CONSTRUCTION EQUIPMENT RELIABILITY ANALYSIS AND FAILURE PREDICTION

FAN QING

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The Hong Kong Polytechnic University

Department of Building and Real Estate

Construction Equipment Reliability Analysis and Failure Prediction

FAN Qing

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CERTIFICATE OF ORIGINALITY

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(Signed)________ ________________

Name of Student__________FAN Qing___

DEDICATION

To my parents and my husband, Max

ABSTRACT

Construction equipment plays an important role in civil engineering works, particularly in infrastructure projects such as railways and bridge construction. Unexpected failures of equipment can cause serious consequences such as increased cost, project period extension, or even safety issues in some cases. Even though different maintenance and reliability prediction methods have been applied by contractors on site, a significant proportion of equipment repairs still follow unexpected failures.

To bridge the gap between failure and preventive maintenance, it is important to discover scientific and precise methods for analyzing and predicting the failures before they happen.

Traditionally, there are a number of standard distribution functions which can be used for reliability analysis. However, a number of books and papers have stressed that the usual non-repairable reliability methodologies, such as the Weibull distribution, are not appropriate for repairable system reliability analyses and have suggested the use of Non-homogeneous Poisson Process (NHPP) models. Most construction equipment and their components are considered to be in the category of repairable system.

Apart from the traditional distributions introduced above, researchers have applied more sophisticated data mining methods to equipment reliability analysis. Time series modeling is one of the more advanced techniques which this research is focused on. Time series analysis can be used to describe and model the historical data, and forecast the future values of the series based on the past values. Construction equipment failure follows the time series pattern, and thus it can be adopted.

The aim of this research is to study the possible methods which can be used to analyze reliability and predict the failures of construction equipment in order to bridge the gap between preventive maintenance and repairs and help to make managerial decisions on equipment allocation and maintenance. The objectives are:

a) To increase the understanding of the nature of failure patterns of the selected construction equipment;
b) To estimate the reliability characteristics of construction equipment in precise quantitative terms by using power law models and time series models;

c) Compare the advantages and disadvantages of the traditional power law models with those of time series models in construction equipment reliability analysis;

d) To give recommendations on construction equipment management and maintenance based on the research findings.

The major works for this research comprise of literature review, data collection, data preparation, quantitative analysis, time series prediction and case studies. A comprehensive literature review on the fields of reliability and construction equipment has been conducted. Quantitative analysis is used in this study including data collection, modelling and validation with the aid of computer software packages. Time series is the main method adopted for reliability analysis and failure prediction while traditional power law models are used as baseline for comparison. Case studies are employed to study the reliability of construction equipment with real maintenance data collected from construction site.

The major findings of the research include: the investigation and analysis of the importance of reliability and failure prediction for construction equipment from the aspects of cost, time and safety; testing the traditional power law model and time series model on failure prediction for construction equipment based on real industry data; studying the construction equipment reliability and failure from both the systems and subsystems levels; taking related factors into consideration and evaluating the importance of these factors (e.g. impact from Time to Repair) in the modelling process of failure prediction; comparing the advantages and disadvantages of power law model and time series model. Based on the results and findings of the data modelling and analysis in this research, advice is given for managerial decisions on construction equipment maintenance to promote the practice of repair before failures.

PUBLICATIONS

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CHAPTER 1 INTRODUCTION

This chapter contains six sections. Section 1.1 introduces the background of this research such as the general research area and reviews of previous research in the area of construction equipment reliability; Section 1.2 indicates the gap in the previous research and identifies the problem; Section 1.3 outlines the purposes and aims of this thesis; Section 1.4 states the significance of the research; Section 1.5 describes the methods used in the study; and Section 1.6 indicates the structure of the thesis and provides the mini-synopses of each chapter.

1.1 BACKGROUND OF THE RESEARCH

Construction equipment is a key resource in all building and construction projects. Contractors owning a large equipment fleet or plant owners should take all necessary measures to maximize equipment utilization and minimize equipment failures. Although different maintenance methods such as preventive maintenance and repairs have been adopted for construction equipment, unexpected breakdown is usually difficult to predict. According to a survey in the US, approximately 46% of major equipment repairs followed an unexpected failure (Fan, 2012). Therefore, predicting failures and repairing equipment before it breaks down is essential for effective cost management of construction equipment and the project as a whole.

Repairs are often easy, but the collateral damage caused by the breakdown is more severe. For example, a $100 hose can cause a $2,000 loss in production and a $500 bearing can ruin a $7,000 transmission (Vorster, 2004). The cost reports usually do not comprise collateral costs so that it is very difficult to measure and the costs are easily disregarded. However, if completing construction on time and on budget is required, then the collateral cost of equipment failures in the field cannot be simply covered without question. The frequency of failures and influence that breakdowns have on projects are key elements in managing construction equipment or the whole fleet.

Therefore, “prevention is better than cure” is the principle that equipment managers should adhere to in construction equipment management and maintenance. Good managers understand that maintenance actions taken before failure are more cost-effective, less disruptive, and easier to manage than repair actions taken after the machine has broken down and defined both the time and place for the urgently required repair action. Many contractors have taken such measures as monitoring and tracking of the condition of equipment to identify signs of failure or near-failure and conducting repairs or replacements of some components based on the manufacturer’s recommendations or on industrial benchmarks of the expected life of equipment components. However the effectiveness of such strategies is still unsatisfactory as large numbers of unexpected failures still occur.

There has been some research undertaken in the area of construction equipment reliability and maintenance but mostly in qualitative terms; few have been interpreted on a quantitative level with reasonable accuracy. Vorster (2005) used an impending failure matrix to demonstrate strategies to bridge the gap between preventive maintenance and repair. Steward (2006) performed lifecycle research on several construction equipment pieces (excavator, wheel-loader life, crawler-bulldozer, backhoe-loader, and articulated-dump-truck) by dividing the equipment life into B20, B50 and B80. Fan (2012) carried out a comparative study on construction equipment reliability with power law model and time series model, although it was focused on the comparison of the two research methods.

It is essential to find a more scientific and precise way to analyze and predict construction equipment failures before they happen. Some researchers have done relevant research on construction equipment maintenance but yet have not developed quantitative measures for predicting failures with reasonable accuracy. As computer technology has developed rapidly in the last few decades, we believe that with the aid of advanced computational tools and mathematical concepts such time series forecast, the problem can be resolved more effectively.

1.2 PROBLEM STATEMENT

The unexpected failure of construction equipment usually causes large repair cost and even more severe collateral costs. Repair after breakdown and preventive maintenance are easy, like work is set in a maintenance check, etc. Based on a preventive maintenance program, a piece of equipment can be allowed to run to failure before any extra measure is taken. However, this kind of behavior neglects the disrupted operations, increased repair costs, collateral cost of lost production, and crisis management.

Therefore, predicting equipment failures is necessary to reduce repair cost and manage project and equipment costs. There are some articles stressing the importance of repair before failure, however, few present effective ways of predicting failures accurately (Steward, 2006; Steward, 2005; Vorster, 2005). This is a motivating factor for the aim of this research, i.e. quantify the equipment reliability and failure indicators to minimize unexpected failures. This research adopts two different reliability modelling approaches to predict equipment failures and to bridge the preventive maintenance and repairs, which is also known as predictive maintenance.

Models and rules based on power law and time series techniques are studied and tested. The results obtained from these studies could possibly tell equipment managers what must be done, when it must be done and so on before a failure happens. Questions such as "what is the time remaining until the next major failure for this piece of equipment?", "what are the failures which occur frequently, and what are the prevailing conditions associated with these failures?" can perhaps be answered. Actions could be taken before the equipment failures actually happen. The findings from this research will benefit the entire construction and building industry by facilitating improved proactive equipment maintenance management.

Traditional methods for equipment reliability analysis are power law models and Weibull distribution. However, we find that time series forecast can be used for failure prediction and postulate it would be more accurate than those traditional methods. A time series is a set of observations measured sequentially through time (Chatfield, 2000). Time series analysis can be used to describe and model the selected data, and forecast the future values of the series based on the past values. Construction equipment failure follows the time series analysis pattern. Particularly the highly popularized Box-Jenkins autoregressive integrated moving average (ARIMA) model has been successfully applied in not only economic time series forecasting, but also as a promising tool for modeling the empirical dependencies between successive times between failures (Walls & Bendell, 1987). This research adopts time series techniques to extract rules and patterns from large amounts of data on equipment failures collected from the contractors for construction equipment failure analysis and prediction. The results from these two different modeling approaches are analyzed and compared in the research.

In this project, both descriptive and predictive models of construction equipment failures are developed through applying time series techniques on the failure events. The goal is to have zero on-shift failures and we believe that this research can help researchers, contractors and equipment managers move closer to that target. The study also reveals that reliability analysis for construction equipment can be used for designing a predictive maintenance program.

1.3 RESEARCH OBJECTIVES

This research aims to find a way to analyze and predict construction equipment failures to reduce the cost caused by emergency repairs. The objectives are:

a) To increase the understanding of the nature of failure patterns of the selected construction equipment;
b) To estimate the reliability characteristics of construction equipment in precise quantitative terms by using power law models and time series models;
c) Compare the advantages and disadvantages of the traditional power law models with those of time series models in construction equipment reliability analysis;

d) To give recommendations on construction equipment management and maintenance based on the research findings.

Methodologies and methods adopted for achieving these objectives are presented in the Section 1.5.

1.4 SIGNIFICANCE OF THE RESEARCH

This research has both theoretical and practical values which are elaborated below.

There is presently a lack of existing research on construction equipment reliability analysis and failure prediction, especially utilizing quantitative methods. Most research on construction equipment management and maintenance are performed using qualitative methodologies (Steward, 2007; Vorster 2007).

Although there are some published works on the reliability of plants or equipment using quantitative methods in other industries such as mining and the aviation industries, little research has been done in the building construction industry (Barabady & Kumar, 2008; Weckman, et al, 2001). Furthermore, most of these researchers used traditional reliability methods such as Weibull distribution; the most common probability distributions will be introduced briefly in Chapter 2. Data mining methods such as time series analysis prediction are relatively new for reliability analysis. These techniques are still under development in reliability engineering, especially in the building construction industry.

The contribution and uniqueness of this research is that we adopted both traditional probability distribution methods and more advanced data mining methods such as time series for reliability analysis of construction equipment. Comparison of the two methods is also made at the end of the thesis. Moreover, case studies are conducted in this research so that real life cases about the failure and maintenance of construction equipment provide strong supporting evidence to the theoretical framework.

1.5 RESEARCH METHODOLOGY

The selection of appropriate research method depends on the research objectives and questions. Appropriate research methods help to logically underpin the design of research questions, data collection, data analysis and conclusions. The major research work in this research includes literature review, data collection, data preparation, quantitative analysis, time series prediction and case study. The details of these methods are described as follows:

Literature review

A comprehensive literature review has been conducted in this thesis. It builds a solid theoretical understanding of the topic by reviewing previous relevant research work to justify the originality of this research. Literature review is a critical endeavor for this research. As opined by previous researchers, there is a necessity to uncover what is already known in the body of knowledge prior to initiating any research study. In this research, literature including books, journals, conference papers, on-line sources and others which have covered the topic of reliability engineering and construction equipment maintenance have been reviewed and studied.

Quantitative analysis

Quantitative research refers to the systematic empirical investigation of quantitative properties and phenomena and their relationships. Quantitative analysis includes developing or employing mathematical models, theories or hypotheses pertaining to phenomena. Quantitative analysis in this study includes data collection, modelling, validation and employment by using computer software such as Microsoft Excel, RGA (ReliaSoft, 2010), JMP (SAS, 2012), and DTREG (Sherrod, 2003). Data analysis includes descriptive analysis and predictive analysis, and the latter is conducted in this research. The modelling approaches are comprised of traditional statistical analysis Non-homogeneous Poisson Process (NHPP) and time series prediction.

Time Series analysis and forecast

Time series is used for reliability analysis and failure prediction of construction equipment in this research. ARIMA modelling has been studied and used in this case and the results are compared with the ones obtained from the traditional Power Law models. The three main stages are model identification, model fitting and model checking and have been rigorously implemented and repeated to achieve the objectives of this study. The concept of time series analysis and forecast is introduced in Chapter 3.

Case Study

Case study is an important research strategy employed in this project for studying the reliability of the construction equipment. Real data collected from construction sites are screened and analyzed by using the selected data mining algorithms. Results such as equipment failure patterns and prototype decision support module are directed and validated. For eight groups of different construction equipment (i.e., bulldozer, scraper), failure and maintenance data have been obtained from a Canadian contractor. Discussions and comparisons are presented after the presentation of the result from the analysis of the real data.

Factors affecting equipment failures are also quantified for future construction equipment management and maintenance.

1.6 OUTLINE OF THE THESIS

This thesis consists of seven chapters which are explained as follows.

Chapter 1 introduces the background of the research, problem statement, scope of the research, aims and objectives, research methodology, significance of the research, and outline of the thesis.

Chapter 2 presents a comprehensive literature review for this research. Fundamental theories of reliability engineering such as the definition and characteristics of reliability are explained. Literature on reliability engineering in the construction industry and other relevant industries (i.e., mining, manufacture) is reviewed and analyzed. Basic construction equipment maintenance methods are explored with focus on the optimum preventive and predictive maintenance.

Chapter 3 examines the reliability modelling approach which includes traditional statistical methods and data mining methods. Power Law Model and time series prediction is studied in depth and introduced for the application in the case study in the next chapter.

Chapter 4 demonstrates the reliability analysis and failure prediction of construction equipment based on real industry data through case study. The presentation is made in the order of data modelling process, which is: data preparation, data analysis/modelling, model validation and model deployment.

Chapter 5 contains a reliability analysis of the critical subsystems of some construction equipment. This research not only focuses on the systems, but also explores the equipment from the lower level of subsystems. Pareto analysis and other methods were employed to identify the critical components for construction equipment. Attributes being considered include the counts of failures, TBF and TTR. Reliability importance analysis is important because by identifying the critical (weakest) components of a system and implementing appropriate measures, the system reliability can be improved.

Chapter 6 presents the findings from literature review, case study and data analysis. There are six major findings summarized in this thesis. Comparison between the Power Law Model and time series analysis is made with discussions in this chapter.

Chapter 7 concludes the research works and the thesis as well as gives suggestions on future research.

CHAPTER 2 LITERATURE REVIEW

This chapter introduces the basic concepts and theories of construction equipment, maintenance, and reliability engineering obtained from literature review. Section 2.1 presents the introduction of construction equipment and common maintenance methods. This section also examines and summarizes the importance of conducting reliability analysis for construction equipment. Section 2.2 introduces the fundamental theory of reliability, which includes the definitions of reliability and failure, characteristics of reliability, availability and maintainability, and probability distributions for reliability evaluation. Section 2.3 shows the review of the past research on reliability engineering in construction industry and other relevant industries.

2.1 CONSTRUCTION EQUIPMENT RELIABILITY AND MAINTENANCE

2.1.1 CONSTRUCTION EQUIPMENT

Construction processes require many different types of equipment. Some equipment is designed for specific purposes or projects and might be considered custom made. However, most construction equipment will serve with flexibility in a variety of projects or jobs.

Common construction equipment/plants include: bulldozers, scrapers, graders, tractor shovels, excavators, transport vehicles, excavators, transport vehicles, hoists, cranes, and concreting plant and so on.

Importance of Construction Equipment/Plant

Items of builder’s plant ranging from small hand held power tools to larger pieces of plant such as mechanical excavators and tower cranes can be considered for use for one or more of the following reasons:

- Increased production;
- Reduction in overall construction costs;

- Eliminate heavy manual work thus reducing fatigue and as a consequence of increasing productivity;
- Maintain the high standards required particularly in the context of structural engineering and foundation works.

	
Trucks (240H_075)	Scrapers (631E_016)
	
Wheel loaders (988B_034)	Bulldozers (D11_107)
	
Grader (GRAD_035)	Tractor (HYCR_035)

	
Shovel (SHOVEL~1)	

Figure 2.1 Examples of Construction Equipment

Productivity of a Plant

From the economic consideration, an economic plant must be fully utilized and not left standing idle since the plant, whether hired or owned, will have to be paid for even if it is non-productive. Full utilization of plant is usually considered to be in the region of 85% of on-site time (Chudley & Greeno, 2006). Thus, to maintain a high productivity of construction equipment and not to disrupt the construction programme, making an allowance for routine, daily and planned maintenance and avoiding the unexpected breakdowns is essential.

The factors affecting the productivity of a plant may include task efficiency of the machine, operator's efficiency, and for some special equipment such as excavators may also take type of soil into consideration. Some research articles have pointed out that machines are often traded or replaced at some multiple of the engine life, with transmissions, hydraulic pumps, and undercarriage influencing the decision to various degrees depending on the type of machine and working conditions (Kannan, 2011; Steward, 2004).

2.1.2 SIGNIFICANCE OF CONSTRUCTION EQUIPMENT RELIABILITY

The unexpected failures of construction equipment usually cause a large amount of repair costs and even more severe collateral costs. Taking repair after breakdown and preventive maintenance is an easy strategy, as time is set by the maintenance cycle, task is arranged in a maintenance check, and work is performed in agreement with operations. Based on a preventive maintenance program, a piece of equipment can be allowed to run to failure before any extra measure is taken. However, this kind of behavior disregard the disrupted operations, increased repair costs, collateral cost of lost production, and crisis management.

The importance of construction equipment reliability analysis and its effects on construction projects can be explored from the following three aspects: cost, time and safety (Figure 2.2).

Figure 2.2 Importance of construction equipment reliability

Equipment Failure Cost

Equipment costs can normally be divided into three categories: owning costs, operating costs, and consequential costs. Owning costs covers transactions such as purchase, finance and resale; operating costs includes fuel, consumables, repair, and maintenance. The third category, consequential costs is widely acknowledged but often disregarded. They may cover the intangible costs arising from the fact that equipment often performs less well than expected and thereby impacts on many aspects of the production process.

Many authors have mentioned consequential costs in their research. The basic premise is that equipment failure forces construction supervisors to change previously laid and presumably optimal construction plans, and these changes sequentially cause consequential costs.

Project Schedule

From the perspective of project schedule, unexpected breakdown of construction equipment may terminate an aspect of the work and this in turn may delay the pace of the project.

Safety Issues

Safety is another noticeable issue in construction equipment management and maintenance. In 1968 (H.M.) over 200 men lost their lives and a further 40,000 were injured on construction sites. These figures reflect human suffering and significant material loss, and it should be everyone's concern to try to reduce them.

The unreliability of equipment can cause serious accidents. The reasons may include machines being overloaded, continuous strain on a machine or part, machines used incorrectly, bad or lack of maintenance, etc. any of the above misbehavior may lead to a dangerous occurrence, and it is only when an accident (an unplanned event resulting in personnel injury) results that people get really concerned.

2.1.3 CONSTRUCTION EQUIPMENT RELIABILITY AND MAINTENANCE

Construction equipment, like any other machine, can be expected to break down during its working life. This may be due to normal wear and tear, or a sudden failure or a component part. The primary purpose of providing maintenance is to reduce the incidence of failure, by either replacement, repair or servicing, in order to achieve an economical level of utilization during the working life of the machine (Vorster, 1987).

For the majority manufacturing or production plants, maintenance costs are a significant part of the total operating costs. In some cases, maintenance costs can account for between 15% and 60% of the total cost of production. According to a recent survey, it seems that one-third of all maintenance costs are due to unnecessary or improperly carried out maintenance. For an instance, the U.S. construction industry spends more than $200 billion each year on maintenance of plant equipment, which proves the importance of proper maintenance operations (Mobley, 2002).

The general opinion has been "Maintenance is a necessary evil" or "Nothing can be done to improve maintenance costs" in the past few decades. However, the development of computer-based instrumentation that can be used to monitor the operating condition of plant equipment, machinery and systems, has provided the means to manage maintenance operations. Main functions include reducing or eliminating unnecessary repairs, and prevent catastrophic machine failures.

The maintenance options are shown in Figure 2.3. There are generally three recommended types of maintenance for equipment or plant, which are: maintenance improvement, corrective maintenance, and preventive maintenance. Maintenance improvement is the first and most valuable one which endeavors to reduce or remove the need for maintenance.

Corrective maintenance deals with the emergency, repair, remedial and unscheduled events. Repairs are always needed. At present, most maintenance is corrective. However, there is a need of detecting incipient problems before they cause serious failures as well as correcting the defects at the most efficient cost. This demand lead the focus to the third type of maintenance – preventive maintenance.

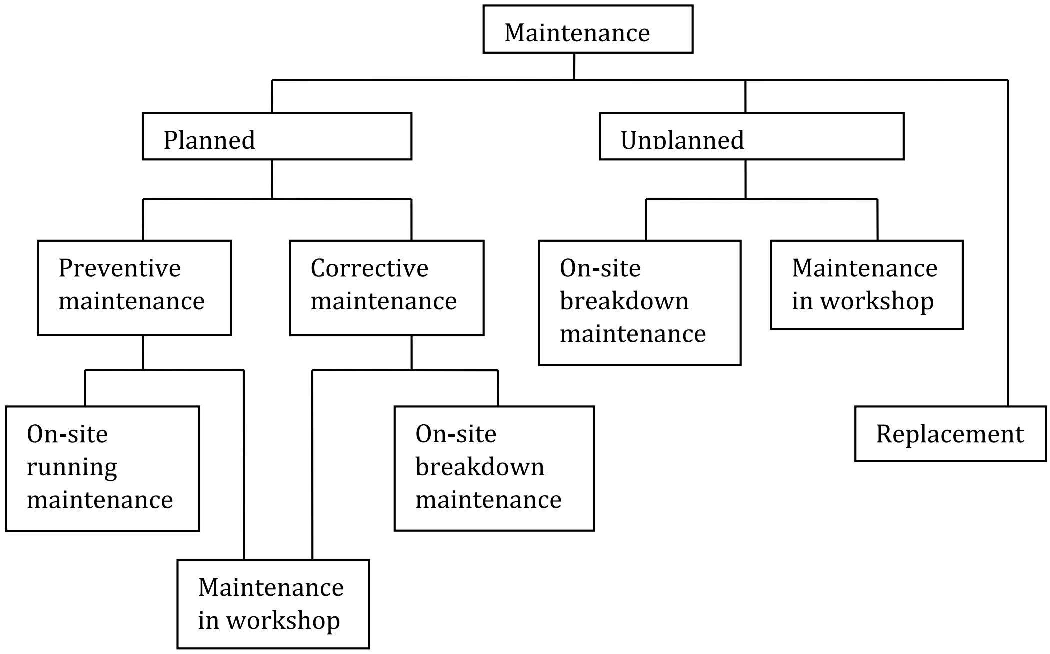

Figure 2.3 Traditional construction equipment maintenance options (Harris and McCaffer, 1991)

There are three types of preventive maintenance: reactive, condition monitoring, and scheduled.

The purpose of preventive maintenance is to prevent unscheduled breakdown of construction equipment and early equipment damage that would lead to corrective maintenance or other repair activities.

Schedules of equipment repairs in preventive maintenance management are mostly based on the MTTF statistic. The MTTF or bathtub curve (Figure 2.4) indicates that a new machine has a high probability of failure at the beginning. After that the probability of failure is basically stable for a period and will increase at the end of the machine life.

The actual programs of preventive maintenance implementation can be very different depends on the situation. Some simple programs might comprise only minor adjustments and lubrication. On the other hand, comprehensive preventive maintenance programs usually comprise not only lubrication, but also repairs, adjustments, and machine rebuilds for all critical plant machinery.

Nevertheless, the common determinant for all of these preventive maintenance programs is – time.

Overall, preventive maintenance has many advantages compared with corrective or other maintenance. Use of on-condition or condition-monitoring techniques is usually better than fixed intervals.

2.1.4 PREDICTIVE MAINTENANCE

The common premise of predictive maintenance is that regular monitoring of the actual mechanical condition, operating efficiency, and other indicators of the operating condition of machine-trains and process systems will provide the data required to ensure the maximum interval between repairs and minimize the number and cost of unscheduled outages created by machine-train failures.

Predictive maintenance is a philosophy or attitude that, simply stated, uses the actual operating condition of plant equipment and systems to optimize total plant operation. A comprehensive predictive maintenance management program uses the most cost-effective tools to secure the actual operating condition of critical components/ subsystems and based on these real data plans all the necessary maintenance activities.

Predictive maintenance is a condition-driven preventive maintenance program. Instead of relying on industrial or in-plant average-life statistics to schedule maintenance activities, predictive maintenance uses direct monitoring of the mechanical condition, system efficiency, and other indicators to determine the actual MTTF or loss of efficiency for the equipment.

Significance of Predictive Maintenance

Predictive maintenance is not a substitute for the more traditional maintenance management methods. It is, however, a valuable addition to a comprehensive, total-plant maintenance program. Where traditional maintenance management programs rely on routine servicing of all machinery and fast response to unexpected failures, a predictive maintenance program schedules specific maintenance tasks as they are actually required by plant equipment. Predictive maintenance can provide a more reliable scheduling tool for routine preventive maintenance programs and diminish the number of unexpected failures. This research aims to predict the failures based on reliability analysis and the experiment results can be used to plan predictive maintenance.

2.2. INTRODUCTION TO RELIABILITY ENGINEERING

2.2.1 DEFINITIONS OF RELIABILITY

The definition of Reliability given in BS4778 is "*The ability of an item to perform a required function under stated conditions for a stated period of time*". The usual engineering definition of Reliability stated in O'Conner (2002)'s book is "*The probability that an item will perform a required function without failure under stated conditions for a stated period of time*".

Reliability can also be expressed as the number of failures over a period. Mathematically, reliability can be defined as shown in Formula 2.1, which represents the likelihood of a given system being operational during the project time.

$$R(t) = P\,(T > t), \qquad t \geq 0$$

$$\lim_{t \to \infty} R(t) = 0 \qquad [2.1]$$

T is a random variable representing the time to failure, and t the mission time. Reliability is the probability that a system will be successfully operating during the mission time (Bauer, 2009).

The definition of Failure given in BS4778 is "*The termination of the ability of an item to perform a required function*". Mathematically, probability of failure, often denoted as F(t), is the probability that the system will fail by time t:

$$F(t) = P\,(T \leq t), \qquad t \geq 0$$

$$\lim_{t \to \infty} F(t) = 1 \qquad [2.2]$$

F(t) is also called the failure distribution function, or the cumulative failure distribution function. The relationship of reliability and failure is defined as:

$$R(t) = 1 - F(t) \qquad [2.3]$$

The failure density function, f(t), which is equivalent to the probability density function, is derivative of F(t).

$$f(t) = \frac{dF(t)}{dt} = -\frac{dR(t)}{dt} \qquad [2.4]$$

When reliabilities are being computed, it is the function R(t) which is normally used. When failure probabilities are being computed, it is the function F(t) which is normally used. In addition, the diagram of the probability density function (PDF) provides a visual representation of the failure distribution.

When measuring or predicting reliability, it is necessary to distinguish between repairable and non-repairable equipment.

Non-repairable equipment can be systems comprised of many parts or individual parts. When a part fails, the system usually fails and therefore, the system reliability is a function of the time to the first part failure. For non-repairable equipment, during the item's life the instantaneous probability of the first and only failure is called the hazard rate.

For repairable equipment, reliability is the probability that more than one failure can occur in the period of interest. This differs from hazard rate for non-repairable items, and can be described as the failure rate or the rate of occurrence of failures (ROCOF). Construction equipment is usually considered to be in the category of repairable systems.

2.2.2 CHARACTERISTICS OF RELIABILITY

There are quite a few indices existing for quantifying the reliability of a product, which are described as follows.

For non-repairable items:

Mean time to failure (MTTF) - The definition of MTTF given in BS4778 is “For a stated period in the life of an item, the ratio of the cumulative time for a sample to the total number of failures in the sample during the period under stated conditions”.

For repairable items:

Failure rate (Hazard rate) - The mean number of failures in a given time. The definition of observed failure rate given in BS4778 is “For a stated period in the life of an item, the ratio of the total number of failures in a sample to the cumulative observed time on that sample”. The observed failure rate is to be associated with particular and stated time intervals (or summation of intervals) in the life of the item, and under stated conditions.

Mean time between failures (MTBF) - The definition of MTBF given in BS4778 is “For a stated period in the life of an item, the mean value of the length of time between consecutive failures computed as the ratio of the cumulative observed time to the number of failures under stated conditions”. For repaired items, it is often assumed that failures occur at a constant rate, in which case the failure rate $\lambda = (\mathrm{MTBF})^{-1}$.

Failure Rate (Hazard Rate)

In terms of failure, the failure rate is a measure of the rate at which failures occur.

The failure rate can be defined as

$$\frac{R(t)-R(t+\Delta t)}{\Delta t \mathrm{R(t)}} \qquad [2.5]$$

The hazard function h(t) is the instantaneous failure rate, which can be defined as the limit of the failure rate as the interval approaches zero as expressed in the following formula:

$$h(t) = \lim_{\Delta t \to 0} \frac{R(t)-R(t+\Delta t)}{\Delta t R(t)}$$

$$= \frac{-dR(t)}{R(t)dt} \quad [2.6]$$

For both repairable and non-repairable items, failures vary with time, while the failure rate (hazard rate) can either be decreasing, increasing, or be constant. The pattern of failures with time can be illustrated by use of the bathtub curve (Figure 2.4). It shows an initial infant mortality period with a decreasing hazard/failure rate, an intermediate useful life period and a final wear out period.

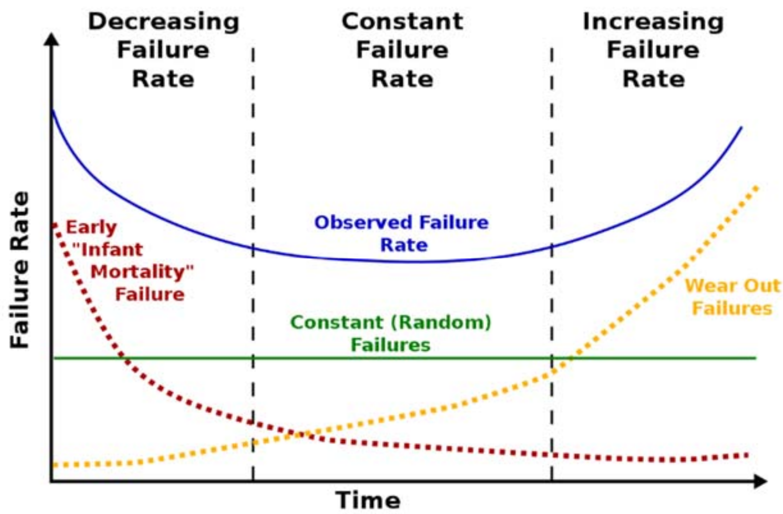

Figure 2.4 The 'bathtub' curve (O'Conner, 2002)

<u>Mean Time to Failure (MTTF)</u>

Mean time to failure (MTTF) is the expected average time that the system is likely to operate successfully before a failure occurs. The MTTF function is:

$$MTTF = \int_0^\infty t f(t) dt$$

$$= \int_0^\infty R(t) dt \quad [2.7]$$

<u>Mean Time between Failure (MTBF)</u>

The definition of MTBF given in BS4778 has been introduced earlier. It is basically the mean value of the length of time between consecutive failures. For repaired items, it is often assumed that failures occur at a constant rate, in which case the failure rate $\lambda = (MTBF)^{-1}$.

Mathematically,

$$MTBF = MTTF + MTTR \qquad [2.8]$$

MTTR symbolizes mean time to repair. The relationship between MTBF, MTTF and MTTR are shown in Figure 2.5.

The utilization of equipment/plant is directly related to the average value of two indicators, namely MTBF and MTTR, for all the subsystems and delays.

The effect of the maintenance plan, operating conditions during excavation such as water inflow, and reliability functions of the components, directly affects MTBF of the overall construction equipment system and its back-up system.

According to Regattieri, et al (2010), the factors affecting MTTR of construction equipment may include: the competence of the equipment crew, inventory system of spare parts, production of works, the level of the ongoing geotechnical investigation and monitoring during excavation, the response speed of the crew to changing ground conditions, and level of preparation of the on-site management for contingencies (such as high water inflow).

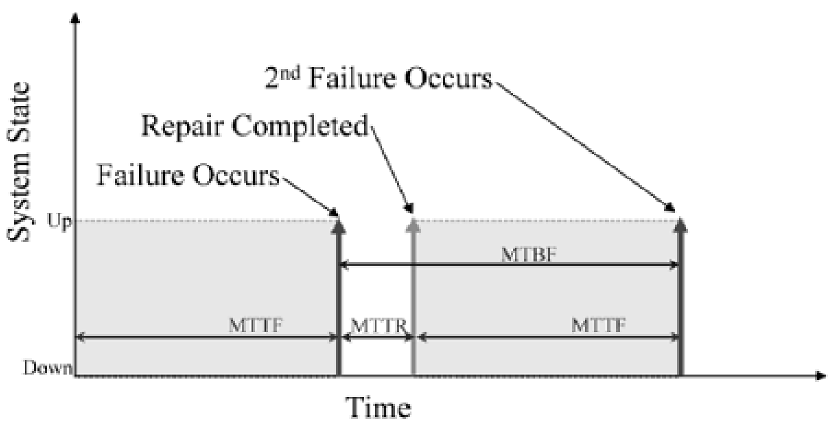

Figure 2.5 MTTR, MTBF, and MTTF (Bauer, 2009)

2.2.3 RELIABILITY, AVAILABILITY AND MAINTAINABILITY

Effectiveness of construction equipment is principally influenced by the reliability, availability, and maintainability of the system, and its capability to perform as expected.

Availability is defined as the probability that the system is in normal operation. In other words, it means a measure that allows for a system to be repaired when failures occur. For repairable systems, availability (A) is a measure of successful operation for repairable systems.

Reliability and maintainability are often related to availability by the formula:

$$\text{Availability} = \frac{\text{MTTF}}{\text{MTTF} + \text{MTTR}} \qquad [2.9]$$

where MTTR is the mean time to repair. This is the simplest steady-state situation. It is clear that availability improvements can be achieved by improving either MTBF or MTTR.

2.3 RELIABILITY ENGINEERING IN CONSTRUCTION AND RELEVANT INDUSTRIES

2.3.1 THE DEVELOPMENT OF RELIABILITY ENGINEERING

Reliability engineering, originated in the United States during the 1950s, is a distinct engineering discipline. As the increasing complexity of military electronic systems which was generating failure rates greatly reduced availability and increased costs, the US Department of Defense and the electronics industry jointly set up the Advisory Group on Reliability of Electronic Equipment (AGREE) in 1952.

In the 1980s, the UK government built Defence Standard 00-40, The Management of Reliability and Maintainability. The British Standards Institution further issued BS5760 – Guide on Reliability of Systems, Equipment and Components.

At the meantime, the principles of 'Total quality management' (TQM) and continuous improvement were brought forward by Japanese and American pioneers. These ideas led to great increases in productivity and quality. Items such as electronic systems and components, automobiles and machine tools reached levels of reliability far beyond previous experience.

Increasingly sophisticated statistical methods have also aided the development of reliability engineering. Much research and literature has focused on this subject. However, random variations often render quantitative approaches difficult or invalid. Therefore, our research will not only cover the traditional statistical methods but will also investigate new mathematical techniques such as data mining for reliability analysis.

2.3.2 RELIABILITY RESEARCH IN OTHER INDUSTRIES

No one disputes the need for equipment to be reliable. Organizations such as airlines, the military and public utilities are aware of the costs of unreliability. As such, reliability analysis techniques have been increasingly utilized for the planning and operation of automatic and complex systems in some industries. Since failure cannot be prevented entirely, it is important to minimize both its probability of occurrence and the impact of failures when they do occur (Blischke, 2003).

Roberts and Mann (1993) suggested in their paper that the Crow model (Crow, 1990), or power law Non-homogenous Poisson Process (NHPP) is recognized by the reliability community as being one of the best models for repairable systems. However, a continuous distribution such as the Weibull is more valuable in that they give failure prediction results that can be traced to individual components. They used the Crow model to predict when the overall system will be down, and then the Monte Carlo simulation which utilizes Weibull parameters to predict the number of failures from each of the included components.

Aircraft system such as jet engine in the aviation industry is an example of a complex repairable system (Downing, 2011). Some papers discussed the reliability analysis and failure prediction of such systems by using statistical methods and data mining methods (Weckman, etc., 2001; Letourneau, etc., 1999). Weckman etc. (2001) discussed how the Weibull process, a non-homogenous Poisson (NHPP) process can be used in modeling jet engine life. The overall capability of the model is measured by examining both data fit and forecasting accuracy. The Weibull process can also be referred as the Power Law process, Weibull restoration process, NHPP with Weibull intensity function, Weibull Poisson process, and more recently as the Power Law NHPP. There are also some research have adopted time series models and other advanced methods such as neural networks for reliability analysis and forecast of repairable systems in manufacture industry (Ho & Xie, 1998; Xu, et al., 2003; Chen, 2007). For example, Ho, et al (2002) carried out a comparative study of neural network and ARIMA modelling in time series prediction for repairable system failure analysis.

2.3.3 RELIABILITY RESEARCH IN CONSTRUCTION AND MINING INDUSTRY

Much research has been carried on reliability analysis of mining equipment such as load-haul-dump machines (Samanta, etc, 2004; Kumar and Klefsjo, 1992; Kumar, et al, 1989). The function of Load-haul-dump machines is to pick up ore from the mining points and dump it into either trucks or other equipment. Reliability assessments of repairable mining machines have been reported in these papers with probability distributions fitted for the characterization of failure data. Other mining equipment such as longwall face equipment and crushing plant have also been studied for reliability analysis (Mandal, 1996; Barabady, 2005; Barabady and Kumar, 2008). Reliability characteristics Time between failures (TBF) and Time to repair (TTR) were analyzed for a complicated crushing plant. With the aid of computer software, parameters of some probability distributions like Lognormal and Weibull distributions were estimated. More sophisticated mathematic methods have also been investigated and applied to mining equipment reliability assessment such as genetic algorithms (Vagenas & Nuziale, 2001; Vayenas & Yuriy, 2007; Peng &Vayenas, 2014).

There are books and papers involving the reliability analysis of building components and civil engineering systems such as bridge and substructure (Blischke & Murthy, 2003). However, not much research have been conducted on the reliability analysis of construction equipment or plant (Nepal & Park, 2004). Vorster (2005) used an impending failure matrix to demonstrate the strategies to bridge the gap between preventive maintenance and repair. Steward (2006) had a lifecycle research on several construction equipment types (excavator, wheel-loader life, crawler-bulldozer, backhoe-loader, and articulated-dump-truck) by dividing the equipment life into B_{20}, B_{50} and B_{80}. Fan (2012) did a comparative analysis of construction equipment (D11 bulldozer system) failures using the classical power law models and the new time series models. He found out that the power law models are easy to apply and are capable of predicting reliability metrics at both the system and subsystem levels with faire results, while time series models based on predictive data mining algorithms are more flexible, comprehensive, and accurate by taking various influencing factors into account.

CHAPTER 3 RELIABILITY MODELING APPROCH

3.1 INTRODUCTION

In this chapter, some basic approaches for reliability analysis are going to be introduced and discussed. The focus is on the methods which are suitable for repairable systems rather than non-repairable systems, as construction equipment is mostly considered to consist of repairable systems. The two reliability modelling approaches used in this research are traditional statistical method named power law model and more sophisticated time series models.

The definition of a time series is a set of attribute values over a period of time. As the past values have impact on the current and future behavior, the historical time series plot can be used to predict future failures in the case of construction equipment reliability study. It is worth mentioning here that the Markov model, which has been considered by many researchers as a powerful tool for reliability analysis, is not adopted. The reason it is not adopted in this research is that in the Markov model the future values depend only on the present state and is independent of history, which does not accord with the situation of a construction equipment failure.

3.2 STATISTICAL METHODS

Commonly used statistical models for reliability analysis include: binomial distribution, exponential distribution and Poisson distribution, normal distribution and lognormal distribution, and Weibull distribution. Some of the common ones are introduced in Chapter 2. In this chapter, power law model is introduced and further applied to the research. It is also called the Weibull process which differs from the concept of Weilbull distribution as explained in Chapter 2.

3.2.1 RELIABILITY ANALYSIS PROCESS

The classical reliability analysis process of a repairable system is illustrated in Figure 3.1, which explains from the first step of data collection to the last step of reliability analysis by Ascher and Feingold (1984) The sources of data in a piece of construction equipment may include operational and maintenance information, maintenance reports, and data from sensors on equipment.

A test for independence can be performed by using serial correlation test which will detect the presence of dependent data (Kumar and Klefjso, 1992). In this test, the Time to Failure data is plotted against a one lag time data. If the data is randomly scattered, it can be concluded that one failure to the next was Independence. In other words, the current failure does not have any influence over immediate subsequent failure.

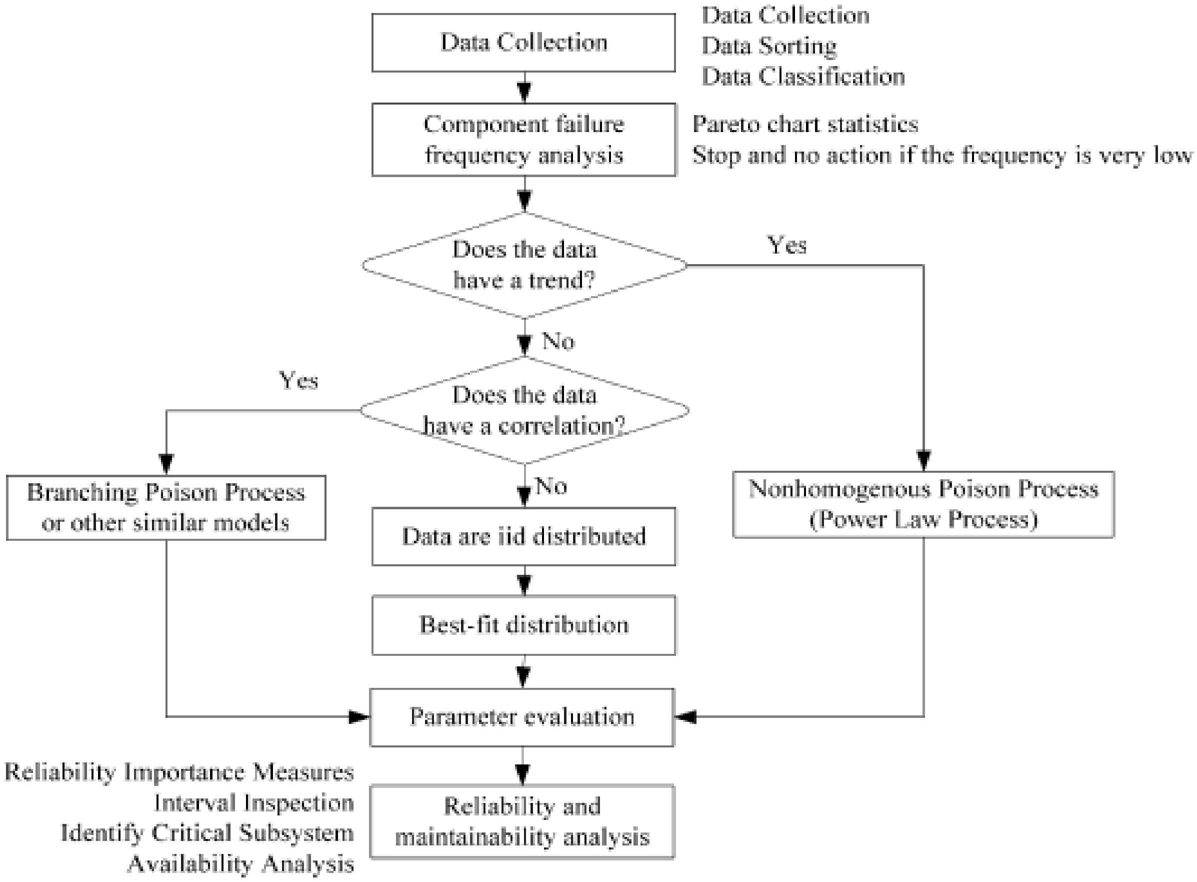

Figure 3.1 Reliability analysis process of a repairable system (Ascher and Feingold, 1984)

For the use of time series, the data series should be dependent. This is the case with failure data, i.e., the current failure have influences over the immediate subsequent failure.

Usually the first step in reliability analysis of a repairable system is to collecting, sorting and classifying significant data. The second step is component failure frequency analysis. Pareto chart statistics is a common method to find out those important subsystems. It is often found that a majority of failure in a product is a result of a minority of potential causes.

The next step is to check if the data has a trend or not. If the answer is yes, then a Nonhomogeneous Poisson Process or so named power law process can be adopted for data modelling. If there is no trend and the data has no correlation, then the data is assumed to be independent and identically distributed (iid). Two common methods used to validate the iid assumption are the trend test and the serial correlation test and is described by practical example in Refs (Kumar and Klefsjo, 1992; Ascher and Feingold, 1984). The techniques involved fitting a distribution function to an iid variable is very different from the approach for fitting an NHPP to non-stationary data. For repairable systems such as construction equipment, the most commonly applied method is the NHPP model which based on the power law process. After the validation of the stationary of the data, the next step is parameter valuation and followed by reliability and maintainability analysis.

A number of books and papers have stressed that the usual non-repairable reliability methodologies, such as the Weibull distribution, are not appropriate for repairable system reliability analyses and have suggested the use of Non-homogeneous Poisson Process (NHPP) models (Crow, 1900; Ascher and Feingold, 1984). Table 3.1 gives a summary of the statistical methods used for reliability analysis and respective software.

Table 3.1 Statistical methods for reliability analysis of repairable multi-component systems

	Reliability Characteristics	Statistical Methods	Software	Maintenance
System	Give failure rate of the system Determine when the overall system down	The Crow model (NHPP) Exponential/ Lognormal/ Normal/ Weibull distribution	ReliaSoft's RGA7; Weibull ++6	Optimum preventive maintenance Predictive maintenance
Components/ Subsystems	Predict the frequency of failures of each component Identify the critical subsystems or component	Weilbull analysis (i.e., Monte Carlo simulation)		

3.2.2 CLASSICAL STATISTICAL TECHNIQUES

There are a number of widely used standard distribution functions, include binomial, Poisson, Weibull, normal, exponential, lognormal, gamma, and Rayleigh, etc. The detailed introduction to these probability models have been presented in many literature. This section only gives a brief introduction to the distributions which are related to this research.

<u>Poisson distribution</u>

Poisson distributions, similar to some other distributions, are used to analyze discrete random events. The major difference is that in a Poisson distribution, only the occurrence of an event is counted, and its nonoccurrence is not counted. The followings are some examples of a Poisson distribution:

- The number of calls in a given period
- The number of people coming to a bus stop
- The number of failures of a system

The probability of having x failures by time t of a Poisson distribution can be calculated as follows:

$$\Pr(X = x) = \frac{(\lambda t)^x e^{-\lambda t}}{x!} \qquad \text{for } x = 0, 1, 2\ldots \qquad [3.1]$$

Where λ is the average failure rate of a system, and x is the number of failures by time t.

The mean and the variance of a Poisson distribution can be calculated separately as follows:

$$E(X) = \lambda t \qquad [3.2]$$

And

$$V(X) = \lambda t \qquad [3.3]$$

<u>Weibull distribution</u>

In probability theory and statistics, the Weibull distribution is a continuous probability distribution. It is named after Waloddi Weibull, who described it in detail in 1951.

Compared with the exponential distribution which is limited in its application due to the memoryless property, the Weibull distribution is a generalization of the exponential distribution. As Weibull distribution has no specific characteristic shape, it can be shaped to represent many different distributions, depending on what the values of the parameters are in its reliability function. It also can be shaped to fit to experimental data that cannot be characterized as a particular distribution.

3.2.3 POWER LAW NHPP (WEIBULL PROCESS)

A power law model indicates that the failures of a complex system are time dependent and follow the NHPP. The power law model was first proposed by Duane (1964) to describe the failures of a complex system at the stage of development.

For a unit of construction machine under the policy of minimum repair (just conduct minimum repair to bring the machine back to working order), the system failure intensity function can be expressed by a power law model as follows:

$$u(t) = \lambda\beta t^{\beta-1}, \quad t>0 \qquad [3.4]$$

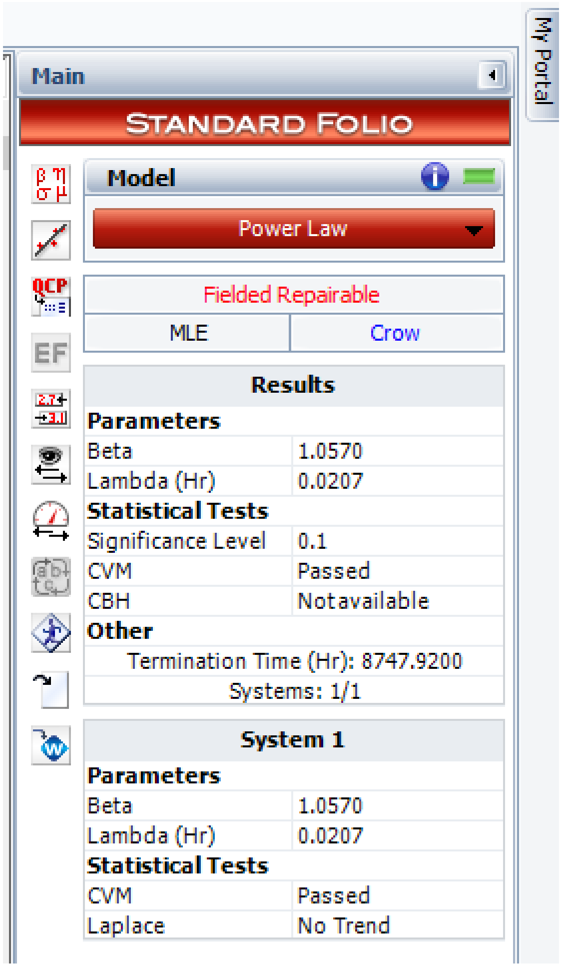

Figure 3.2 Power Law Modelling Process

where λ is the failure rate and t is the age of the system. When β = 1, the instantaneous failure intensity is a constant, the equipment has stable reliability;

when β > 1, the equipment is in the wear-out stage; when β < 1, the equipment is in the burn-in stage. It shows that the power law model can well describe the "bathtub" curve which construction equipment follows. Figure 3.2 shows an example of the modelling process using power law model on RGA 7 platform. The parameters lambda and beta are calculated and presented in the figure.

3.3 TIME SERIES ANALYSIS AND PREDICTION

3.3.1 INTRODUCTION

A time series is a set of attribute values over a period of time. The definition is given as follows (Dunham, 2003):

> *"Given an attribute, A, a time series is a set of n values: {<t_1, a_1>, <t_2, a_2>, …, <t_n,a_n}>}. Here there are n time values and for each a corresponding value of A. Often the values are identified for specific well-defined points in time, in which case the values may be viewed as a vector < a_1, a_2, …, a_n>."*

The mathematical equation of a time series could be:

$$Y_t = f\,(Y_{t-1}, Y_{t-2}, Y_{t-3},\ldots, Y_{t-n}) + e_t \qquad [3.5]$$

Where Y_t is the value of Y at the corresponding time t, Y_{t-1} to Y_{t-n} represent the previous value of Y, and e_t stands for noise that does not obey the predictable pattern.

Time series analysis may be viewed as finding patterns in the data and predicting future values. The values usually are obtained as evenly spaced time points (daily, weekly, hourly, etc.). There are three basic functions performed in time series analysis: distance measurements are used to determine the similarity between different time series; the structure of the line is examined to determine (and perhaps classify) its behavior; the historical time series plot used to predict future values. In this research, the third function is performed in time series analysis to predict the future failures based on historical failures of construction equipment. Normally time series follows the one or more of the following four patterns, which are (Tiao, 2001):

- Trends - a trend can be viewed as systematic nonrepetitive changes (linear or nonlinear) to the attribute values over time.
- Cycles - means the observed behavior is cyclic.
- Seasonal - means the detected patterns are based on time of year or month or day.
- Outliers - means irregular fluctuations. Various approaches may be applied to remove or reduce the impact of outliers and to assist pattern detection.

Models for time series data can have many forms and represent different stochastic processes. When modeling variations in the level of a process, three broad classes of practical importance are the autoregressive (AR) models, the integrated (I) models, and the moving average (MA) models. These three classes depend linearly on previous data points. Combinations of these models produce autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models.

ARIMA models

ARIMA (p,d,q) is short for autoregressive integrated moving average model where parameters p, d, and q refer to the order of the autoregressive, integrated, and moving average parts of the model respectively. Parameter p, d, and q should be non-negative integers. In Box-Jenkins approach to time-series modelling, ARIMA models is an important constitute (Box, et al, 1994).

Autoregressive (AR) processes - a time series $\{X_t\}$ is said to be an autoregressive process of order p (abbreviated AR (P)) if it is a weighted linear sum of the past p values plus a random shock.

Moving average (MA) processes - a time series $\{X_t\}$ is said to be a moving average process of order 1 (abbreviated MA (q)) if it is a weighted linear sum of the last q random shocks.

ARMA is a mixed autoregressive moving average model with p autoregressive terms and q moving average terms. The mathematical function can be expressed as:

$$\emptyset\,(B)X_t = \theta\,(B)Z_t \qquad [3.6]$$

where $\emptyset\,(B),\ ,\ \theta\,(B)$ are polynomials in B of finite order p, q, respectively.

In reality, many time series are non-stationary so that stationary AR, MA or ARMA processes cannot be applied directly. There are several methods to solve this problem and one of them is to apply differencing to make the time series stationary. An ARIMA (p,d,q) process means a time series that has been differenced d times before fitting an ARMA (p,q) process where d symbolizes the number of differences taken and the letter "I" stands for integrated. Mathematically,

$$\emptyset\,(B)(1-B)^d X_t = \theta\,(B)Z_t \qquad [3.7]$$

Similarly, a seasonal model can be represented as ARIMA (p,d,q)(P,D,Q). The Microsoft time series algorithm (SQL Server, 2014) discovered that the ARIMA algorithm is optimized for long-term prediction and their ARTXP algorithm is optimized for short-term predictions in SQL Server. Maia et al. (2008) believes that it is advantageous to model linear and non-linear patterns separately by using different models and then combine the forecasts to improve the overall modeling and forecasting performance.

3.3.2 MODELING PROCESS

The original Box-Jenkins model (1976) takes an iterative three-stage modeling approach, which are: model identification or model selection, parameter estimation, and model checking.

The first step of the Box-Jenkins modelling process is model identification or so-called model selection, which is ensuring that variables are stationary and identifying seasonality in the dependent series. Plots of the autocorrelation (ACF) and partial autocorrelation functions (PACF) of the dependent time series are used to decide which (if any) autoregressive or moving average component should be used in the model.

The second step is parameter estimation which generate the coefficients that best fit the selected ARIMA model by using computation algorithms. The most common methods include maximum likelihood estimation and non-linear least-squares estimation.

The third step is model checking which tests whether the estimated model conforms to the specifications of a stationary univariate process. In particular, the residuals should be independent of each other and constant in mean and variance over time. It is helpful to identify misspecification by plotting the mean and variance, or ACF and PACF of the residuals. At the end, if the result is inadequate, it is required to return to step one and build a more appropriate model.

Most statistical time series model building have the following three major stages, which are similar to the original Box-Jenkins model:

- Model specification/ identification/ selection
- Model fitting/ parameter estimation
- Model verification/ checking

Chatfield (2000) has provided explicit explanation to these tree stages for building a statistical time series model.

Trend removal and stationary time series

A time series is said to be stationary if both its mean (the value about which it is oscillating), and its variance (amplitude) remain constant through time. Classical Box-Jenkins ARMA models only work satisfactorily with stationary time series, so for those types of models it is essential to perform transformations on the series to make it stationary. Usually time series do not present a fixed mean, therefore, removing trends from time series and adjusting the amplitude are usually required before modeling the data. The software DTREG includes facilities that can automatically identify and remove the trend and it uses regression to fit either a linear or exponential function to the data. However, not all software has this function, in some cases manual operations may be necessary.

There are several ways to remove the trend, or so-called detrending. Differencing and log transformation are two common ways, and in the case study of this thesis, log transformation is used to stabilize the mean and variance. The meaning of differencing is to calculate the difference between two observed values at fixed time interval. For example, a difference of one time interval apart is calculated by subtracting value 1 from value 2, then 2 from 3, and on, and plotting that data to determine if the mean is zero and the variance is constant or not. If differencing of one does not detrend the data, then repeat the process if necessary to stabilize the mean and variance. The advantage of differencing is ease of use and simplicity, while the disadvantage is over-correcting for trends, which skews the correlations in a negative direction.

The differenced series is given by

$$w_t = (1-\mathrm{B})^d (1-\mathrm{B}^s)^D y_t \qquad [3.8]$$

Where t denotes time and B is the backshift operator defined by $\mathbf{B}y_t = y_{t-1}$. Other symbols D is the seasonal differencing order, d represents the nonseasonal differencing order, and s is the number of periods per season. If the value of the differencing order is zero that means there is no differencing of that kind.

Another method can be used to remove trends is ordinary least squares analysis.

Trend removal is almost always beneficial; however, variance stabilization (amplitude adjustment) is beneficial about 20% of the time and harmful about 80% of the time based on experiments (Senter, 2008).

Autocorrelations (ACF) and Partial Autocorrelations (PACF)

Usually, Autocorrelations Functions (ACF) and Partial Autocorrelations Functions (PACF) are used to describe how and to what degree each point is correlated with previous values in the series (as shown in Figure 3.3).

The correlation between all the pairs of points in the time series can be described by autocorrelation graph with a specified separation in time or lag. The autocorrelation for the k^{th} lag is

$$r_k = \frac{c_k}{c_0}$$

$$c_k = \frac{1}{N}\sum_{t=k+1}^{N}(y_t - \bar{y})(y_{t-k} - \bar{y}) \qquad [3.9]$$

Where t denotes time, k is the number of lags, and $\bar{y}$ is the mean of the N nonmissing points in the time series.

Other graphs such as variograms (a characterization of process disturbances), autoregressive (AR) coefficients, and spectral density plots can also be used to identify the type of model appropriate for describing and predicting the evolution of the time series (SAS, 2012).

```
 ==============  Autocorrelations and Partial Autocorrelations  ==============

------------------------------  Autocorrelations  ------------------------------

Lag  Correlation   Std.Err.      t     -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
  1  -0.03983188   0.057543    0.692   |                  . | .                  |
  2  -0.02553715   0.057634    0.443   |                  . | .                  |
  3  -0.06519376   0.057672    1.130   |                  . | .                  |
  4  -0.04279580   0.057915    0.739   |                  . | .                  |
  5   0.07932120   0.058020    1.367   |                  . |**                  |
  6  -0.01368337   0.058378    0.234   |                  . | .                  |
  7  -0.11005582   0.058389    1.885   |                  .*| .                  |
  8  -0.00668735   0.059072    0.113   |                  . | .                  |
  9  -0.11614995   0.059074    1.966   |                  .*| .                  |
 10   0.02308963   0.059825    0.386   |                  . | .                  |
 11  -0.07125172   0.059855    1.190   |                  . | .                  |
 12  -0.04980398   0.060135    0.828   |                  . | .                  |

--------------------------  Partial Autocorrelations  --------------------------

Lag  Correlation   Std.Err.      t     -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
  1  -0.03983188   0.057260    0.696   |                  . | .                  |
  2  -0.02716684   0.057260    0.474   |                  . | .                  |
  3  -0.06747747   0.057260    1.178   |                  . | .                  |
  4  -0.04937367   0.057260    0.862   |                  . | .                  |
  5   0.07222886   0.057260    1.261   |                  . |*.                  |
  6  -0.01433504   0.057260    0.250   |                  . | .                  |
  7  -0.11485300   0.057260    2.006   |                  .*| .                  |
  8  -0.00901908   0.057260    0.158   |                  . | .                  |
  9  -0.12017815   0.057260    2.099   |                  .*| .                  |
 10  -0.01063010   0.057260    0.186   |                  . | .                  |
 11  -0.08986090   0.057260    1.569   |                  .*| .                  |
 12  -0.06166693   0.057260    1.077   |                  . | .                  |
```

Figure 3.3 Examples of Autocorrelation and Partial Correlation Plots

3.3.3 MODEL FITTING CRITERION

There are several different metrics for evaluating the fitness of a model. By comparing the values of these metrics, the best fit model can be found. Figure 3.4 shows an example of the criterions used in software JMP, which contains DF, sum of squared errors, variance estimate, standard deviation, AIC, BIC, RSquare, RSquare Adj, MAPE, MAE, -2LogLikelihood and so on.

Model: ARIMA(1, 1, 1)

Model Summary

DF	140	Stable	Yes
Sum of Squared Errors	137052.119	Invertible	Yes
Variance Estimate	978.943704		
Standard Deviation	31.2880761		
Akaike's 'A' Information Criterion	1394.12154		
Schwarz's Bayesian Criterion	1403.01008		
RSquare	0.93245111		
RSquare Adj	0.93148612		
MAPE	8.68705796		
MAE	24.3641658		
-2LogLikelihood	1388.12154		

Figure 3.4 Example of Model Fitting Criterion

RSquare, can also be wrote as R^2, measures the proportion of the total variation explained by the model. It usually increases as the number of parameters increases. If the model fits the series well, then the model error sum of squares (SSE) is smaller than the total sum of the squares (SST). However, if the model fits the series badly, the SSE might be larger than the SST. A similar fitting criterion called adjusted-R^2, makes some attempt to take account of the number of parameters fitted.

The most commonly used fitting criterion for time series models is so-called Akaike"s Information Criterion (AIC), since more sophisticated model-selection statistics are generally preferred. The mathematical function is expressed as follows:

$$AIC = -2 \ln (\text{max. likelihood}) + 2p \qquad [3.10]$$

Where p denotes the number of independent parameters estimated in the model. AIC essentially chooses the model with the best fit, as measured by the likelihood function, provided a penalty term that increases with the number of parameters fitted in the model. Therefore, it should prevent overfitting.

In addition to AIC, another widely used fitting criterion for time series models is the Bayesian Information Criterion (BIC). BIC essentially replaces the term 2p in the AIC with the expression p + p InN. The BIC is similar to the AIC but penalizes the addition of extra parameters more severely than the AIC. When the number of model parameters is high compared with the number of observations in time series analysis, BIC is considered to be more suitable than the ordinary AIC.

Other metrics can be used to evaluate the fitness of a model include degree of freedom (DF), sum of squared errors (SSE), variance, standard deviation, MAPE, MAE, -2LogLikelihood. MAPE is the mean absolute percentage error and MAE is the mean absolute error. -2LogLikelihood is minus two times the natural log of the likelihood function evaluated at the best-fit parameter estimates. The theory is that the smaller of the value, the better of the fitness of a model.

CHAPTER 4 CASE STUDIES ON RELIABILITY MODELLING

In previous chapters, the concept of reliability engineering and several reliability modelling approaches have been introduced and discussed. This chapter is going to apply these methods to real cases by analyzing the data collected from the construction industry with the aid of computer software. Section 4.1 introduces the background of the case study and Section 4.2 presents the data preparation stage in the reliability analysis process. Section 4.3 and 4.4 demonstrate the modelling process and results using power law models and time series models respectively. Section 4.5 summaries the outcomes of this chapter and raises discussions of the methods and findings.

4.1 BACKGROUND

Several papers have emphasized that equipment mangers should focus on repair before equipment breakdown and effort to bridge the gap between preventive maintenance and repair (Vorster, 2004). To achieve this goal, reliable machine information such as component lives and machine history is needed.

The data used in the case study are from a contractor's equipment fleet which is working on an oil sand project on a 3-shift schedule. Among the pieces of equipment in this fleet are bulldozers, graders, trucks, backhoes, etc. The contractor has a team of operators, superintendents, project managers working on the jobsite and keeping full working records of downtime, uptime, failure events, and repair details on each unit. Apart from the preventive maintenance and scheduled overhauls, there are unscheduled random failures on each equipment unit. The contractor is keen to predict the reliability of each unit so that better decisions on allocations of equipment and maintenance resources can be made for scheduling purpose.

Although traditional reliability theory can be applied to the heavy equipment in service, there are practical obstacles which make it difficult to apply these reliability modeling techniques originally developed from the manufacturing industry. The construction environment is highly uncontrollable with constantly changing weather conditions, job natures, and operating conditions, all of which have an impact on the equipment reliability. Each unscheduled critical failure leads to an emergency repair and causes interruptions to construction works with varying financial impact; under some critical failure circumstances, the equipment cannot be repaired on the jobsite and must be brought to a distant shop for extensive repairs.

The maintenance and repair details were written down in the records and the useful information has been reorganized for reliability analysis and failure prediction. A sample of this is shown in Table 4.1. Construction equipment is a complex system comprising of various subsystems: engine, braking system, hydraulic system, undercarriage, etc., these subsystems and components have different economic lives and different reliability metrics. They are not completely independent and must be kept in working conditions and work in coordination for the equipment to function properly.

For each equipment unit, the contractor is interested in predicting the equipment reliability metrics for use in the planning period, such as rate of failures, reliability level for the scheduled mission, availability, time between failures (TBF), time to repair (TTR), and length of uninterrupted working hours without failure given a minimum reliability level. Predictions at both system level and subsystem levels are desired for management decisions for the upcoming planning periods.

Table 4.1 Sample reliability data of bulldozer obtained from the field

Failure Event	Time Down	Time Up	TBF	TTR	Location	Class	Trade	Workforce	labour-hours	Name	Reason Down
1	7/1/95 5:01	7/1/95 8:22		3.35	Steam Bay	Steam	MECH		0.00	HISCO	STEAM FOR P2 SERVICE
2	7/1/95 8:23	7/1/95 13:09	0.02	4.77	Shop	Service	MECH	2	9.53	ACTIN	P2 SERVICE
3	7/3/95 10:25	7/3/95 11:48	45.27	1.38	Field	Air Conditioning	MECH		0.00	HERRI	AIR CONDITIONING - POLAR AIR
4	7/4/95 1:00	7/4/95 1:15	13.20	0.25	Field	Drive System	MECH	1	0.25	MCCAN	ENGINE OIL DIPSTICK
5	7/17/95 13:00	7/17/95 13:20	323.75	0.33	Field	Field Service	MECH	1	0.33	KOSTI	FIELD SERVICE
6	7/17/95 21:50	7/17/95 22:00	8.50	0.17	Field	Repair Light	MECH	1	0.17	ANTHO	HEADLIGHTS NOT WORKING
7	7/19/95 9:00	7/19/95 12:14	35.00	3.23	Shop	Drive System	MECH	2	6.47	RYAN,	CHANGE OILS FINAL DRIVES
8	7/19/95 14:00	7/19/95 14:20	1.77	0.33	Field	Air System	MECH	1	0.33	FOY,	NO POWER
9	7/26/95 23:45	7/27/95 0:15	177.42	0.50	Field	Repair Light	MECH	1	0.50	AGNEW	NO TAIL LIGHTS
10	7/29/95 7:55	7/29/95 11:34	55.67	3.65	Steam Bay	Steam	MECH		0.00	ANTHO	STEAMING FOR P 2 SERVICE
11	7/29/95 11:35	7/29/95 15:49	0.02	4.23	Shop	Service	MECH	2	8.47	ACTIN	P2 SERVICE.
12	7/29/95 15:50	7/30/95 20:58	0.02	29.13	Shop	Engine	MECH	2	58.27	RYAN,	MID LIFE TUNE UP W.O. 397256
13	7/31/95 0:01	7/31/95 1:20	3.05	1.32	Field	Engine	MECH	1	1.32	ANTHO	LINKAGE JAMMED
14	7/31/95 8:30	7/31/95 9:30	7.17	1.00	Field	Air System	MECH	1	1.00	AGNEW	WING NUT OFF AIR FILTER
15	8/3/95 2:15	8/3/95 2:30	64.75	0.25	Field	Cooling Systems	MECH	1	0.25	ACTIN	OVERHEATING
16	8/5/95 13:25	8/5/95 14:15	58.92	0.83	Field	Cooling Systems	MECH	1	0.83	ANTHO	ENGINE COOLANT LIGHT ON
17	8/8/95 16:30	8/8/95 16:40	74.25	0.17	Field	Under Carriage	MECH	1	0.17	ACTIN	TRACKS NEED ADJUSTING
18	8/13/95 3:00	8/13/95 3:30	106.33	0.50	Field	Field Service	MECH	1	0.50	ACTIN	FIELD SERVICE
19	8/15/95 15:00	8/15/95 15:30	59.50	0.50	Field	Air Conditioning	MECH		0.00	POIRI	A/C NOT WORKING
20	8/23/95 5:20	8/23/95 13:29	181.83	8.15	Shop	Under Carriage	MECH	2	16.30	HELM,	UNDER CARRIAGE TO FINNING
21	8/26/95 8:07	8/26/95 15:00	66.63	6.88	Steam Bay	Steam	MECH		0.00	ACTIN	STEAM FOR SERVICE
22	8/26/95 15:01	8/26/95 17:32	0.02	2.52	Shop	Service	MECH	2	5.03	ACTIN	P2 SERVICE
23	8/26/95 17:35	8/26/95 18:54	0.05	1.32	Steam Bay	Steam	MECH		0.00	ACTIN	STEAM FOR CUTTING EDGES CHANGE.
24	8/26/95 18:55	8/26/95 21:10	0.02	2.25	Steam Bay	Steam	MECH		0.00	ACTIN	CHANGE CUTTING EDGES
25	8/26/95 21:12	8/26/95 23:07	0.03	1.92	Shop	Cutting Edge	MECH	2	3.83	ANTHO	REPLACE CUTTING EDGES AND CORNER BITS
26	9/4/95 11:00	9/4/95 19:18	203.88	8.30	Shop	Hydraulic System	MECH	2	16.60	ACTIN	HYD. LEAK
27	9/13/95 9:00	9/13/95 9:20	205.70	0.33	Field	Electrical	MECH	1	0.33	MOORE	WIRING PROBLEMS
28	9/13/95 18:53	9/13/95 19:30	9.55	0.62	Field	Air System	MECH	1	0.62	WHITE	HYD. LEAK
29	9/13/95 19:31	9/13/95 23:33	0.02	4.03	Field	Float	MECH		0.00	ACTIN	HYD. LEAK
30	9/13/95 23:33	9/15/95 3:44	0.00	28.18	Field	Wait	MECH		0.00	HISCO	FAN MOTOR HOSE BLOWN - WAITING MANPOWER

4.2 DATA PREPARATION

Three basic steps have been taken at the initially for determining reliability characteristics: data collection, data sorting and data classification (i.e., total working hours, total breakdown hours, total maintenance hours, TBF, TTR, failure frequency, etc.). As mentioned earlier, there are several data sources in a construction equipment that can be used for reliability modeling. In this case study, data for modelling is extracted from the maintenance records of a contractor's company.

Whenever the risks or costs of failure are high, then a formal reliability programme is required. When the system is more complex, or have more components, the risks of failure usually also increase. Thus, reliability programmes are required for any equipment whose complexity leads to an appreciable risk.

The basic steps taken for determining reliability characteristics are shown in the following diagram (Figure 4.1). The data collection and estimation processes continue through all the phases, and there are several mini steps under each big step. Throughout the building construction lifecycle, the reliability is assessed. The whole process includes the initial predictions based on the past failure data, and then the validation of forecast results and subsequently the building up of a predictive maintenance plan based on the predictions. This reliability analysis process of construction equipment is accomplished by using power law models and time series models respectively in the following sections.

Table 4.2 show a sample of reorganized data of construction equipment failures with information of time between failures (TBF) and time to repair (TTR) as well as cumulative TBF and TTR presented.

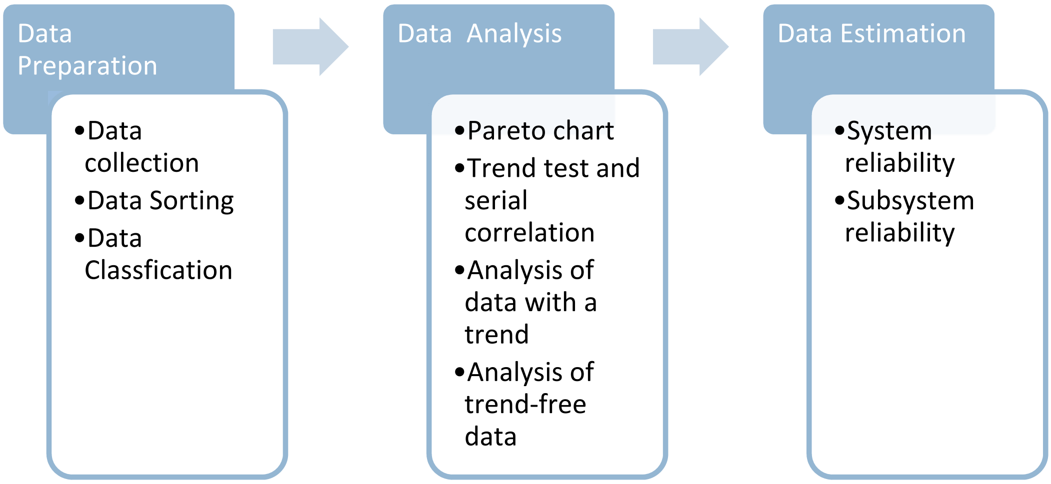

Figure 4.1 Reliability analysis process of construction equipment

Table 4.2 Sample of TBF and TTR data set of a piece of construction equipment

Index	Cumulative TBF	TBF	Cumulative TTR	TTR
1	142.00	142.00	3.20	3.20
2	194.03	52.03	14.78	11.58
3	471.00	276.97	53.15	38.37
4	621.00	150.00	54.98	1.83
5	766.00	145.00	61.50	6.52
6	993.00	227.00	88.93	27.43
7	1151.00	158.00	104.87	15.93
8	1190.00	39.00	105.88	1.02
9	1436.50	246.50	106.38	0.50
10	1525.28	88.78	113.63	7.25
11	1829.00	303.72	114.80	1.17
12	1910.00	81.00	142.20	27.40
13	2040.50	130.50	235.10	92.90
14	2285.50	245.00	297.87	62.77
15	2459.50	174.00	298.20	0.33
16	2664.00	204.50	298.53	0.33
17	2799.50	135.50	299.48	0.95
18	2948.33	148.83	308.07	8.58
19	3141.00	192.67	309.07	1.00
20	3141.00	0.00	309.07	0.00
21	3359.42	218.42	309.57	0.50

22	3536.02	176.60	323.40	13.83
23	3751.75	215.73	325.12	1.72
24	3958.02	206.27	335.37	10.25
25	4082.00	123.98	340.62	5.25
26	4315.50	233.50	380.63	40.02
27	4521.58	206.08	412.57	31.93
28	4688.02	166.43	500.83	88.27
29	4824.00	135.98	501.33	0.50
30	4974.37	150.37	505.68	4.35

4.3 MODELLING PROCESS OF POWER LAW MODELS (NHPP)

4.3.1 DATA MODELLING

After the data have been reorganized and cleaned, the next step is to choose the suitable modeling method for reliability analysis.

The Crow model, or power law non-homogenous Poisson process, is recognized by the reliability community as being one of the best models for repairable systems. It can determine when the overall system will be down, while the Monte Carlo simulation that utilizes Weibull parameters could predicts the frequency of failures of each component in a specific time frame. By identifying the critical components or subsystems, the information can be used to assist in deciding maintenance intervals to design an optimum preventive or predictive maintenance program.

The construction equipment used for modelling and demonstration in this case study is the bulldozer. Figure 4.2 shows a software platform named RGA7 for power law modeling and calculating the parameters of the model. In this case, 429 data points are used for reliability analysis and the results show that lambda equals to 0.0044 and beta is 1.1758, which implies that the equipment is at the wear-out stage according to the bathtub curve which has been introduced in Chapter 2. Plots and tables of MTBF vs. time are presented in the next section.

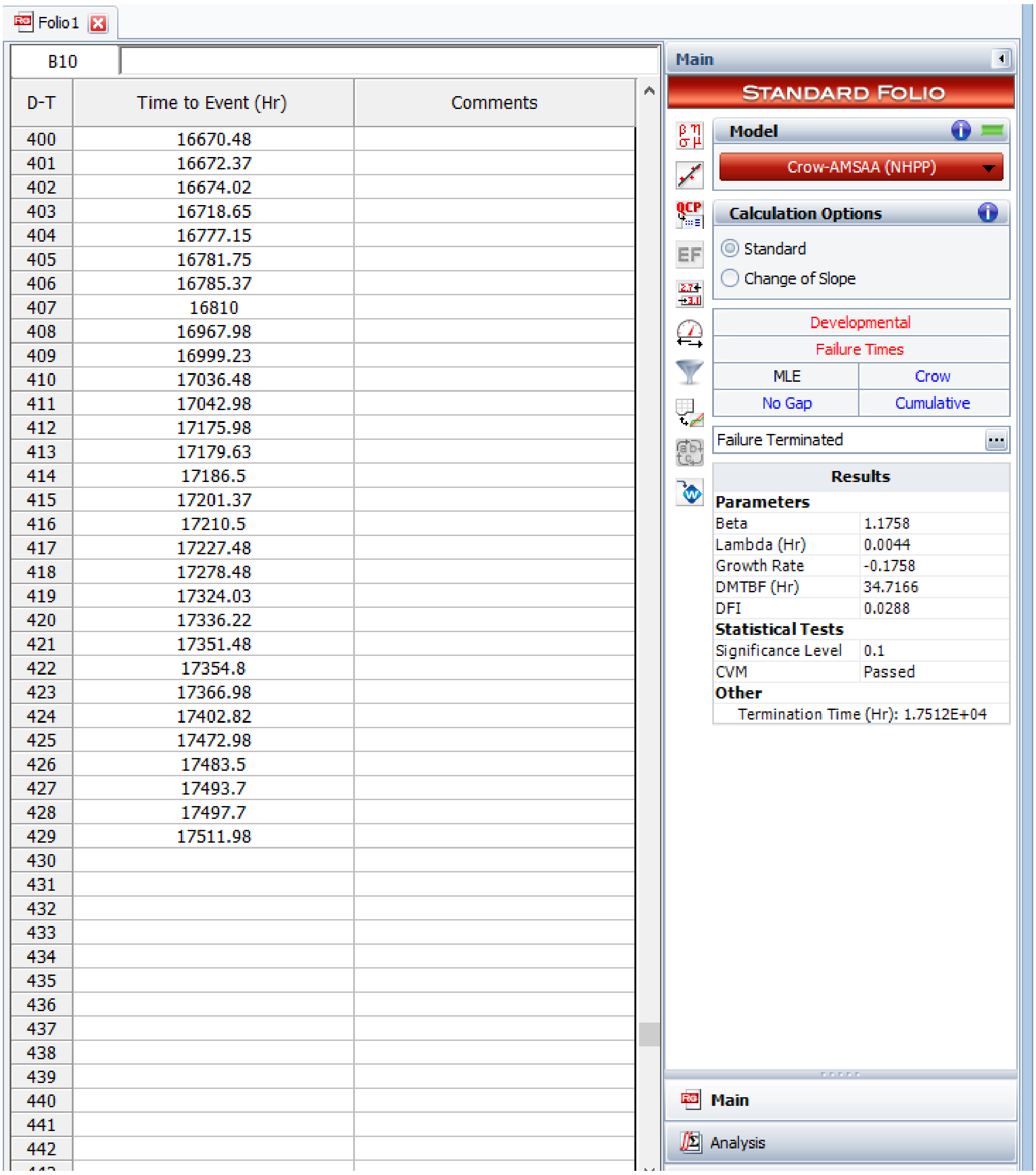

Figure 4.2 Reliability analysis of construction equipment bulldozer by using NHPP model in RGA 7

4.3.2 RESULTS FROM POWER LAW MODELS

With the aid of computer software RGA7, the relation of MTBF with time can be derived (Figure 4.3). So is the relationship of cumulative number of failures with time (Figure 4.4). It can be observed from the diagram that the MTBF has a slight trend of decreasing as the time goes on with the cumulative number of failures increases with time. Although a straight line can be used to fit failure data at the system level, some noisy data exists due to influences on the arrival pattern of equipment failures from some external factors.

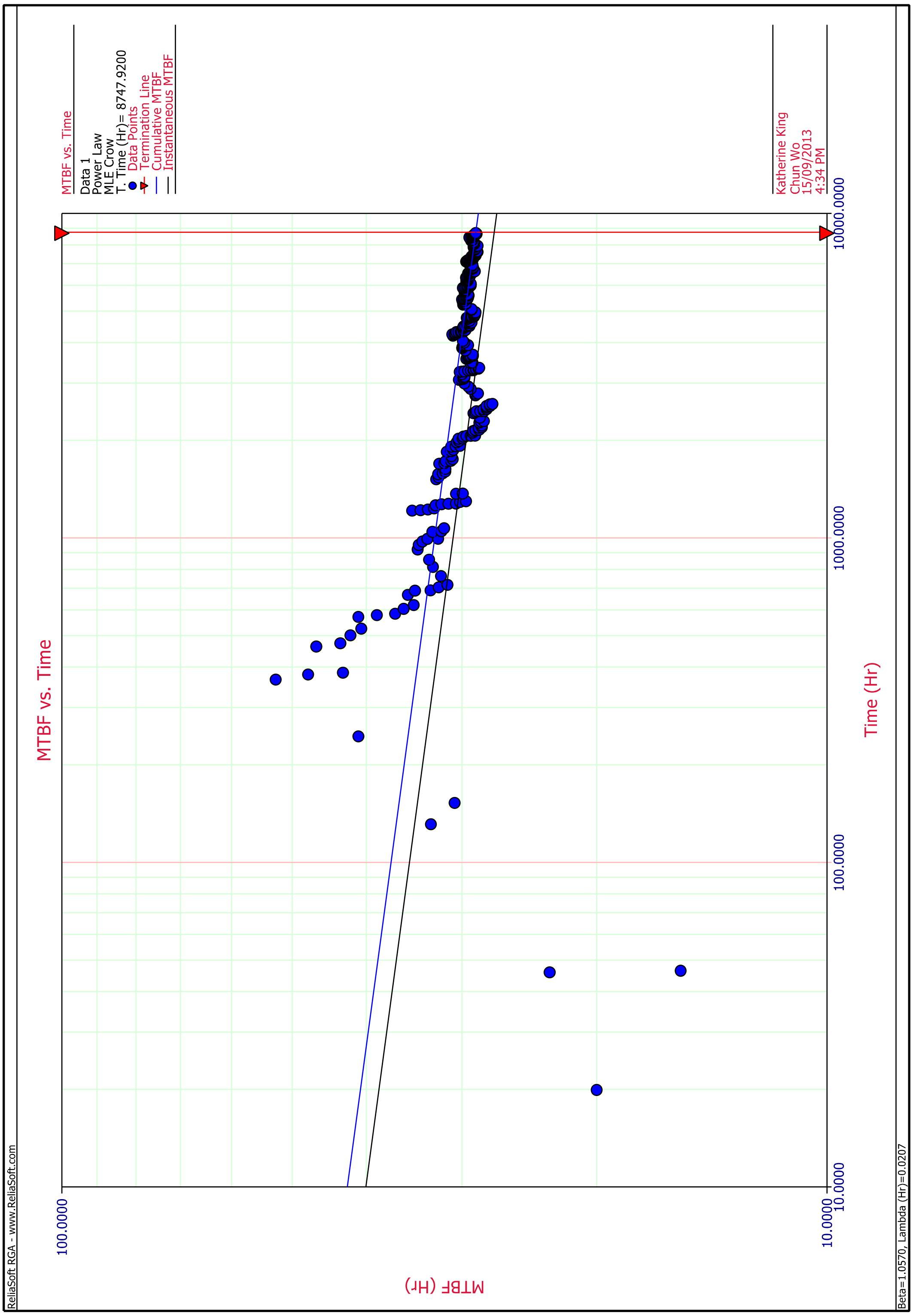

Figure 4.3 MTBF vs. Time

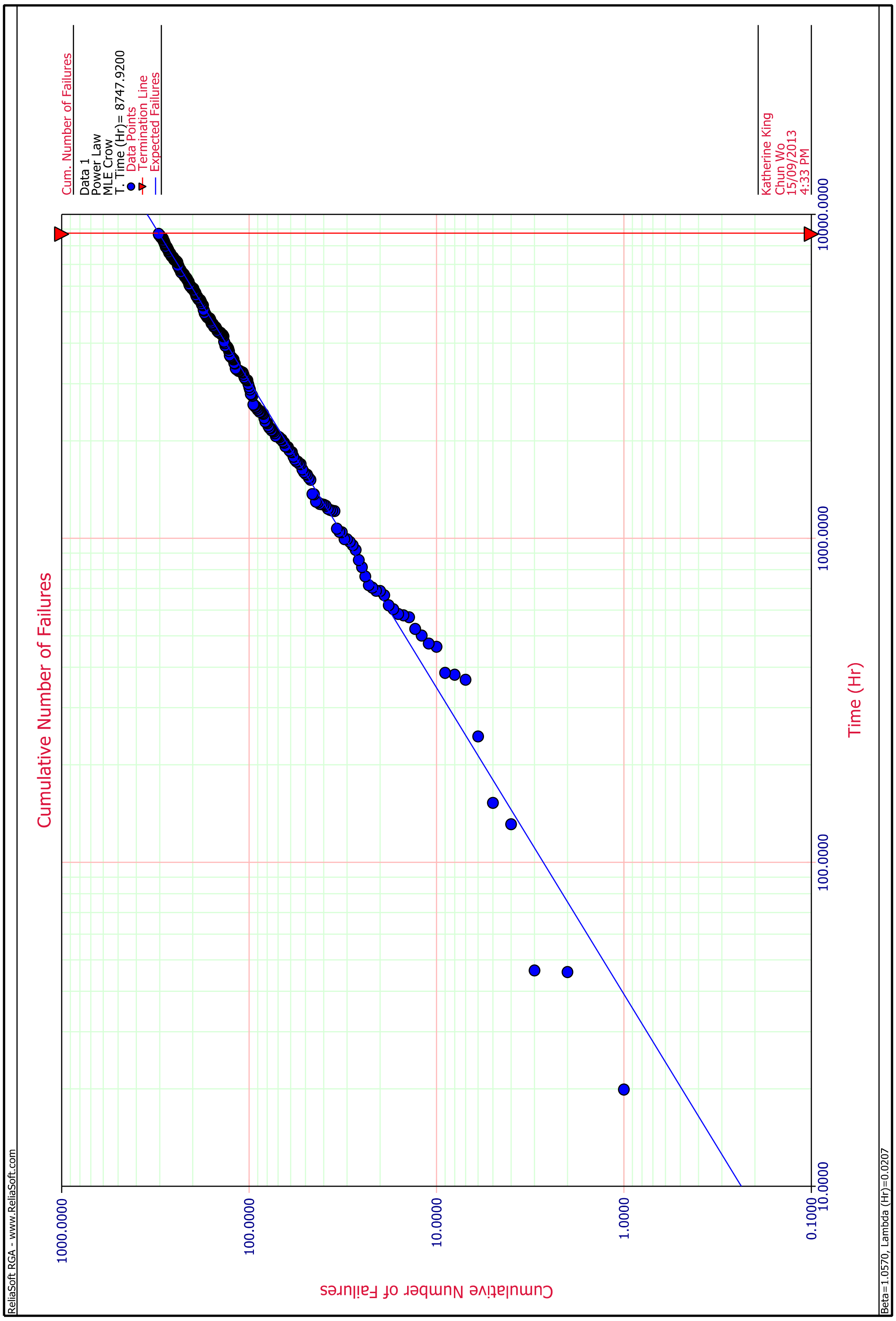

Figure 4.4 Cumulative numbers of failures vs. time

Apart from the diagram showing the relationships of MTBF with time and cumulative number of failures with time, several reliability metrics can be derived from the power law model. For example, the instantaneous MTBF

(IMTBF) at a specific time can be calculated. Figure 4.5 presents the IMTBF to be 34.53hr at the time of 18000hr with the upper bound to be 38.92hr and lower bound to be 31.06hr when the confidence level is set to be 0.9. Other reliability metrics such as cumulative MTBF, cumulative failure intensity and instantaneous failure intensity can also be generated from power law models with the aid of RGA7.

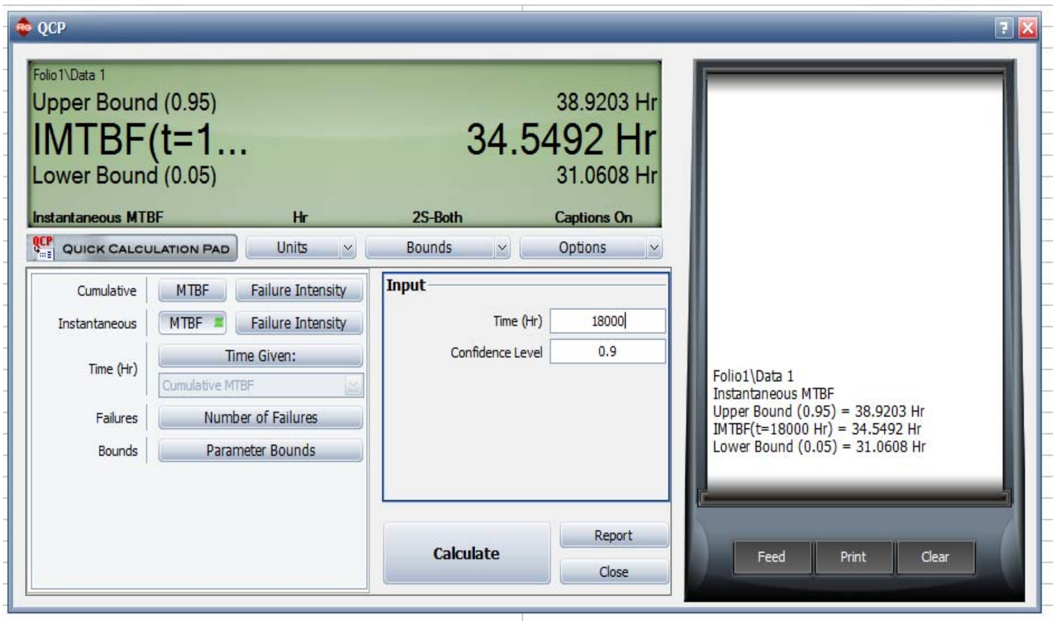

Figure 4.5 Calculation of IMTBF

Another case study being presented here is the research results for the truck. A sample size of 305 data points have been extracted for reliability analysis and failure prediction in the truck by both power law models and time series analysis for comparison. Table 4.3 shows the predictions of the MTBF between Intervals# 294 and 305 by using the Power Law Models. The values of the same intervals (294 to 305) by using time series models are predicted and presented in the next section for comparison. The predicted MTBF is presented in the table as well the original values. The upper and lower bounds of MTBF with a confidence interval of 90% are also shown in the same table. It can be seen that the IMTBF is decreasing as time goes on, which is the same as Figure 4.3 illustrates. Thus, it is found that this construction equipment bulldozer is at the wear-out stage. Special attention should be paid to this piece of equipment and change of new equipment should be implemented when it is suitable.

Table 4.3 Instantaneous MTBF predicted in RGA7 with two-sided confidence level of 0.9

No	TBF (H	Cumulative TBF (Hr)	Upper Bound (0.95)	IMTBF(t=8748Hr)	Lower Bound (0.05)
294	15.75	8510.57	Upper Bound (0.95) = 33.6393 Hr	IMTBF(t=8748 Hr) = 29.4884 Hr	Lower Bound (0.05) = 25.6108 Hr
295	15.43	8526.00	Upper Bound (0.95) = 33.4060 Hr	IMTBF(t=8748 Hr) = 29.2903 Hr	Lower Bound (0.05) = 25.4451 Hr
296	2.33	8528.33	Upper Bound (0.95) = 33.1749 Hr	IMTBF(t=8748 Hr) = 29.0940 Hr	Lower Bound (0.05) = 25.2808 Hr
297	33.33	8561.67	Upper Bound (0.95) = 32.9462 Hr	IMTBF(t=8748 Hr) = 28.8996 Hr	Lower Bound (0.05) = 25.1181 Hr
298	15.25	8576.92	Upper Bound (0.95) = 32.7193 Hr	IMTBF(t=8748 Hr) = 28.7068 Hr	Lower Bound (0.05) = 24.9567 Hr
299	49.92	8626.83	Upper Bound (0.95) = 32.4947 Hr	IMTBF(t=8748 Hr) = 28.5158 Hr	Lower Bound (0.05) = 24.7967 Hr
300	15.43	8642.27	Upper Bound (0.95) = 32.2717 Hr	IMTBF(t=8748 Hr) = 28.3261 Hr	Lower Bound (0.05) = 24.6377 Hr
301	4.58	8646.85	Upper Bound (0.95) = 32.0508 Hr	IMTBF(t=8748 Hr) = 28.1381 Hr	Lower Bound (0.05) = 24.4801 Hr
302	29.15	8676.00	Upper Bound (0.95) = 31.8320 Hr	IMTBF(t=8748 Hr) = 27.9520 Hr	Lower Bound (0.05) = 24.3240 Hr
303	2.50	8678.50	Upper Bound (0.95) = 31.6152 Hr	IMTBF(t=8748 Hr) = 27.7674 Hr	Lower Bound (0.05) = 24.1692 Hr
304	17.42	8695.92	Upper Bound (0.95) = 31.4005 Hr	IMTBF(t=8748 Hr) = 27.5845 Hr	Lower Bound (0.05) = 24.0157 Hr
305	52.00	8747.92	Upper Bound (0.95) = 31.1877 Hr	IMTBF(t=8748 Hr) = 27.4033 Hr	Lower Bound (0.05) = 23.8636 Hr

4.4 TIME SERIES MODELLING PROCESS

4.4.1 DATA ANALYSIS/ MODELING

Apart from power law models, time series models are also built for construction equipment reliability analysis with the aid of computer software named JMP and DTREG (SAS, 2012; Sherrod, 2003). As can be seen from the software platform, two options could be selected: generate a normal predictive model and generate a time series forecasting model. What we chose is the latter option. Again there are many types of model which can be built in DTREG (Figure 4.6), and here we use "linear regression" as the simplest method. This is because of the concept of "parsimony". We have seen that the mathematical models we need to employ contain certain constants or parameters whose values must be estimated from the data. It is important, in practice, that we employ the smallest possible number of parameters for adequate representations.

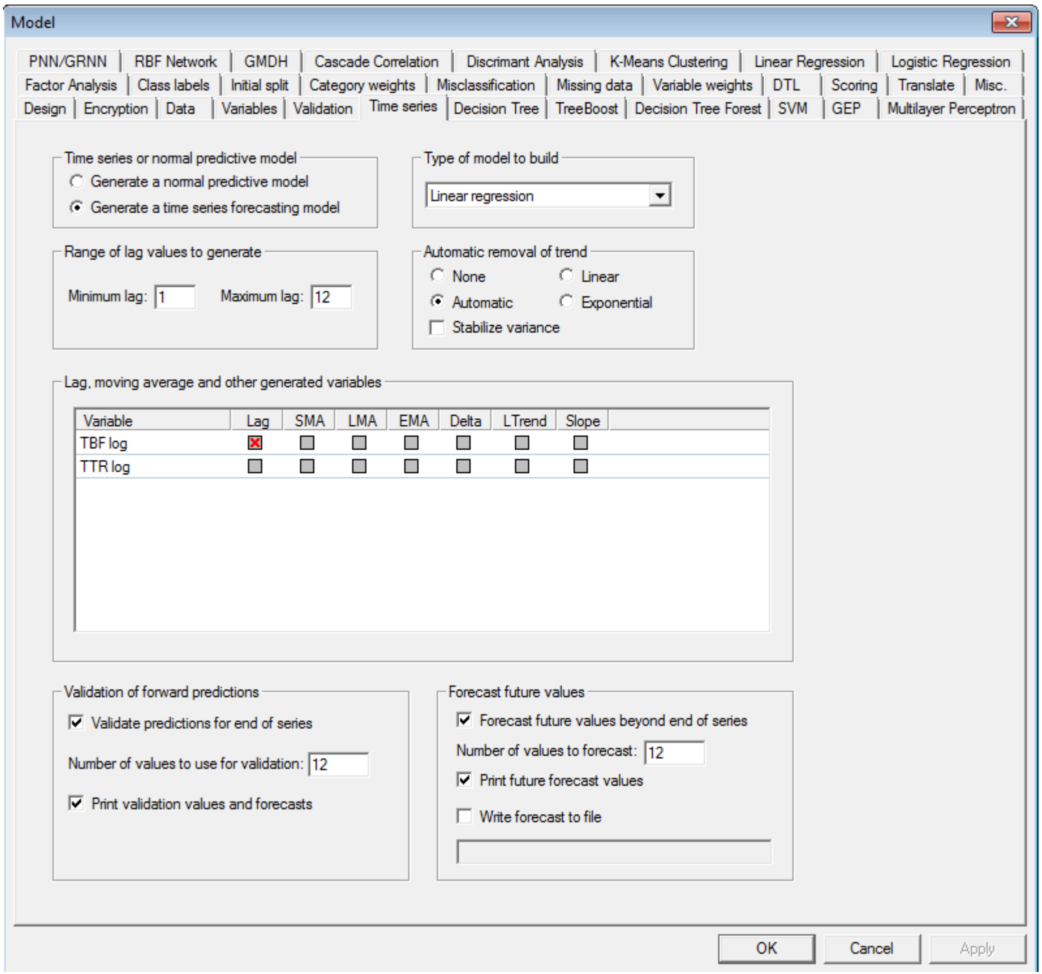

Figure 4.6 Time Series Modelling Process

In Figure 4.6, there are two variables indicated for the time series prediction, namely time between failures (TBF) and time to repair (TTR). Where there is word "log" behind the TBF and TTR, it means that both series of data have been transformed by using logarithm function. At the bottom part of the interface, "validate prediction for end of series" and "forecast future values beyond end of series" are ticked and a number of 12 are inputted for both cases for the reason of seasonal effects.

The third stage "model estimation" is presented with the predicted results obtained in the next section.

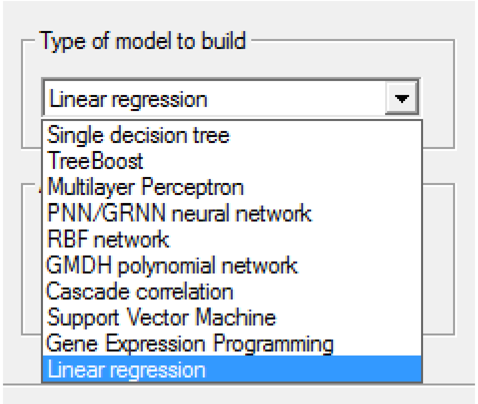

Figure 4.7 Types of model can be built for time series prediction in DTREG

4.4.2 MODEL EVALUATION

As explained earlier in Chapter 3, there are several metrics that could be used for evaluating the fitness of a model (Figure 3.4). Different software packages may provide slightly different metrics for evaluating the fitness. Figure 4.8 presents the criterions being used in the software DTREG which is adopted for time series analysis in this case. Among the various metrics, the proportion of variance (R^2) and correlation between actual and predicted are the most important metrics. In this case, the figures for these two criterions are 0.10790 and 0.330022 respectively. The causes of the low values could be the irregular fluctuations or outliers are too high in the case.

```
Mean target value for input data = 1.1785188
Mean target value for predicted values = 1.1760815

Variance in input data = 0.3373394
Residual (unexplained) variance after model fit = 0.3009392
Proportion of variance explained by model (R^2) = 0.10790  (10.790%)

Coefficient of variation (CV) = 0.465482
Normalized mean square error (NMSE) = 0.892096
Correlation between actual and predicted = 0.330022

Maximum error = 1.6895153
RMSE (Root Mean Squared Error) = 0.5485792
MSE (Mean Squared Error) = 0.3009392
MAE (Mean Absolute Error) = 0.4383436
MAPE (Mean Absolute Percentage Error) = 103.5211
```

Figure 4.8 Evaluation of the fitness of the time series model

4.4.3 RESULTS FROM TIME SERIES MODELS

As discussed earlier, for system reliability analysis, the deliverables from modelling may include: expected number of failures, conditional reliability and unreliability, MTBF or failure intensity, and system operation plot. The system operation plot of a construction equipment is presented in the next chapter with the illustration of Figure 5.12. In this case study, the reliability metrics have been procured include the number of failures and TBF with confidence levels. TTR is also taken into consideration in time series analysis while predicting TBF. Table 4.4 shows an example of the prediction of numbers of failures per interval by using time series models. Time series models generally can detect changes in the failure pattern and respond well enough.

Table 4.4 Prediction of numbers of failures per interval by time series models

Failure Interval	Actual Failures	Predicted Failures	Absolute Error
25	1	1.62	-0.62
26	2	1.61	0.39
27	5	1.60	3.40
28	4	1.58	2.40
29	1	1.57	0.57
30	2	1.55	0.45

Table 4.5 & 4.6 present the results of the predictions of TBF per interval (weekly) of the construction equipment truck, which can be compared with the results obtained from power law models as shown in Table 4.3.The same number of data points (305) were used in the data modelling. A summary of the predictive errors in absolute error is also presented in the table. By comparing the forecast with the actual numbers of failures ("Absolute error"), it can be noted that time series models can give more satisfactory predictions than power law models.

Table 4.5 shows the predicted TBF as compared with the actual TBF of a construction equipment truck (240H_075). The data in Table 4.6 has been modified using logarithm and the results appears better than the one on the left which not been modified. The error percentages are mostly within 50% which indicates that the results from the time series modeling are quite satisfactory.

The statistics calculated from time series model are summarized as follows:

Exponential trend:

TBF (log) = 1.162166 + 0.163911*exp (-0.034805*row)

And the variance explained by trend equals 0.301%.

Table 4.5 Validation results of time series analysis

Row	Actual	Predicted	Error
294	15.750000	16.735053	-0.985053
295	15.430000	12.918207	2.511793
296	2.330000	14.819318	-12.489318
297	33.330000	22.148179	11.181821
298	15.250000	16.843528	-1.593528
299	49.920000	14.548194	35.371806
300	15.430000	15.336325	0.093675
301	4.580000	24.255259	-19.675259
302	29.150000	23.409228	5.592087
303	2.50000	22.409228	-19.909228
304	17.420000	20.152580	-2.732580
305	52.0000	19.305280	32.694720

Table 4.6 Validation results of time series analysis after logarithmic transformation

Row	Actual	Predicted	Error
294	1.1973000	1.0092817	0.1880183
295	1.1885000	0.9902672	0.1982328
296	0.3680000	0.9574823	-0.5894823
297	1.5229000	0.7814389	0.7414611
298	1.1833000	0.7893086	0.3939914
299	1.6982000	0.9986845	0.6995155

300	1.1885000	1.0403445	0.1481555
301	0.6612000	1.0187228	-0.3575228
302	1.4646000	1.1203957	0.3442043
303	0.3979000	1.0455107	-0.6476107
304	1.2410000	1.1410082	0.0999918
305	1.7160000	1.1042755	0.6117245

Figure 4.9 shows the time series trend for TBF after logarithmic transformation while the black squares represent the actual failure intervals and the red triangles represent the forecasted failure intervals. The blue trend line shows TBF over time and in this case shows a slight downwards trend, which suggests that the equipment is entering the wear out stage. Figure 4.10 is similar to Figure 4.9 and shows the time series values for TBF afther logarithmic transformation. The black squares and red triangles have the same meanings, while the green points represent the predicted values and blue points are the validation values which fall in the time interval of 294 and 305 in this case study.

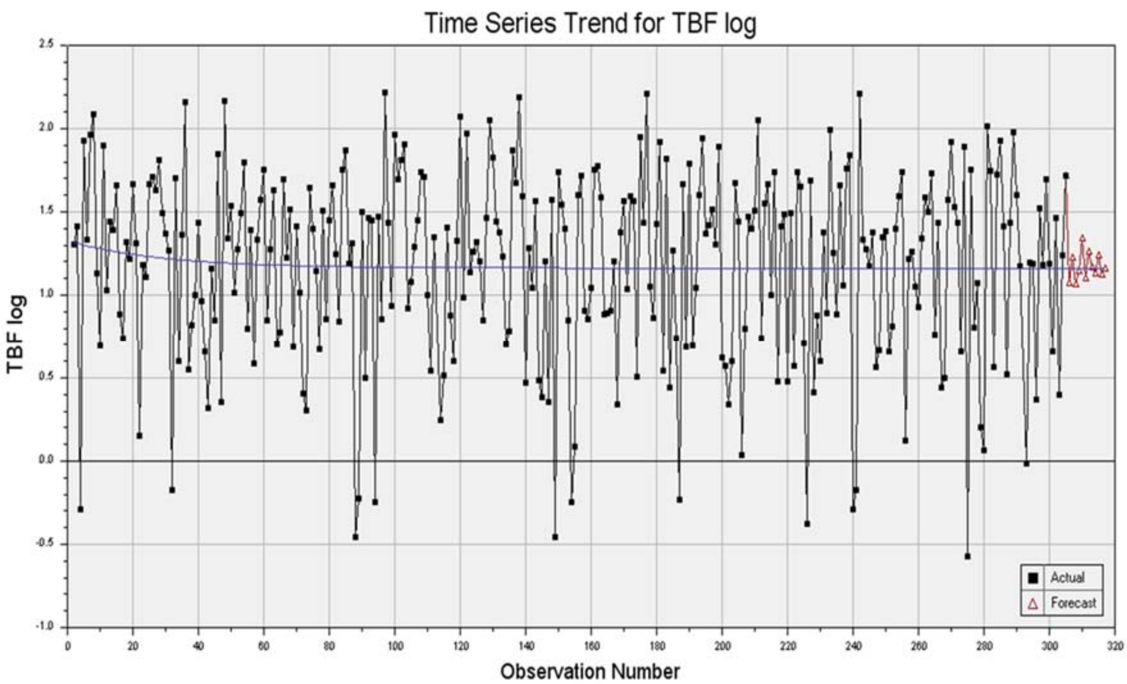

Figure 4.9 Time series trend for TBF (after logarithmic transformation)

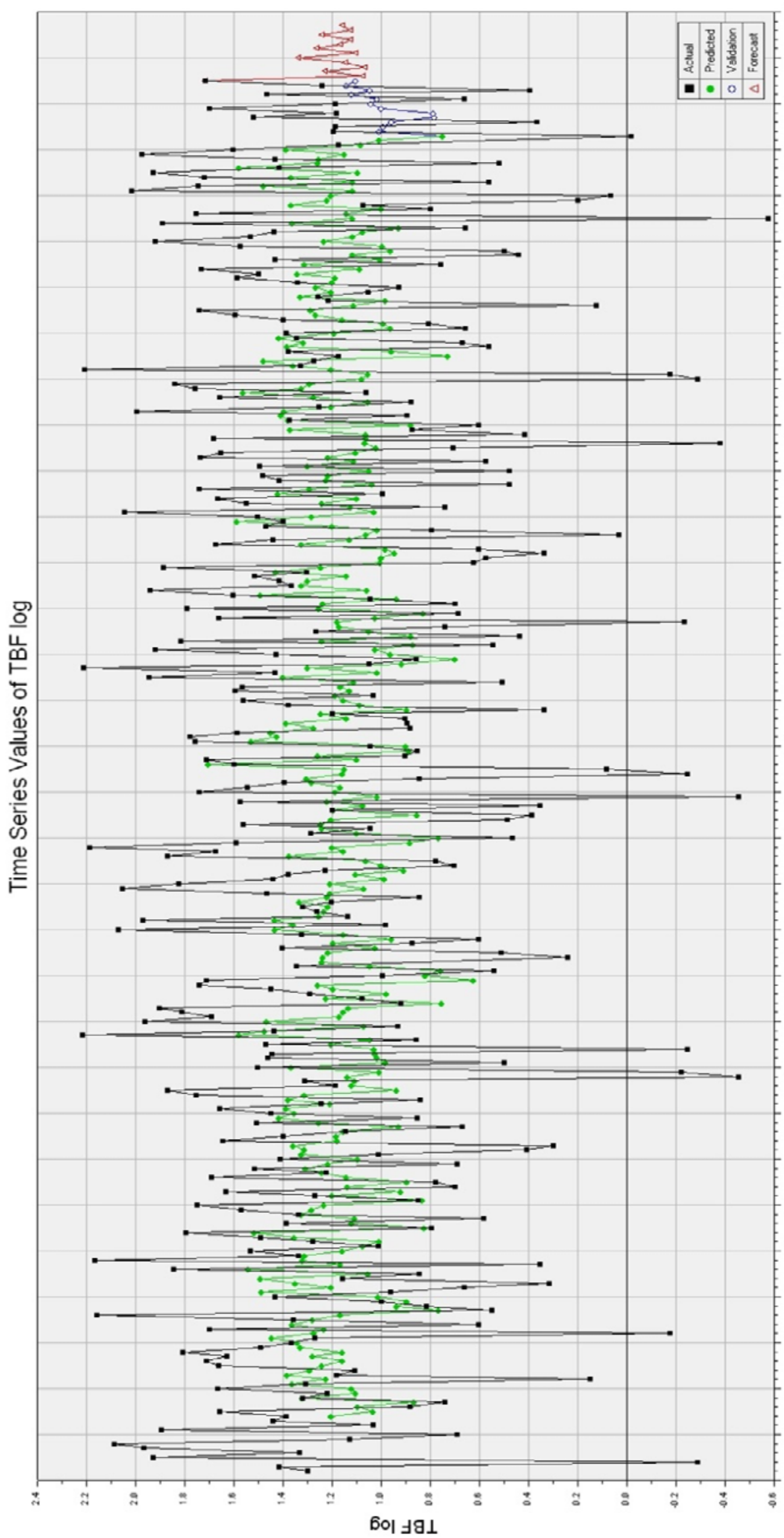

Figure 4.10 Time series analysis and prediction for TBF (after logarithmic transformation)

Table 4.7 presents the ARIMA time series prediction of TBF with 95% upper and lower confidence levels.

Table 4.7 Time series prediction of TBF with upper and lower confidence levels

Row	Actual TBF	Predicted TBF	Upper CL (0.95) TBF	Lower CL (0.95) TBF	Residual TBF
25	356.50	338.38	473.02	203.74	18.12
26	226.00	226.04	360.68	91.40	-0.04
27	315.50	243.51	378.15	108.87	71.99
28	160.90	174.04	308.68	39.40	-13.14
29	297.10	256.16	390.80	121.51	40.94
30	287.17	203.89	338.53	69.24	83.28
31	30.33	162.87	297.51	28.23	-132.54
32	424.42	371.86	506.50	237.22	52.56
33	247.60	192.50	327.14	57.86	55.10
34	234.48	189.98	324.63	55.34	44.50
35	270.52	200.24	334.88	65.60	70.28
36	204.00	175.14	309.78	40.50	28.86

Model validation: the model was validated by comparing the predicted failure data to the actual system failure data. The results in Table 4.6 show the predicted failure time based on mean time between failures (MTBF) compared with the actual occurrence of failure. In the JMP software, several validation options are provided for model selection, which include AIC, SBC, R-Square, -2LogLikelihood (-2LogLH). By comparing these options, it is found the MA(1) model is the most suitable one in this case (Figure 4.11).

Model Comparison

Report	Graph	Model	DF	Variance	AIC	SBC	RSquare	-2LogLH	Weights	MAPE	MAE
☑	☐	MA(1)	34	4719.1123	412.25417	415.42121	0.455	408.25417	0.697041	46.912188	58.502592
☑	☐	ARMA(1, 1)	33	4822.3991	414.09458	418.84514	0.457	408.09458	0.277726	46.251422	57.849199
☑	☐	ARIMA(1, 1, 1)	32	7475.5329	419.06263	423.72868	0.108	413.06263	0.023164	54.027829	71.517867
☑	☐	AR(1)	34	7146.3323	423.89406	427.06109	0.277	419.89406	0.002069	53.339868	67.149779

Figure 4.11 Model comparison

Time between failures (TBF) and time to repair (TTR) are the most commonly used reliability metrics which need to be predicted. TTR measures the time needed to fix a failure. In this case, we not only predict the number of failures of a piece of construction equipment, but also perform a forecast of the TBF with TTR contributed as a predictor time series (Table 4.8 & 4.9).

The utilization of the equipment is directly related to two parameters, namely TBF and TTR, for all the systems and subsystems. Time to repair (TTR), is a crucial parameter, indicating that equipment parts will soon return to normal and have a great impact on the overall stability of the system. Table 4.9 presents the prediction of the Cumulative TBF based two parameters: TBF as well as TTR. It is apparent that adding TTR as a parameter in time series forecast gives different result than the one using TBF as the only time series. From the experiment results we noticed that the time spend on repairing the equipment (i.e., TTR) has impact on the occurrence of next failure (TBF). Therefore, TTR can be taken into consideration when conducting reliability analysis and failure forecast of construction equipment.

Table 4.8 Time series prediction using TBF as the only parameter

--- Validation Time Series Values ---

Row	Actual	Predicted	Error	Error %
31	30.33000	195.42110	-165.09110	544.316
32	424.42000	291.43612	132.98388	31.333
33	247.60000	243.31995	4.28005	1.729
34	234.48000	245.41212	-10.93212	4.662
35	270.52000	270.65061	-0.13061	0.048
36	204.00000	247.10309	-43.10309	21.129

--- Forecast Time Series Values ---

Row	Predicted
37	300.30521
38	237.40540
39	232.99696
40	293.33548
41	238.90645
42	260.42574

Table 4.9 Time series prediction using both TBF and TTR as parameters

--- Validation Time Series Values ---

Row	Actual	Predicted	Error	Error %
31	30.33000	196.45928	-166.12928	547.739
32	424.42000	267.49719	156.92281	36.973
33	247.60000	260.94599	-13.34599	5.390
34	234.48000	249.07135	-14.59135	6.223
35	270.52000	245.85686	24.66314	9.117
36	204.00000	259.71238	-55.71238	27.310

--- Forecast Time Series Values ---

Row	Predicted
37	370.79594
38	237.45276
39	271.81419
40	293.55519
41	276.96399
42	277.00491

4.5 SUMMARY AND DISCUSSIONS

To summarize, there are basically two undertakings in this case study, which are: the comparison of the two different reliability modelling approaches and their applications to construction equipment, the findings and their impact on equipment management decisions. The following will discuss these two aspects respectively.

4.5.1 COMPARISON OF TIME SERIES WITH POWER LAW MODEL

From the aspect of the methodology chosen for system and subsystem analysis, a comparative study between power law models and time series models is made for reliability analysis and forecasting failures of construction equipment, with emphasis on their predictive performance. It can be noticed that time series forecast techniques will be a suitable alternative in modeling the failure patterns of construction equipment. By iteratively adjusting the weights in the time series models, better estimates can be obtained. By comparing the results obtained from time series models and power law models, the advantages and disadvantages of the two models are found out.

Time series models usually require a sample size of at least 50 for analysis while power law model requires less data. The assumption of power law models is Non-homogenous Poisson process (NHPP) which is a random failure process with different intensities at different stages of equipment life. On the other hand, time series models use very few assumptions and are very flexible. Data series with underlying patterns are caused by both randomness and a large number of external and internal influencing factors. In Chapter 5, the applications of these two models to subsystems will be compared and discussed. The combined comparison made in these two chapters is summarized in Chapter 6 with the illustrations in Table 6.1.

Apart from the contributions to construction equipment maintenance and management decisions, this research also demonstrates that the ARIMA model is a viable alternative that gives satisfactory results in terms of its predictive performance. The result is valuable in planning a system shutdown depending on the organization's reliability target.

4.5.2 IMPACT ON MANAGEMENT DECISIONS

The reliability assessment of construction equipment can affect decision making in selecting the right maintenance and utilization strategy in civil engineering projects.

As introduced earlier in Chapter 2, traditional construction equipment maintenance options are not sufficient and there is a need for implementing predictive maintenance. Predictive maintenance is able to maximize the intervals between repairs and decrease the number of unscheduled breakdowns and more cost effective. However, this measure requires indicators to determine the actual MTTF or loss of efficiency of the equipment.

The results obtained from the models and analysis in this chapter are valuable indicators for predictive maintenance. By analyzing the reliability of a particular piece of construction equipment, trends of failures of this equipment can be detected; furthermore, the numbers of failures and the MTBF for a fixed interval can be predicted, as illustrated earlier. Based on this information, the equipment manager can recognize the status of the equipment and make adequate maintenance service accordingly.

Apart from arranging predictive maintenance for a particular piece of equipment, the allocation of equipment can also be judged by the reliability analysis. From the case study, the status of a piece of equipment can be detected, whether in the infant mortality stage, useful life or wear out stage of a bathtub curve. The example used in this case, the bulldozer, is found out to be at the wear out stage by using power law models and time series models, which means this particular equipment is getting deteriorated and unreliable. Allocation of unreliable and aged equipment should be cautious because of its low working efficiency and the reality that spare parts are often not easily available in local markets. Equipment managers should replace this kind of equipment with the ones having higher availability or assign these machines to operations where they do not work alone, or with backup plan.

CHAPTER 5 CONSTRUCTION EQUIPMENT SUBSYSTEMS

5.1 SUBSYSTEMS RELIABILITY

A complex system may include many components and interfaces, such as cars, aircrafts, and construction equipment. Typical construction equipment has around 20 subsystems/components which should be taken into consideration in failure analysis. In this chapter, the data analysis and modelling process is applied to the equipment subsystems and the critical components to examine the equipment failures at a subsystem level.

Systems, like cars, aircrafts and construction equipment, usually include many components and interfaces. Components can be divided into two groups, which are: intrinsically reliable components and intrinsically unreliable components. Intrinsically reliable components refer to those that have high margins between their strength and stresses that could cause failure, as well as not wear out within their practicable lifetime. On the other hand, intrinsically unreliable components are those with low design margins or which wear out within their practicable life time. Examples include badly applied components and parts that move in contact with others, such as power drive belts, bearings and gears.

For a non-repairable item, when a part fails in a non-repairable system, the system usually fails and the system reliability is, therefore, a function of the time to the first part failure. For a repairable item, reliability is the probability that failure will not occur in the period of interest, when more than one failure can occur. Most construction equipment types are considered to be repairable systems.

Reliability is the ability of an item to perform a required function under stated conditions for a stated period of time. One of the purposes of system reliability analysis is to identify the weakness in a system and to quantify the impact of component failures. The so-called “reliability importance” is used for this purpose. These importance measures provide a numerical rank to determine which components are more important to system reliability improvement or more critical to system failure.

5.1.1 SERIAL AND PARALLEL CONFIGURATIONS

In analyzing a complex system, a particular failure law may be applied to the entire system. However, an alternative approach is to apply reliability modelling on the important components of the system, and base on the components reliability to calculate the reliability of the system.

There are two different ways for components of a system to be connected to one another: in either a serial or a parallel configuration. In series configuration, if a system need to function, then all components are required to function; however, in a parallel configuration, if a system need to function, then at least one component must function. In the following discussions, all components are considered critical in a sense that their functions must be performed in order for the system to continue to perform. Under this concept, if either of two serially related components fails, the system will fail. The series relationship is represented by the reliability block diagram of Figure 5.1.

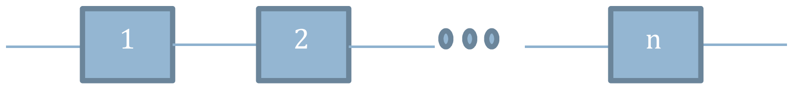

Figure 5.1 Reliability block diagram for components in series

Since reliability is a probability, the system reliability R_s may be determined from the component reliabilities in the following way.

The system reliability is given by

$$R_s(\mathrm{t}) = \prod_{i=1}^{n} R_i(t) \qquad [5.1]$$

Majority of construction equipment design follows the pattern of serial configuration. The details of some construction equipment are presented and illustrated in the next section.

In parallel configuration, two or more components can be in parallel, or redundant. If one or more units operate, the system continues to operate. Only when all the components in parallel fail, the system fails. Reliability block diagram for components in parallel is illustrated in Figure 5.2.

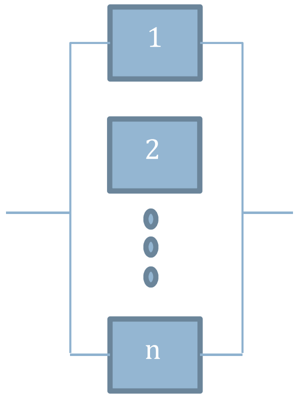

Figure 5.2 Reliability block diagram for components in parallel

The function for system reliability of *n* parallel and independent components is presented as Formula 5.2. The system reliability is the deduction of the probability that all *n* components fail from integer "1". On other words, the system reliability is the probability that at least one component does not fail. The equation is,

$$R_s(\mathrm{t}) = 1 - \prod_{i=1}^{n}[1 - R_i(t)] \qquad [5.2]$$

Though some electrical system in an equipment may be in parallel, it is generally considered that subsystems in a construction equipment to be in series configuration.

5.1.2 CONSTRUCTION EQUIPMENT COMPONENTS

There are a number of construction equipment categories based on the classification of their functions, which include excavating equipment, hauling equipment, loading equipment, grading equipment, hoisting equipment, concrete equipment. The data we used in this research are extracted from the following eight construction equipment categories, i.e., trucks, scrapers, wheel loaders, two bulldozers, graders, and tractors. Among them, the shovel is excavating equipment, the bulldozers and scraper are loading equipment, and truck is hauling equipment.

In this research, six different types of construction equipment were examined for subsystem reliability analysis as there are relevant maintenance records available. These six construction equipment pieces are: scrapers, wheel loaders, two different bulldozers, graders, and tractors.

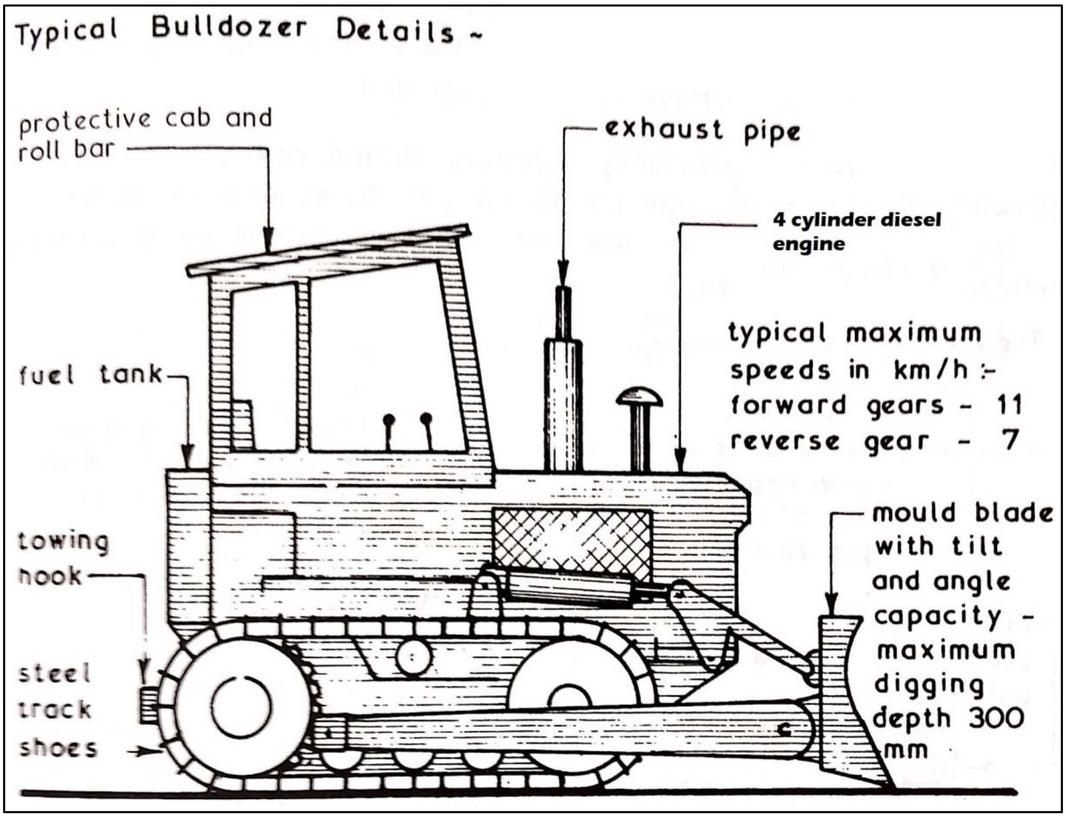

Figure 5.3 Typical bulldozer details (Harris and McCaffer, 1991)

Bulldozer is a multifunctional piece of engineering equipment, which is applicable for work including excavation, short distance transport and unloading. It consists of a track or wheel mounted power unit with a mould blade at the front which is controlled by hydraulic rams. Many bulldozers have the capacity to adjust the mould blade to form an angle. A bulldozer and its capacity to tilt the mould blade about a central swivel point are shown in Figure 5.3.

A bulldozer can perform functions such as shallow excavations up to 300mm deep both on level ground and sidehill cutting. Other major functions may include clearance of shrubs and small trees by using raised mould blade as a pusher arm; acting as a pusher to scraper machine and acting as a towing tractor.

Similar to bulldozers, graders also have a long slender adjustable mould blade, which is usually slung under the centre of the machine (Figure 5.4).

The main function of a grader is to finish or grade the upper surface of a large area, normally after the operation of bulldozing or scraping. Different from bulldozer which is suitable for site excavation work because of the power, grader, however, can produce a fine and accurate finish. The basic formats of most graders available are four wheeled and six wheeled. The first type has all the four wheels driven and steered, which gives the machine the ability to offset and crab along its direction of travel; while six wheeled graders have 4 wheels in tandem drive at the rear and 2 front tilting idler wheels giving it the ability to counteract side thrust.

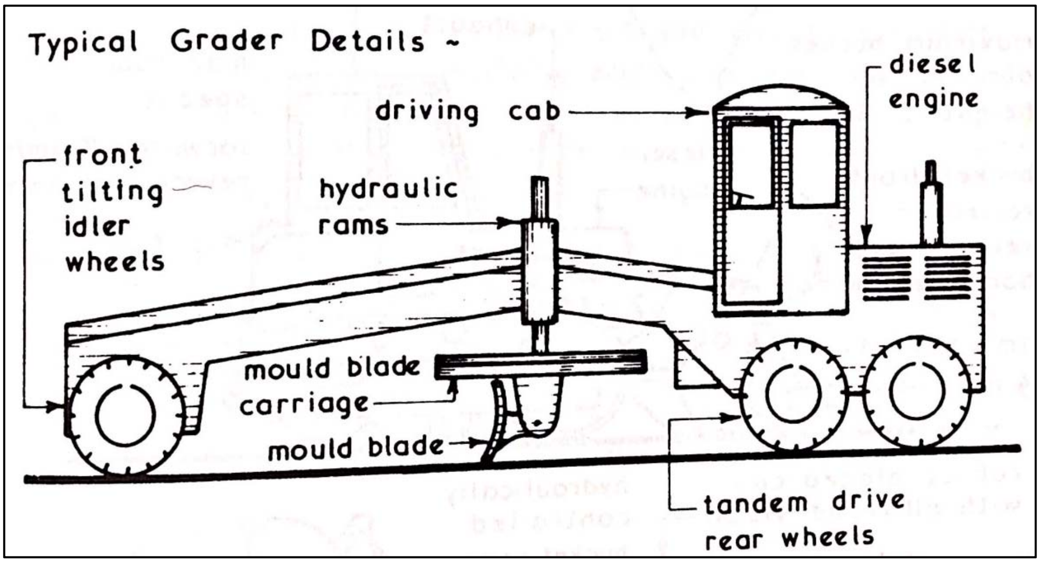

Figure 5.4 Typical grader details (Harris and McCaffer, 1991)

A scraper contains a lowered scraper bowl for cutting and collecting soil where sites require work involving large volume of earth (Figure 5.5). The working theory of a scraper is that when the bowl is full the apron at the cutting edge will be closed to retain the earth. Then the bowl is raised for travelling to the disposal area. On arrival the scraper bowl is lowered, the apron will be opened and the soil pushed out by the tailgate as the machine moves forwards. There are three types of scrapers available, which are: towed scrapers, two axle scrapers and three axle scrapers.

Scrapers are suggested to operate downhill if possible and on smooth haul roads in order to obtain maximum efficiency. Hard surfaces should be broken up before scraping and be assisted over the last few metres by a pushing vehicle such as a bulldozer.

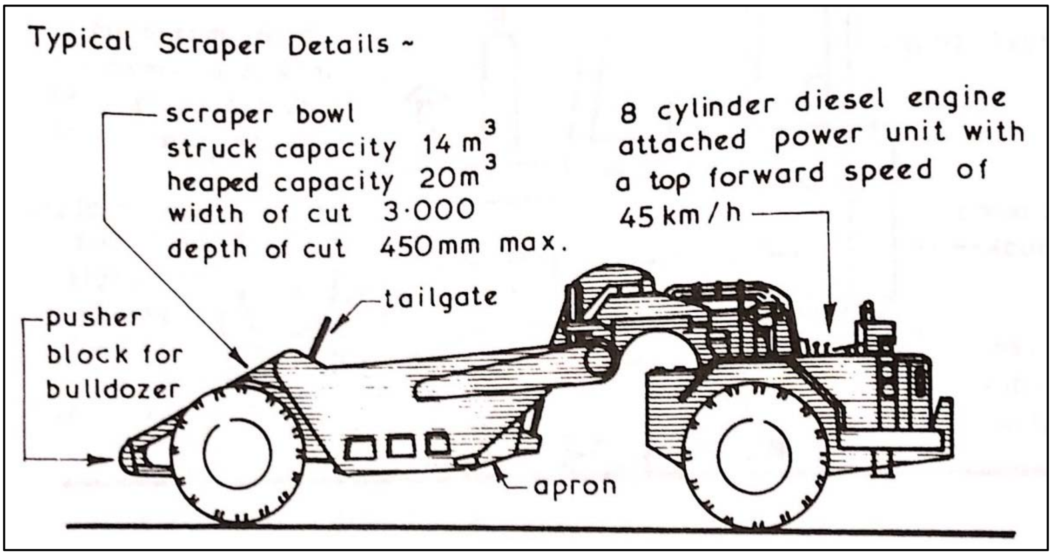

Figure 5.5 Typical scraper details (Harris and McCaffer, 1991)

Some basic components are common to many types of construction equipment - these include power sources, power transfer from engine to wheels or crawler tracks, kinds of mountings, and means of propulsion.

Power sources of construction equipment usually contain internal combustion engines, electric generators and motors, compressed air, and hydraulic systems. Some equipment uses more than one power source. For example, large off-highway trucks may be driven by electrical wheels, the electricity being generated by an on-board diesel-powered generator; scrapers are driven by diesel engines and operating parts of the machine are operated by hydraulic cylinders.

Crawlers and wheel mountings are common to tractors, excavators, cranes, and material-handling and paving equipment.

5.2 IDENTIFY CRITICAL COMPONENTS

One of the objectives in this research is to identify the critical components in an equipment system. Further improvements to these critical components such as effective maintenance policies will be required to improve the operational reliability and availability.

For any machine component failures directly affecting the productivity, construction quality and safety, reduction of downtime therefore becomes one of the major goals. The research tasks include: 1) identify the critical components that cause predominant machine failures and improve their reliability; 2) develop a maintenance policy based on the lifetime of individual components so that maintenance policy will be focused and cost effective.

Subsystems are key parts of a system because the critical subsystems/components with lower reliability determine the whole system's reliability. The importance of critical component in reliability analysis has been noticed by many researchers (Lin & Titmuss, 1995). Some even only focus on the reliability analysis of a particular critical component in a system, such as engine reliability (Hong, 2006).

Component importance analysis is significant for system reliability analysis, which enables the critical components (or weakest areas) of a system to be identified and suggests modifications that will enhance the system reliability (Besson and Andrews, 2003).

The component reliability importance measure is defined as the probability that component *i* is critical to system failure. The reliability importance, I, of component i in a system of n subsystems can be calculated as:

$$I(i) = \frac{\partial R_S(t)}{\partial R_i(t)} \qquad [5.3]$$

Where $R_i(t)$ is the subsystem/component reliability and $R_s(t)$ is the system reliability. If the reliability of a system needs to be improved, then efforts should first be spent on improving the component reliability which has the biggest effect on system reliability.

As construction equipment usually is in a series configuration, it means only when all the subsystems are operating well, then the whole system can function well. The reliability of the system (R_s) is given by:

$$R_s = \prod_{i=1}^{n} R_i \qquad [5.4]$$

Where R_i is the reliability of the different subsystems.

With the parameters of the best-fit distribution derived from computer software, the theoretical reliabilities for the subsystems at the end of different time intervals can be computed. The possible probability distributions for reliability analysis include Weibull, Exponential, and Lognormal distributions.

Pareto analysis is used in this research to identify the critical components of a construction equipment system. Historical data was obtained from maintenance records and analyzed. Table 5.1 shows an example of a piece of equipment (bulldozer), in which the components have been divided into three different groups "ABC" indicating their different degree of importance. The cumulative percentage falls under 60% is categories into Group "A"; between 60% and 85% is put into Group "B" and above 85% is put into Group "C". Group "A" items are considered to be the more critical components that affect the breakdown of the whole system more severely while Group "B" and "C" items can be neglected in the analysis. The full set of classifications is attached in Appendix 3. It can be observed that there are five critical components for the bulldozer, which are: undercarriage, ripper teeth, repair light, cab, and electrical. Among these, undercarriage is the most critical component.

Table 5.1 Critical components of the bulldozer based on numbers of failures

Components	Count of failures	%	Cumulative %	Category
			0.00%	
Undercarriage	67	20.55%	20.55%	A
Ripper Teeth	35	10.74%	31.29%	A
Repair Light	27	8.28%	39.57%	A
Cab	25	7.67%	47.24%	A
Electrical	21	6.44%	53.68%	A
Float	21	6.44%	60.12%	B
Hydraulic System	21	6.44%	66.56%	B
Cooling Systems	13	3.99%	70.55%	B
Drive System	13	3.99%	74.54%	B
Engine	12	3.68%	78.22%	B
Air Conditioning	11	3.37%	81.60%	B
Welding	11	3.37%	84.97%	B
Blade	10	3.07%	88.04%	C
Air System	9	2.76%	90.80%	C
Cutting Edge	7	2.15%	92.94%	C
Grease System	4	1.23%	94.17%	C
Ice Lugging	3	0.92%	95.09%	C
Oil Leak	3	0.92%	96.01%	C
Steering System	3	0.92%	96.93%	C
Fuel System	2	0.61%	97.55%	C
Oil Sample	2	0.61%	98.16%	C
Starting System	2	0.61%	98.77%	C
Equalizer	1	0.31%	99.08%	C
Heating System	1	0.31%	99.39%	C
Low Power	1	0.31%	99.69%	C
Torque	1	0.31%	100.00%	C

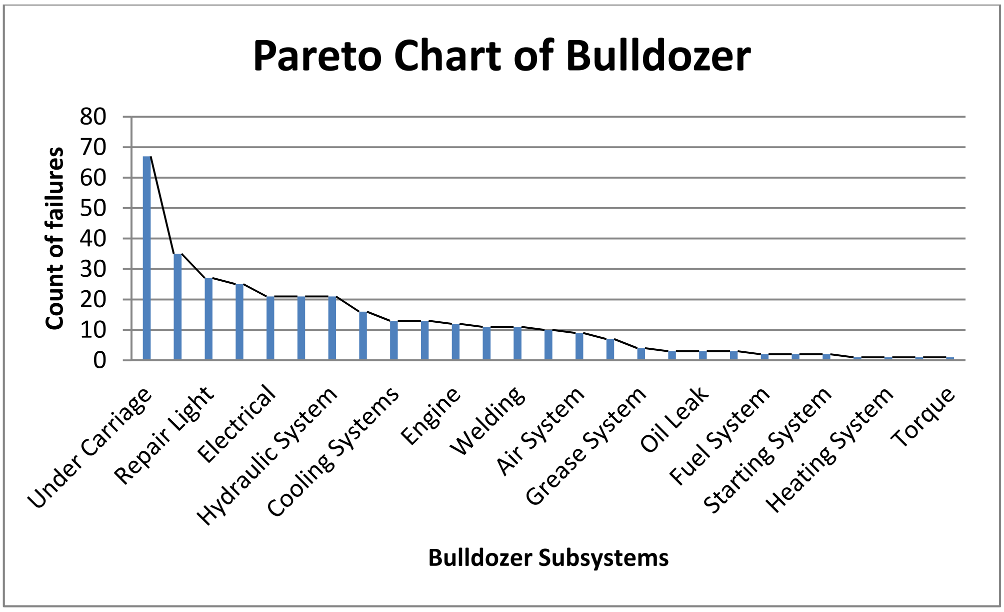

Figure 5.6 Pareto chart of bulldozer subsystems based on numbers of failures

The failure of the component “undercarriage” was the number one cause of loss of production time in the bulldozer, which means the undercarriage is the most critical component in this situation. By analyzing and improving the reliability of this component, the reliability of the system could also be improved.

Figure 5.6 shows the Pareto analysis of the subsystems of the bulldozer. It can be observed that “undercarriage” and “ripper teeth” are most critical. Then efforts should first be dedicated to improve the reliability of these two subsystems, as they have the biggest effect on system reliability.

Count of failures is one method for identifying the critical components; however, number of failures is not the only contributory parameter; time between failures (TBF) and time to repair (TTR) may also affect how important a subsystem to the system. Table 5.2 shows the identification of the critical components of a bulldozer by analyzing the TBF of each component through Pareto analysis.Only those components which fell into category A are presented here; the full table is shown in the Appendix Table A3.3b. The identified four most important components are the same as the ones based on counts of failures; except for one component “electrical” which falls into category B with a cumulative percentage of 68.94%.

Table 5.2 Critical components of the bulldozer based on TBF

Components	TBF	%	Cumulative %	Category
			0.00%	
Undercarriage	3204.03	22.60%	22.60%	A
Ripper Teeth	1704.27	12.02%	34.62%	A
Repair Light	1636.70	11.54%	46.17%	A
Cab	1181.20	8.33%	54.50%	A

Table 5.3 presents the results of Pareto analysis based on the analysis of TTR of each component. The top component is still "undercarriage"; however, the other three are different from the previous results based on counts of failures and TBF, which are: air system, hydraulic system and cooling systems. The reason for this difference is that some sub-system may break down often but may be easy to repair; however, on the other hand, other sub-systems may break down rarely but take long time to repair, such as the "air system". Based on different standards, either time between failures or time to repair, the critical components identified can vary. Therefore, both the frequency of failures and the impact of the failures should both be considered in identification of critical components.

Table 5.3 Critical components of bulldozer based on TTR

	TTR	%	Cumulative %	Category
	0.00			
Undercarriage	618.50	27.34%	27.34%	A
Air System	362.37	16.02%	43.36%	A
Hydraulic System	181.55	8.03%	51.39%	A
Cooling Systems	157.38	6.96%	58.35%	A
Electrical	134.22	5.93%	64.28%	B
Welding	129.65	5.73%	70.01%	B
Engine	98.23	4.34%	74.35%	B
Blade	88.98	3.93%	78.29%	B
Drive System	80.12	3.54%	81.83%	B
Float	73.25	3.24%	85.07%	C
Equalizer	72.80	3.22%	88.29%	C
Cutting Edge	52.22	2.31%	90.59%	C

Ice Lugging	43.92	1.94%	92.54%	C
Repair Light	38.38	1.70%	94.23%	C
Cab	31.83	1.41%	95.64%	C
Grease System	24.43	1.08%	96.72%	C
Oil Leak	20.52	0.91%	97.63%	C
Torque	18.03	0.80%	98.42%	C
Air Conditioning	14.93	0.66%	99.08%	C
Ripper Teeth	13.98	0.62%	99.70%	C
Steering System	3.20	0.14%	99.84%	C
Starting System	1.52	0.07%	99.91%	C
Fuel System	1.08	0.05%	99.96%	C
Oil Sample	0.67	0.03%	99.99%	C
Low Power	0.17	0.01%	100.00%	C
Heating System	0.08	0.00%	100.00%	C

5.3 POWER LAW MODELLING OF SUBSYSTEMS

After the critical components in a system have been identified, the next step is to analyze the reliability of these components. Reliability attributes include reliability (R), failure intensity, numbers of failures, MTBF, MTTF and MTTR, etc. The two different models, i.e., power law model and time series model, are adopted for subsystem analysis, to analyze reliability characteristics. A comparison of the two methods is also conducted and summarized at the end of this chapter to show the strengths and weaknesses of each method.

Reliasoft's RGA 7 is chosen to aid the modelling and analysis process. The reliability of the bulldozer and its subsystems is analyzed and presented in Table 5.4.

The reliability of the bulldozer and the five most critical subsystems is calculated and tabulated in Figure 5.7. The Crow-AMSAA (NHPP) model was selected in the process. The parameters such as beta and lambda of the system were generated automatically by the program. Parameters of each critical component are also generated in the standard folio, as well as the statistical tests of Cramer-von Mises (CVM) and Laplace trend. As can be observed, the component undercarriage has passed the CVM test and the Laplace trend is deteriorating. It is identical to the trend of cumulative number of failures and

MTBF that will be illustrated in the next section. The statistical tests of other bulldozer critical components are summarized in Table 5.3.

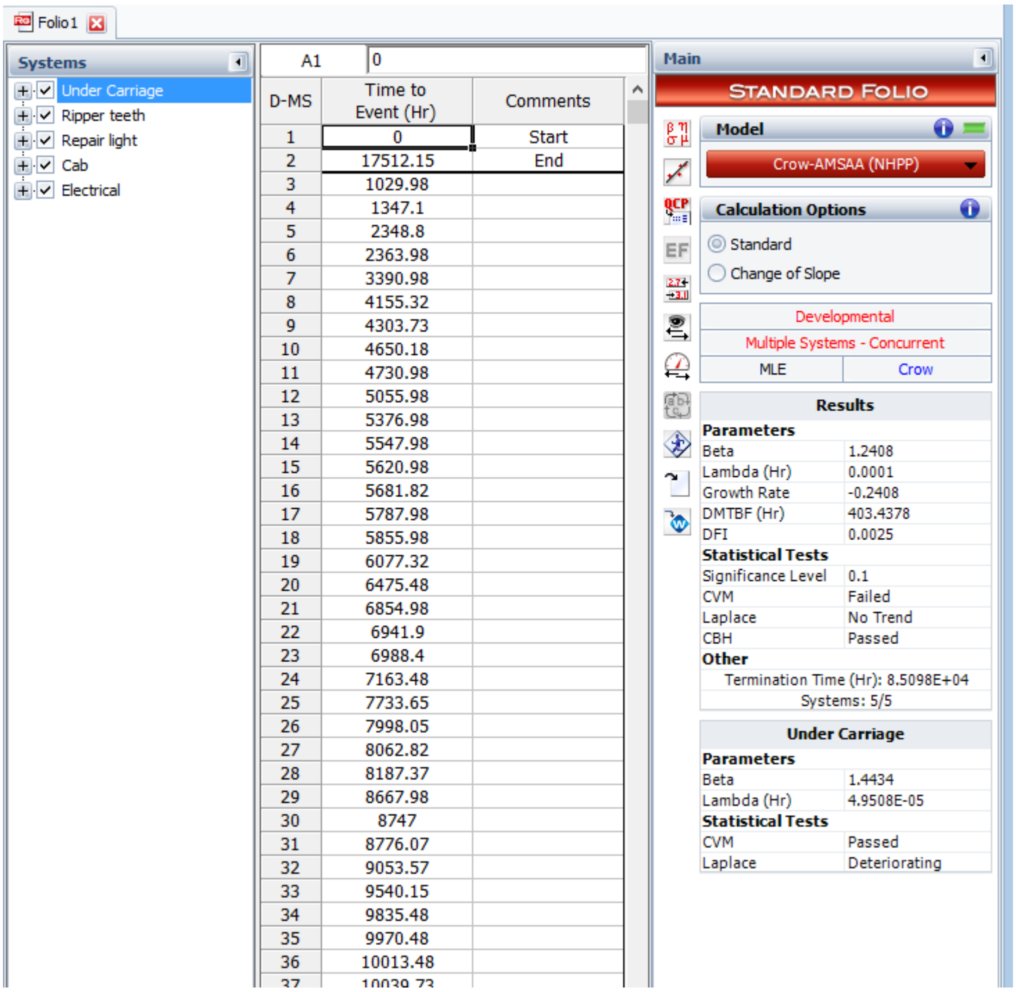

Figure 5.7 Reliability analysis of construction equipment component by using NHPP model

Table 5.4 Statistical tests report of the system and subsystems of bulldozer

	Result	Lower	Test Value	Upper
Equivalent System				
Cramér-von Mises	Failed	-	0.2773	0.173
Laplace Trend	No Trend	-1.6449	1.5138	1.6449
Common Beta Hypothesis	Passed	1.0636	5.3575	7.7794
Undercarriage				
Cramér-von Mises	Passed	-	0.0858	0.173
Laplace Trend	Deteriorating	-1.6449	2.1706	1.6449

Ripper teeth				
Cramér-von Mises	Failed	-	0.295	0.1721
Laplace Trend	No Trend	-1.6449	1.3687	1.6449
Repair light				
Cramér-von Mises	Passed	-	0.0685	0.172
Laplace Trend	No Trend	-1.6449	0.5128	1.6449
Cab				
Cramér-von Mises	Failed	-	0.1806	0.172
Laplace Trend	No Trend	-1.6449	-0.4093	1.6449
Electrical				
Cramér-von Mises	Failed	-	0.2446	0.172
Laplace Trend	Improving	-1.6449	-1.8017	1.6449

From Table 5.4, it can be observed that three of the critical components have no trend: ripper teeth, repair light and cab, while the undercarriage has a deteriorating trend and electrical system has an improving trend. This shows that undercarriage is at wear out stage and should be replaced by new component as soon as possible; however, electrical system is relatively new compared with other four components.

Figure 5.8 shows the trend of the cumulative number of failures of the undercarriage component. It can be observed that there are more failures with the time go on. An analysis of the other four critical components, namely, ripper teeth, repair light, cab and electrical system, have been also been conducted in this research. The results include cumulative number of failures, MTBF and failure intensity vs. time. The results are attached in Appendix 4.

The relationship between MTBF and time for the undercarriage component is shown in Figure 5.9. As time goes on, the mean time between failures decreases. Figure 5.10 presents the relationship of failure intensity with time, which shows an increase over time. This behavior is consistent with the trend of cumulative number of failures. All of these three figures suggest that the undercarriage is in the third stage of the bathtub curve, which is the wear out stage. The reliability analysis results of the other four critical components (ripper teeth, repair light, cab and electrical) by power law modelling are presented in Appendix 4, with the figures of MTBF vs. time, cumulative number of failures, as well as the failure intensity vs. time.

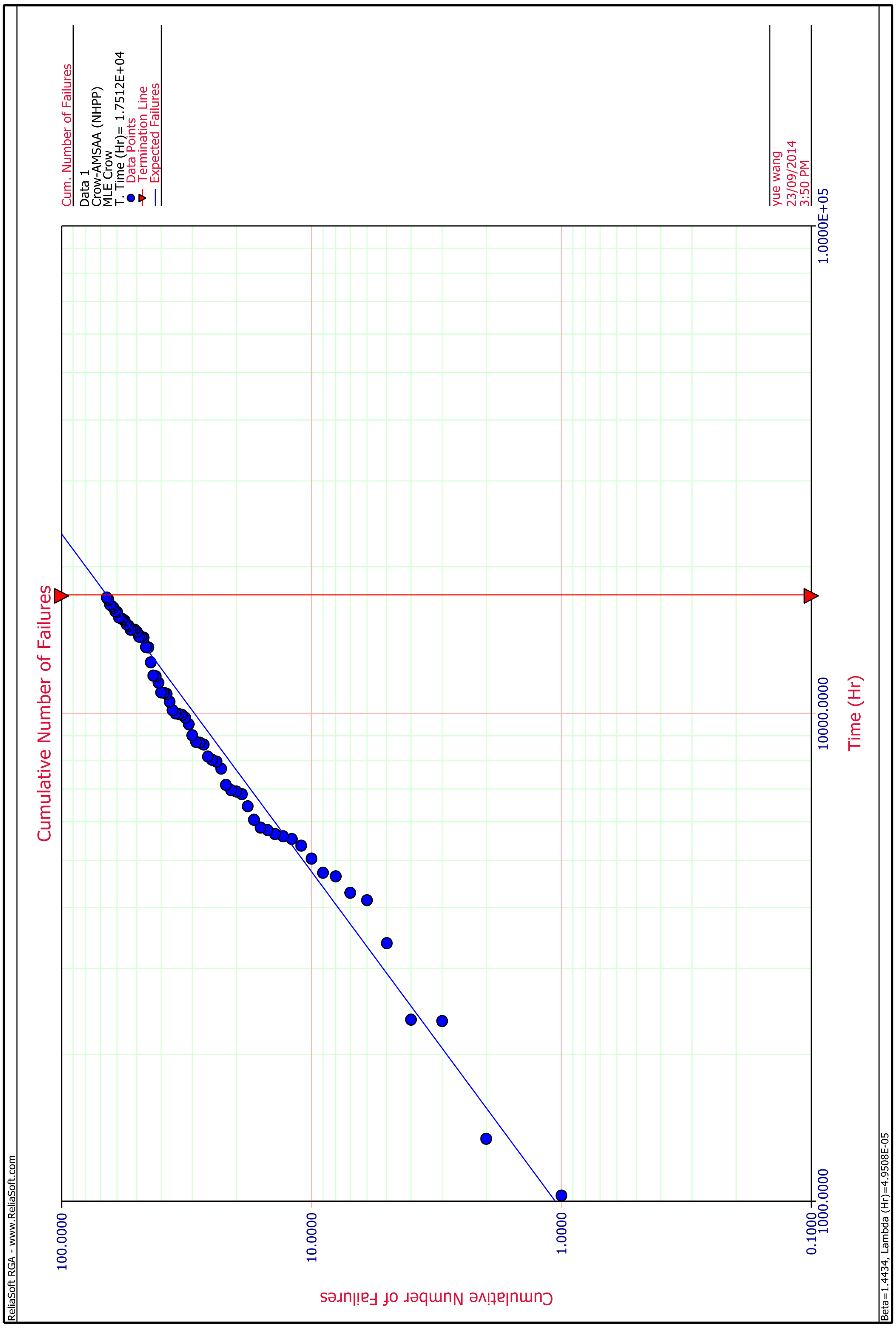

Figure 5.8 Cumulative numbers of failures of the undercarriage analyzed in RGA7

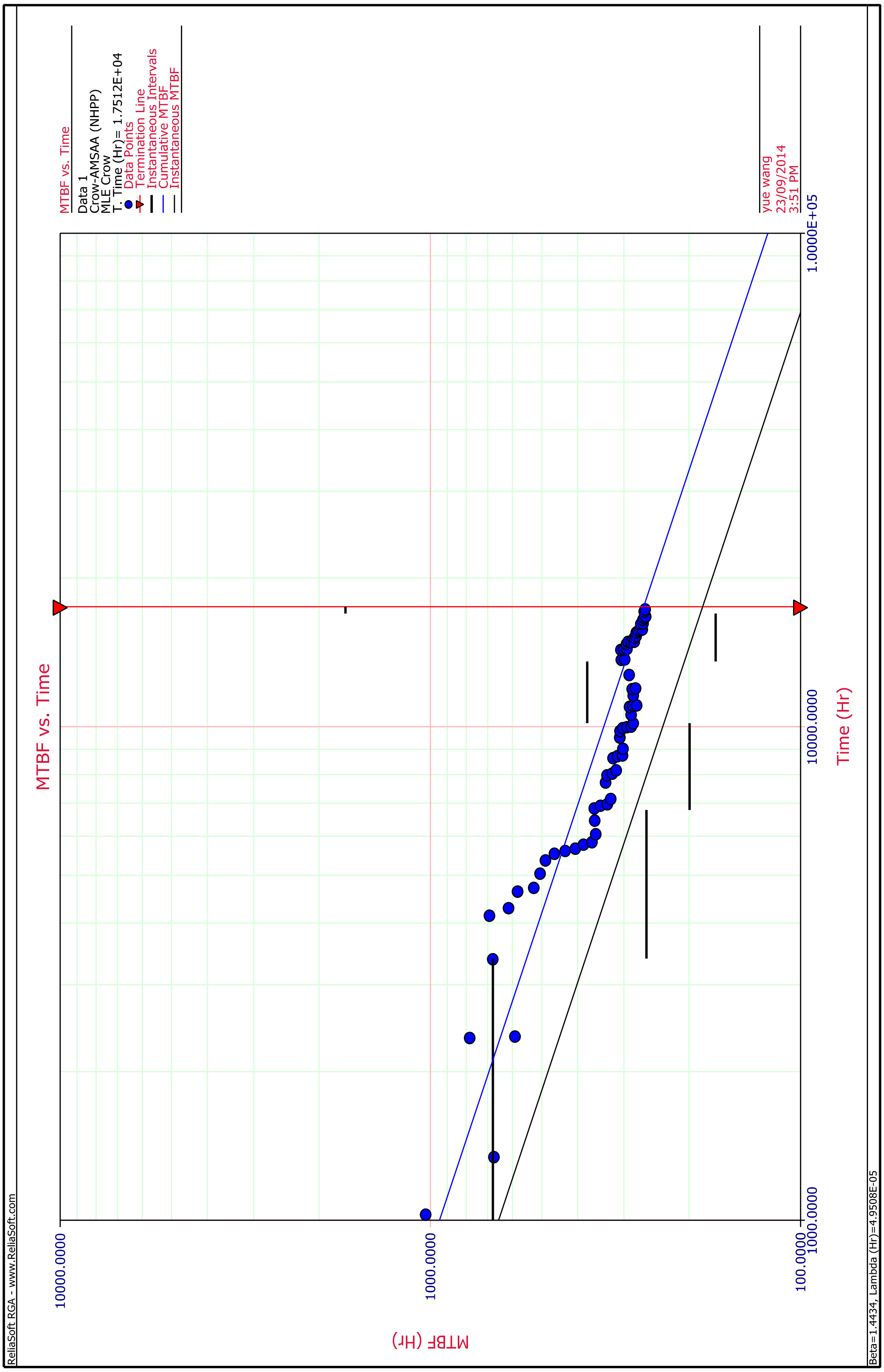

Figure 5.9 MTBF vs. Time of undercarriage analyzed in RGA7

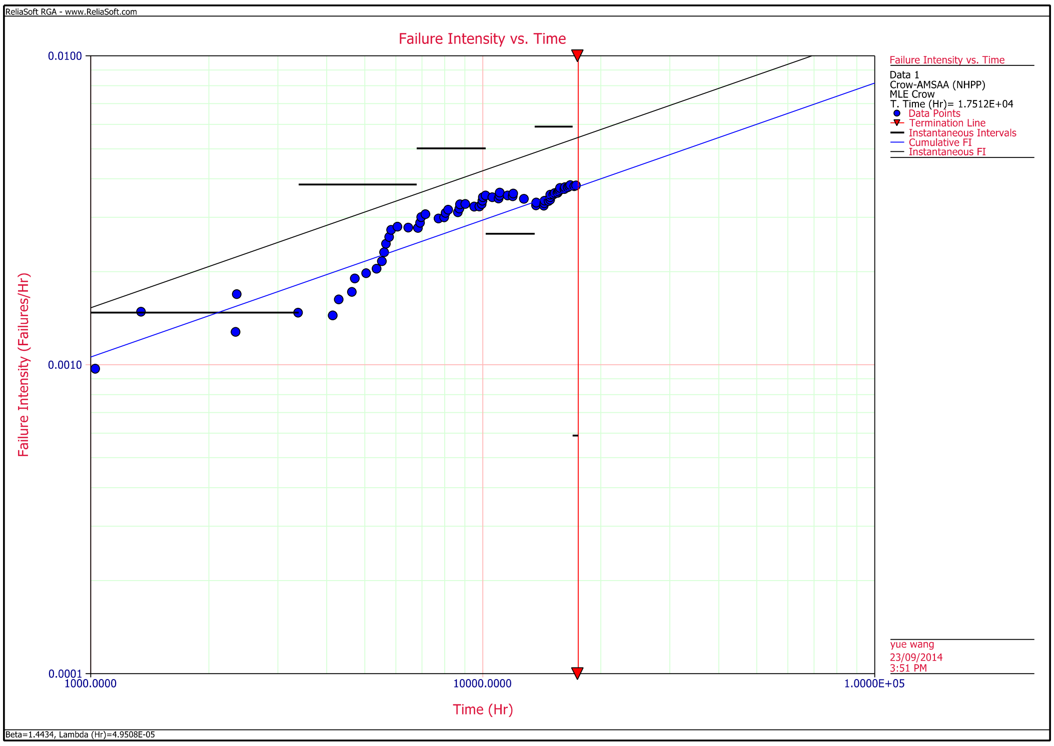

Figure 5.10 Failure intensity vs. Time of the undercarriage analyzed in RGA7

An instantaneous MTBF can be calculated at a specified time in the power law model. For example, when the time is set to be 17512.15hr, the calculated IMTBF is 183.83hr. With a two-sided confidence level of 0.95, the upper and lower bound of IMTBF are also generated in the analysis, which are 251.89hr and 126.46hr respectively (Figure 5.11).

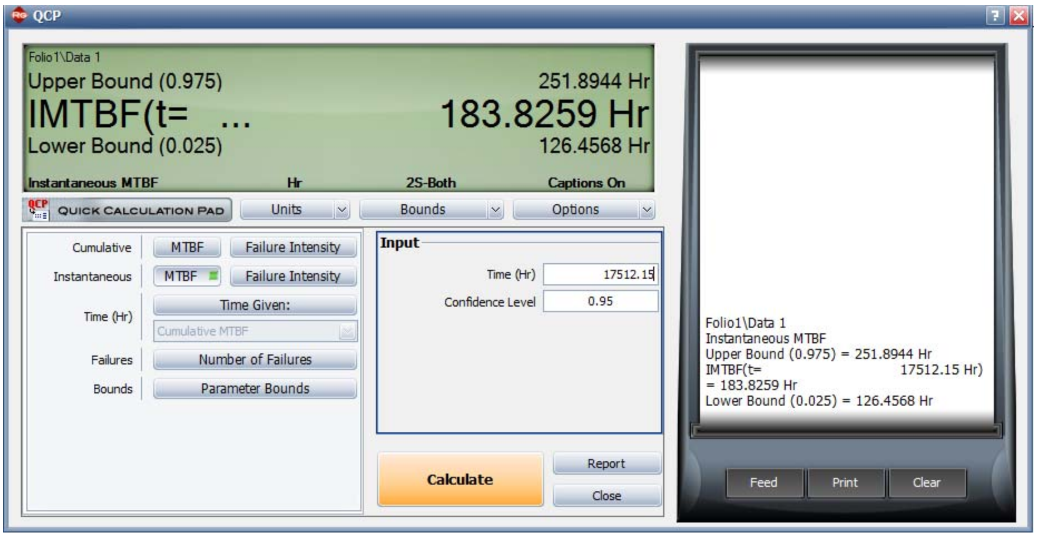

Figure 5.11 Calculation of IMTBF of undercarriage

Figure 5.12 shows the system operation analysis of the five critical subsystems, and each subsystem has its own specific failure pattern.

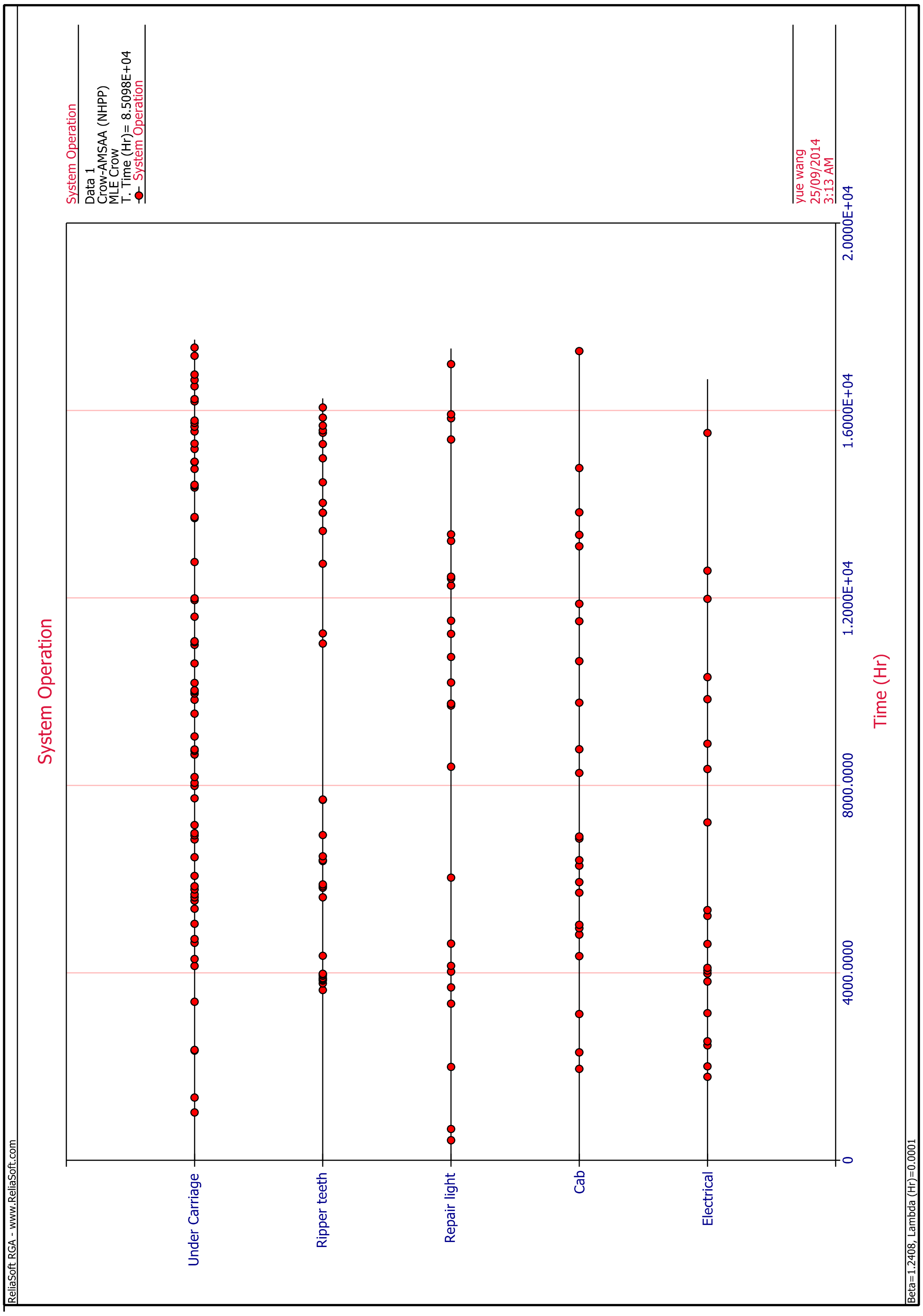

Figure 5.12 System operation of the equipment bulldozer

Table 5.5 shows the time series analysis results of this component and presents the predicted counts of failures comparing with the actual numbers of the number one critical component "undercarriage" of the construction equipment bulldozer.

Table 5.5 Time series analysis and prediction of the number of failures of the critical component "undercarriage" of bulldozer

--- Validation Time Series Values ---

Row	Actual	Predicted	Error
94	2.0000000	1.0569368	0.9430632
95	2.0000000	1.3115465	0.6884535
96	0.0000000	1.1700758	-1.1700758
97	0.0000000	1.0026758	-1.0026758
98	2.0000000	1.0788330	0.9211670
99	0.0000000	0.5095497	-0.5095497
100	0.0000000	0.7955536	-0.7955536
101	1.0000000	0.7189988	0.2810012
102	0.0000000	0.8213883	-0.8213883
103	1.0000000	1.1371008	-0.1371008
104	1.0000000	0.8400329	0.1599671
105	1.0000000	0.8353495	0.1646505

--- Forecast Time Series Values ---

Row	Predicted
106	0.6110358
107	0.7026749
108	0.8029839
109	1.0168993
110	0.9793741
111	1.2215998
112	1.0592241
113	0.8921138
114	0.9388482
115	0.9248247
116	1.0429345
117	1.1228004

The first column "Row" of the table represents the working weeks. In this case, the validation data is from week 94 to week 105, and the forecast data is from

106 to 117. The actual numbers of failures in every week is between 0 and 2, which means in some weeks the undercarriage experienced a breakdown once or twice in each week, but in some weeks no failure occurred. The predicted values vary from 0.51 to 1.31, which is very close to the real values and even has a smaller range. It can be interpreted as follows: if the predicted value is higher than 1.0, it would very likely have failures in that week, and there is a good chance that breakdowns may occur more than once. If the predicted value is between 0.5 and 1.0, the chance of having failures increases when the value is closer to 1.0.

In addition to the most critical component "undercarriage" other critical components of the bulldozer are also studied and analyzed. Table 5.6 and 5.7 are examples of time series forecast of the critical component "ripper teeth" and "repair light". Due to the fact that the size of datasets for these critical components in each interval are generally smaller compared with "undercarriage" and the system itself, the forecast results are less satisfactory than the previous ones, as can be observed from the tables. The figures of time series trend of the selected critical components are attached in Appendix 5.

Table 5.6 Time series analysis and prediction of the number of failures of the critical component "Ripper Teeth"

--- Validation Time Series Values ---

Row	Actual	Predicted	Error
95	3.0000000	-0.1973277	3.1973277
96	0.0000000	0.4895169	-0.4895169
97	1.0000000	0.6122650	0.3877350
98	0.0000000	-0.0991004	0.0991004
99	1.0000000	0.1238339	0.8761661
100	0.0000000	1.0171464	-1.0171464
101	0.0000000	0.1804146	-0.1804146
102	0.0000000	0.1785903	-0.1785903
103	0.0000000	0.3502036	-0.3502036
104	0.0000000	0.1539367	-0.1539367
105	0.0000000	0.6203849	-0.6203849
106	0.0000000	-0.1547804	0.1547804

Table 5.7 Time series analysis and prediction of the number of failures of the critical component "Repair Light"

--- Validation Time Series Values ---

Row	Actual	Predicted	Error
94	0.0000000	-1.2352860	1.2352860
95	1.0000000	0.1516206	0.8483794
96	1.0000000	0.8600184	0.1399816
97	0.0000000	1.2103516	-1.2103516
98	0.0000000	-0.4998561	0.4998561
99	0.0000000	-0.6351522	0.6351522
100	0.0000000	0.4756684	-0.4756684
101	0.0000000	0.4591988	-0.4591988
102	1.0000000	0.0087443	0.9912557
103	0.0000000	0.1937664	-0.1937664
104	1.0000000	0.9924332	0.0075668
105	0.0000000	0.3044511	-0.3044511

Figure 5.13 shows the trend of the failures of the critical component "undercarriage" of the bulldozer and it can be observed that the straight line shows a trend of increasing numbers of failures over time.

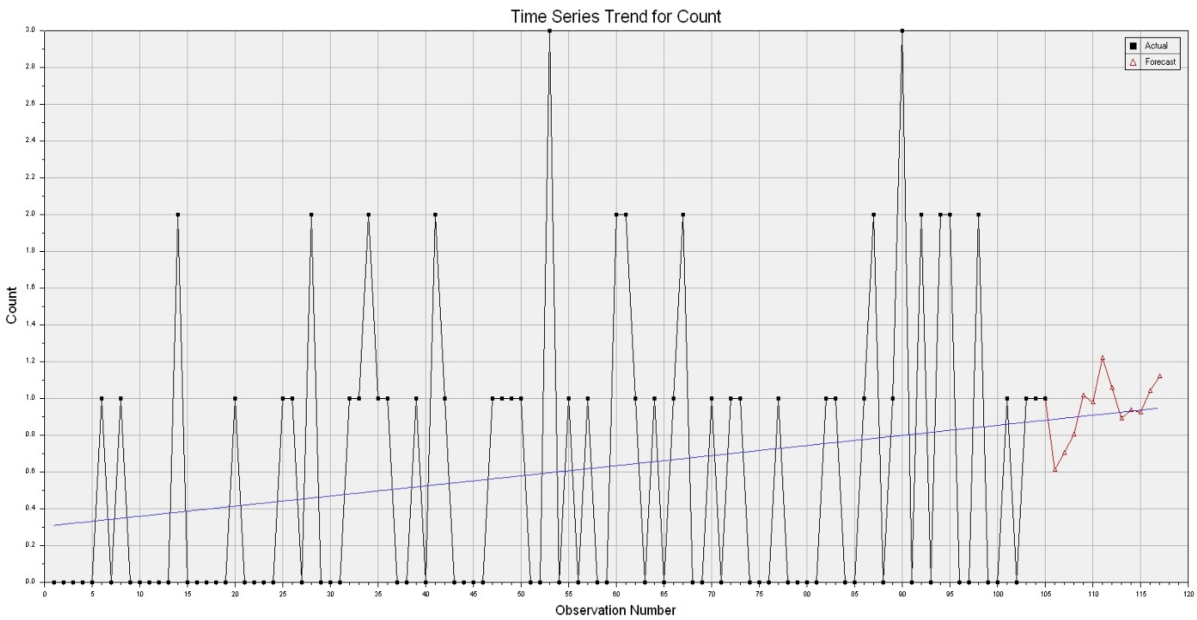

Figure 5.13 Time series trend of the numbers of failures of "Undercarriage" in bulldozer (D11_107)

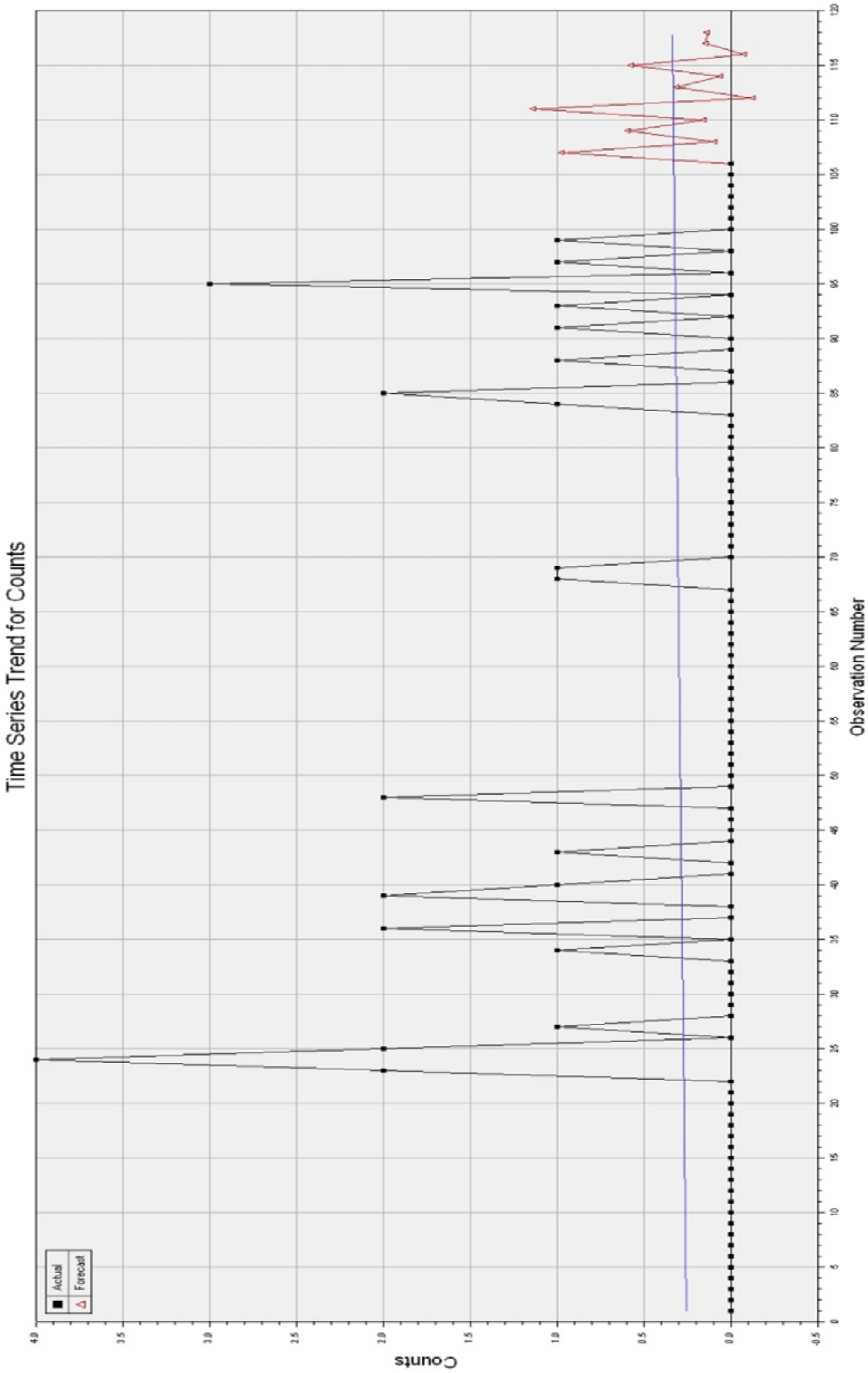

Figure 5.14 Time series trend of the numbers of failures of "Ripper Teeth" in bulldozer (D11_107)

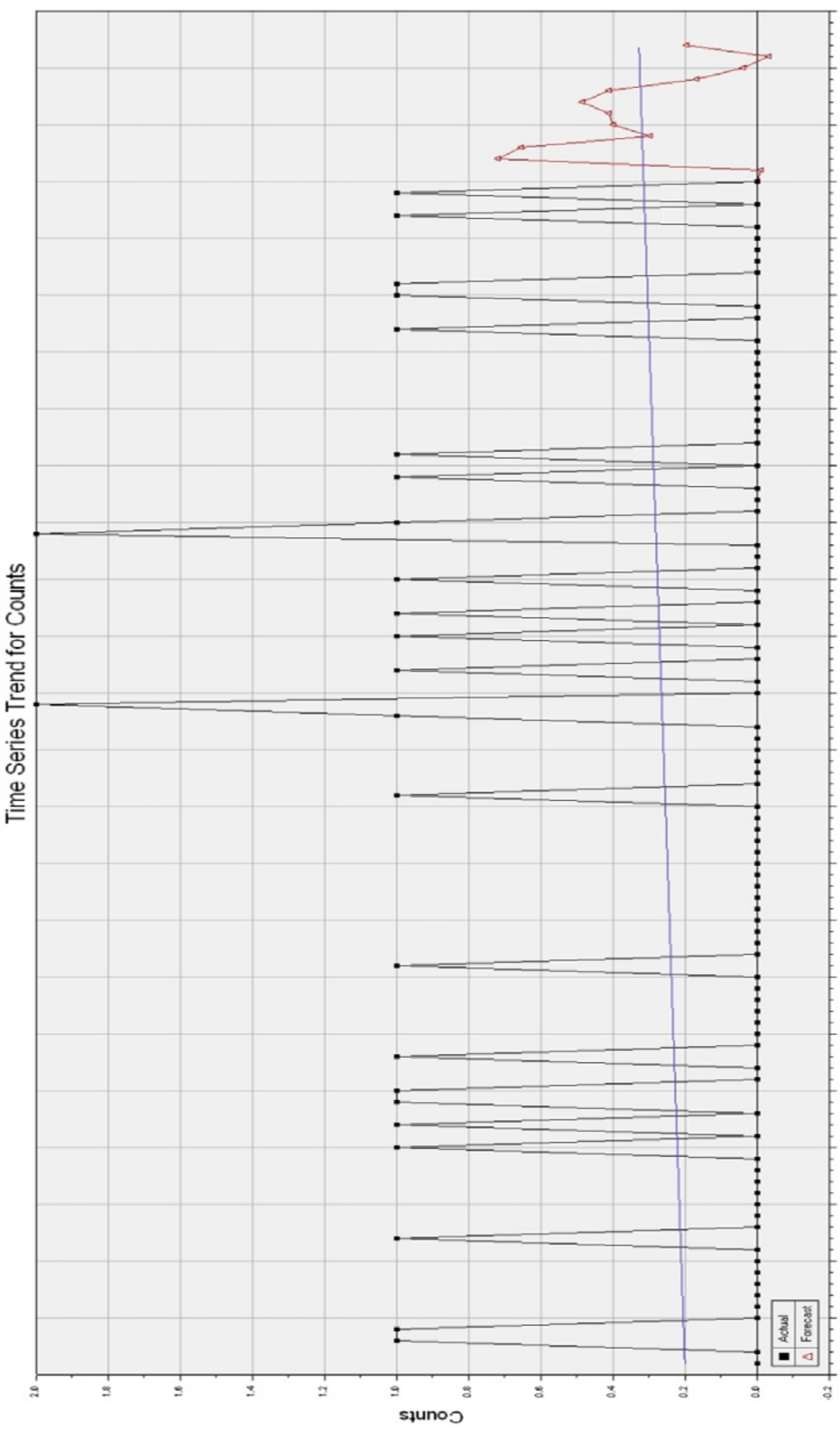

Figure 5.15 Time series trend of the numbers of failures of "Repair Light" in bulldozer

The other five critical components have also been modelled and analyzed using time series analysis models (Figure 5.14 & 5.15). More figures of number of failures trend are presented in Appendix 5.

Table 5.8 shows the forecasting results for the expected number of failures of the bulldozer by using time series modelling with a data size of 106. The comparison of the actual failures and predicted values is presented in terms of absolute error in the table and it can be noted that the predicted values are reasonably close to the actual value and error is acceptable. As the size of data is relatively small for subsystems compared with systems, the error between predicted values and actual values might be larger in this case. The prediction on the number of failures is shown in Figure 5.16 and there is trend of a nonlinear increasing of failures as the time goes on in this case. After comparing the system with the critical subsystems, it can be concluded that each component has its own unique reliability growth. By combining these five critical subsystems, the reliability of the system "bulldozer" can be delivered. This result will be different from the system reliability calculated without identifying the critical components, and the former result is supposed to be more accurate.

Table 5.8 Time series analysis and prediction of the number of failures of the bulldozer

--- Validation Time Series Values ---

Row	Actual	Predicted	Error
95	5.0000000	7.5600328	-2.5600328
96	6.0000000	4.7259117	1.2740883
97	4.0000000	5.3177360	-1.3177360
98	5.0000000	1.9024547	3.0975453
99	6.0000000	8.9489356	-2.9489356
100	2.0000000	6.4596874	-4.4596874
101	9.0000000	3.3693709	5.6306291
102	5.0000000	6.5575511	-1.5575511
103	3.0000000	7.3623140	-4.3623140
104	2.0000000	4.7921760	-2.7921760
105	9.0000000	7.4634221	1.5365779
106	9.0000000	4.5718566	4.4281434

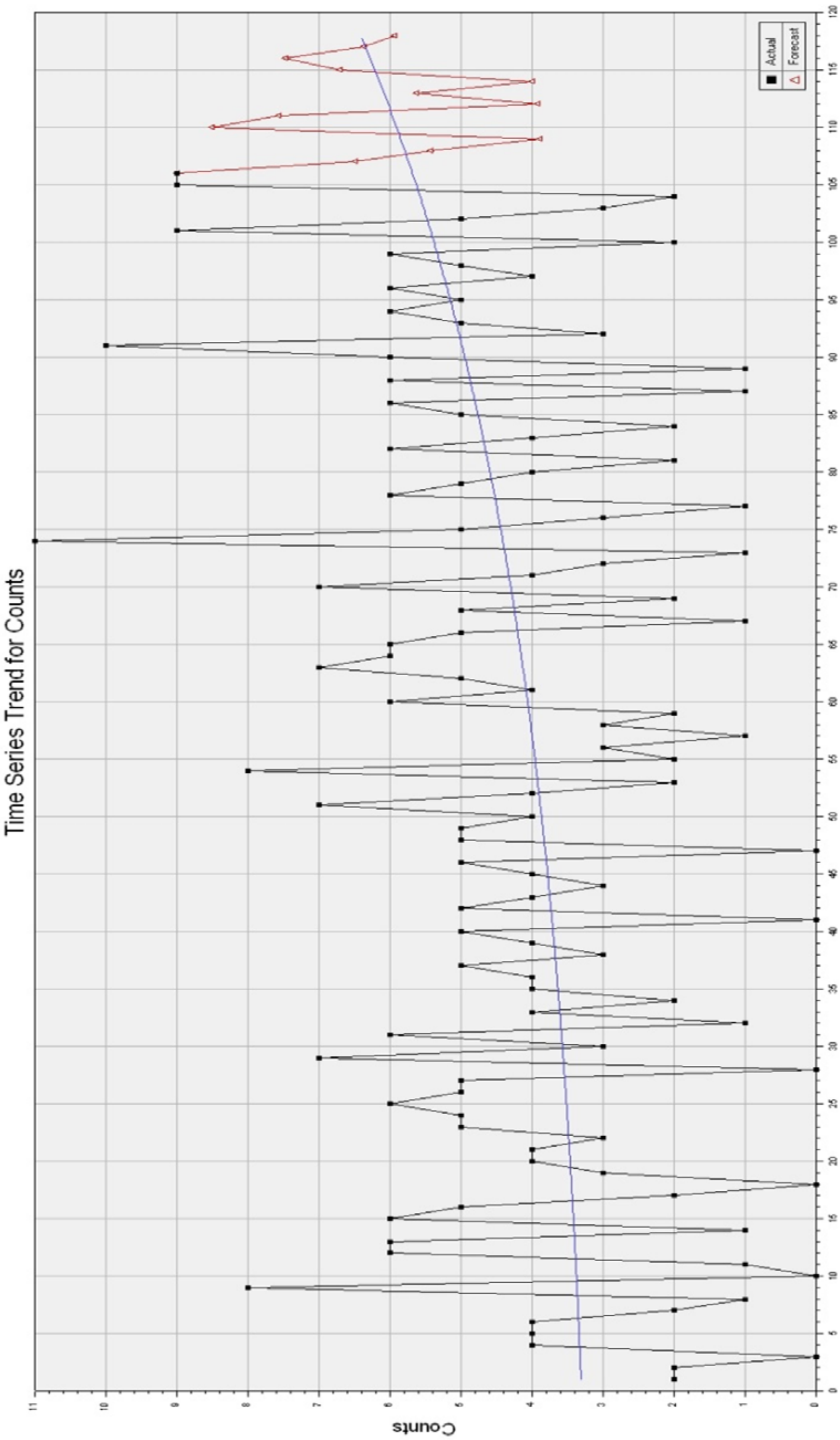

Figure 5.16 Time series trend of the numbers of failures of the bulldozer (D11_107)

TBF is another important measure of system and subsystem reliability. In Table 5.9, time between failures from weeks 94 to 105 is used as validation data in time series modelling. The predicted values are compared with the actual values with error and error percentages shown in the table. TBF of periods between 106 and 117 are forecasted in advance.

Table 5.9 Time series analysis and prediction of TBF of the critical component "undercarriage" of bulldozer

--- Validation Time Series Values ---

Row	Actual	Predicted	Error
94	26.050000	-14.254315	40.304315
95	29.550000	24.922561	4.627439
96	0.000000	23.535551	-23.535551
97	0.000000	7.248977	-7.248977
98	22.680000	15.412496	7.267504
99	0.000000	2.179171	-2.179171
100	0.000000	21.478117	-21.478117
101	44.630000	7.317586	37.312414
102	0.000000	-20.223017	20.223017
103	6.500000	16.118215	-9.618215
104	12.180000	-22.054518	34.234518
105	14.280000	-51.011092	65.291092

--- Forecast Time Series Values ---

Row	Predicted
106	-25.95901
107	-31.38514
108	-52.85315
109	-34.99124
110	-49.22139
111	-74.35522
112	-91.88395
113	-139.33071
114	-153.78172
115	-173.69239
116	-236.02495
117	-308.38516

5.5 SUMMARY & DISCUSSIONS

The reliability of subsystems and the relationship between systems and subsystems of construction equipment are studied in this research. Both traditional power law models and time series models are adopted and applied to the analysis; comparison of these two methods is analyzed and presented below.

5.5.1 COMPARISON OF POWER LAW MODELS AND TIME SERIES MODELS

The conceptual comparison of the two types of models has already been discussed in Chapter 4. In this chapter, both power law models and time series models have been applied to the reliability analysis of construction equipment subsystems, as well the results have been presented respectively. It is observed that time series models are more complex to operate on subsystems than power law models. On the other hand, time series models are more flexible then power law models as the former one can better detect the change of the failure patterns. However, the error rate may be high for subsystems reliability analysis because of less data compared with the system level in time series modelling. The summary of the comparisons is presented in Chapter 6 with the illustration in Table 6.1.

5.5.2 CRITICAL COMPONENTS OF CONSTRUCTION EQUIPMENT

With the aid of Pareto analysis, the critical components of the selected construction equipment pieces are identified in the research. The results are summarized in Table 5.10. In this research, the bulldozer is chosen for study on reliability analysis of construction equipment at a subsystem level as the maintenance data are abundant and balanced in representing subsystem reliability.

Table 5.10 Critical components of different construction equipment

Construction equipment	Critical components
Scrapers	Engine, air system, braking system, cutting edge, drive system
Wheel loaders	Hydraulic system, engine, repair light, electrical
Bulldozers	Undercarriage, ripper teeth, repair light, cab, electrical*
Graders	Cutting edge, drive system, repair light, engine
Tractors	Misc., engine, hydraulic system
Bulldozers 2	Electrical, undercarriage, repair light, engine, drive system, cab

By modelling and analyzing the reliability of an individual critical component, its failure pattern can be observed. For example, the component undercarriage exhibits a trend of an increasing number of failures over time; however, the component ripper teeth does not show any trend. Figure 5.17 illustrates the critical components of a bulldozer with criticality information while the darker colors indicate more critical components. Based on their different failure patterns, different maintenance decisions can be made. Replacement, repair or other actions can be implemented based on these reliability analysis results.

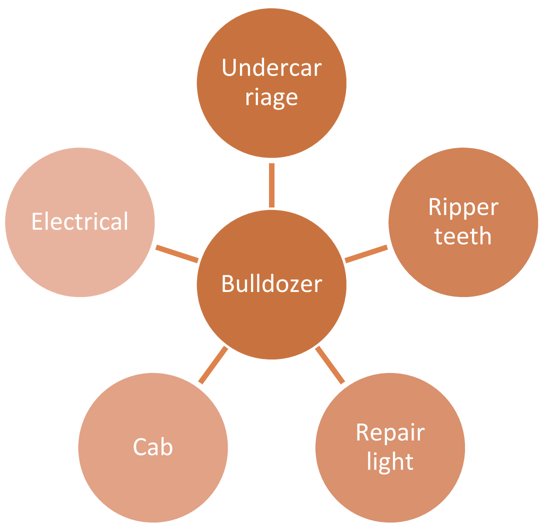

Figure 5.17 Critical components of a bulldozer in reliability

Another issue to address is the root causes of the system and subsystem failures. By analyzing the data from the maintenance records, the common reasons of undercarriage breakdown are shown to be as follows: tracks need adjusting, broken roller bolts, undercarriage to finning, charging problem, etc. (Table 5.11).

Table 5.11 Common reasons of bulldozers critical components breakdown

Bulldozer critical components	Common reasons of breakdown
Undercarriage	Tracks need adjusting; broken roller bolts, undercarriage to finning, charging problem, etc.

5.5.3 MAINTENANCE AND REPLACEMENT STRATEGY

From the point of view of construction equipment allocation and maintenance management, the results from the subsystems reliability analysis are very helpful in optimizing maintenance intervals. An age replacement policy can be applied which suggests a component is either replaced at the time of failure or T units of time after installation, whichever comes first.

From Table 5.10, it is observed that some of the critical components appear several times in different categories of construction equipment. For example, the component engine appeared in three different construction equipment to be critical. It indicates that engine can be a critical component for many construction equipment and perhaps requires special attention in maintenance management. Also, the repair light, electrical and drive system items appear more often than other critical components. Figure 5.18 divides these critical subsystems into three different categories, namely high, middle and low occurrence. Those components presented in the high occurrence category should be given a high priority in equipment maintenance to reduce the unexpected failures in site operations.

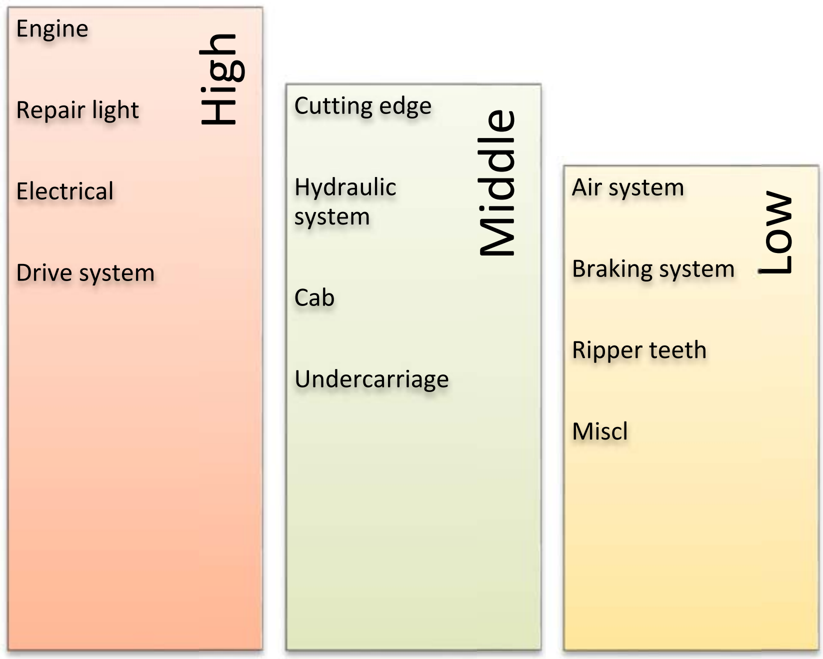

Figure 5.18 Common critical components of analyzed construction equipment

CHAPTER 6 FINDINGS AND DISCUSSIONS

6.1 INTRODUCTION

This chapter presents the findings from this research. In previous chapters, power law model (NHPP) and time series prediction have been adopted for reliability analysis and failure prediction based on real construction equipment failure and maintenance data at the system and subsystem levels. In this chapter, the major findings of this research are summarized and discussed.

6.2 FINDINGS & DICUSSIONS

There are several findings from this project. First of all, the importance of construction equipment reliability analysis and failure prediction was studied in a literature review. It is observed that unexpected failures and unreliable equipment may affect the construction project by increasing the maintenance cost and collateral cost, or extending the project period, and leading to safety problems. These arguments have been elaborated in Chapter 2.

Calculation of reliability metrics

Common reliability metrics including number of failures, time between failures (TBF) and time to repair (TTR) were analyzed and predicted by using both power law models and time series models. The predicted values are compared with the actual values and the errors between them are also presented in the tables. Most of the results are satisfactory. For time series modelling, the best fitted models are selected under the comparison of the criterions such as AIC and BIC, in order to achieve the more accurate forecasts. The obtained reliability metrics can be used to help construction equipment maintenance and allocation decisions, which will be discussed in the following context.

Furthermore, this research not only predicted the number of failures of a piece of construction equipment, but also performed forecast on the TBF with TTR contributed as a predictor or leading variable. TTR, is a crucial parameter, indicating that equipment parts will soon return to normal and have a great impact on the overall stability of the system. From the experimental results, it is noticed that the time spend on repairing the equipment has some impact on the occurrence of the next failure (TBF). Therefore, TTR is suggested to be taken in consideration when operating reliability analysis and failure forecast of construction equipment.

<u>Comparison of power law model and time series model</u>

The traditional power law models and more sophisticated time series models have been used and compared in the research. Their strengths and weaknesses are identified and presented in Table 6.1. It was found out that both methods are capable of analyzing and predicting the failures of construction equipment but with different degrees of accuracy and interpretability.

As the results show, both power law models and time series models can be used for forecasting of reliability metrics of construction equipment; however, both have advantages and disadvantages. ARIMA time series models make very little assumption and are very flexible. It is theoretically and statistically sound in its foundation and no a priori postulation of models is required when analyzing failure data. It can be observed that the ARIMA model is a viable alternative that gives satisfactory results in terms of its predictive performance.

<u>Identifying critical components of construction equipment</u>

Another major contribution is that this research not only focuses on the system itself, but also examined the relationship between system and subsystems. Effort was spent in identifying the critical components of a system so that special treatment could be arranged for these critical parts.

Methods have been studied to identify the critical components and reliability analysis on these critical components has been conducted.

Category A components are identified and considered as the important subsystems for a piece of equipment. For bulldozer, the following five components are the critical ones, which are: undercarriage, reaper teeth, repair light, cab and electrical.

Table 6.1 Comparison of power law models and time series models

Comparison	Power Law Models	Time Series Models
Data requirements	>30	> 50
Theory	Non Homogenous Poisson Process (NHPP)	ARIMA and other predictive models
Data	Times to failure	Fixed intervals but can be expanded to interval-based data
Flexibility	No	Able to detect the change of failure pattern
Subsystems analysis	Easy	Difficult
Complexity of model	Low	Medium to high
Accuracy	Moderate	Higher
Other		Seasonal effect

Impact on management decisions

Based on the results and findings of the data modelling and analysis in this research, advices are given for managerial decision on future construction equipment maintenance and promote repairs before breakdown.

The reliability assessment of construction equipment can affect the decision in selecting the right maintenance strategy in civil engineering project. In the previous chapters, by analyzing the reliability of a particular piece of equipment (bulldozer), trend of failures is detected, and the number of failures and MTBF for a fixed interval can be predicted. The result is valuable in planning system maintenance and repairs. Based on this information, the equipment manager will be able to recognize the status of the equipment and make proactive maintenance services accordingly. The details have been elaborated in the summary section of Chapter 4 and 5 respectively.

6.3 LIMITATIONS AND FUTURE RESEARCH

No research can be perfect, there are always some shortcomings in any research. One of the limitations of this research is the data size for subsystem reliability analysis. For both power law models and time series models, there are requirements for a minimum size of data, which are 30 for the former one and 50 for the latter. In this research, all the data modelling have fulfilled the requirements; however, the accuracy of prediction results might be improved if a bigger sized of data is used, as the theory is that the larger the size of data, the more accurate forecast will be. If more data on subsystems breakdown can be tracked and obtained in future research, the accuracy of the modelling results should be improved to some extent.

Another limitation is still about data. It might be noticed that the maintenance records obtained from industry are not very updated. It is not obvious that if it will affect the result and accuracy of the analysis; however, more updated maintenance records and newer equipment probably do will derive some different results for the research. In the research process, we have tried to negotiate with the staff in the government department and companies, but did not get the information we need. We can maybe try to contact other departments/companies for newer construction equipment data in future research.

Moreover, in this research, basically only time series ARIMA model has been investigated and applied to the case studies. In future research, we would like to involve other sophisticated reliability analysis methods, such as Genetic Algorithm, PNN/GRNN neural network.

Apart from the above limitations, there also are some common errors usually existing in most research or studies, such as human errors and randomness.

Human error: human errors can occur during the data collection and modelling process. Firstly, there might be mistakes and errors existing in the maintenance sheet recorded by site workers. Secondly, the models are not perfect and parameters can always be fine-tuned in the modelling process.

Randomness: it is the largest contributing factor to the errors of prediction due to random nature of system failures. To minimize the errors of prediction and improve the accuracy, effort can be put into increasing the size of data, reducing possible human error, as well as further optimizing the models for reliability analysis.

CHAPTER 7 CONCLUSIONS

This research investigates the reliability of construction equipment and the different methods for modeling and analyzing the reliability metrics at system and subsystem levels.

Construction equipment is an important resource in construction projects, particularly in civil engineering and infrastructure projects. Although regular maintenance is implemented by most contractors on site, still a considerable amount of equipment repairs follow unexpected failures. These unexpected equipment failures can cause serious consequences such as extra cost, project period extension, and safety issues. Therefore, it is necessary to study and understand the reliability of the construction equipment as well as predict the pending failures before the breakdown.

This research aims to investigate the possible methods that can be adopted for analysing the equipment reliability and predicting the failures as well as the application of the experimental results to construction equipment maintenance and management.

Several methodologies have been employed in this research, which comprises a comprehensive literature review of reliability theories, and related research work, reliability analysis approaches, case study, data modelling and analysis. Two descriptive and predictive models are studied and adopted in the process, which are the traditional power law model and more advanced time series models. There are a number of probability distributions commonly used in reliability engineering; however, time-dependent power law models, also named Non-homogeneous Poisson Process (NHPP) models, are universally agreed as most suitable method for repairable systems such as construction equipment. Time series modelling is one of the more sophisticated techniques that can be used to describe and model the selected data, and forecast the future values of the maintenance series based on the past values. Construction equipment failure follows the time series features and patterns, and this makes the time series models suitable for application in this research. Both of the two methods are applied and models are built to analyse the characteristics of reliability like numbers of failures, time between failures (TBF) and time to repair (TTR). Comparison of the two methods is also performed with their strengths and weaknesses summarized in the thesis. Failure and maintenance data on eight types of construction equipment were collected from construction site and modelled in the case study, to validate and compare the prediction results.

Furthermore, the research not only focuses on construction equipment systems, it also explores the equipment from the level of subsystems. Pareto analysis and other methods are used to identify the critical components for the construction equipment. Attributes being considered include the counts of failures, TBF and TTR. Reliability importance analysis is significant in system reliability analysis from the subsystem level. By identifying the critical components and suggesting modifications, system reliability can then be calculated and the maintenance focus can be put on these critical areas.

The major findings of this project include: 1) conducted a critical review on the reliability analysis and failure prediction of construction equipment, identifying the reliability metrics, reliability modelling approaches and needs for predictive analysis in support of construction equipment maintenance management and utilization.; 2) applied the traditional power law models and more sophisticated time series models and found that both are suitable for construction equipment reliability analysis, however, each has its own advantages and disadvantages; 3) critical components are identified and the reliability of subsystems is analysed to give an insight into the research on the systems; 4) benefits of this research in improving the decisions on equipment management are discussed based on the results and findings from data modelling and experimental analysis.

Based on the results of the research and case studies, some recommendations can be given to the maintenance and management of construction equipment.

First of all, it is recommended that predictive maintenance is more advantageous than other common maintenance options for construction equipment. The principle of predictive maintenance is to repair the equipment before the failures occur, so that it can reduce the unscheduled outages and unexpected cost. In order to implement predictive maintenance, reliability elements such as MTBF, numbers of failures should be available for the analysis and prediction. In this research, by applying power law modelling and time series modelling on data of failures, the mentioned reliability elements have been derived and presented in previous chapters.

Apart from predictive maintenance, there are also some advice on construction equipment allocations. As shown in the chapter of cases studies, the status of a particular construction equipment can be detected, either in the infant mortality stage, useful life, or wear out stage of the bathtub curve. If the equipment is in the wear out stage, equipment managers should replace it with the one having higher availability, or with backup plan.

Last but not least, recommendations are given to the construction equipment subsystems maintenance and replacement policies. In chapter 5, the research has been focused on identifying the critical components and their reliability analysis. Five types of construction equipment have been investigated and their respective critical components have been recognized, which require particular attention in maintenance process. It is summarized that for most construction equipment, the most critical components include engine, repair light, electrical and drive system, and the second tier include cutting edge, hydraulic system, cab and undercarriage, etc. Again, reliability analysis and failure prediction have been conducted on the critical components. Depending on the status of these components separately, an age replacement policy should be implemented whether the component will be repaired or replaced before breakdown, so that maintenance cost effective can be achieved.

APPENDICES

APPENDIX 1 – MAINTENANCE RECORDS OF SELECTED CONSTRUCTION EQUIPMENT

APPENDIX 2 – CLEANED AND REORGANIZED DATA

APPENDIX 3 – PARETO ANALYSIS FOR IDENTIFYING CRITICAL COMPONENTS

APPENDIX 4 – POWER LAW ANALYSIS OF CRITICAL COMPONENTS

APPENDIX 5 – TIME SERIES ANALYSIS OF CRITICAL COMPONENTS

APPENDIX 6 – POWER LAW MODELS OF REALIBLITY METRICS

APPENDIX 7 – TIME SERIES MODELS OF REALIBLITY METRICS

APPENDIX 1 – MAINTENANCE RECORDS OF SELECTED CONSTRUCTION EQUIPMENT

Table A1 – Sample of maintenance records of the bulldozer (D11_107)

Time Down	Name	Trade	Class	Reason Down	Status 3	Time Up	Code	Work Done	Down Time	Location	Workforce
96/08/14 13:20	COOK,	MECH	Air Conditioning	Check A/C	UP	96/08/14 14:25	147363	Adjusted A/C charge	1.08	Field	
96/08/26 08:55	ACTIN	MECH	Air Conditioning	A/C REPAIRS	UP	96/08/26 11:00	150346	CHANGED COMPRE	2.08	Field	
97/04/05 14:41	GAULT	MECH	Air Conditioning	A/C REPAIRS	UP	97/04/05 17:30		INSTALLED NEW CO	2.82	Field	
96/06/07 08:20	ACTIN	MECH	Air Conditioning	A/C REPAIRS	UP	96/06/07 10:00	147363	REPLACED BLADE	1.67	Field	
95/08/15 15:00	POIRI	MECH	Air Conditioning	A/C NOT WO	UP	95/08/15 15:30	731089	ADJUSTED CHARGE	0.5	Field	
96/06/06 08:23	COOK,	MECH	Air Conditioning	A/C REPAIRS	UP	96/06/06 08:29	147363	NO PROBLEM FOUN	0.1	Field	
96/07/16 14:35	CULL,	MECH	Air Conditioning	POLAR AIR T	UP	96/07/16 16:55	150343	R & R BELTS/ ADDE	2.33	Field	
96/06/26 09:00	POIRI	MECH	Air Conditioning	A/C REPAIR	UP	96/06/26 09:38	147363	REPLACE VAPOUR/	0.63	Field	
95/07/03 10:25	HERRI	MECH	Air Conditioning	AIR CONDITIC	UP	95/07/03 11:48	551903	PRESSURE TESTED	1.38	Field	
97/05/04 10:24	ACTIN	MECH	Air Conditioning	A/C REPAIRS	UP	97/05/04 11:49	ACVR11	REPAIRED LEAK AN	1.42	Field	
96/08/22 12:45	CULL,	MECH	Air Conditioning	POLAIR AIR T	UP	96/08/22 13:40	150343	REPLACED BOLTS C	0.92	Field	
96/05/04 11:19	ACTIN	MECH	Air System	RESEAL TRA	UP	96/05/05 15:37	396660	REPLACE TRANSMIS	28.3	Shop	2
96/03/28 08:00	MARTI	MECH	Air System	HYD. LEAK	UP	96/04/09 02:30	387962	repaired oil leaks, rep.	282.5	Shop	2
96/05/08 04:20	GAULT	MECH	Air System	REPAIR LEAK	UP	96/05/08 12:12		REPAIR LEAK AT TR	7.87	Shop	2
95/07/31 08:30	AGNEW	MECH	Air System	WING NUT OF	UP	95/07/31 09:30	731089	REPL. BOLTS IN AIR	1	Field	1
95/07/19 14:00	FOY,	MECH	Air System	NO POWER	UP	95/07/19 14:20		REPAIR ENGINE AIR	0.33	Field	1
95/09/13 18:53	WHITE	MECH	Air System	HYD. LEAK	UP	95/09/13 19:30	731089	REPAIRED HYD. LEA	0.62	Field	1
97/01/15 07:35	GAULT	MECH	Air System	INSTALL L/H	UP	97/01/16 11:00	ADJQ01	Installed side frame /	27.42	Shop	2
97/06/23 20:00	ACTIN	MECH	Air System	TORQUE LIG	UP	97/06/23 21:22	ACVR11	REPAIRED BROKEN	1.37	Field	1
96/12/22 13:31	ACTIN	MECH	Air System	REPAIR TILT	UP	96/12/23 02:29	ACLD01	REPLACED TILT HOS	12.97	Shop	2
96/06/13 11:40	CULL,	MECH	Blade	HYD. LEAK O	UP	96/06/13 12:02	147363	REPLACED O RING	0.37	Field	1
97/04/04 14:28	ACTIN	MECH	Blade	REPLACE HY	UP	97/04/05 14:40	AJAS01	REPLD HYD PUMP A	24.2	Shop	2
97/04/30 23:03	COOK,	MECH	Blade	BLADE LIGHT	UP	97/05/01 00:01	ACVR11	REPLD SEALED BEA	0.97	Field	1
97/05/25 16:30	ACTIN	MECH	Blade	HYD. LEAK -	UP	97/05/25 16:50	ACVR11	REPLACED O'RING F	0.33	Field	1
96/09/17 09:55	ACTIN	MECH	Blade	LOOSE BOLT	UP	96/09/17 10:27	147363	REPLACED NUTS AN	0.53	Field	1
96/09/03 05:37	GAULT	MECH	Blade	REPLACE TR	UP	96/09/03 19:30	252241	TRANS AND BEVEL	13.88	Shop	2
96/09/03 19:31	ACTIN	MECH	Blade	REPLACE LH	UP	96/09/03 22:00		SYTEM UPDATE / C	2.48	Shop	2
96/09/03 22:01	ACTIN	MECH	Blade	COMPONENT	UP	96/09/05 15:30	161518	COMPONENT CHAN	41.48	Shop	2
96/07/06 00:05	ACTIN	MECH	Blade	LIGHT OUT O	UP	96/07/06 00:25	147363	REPLACE TWO REA	0.33	Field	1
96/10/29 02:01	ANTHO	MECH	Blade	RIPPER PIN F	UP	96/10/29 06:25	169257	REPLACED R/H BLA	4.4	Shop	2
95/12/27 12:45	MCCAN	NON-M	Cab	Window	UP	95/12/27 13:24	731089	Replaced door glass	0.65	Field	
96/04/12 14:00	POIRI	MECH	Cab	REPLACE GL	UP	96/04/12 14:20	147363	COMPLETED	0.33	Field	
96/03/23 14:30	ACTIN	MECH	Cab	OIL SAMPLE,	UP	96/03/23 15:00	967796	OIL SAMPLE TAKEN	0.5	Field	1
96/03/15 15:25	CULL,	MECH	Cab	REPLACE SE	UP	96/03/15 15:40	147363	REPLACED SEAT BE	0.25	Field	1
96/03/02 21:45	CULL,	MECH	Cab	TOP LIGHTS	UP	96/03/02 22:00	147363	REPAIRED WIRING T	0.25	Field	1

Table A2.1 – Summary of the failures of all the equipment

	1	2		3		4	
Systems	Trucks	Scrapers		Wheel loaders		Bulldozers	
File Name	240H_075	631E_016		988B_034		D11_107	
Data No.	305	108		135		430	
Subsystems	-	20		21		30	
1		Air System	8	Air Conditioning	5	Air Conditioning	11
2		Braking System	5	Air System	2	Air System	9
3		Cab	3	Braking System	5	Blade	10
4		Cooling Systems	2	Cab	6	Cab	25
5		Cutting Edge	5	Cooling System	1	Cooling Systems	13
6		Drive System	5	Drive System	5	Cutting Edge	7
7		Electrical	5	Electrical	7	Drive System	13
8		Engine	16	Engine	15	Electrical	21
9		Field Service	5	Field Service	1	Engine	12
10		Fuel System	5	Fuel System	5	Equalizer	1
11		Hydraulic System	5	Grease System	1	Field Service	14
12		Low Power	1	Heating System	1	Float	21
13		Miscl	2	Hydraulic System	22	Fuel System	2
14		Oil Sample	2	Low Power	1	Grease System	4
15		Service	12	Miscl	4	Heating System	1
16		Starting System	1	Oil Sample	2	Hydraulic System	21
17		Steam	13	Repair Light	9	Ice Lugging	3
18		Torque	1	Steam	23	Low Power	1
19		Wait	10	Steering System	1	Oil Leak	3
20		Welding	2	Wait	13	Oil Sample	2
21				Welding	6	Repair Light	27
22						Ripper Teeth	35
23						Service	32
24						Starting System	2
25						Steam	42
26						Steering System	3

27				Torque	1
28				Undercarriage	67
29				Wait	16
30				Welding	11
31					
32					

Table A2.1 – Summary of the failures of all the equipment (Con't)

Systems	5		6		7	8	
File Name	Graders		Tractors		Shovels	Bulldozers 2	
Data No.	GRAD_035		HYCR_035		SHOVEL~1	TLNGSDOZ	
Subsystems	275		63		277	612	
1	29		19		-	32	
2	Air Conditioning	5	Air System	4		Air Conditioning	4
3	Air System	8	Axle	1		Air System	16
4	Axle	5	Braking System	2		Blade	10
5	Blade	6	Cab	2		Braking System	4
6	Braking System	5	Drive System	1		Cab	18
7	Cab	12	Electrical	4		Component Change Out	2
8	Cooling Systems	6	Engine	9		Cooling Systems	18
9	Cutting Edge	71	Heating System	1		Cutting Edge	1
10	Drive System	19	Hydraulic System	6		Drive System	20
11	Electrical	14	Miscl	12		Electrical	40
12	Engine	15	Oil Sample	2		Engine	25
13	Field Service	2	Repair Light	1		Equalizer	1
14	Float	1	Service	8		Field Service	15
15	Frame	2	Starting System	1		Float	17
16	Fuel System	1	Steam	3		Fuel System	8
17	Grease System	6	Steering System	1		Hard Nose / Grill	1
18	Hydraulic System	7	Wait	2		Heating System	4
19	Miscl	7	Welding	2		Hydraulic	7

						System	
20	Oil Sample	5	Wheels	1		Low Power	4
21	Repair Light	17				Miscl	11
22	Ripper Teeth	2				Oil Sample	1
23	Sensor	2				Repair Light	26
24	Service	13				Service	185
25	Starting System	1				Starting System	2
26	Steam	21				Steam	84
27	Steering System	3				Steering System	2
28	Tandem	3				Sunk	1
29	Tire	1				Training	1
30	Wait	15				Undercarriage	30
31						Wait	44
32						Welding	8
						Winch	2

Table A2.2.1 – Summary of number of failures of scrapers (631E_016)

Weeks	Number of failures	Weeks (Con't)	Number of failures (Con't)
1	4	19	2
2	1	20	6
3	5	21	3
4	5	22	4
5	2	23	1
6	4	24	1
7	2	25	4
8	1	26	4
9	4	27	7
10	2	28	7
11	6	29	1
12	1	30	2
13	3	31	3
14	1	32	1
15	2	33	2
16	2	34	2
17	2	35	7
18	1	36	3

Table A2.2.2 – Summary of number of failures of bulldozers (D11_107)

Weeks	Number of failures	Weeks (Con't)	Number of failures
1	2	54	8
2	2	55	2
3	0	56	3
4	4	57	1
5	4	58	3
6	4	59	2
7	2	60	6
8	1	61	4
9	8	62	5
10	0	63	7
11	1	64	6
12	6	65	6
13	6	66	5
14	1	67	1
15	6	68	5
16	5	69	2
17	2	70	7
18	0	71	4
19	3	72	3
20	4	73	1
21	4	74	11
22	3	75	5
23	5	76	3
24	5	77	1
25	6	78	6
26	5	79	5
27	5	80	4
28	0	81	2
29	7	82	6
30	3	83	4
31	6	84	2
32	1	85	5
33	4	86	6
34	2	87	1
35	4	88	6

36	4	89	1
37	5	90	6
38	3	91	10
39	4	92	3
40	5	93	5
41	0	94	6
42	5	95	5
43	4	96	6
44	3	97	4
45	4	98	5
46	5	99	6
47	0	100	2
48	5	101	9
49	5	102	5
50	4	103	3
51	7	104	2
52	4	105	9
53	2	106	9

Table A2.3.1 – Summary of TBF and TTR of trucks (240H_075)

Weeks	Cumulative TBF	TBF	Cumulative TTR	TTR
1	131.75	131.75	16.72	16.72
2	245.83	114.08	34.97	18.25
3	475.83	230.00	43.75	8.78
4	624.33	148.50	85.67	41.92
5	766.78	142.45	94.77	9.10
6	979.83	213.05	101.48	6.72
7	1076.25	96.42	104.98	3.50
8	1304.17	227.92	167.18	62.20
9	1376.58	72.42	168.02	0.83
10	1639.83	263.25	206.65	38.63
11	1795.62	155.78	224.87	18.22
12	1981.23	185.62	264.25	39.38
13	2146.08	164.85	269.10	4.85
14	2302.50	156.42	278.90	9.80
15	2470.85	168.35	310.45	31.55

16	2600.10	129.25	360.12	49.67
17	2801.33	201.23	362.12	2.00
18	2942.58	141.25	365.20	3.08
19	3155.58	213.00	383.52	18.32
20	3328.33	172.75	413.72	30.20
21	3488.47	160.13	423.97	10.25
22	3657.83	169.37	430.90	6.93
23	3800.08	142.25	431.75	0.85
24	3946.77	146.68	446.70	14.95
25	4068.33	121.57	447.08	0.38
26	4336.93	268.60	456.93	9.85
27	4507.83	170.90	469.02	12.08
28	4634.60	126.77	506.62	37.60
29	4831.85	197.25	534.02	27.40
30	4982.83	150.98	538.27	4.25
31	5098.33	115.50	542.52	4.25
32	5306.85	208.52	587.52	45.00
33	5486.42	179.57	608.05	20.53
34	5655.75	169.33	650.32	42.27
35	5845.92	190.17	665.78	15.47
36	6019.83	173.92	684.43	18.65
37	6106.33	86.50	686.10	1.67
38	6315.25	208.92	696.30	10.20
39	6522.38	207.13	699.22	2.92
40	6667.00	144.62	727.45	28.23
41	6848.50	181.50	757.18	29.73
42	6976.10	127.60	768.35	11.17
43	7193.33	217.23	770.60	2.25
44	7347.83	154.50	801.68	31.08
45	7519.33	171.50	817.23	15.55
46	7681.33	162.00	873.85	56.62
47	7830.80	149.47	875.80	1.95
48	7986.83	156.03	896.20	20.40
49	8202.58	215.75	898.53	2.33
50	8344.33	141.75	901.37	2.83
51	8528.33	184.00	953.77	52.40
52	8695.92	167.58	970.10	16.33

Table A2.3.2 – Summary of TBF and TTR of scrapers (631E_016)

Weeks	Cumulative TBF	TBF	Cumulative TTR	TTR
1	142.00	142.00	3.20	3.20
2	194.03	52.03	14.78	11.58
3	471.00	276.97	53.15	38.37
4	621.00	150.00	54.98	1.83
5	766.00	145.00	61.50	6.52
6	993.00	227.00	88.93	27.43
7	1151.00	158.00	104.87	15.93
8	1190.00	39.00	105.88	1.02
9	1436.50	246.50	106.38	0.50
10	1525.28	88.78	113.63	7.25
11	1829.00	303.72	114.80	1.17
12	1910.00	81.00	142.20	27.40
13	2040.50	130.50	235.10	92.90
14	2285.50	245.00	297.87	62.77
15	2459.50	174.00	298.20	0.33
16	2664.00	204.50	298.53	0.33
17	2799.50	135.50	299.48	0.95
18	2948.33	148.83	308.07	8.58
19	3141.00	192.67	309.07	1.00
20	3141.00	0.00	309.07	0.00
21	3359.42	218.42	309.57	0.50
22	3536.02	176.60	323.40	13.83
23	3751.75	215.73	325.12	1.72
24	3958.02	206.27	335.37	10.25
25	4082.00	123.98	340.62	5.25
26	4315.50	233.50	380.63	40.02
27	4521.58	206.08	412.57	31.93
28	4688.02	166.43	500.83	88.27
29	4824.00	135.98	501.33	0.50
30	4974.37	150.37	505.68	4.35

Table A2.3.4 – Summary of TBF and TTR of bulldozers (D11_107)

Weeks	Cumulative TBF	TBF	Cumulative TTR	TTR
			3.35	3.35
0	3.37	3.37	8.12	4.77
1	67.98	64.62	9.75	1.63
2	67.98	0.00	9.75	0.00
3	440.98	373.00	13.82	4.07
4	682.82	241.83	51.33	37.52
5	848.40	165.58	54.73	3.40
6	1029.98	181.58	55.40	0.67
7	1089.98	60.00	55.90	0.50
8	1360.18	270.20	78.93	23.03
9	1360.18	0.00	78.93	0.00
10	1565.98	205.80	87.23	8.30
11	1848.98	283.00	121.92	34.68
12	2023.53	174.55	132.23	10.32
13	2128.82	105.28	132.57	0.33
14	2363.98	235.17	146.93	14.37
15	2548.15	184.17	155.18	8.25
16	2695.48	147.33	166.37	11.18
17	2695.48	0.00	166.37	0.00
18	3009.42	313.93	196.65	30.28
19	3196.02	186.60	227.68	31.03
20	3391.43	195.42	257.28	29.60
21	3530.98	139.55	279.63	22.35
22	3700.23	169.25	293.20	13.57
23	3897.98	197.75	296.12	2.92
24	4052.82	154.83	332.60	36.48
25	4195.98	143.17	393.15	60.55
26	4408.48	212.50	439.00	45.85
27	4408.48	0.00	439.00	0.00
28	4741.15	332.67	484.45	45.45
29	4846.65	105.50	526.13	41.68
30	5069.48	222.83	565.62	39.48
31	5196.98	127.50	565.87	0.25
32	5381.98	185.00	617.55	51.68
33	5547.98	166.00	665.70	48.15

34	5719.15	171.17	676.68	10.98
35	5896.73	177.58	686.08	9.40
36	6077.32	180.58	703.27	17.18
37	6202.40	125.08	736.00	32.73
38	6415.00	212.60	738.50	2.50
39	6496.23	81.23	758.28	19.78
40	6496.23	0.00	758.28	0.00
41	6917.67	421.43	1062.48	304.20
42	7065.48	147.82	1081.98	19.50
43	7218.82	153.33	1087.80	5.82
44	7398.30	179.48	1172.13	84.33
45	7526.95	128.65	1197.75	25.62
46	7526.95	0.00	1197.75	0.00
47	7739.23	212.28	1199.92	2.17
48	7851.98	112.75	1232.55	32.63
49	8066.73	214.75	1270.13	37.58
50	8273.65	206.92	1317.72	47.58
51	8409.50	135.85	1306.10	-11.62
52	8584.40	174.90	1383.15	77.05
53	8776.07	191.67	1439.93	56.78
54	8899.07	123.00	1440.70	0.77
55	9061.00	161.93	1497.92	57.22
56	9153.57	92.57	1500.25	2.33
57	9420.65	267.08	1535.28	35.03
58	9545.23	124.58	1536.92	1.63
59	9778.00	232.77	1549.42	12.50
60	9893.15	115.15	1558.08	8.67
61	10106.73	213.58	1583.10	25.02
62	10253.50	146.77	1664.53	81.43
63	10424.98	171.48	1724.15	59.62
64	10611.98	187.00	1760.65	36.50
65	10761.17	149.18	1787.43	26.78
66	10876.98	115.82	1787.68	0.25
67	11128.65	251.67	1790.85	3.17
68	11252.98	124.33	1791.35	0.50
69	11437.32	184.33	1821.35	30.00
70	11608.23	170.92	1827.52	6.17
71	11674.98	66.75	1849.93	22.42
72	11884.82	209.83	1850.50	0.57

73	12107.15	222.33	1937.85	87.35
74	12279.48	172.33	1955.90	18.05
75	12467.58	188.10	1961.47	5.57
76	12590.98	123.40	1962.47	1.00
77	12786.50	195.52	2016.27	53.80
78	12965.75	179.25	2109.88	93.62
79	13123.15	157.40	2124.68	14.80
80	13288.32	165.17	2137.68	13.00
81	13462.50	174.18	2176.95	39.27
82	13566.98	104.48	2273.83	96.88
83	13736.15	169.17	2278.83	5.00
84	13904.73	168.58	2298.40	19.57
85	14143.00	238.27	2352.58	54.18
86	14214.98	71.98	2360.18	7.60
87	14476.98	262.00	2379.62	19.43
88	14518.82	41.83	2379.78	0.17
89	14790.57	271.75	2402.37	22.58
90	14987.50	196.93	2455.43	53.07
91	15157.27	169.77	2468.15	12.72
92	15303.72	146.45	2472.87	4.72
93	15468.50	164.78	2506.88	34.02
94	15663.28	194.78	2541.75	34.87
95	15832.98	169.70	2576.98	35.23
96	15987.08	154.10	2578.92	1.93
97	16157.38	170.30	2592.70	13.78
98	16258.95	101.57	2601.68	8.98
99	16493.57	234.62	2602.68	1.00
100	16672.37	178.80	2610.62	7.93
101	16785.37	113.00	2673.80	63.18
102	16999.23	213.87	2721.92	48.12
103	17042.98	43.75	2723.50	1.58
104	17336.22	293.23	2766.32	42.82
105	17511.98	175.77	2799.58	33.27

APPENDIX 3 – PARETO ANALYSIS FOR IDENTIFYING CRITICAL COMPONENTS

Table A3.1 – Pareto analysis of scrapers (631E_016)

Components	Count of Failures	%	Cumulative %	Category
			0.00%	
Engine	16	23.53%	23.53%	A
Air System	8	11.76%	35.29%	A
Braking System	5	7.35%	42.65%	A
Cutting Edge	5	7.35%	50.00%	A
Drive System	5	7.35%	57.35%	A
Electrical	5	7.35%	64.71%	B
Fuel System	5	7.35%	72.06%	B
Hydraulic System	5	7.35%	79.41%	B
Cab	3	4.41%	83.82%	B
Cooling Systems	2	2.94%	86.76%	C
Miscl	2	2.94%	89.71%	C
Oil Sample	2	2.94%	92.65%	C
Welding	2	2.94%	95.59%	C
Low Power	1	1.47%	97.06%	C
Starting System	1	1.47%	98.53%	C
Torque	1	1.47%	100.00%	C

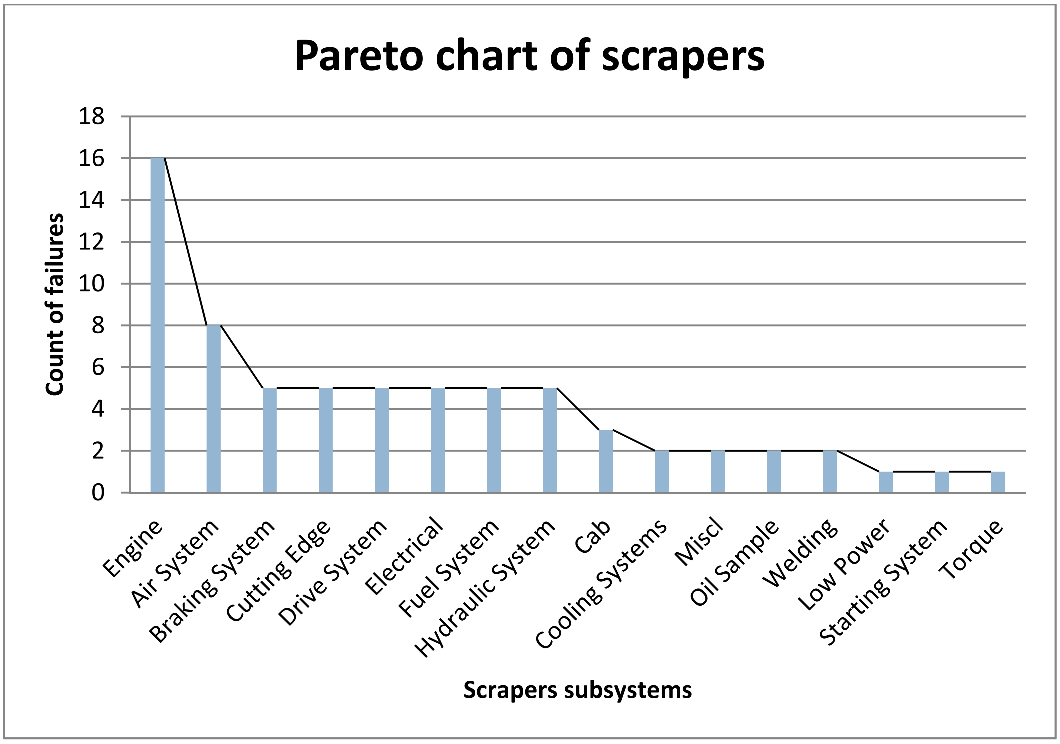

Figure A3.1 – Pareto chart of scrapers (631E_016)

Table A3.2 – Pareto analysis of wheel loaders (988b_034)

Components	Count of Failures	%	cumulative %	Category
			0.00%	
Hydraulic System	22	22.45%	22.45%	A
Engine	15	15.31%	37.76%	A
Repair Light	9	9.18%	46.94%	A
Electrical	7	7.14%	54.08%	A
Welding	6	6.12%	60.20%	B
Cab	6	6.12%	66.33%	B
Fuel System	5	5.10%	71.43%	B
Drive System	5	5.10%	76.53%	B
Braking System	5	5.10%	81.63%	B
Air Conditioning	5	5.10%	86.73%	C
Miscl	4	4.08%	90.82%	C
Oil Sample	2	2.04%	92.86%	C
Air System	2	2.04%	94.90%	C

Steering System	1	1.02%	95.92%	C
Low Power	1	1.02%	96.94%	C
Heating System	1	1.02%	97.96%	C
Grease System	1	1.02%	98.98%	C
Cooling System	1	1.02%	100.00%	C

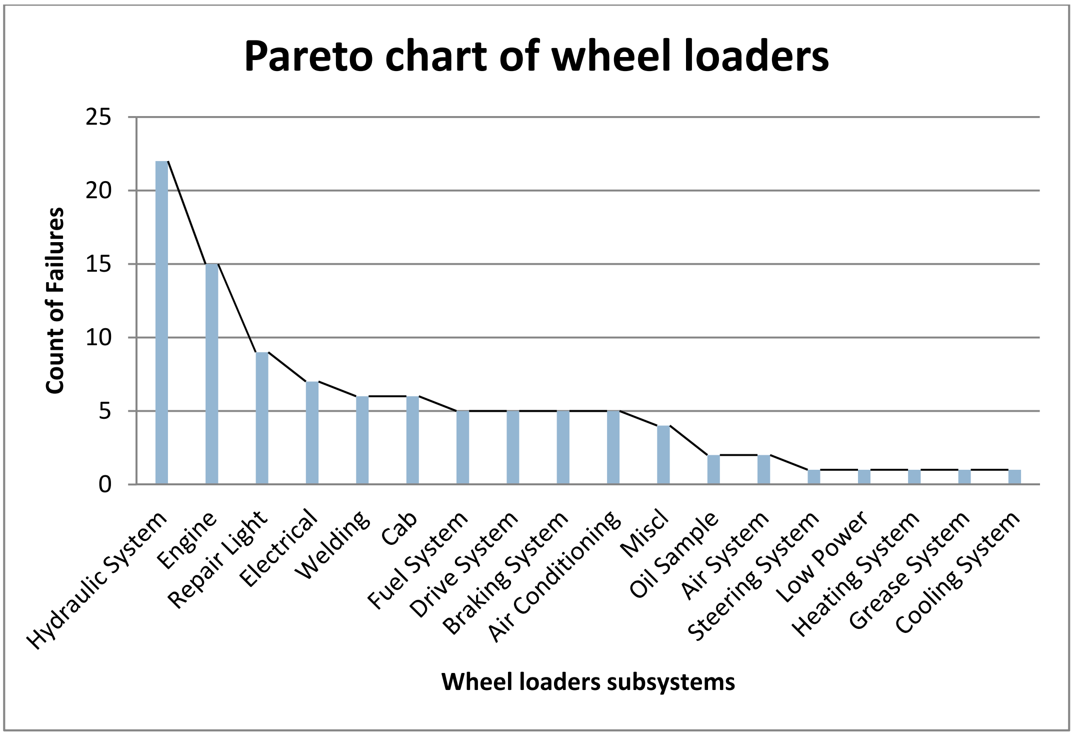

Figure A3.2 – Pareto chart of wheel loaders (988b_034)

Table A3.3 – Pareto analysis of bulldozers (D11_107)

Components	Count of Failures	%	cumulative %	Category
			0.00%	
Undercarriage	67	20.55%	20.55%	A
Ripper Teeth	35	10.74%	31.29%	A
Repair Light	27	8.28%	39.57%	A
Cab	25	7.67%	47.24%	A
Electrical	21	6.44%	53.68%	A
Float	21	6.44%	60.12%	B
Hydraulic System	21	6.44%	66.56%	B

Cooling Systems	13	3.99%	70.55%	B
Drive System	13	3.99%	74.54%	B
Engine	12	3.68%	78.22%	B
Air Conditioning	11	3.37%	81.60%	B
Welding	11	3.37%	84.97%	B
Blade	10	3.07%	88.04%	C
Air System	9	2.76%	90.80%	C
Cutting Edge	7	2.15%	92.94%	C
Grease System	4	1.23%	94.17%	C
Ice Lugging	3	0.92%	95.09%	C
Oil Leak	3	0.92%	96.01%	C
Steering System	3	0.92%	96.93%	C
Fuel System	2	0.61%	97.55%	C
Oil Sample	2	0.61%	98.16%	C
Starting System	2	0.61%	98.77%	C
Equalizer	1	0.31%	99.08%	C
Heating System	1	0.31%	99.39%	C
Low Power	1	0.31%	99.69%	C
Torque	1	0.31%	100.00%	C

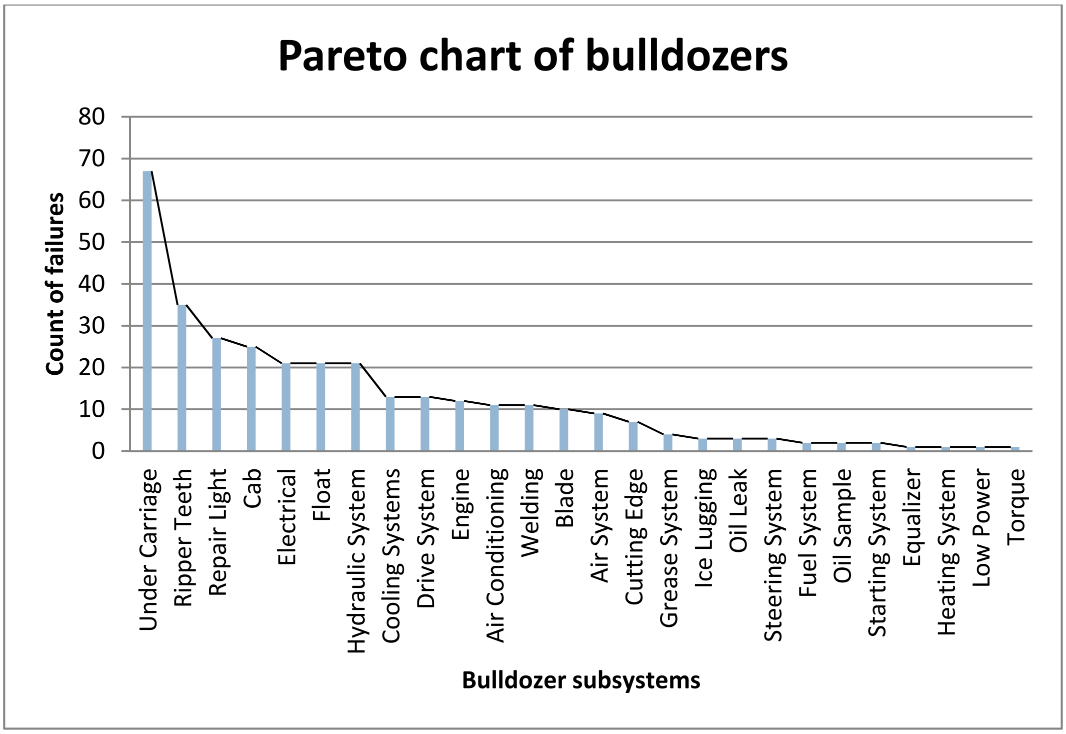

Figure A3.3 – Pareto chart of bulldozers (D11_107)

Table A3.3b – Pareto analysis of bulldozers based on TBF (D11_107)

Components	TBF	%	Cumulative %	Category
			0.00%	
Undercarriage	3204.03	22.60%	22.60%	A
Ripper Teeth	1704.27	12.02%	34.62%	A
Repair Light	1636.70	11.54%	46.17%	A
Cab	1181.20	8.33%	54.50%	A
Float	1131.13	7.98%	62.48%	B
Electrical	916.07	6.46%	68.94%	B
Hydraulic System	650.43	4.59%	73.53%	B
Engine	534.72	3.77%	77.30%	B
Drive System	486.98	3.43%	80.73%	B
Air Conditioning	415.72	2.93%	83.66%	B
Blade	381.67	2.69%	86.36%	C
Cooling Systems	342.45	2.42%	88.77%	C
Welding	290.67	2.05%	90.82%	C
Ice Lugging	240.85	1.70%	92.52%	C

Fuel System	170.98	1.21%	93.73%	C
Oil Leak	143.50	1.01%	94.74%	C
Cutting Edge	129.90	0.92%	95.66%	C
Low Power	123.98	0.87%	96.53%	C
Oil Sample	103.25	0.73%	97.26%	C
Grease System	101.62	0.72%	97.98%	C
Heating System	86.52	0.61%	98.59%	C
Air System	78.35	0.55%	99.14%	C
Steering System	60.95	0.43%	99.57%	C
Starting System	54.45	0.38%	99.95%	C
Equalizer	6.28	0.04%	100.00%	C
Torque	0.52	0.00%	100.00%	C

Table A3.4 – Pareto analysis of graders (GRAD_035)

Components	Count of Failures	%	cumulative %	Category
			0.00%	
Cutting Edge	71	31.70%	31.70%	A
Drive System	19	8.48%	40.18%	A
Repair Light	17	7.59%	47.77%	A
Engine	15	6.70%	54.46%	A
Electrical	14	6.25%	60.71%	B
Cab	12	5.36%	66.07%	B
Air System	8	3.57%	69.64%	B
Hydraulic System	7	3.13%	72.77%	B
Miscl	7	3.13%	75.89%	B
Blade	6	2.68%	78.57%	B
Cooling Systems	6	2.68%	81.25%	B
Grease System	6	2.68%	83.93%	B
Air Conditioning	5	2.23%	86.16%	C
Axle	5	2.23%	88.39%	C
Braking System	5	2.23%	90.63%	C

Oil Sample	5	2.23%	92.86%	C
Steering System	3	1.34%	94.20%	C
Tandem	3	1.34%	95.54%	C
Frame	2	0.89%	96.43%	C
Ripper Teeth	2	0.89%	97.32%	C
Sensor	2	0.89%	98.21%	C
Float	1	0.45%	98.66%	C
Fuel System	1	0.45%	99.11%	C
Starting System	1	0.45%	99.55%	C
Tire	1	0.45%	100.00%	C

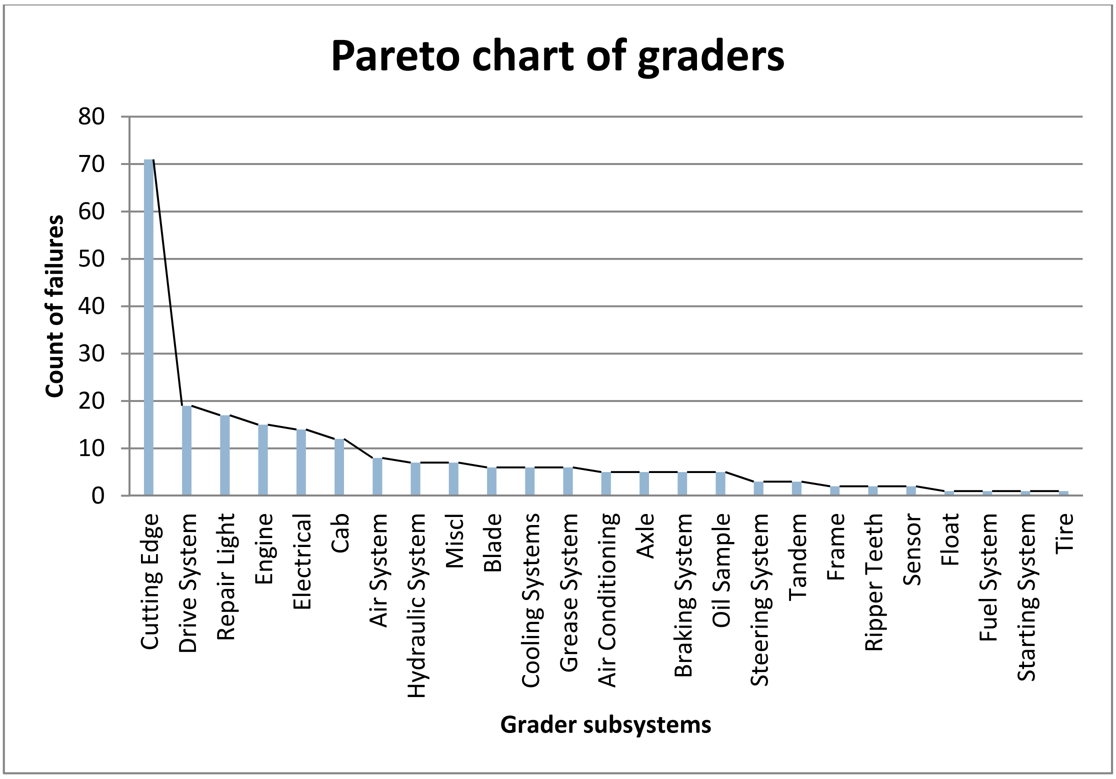

Figure A3.4 – Pareto chart of graders (GRAD_035)

Table A3.5 – Pareto analysis of tractors (HYCR_035)

Components	Count of Failures	%	cumulative %	Category
			0.00%	
Miscl	12	24.00%	24.00%	A
Engine	9	18.00%	42.00%	A
Hydraulic System	6	12.00%	54.00%	A
Air System	4	8.00%	62.00%	B
Electrical	4	8.00%	70.00%	B
Braking System	2	4.00%	74.00%	B
Cab	2	4.00%	78.00%	B
Oil Sample	2	4.00%	82.00%	B
Welding	2	4.00%	86.00%	C
Axle	1	2.00%	88.00%	C
Drive System	1	2.00%	90.00%	C
Heating System	1	2.00%	92.00%	C
Repair Light	1	2.00%	94.00%	C
Starting System	1	2.00%	96.00%	C
Steering System	1	2.00%	98.00%	C
Wheels	1	2.00%	100.00%	C

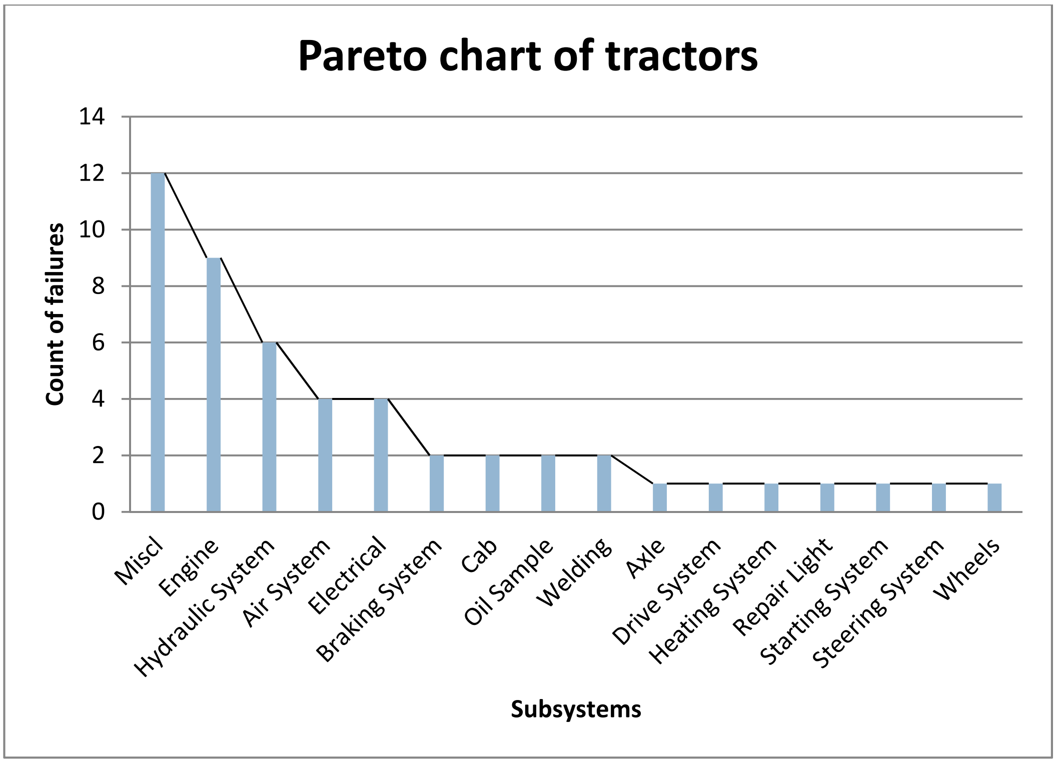

Figure A3.5 – Pareto chart of tractors (HYCR_035)

Table A3.6 – Pareto analysis of bulldozers 2 (TLNGDOZ)

Components	Count of Failures	%	cumulative %	Category
			0.00%	
Electrical	40	14.08%	14.08%	A
Undercarriage	30	10.56%	24.65%	A
Repair Light	26	9.15%	33.80%	A
Engine	25	8.80%	42.61%	A
Drive System	20	7.04%	49.65%	A
Cab	18	6.34%	55.99%	A
Cooling Systems	18	6.34%	62.32%	B
Float	17	5.99%	68.31%	B
Air System	16	5.63%	73.94%	B
Miscl	11	3.87%	77.82%	B
Blade	10	3.52%	81.34%	B
Fuel System	8	2.82%	84.15%	B
Welding	8	2.82%	86.97%	C

Hydraulic System	7	2.46%	89.44%	C
Air Conditioning	4	1.41%	90.85%	C
Braking System	4	1.41%	92.25%	C
Heating System	4	1.41%	93.66%	C
Low Power	4	1.41%	95.07%	C
Component Change Out	2	0.70%	95.77%	C
Starting System	2	0.70%	96.48%	C
Steering System	2	0.70%	97.18%	C
Winch	2	0.70%	97.89%	C
Cutting Edge	1	0.35%	98.24%	C
Equalizer	1	0.35%	98.59%	C
Hard Nose / Grill	1	0.35%	98.94%	C
Oil Sample	1	0.35%	99.30%	C
Sunk	1	0.35%	99.65%	C
Training	1	0.35%	100.00%	C

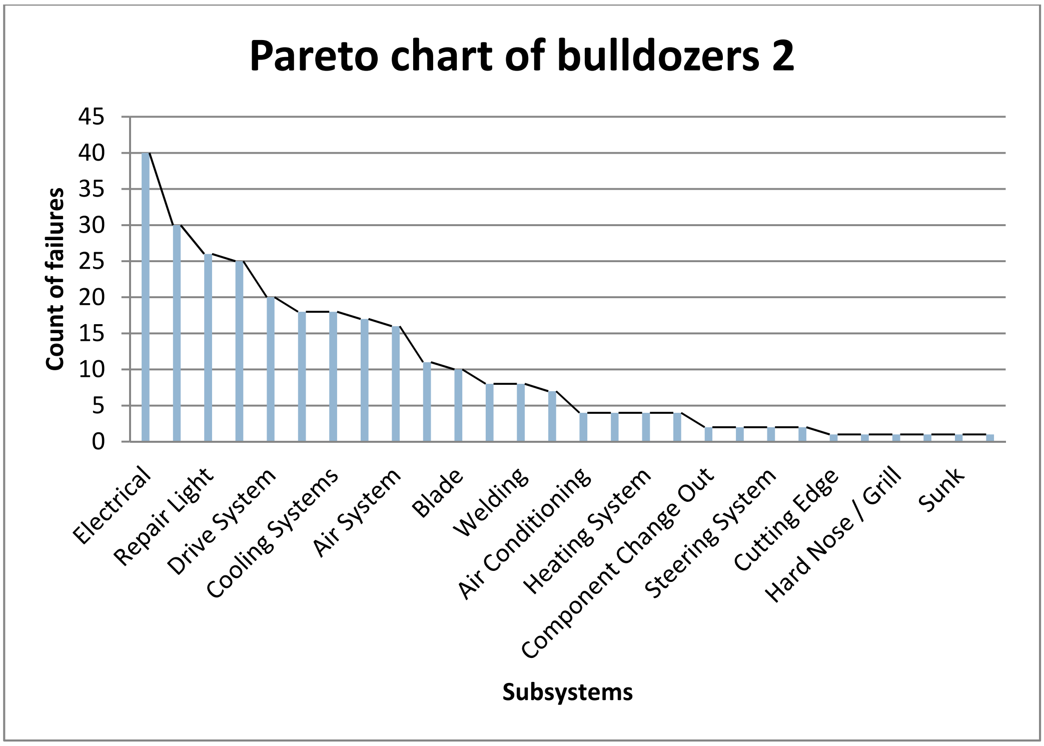

Figure A3.6 – Pareto chart of bulldozers 2 (TLNGDOZ)

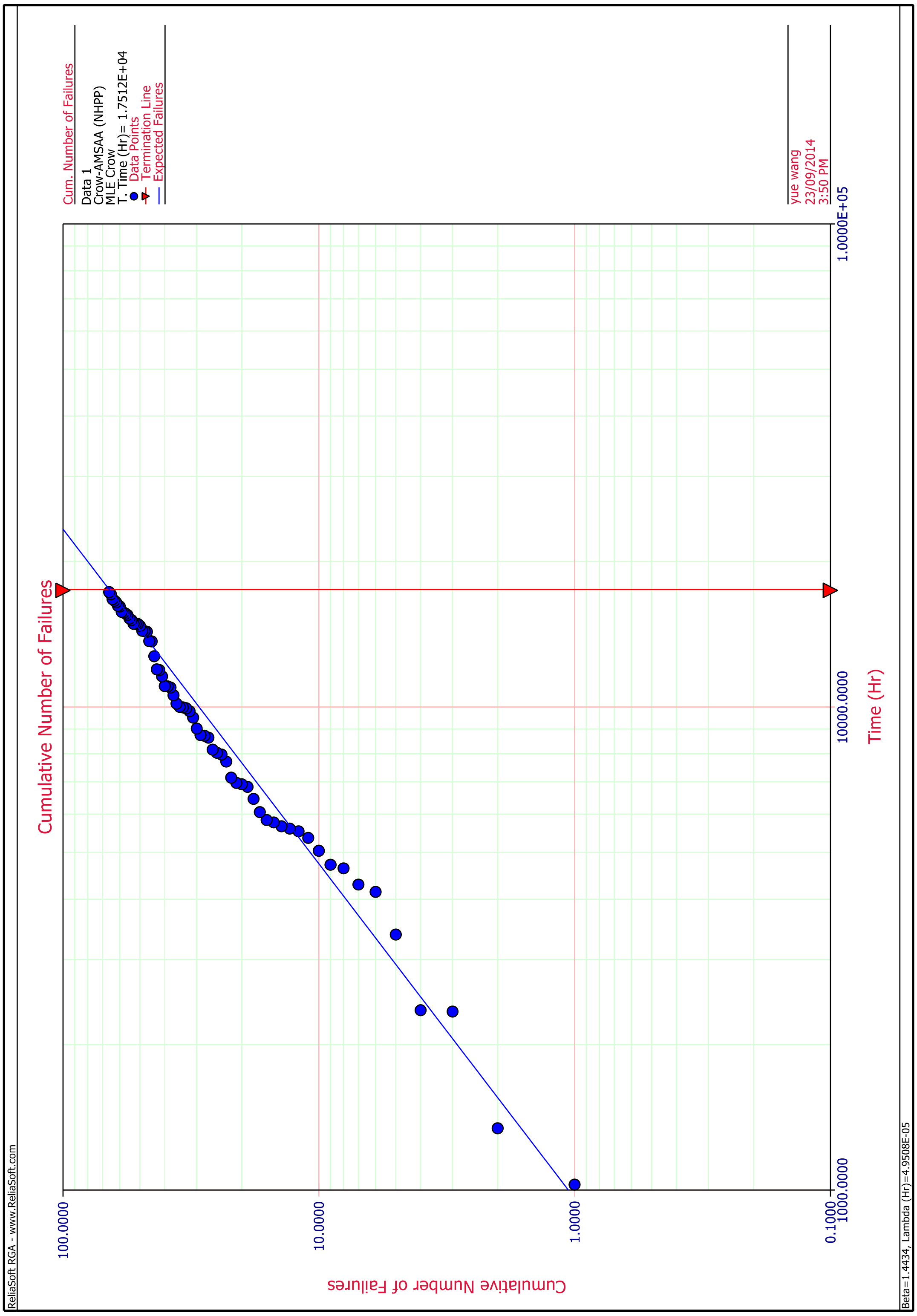

Figure A4.1.1 – Cumulative number of failures of bulldozer critical component "undercarriage"

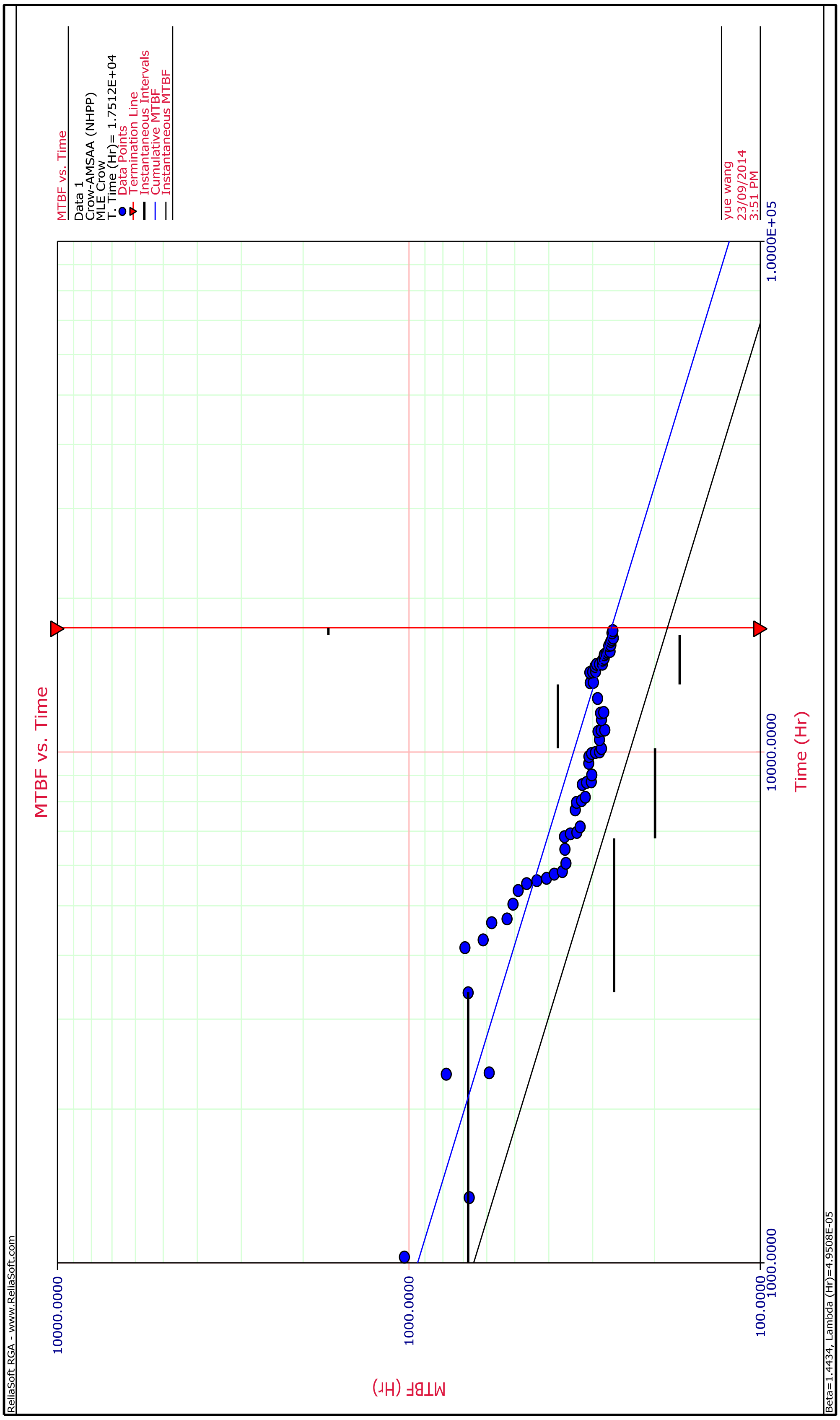

Figure A4.1.2 – MTBF vs. time of bulldozer critical component "undercarriage"

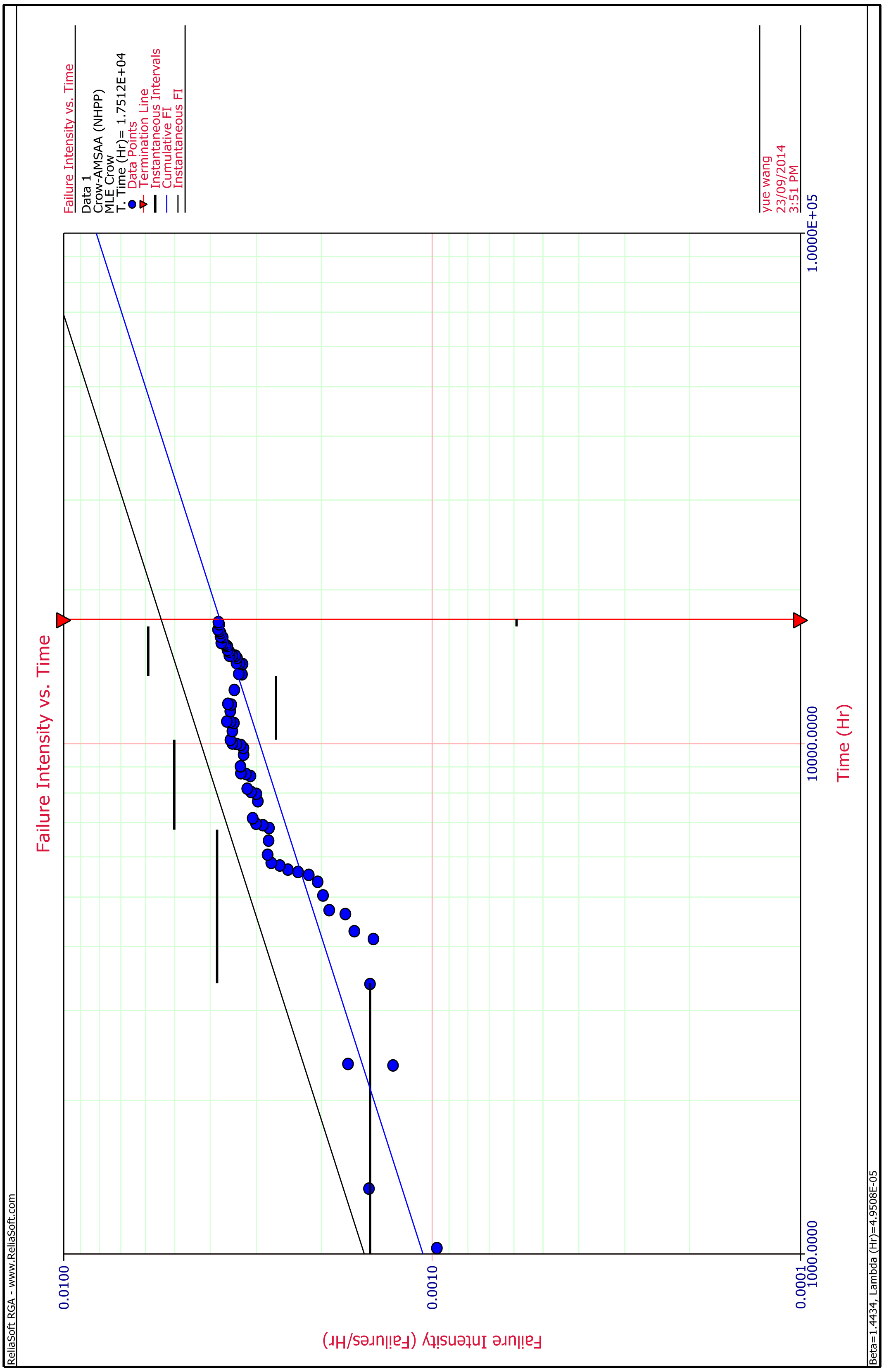

Figure A4.2.3 – Failure intensity vs. time of bulldozer critical component “ripper teeth”

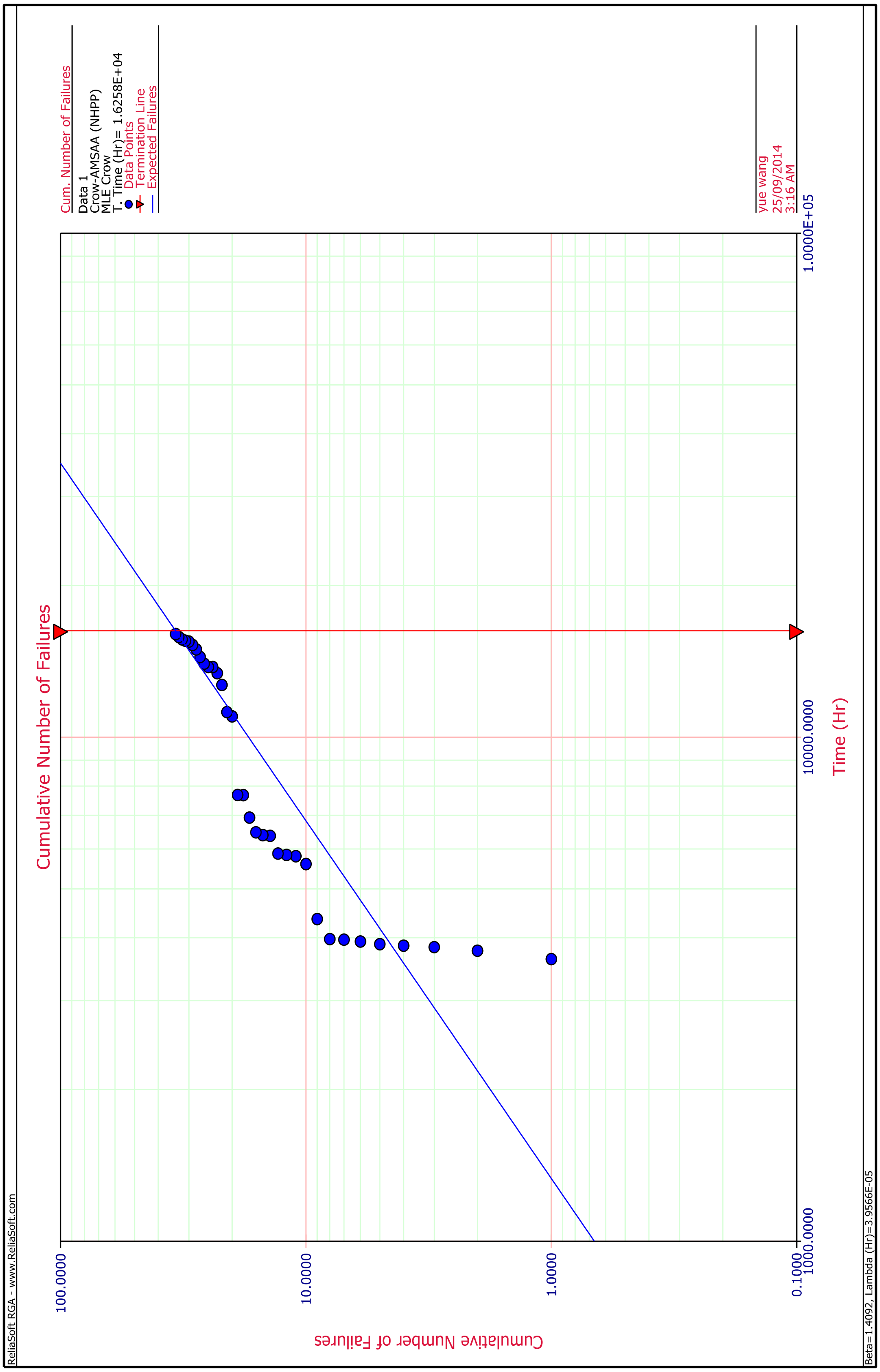

Figure A4.2.1 – Cumulative number of failures of bulldozer critical component “ripper teeth”

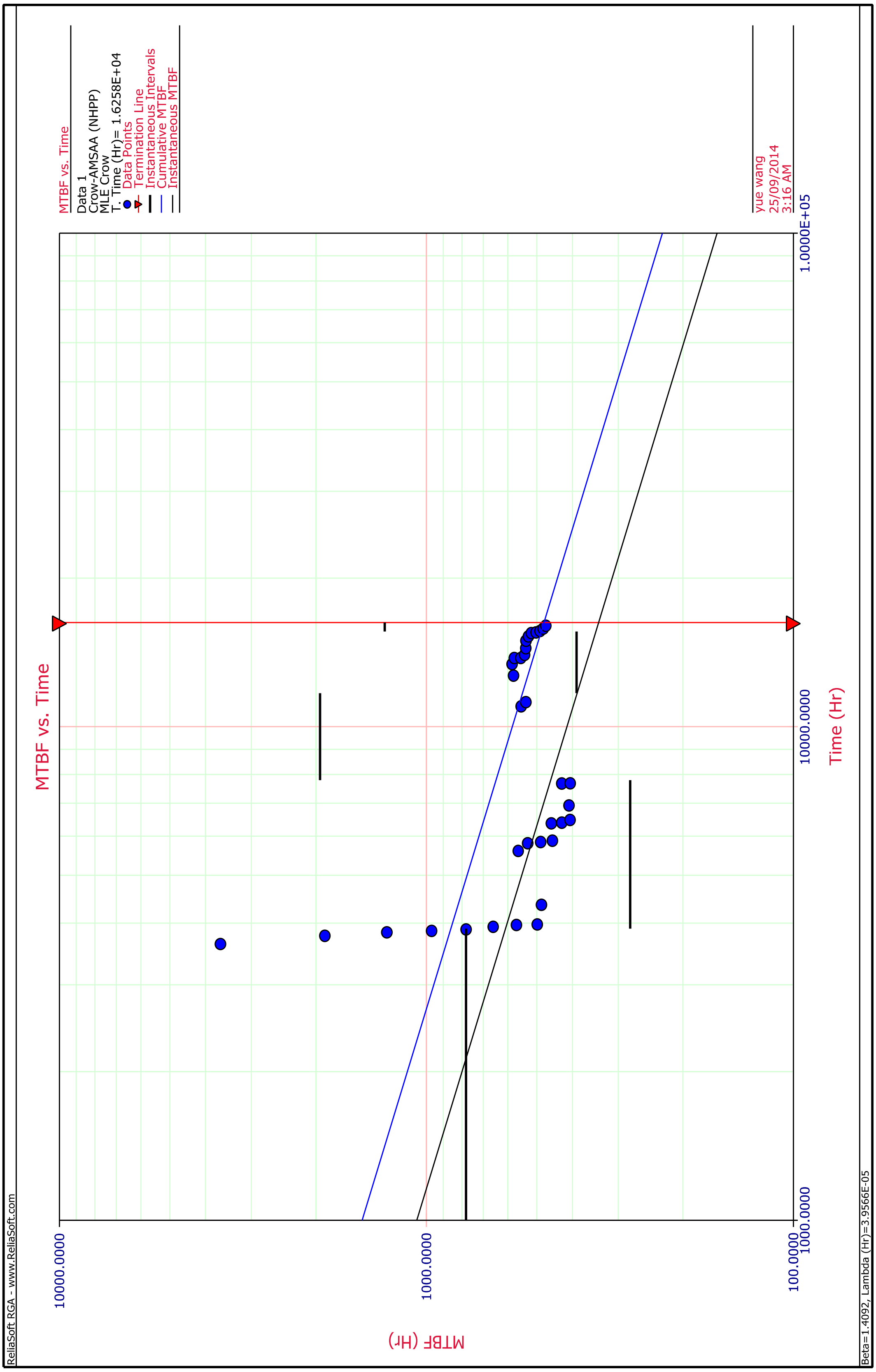

Figure A4.2.2 – MTBF vs. time of bulldozer critical component “ripper teeth”

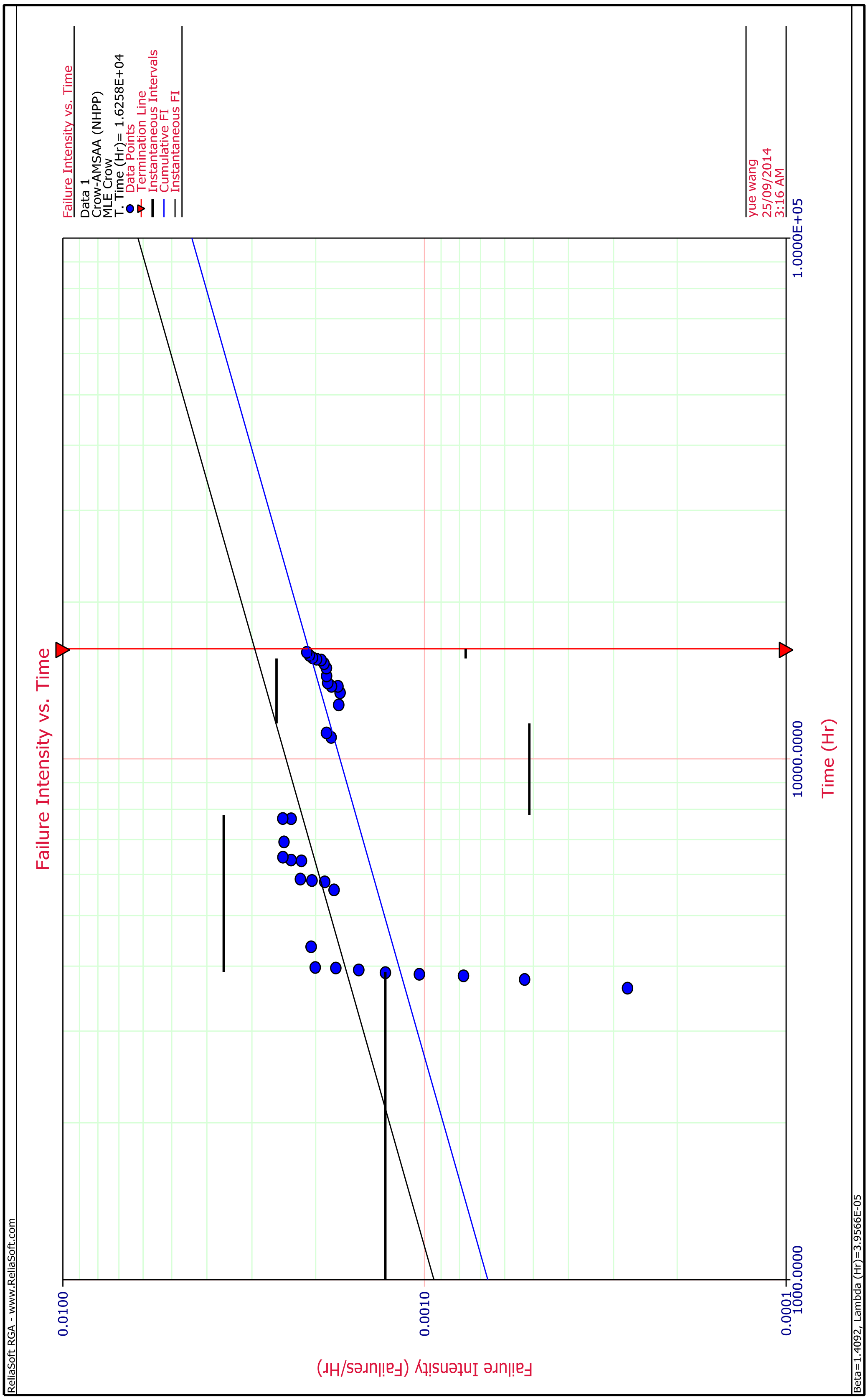

Figure A4.2.3 – Failure intensity vs. time of bulldozer critical component “ripper teeth”

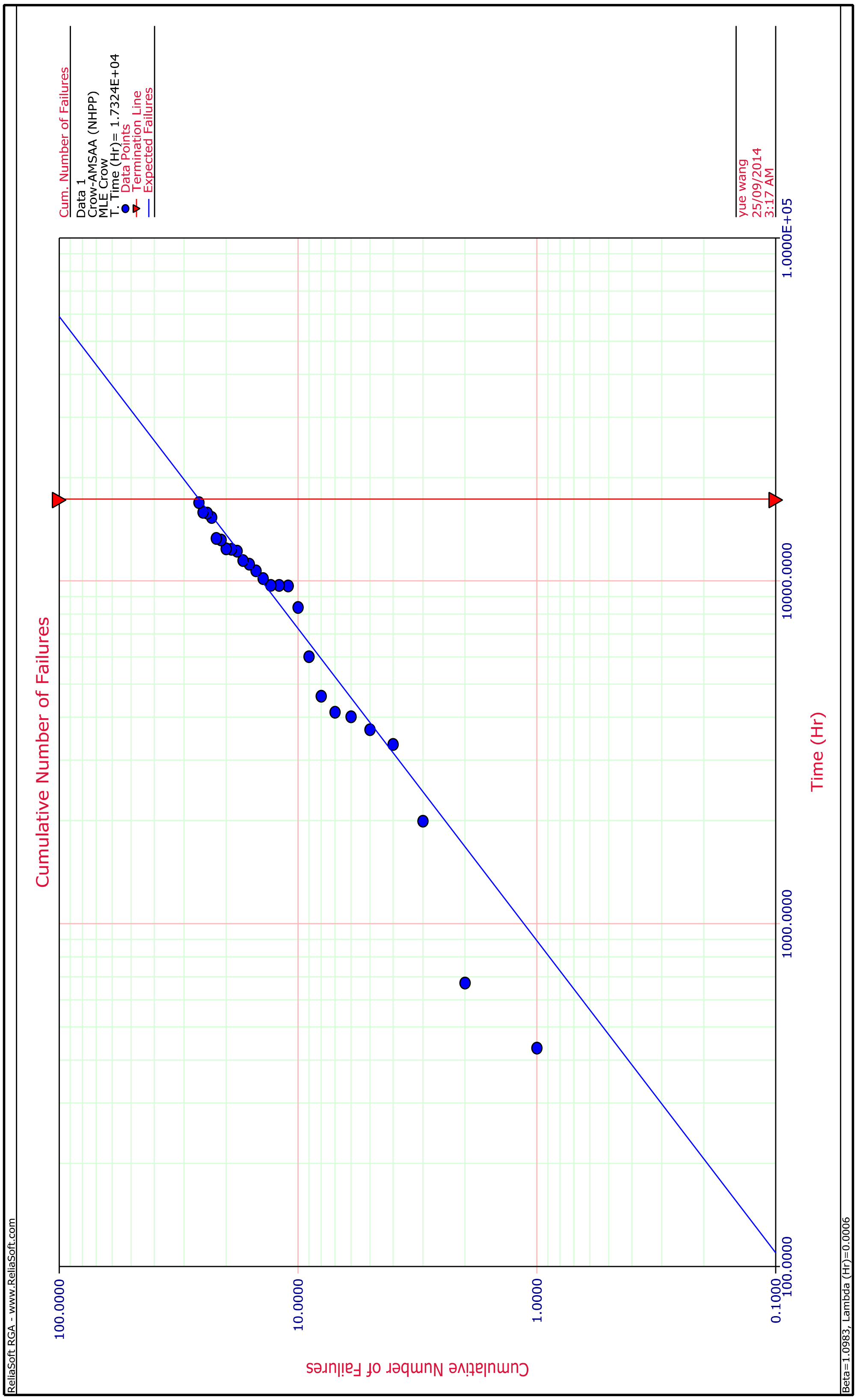

Figure A4.3.1 – Cumulative number of failures of bulldozer critical component "repair light"

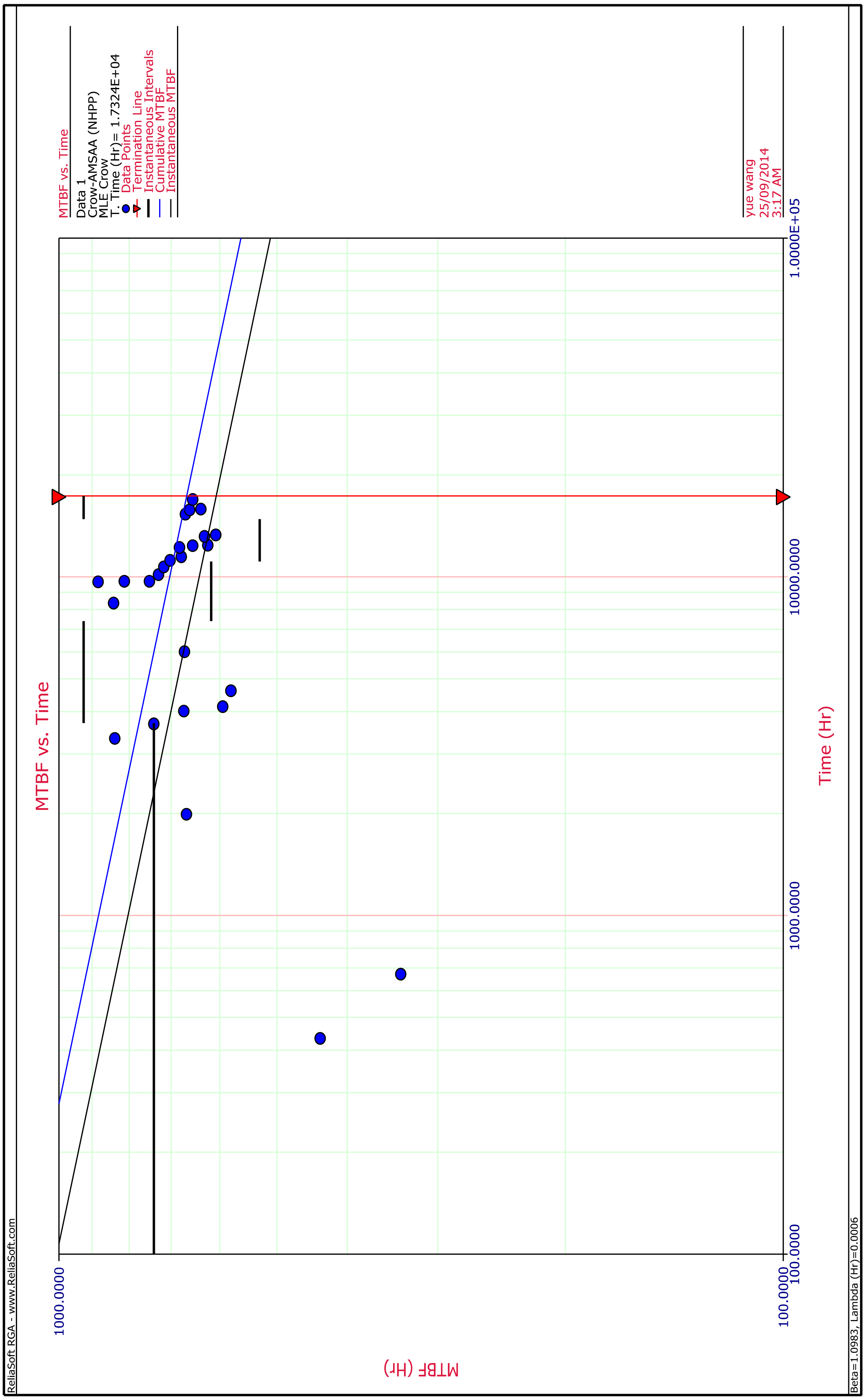

Figure A4.3.2 – MTBF vs. time of bulldozer critical component “repair light”

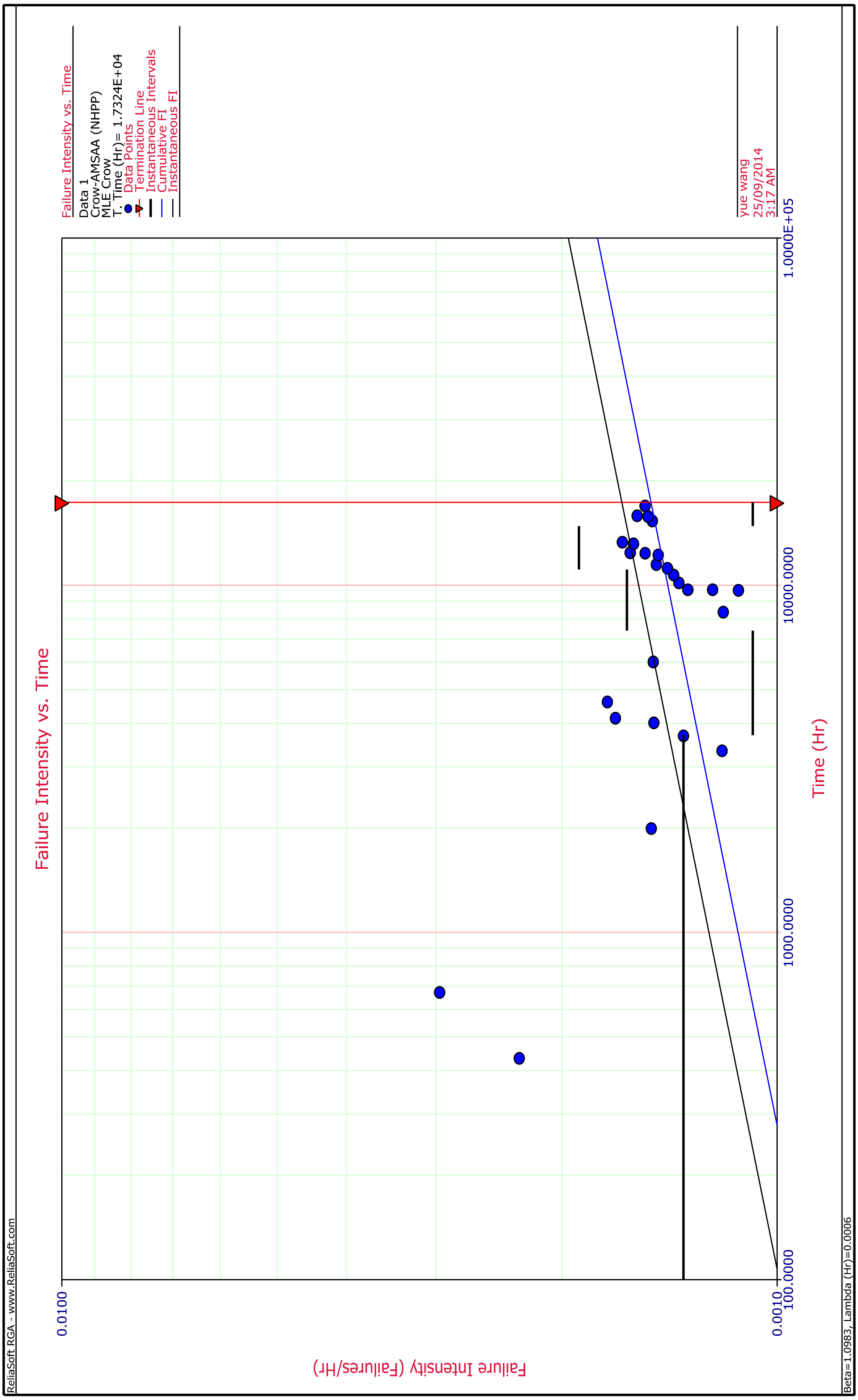

Figure A4.3.3 – Failure intensity vs. time of bulldozer critical component “repair light”

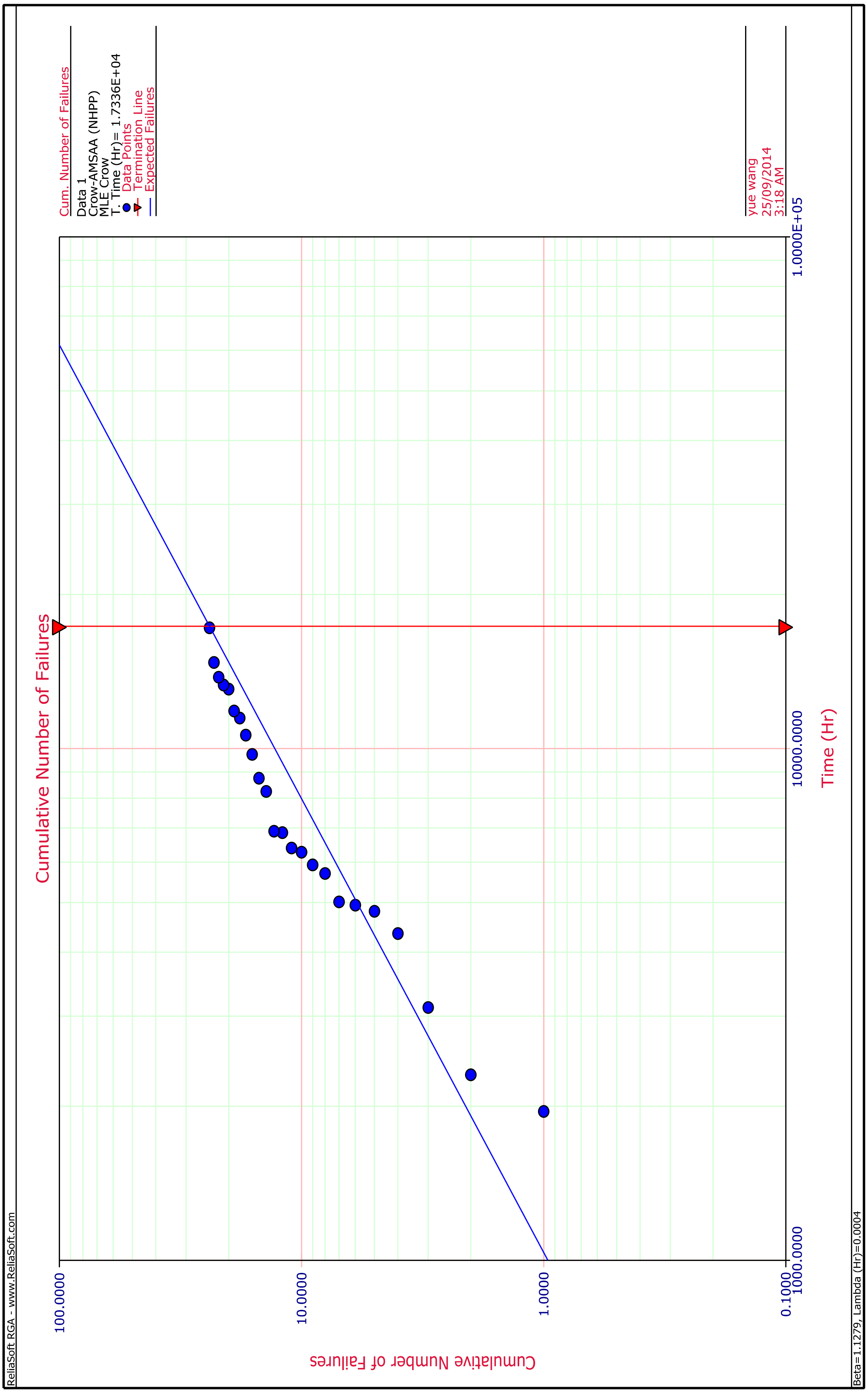

Figure A4.4.1 – Cumulative number of failures of bulldozer critical component “cab”

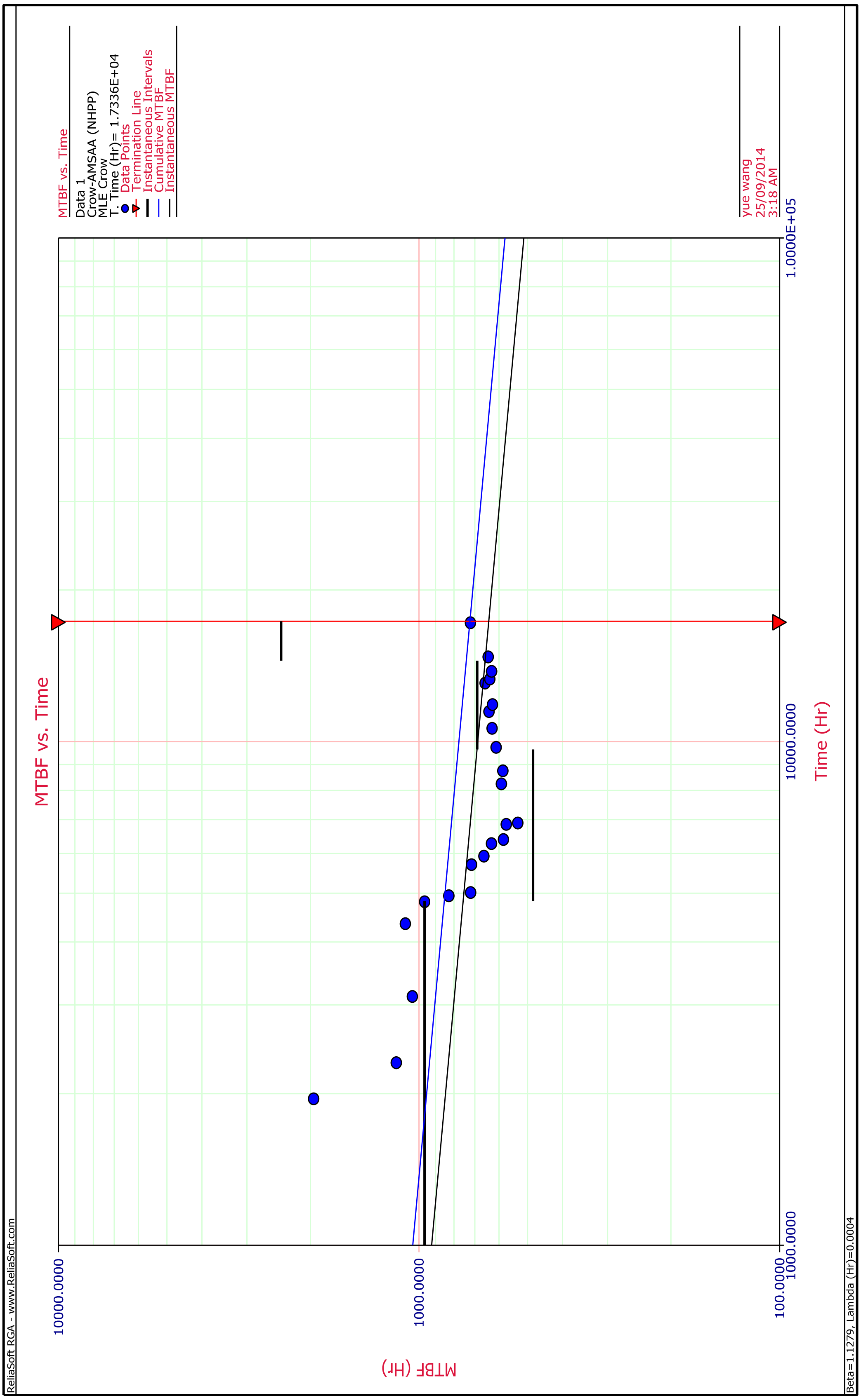

Figure A4.4.2 – MTBF vs. time of bulldozer critical component “cab”

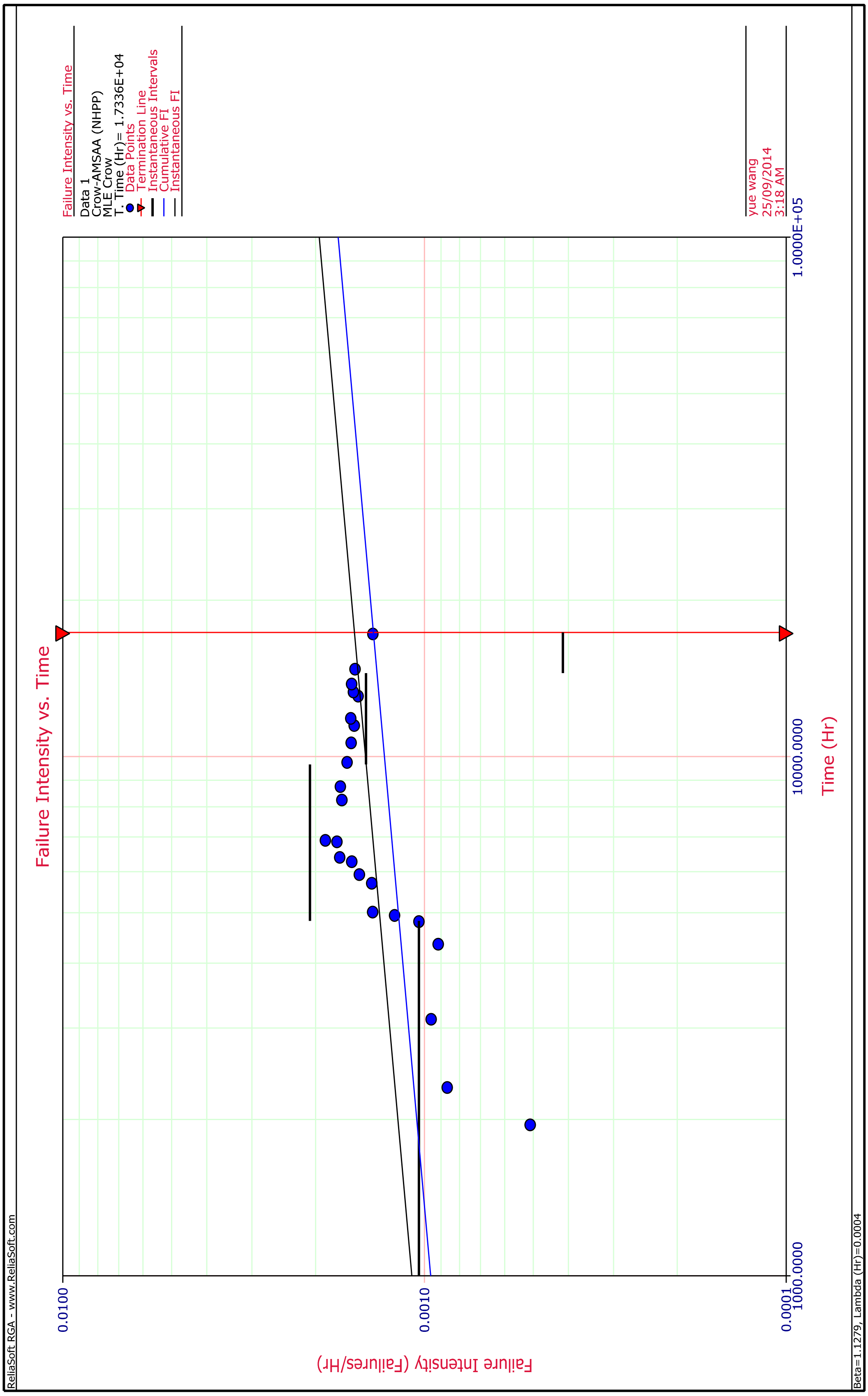

Figure A4.4.3 – Failure intensity vs. time of bulldozer critical component “cab”

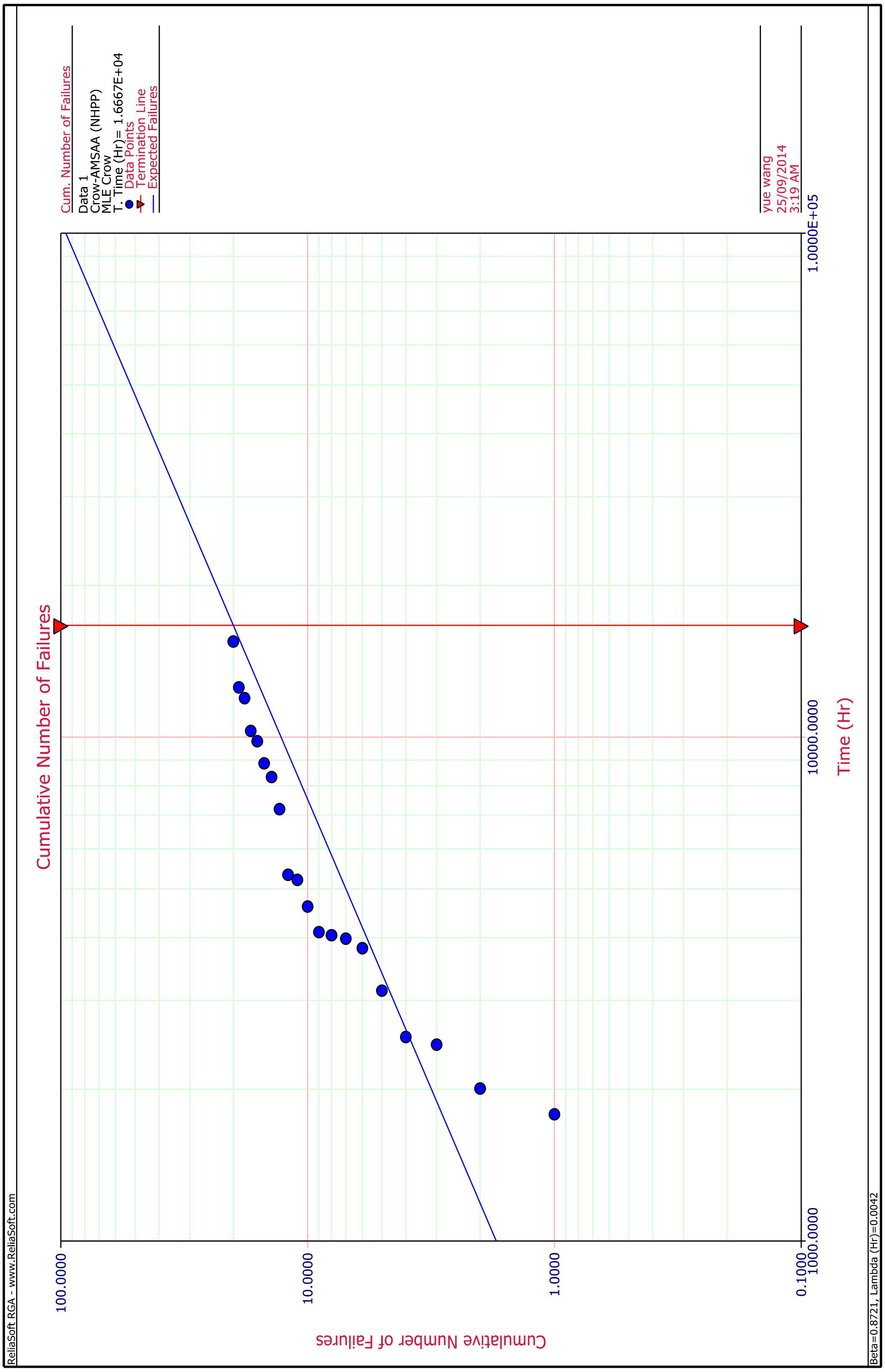

Figure A4.1.2 – Cumulative number of failures of bulldozer critical component “electrical”

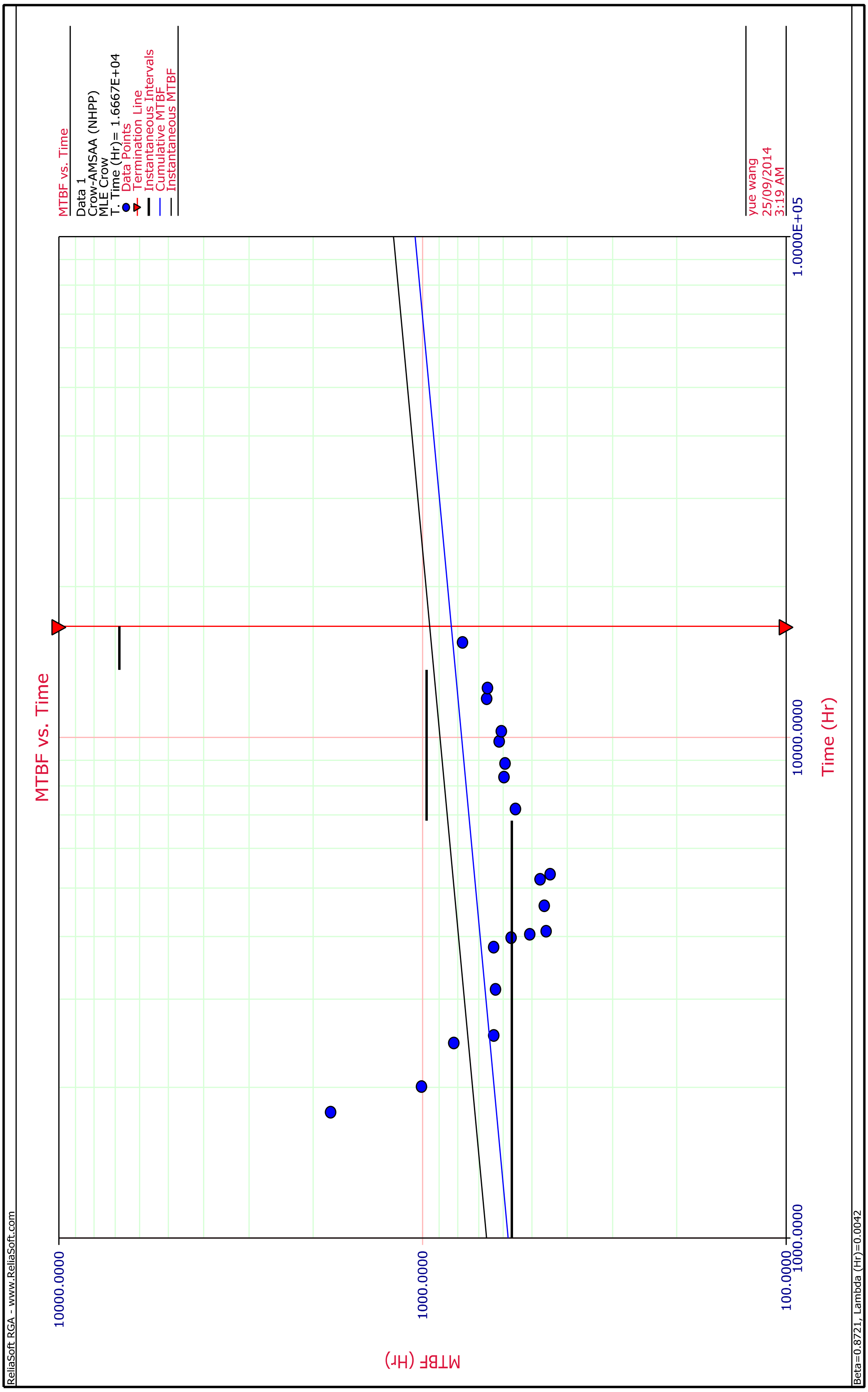

Figure A4.5.2 – MTBF vs. time of bulldozer critical component “electrical”

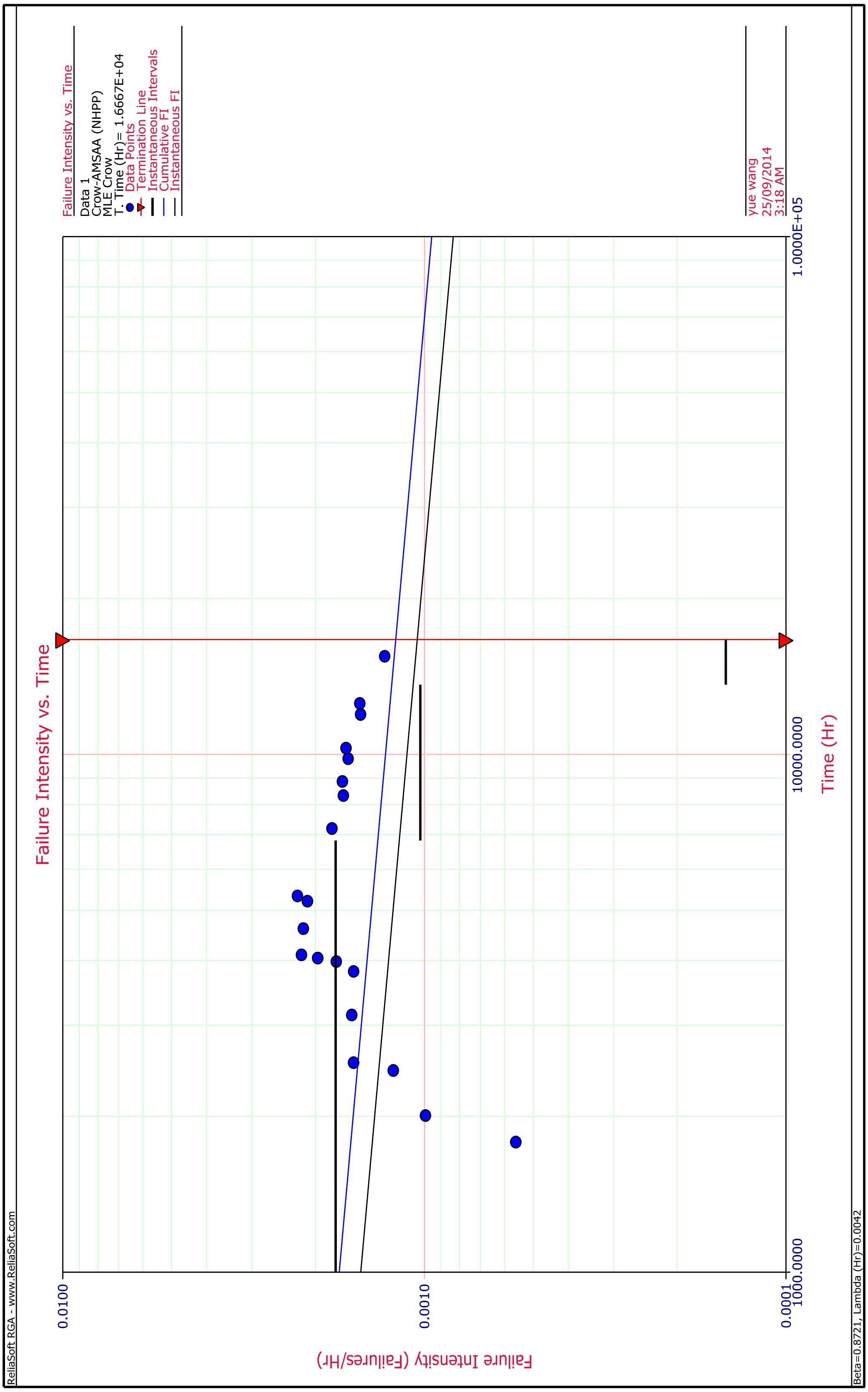

Figure A4.5.3 – Failure intensity vs. time of bulldozer critical component "electrical"

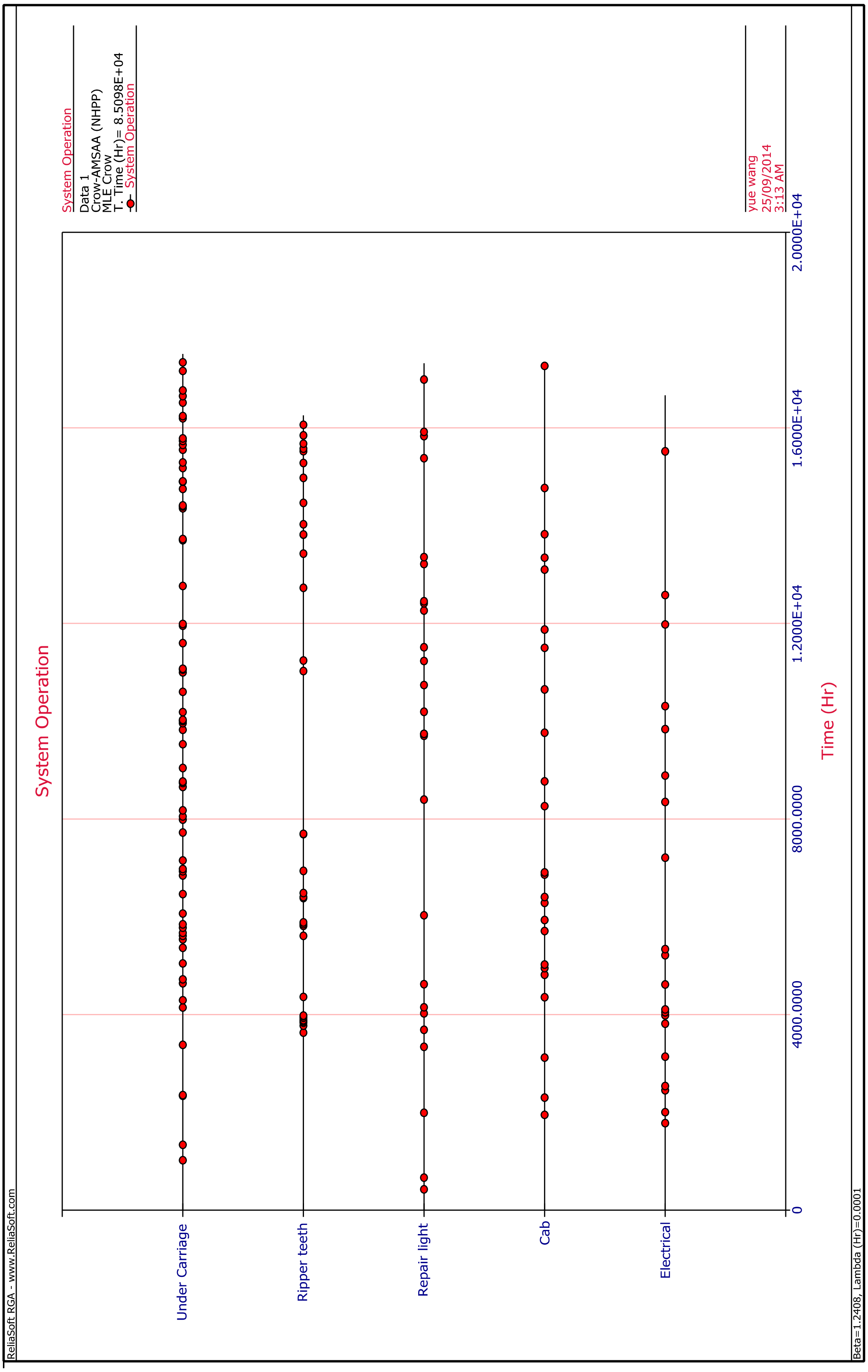

Figure A4.5 – System operation of construction equipment bulldozer

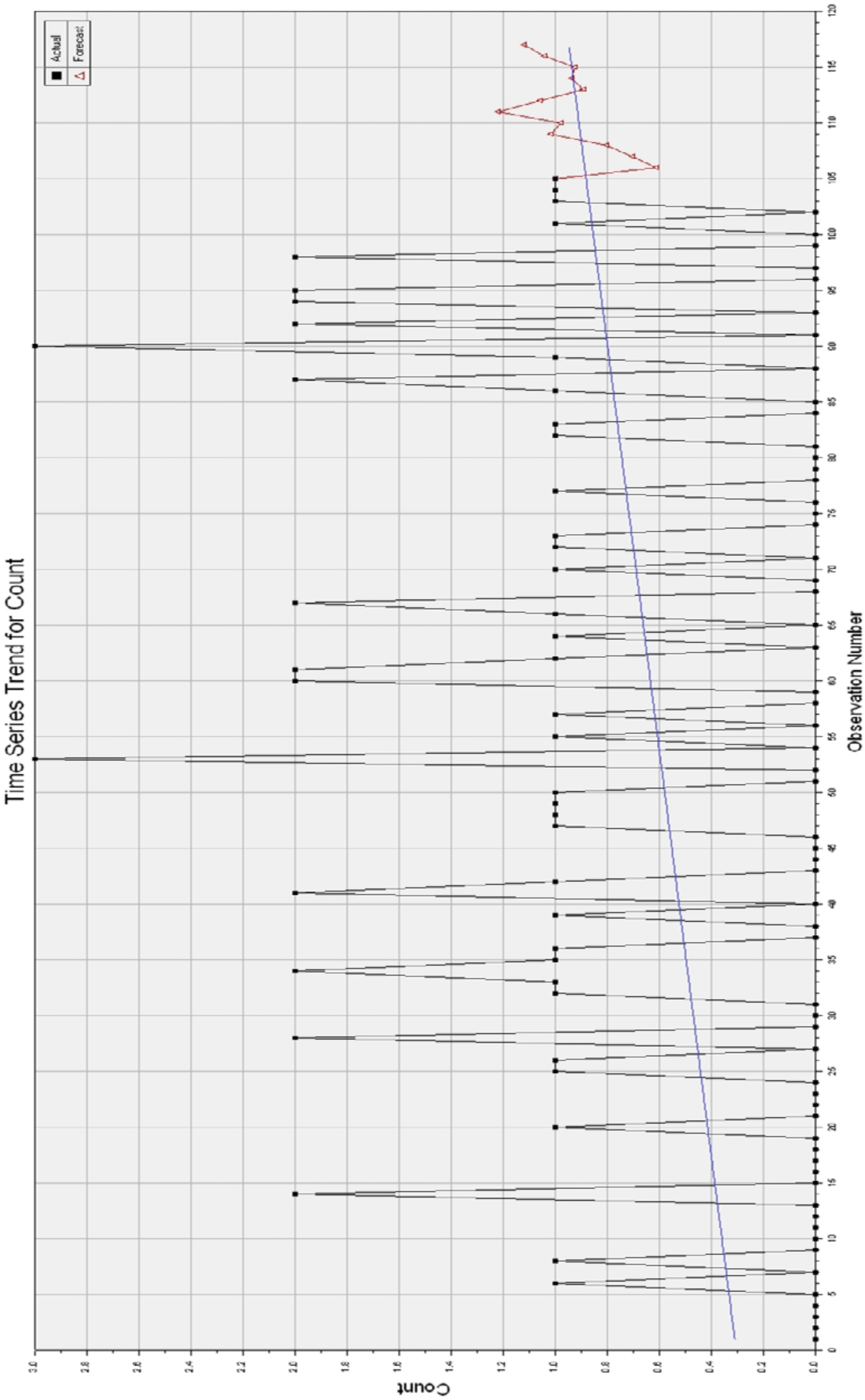

Figure A5.1 – Prediction of number of failures of the critical component undercarriage of construction equipment bulldozer

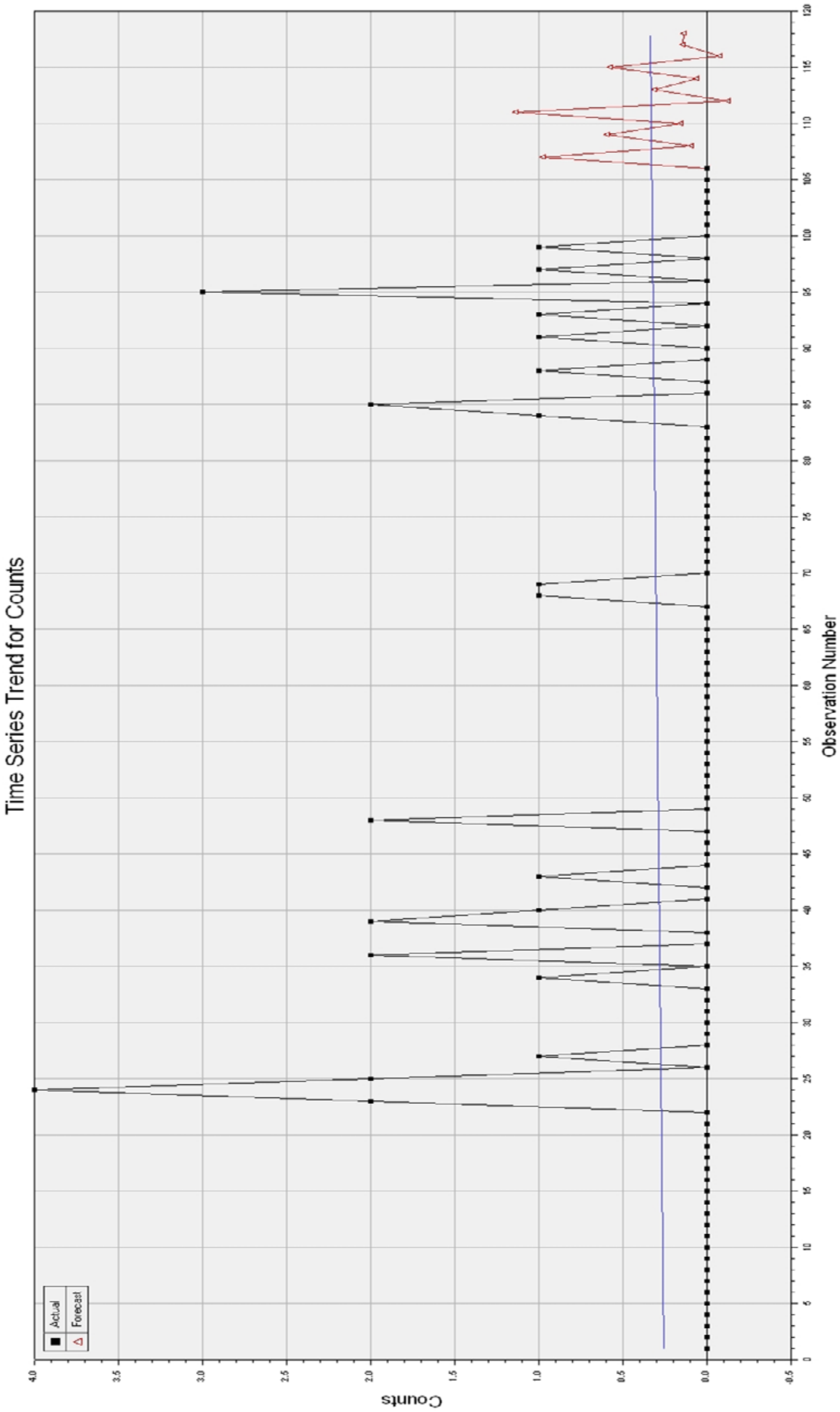

Figure A5.2 – Prediction of number of failures of the critical component ripper teeth of construction equipment bulldozer

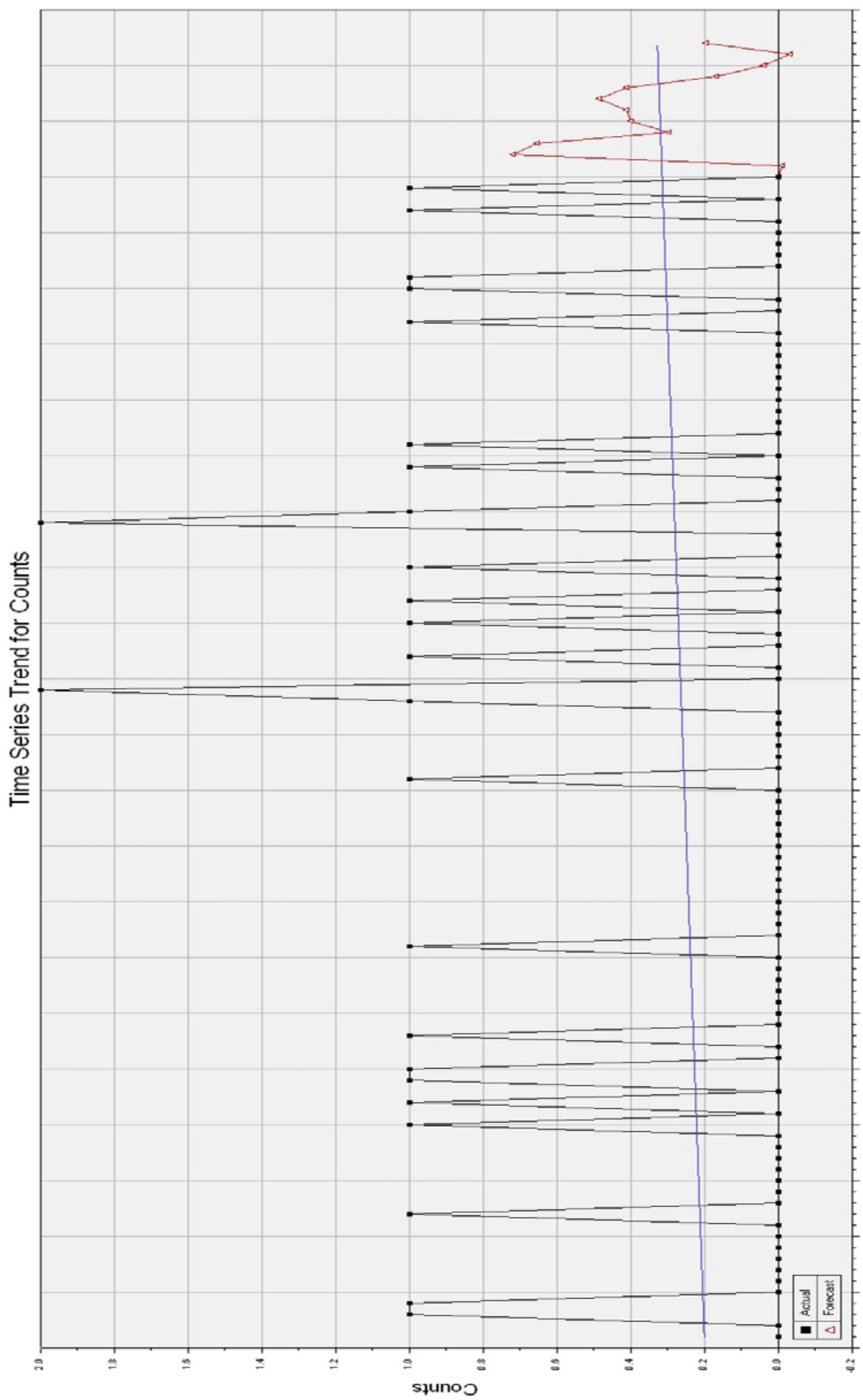

Figure A5.3 – Prediction of number of failures of the critical component repair light of construction equipment bulldozer

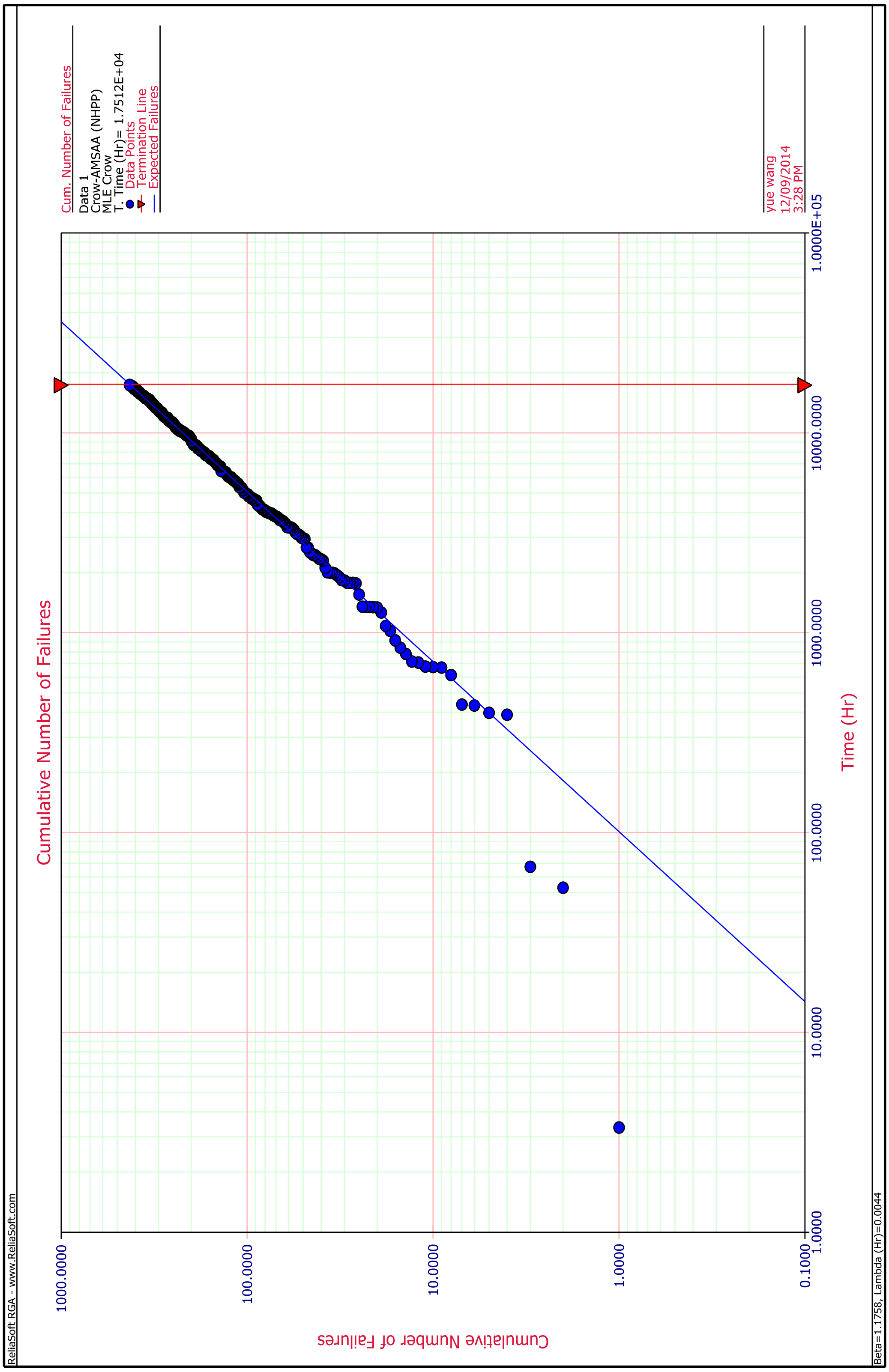

Figure A6.4.1 – Cumulative number of failures of construction equipment bulldozer

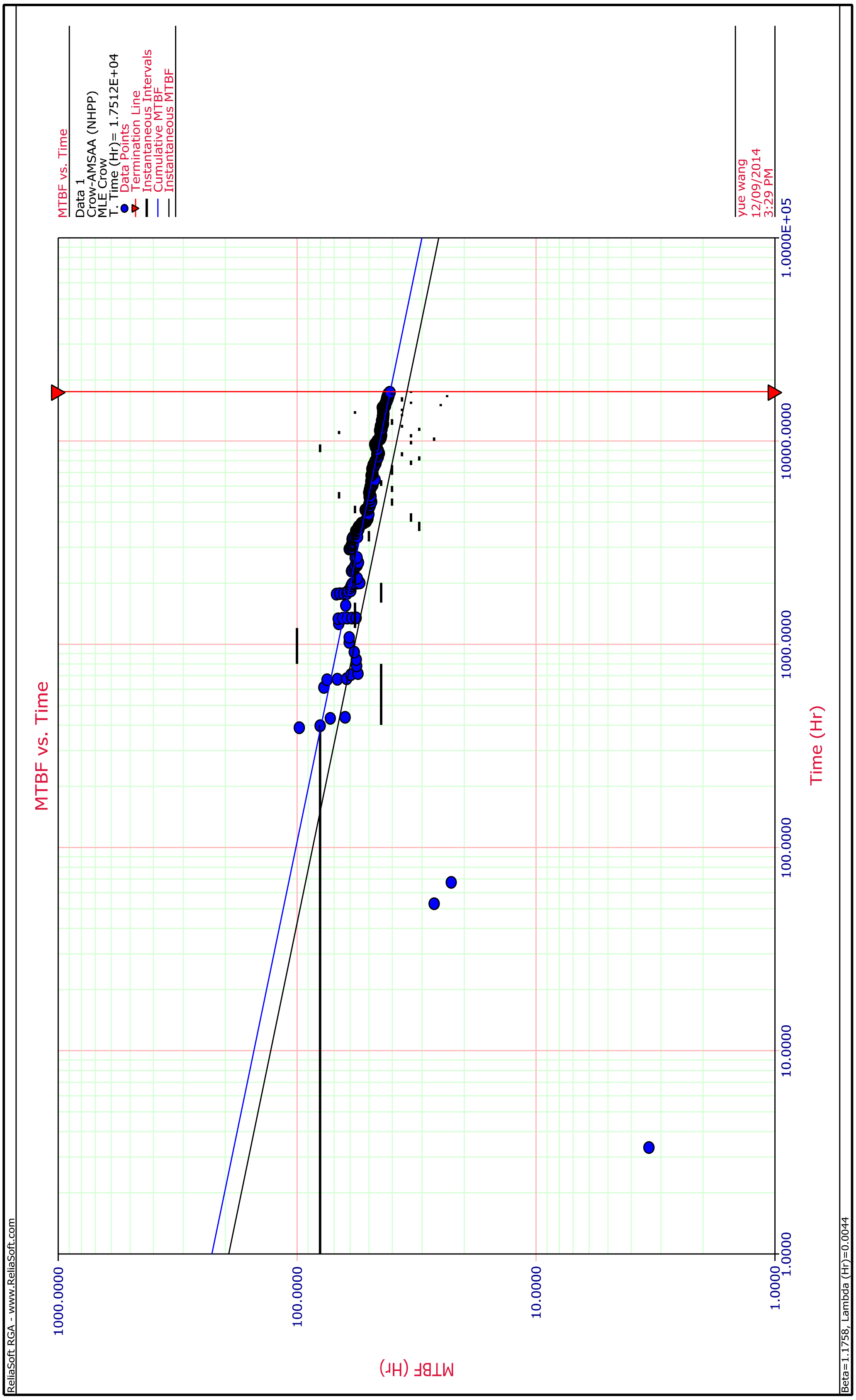

Figure A6.4.2 – MTBF vs. time of construction equipment bulldozer

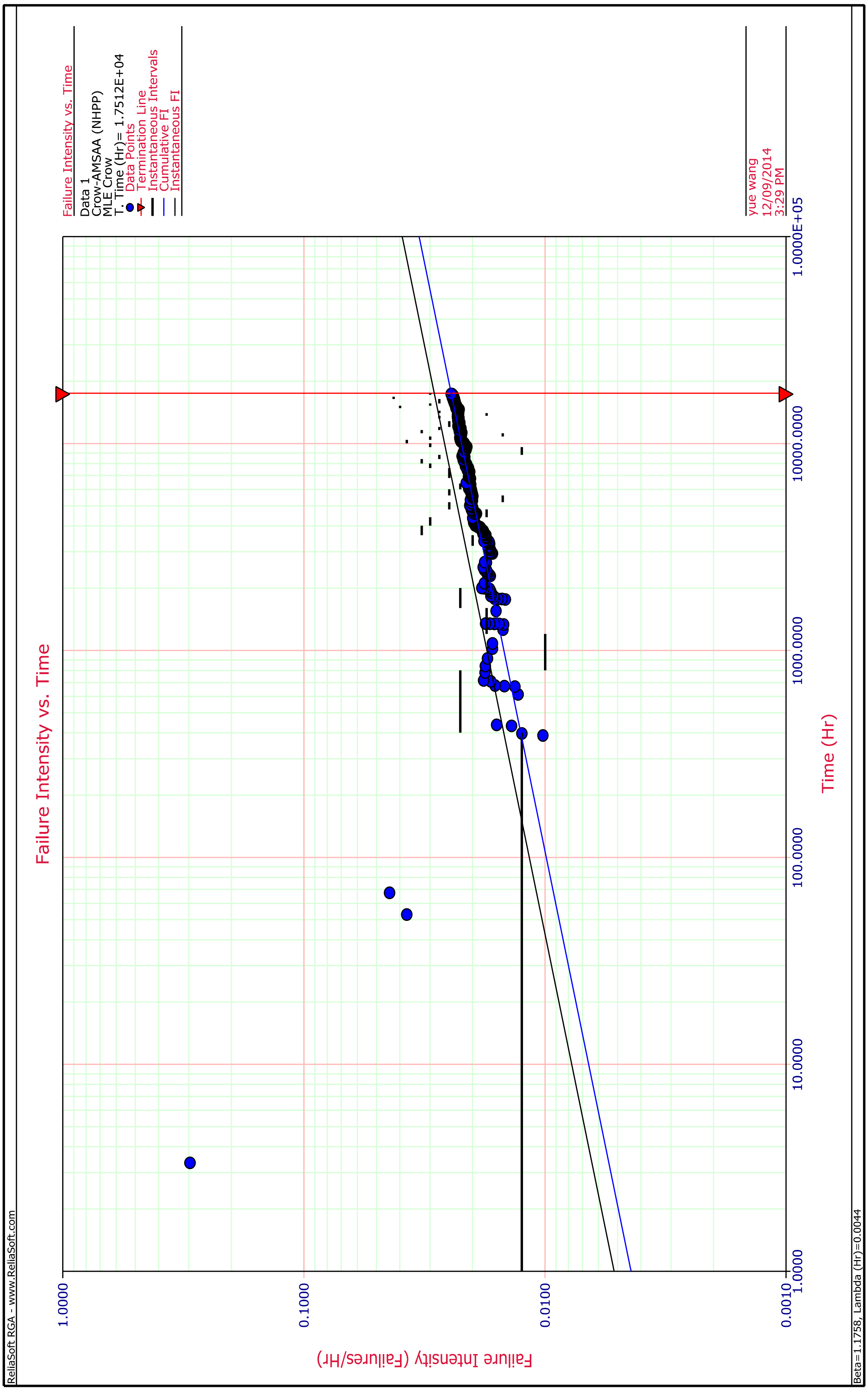

Figure A6.4.3 – Failure intensity vs. time of construction equipment bulldozer

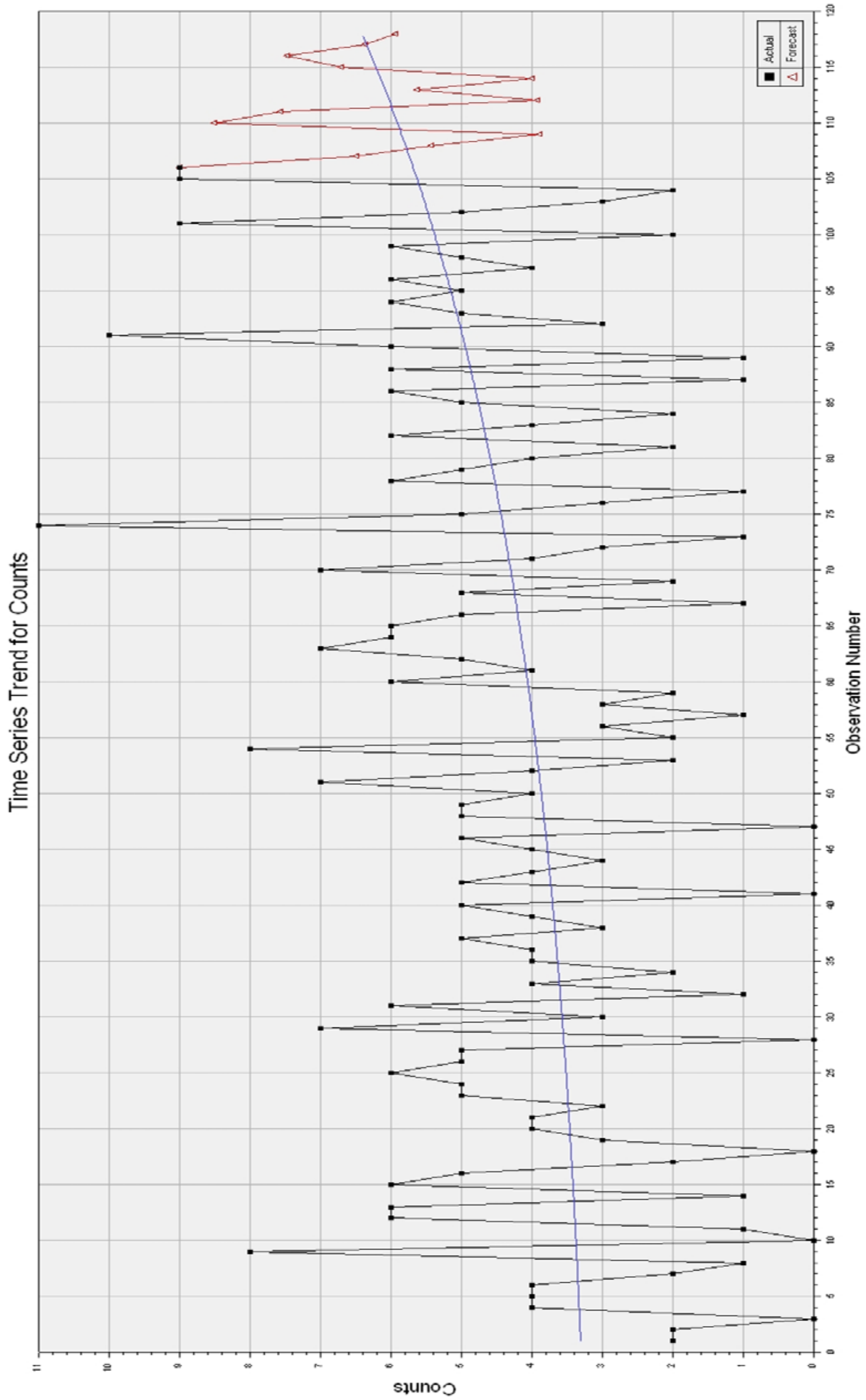

Figure A7.4.1 – Prediction of numbers of failures of construction equipment bulldozer

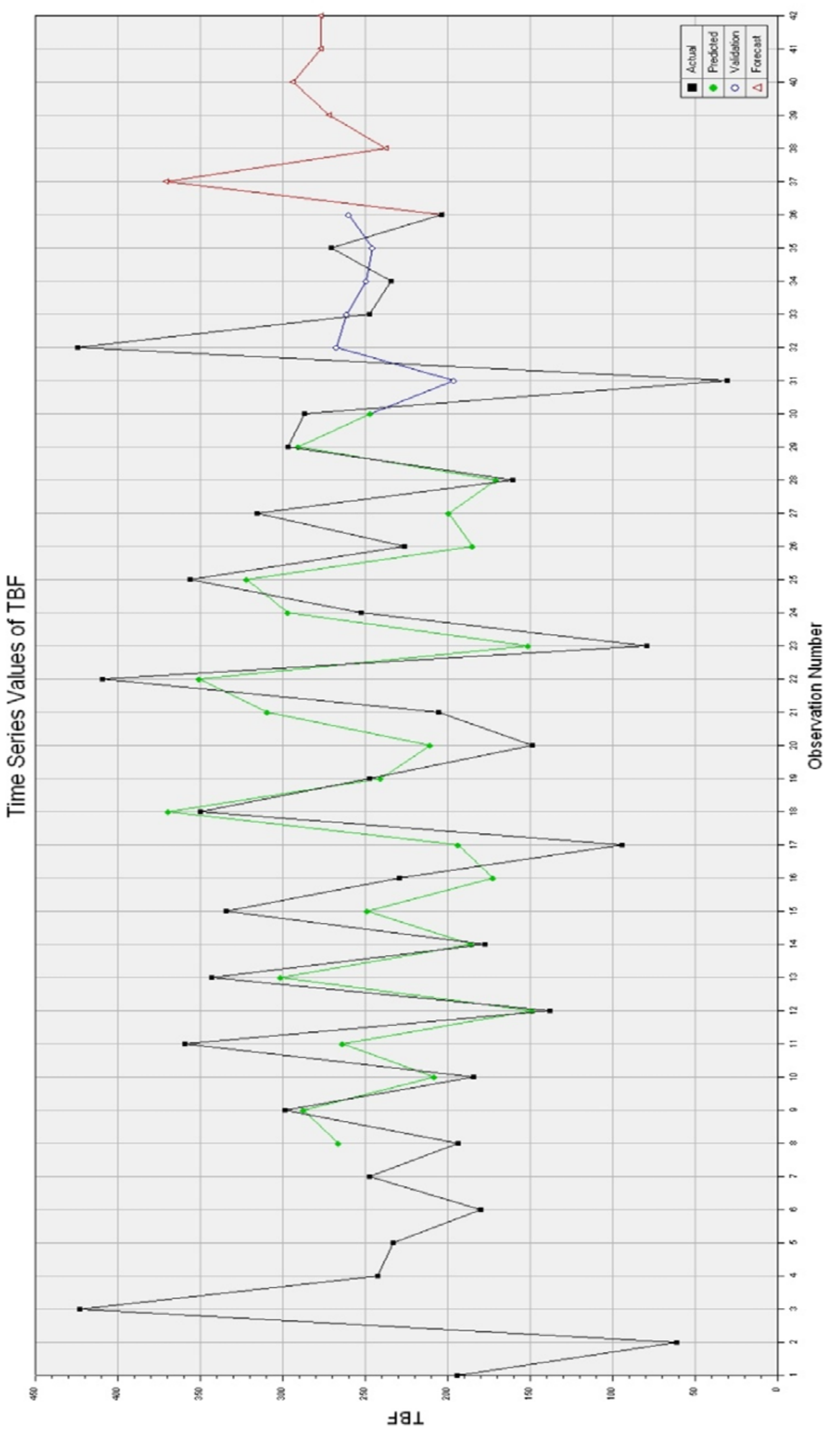

Figure A7.4.2 – Prediction of TBF of construction equipment bulldozer

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