Proceedings of the 2016 Joint Rail Conference
JRC2016
April 12-15, 2016, Columbia, SC, USA

JRC 2016-5742

A PRELIMINARY METHODOLOGY FOR BROKEN RAIL CAUSED FREIGHT TRAIN DERAILMENT RISK ANALYSIS

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ABSTRACT

This paper investigates the influence of rail age, annual traffic density, and inspection frequency on broken-rail-caused train derailment risk. First, we estimate the probability of a broken-rail-caused train derailment based on a sequence of stochastic processes including rail defect formation, growth, detection and the likelihood that a broken rail causes a derailment. In addition to derailment frequency, we also estimate derailment severity, which is measured by the average number of railcars derailed per train derailment, based on FRA-reportable train derailment data. The preliminary risk analysis model provides a quantitative approach to understand broken rail risk, and potentially aid in development of effective ways to mitigate derailment risk.

INTRODUCTION

Improving train operating safety has long been a priority of the rail industry and government. Broken rail is the leading derailment cause on U.S. freight railroads [1,2]. Inspecting either visually or with modern ultrasonic technology allows the railroad industry to detect rail defects before they grow and cause a derailment. Since more frequent inspections require greater capital investment, a risk-informed rail inspection schedule can aid in risk mitigation in a cost-efficient manner. It is important to understand how the broken rail derailment risk varies with influencing factors, such as rail age (cumulative tonnage on the rail) and traffic density. In this paper, a practical risk analysis model is developed that accounts for rail defect formation, growth, detection and derailment likelihood. The model estimates annual broken-rail-caused derailment frequency and severity (derailment severity is measured by the number of railcars derailed) on any specific track segment, given rail age, annual inspection frequency and annual traffic density.

The paper is structured as follows. First, we present a step-by-step procedure for calculating the derailment risk. Next, we estimate the risk parameters based on the literature and the FRA accident data [3]. A numerical case study is developed to illustrate the application of the risk model. Based on the results from the numerical example, we discuss the contribution of this research to the literature and practice. Lastly, we summarize principal findings of this study.

METHODOLOGY

In this research, the risk of a train derailment is defined as the product of the probability of a derailment and the consequences of that derailment. This paper focused on broken-rail-caused freight-train derailments on mainlines. The consequence of a derailment is represented by the number of railcars derailed per derailment [1]. The risk methodology can be adapted to account for other types of damages in the future.

According to the risk definition, either an increase in the probability of a train derailment or the consequences of that derailment could increase the risk. The following analyses detail the assessment of the derailment likelihood and severity, due to broken rails. Figure 1 presents a technical roadmap for broken-rail-caused derailment risk assessment.

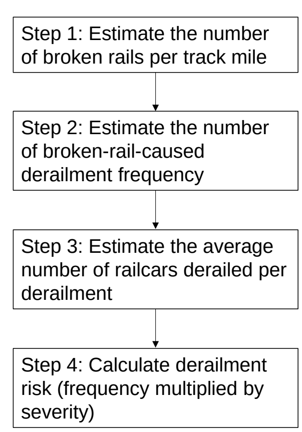

Figure 1 Derailment risk analysis framework

$$R = B \times F \times S \quad (1)$$

where:
R= annual derailment risk per track mile (total number of railcars derailed)
B = annual number of broken rails per track mile
F = proportion of broken rails that may cause derailments
C = average number of railcars derailed per derailment

Step 1: estimate the number of broken rails (B)

A number of factors can affect the rate of broken rails, such as temperature differential, rail age, traffic density, curvature, roadbed condition, axle load, vehicle dynamics, rail wear and others [4]. The Volpe National Transportation Systems Center has developed an engineering model that incorporates rail defect formation, growth and detection processes [5,6]. According to the Volpe model, a rail defect is assumed to form at an increasing rate as the rail ages due to the accumulation of tonnage. The model for the rate of defect formation is derived based on a Weibull distribution. The Weibull distribution model was calibrated based on observations of defect occurrence on the Facility for Accelerated Service Testing (FAST) at the Transportation Test Center in Pueblo, Colorado and on several segments of revenue track studied by the Association of American Railroads. After a defect was formed, its size progression was calibrated from the original detail fracture growth test conducted at FAST and has been further verified and validated by tests conducted through a joint international research effort supported by the Union of International Railways/World Executive Council [4]. Temperature differential, axle load, track modulus, rail wear and other factors were found to affect defect size growth. The probability of detecting a rail defect depends on the equipment used and the size of the defect. Although larger defects are more likely to be detected, they still can be missed during the inspection process [4].

The Volpe model focuses on rail fatigue defects, such as detail fractures, transverse/compound fissures, and vertical split head defects. Note that the Volpe model was developed in 1990s based on rail infrastructure conditions then. We are unaware of recent updates to this model. This may introduce some level of uncertainty when applying this model to predict rail defects under today's infrastructure conditions. A more detailed description of the Volpe model has been provided in Orringer (1990), and thus not duplicated herein.

The outputs of the Volpe model were used to develop a statistical model that approximate the parametric relationship between the number of rail breaks and inspection frequency, given rail age and annual traffic density level [7]:

$$B = a \times \exp(b \times K) \quad (2)$$

where:
a, b = parameter coefficients, depending on traffic density and rail age
K = annual inspection frequency

For example, when the initial rail age is 300 MGT and annual traffic density is 80 MGT, parameter coefficient *a* is equal to 0.7547 and *b* is -0.567, referring to Liu et al. in 2014. Therefore, if there are four inspections per year (K = 4), the estimated number of broken rails per track miles is $0.7547 \times \exp(-0.567 \times 4) = 0.078$.

Step 2: estimate the proportion of broken rails causing derailments (F)

Previous studies assumed that an average of 0.5 to 1 percent of broken rail resulted in derailments [8,9]. This likelihood may vary depending on operating and infrastructure characteristics. Due to data limitations, for illustrative purposes, we set F = 0.01 in this paper.

Step 3: Derailment severity (C)

Train derailment severity can be evaluated using a range of metrics, such as the number of cars derailed, property damage, casualties, or environmental impact. Among these metrics, the number of cars derailed is related to accident kinetic energy and has been used in the literature [1, 2]. Accident speed was found to be a significant factor that affects the number of cars derailed [10,11]. Based on the FRA-reportable Class I railroad freight-train derailment data on mainlines, Liu et al. (2011) developed a nonlinear function to estimate the average number of railcars derailed:

$$S = C \times V^{D} \quad (3)$$

where
S = average number of cars derailed in a freight train derailment
C, D = model coefficients by accident cause (C=1.83; D = 0.622 for broken rails) [10]
V = train speed in mph

For example, if the operating speed is 40 mph (V = 40), the average number of a derailment due to a broken rail is approximately $1.83 \times 40^{0.622} = 18.2$. Note that the model from Liu et al. (2011) was based on all types of train configuration and length. Further research is needed to better understand train derailment severity by additional influencing factors.

Step 4: Derailment risk (R)

In this paper, derailment risk is interpreted as the total number of cars derailed due to broken rails. The risk methodology can be adapted to other derailment severities as well. Based on Equation (1), given initial rail age of 300 MGT, annual traffic density of 80 MGT, operational speed of 40 mph and annually four inspections, the estimated derailment risk due to broken rails is:

$R = B \times F \times S = 0.078 \times 0.01 \times 18.2 = 0.0142$ broken-rail-caused cars derailed per track mile per year

SENSITIVITY ANALYSIS

To illustrate methodology application, we develop a sensitivity analysis to understand derailment risk by rail age, traffic density and annual rail inspection frequency. We consider a track segment with rail age of 300 million gross tons (MGT) and annual traffic density of 80 MGT. It is assumed that the speed is 40 mph. Figure 2 illustrates annual broken-rail-caused derailment risk by rail defect inspection frequency. The analysis is based on the assumption that rail age is 300 MGT, annual traffic density 80 MGT, and the operating speed is 40 mph. The graph illustrates a negative exponential relationship between the annual inspection frequency and derailment risk. For example, when there are two inspections per year, the estimated annual derailment risk due to broken rails is 0.035. The derailment risk is reduced to 0.009 when there are five inspections per year (a 74 percent reduction). The analysis shows that increased rail inspection frequency reduces the rate of undetected rail defects, thereby reducing derailment risk.

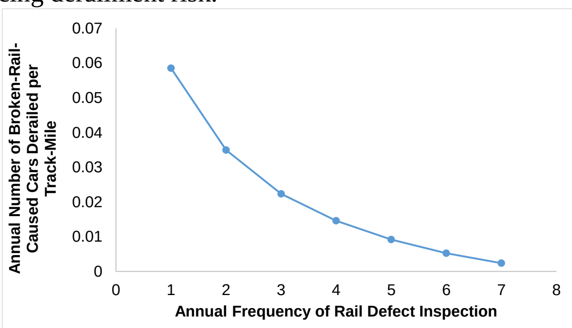

Figure 2 Derailment risk by inspection frequency (rail age is 300 MGT, annual traffic density 80 MGT, operating speed is 40 mph)

Next, a sensitivity analysis was conducted to understand how the risk varies with rail age (Figure 3). It is assumed that the annual traffic density is 80 MGT, there are 4 inspections per year, and the operating speed is 40 mph. It shows that a positive exponential relationship exists between the rail age and derailment risk. For example, at 300 MGT initial rail age, the annual broken rail caused derailment risk is 0.015. The risk increases to 0.038 if the rail age is 500 MGT. This is probably because that rail defect rate occurs at a faster rate when rail ages [5].

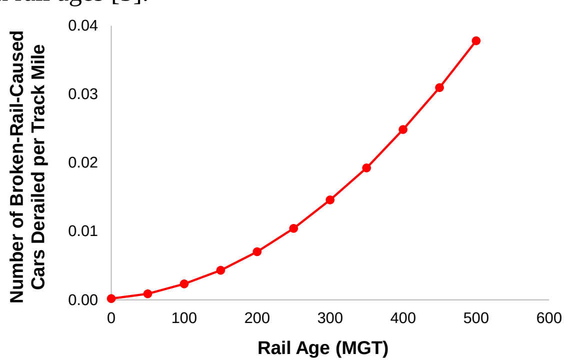

Figure 3 Derailment risk by rail age (annual traffic density is 80 MGT, 4 inspections per year, operating speed is 40 mph)

Figure 4 describes the relationship between the risk and annual traffic density. It is assumed that the rail age is 300 MGT, there are 4 inspections per year, and the operating speed is 40 mph. A positive exponential relationship is seen in the figure, indicating that the more traffic a segment of rail experienced by the rail on an annual basis, the higher the risk, given all else being equal. For example, if annual traffic density is 50 MGT, the risk is 0.002 if the rail is inspected four times per year. This risk would increase to 0.015 if the annual traffic density is 80 MGT and there are still four inspections per year. This is probably because more loading cycles (higher traffic density) between inspections increase the rate of rail defect growth, thereby increasing the chance of rail breaks. This also partly explains the fact that higher density tracks typically receive more frequent inspections to control the risk.

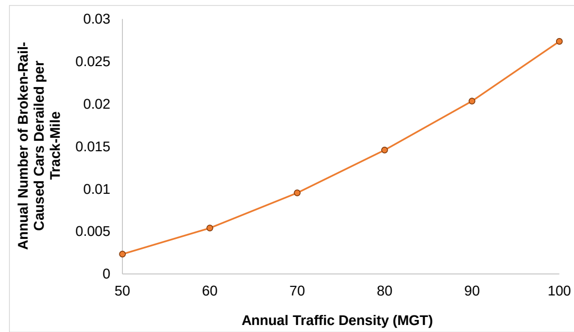

Figure 4 Derailment risk by annual traffic density (rail age is 300 MGT, 4 inspections per year, operating speed is 40 mph)

CONCLUSION

This paper describes a preliminary analytical framework to quantitatively evaluate the effect of rail age, annual inspection frequency, and annual traffic density on broken-rail-caused derailment risk, which is measured by total number of cars derailed per track mile. The analysis found that, given all else being equal, derailment risk is reduced when inspection frequency increases. Also, a higher traffic density or rail age is associated with a higher derailment risk level. A further study can be developed to optimize annual rail inspection frequency, accounting for the tradeoff between the safety and cost.

ACKNOWLEDGEMENT

The first two authors appreciate the research fund from the Aresty Undergraduate Research Program at Rutgers University.

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