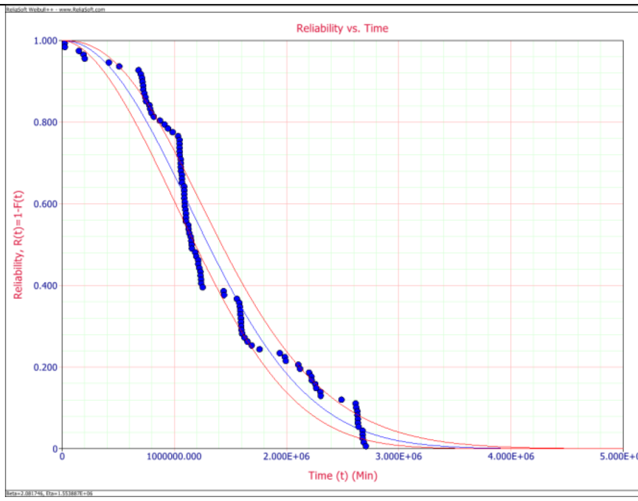


Mountain 95.1





Mountain 111.7



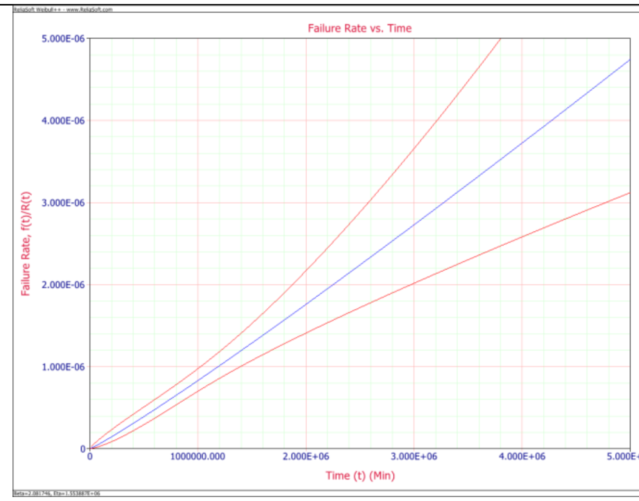
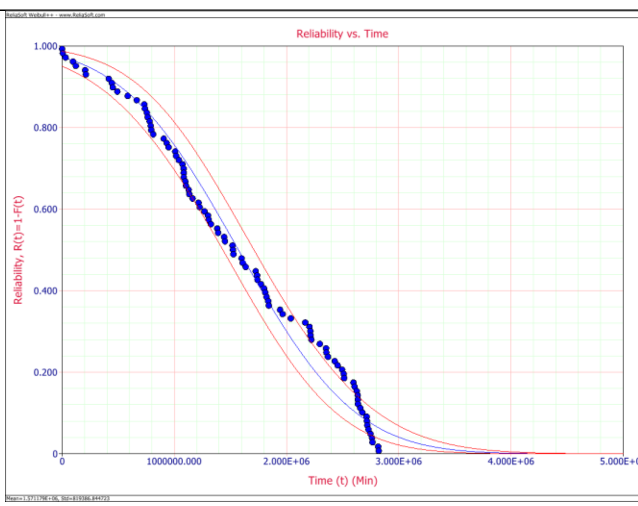
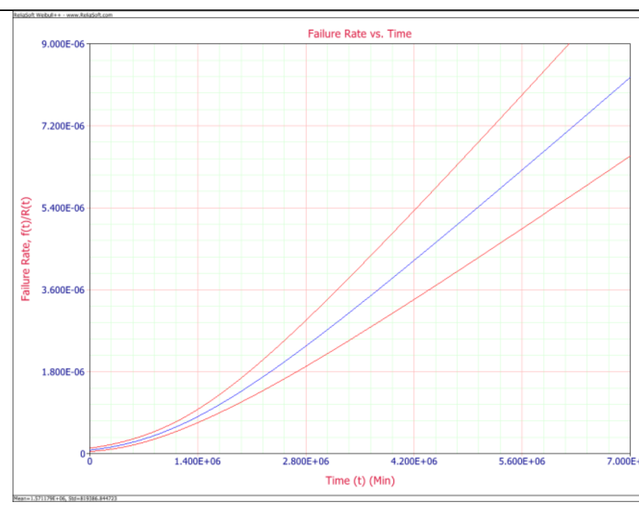


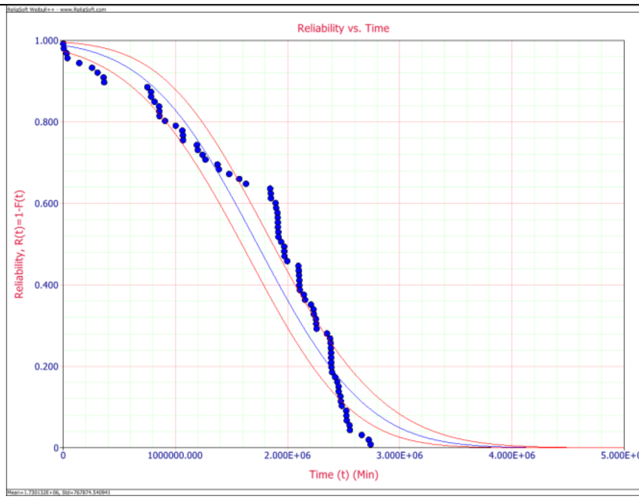
Figure a-20: Reliability-Time and Failure rate-time for the detectors in Mountain Subdivision

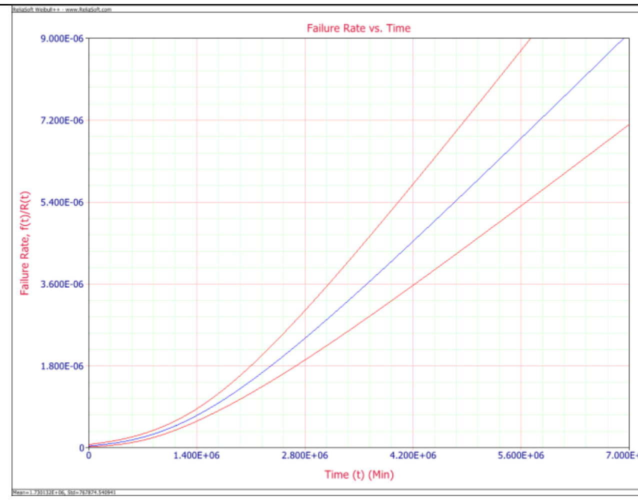
Shuswap 19.7



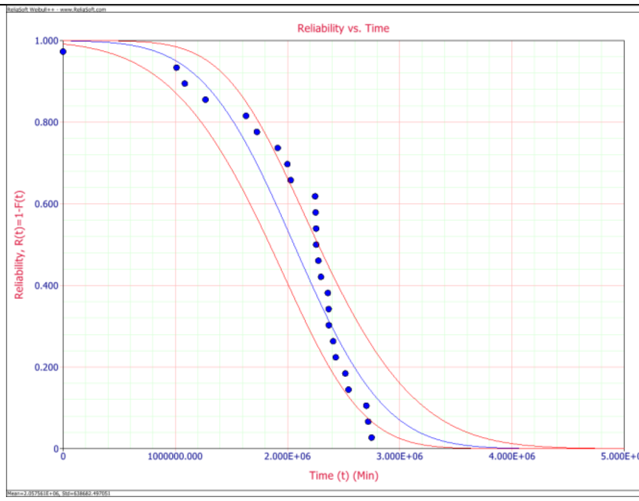


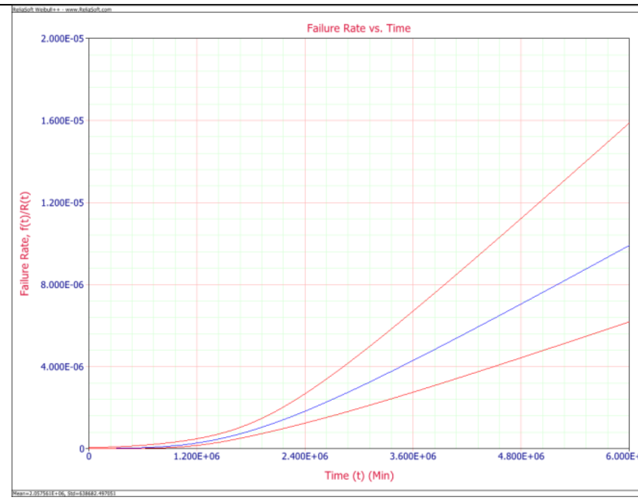
Shuswap 40.8



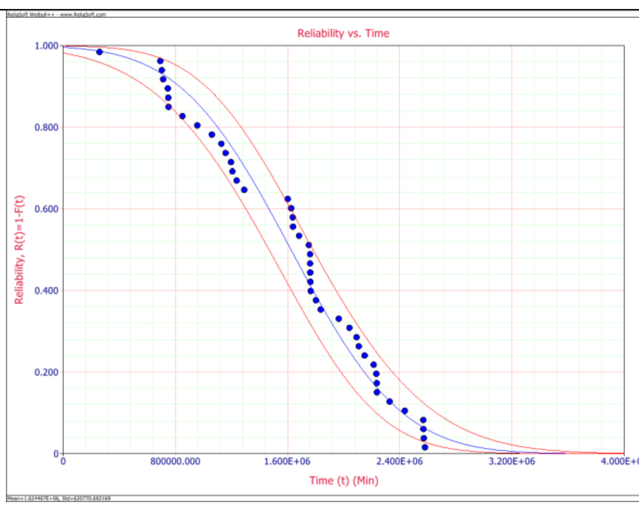


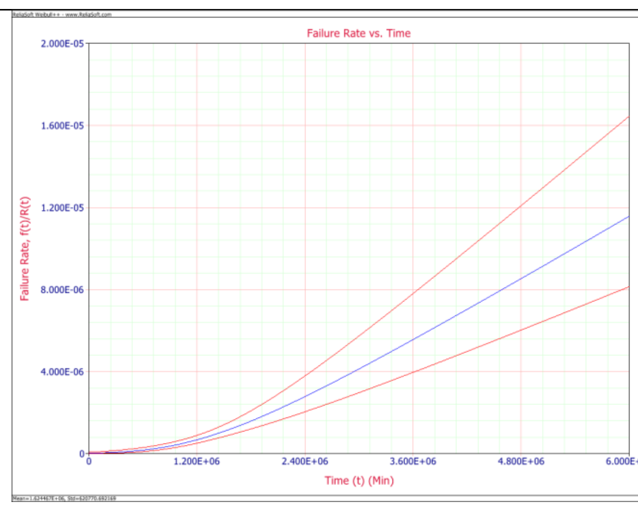
Shuswap 59.1

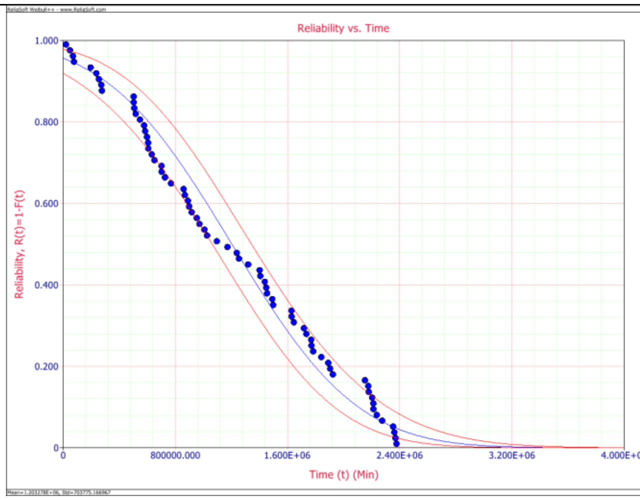
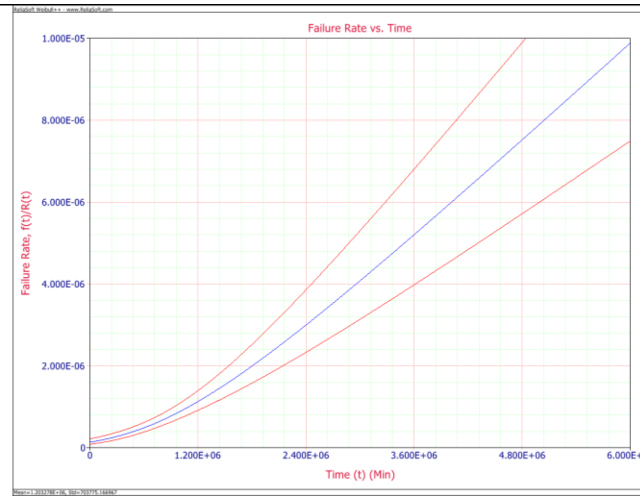
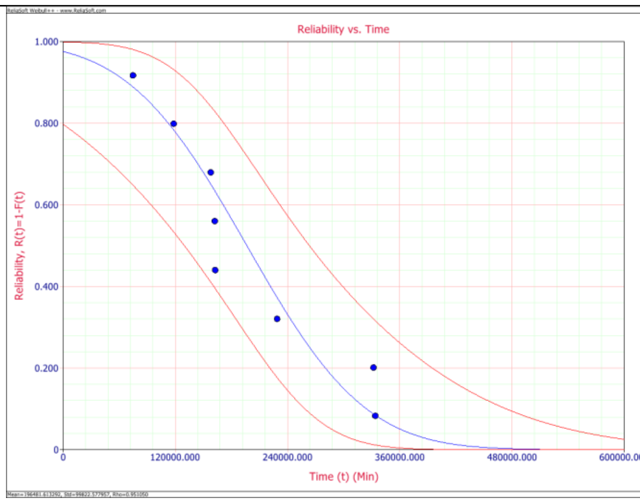
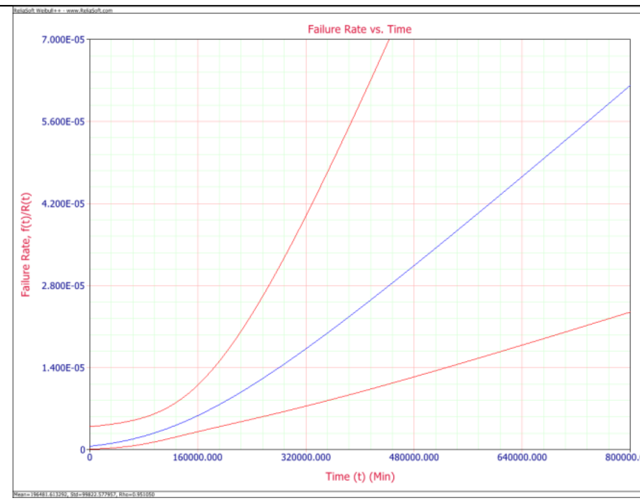
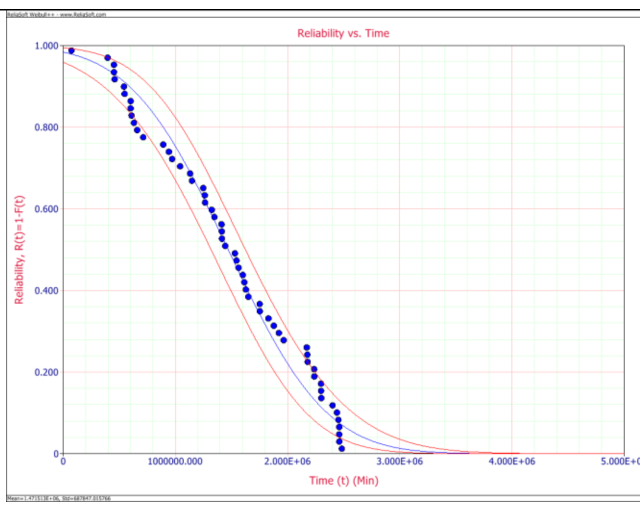
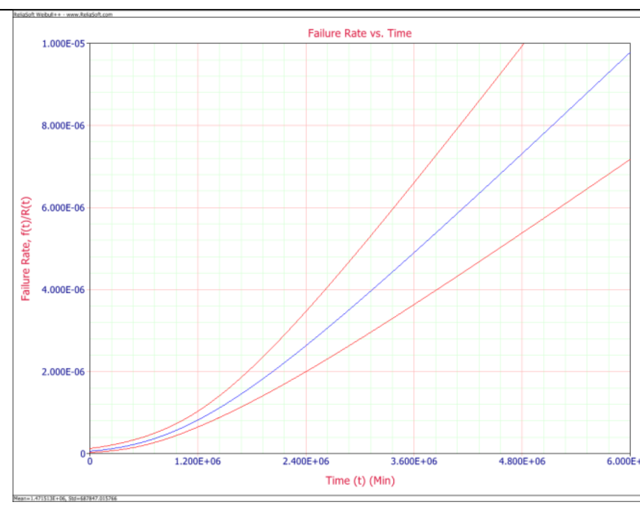




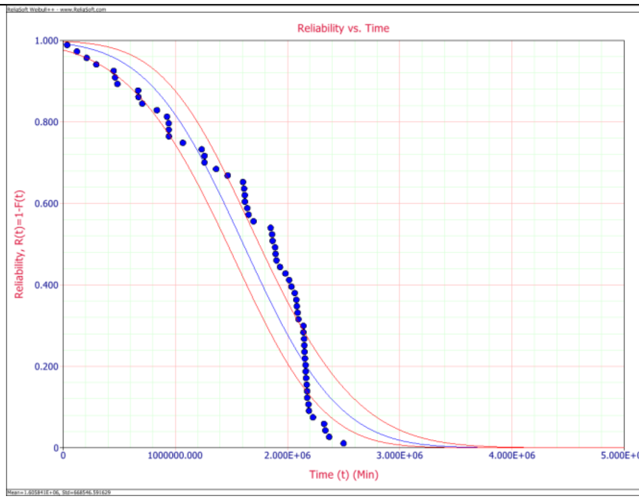
Shuswap 77.4





Shuswap 77.5		
Shuswap 90		
Shuswap 97.9		

Shuswap 118.5



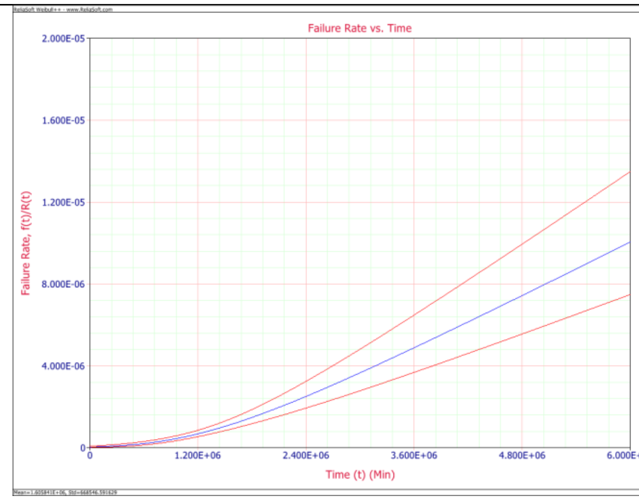
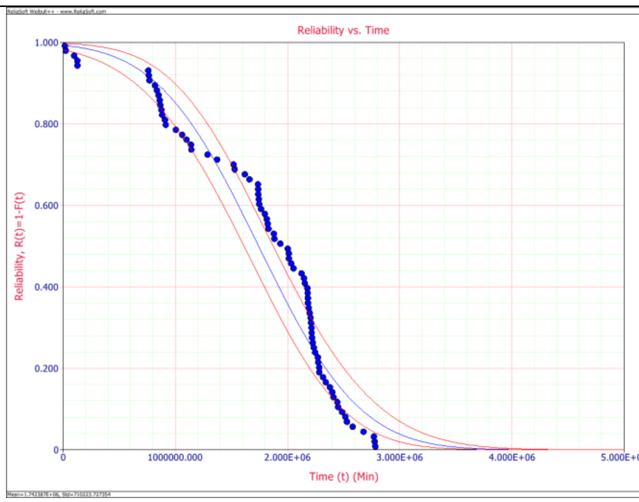
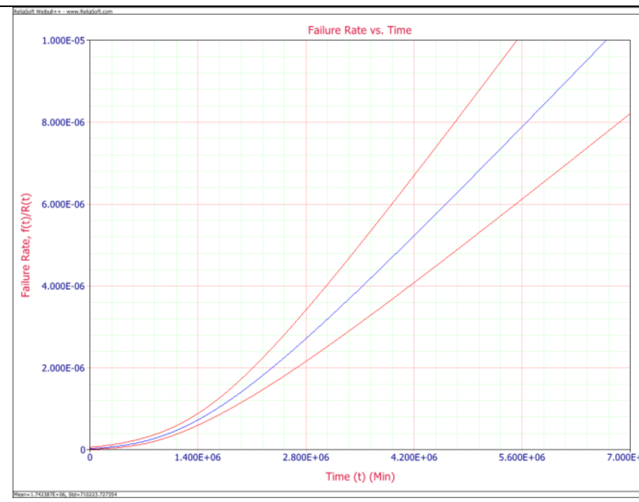


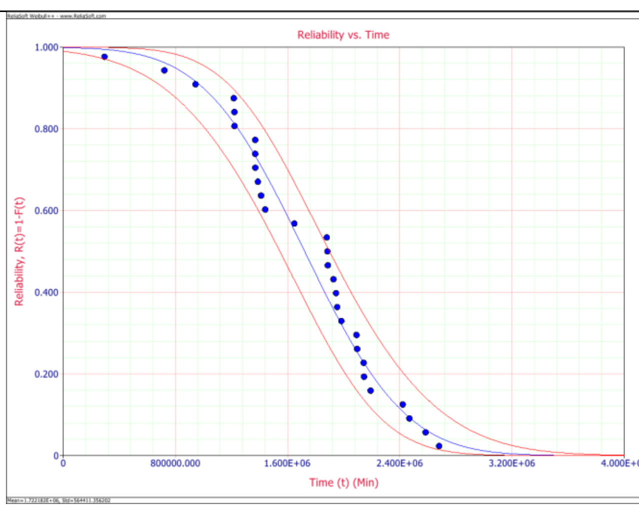
Figure a-21: Reliability-Time and Failure rate-time for the detectors in Shuswap Subdivision

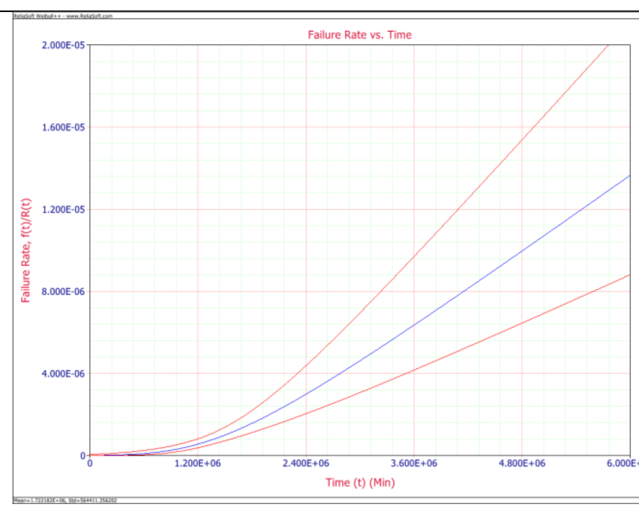
Thompson 11.8



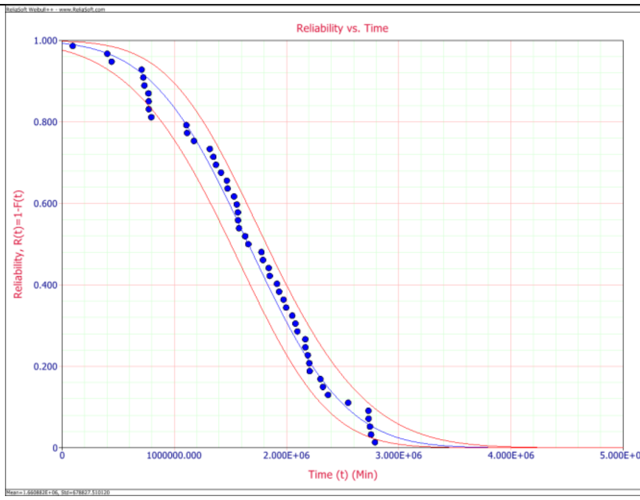


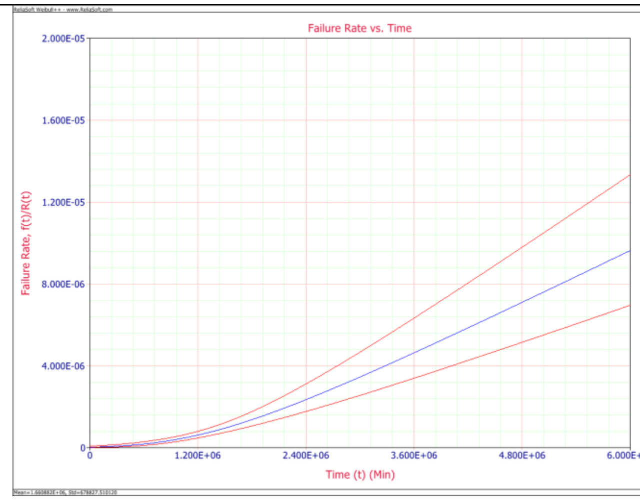
Thompson 35.5



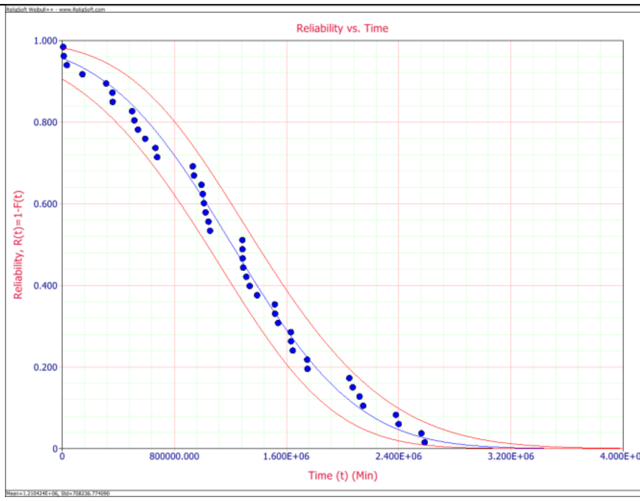


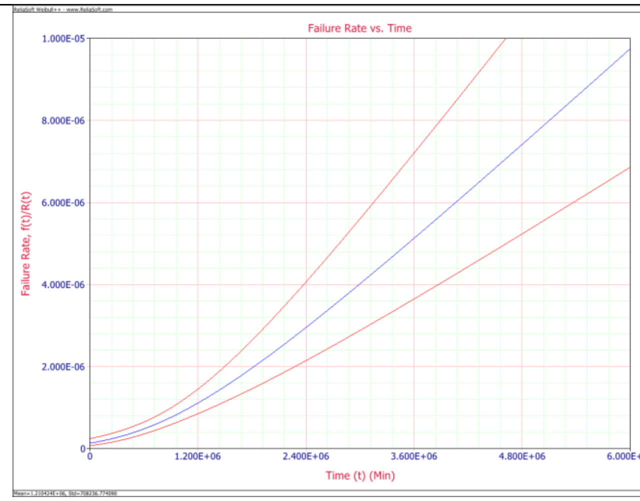
Thompson 44.3



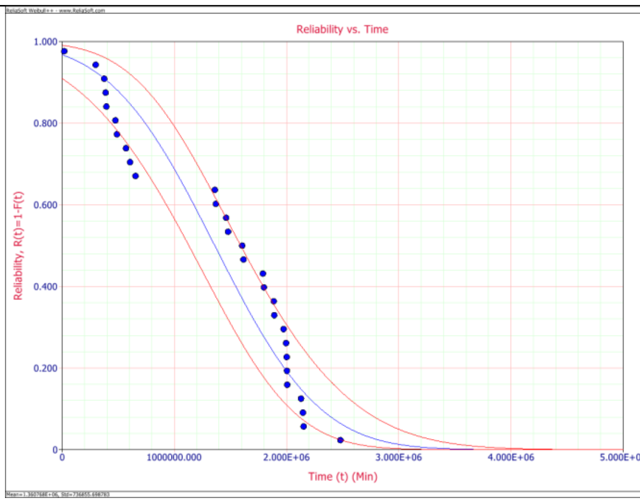


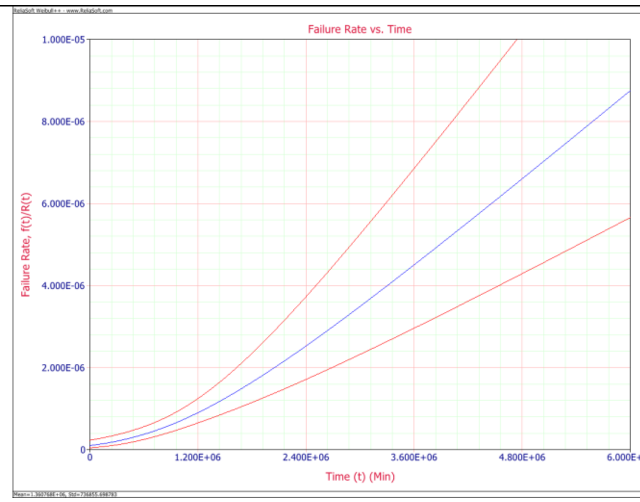
Thompson 60.5





Thompson 81.9





Thompson 98.1

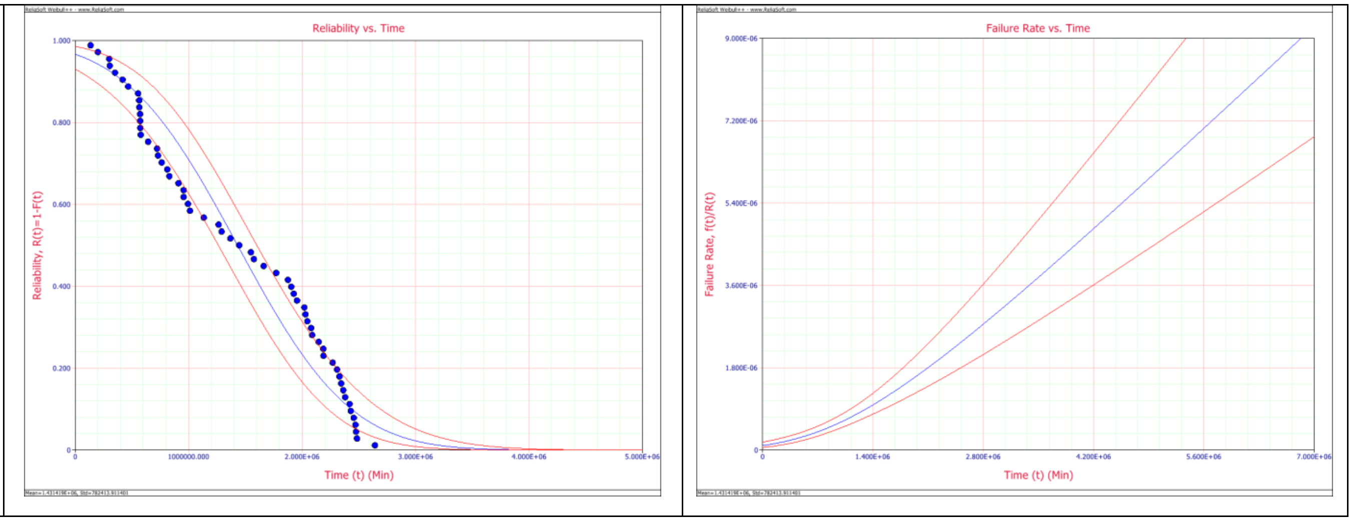
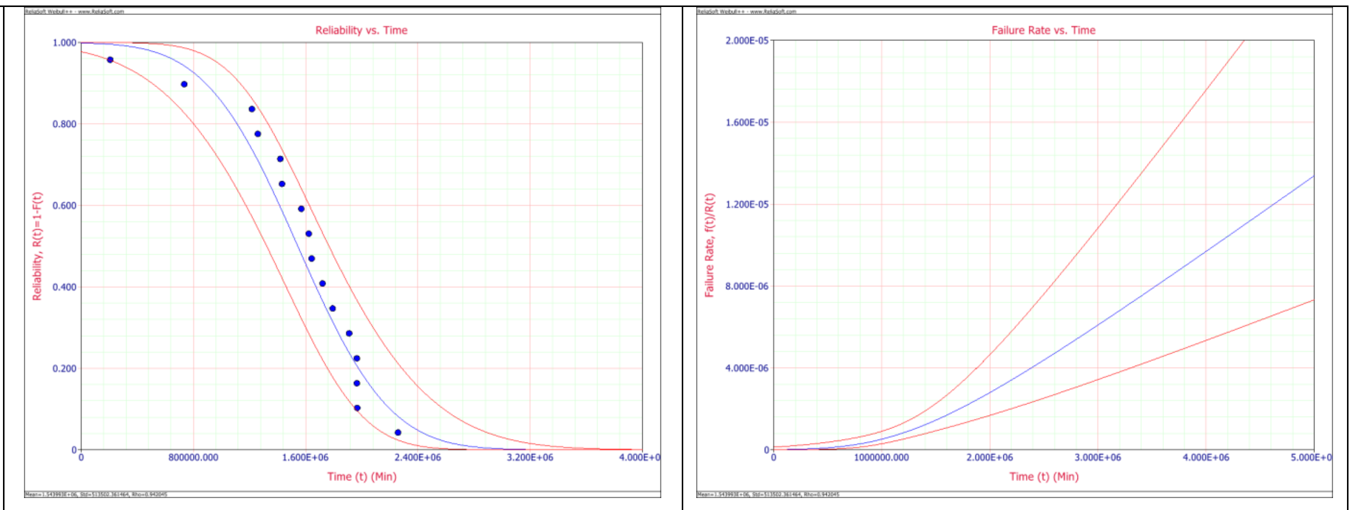
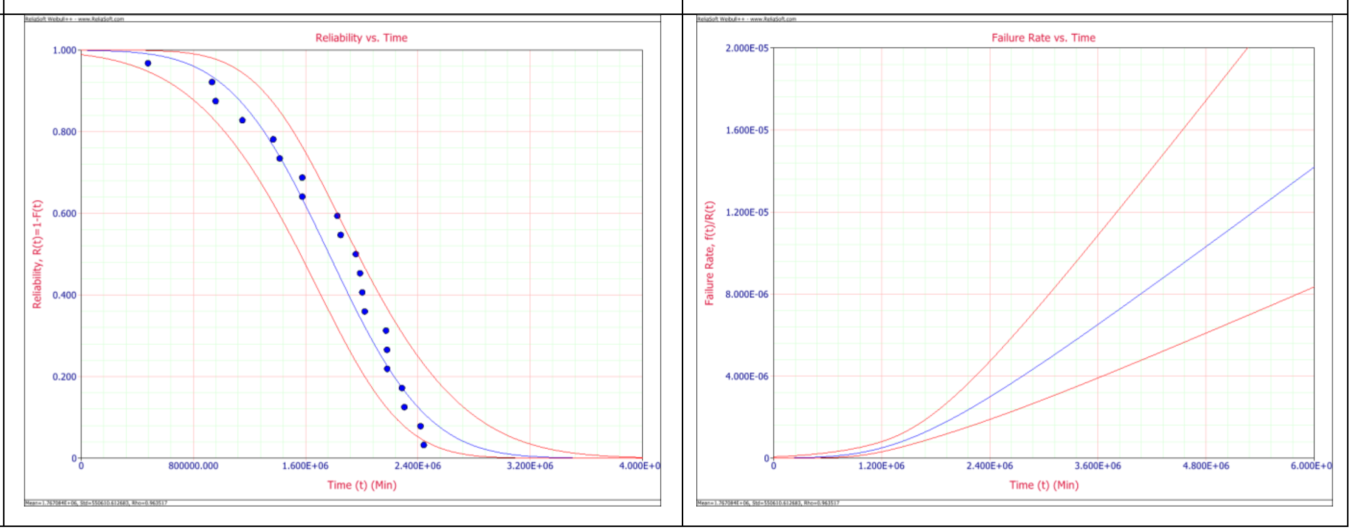


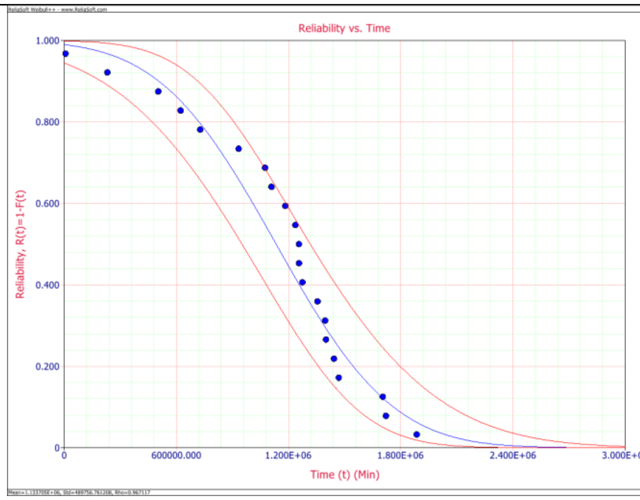
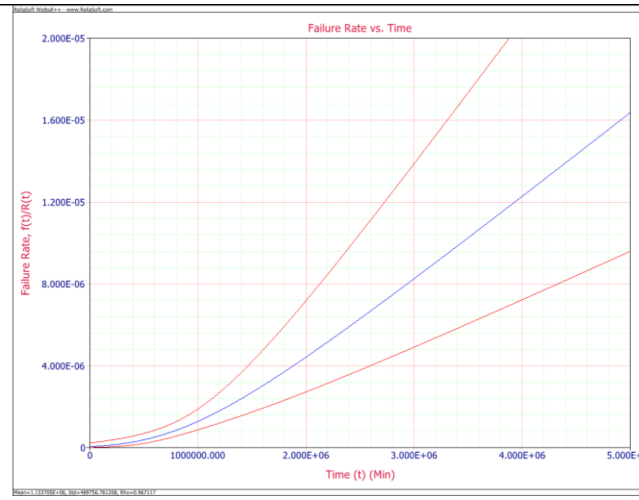
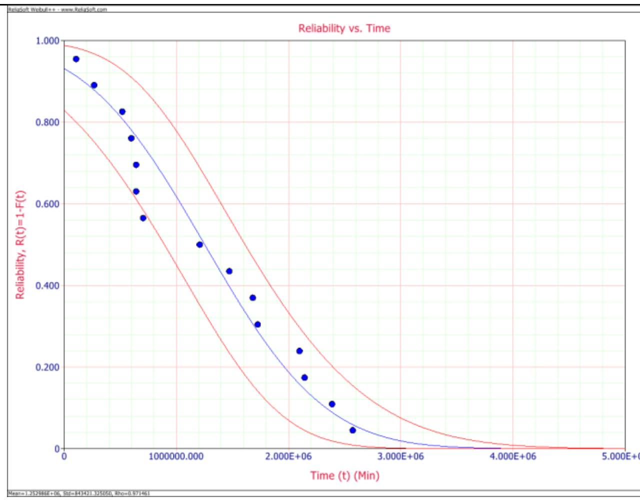
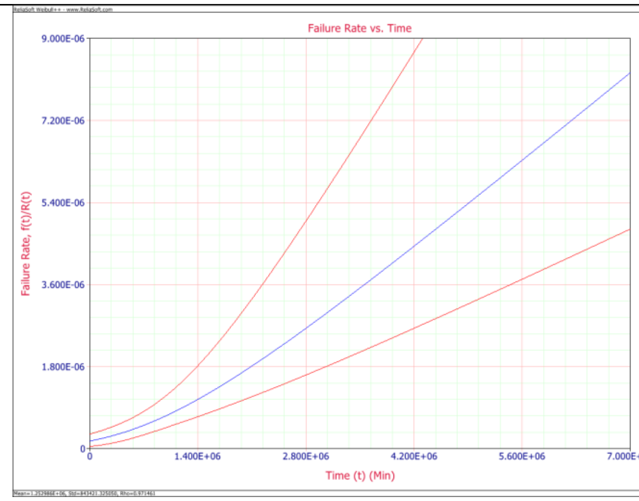
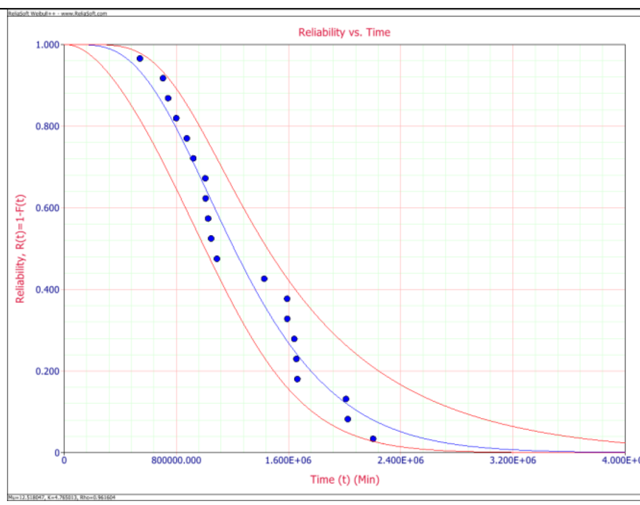
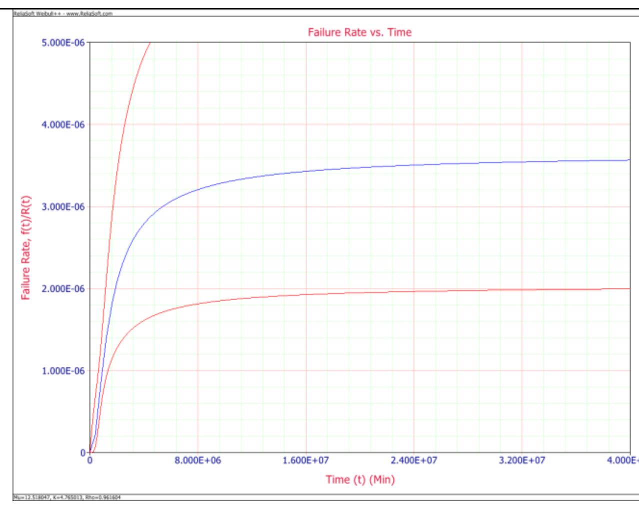
Figure a-22: Reliability-Time and Failure rate-time for the detectors in Thompson Subdivision

Windermere 8.5



Windermere 25.2



Windermere 50.4		
Windermere 54.7		
Windermere 97.2		

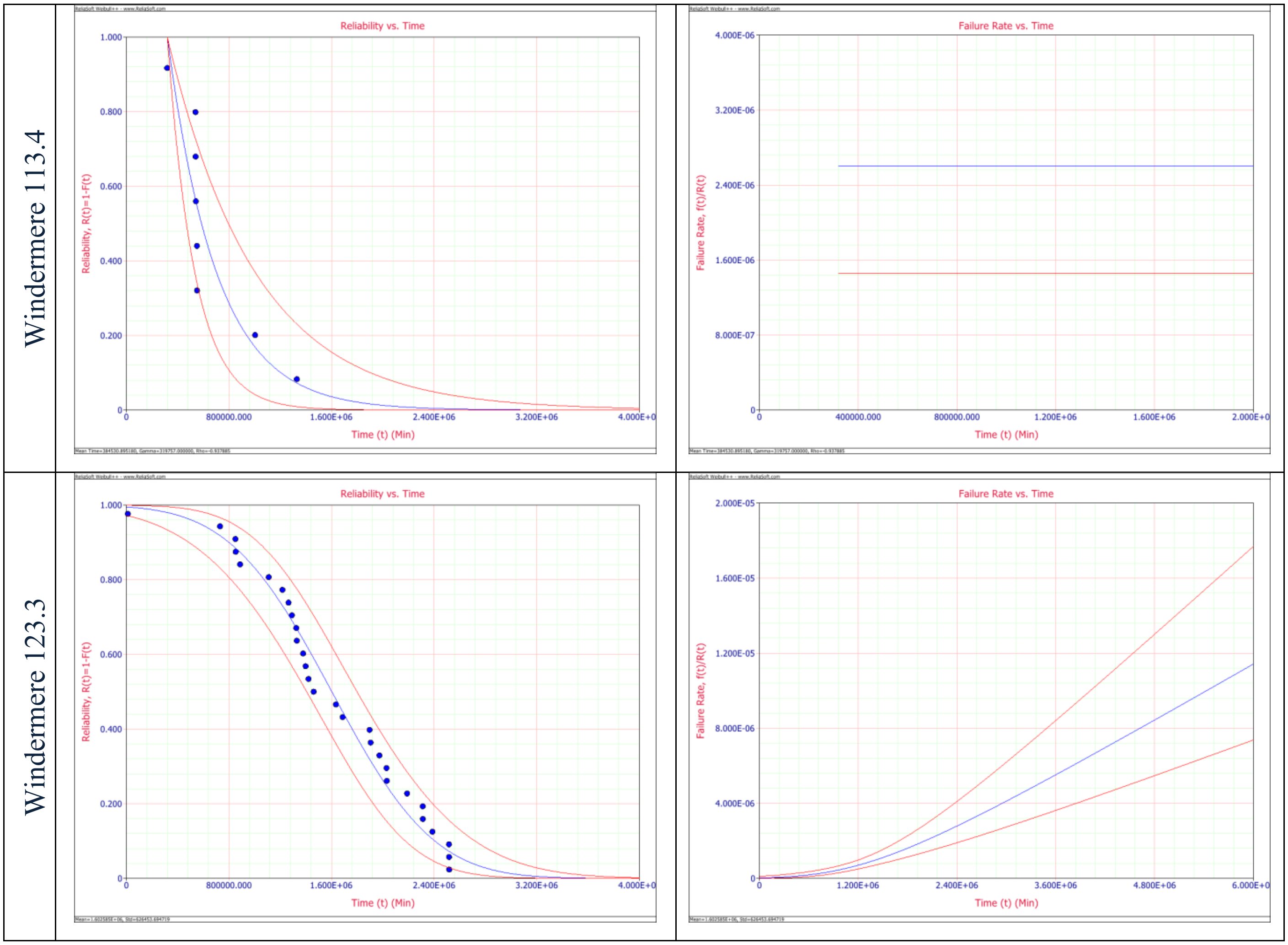
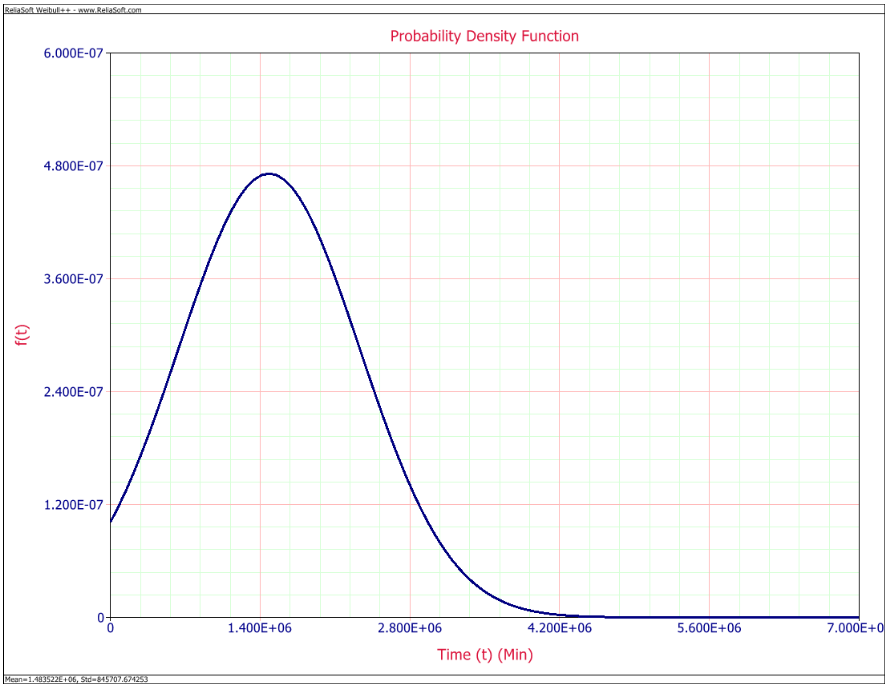
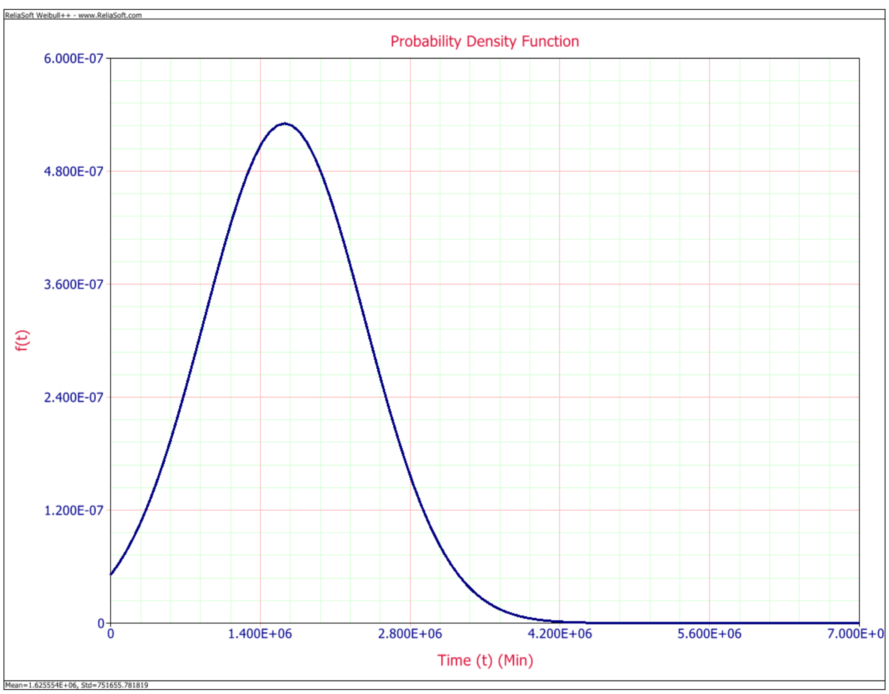


Figure a-23: Reliability-Time and Failure rate-time for the detectors in Windermere Subdivision

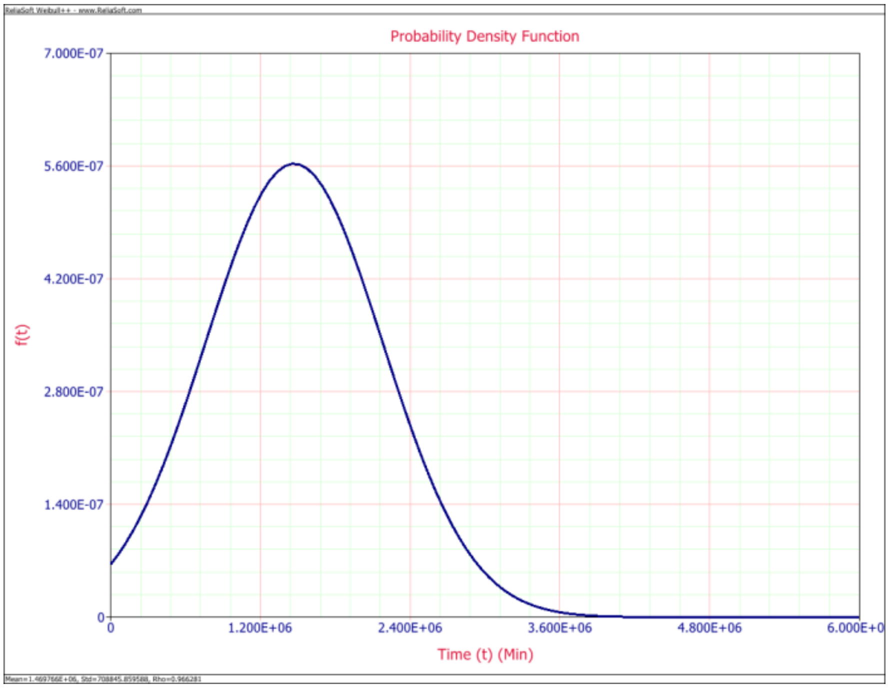
The normal PDF of the data set for each subdivision:



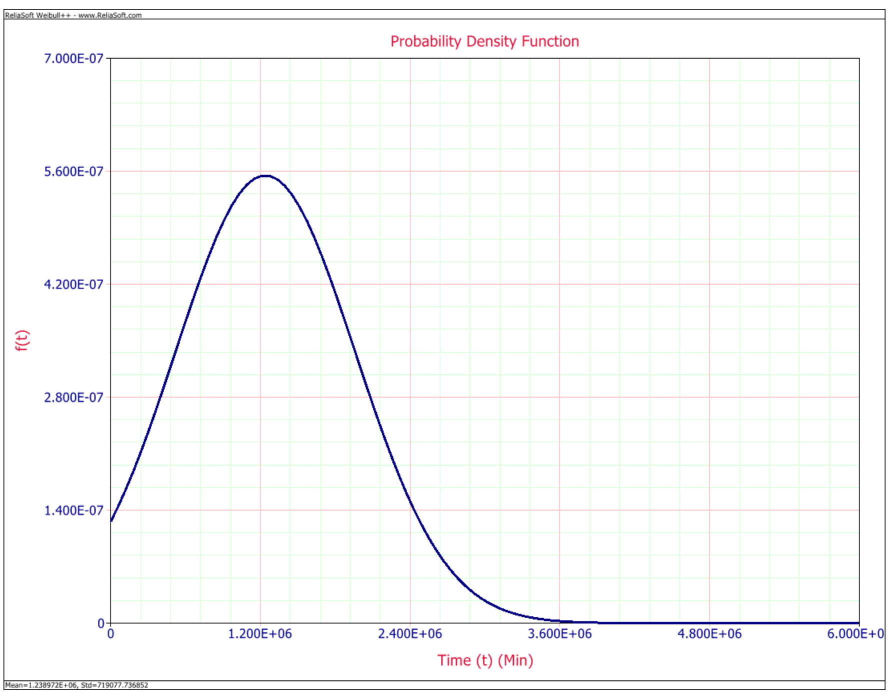
Cascade



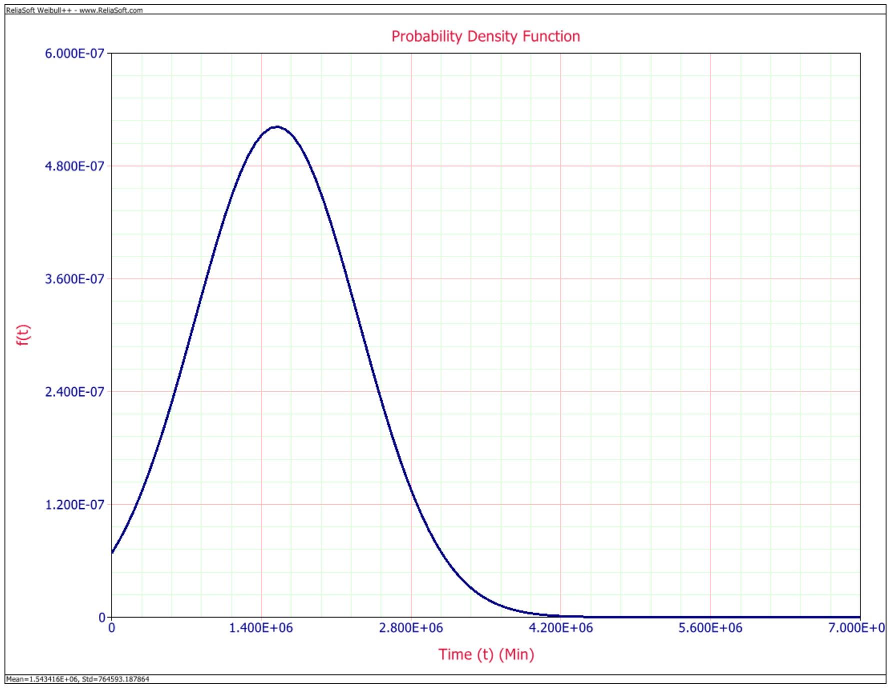
Cranbrook



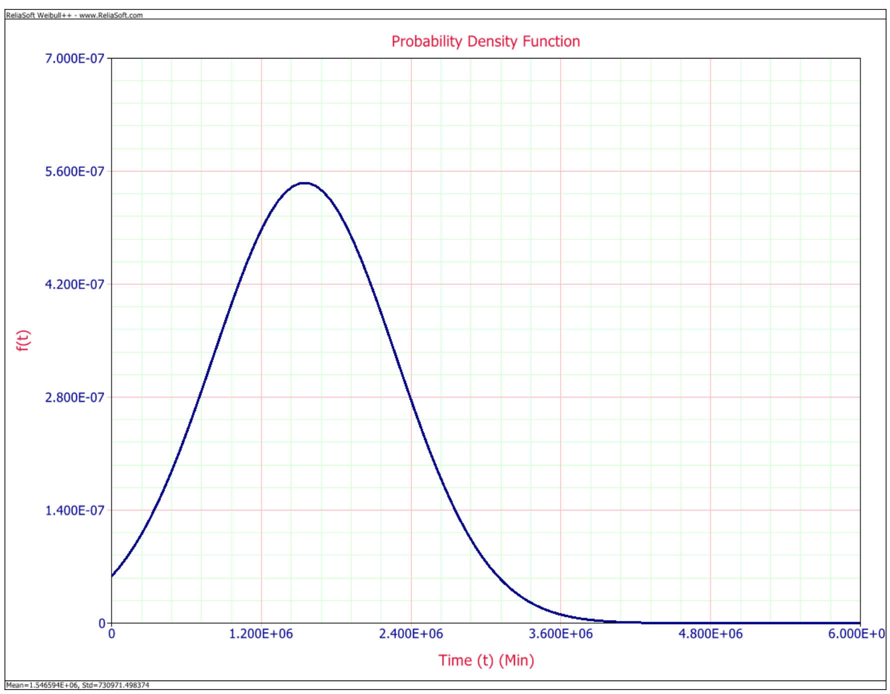
Fording River



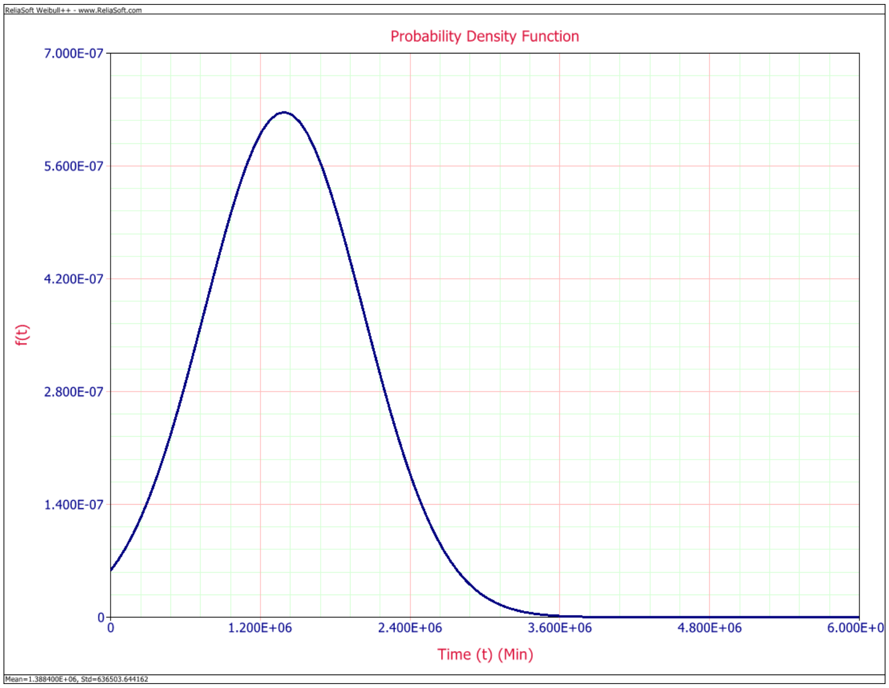
Mountain



Shuswap



Thompson

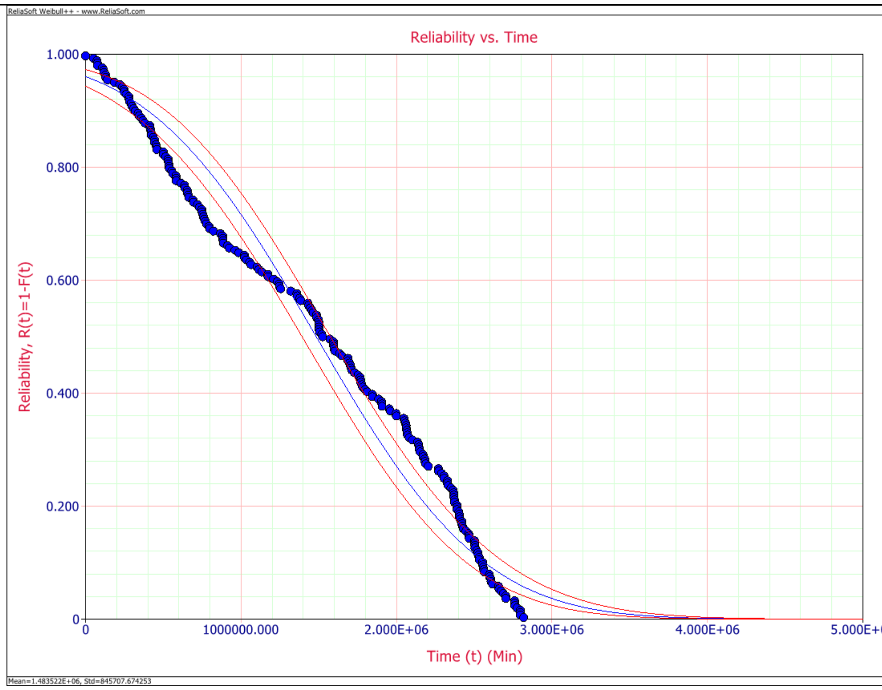


Windermere

Figure a-24: PDF plots for the detectors in each subdivision

The Reliability values versus time and failure rate versus time plots for the subdivisions:

Cascade



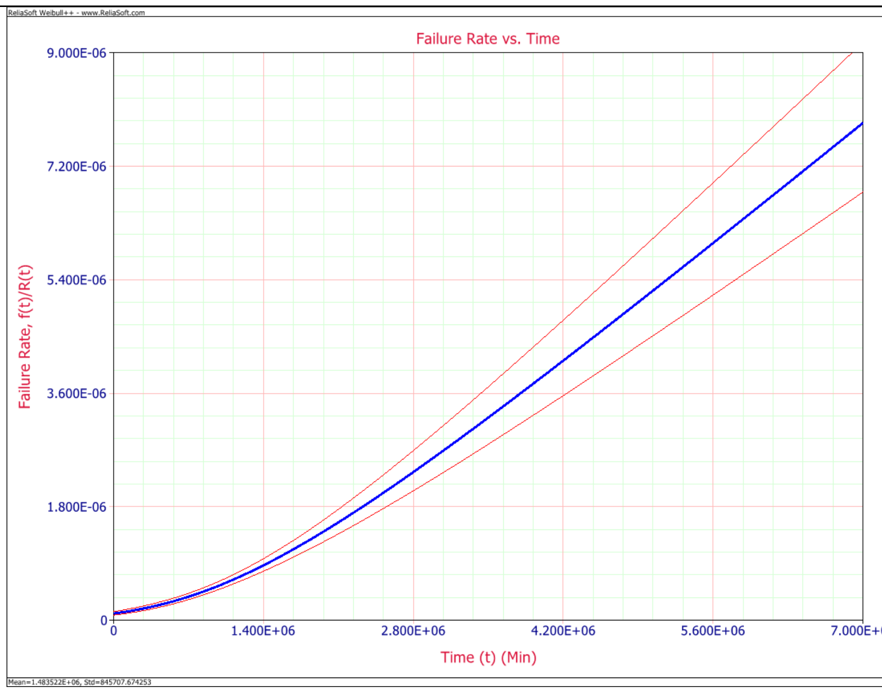


Figure a-25: Reliability-Time and Failure rate-time for all the detectors in Cascade Subdivision

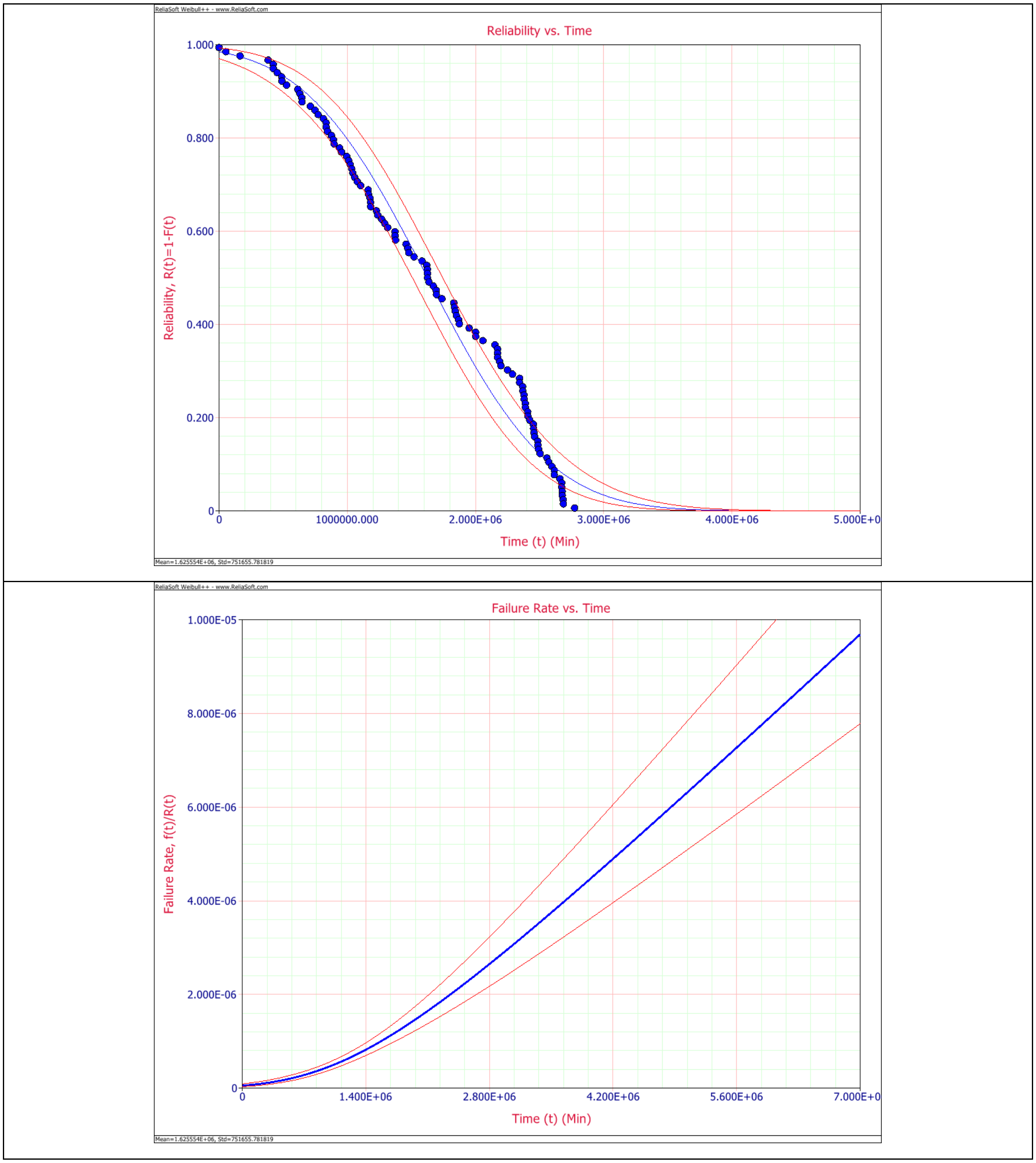


Figure a-26: Reliability-Time and Failure rate-time for all the detectors in Cranbrook Subdivision

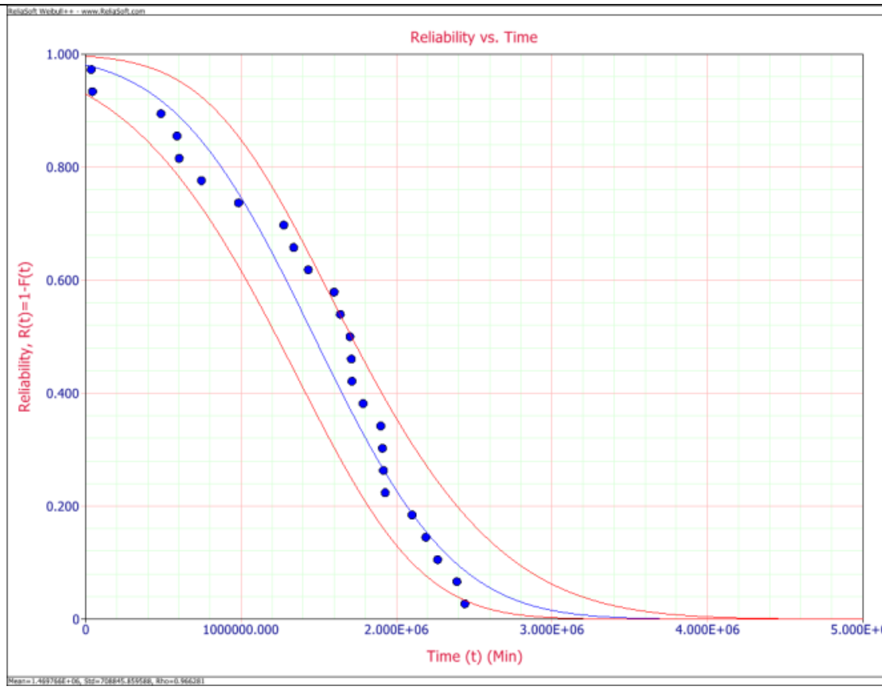
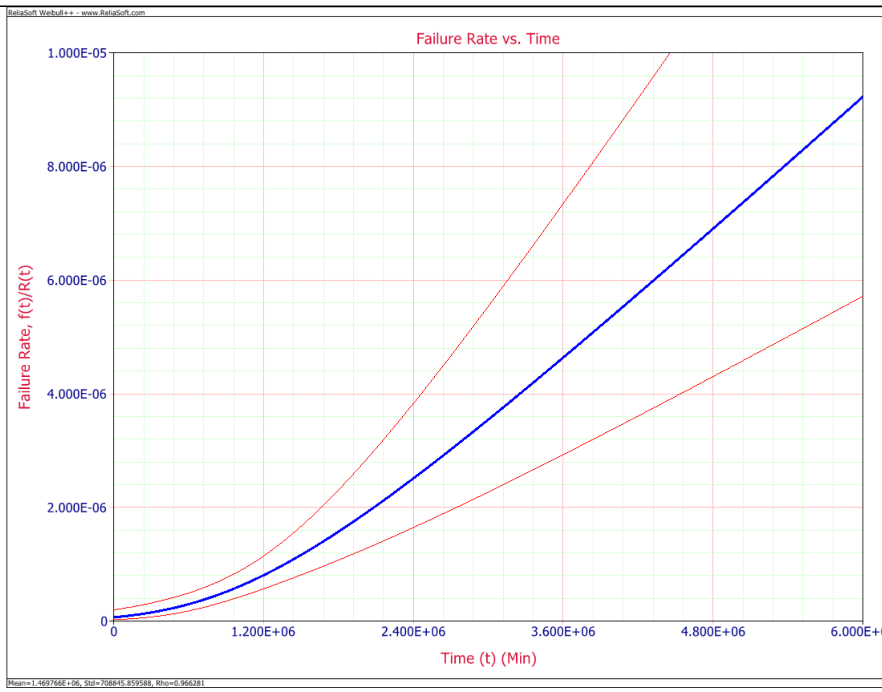
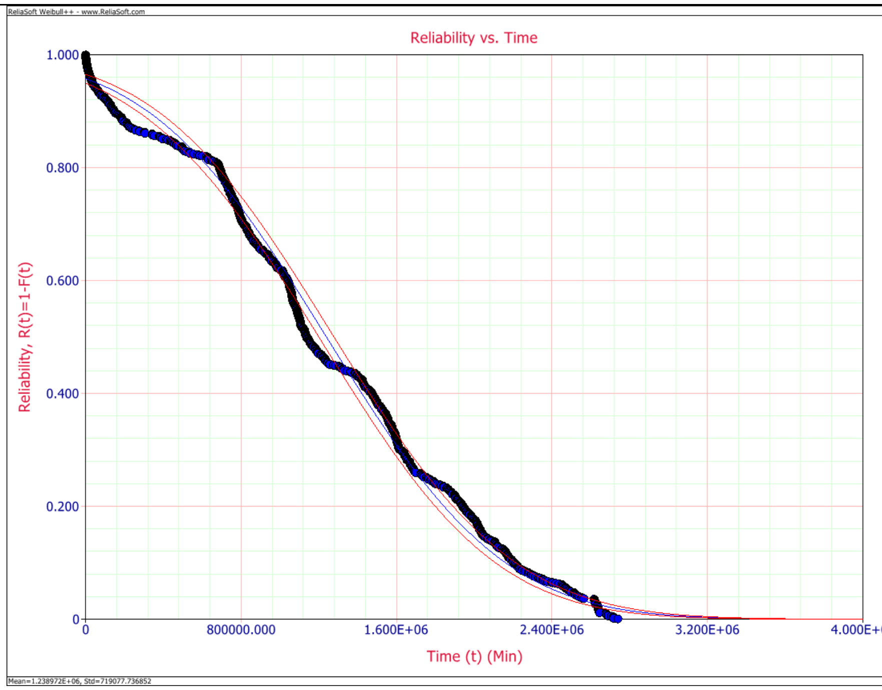
Fording River



Figure a-27: Reliability-Time and Failure rate-time for all the detectors in Fording River Subdivision

Mountain



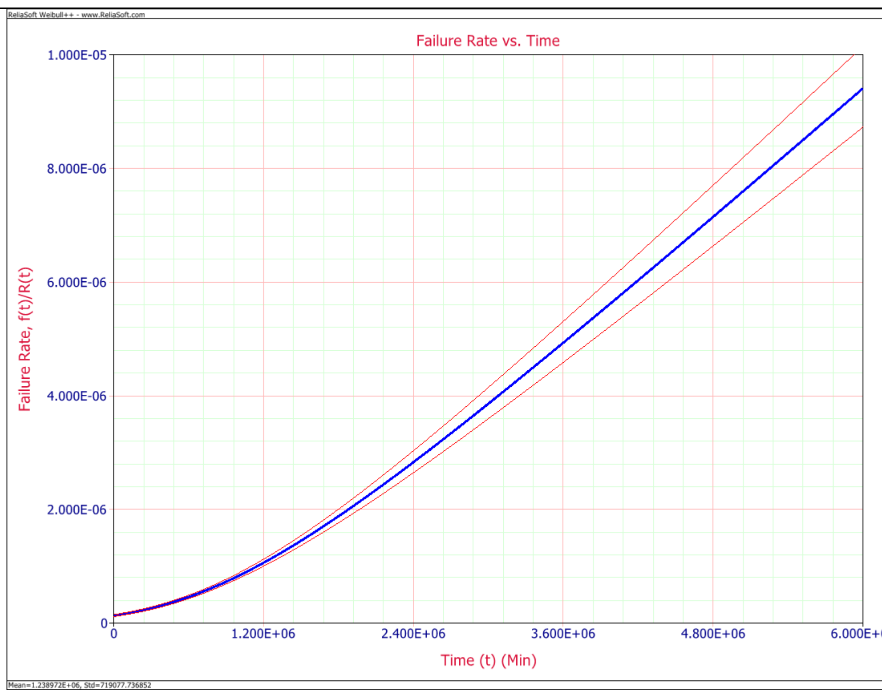


Figure a-28: Reliability-Time and Failure rate-time for all the detectors in Mountain Subdivision

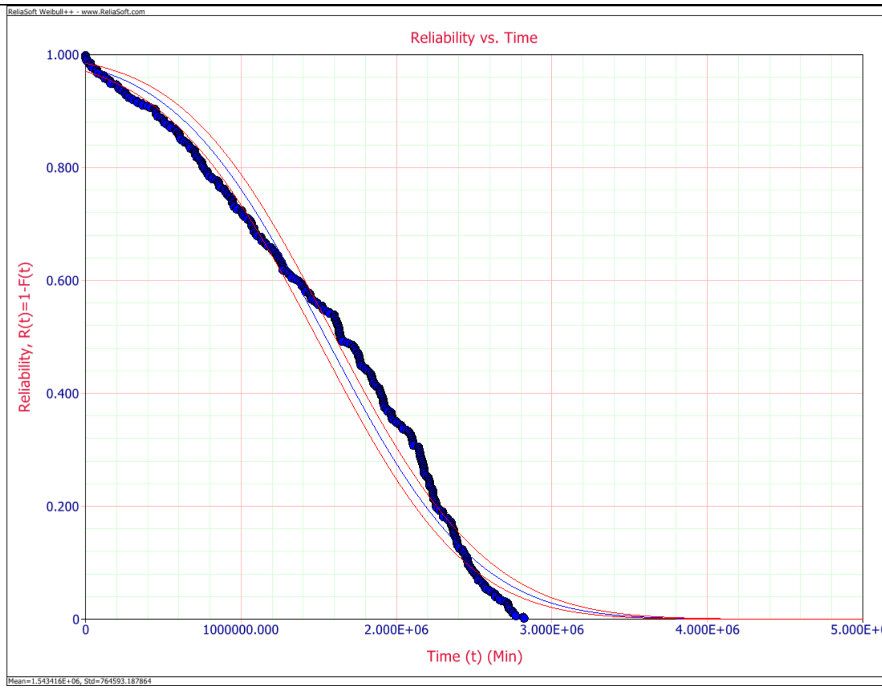
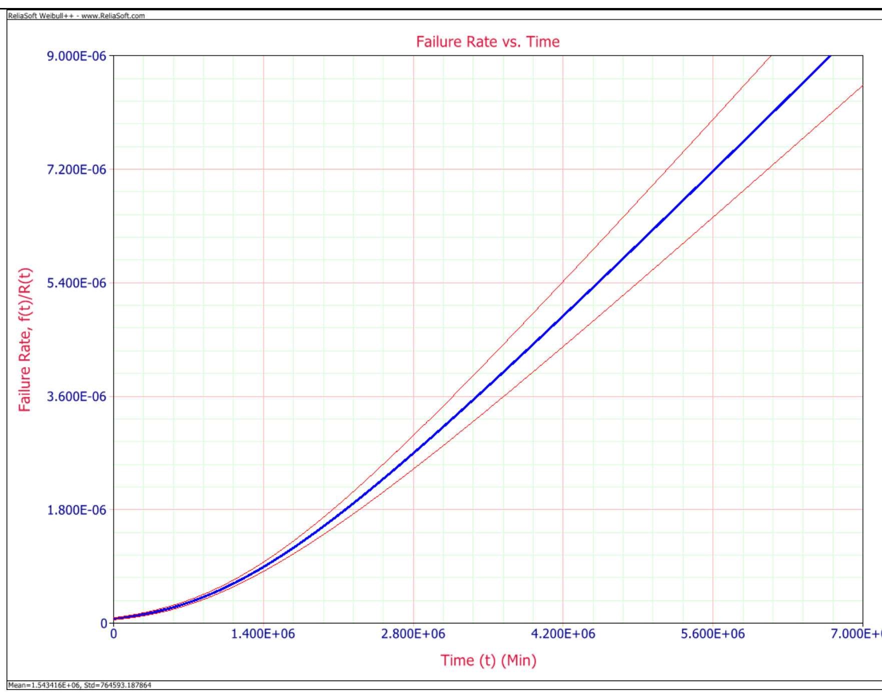
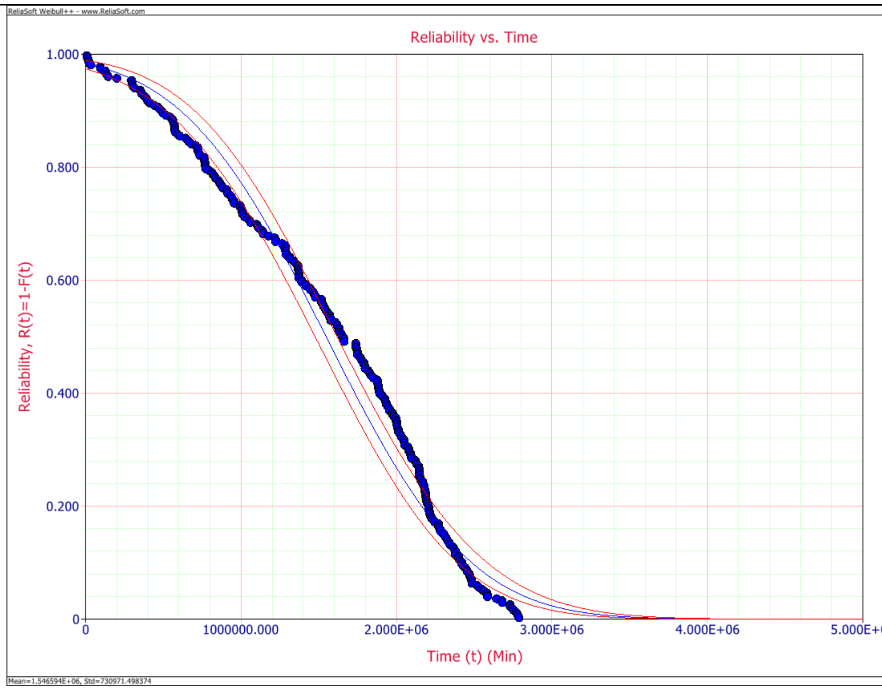
Shuswap
ReliaSoft Weibull++ - www.ReliaSoft.com
Reliability vs. Time
Reliability, R(t)=1-F(t)
1.000
0.800
0.600
0.400
0.200
0
1000000.000
2.000E+06
3.000E+06
4.000E+06
5.000E+0
Time (t) (Min)
Mean=1.543416E+06, Std=764593.187864
ReliaSoft Weibull++ - www.ReliaSoft.com
Failure Rate vs. Time
Failure Rate, f(t)/R(t)
9.000E-06
7.200E-06
5.400E-06
3.600E-06
1.800E-06
0
1.400E+06
2.800E+06
4.200E+06
5.600E+06
7.000E+0
Time (t) (Min)
Mean=1.543416E+06, Std=764593.187864

Figure a-29: Reliability-Time and Failure rate-time for all the detectors in Shuswap Subdivision

Thompson


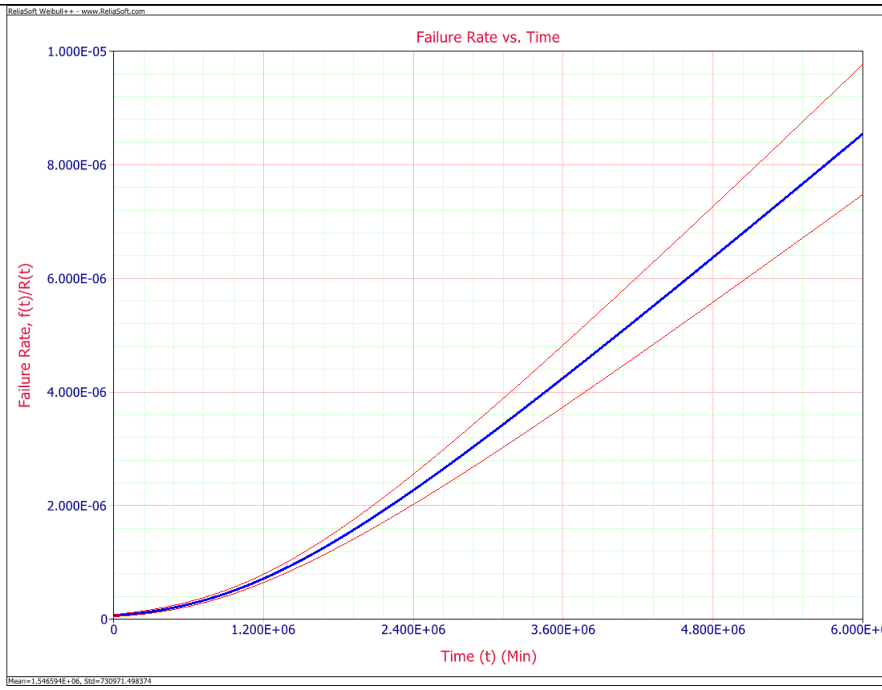
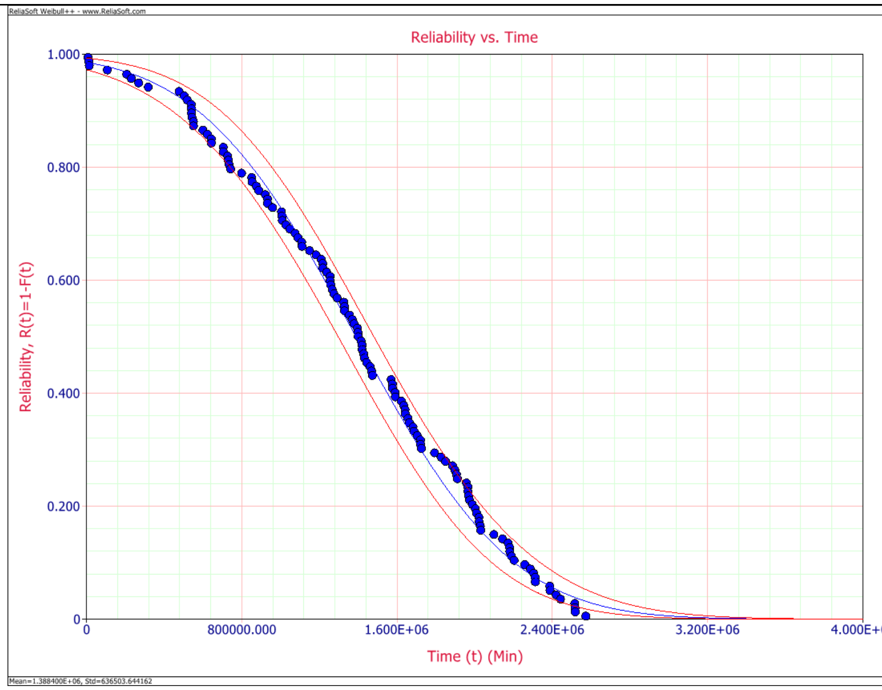


Figure a-30: Reliability-Time and Failure rate-time for all the detectors in Thompson Subdivision

Windermere



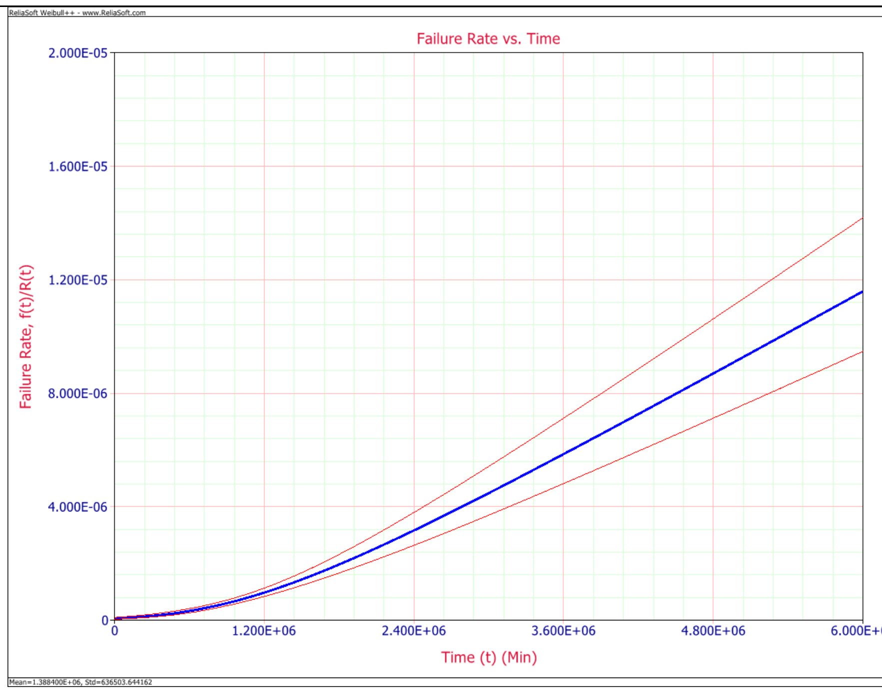
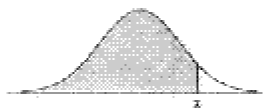


Figure a-31: Reliability-Time and Failure rate-time for all the detectors in Windermere Subdivision

Appendix D

Tables of the Normal Distribution



Probability Content from -oo to Z

Z	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
0.0	0.5000	0.5040	0.5080	0.5120	0.5160	0.5199	0.5239	0.5279	0.5319	0.5359
0.1	0.5398	0.5438	0.5478	0.5517	0.5557	0.5596	0.5636	0.5675	0.5714	0.5753
0.2	0.5793	0.5832	0.5871	0.5910	0.5948	0.5987	0.6026	0.6064	0.6103	0.6141
0.3	0.6179	0.6217	0.6255	0.6293	0.6331	0.6368	0.6406	0.6443	0.6480	0.6517
0.4	0.6554	0.6591	0.6628	0.6664	0.6700	0.6736	0.6772	0.6808	0.6844	0.6879
0.5	0.6915	0.6950	0.6985	0.7019	0.7054	0.7088	0.7123	0.7157	0.7190	0.7224
0.6	0.7257	0.7291	0.7324	0.7357	0.7389	0.7422	0.7454	0.7486	0.7517	0.7549
0.7	0.7580	0.7611	0.7642	0.7673	0.7704	0.7734	0.7764	0.7794	0.7823	0.7852
0.8	0.7881	0.7910	0.7939	0.7967	0.7995	0.8023	0.8051	0.8078	0.8106	0.8133
0.9	0.8159	0.8186	0.8212	0.8238	0.8264	0.8289	0.8315	0.8340	0.8365	0.8389
1.0	0.8413	0.8438	0.8461	0.8485	0.8508	0.8531	0.8554	0.8577	0.8599	0.8621
1.1	0.8643	0.8665	0.8686	0.8708	0.8729	0.8749	0.8770	0.8790	0.8810	0.8830
1.2	0.8849	0.8869	0.8888	0.8907	0.8925	0.8944	0.8962	0.8980	0.8997	0.9015
1.3	0.9032	0.9049	0.9066	0.9082	0.9099	0.9115	0.9131	0.9147	0.9162	0.9177
1.4	0.9192	0.9207	0.9222	0.9236	0.9251	0.9265	0.9279	0.9292	0.9306	0.9319
1.5	0.9332	0.9345	0.9357	0.9370	0.9382	0.9394	0.9406	0.9418	0.9429	0.9441
1.6	0.9452	0.9463	0.9474	0.9484	0.9495	0.9505	0.9515	0.9525	0.9535	0.9545
1.7	0.9554	0.9564	0.9573	0.9582	0.9591	0.9599	0.9608	0.9616	0.9625	0.9633
1.8	0.9641	0.9649	0.9656	0.9664	0.9671	0.9678	0.9686	0.9693	0.9699	0.9706
1.9	0.9713	0.9719	0.9726	0.9732	0.9738	0.9744	0.9750	0.9756	0.9761	0.9767
2.0	0.9772	0.9778	0.9783	0.9788	0.9793	0.9798	0.9803	0.9808	0.9812	0.9817
2.1	0.9821	0.9826	0.9830	0.9834	0.9838	0.9842	0.9846	0.9850	0.9854	0.9857
2.2	0.9861	0.9864	0.9868	0.9871	0.9875	0.9878	0.9881	0.9884	0.9887	0.9890
2.3	0.9893	0.9896	0.9898	0.9901	0.9904	0.9906	0.9909	0.9911	0.9913	0.9916
2.4	0.9918	0.9920	0.9922	0.9925	0.9927	0.9929	0.9931	0.9932	0.9934	0.9936
2.5	0.9938	0.9940	0.9941	0.9943	0.9945	0.9946	0.9948	0.9949	0.9951	0.9952
2.6	0.9953	0.9955	0.9956	0.9957	0.9959	0.9960	0.9961	0.9962	0.9963	0.9964
2.7	0.9965	0.9966	0.9967	0.9968	0.9969	0.9970	0.9971	0.9972	0.9973	0.9974
2.8	0.9974	0.9975	0.9976	0.9977	0.9977	0.9978	0.9979	0.9979	0.9980	0.9981
2.9	0.9981	0.9982	0.9982	0.9983	0.9984	0.9984	0.9985	0.9985	0.9986	0.9986
3.0	0.9987	0.9987	0.9987	0.9988	0.9988	0.9989	0.9989	0.9989	0.9990	0.9990

Fig a-2: Normal distribution reference table