A PREDICTION MODEL FOR BROKEN RAILS AND AN ANALYSIS OF THEIR ECONOMIC IMPACT

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Revised
Submission Date: 7/11/08

Word Count: 7,252 (6,252 words, 3 Tables, 1 Figure)

ABSTRACT

Broken rails are the leading cause of major derailments in North America. Class I freight railroads average 84 mainline broken-rail derailments per year with an average track and equipment cost of approximately $525,000 per incident. The number of mainline broken-rail-caused derailments has increased from 77 in 1997, to 91 in 2006; therefore, efforts to reduce their occurrence remain important. We conducted an analysis of the factors that influence the occurrence of broken rails and developed a quantitative model to predict locations where they are most likely to occur. Among the factors considered were track and rail characteristics, maintenance activities and frequency, and on-track testing results. Analysis of these factors involved the use of logistic regression techniques to develop a statistical model for the prediction of broken rail locations. For such a model to have value for railroads it must be feasible to use and provide information in a useful manner. Consequently, an optimal prediction model containing only the top eight factors related to broken rails was developed. The economic impact of broken rail events was also studied. This included the costs associated with broken rail derailments and service failures, as well as the cost of typical prevention measures. A train delay calculator was also developed based on industry operating averages. Overall, the information presented here can assist railroads to more effectively allocate resources to prevent the occurrence of broken rails.

INTRODUCTION

Understanding the factors related to broken rails is an important topic for U.S. freight railroads and is becoming more so because of the increase in their occurrence in recent years. This increase is due to several factors, but the combination of increased traffic and heavier axle loads are probably the most important. Broken rails are generally caused by the undetected growth of either internal or surface defects in the rail (*1*). Previous research has focused on both mechanistic analyses (*2-8*) and statistical analyses (*9-13*) in order to understand the factors that cause crack growth in rails and ultimately broken rails.

The first objective of this analysis was to develop a predictive tool that will enable railroads to identify locations with a high probability of broken rail. The possible predictive factors that were evaluated included rail characteristics, infrastructure data, maintenance activity, operational information, and rail testing results. The second objective was to study the economic impact of broken rails based on industry operating averages. Our analysis on this topic incorporates previous work that developed a framework for the cost of broken rails (*14*). The purpose of this paper is to provide information to enable more efficient evaluation of options to reduce the occurence of broken rails.

DEVELOPMENT OF SERVICE FAILURE PREDICTION MODEL

The first objective of this paper was to develop a model to identify locations in the rail network with a high probability of broken rail occurrence based on broken rail service failure data and possible influence factors. All of the factors that might affect service failure occurrence and for which we had data were considered in this analysis. Several broken rail predictive models were developed and evaluated using logistic regression techniques.

Data Available for Study

In order to develop a predictive tool, it is desirable to initially consider as many factors as possible that might affect the occurrence of broken rails. From the standpoint of rail maintenance planning it is important to determine which factors are and are not correlated with broken rail occurence. Therefore the analysis included a wide-range of possible variables for which data were available. This included track and rail characteristics such as rail age, rail curvature, track speed, grade, and rail weight. Also, changes in track modulus due to the presence of infrastructure features such as bridges and turnouts have a potential effect on rail defect growth and were examined as well. Additionally, maintenance activities were included that can reduce the likelihood of broken rail occurrence, such as rail grinding and tie replacement. Finally, track geometry and ultrasonic testing for rail defects were used by railroads to assess the condition of track and therefore the results of these tests are included as they may provide predictive information about broken rail occurrence.

The BNSF Railway provided data on the location of service failures and a variety of other infrastructure, inspection and operational parameters. In this study a "service failure" was defined as an incident where a track was taken out of service due to a broken rail. A database was developed from approximately 23,000 miles of mainline track maintained by the BNSF Railway covering the four-year period, 2003 through 2006. BNSF's network was divided into 0.01-mile-long segments (approximately 53 feet each) and the location of each reported service failure was recorded. BNSF experienced 12,685 service failures during the four-year study period. For the case of modeling rare events it is common to sample all of the rare events and compare these with a similar sized sample of instances where the event did not occur (*15*). Therefore an additional 12,685 0.01-mile segments that did not experience a service failure

during the four-year period were randomly selected from the same network. Each non-failure location was also assigned a random date within the four-year time period for use in evaluating certain temporal variables that might be factors. Thus, the dataset used in this analysis included a total of 25,370 segment locations and dates when a service failure did or did not occur in the railroad's network during the study period. All available rail characteristics, infrastructure data, maintenance activity, operational information, and track testing results were linked to each of these locations, for a total of 28 unique input variables.

Evaluation of Previous Service Failure Model

In a previous study Dick developed a predictive model of service failures based on relevant track and traffic data for a two-year period (*10, 11*). The outcome of that study was a multivariate statistical model that could quantify the probability of a service failure at any particular location based on a number of track and traffic related variables. Dick's model used 11 possible predictor factors for broken rails and could correctly classify failure locations with 87.4% accuracy using the dataset provided to him.

Our first step was to test this model using data from a more recent two-year period. From 2005 through 2006, the BNSF experienced 6,613 service failures and data on these, along with 6,613 randomly selected non-failure locations, were analyzed. 7,247 of the 13,226 cases were classified correctly (54.8%), considerably lower than in the earlier study causing us to ask why the predictive power seemed to have declined. Examination of the service failure dataset used previously revealed that it may not have included all the trackage from the network. This resulted in a dataset that generated the particular model and accuracy levels reported in the

earlier study (*10, 11*). Therefore a new, updated statistical model was developed to predict service failure locations.

Development of Updated Statistical Classification Model

The updated model that was developed to predict service failure locations used similar logistic regression techniques. Logistic regression was selected because it is a discrete choice model that calculates the probability of failure based on available input variables. These probabilities are used to classify each case as either failure or non-failure. A statistical regression equation was developed based on the significant input parameters to determine the probability of failure. To find the best classification model, the input parameters were evaluated with and without multiple-term interactions allowed.

Logistic Regression Methodology and Techniques

The model was developed as a discrete choice classification problem of either failure or non-failure using the new dataset described above. The objective was to find the best combination of variables and mathematical relationships among the 28 available input variables to predict the occurrence of broken rails. The service failure probability model was developed using Statistical Analysis Software (SAS) and the LOGISTIC procedure (*16*). This procedure fits a discrete choice logistic regression model to the input data. The output of this model is an index value between zero and one corresponding to the probability of a service failure occurrence.

Four commonly used variable selection techniques were evaluated in this analysis to find the best model. The simplest method is referred to as "full-model", or variable selection type

"none" in SAS. The full-model method uses every available input variable to determine the best regression model. The next technique examined was selection type "forward", which evaluates each input variable and systematically adds the most significant variables to the model. The forward selection process continues adding the most significant variable until no additional variables meet a defined significance level for inclusion in the model. The entry and removal level used in this analysis for all variable selection techniques was a 0.05 significance threshold. The "backward" variable selection technique was also used. This method starts with all input variables included in the model. In the first step, the model determines the least significant variable that does not meet the defined significance level and removes it from the model. This process continues until no other variables included in the model meet the defined criteria for removal. The final logistic regression selection technique used was "step-wise" selection. The step-wise selection method is similar to the forward selection method because the model begins with the most significant terms and continues adding terms step-by-step. However, unlike the forward selection method, the step-wise process evaluates the importance of all model terms after each step. If any term is determined to be insignificant, based on the defined significance level, that term is removed and the process continues. The step-wise selection process ends when no further variables are added or removed from the model based on the defined entry and exit thresholds.

Previous work has shown that use of only one of the above-described variable selection techniques may not lead to the optimal logistic regression model (*17*). None of the variable selection techniques are necessarily superior to others, but instead all methods should be used to find the best model for the data. Models developed using each of the techniques should be

compared for similarities and these similarities may reveal a near-optimal model. In this study, each of the four variable selection techniques was evaluated.

Simple Logistic Regression Model

The first logistic regression model constructed was a multivariate analysis that did not allow for variable interaction. All four logistic regression selection techniques were used to determine the best model and each had a similar classification accuracy of 66.3% (Table 1a). Additionally, the different techniques selected the same 23 variables and resulted in the same logistic regression equation.

The new prediction model increased the accuracy of classification for the most recent service failure data by 11.5% compared to Dick's model when applied to the same data. It also had more variables compared to Dick's model. In particular the first five terms, or most significant factors, in the new model were: presence of an ultrasonic defect, rail type, annual tonnage, average tons per car, and presence of a geometric defect. Of these five terms neither ultrasonic nor geometric defects had been included in Dick's model because the data were not available in the earlier dataset he used. Additionally, the presence of infrastructure features, such as bridges, grade crossings, and diamonds, were not previously evaluated, but also had influence in the new statistical model.

Multiple Term Interaction Logistic Regression Model

The next group of regression models considered allowed for variable interaction. Variable interaction is an important factor for prediction models because some input variables may not be independent and interact in a non-additive manner to affect service failure

occurrence. For example, rail age and degree of curve may each have an independent effect on the likelihood of a service failure; however, the combined effect of rail age multiplied by the degree of curvature may produce a stronger correlation with service failure locations. The software package included with SAS allows for a development of two-term interaction models. The initial model considered 28 independent variables; the two-term interaction model therefore considers 406 possible variables.

Again, each of the four logistic regression techniques was used to develop service failure classification models with two-term interaction. The procedures followed in this part of the analysis were the same as in the simple logistic regression model. The most accurate model, using two-term interaction, was the backward selection technique. This model classified 71.0% of the cases correctly, an increase in accuracy of 4.8% compared to simple regression (Table 1b). In this case, the full-model included only 363 of the total possible 406 variables due to the fact that the interaction of some of the variables produced the same value as another input parameter. For example, the product of the variables rail age and annual gross tons is the same value as the parameter for accumulated tons on the rail. When the SAS software encounters situations such as this, the redundant variable is removed from the model.

Evaluation of Prediction Models

To determine if the predictive ability of the statistical models are robust each model must to be tested against validation data, or "unseen" cases; consequently the data in this study were separated into two groups. Of the 25,370 total cases, 15,222 cases (60%) were randomly selected and included in a training sample. The remaining 10,148 cases (40%) were retained in a testing sample, or validation group. The most accurate models for simple and two-term

interaction techniques were selected to evaluate against the testing sample. The modeling techniques were repeated to create logistic regression equations based only on the training sample. The regression equations were then used to calculate the probability of failure for each case in the testing sample. The predicted classifications, based on the newly developed equations, were then compared to the actual events that occurred in the "training" dataset and the accuracy was assessed and compared for each model.

The results from this analysis showed that the simple logistic regression model performed well against the testing sample (0.4% decrease) and therefore was robust for service failure prediction (Table 1c). However, the model that allowed for two-term variable interaction had a large reduction in accuracy when used on the testing sample (14.1% decrease) and therefore over fit the data (Table 1c). We concluded that the two-term variable interaction model was not robust and unlikely to be useful as a predictive tool.

Practical Statistical Prediction Model

As stated above, the objective of this analysis was to develop an accurate, understandable tool that railroads could easily implement to assist with maintenance planning. The simple logistic regression model evaluated in this study contained 23 input parameters but requires more information than is desirable for normal use by railroads. A simpler model requiring fewer input parameters that retains sufficiently high accuracy would be preferable. To determine such a model, the logistic regression method was used with the "score" variable selection technique. This technique determines the most important variables for accurate prediction for different model sizes. A score analysis was completed to calculate the best model for a varying number of

parameters. Table 2 shows which variables were added or removed at each iteration as the model is developed using this technique.

In general the accuracy of the model increases with the number of parameters (Table 2, Figure 1). However, in a few cases, the addition of another variable did not improve the model, most notably the six-variable model. This is because the model is being forced to use the best six variables, which has a lower level of accuracy then the five-variable model in this case. In situations like this, the larger model is undesirable and would not be selected as a final model.

From this analysis we identified a "practical" model, using only eight parameters, that balanced the number of input variables versus classification accuracy (Figure 1). The calculated logistic regression equation presented a reasonably simple model that can be understood and used, but also has an accuracy of 64.7%. This is a decrease of only 1.6% from the basic step-wise regression model with 23 parameters, but is much simpler to use and evaluate. The model was also tested against validation data and found to be robust for unseen cases (0.9% loss of accuracy).

Transformation to a Prospective Prediction Model

Each of the classification models described in this study were retrospective models created using a dataset in which half the records had a service failure and half did not. A final transformation is needed to develop a "prospective" model that can be used to predict the location of service failures. Previous work has shown how the transformation can be done using a logistic regression model (*11, 15*). The transformation was completed with adjustment of the model specific constant, Z, to reflect the average service failure probability across the entire system. During the four-year period, there were 12,685 service failures. In 2006, BNSF

maintained 23,358 miles of mainline track (*19*). This corresponds to a total of approximately

2.34 million 0.01-mile-long segments. The average probability that a service failure will occur

on any particular segment during a similar four-year period is thus 0.00543. This probability

was converted into a new model-specific constant using the log-odds operator:

$$Z^* = Z + \ln(\tfrac{P_{SFAVG}}{1-P_{SFAVG}}) = 4.94 + \ln(\tfrac{.00543}{1-.00543}) = -0.270 \tag{Eq. 1}$$

$$P_{SF2} = \frac{e^u}{(1+e^u)} \tag{Eq. 2}$$

$$\begin{aligned} U = {}&Z^* - 0.0454S - 1.35R - 0.0106A + 0.00899T \\ &+ 0.0232L + 1.61I + 0.823G + 1.63B \end{aligned} \tag{Eq. 3}$$

where,

Z^* = -0.270, adjusted model constant

Z = 4.94, model specific constant

P_{SF2} = probability that a service failure occurred during a four-year period

S = rail weight (in pounds per yard)

R = rail type (1 if welded, 0 if bolted)

A = rail age (in years)

T = annual traffic (in million gross tons)

L = weight of car (in tons)

I = presence of an ultrasonic defect in the last three years (1 if present, 0 otherwise)

G = presence of a geometric defect in the last three years (1 if present, 0 otherwise)

B = presence of a bridge within 200 feet of segment (1 if present, 0 otherwise)

The previous model specific constant, Z, is replaced in the logistic regression equation by the adjusted constant, Z*, as shown in Equation 1. Therefore, Equations 2 & 3 represent the prospective practical service failure model, with an updated value for U, for the prediction of service failures during a four-year period. This equation can be used to determine specific locations with a high likelihood of a service failure as well as the overall service failure rate for any specific line.

ECONOMIC IMPACT OF BROKEN RAILS

The second topic in this paper was to evaluate the economic impact of broken rails and their respective prevention techniques. The previous section considered various factors to predict locations that have a high probability of broken rail occurrence. However, understanding where broken rails are most likely to occur is necessary, but not sufficient for cost-effective management of the problem. Additional information on the economic impact of broken rails as well as the cost and effectiveness of various preventive strategies is also needed. In this section the costs associated with broken rail derailments, service failures, train delay, and typical prevention measures are explored. The results of this analysis are presented to assist railroads to make better informed decisions regarding maintenance and prevention of broken rails.

Framework of Economic Impact of Broken Rails

Economic analysis of railroad engineering and operations is a topic that has been the subject of extensive study for over a century and a half. Among the most well-known early treatises on railway economics was by Wellington (*19*). More recent research has focused on specific topics of railway economics; some that is applicable to this analysis, includes the

expected life of rail and rail renewal (*20, 21*). However, the economic costs specifically associated with broken rails have not previously been quantified. The potential costs associated with broken rails have been explored as part of an overall analysis of rail defects (*14*). This work stated that the cost of broken rails includes inspection of track, train delay, remedial treatments, pre-emptive treatments, derailments, and loss of business. The cost of a specific broken rail event will vary based on many factors, but the intention of this analysis was to calculate typical expected costs based on past averages of similar events.

Costs Associated with Broken Rail Derailments

Broken rail derailments are the most common cause of major derailments on U.S. railroads (*22*) and their economic impact can be substantial. Such accidents are also a major disruption to railroad operations. The costs associated with broken rail derailments include track damage, equipment damage, accident clean-up, labor and materials for repair, train delay, lading damage, and loss of future business. Railroads are generally apprehensive about sharing complete information on derailment related costs; but some information is publicly available (*23*). This information was supplemented by interviews with railroad industry experts and other research to further understand the associated costs.

The Federal Railroad Administration (FRA) requires that railroads report equipment and track damage for railway accidents that exceed a specified monetary threshold ($7,700 in 2006). The cost of equipment damage includes repair or replacement of on-track equipment such as cars, locomotives, and maintenance equipment, including both labor and materials.   Similarly, track-related damage costs that must be reported to FRA include the cost of repair or replacement of track, signals, and track structures, such as bridges and grade crossings, as well as

all the labor and materials needed. Track damage also includes the costs of accident clean-up, such as clearing the right of way of damaged cars, spilled lading, and the cost of third-parties contracted to assist with accident clean-up. Costs due to environmental and hazardous material clean-up from accidents are not included in the FRA reportable costs, nor are evacuation or litigation costs. During the four-year study period, U.S. Class I freight railroads experienced 335 mainline broken rail derailments. The total FRA-reportable costs of these derailments exceeded $176 million in equipment and track damage, for an average of $525,400 per incident.

Besides reportable equipment and track damage, another important cost associated with broken rail derailments is train delay. Train delay cost is based on the time of track-outage as well as the number of trains delayed and is described later in this paper. Some of the factors that affect track-outage time are the severity of the accident, access to the site, if hazardous materials were involved, or if the accident is near a metropolitan area. Interview with industry experts indicated that a moderate to large scale broken rail derailment will take approximately 24 hours to return the track to service, although they can take longer depending on the circumstances and location of the accident.

Other costs associated with broken rail derailments include lading damage and loss of business or customers. The cost of lading damage is not reported to the FRA and therefore not available in their database. Depending on what is lost or damaged, it may vary from a few thousands to millions of dollars per incident. Similarly, the loss of future business due to broken rail derailments is also difficult to quantify.

Costs Associated with Service Failures

Service failures have a much lower cost per event than broken rail derailments, but occur about 150 times more frequently (*24*). Generally, service failures are detected by the signal system, a track inspector, or a train crew. Once detected, trains typically do not proceed over that section of track until the rail has been repaired. Although, FRA regulations allow trains to be moved at walking speed over a broken rail while the break is monitored by a qualified railroad employee, this practice is not generally used by the major U.S. railroads. Instead, trains are halted and a repair crew dispatched to remove and replace the broken rail before trains may proceed.

The costs associated with service failures include material, labor, and train delay costs. One railroad industry expert stated that the average material and labor cost for a service failure is $1,500, which includes mobilization of the crew and materials. Another railroad provided further details based on their estimates for average labor and materials for rail repair. The estimated material cost of a 15 foot section of 136 pound rail and two welds is about $375. The estimated labor cost for removing the old rail, unloading and placing new rail, installation of the requisite other track material (OTM), and installing field welds totals $370 for a combined total cost, not including mobilization, of $745. The difference between this value and the $1,500 estimate is the cost of mobilizing the labor and materials needed for the repair. A number of factors must be considered to evaluate the cost of mobilization, such as the time of day, time of year, location of service failure, and availability of materials.

The final cost associated with service failures is the cost of train delay. Railroad industry experts indicated that a typical service failure will result in an approximately four-hour track-outage, from initial notification of the failure until the line is reopened for normal operation.

Again, the delay cost will also depend on the number of trains delayed and can be estimated using the train delay calculator described in the next section.

Train Delay Cost Calculator

Broken rail derailments and service failures both impose train delay cost, but their magnitude differs due the difference in outage time. Total train delay cost is based on the cost per train-hour, the number of trains delayed, and the length of the delay. We incorporated these factors into a calculation of train delay cost using recent operating statistics for U.S. Class I railroads.

Calculation of Train Delay Cost per Train-hour

Single-train delay cost includes four components: car cost, locomotive cost, fuel cost, and crew labor cost. Car delay cost refers to the cost of railroad-owned cars that are delayed and therefore are unavailable for use elsewhere. Privately owned cars were excluded from this analysis because, in many cases, they are charged by the mile. Although the delay of these cars is not a direct cost to railroads, it is nevertheless an additional cost to the rail transport system, but was not calculable in this analysis. The average number of cars per train in 2006 was 69.2 cars (*25*) and 39.8% were railroad owned (*26*). To determine the cost per car, an average car-hire rate was used. Industry experts indicated that a reasonable estimate for this was $0.75 per car-hour in 2006. Therefore, the total average car delay cost per train was computed to be $20.67 per hour (Table 3).

The second component of train delay cost is locomotive delay. This cost was estimated based on the locomotive depreciation that occurs due to the delayed locomotives not being

available for use elsewhere. The average number of locomotives per train in 2006 was 2.7 (*25*).

Class I railroad data indicate that the average cost of new road locomotives, is approximately

$1,877,500, and the salvage value after 25 years is approximately $250,000 (*27*). Assuming a

discount rate of 10%, the annual depreciation for 2006 was $209,383 per locomotive; therefore,

the cost per locomotive-hour was $23.90 or $64.54 per train-hour (Table 3).

The third component of train delay cost is due to the extra fuel consumed due to the

delay. The cost of diesel fuel purchased by Class I railroads in 2006 was $1.93 per gallon (*25*).

The estimated average fuel consumed while a locomotive is idling is approximately 3.5 gallons

per locomotive-hour. Based on an average of 2.7 locomotives per train, the total fuel cost was

$18.24 per train-hour in 2006 (Table 3).

The fourth component of train delay cost accounted for in this analysis is labor expense.

Average hourly wages for train and engine crews on Class I freight railroads in 2006 was $21.40

for straight time and $31.45 for overtime pay (*28*). For the calculation of labor cost, only the

overtime rate was used based on the assumption that a train delay of more than a few hours will

generally result in overtime pay for the train crew. Additionally, the labor cost includes fringe

benefits, such as vacation pay, holiday pay, railroad retirement, unemployment, health welfare,

and group life insurance. Fringe benefits were estimated to be approximately 75% of wages.

Therefore, based on a two-person train crew, the labor cost of delay was $110.08 per train-hour

(Table 3).

Summing these four components of train-delay cost yields a total of $213.52 per train-

hour. Although this captures most of typical elements of train delay cost it is still only a partial

estimate because not all costs could be included due to limitations in data availability. For

example, in some delay situations crews must be replaced due to federal hours-of-service

regulations that limit crew members to a maximum period on duty of 12 hours each. There may

also be extra stopping and starting of the train resulting in extra fuel consumption and wear and

tear on brakes and other components. Nevertheless, this figure is consistent with industry expert

opinion that the cost of delay for a single train is in the range of $200 to $300 per hour.

Cost of Multiple Train Delay

The number of trains delayed and the duration of their delay during a track-outage should

also be considered in the calculation of train delay cost. These values can be approximated

based on the density of the line and the number of mainline tracks. To determine the number of

trains delayed, we assumed that trains will arrive in constant time intervals from both directions.

The average train operated on U.S. Class I railroads in 2006 was 6,312 gross tons, including cars

and locomotives (*25*). Therefore, the average number of trains per year for a particular line is the

annual gross tonnage (in millions) (ANMGT) of that line divided by 0.006312 million-tons per

train. The interval between trains, *t*, was then determined by dividing the number of hours per

year, 8,766, by the number of trains per year:

$$n = \text{Number of trains per year} = \frac{\text{Annual MGTs}}{\text{tons per train (millions)}} = \frac{ANMGT}{0.006312} \qquad \text{(Eq. 4)}$$

$$t = \text{hours per train arrival} = \frac{\text{hours per year}}{\text{trains per year}} = \frac{8,766}{n} = \frac{55.33}{ANMGT} \qquad \text{(Eq. 5)}$$

The total cost of train delay can then be calculated by the cost of delay per train-hour and

the hours per train arrival of the particular line. The total number of trains delayed is determined

by dividing the total delay time by the hours per train arrival. The length of delay for each train is based on the time of their respective arrival. The total cost due to train delay from a service interruption can be calculated using the following formula:

$$C = Tx + \sum_{n=1}^{m}(T - nt)x \qquad \text{(Eq. 6)}$$

where,

C = total train delay cost for multiple trains

T = total delay time for service interruption

x = cost of delay per train-hour ($213.52)

m = number of following trains delayed = T/t (rounded to the nearest integer)

t = hours per train arrival = $55.33 / ANMGT$

The total train delay cost presented in Equation 6 is valid for broken rail scenarios in which no trains can proceed due to the event. This would include service failures on single track territory or broken rail derailments on single and often on multiple track territory because trains would be unable to proceed. However, Equation 6 must be adjusted for situations in which a service failure occurs on one track in multiple track territory. In these situations trains will be able to proceed on the other mainline track and there will not be complete (100%) delay. It can be assumed that a service interruption on a single track may cause up to half the trains (50%) to be delayed (i.e. traffic in one direction stops). However, in most cases, less than 50% of trains would be delayed because of the ability to route some trains on the other track without delaying them. In these situations the extent of the delay will depend on the traffic density of the line.

Costs Associated with Broken Rail Preventive Measures

To determine the full economic impact of broken rails, the costs associated with preventive measures also need to be quantified. Typical, preventive measures include rail inspection for defects, rail grinding, and rail replacement and renewal. These preventive measures decrease the likelihood of a broken rail; however, they also extend the life of the overall track structure. For example, rail grinding improves the wheel-rail interface and extends rail life, as well as preventing certain types of crack growth that can lead to broken rails. Consequently, allocation of the cost related to broken rail prevention cannot be determined.

One of the most effective and widely used broken rail prevention measures is ultrasonic and geometric inspection of track (*12*). The cost of inspections is dependent on their frequency. The BNSF Railway uses a risk-based approach for inspection frequency (*29*) in which the calculated risk factor for any particular line depends on several variables. These include the number of previously detected defects, if the line carries passengers and/or hazardous materials, and the railroad-determined importance of the line.

Railroads also use rail grinding to eliminate surface defects and prolong the life of rail. Selection of grinding locations is typically based on rail age, traffic density, and the number of previously detected surface defects. Additionally, railroads complete rail surfacing projects to maintain stable and properly aligned track structure for many reasons, including slowing potential crack growth. Finally, rail renewal and replacement projects are crucial for large railroads to prevent broken rails and other track-related accident causes. However, rail replacement occurs due to both wear and fatigue crack growth, so allocation of this expense is not possible without knowing the percentage of rail replaced due to these different causes. Quantifying the costs of these prevention and maintenance measures is difficult due to limited

available information. Future work is needed on this topic to fully understand the costs indirectly related to broken rails.

CONCLUSIONS

Understanding the factors related to broken rails is important for identifying and implementing the most effective and efficient broken rail reduction measures. In this paper we present an analysis using recent data that includes a number of factors with the potential to affect rail crack growth and service failure occurrence. The dataset included 28 factors on track and rail characteristics, infrastructure features, maintenance activities, and on-track testing results. Several techniques involving logistic regression were implemented to determine the most accurate and robust service failure prediction model. A "practical" logistic regression model was ultimately selected because it was accurate, understandable, and useable. This model included only eight parameters and had a predictive accuracy of 64.7%. The most important factors related to service failures were rail weight, rail type, rail age, annual traffic, weight of car, presence of an ultrasonic defect, presence of a geometric defect, and the presence of a bridge.

This paper also presented an analysis of the economic impact of broken rails. From 2003 through 2006 broken rails were responsible for 335 FRA-reportable mainline derailments on Class I freight railroads, or about 84 per year. The average cost of damage to track and equipment from these accidents was $525,000 per incident and the average annual cost was $44 million. In addition to the FRA-reportable costs, expenses due to broken-rail-accident-caused train delay are estimated to be about $3 million per year, based on the rate of broken rail occurrence and 142,428 miles of mainline track operated by Class I railroads (*25*). Class I railroads also incur about $19 million per year for repair of service failures, and an additional

expense of $17 million due to the train delay that results from their occurrence. The cost of preventive measures, such as rail inspection, rail grinding, track surfacing, and rail replacement should also be considered when evaluating the overall cost of broken rails. However, many of these activities provide multiple benefits and therefore the direct cost to broken rails is difficult to determine.

FUTURE RESEACH

Future work may be possible to improve the accuracy of the service failure prediction models. The models presented in this analysis had an accuracy ranging from about 65% to 70% for prediction of service failures leaving about 30% to 35% of the variance unexplained. Examination of additional factors that affect crack growth may help to understand this variance. Some of the factors that could be considered include location-specific climatic data, flat wheel incidence, and track inspection data.

Future research regarding the economic impact of broken rails is also possible. Additional work on this topic could include research on hard-to-quantify values associated with broken rails. Some of these factors include the average cost of lading loss in a broken rail derailment, the financial impact of loss of business from accidents and train delays, and the costs associated with different broken rail prevention measures.

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TABLE 1 Logistic Regression Prediction Models Using Different Variable Selection

Techniques

Table 1a: Simple Logistic Regression Analysis

Regression Technique	Number of Parameters in Model	Number of Cases Correctly Classified	Accuracy of Classification	False Positives	False Negatives
Full-Model	28	16,820	66.3%	12.8%	20.9%
Forward	23	16,822	66.3%	12.8%	20.9%
Backward	23	16,822	66.3%	12.8%	20.9%
Step-wise	**23**	**16,822**	**66.3%**	**12.8%**	**20.9%**

Table 1b: Two-Term Interaction Logistic Regression Analysis

Regression Technique	Number of Parameters in Model	Number of Cases Correctly Classified	Accuracy of Classification	False Positives	False Negatives
Full-Model	363	17,921	70.6%	12.2%	17.1%
Forward	90	17,840	70.3%	12.2%	17.5%
Backward	**145**	**18,025**	**71.0%**	**12.1%**	**16.9%**
Step-wise	62	17,779	70.1%	12.2%	17.7%

Table 1c: Testing of Regression Models for Robustness

Logistic Regression Model	Regression Technique	Accuracy of Initial Classification Model	Accuracy for Training Sample	Accuracy for Testing Sample	Change
Simple Logit	Step-wise	66.3%	66.7%	66.3%	-0.4%
Two-Term Interaction Logit	Backward	71.0%	71.2%	57.1%	-14.1%
Eight-term Logit Model	Step-wise	64.7%	65.1%	64.1%	-0.9%

TABLE 2 Optimal Service Failure Prediction Models by Number of Allowed Parameters

Parameters in Model	Parameters Removed	Parameters Added (if any)	Accuracy of Classification	False Positives	False Negatives
23	--	--	66.3%	12.8%	20.9%
22	Turnout	--	66.3%	12.9%	20.9%
21	Age of Rail	--	66.3%	13.0%	20.7%
20	Length of Grade	--	66.3%	12.9%	20.8%
19	Degree of Curve	--	66.4%	12.8%	20.8%
18	Average Tons per Car	--	66.4%	12.8%	20.7%
17	Culvert	--	66.3%	12.9%	20.8%
16	Tie Work Completed	--	66.4%	12.8%	20.8%
15	Superelevation	--	66.3%	13.0%	20.7%
14	Diamond	--	66.3%	13.0%	20.7%
13	Grade Crossing	--	65.9%	13.2%	20.9%
12	Speed, Annual Trains, Average Dynamic Tons, & Annual Wheel Passes	Average Tons per Car, Degree of Curve, & Grade Crossing	65.3%	13.5%	21.2%
11	Grade Crossing	--	65.3%	14.1%	20.6%
10	Out-of-Face Rail Grinding	--	65.3%	13.1%	21.6%
9	Accumulated MGTs & Degree of Curve	Age of Rail	64.8%	13.0%	22.2%
8	Curve Rail Grinding	--	64.7%	12.8%	22.5%
7	Age of Rail	--	64.3%	12.1%	23.6%
6	Bridge	--	63.3%	12.9%	23.8%
5	Rail Weight	--	64.0%	11.1%	24.9%
4	Geometric Defect	--	62.4%	10.9%	26.7%
3	Average Tons per Car	--	62.8%	10.7%	26.5%
2	Annual MGTs	--	60.0%	4.4%	35.6%
1	Rail Type	--	56.2%	1.6%	42.1%
0	Ultrasonic Defect	--	--	--	--

TABLE 3 Breakdown of Train Delay Cost per Train-hour

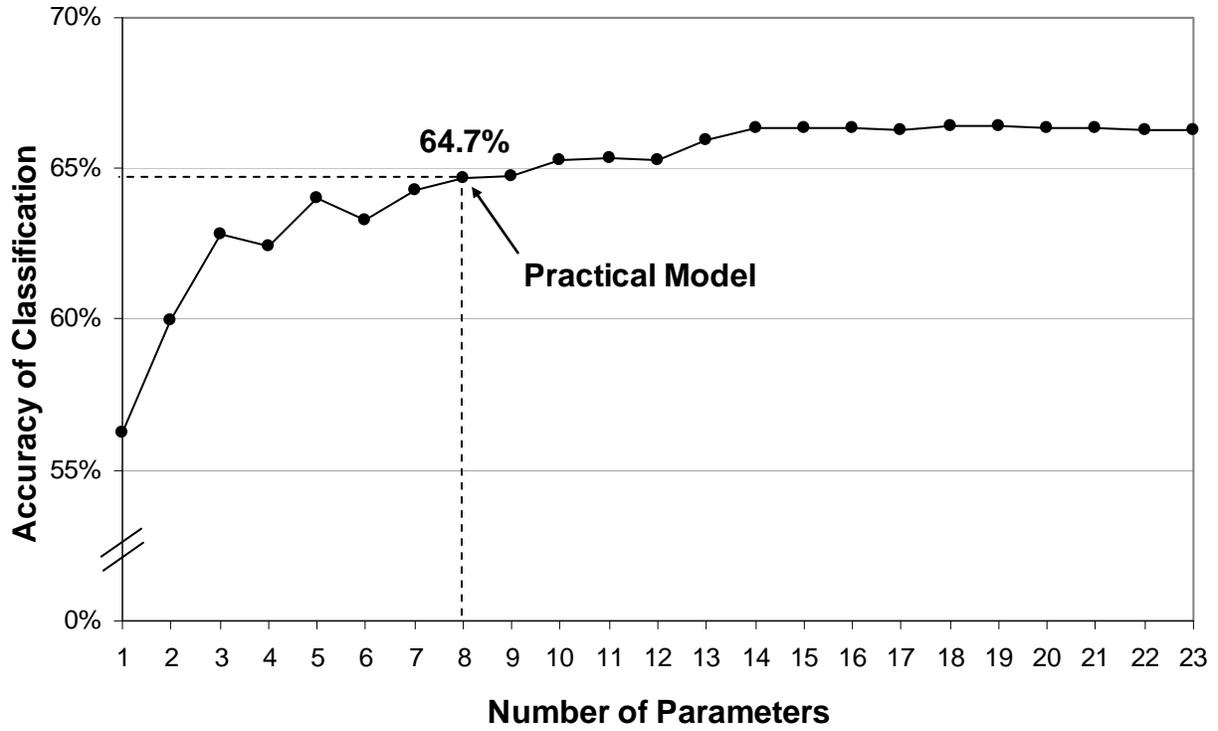|	
Car Cost	
Average number of Cars per train	69.2
Car Hire per hour	$0.75
Percent of cars owned by railroad	39.8%
Total per Train-hour	**$20.67**
Locomotive Cost	
Average number of Locomotives per train	2.7
Average cost of new locomotive	$1,877,500
Average Life of locomotive	25
Average salvage value	$250,000
Discount Rate	10%
Average cost per locomotive year	$209,383
Total per Train-hour	**$64.54**
Fuel Cost	
Average number of Locomotives per train	2.7
Gallons per Hour In idle	3.5
Cost per Gallon	$1.93
Total per Train-hour	**$18.24**
Crew Cost	
Number of employees per train	2
Average Hourly Pay	$21.40
Average Overtime Pay	$31.45
Percent of wage for fringe benefits	75%
Total per Train-hour	**$110.08**
TOTAL COST PER TRAIN HOUR	**$213.52**

FIGURE 1 Accuracy of Prediction based on Number of Allowable Parameters

LIST OF TABLES & FIGURES