Forecasting the Risk of Rail Service Failures Between Successive Rail Inspections using Hazard Based Models

by

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February 2018

A thesis submitted to the faculty of the Graduate School of the University at Buffalo, State University of New York in partial fulfillment of the requirements for the degree of

Master of Science

Department of Industrial and Systems Engineering
Acknowledgements

I would like to express my gratitude for my thesis advisor, Dr. Qing He for his constant support, guidance and patience. He was constantly guiding me whenever I ran into a trouble spot or had a question about my research or writing. I am thankful for his direction, devotion and encouragement that kept me stay focused on my research.

Finally, I must express my profound gratitude to my parents and to my friends for providing me with unfailing support and continuous encouragement throughout my years of study, through the process of researching and writing this thesis. This accomplishment would not have been possible without them. Thank you.
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Abstract

Service failure is defined as an incident when a defect of the size over the threshold value is noticed and the track is taken out of service. Service failures are of a major concern for the railroad due to its impact on economical and safety aspects of the rail company. Despite of the effective inspection strategies developed by the railroad, service failure may still occur in their network because of the growth of an undetected defect or the defect that is initiated after an inspection. Various factors influence the growth rate of the defect, causing an service failure. Identifying and understanding these factors on the occurrence of failure will assist in accurately predicting the risk of a service failure. This thesis develops an Accelerated Failure Time (AFT) model using the data collected from one of the Class-I railways during the period from 2011 to 2016. Different distributions of the hazard function are evaluated and the log-normal distribution is found to be the best fit. This study identifies the following factors: Past rail defects, past geo-defects, number of days from the last grinding, product of rail age and degrees of curvature and infrastructure related data such as number of turnouts, grade of the rail and the rail segment length to influence the failure time of the rail. Temporal transferability is performed using the data collected in year 2016 and it is found that the estimated parameters are stable over time. The results of this study are useful for railroads to develop efficient strategies in rail inspections and preventive maintenance.

Keywords: Rail service failure, Rail break, Accelerated Failure Time (AFT) model, Hazard model, Survival Analysis
Dedicated to my family and friends...
Chapter 1

Introduction

1.1 Background

Railways play a major role in the freight transportation of Northern America due to its economic advantage for bulk shipments. Safety is of utmost priority for railways as train derailment cause severe unforeseen consequences and potential loss of both life and infrastructure. Fatigue and other failure mechanisms initiates defects in the rail. These defects grow in size during the regular rail operations and may lead to complete rail breakage, when unnoticed (Podofillini et al., 2006). But, when railways notices an defect with size over the threshold value, they will take the rail segment out of service. These incidents are defined as service failures. Broken rails, as a major type of service failure is a leading cause of derailments (Dick et al., 2003). Broken rails cause an average cost of $525,000 per incident due to the damage of track and equipment (Schafer and Barkan, 2008b). Moreover, the additional expenses incurred to Class I railways due to the service
interruptions caused by service failures is found to be $17 million \text{ (Schafer and Barkan, 2008b)}$. Due to its economic and safety impact on the railway operations, a service failure is extremely undesirable in the railway network. Railroad carries out several preventive measures to avoid a broken rail in their network as it not only leads to a derailment but also causes service interruptions.

A internal or the surface defect in the rail potentially leads to a service failure. Railroad follows effective inspection strategies to detect these defects in the rail using ultrasonic inspection devices and take the required action to prevent it’s growth. Every railroad inspects their rail network at regular intervals in accordance with the U.S Federal Rail Administraion (FRA) regulations. However, due to the accuracy of the equipment or the undetectable size of the defect makes it unnoticed during the inspection. These defects grow in size with the accumulation of tonnage and thus lead to a service failure, when its size is greater than the threshold value. In addition, other factors such as the presence of geo-defects, grinding interval, rail characteristics and the infrastructure will further accelerate the failure time, resulting in a service failure sooner than expected. Understanding the effect of these factors on the survival time is important to reduce the risk of a service failure with the additional tonnage.

1.2 Objective

The objective of this thesis is to develop a reliable prediction model that accurately account the influence of various factors on a service failure and further predict the
probability of the occurrence of a service failure. Moreover, it also aims to identify the significant factors that cause the occurrence of a service failure.

This objective is achieved using survival analysis by accounting the impact of co-variates on the tonnage until a service failure. Thus, the developed model will assist the railroad to predict the probability of the rail segment surviving from a service failure, by inputting the values of co-variates.

Following are the steps undertaken in this study:

- Accelerated Failure Time (AFT) model is developed using the data that was collected during the period from 2011 to 2015.

- Four different distributions namely exponential, weibull, log-normal, log-logistic were tested for the best fit of hazard function with the data.

- Both the parameters of the distribution and the variables are calculated for the maximum likelihood of the data under consideration.

- To better understand the effect of individual variable on the survival probabilities, sensitivity analysis is conducted.

- Temporal transferability analysis is performed to justify the applicability of the developed model to predict survival probabilities over time using the data collected in the year 2016

This thesis includes the following contributions:

- For the first time, we study the probability of occurrence of a service failure using AFT model.
• This study identify the following significant factors: Past rail defects (in three years), past geo-defects (in three years), number of days from last grinding, product of rail age and degrees of curvature, number of turnouts, grade of rail and the segment length

• This study perform multiple data fusion processes from various long-term datasets obtained from the railroad that include Tonnage data, inspection schedules, rail defects data, geo-defects data and the data on infrastructure related features such as Rail laid dates, Curvature, Grade and Turnouts.

1.3 Thesis Organisation

The remaining of this thesis is organized as follows. Chapter 2 briefly presents the previous research on the prediction of rail break. Chapter 3 discusses the structure of the data and the steps taken to prepare the final data table, while presenting a few insights of the data. Chapter 4 focuses on the methodology of accelerated failure time models. Chapter 5 presents the experimental results of the model, results of sensitivity analysis accounting the influence of a few important factors and discusses on the temporal transferability of the developed model. Finally, the conclusion and the future scope are discussed in Chapter 6.
Chapter 2

Literature Review

Railway companies are working towards maintaining higher standards of safety by minimizing the risk of derailments. The analysis performed on the FRA data on derailments indicates that the average number of bogies derailed due to rail defects are very high compared to the derailments occurred due to other causes (Dick et al., 2003). Thus, broken rails will derail a higher number of bogies that will cause severe damage to the infrastructure and may also lead to a human loss. Also, a minimal or no service interruptions are desired by a rail company as any delay of the scheduled trains will lead to a loss. Prediction of rail breaks will assist the railway companies to avoid possible derailments and to minimize the service interruptions caused by broken rails. Further, resources can be allocated optimally for the inspection or preventive maintenance of predicted rail breaks. The fact that a rail break is dependent on various factors such as rail age, gross tonnage, the degree of curvature, etc. will allow us to predict the rail break. Although there were many prediction models proposed in the literature, a further research is being
carried out to develop a prediction model that helps in predicting the severity of the rail breaks.

2.1 Rail Break Prediction Methodologies

Various methodologies that have been adopted in the previous studies is presented in the following sections.

2.1.1 Multi-Variate Statistical Analysis

(Dick et al., 2003) presented a parametric discrete choice logit model to predict the locations of the rail break, which was developed using 2 years of rail data. A step-wise regression was used to select the variables and found that the data on rail characteristics, operational information and infrastructure were significant in predicting the rail breaks. The average dynamic loading which should have a positive correlation with breaks had a negative correlation in this model as it lacks the consideration of a few other significant factors. This model did not provide a desired accuracy when tested on the latest service failures data (Schafer and Barkan, 2008b), due to the availability of limited data. So, another model was proposed by the later author by considering a few other factors that had considerable correlation with the rail break, using four years of rail data. These factors include inspection data, infrastructure data, past geometric defects and past rail defects data. Four techniques of variable selection were evaluated and the simple regression model is chosen for the prediction of rail breaks as it was
found to best fit with the test data. While the cumulative tonnage itself will well explain the breaks, consideration of other factors that also correlate with the breaks will improve the prediction accuracy. For example, considering the rail characteristics is important as the crack propagation per fatigue cycle is greater in lighter rail than in the heavier rail. Inspection data will be helpful in increasing the accuracy of predicting rail breaks, as the repair of the detected cracks will limit the growth of crack and increases the useful rail life. So, the later model could better predict the rail break than the former.

2.1.2 Non-Linear Models with Neural or Fuzzy Logic

The non-linear interaction of variables will not be explained by the pure statistical models. To study the non-linear nature of the predictive model, Schafer has employed the Artificial Neural Network (ANN) model to predict the rail break. The ANN would result in discrete values of either a failure or non-failure and does not give any probability value for the break associated with any particular segment. The ANN model resulted in higher accuracy in predicting the breaks than the pure statistical model developed in (Schafer and Barkan, 2008b). ANN would consume a lot of time in the initial learning phase, which makes it not a viable model for studying the large datasets. So, two other hybrid models were developed in (Schafer and Barkan, 2008a) and evaluated for the accuracy. In one of the models, only the significant variables from the previous logit model were provided as inputs to the ANN model as to reduce the time it consumes in learning during the initial phase. In the other model, the probability obtained in the logit model is
given as a parameter to ANN along with the other factors that lead to rail break. Both these models resulted in a higher accuracy than the pure statistical model. However, only a slight difference of about 1-2%, in correctly predicting the breaks, is observed with these two models. Another research (Vesko\v{c}i\v{c} et al., 2012) used the Fuzzy logic method to model the non-linear interaction between the factors effecting the rail break with the limited data. An unique important factor that was considered in (Vesko\v{c}i\v{c} et al., 2012) is the climatic conditions, which the other researchers could not consider due to lack of the data. This model could predict the rail break approximately near to the actual breaks with the limited data, by considering the temperatures at the time of rail break.

2.1.3 Probabilistic Distribution

In both (Chattopadhyay and Kumar, 2009) and (Kumar, 2006) the distribution of rail breaks was found by fitting the data with standard distributions. While it was found that both Weibull and Normal distributions are the best fits, Weibull distribution was preferred over the normal distribution to predict the rail breaks, as it is flexible to adjust with any changes in the data. These parameters were estimated using maximum likelihood estimation. The PDF of the distribution is represented in terms of the cumulative tonnage, which better explains the pattern of rail breaks. However, the other significant factor - rail age was not considered. Different distributions were presented for different seasons and different rail types. Therefore, an appropriate distribution should be chosen first as to predict
a rail break. This increases the complexity of the model, as with many varying parameters we will have one distribution for each combination.

2.1.4 Markov Process

The crack initiation and propagation is a stochastic process which depends on various factors and the transition from one state to other is highly correlated with the preventive measures taken to avoid the failure. A Markov Decision Process was modelled in (Zhao et al., 2007) as to predict the risk of derailment caused by broken rails. As welding defects, inspection, fatigue defects and rail grinding will have an effect on the rail break, four sub models accounting all these factors were integrated into one model to evaluate the risk of derailment caused by broken rails. It was observed that the risk due to weld defects was increasing with the cumulative gross tonnage that a rail has been carried. Also, there is a chance of missing the detection of a few cracks during the Ultra Sonic inspection due to high wagon speed or the expansion of the crack during summers, which will in turn increase the likelihood of a rail break. Thus, the detection rate was accounted into the model (Zhao et al., 2007). While, the preventive grinding procedure will help in reducing the propagation of surface cracks, it will decrease the chances of rail breaks caused by surface cracks. The other model proposed in (Bai et al., 2015) is used to predict the remaining life of the rail. Another Markovian model presented in (Podofillini et al., 2006) classifies the failures into three categories: the cracks that were not detected by the Ultrasonic Inspection Wagon, the cracks which were under observation but propagate to cause failure before the inspection
interval during the period of observation, and the cracks that were decided to be repaired but cause the failure before they were repaired. Unlike (Zhao et al., 2007), (Podofillini et al., 2006) considered all these 3 cases to well model the real-time scenario of the crack propagation. All these states had different transition rates and depended on the factors such as cumulative tonnage, rail age, inspection frequency, etc. that cause a rail break. The expected number of rail breaks is dependent on the inspection strategies as the inspection interval will determine the transition rates that lead to the current state of the crack. Thus, the effect of preventive measures, missing the detection of cracks, weld defects and the fatigue failures will have an effect on the rail break.

2.1.5 Estimation of Number of Rail Breaks Between Two Inspections

A study has been conducted using 10 years of data to model the rate of growth of crack propagation of the defect using mechanical properties in (Orringer et al., 1988) and (Orringer, 1990). This study was a part of the Rail Integrity program that was sponsored by FRA, to deal with the prevention and control of rail failures. A equation to estimate the number of rail breaks that may occur between two inspections intervals was given based on the tonnage and inspection interval. Further, this equation was used to optimize the inspection interval in (Liu et al., 2014).
From the literature it can be seen that rail age, gross tonnage, degree of curvature and the temperature are highly significant factors that can explain the rail break. Although a number of studies has been conducted to predict the rail break, most of these studies did not have the complete rail data. While both the studies of (Dick et al., 2003) and (Schafer and Barkan, 2008b) had the rail data, it was of a very short range of about two to four years. Moreover, they had overlapped the failure segments with an equal number of non-failure segments due to the rare occurrence of rail break, resulting in a loss of a large chunk of the useful data. The study in both (Orringer et al., 1988) and (Orringer, 1990) considered 10 years of data. However, their research was based on mechanical properties of the rail rather than the statistical models. Survival analysis and accelerated failure time models were widely used in the literature of highway accidents in order to estimate the time to event of interest (Hojati et al., 2013), (Weng et al., 2014). Although (He et al., 2015) implemented survival analysis to assess the dynamic derailment risk, no research has been conducted till date to estimate the risk of rail break using survival analysis.
Chapter 3

Data Description and Preparation

North American Railroads collect a wide variety of data to better understand the condition and behaviour of various rail assets. This data is further used in carrying out preventive maintenance of the assets in order to improve the reliability and to minimize risks. Data plays a pivotal role in our study and it was obtained from a Class-I railroad of North America with revenue of $11.8 billion as of 2015. The data collected from their 21000 miles rail network for six years during the period 2011 to 2016, is used in this study. We collected 10 datasets including Tonnage, Ultrasonic Rail Inspection (USI) schedules, Rail defects, Service failures, Geometry defects, Grinding Schedules, Rail age, Curvature, Grade and Turnouts data as shown in Table.3.1. Individual sections are provided to present the summary of data fields, data cleaning and processing of the datasets that are used in this study.
Table 3.1: Datasets available for the study that were provided by railroad

<table>
<thead>
<tr>
<th>Data</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tonnage</td>
<td>Gross tonnage data of from period 2011-2016</td>
</tr>
<tr>
<td>Ultrasonic Rail Inspection Schedules</td>
<td>Schedules of the regular ultrasonic rail inspections</td>
</tr>
<tr>
<td>Rail Defects</td>
<td>The data of defects that were detected during rail inspections</td>
</tr>
<tr>
<td>Service Failures</td>
<td>Data of service failures occurred in the network</td>
</tr>
<tr>
<td>Geo Defects</td>
<td>Geometry defects that were detected by geometry car</td>
</tr>
<tr>
<td>Grinding Schedules</td>
<td>Regular grinding schedule data</td>
</tr>
<tr>
<td>Rail Age</td>
<td>Year during which the rail is laid</td>
</tr>
<tr>
<td>Curvature</td>
<td>Curvature properties of the curves present in the network</td>
</tr>
<tr>
<td>Grade</td>
<td>Slope of the rail</td>
</tr>
<tr>
<td>Turn Outs</td>
<td>Turnouts data of the rail network</td>
</tr>
</tbody>
</table>

3.1 Data Summary

Data was collected at a specific point on the track or on a smaller segments based on the type of measure. To uniquely identify any segment of the track in their network, the railroad uses prefix, track identifier, begin milepost and end milepost.

A prefix is a 3 alphabet coding system that distinguishes the routes/divisions and each prefix may have rail track covering more than one division. Track identifiers are used to differentiate between mainline tracks, sidings, single tracks, etc.

Milepost is used to spot the particular point on the track. While begin and end mileposts are used to spot the specific segment of the track.

The details of each dataset are presented in the following sections.
3.1.1 Tonnage Data

Tonnage is measured by dividing the entire network into several smaller segments with an average length of 1.74 miles. The length of these segments has a distribution as shown in Table. 3.2. To take an advantage of the fact that tonnage doesn’t change on the straight path except when the rail branches, these segments are divided with non-uniform lengths to avoid the entries where tonnage is identical. Gross tonnage, Foreign tonnage, Hazmat tonnage and Net tonnage that have passed on the segment is recorded every month. Every segment in the tonnage table is distinguished by using prefix, track type, begin milepost and end mile post. Figure. 3.1. illustrates the histogram of the gross Tonnage that has passed over these segments during the period 2011-2016.

![Figure 3.1: Tonnage distribution of the segments under consideration](image-url)
3.1.2 Ultrasonic Rail Inspection Schedule Data

Rail is subject to cyclic loads and rolling contact fatigue on every pass of the rail wagon. With the accumulation of tonnage, the induced stress will cause internal microscopic cracks in the rail due to the deformation of the material, while the rolling contact fatigue results in initiation of surface cracks. These cracks will grow in size with the following load cycles during regular rail operations. When the defect is not detected, cracks propagates along the rail and may lead to rail break.

A regular inspection is carried out by railroads using ultrasonic rail equipment, in order to detect these internal rail cracks/ defects and a necessary maintenance action is taken to avoid the propagation of these cracks (Podofillini et al., 2006). Every railroad inspects its rail in accordance with the FRA regulations.

3.1.3 Rail Defect Data

Various types of defects that are detected during the ultrasonic rail inspection are recorded in the Rail defects table. There are 26 different types of defects that can be found during this inspection. A necessary maintenance or repair action will be carried on the rail based on the type and severity of the detected defect. As the defect occurs at a certain point on the track, records in this table are identified using Prefix, Track type and the mile post at which the defect is found. In this study, the side at which the defect occurred is not considered as we treat both the
sides of the track as a single line. The top five rail defects that occurred during the period 2011 to 2016 is as shown in figure. 3.2

![Defect Type]

<table>
<thead>
<tr>
<th>Defect Type</th>
<th>Percentage of total defects</th>
</tr>
</thead>
<tbody>
<tr>
<td>TDD</td>
<td>26.43%</td>
</tr>
<tr>
<td>TW</td>
<td>11.47%</td>
</tr>
<tr>
<td>SSC</td>
<td>10.63%</td>
</tr>
<tr>
<td>EFBW</td>
<td>7.88%</td>
</tr>
<tr>
<td>BHB</td>
<td>6.95%</td>
</tr>
</tbody>
</table>

Figure 3.2: Top five rail defects detected by the ultrasonic vehicle (TDD: Detail Fracture, TW: Thermite Weld, SSC: Shelling, Spauling Corrugation, EFBW: Electric Flashbutt Weld, BHB: Bolt Hole Break)

3.1.4 Service Failures Data

some of the defects remain hidden during the ultrasonic inspection due to its smaller size or due to the miss detection of the ultrasonic equipment. When these defects propagate and grow in size above the threshold limits, before the next inspection, they cause service failures. The service failure data includes a total of 6434 service failures during the period 2011-2016. Of all the service failure defects, service failures caused by the defect type BRO (Ordinary Broken Rail) is dominant, accounting 28.3% of the total service failures. The top five defect types that caused the service failures during the period from 2011 to 2016 is as shown in Table. 3.3.
Table 3.3: Most frequent defect types that are causing service failures

<table>
<thead>
<tr>
<th>Defect Type</th>
<th>Count</th>
<th>Percentage of total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ordinary Break</td>
<td>1826</td>
<td>28.38</td>
</tr>
<tr>
<td>Transverse Detail Fracture</td>
<td>1310</td>
<td>20.36</td>
</tr>
<tr>
<td>Thermite Weld</td>
<td>908</td>
<td>14.11</td>
</tr>
<tr>
<td>Bolt Hole Break</td>
<td>315</td>
<td>4.90</td>
</tr>
<tr>
<td>Crushed Head</td>
<td>274</td>
<td>4.26</td>
</tr>
</tbody>
</table>

3.1.5 Geo-defects Data

The geometrical parameters of track such as alignment of the track, profile and gage of the track alters with time due to various reasons. Rail companies will regularly check for geometric defects using geometry cars and take the necessary action to correct them. The presence of geometry defects will increase the dynamic loads on the rail that in turn will accelerate the growth or occurrence of internal rail defects. The top five geometry defects that were observed from 2011 till 2016 are illustrated in the figure.3.3.

![Exception Type]

Percentage of the exception type

Figure 3.3: Top five geometry defects experienced by the railroad
3.1.6 Grinding Data

In addition to maintaining the surface roughness of the rail, grinding the rail will also remove surface cracks that are caused due to the rolling contact fatigue between wheel and the rail. A very minute amount of the rail surface is cut by grinding till the desired surface roughness is achieved. This process will remove a large extent of rail corrugations. Grinding interval will also have an impact on the rail break as larger the interval greater is the probability of surface cracks to propagate deeper into the rail. We have also considered grinding history of railroad for this study. As grinding is performed on a very large segment of the rail track, the records are identified using prefix, track type, begin milepost and end milepost.

3.1.7 Infrastructure Data

The rail infrastructure data such as the dates the rail is laid, the curvature data and the turnouts data is also available for this study.

The railroad maintains the records of dates on which the rail is first laid. It is common in railways to replace a small segment of a rail when ever required as part of maintenance action or during capital planning.

Curvature data includes the degree of curvature, length of curvature, direction of curvature and spiral lengths. In this study, we consider only the degree of curvature from the curvature data.
Turnouts data include the turnout direction, turnout size and other information.

We only consider the count of turnouts in this study.

### 3.2 Data Preparation

To predict the severity of service failure between two inspections, a table is prepared from the above mentioned datasets mapping the following attributes:

- inspection interval
- gross tonnage
- number of service failures reported between two inspections
- number of ultrasonic defects detected in the past three years
- number of geometry defects detected in last three years
- number of days from the last grinding
- number of turnouts in the segment
- degree of the curvature
- weighted grade of the segment
- age of the track.

The datasets that are provided by the railroad doesn’t have unique segments across all the datasets. While the tonnage is recorded against smaller segments
that are unique over all the years, the segments of inspection schedules data and Grinding data varies each time the activity is performed. Also, the segments of these datasets are very long as inspection and grinding is performed on a large portion of the track at a time. A range to range mapping is performed on these datasets to map these attributes over the segments under consideration. To avoid the loss of data during the range to range mapping, tonnage segments are taken as the reference in this study due to their uniqueness over the years.

The final data table is created by following the below steps as illustrated in figure.

3.4.

Step -1: Identify and extract the unique tonnage segments. The distribution of the segment lengths is as in Table. 3.2.

Step -2: Map the segments under consideration with the inspection data and rearrange the table such that each record denotes a segment of track between between two inspections. So, each record in the table is a unique entry identified by Prefix, Track type, Begin Milepost, End Milepost, Inspection date 1 and Inspection date 2.

Step -3: Mapping Gross tonnage that the segment has carried from the day of first inspection until the day on which a first service failure is identified in the segment. In the absence of service failure, tonnage until the second inspection is mapped.

Step -4: Mapping the number of ultrasonic rail defects that occurred in the segment during the last three years of Inspection date 1, from the Rail defects data.

Step -5: Mapping the number of geometry defects that were detected by geometry car during the last three years of Inspection date 1, from the geometry defects
Step -6: Mapping the number of service failures between two inspections. All of the service failures that are identified during the period between Inspection date 1 and Inspection date 2 are considered from the service failures data.

Step- 7: Mapping the number of days from the day of last grinding on the segment till Inspection date 2, from the historical grinding data.

Step -8: Mapping grade (slope) of the rail from the Rail grade data. In case a part of the segment has one grade and the other part has different grade, the weighted average of the grades is considered.

Step -9: Mapping the degree of curvature from the curvature data, if the segment has any curve else the default value is zero.

Step -10: Mapping the age of rail till the Inspection date 2 from the Rail laid data.

Step -11: Mapping the Count of the turnouts present in that segment from the Turnouts data. The default value in the absence of a turnout is zero.

Step -12: Binary coding of the status of segment at the end of second inspection. '1', if the segment has faced any service failure between two inspections else '0', which means the segment has survived from the service failure.

The attributes of the final table used for building the accelerated failure time model is presented in Table. 3.4. In addition to these attributes, another attribute which is a product of rail age and the degrees of curvature is also considered as it was found significant in the model provided by (Dick et al., 2003).
<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRACK PREFIX</td>
<td>Track Prefix</td>
</tr>
<tr>
<td>TRACK TYPE</td>
<td>Track type identifier</td>
</tr>
<tr>
<td>BEGIN MP</td>
<td>Beginning milepost of the segment</td>
</tr>
<tr>
<td>END MP</td>
<td>Ending milepost of the segment</td>
</tr>
<tr>
<td>SEGMENT LENGTH</td>
<td>Difference between End and Beginning milepost</td>
</tr>
<tr>
<td>INSPECTION DATE 1</td>
<td>Date of the previous inspection</td>
</tr>
<tr>
<td>INSPECTION DATE 2</td>
<td>Date of the following inspection</td>
</tr>
<tr>
<td>INSPECTION INTERVAL</td>
<td>Interval between two inspections (days)</td>
</tr>
<tr>
<td></td>
<td>Tonnage between two inspections or from INSPECTION DATE 1 till the first service failure</td>
</tr>
<tr>
<td>GROSS TONNAGE</td>
<td>Number of rail defects identified in past 3 years</td>
</tr>
<tr>
<td>RAIL DEFECTS 3 YEARS</td>
<td>Number of geometry defects detected in past 3 years</td>
</tr>
<tr>
<td>GEOMETRY DEFECTS 3 YEARS</td>
<td>Number of service failures identified between inspections</td>
</tr>
<tr>
<td>SERVICE FAILURE COUNT</td>
<td>Number of days from last grinding until second inspection</td>
</tr>
<tr>
<td>DAYS FROM LAST GRINDING</td>
<td>Weighted grade of the segment</td>
</tr>
<tr>
<td>WEIGHTED GRADE</td>
<td>Degree of curvature</td>
</tr>
<tr>
<td>CURVE DEGREES</td>
<td>Age of rail during the later inspection</td>
</tr>
<tr>
<td>YEARS FROM RAIL LAID</td>
<td>Product of rail age and degrees of curvature</td>
</tr>
<tr>
<td>PROD AGE CURVATURE</td>
<td>Number of turnouts present in the segment</td>
</tr>
<tr>
<td>NUMBER OF TURNOUTS</td>
<td>1, if a service failure is observed between two inspections else 0</td>
</tr>
</tbody>
</table>
Figure 3.4: Flow chart of the data processing
Chapter 4

Methodology

The statistical methods of survival analysis provide the information on time to the event of interest. Survival regression models such as Accelerated Failure Time (AFT) model will explain the dependability of failure time on the explanatory variables. This model will also estimate the parameters of the underlying failure time distribution in addition to assessing the dependence of failure time on explanatory variables (Kalbfleisch and Prentice, 2011). In this study, a parametric AFT model is used to study the impact of covariates on the rail life defined by the total cumulative tonnage between the last inspection and the occurrence of service failure. As the cumulative tonnage well explains the status of rail, we consider the tonnage as the survival time in this study.
4.1 Survival Analysis Model

Let $T$ be a non-negative random variable that represents the tonnage until a service failure. The cumulative distribution function $F(t)$ gives the probability of tonnage until a service failure $T$ less than or equal to the specified tonnage $t$, which is also called as a failure function.

$$F(t) = P(T \leq t), \quad 0 < t < \infty$$ \hspace{1cm} (4.1)

The probability density function of $T$ is

$$f(t) = \frac{dF(t)}{dt}$$ \hspace{1cm} (4.2)

On the other hand, survival function $S(t)$ will give the probability that the tonnage until a service failure, $T$ exceeds a specified tonnage $t$.

$$S(t) = P(T > t), \quad 0 < t < \infty$$ \hspace{1cm} (4.3)

The survival function is a non-increasing continuous function of tonnage $t$ with $S(0) = 1$ and $S(\infty) = 0$. It means that the probability of a particular segment surviving from the service failure decreases with the accumulation of tonnage. The relation between 4.1 and 4.3 is

$$F(t) = 1 - S(t)$$
In addition, the instantaneous rate at which the service failure occurs given that no service failure has been observed until a tonnage \( t \) is defined by the hazard function \( h(t) \).

\[
h(t) = \lim_{\delta t \to 0} \frac{P(t \leq T \leq t + \delta t | T > t)}{\delta t} = \frac{f(t)}{S(t)} \quad (4.4)
\]

The cumulative hazard until a specified tonnage \( t \) is given as

\[
H(t) = \int_0^t h(t) dt \quad (4.5)
\]

The historical service failure data provides the information on how the service failure rates change with tonnage. This information can be used to model the hazard function. Further, we can use such data to estimate the survival or failure probabilities of the rail segments using the following equation 4.6.

\[
S(t) = 1 - F(t) = \exp[-H(t)] \quad (4.6)
\]

## 4.2 Accelerated Failure Time Model

AFT model will account the effect of covariates on the survival or failure probabilities. If \( S_0 \) is a baseline survival model, the covariates may effect the survival tonnage \( T \) by either accelerating or decelerating the service failure. For example, the presence of any defect in the track segment will accelerate the rate of failure. On the other hand, any treatment that has been taken to suppress the defect
would decelerate the rate of failure. Thus, the survival and hazard function in the AFT model are defined as

\[
S(t|X) = S_0 [t \exp(\beta X)] \quad (4.7)
\]
\[
h(t|X) = h_0 [t \exp(\beta X)] \exp(\beta X) \quad (4.8)
\]

Where \( X \) is the set of covariates and \( \beta \) is the vector of coefficients to these covariates.

From 4.7, it can be seen that the covariates will have a multiplicative effect on the survival function. However, AFT model assumes a log-linear relation of the covariates with survival tonnage \( T \) as in equation 4.9

\[
\log(T) = \beta X + w \quad (4.9)
\]

where \( w \) is the error term. Thus, the covariates will have a linear effect on the logarithmic of \( T \).

### 4.3 Distributions Of The Hazard Function

The distribution of the hazard function is taken into consideration to solve the parametric AFT model. Different distributions of the hazard function such as exponential, weibull, log-normal and log-logistic are considered in this study. The
corresponding hazard functions of the considered distributions (Kalbfleisch and Prentice, 2011; Washington et al., 2010; Hojati et al., 2013) are presented below.

Exponential:

\[ h(t) = \lambda \]  \hspace{1cm} (4.10)

Weibull:

\[ h(t) = p\lambda t^{p-1} \]  \hspace{1cm} (4.11)

Log-normal:

\[ h(t) = \frac{\phi(-p\log(\lambda t))}{\Phi(-p\log(\lambda t))} \]  \hspace{1cm} (4.12)

Log-logistic:

\[ h(t) = \frac{p\lambda t^{p-1}}{1 + (\lambda t)^p} \]  \hspace{1cm} (4.13)

where \( \lambda \) is a location parameter and \( p \) is the shape parameter. While \( \phi(.) \) is the normal probability density function and \( \Phi(.) \) is the normal cumulative distribution function.
The parameters of these distributions can be estimated using the maximum likelihood estimation (MLE) method along with the coefficients of covariates. The distribution that best fits with the rail survival data is chosen based upon the value of Akaike information criterion (AIC) given as $2k - 2ln(\hat{L})$. Where, $k$ is the number of parameters being estimated and $\hat{L}$ is the maximum value of the likelihood function.
Chapter 5

Experimental Results

To study the tonnage (MGT) until the occurrence of a service failure between two ultra sonic rail inspections and the influence of various factors on it, a AFT model is fitted using the data from 2011 to 2015. Further, the data of the year 2016 is used to validate the applicability of the fitted model over time using temporal transferability analysis. Both the results of AFT model and temporal transferability analysis are presented in the following sections. In addition a sensitivity analysis is performed to study the effect of individual factors on the survival probabilities.

5.1 AFT Model Results

The hazard function is fitted with four different distributions, namely exponential, weibull, log-normal and log-logistic to find the best fit with our data. Log-normal distribution is found to best fit the data based upon its lowest AIC value when compared to other distributions of hazard function. The parameter estimates for
location and shape parameters of the log-normal distribution are given in Table 5.1.

The contribution of each variable which may either accelerate or decelerate the survival time is found using the AFT model. Table 5.1 presents the parameter estimates of each variable followed by its exponential value for the different distributions of hazard function. The negative sign of the parameter estimate indicates that the logarithmic of survival tonnage decreases with increase in the value of corresponding variable. As the covariates have a linear relation with the logarithmic of survival tonnage as explained in equation 4.9, the parameter estimate itself will not be able to explain on how the variable influences on the survival tonnage. Instead, the exponential of the parameter estimate will be able to explain whether a particular co-variate accelerates or decelerates the survival tonnage. The relative percentage change in the survival tonnage with a unit increase in corresponding variable is illustrated in the Figure 5.1. It is observed that the segment length of the rail has a greater influence on the survival time. The exponential of its parameter estimate (0.689) indicates that a mile increase in the segment length would shorten the survival time to 0.689 times the base survival time. This can also be inferred as a mile increase in segment length will decelerate the survival tonnage by 31.1%. In other words, it accelerates the failure time by 31.1% compared to the ideal failure time. This inference is obvious as greater the segment size of the rail, greater will be the likelihood of that segment prone to a service failure.
Table 5.1: Summary of AFT results. Estimated value of the parameter followed by the exponential value

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Exponential</th>
<th>Weibull</th>
<th>Log-Normal</th>
<th>Log-Logistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>PastGeoDefectsCount</td>
<td>-0.089 (0.915)</td>
<td>-0.08 (0.923)</td>
<td>-0.116 (0.89)</td>
<td>-0.099 (0.906)</td>
</tr>
<tr>
<td>PastDefectsCount</td>
<td>-0.114 (0.892)</td>
<td>-0.098 (0.907)</td>
<td>-0.121 (0.886)</td>
<td>-0.1 (0.905)</td>
</tr>
<tr>
<td>productofAgeCurve</td>
<td>-0.21 (0.811)</td>
<td>-0.162 (0.851)</td>
<td>-0.13 (0.878)</td>
<td>-0.151 (0.86)</td>
</tr>
<tr>
<td>Weighted_Grade</td>
<td>-0.022 (0.979)</td>
<td>-0.019 (0.981)</td>
<td>-0.007 (0.993)</td>
<td>-0.015 (0.985)</td>
</tr>
<tr>
<td>NumberOfTurnOuts</td>
<td>-0.062 (0.94)</td>
<td>-0.054 (0.948)</td>
<td>-0.072 (0.93)</td>
<td>-0.062 (0.94)</td>
</tr>
<tr>
<td>DaysFromLastGrind</td>
<td>-0.101 (0.904)</td>
<td>-0.094 (0.911)</td>
<td>-0.121 (0.886)</td>
<td>-0.095 (0.909)</td>
</tr>
<tr>
<td>SegmentLength</td>
<td>-0.345 (0.708)</td>
<td>-0.262 (0.769)</td>
<td>-0.372 (0.689)</td>
<td>-0.302 (0.739)</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>20.134</td>
<td>19.117</td>
<td>20.152</td>
<td>19.075</td>
</tr>
</tbody>
</table>

Loglik(model)          | -67359.8     | -67179.9 | -67012.6    | -67102.4     |
Loglik(intercept only) | -68781.3     | -68686.4 | -68660.3    | -68683.6     |
AIC                    | 134735.6     | 134377.8 | 134043.2    | 134222.8     |
Scale (1/Shape)        | 1            | 0.755    | 1.93        | 0.741        |
log(Scale)             | -0.281       | 0.656    | -0.3        |
Similar to the finding in (Dick et al., 2003), the product of rail age and the degree of curvature is found to be negatively correlated with the failure time in our study. This factor decelerates the survival tonnage by 12% indicating that older the rail segment or higher the degree of curvature in the segment, the survival probability declines. It is also observed that the increase in the variable ‘DaysFromLastGrind’, which accounts the number of days from the last grinding on the rail segment would accelerate failure time by 11%. Grinding of rail segments prevents the surface cracks to propagate through the rail. However, when the grinding is delayed, the likelihood of a service failure increases as the surface cracks will have enough time to grow in size causing a service failure.

Both the variables ‘PastDefectsCount’ and ‘PastGeoDefectsCount’ which are the measure of past rail defects and the past geometry defects that has occurred in
the past three years respectively, are observed to decelerate the survival time by 11%. Whenever a defect is found during the regular inspection, a necessary maintenance action is taken to repair or replace the rail. The repaired rail segment may not be as good as the replaced rail. Therefore, past defects will well explain its condition and these variables are found to be significant in our study. Moreover, the infrastructure data such as the number of turnouts and the grade of rail are also observed to decelerate the survival tonnage by 7% and 1% respectively. The grade of the rail has a less impact on the survival of rail segment compared to the number of turnouts.

5.2 Sensitivity Analysis

The survival curve of the fitted data from 2011 to 2015 is as depicted in the Figure. 5.2. As service failure is a rare event, a very small portion of these segments (3279 of 236344) is prone to a service failure between two successive ultrasonic inspections. Figure 5.3 illustrates the prediction of the developed model on how the survival probability of these rail segments be impacted with the additional tonnage between two inspections. This curve can be used to infer the risk of a rail segment prone to a service failure with the increase in cumulative tonnage from the previous rail inspection. For example, a gross tonnage of 500MGT would result in a probability of 0.29 that a service failure occurs in the segment.

The effect of each variable on the survival probability of the rail segment is studied using the fitted AFT model on a data sample of 100 records is drawn from the
available data. It is clearly observed in Figures. 5.4 and Figure 5.5 that the presence of a geometry defect or a rail defect in the rail segment will accelerate the segment to fail sooner than those segments without these defects. Figure.
5.6 shows the impact of the presence of a turnout on the survival probability. A segment with a turnout will tend to fail faster than the one without a turnout. Moreover, the consideration of a longer segment will result in a much lower survival probability than a shorter rail segment as depicted in Figure. 5.7.

### 5.3 Temporal Transferability

Temporal transferability is a method to justify the adaptability of the generated prediction model over time. It will ensure that the estimated parameters are applicable on the data that is generated over the years in the future. The data generated in the year 2016 is used to check if the model built using the data from
**Figure 5.5:** Effect of rail defects on the survival probability

**Figure 5.6:** Effect of turnouts presence on the survival probability
Figure 5.7: Effect of segment length on the survival probability

2011 to 2015 is transferable over time. The result is achieved using a likelihood ratio test (Washington et al., 2010), using the $X^2$ statistic in Equation 5.1.

\[
X^2 = -2[LL(\beta_T) - LL(\beta_a) - LL(\beta_b)]
\]  \hspace{1cm} (5.1)

Where $LL(\beta_T)$ is the log likelihood of the model generated using data from 2011 to 2016, and $LL(\beta_a)$ and $LL(\beta_b)$ are the log likelihood values at the convergence of the individual models generated using the data 2011 to 2015 (Dataset A) and 2016 (Dataset B) respectively. $X^2$ gives the probability that the models of dataset A and dataset B will have different parameters. The probability is inferred using the $\chi^2$ distribution with the degrees of freedom equal to the sum of parameters.
estimated in the models using dataset A and dataset B minus the number of parameters estimated in the combined model.

The $\chi^2$ score is found to be 70, given that the value of $LL(\beta_T) = -77334.2$, $LL(\beta_a) = -67012.6$ and $LL(\beta_b) = -10286.6$ with the degrees of freedom equal to 7. The resulted p-value is $1.47e-12$ indicating that the parameters estimated using the data from 2011 to 2015 is valid on the model with 2016 data. Hence, this model is transferable over time and is valid on any data that is generated over the coming years.
Chapter 6

Conclusions and Future Research Directions

6.1 Conclusions

This study aims to access the risk of a service failure with the increase in gross tonnage since the last ultrasonic inspection. Moreover, the influence of various factors is also examined by fitting a parametric accelerated failure time (AFT) survival model using the data collected from 2011 to 2015. Different distributions of the hazard function such as exponential, weibull, log-normal and log-logistic are considered to fit the data. Both the parameters of the distributions and the coefficients for the considered factors are estimated to maximize the likelihood of the fitted data. These estimates are further used to study the survival probabilities of the rail segments. In addition, the influence of geo-defects, rail defects, turnouts
and segment length on the survival probabilities is also examined. Finally, a temporal transferability is applied to verify the model with the data collected in the year 2016 using a likelihood ratio test.

It is observed that the log-normal distribution best fits with the data. Every variable under consideration is found to accelerate the failure time. In other words, they decelerate the survival time of the rail segment. Segment length has a major impact compared to other variables as a unit increase in the segment length will speed up the failure of rail segment by 31%. The other factors including past rail defects (in three years) and past geo-defects (in three years) also accelerate the failure time by 11%. Also, the number of days from last grinding accelerates the failure time by 11%. Moreover, the product of rail age and the degrees of curvature also has negative correlation on the survival time. It accelerates the failure time by 12%.

As the service failure is not a desirable event, the rail road should focus on reducing the slope of survival curve in Figure. 5.3 by minimizing the impacts of these co-variates. It is suggested to take additional caution on the rail segments having higher values for these variables. It is suggested to record the data on a shorter segment lengths to be more certain on the risk of service failure. The impact of past rail defects and the past geo-defects can be reduced by minimizing their occurrence either by accurately predicting the defects or by decreasing the inspection intervals. The impact of the variable 'DaysFromLastGrind' can be reduced by decreasing the grinding interval. As the degree of curvature is not a controllable factor, the age of rail may be reduced by replacing the rail at certain longer intervals.
However as the rail replacement is a expensive process, railroad should make a trade-off between the risk of service failure and replacement of a rail. The impact of Infrastructure related features such as number of turnouts and the grade of rail are not controllable once the raid is laid as per the infrastructure requirements.

A sensitivity analysis of the survival probabilities indicates the decrease in survival time for each factor. Railroad can use these curves to access the impact of the variables such as past geo-defects and past rail defects and take necessary countermeasures on the segments that are prone to these defects.

The results from temporal transferability analysis indicate that the estimated parameters are valid to predict the survival probabilities on the data generated over time. Hence, the railroad can use this model to estimate the failure probabilities by inputting the values of respective variables in the model. This information will assist the railroad in the decision making of required maintenance actions to be carried as to mitigate the negative impacts of these factors on the rail segment, which lead to a service failure if no action is taken.

6.2 Future Research Directions

The AFT model has been developed with the available data from the railroad. Future research may use the results of this model in optimizing the inspection intervals as to achieve the desired service failure rate. It is also suggested to consider the collection and inclusion of additional factors such as speed on the rail, weight of rail, ballast condition, e.t.c.
Currently, we consider the parameters of hazard function distribution to be constant assuming that the effect of an individual variable to be the same across each observation. Further research can be conducted to test the unobserved heterogeneity using random parameters AFT model. Competing risk analysis may also be incorporated to study the varying influence on the different service failure types.

In addition, it is also recommended to conduct research on service failure prediction using non-parametric models and other data mining methods.
Bibliography


Bibliography

