ANALYSIS OF FACTORS AFFECTING THE LOCATION AND FREQUENCY OF BROKEN RAILS

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Introduction

Since 1980, the overall derailment rate on US railroads has declined by over 60% (United States Department of Transportation [USDOT] Federal Railroad Administration [FRA] 1999, 2000). This dramatic improvement is the result of major capital investments in infrastructure and equipment, employee training efforts and the continued development and implementation of improved technology. Most of this improvement in safety took place in the 1980s. Although the trend continued through the 1990s, it was at a lower rate. North American railroads have not lessened their goal of safety improvement, but much of the benefit of previous investments in infrastructure and equipment had been achieved. Ironically, this makes identification and implementation of further steps forward more challenging because there is less empirical information on which causes are contributing the greatest risk. Consequently, the use of more sophisticated risk analysis methods to identify the best options for improvement need to be employed. Of particular interest is reduction in the occurrence of accidents that result in the release of dangerous goods (DG) Although all accidents are a source of concern, DG accidents rank among the highest concern because of the additional hazard to people and property if there is a major release.

In this paper we present the results of a risk analysis of railroad derailment causes intended to provide insight into the causes most likely to lead to a DG release. Based on that analysis, we developed a statistical model that is intended to improve the ability to predict the occurrence of one of the major causes of serious derailments, broken rails. Derailments caused by broken rails have been a safety concern of the railway industry for over a century (Thompson 1992, Aldrich 1999). Improvements in rail manufacturing and inspection and rail defect detection have greatly reduced the incidence of broken rails; however, broken rails are a frequent cause of service interruptions, and remain one of the leading causes of derailments. Improving the ability to predict where broken rails are likely to occur has both economic and safety benefits because it would enable more effective allocation of resources to detect and prevent broken rails (Palese & Wright 2000, Palese & Zarembski 2001).

Definition of a Severe Derailment

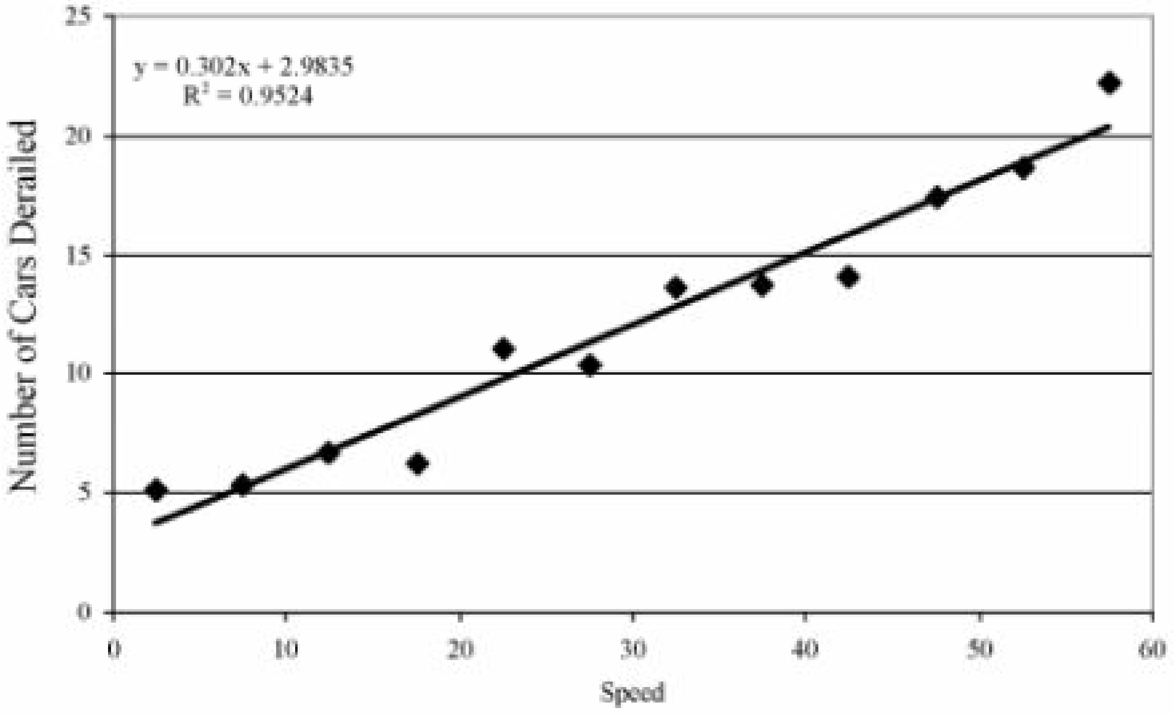
The FRA requires that railroads report the occurrence of all accidents that exceed certain minimal threshold criteria (USDOT FRA 1999). These reports include detailed information on the circumstances and cause(s) of the accident, as well as various quantitative measures of the consequences. The FRA compiles these reports into a comprehensive database on railroad accidents that is available for research and analysis (FRA 2000). We analyzed these data for mainline accidents for the 5-year interval 1994 to 1998 to develop quantitative estimates of the risk associated with different derailment causes.

Our principal interest was in identifying the causes of accidents most likely to result in release of dangerous goods. The frequency of these events has declined in parallel with the decline in accidents (Harvey et al. 1987, Barkan et al. 2000), as well as due to improvements in railroad tank car damage resistance (Barkan et al. 1992, Barkan & Pasternak 1999). In recent years there have typically been about 40 to 45 such accidents annually (FRA 1999, 2000) and many of these are relatively minor incidents. Consequently, the statistical basis for developing insights about the most important accident causes is not very large. To improve the robustness of our inferences, we needed to develop a proxy statistic that was a both a reliable predictor of the conditions that can lead to a DG release event, and could be measured in a large number of accidents.

Several derailment parameters were examined to determine if they could be used as a predictor of DG release probability. One candidate parameter was the total monetary damages due to the accident. However, this metric proved unsatisfactory because monetary damages are subject to substantial additional sources of variance from factors such as the difference in cost between locomotives and freight cars, the variability in the value of damaged lading, and the difference between repairing regular track versus special track work such as turnouts and crossings. Variation in any or all of these contributes to widely varying values for monetary damages in accidents. Much of this variation is unrelated to the physical forces that actually cause damage to railcars and the resultant DG releases.

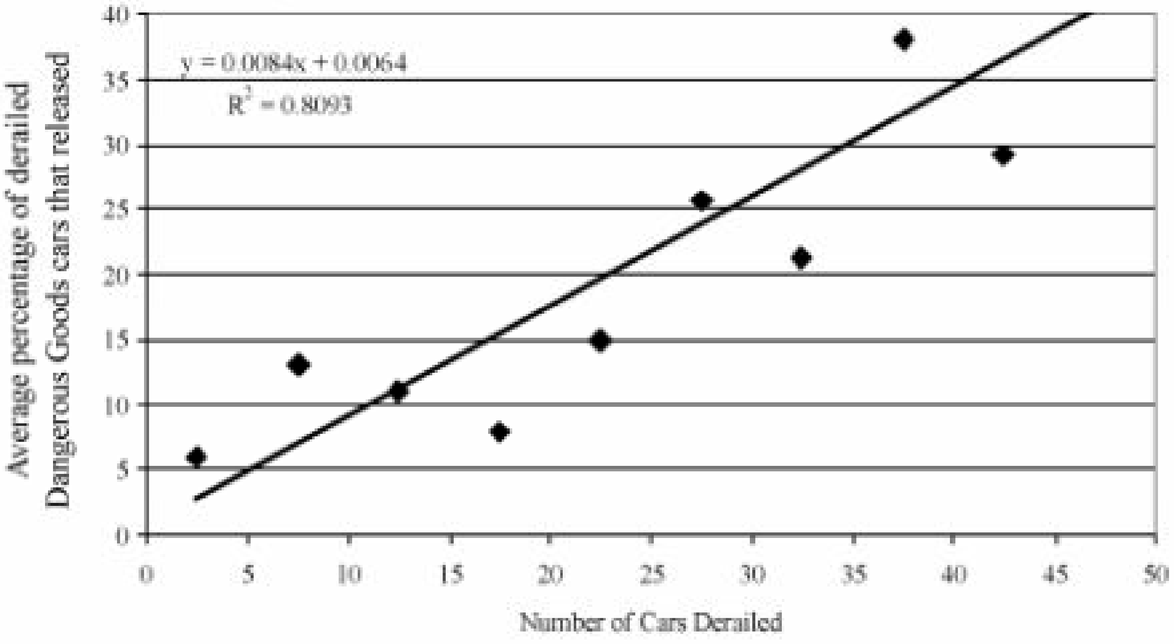
As an alternative to monetary damage, we considered the number of cars derailed per accident. This parameter is recorded in the FRA database and is likely to be affected by many of the same physical factors that contribute to the probability of damage to a railcar carrying DG. The number of cars derailed is expected to be a function of derailment speed. At higher speeds, there will be greater momentum and kinetic energy and correspondingly more cars derailed. We examined this relationship and as expected found a strong linear relationship (Figure 1).

Figure 1. Relationship between speed and number of cars derailed
(mainline accidents in which at least one Dangerous Goods car derailed)



For similar reasons, we expected that the greater forces associated with accidents resulting in large numbers of cars derailed would be correlated with a higher probability of railcar damage sufficient to cause a DG release. We examined this by comparing the number of cars derailed in accidents with the fraction of derailed DG cars that released and again found a significant linear relationship (Figure 2).

Figure 2. Relationship between the number of cars derailed and the percentage of Dangerous Goods cars that release (given that at least one DG car is derailed in the accident)



These relationships are intuitive but they provide a quantitative basis for further analysis of the importance of different accident causes. In particular, they suggest that the number of cars derailed can be used as a "proxy" variable for prediction of accident conditions likely to lead to a release if a DG car is involved. The advantage this offers is a larger, more robust body of data to draw upon for analysis of accident causes than would be possible if we relied only on data from accidents with DG releases.

Derailment Severity-Frequency Analysis

To determine the causes of accidents most likely to lead to conditions that could result in a DG release, we conducted a simple risk analysis using the FRA data for the 3,504 mainline derailments that occurred during the interval referenced above. The FRA reporting system requires identification of a primary cause (and other contributing causes if applicable). The data were grouped by the primary FRA cause code, and the average number of cars derailed in accidents attributed to that code. The resulting values were then plotted against the frequency of derailments caused by the same code (Figure 3).

Figure 3. Frequency/severity graph of mainline derailments

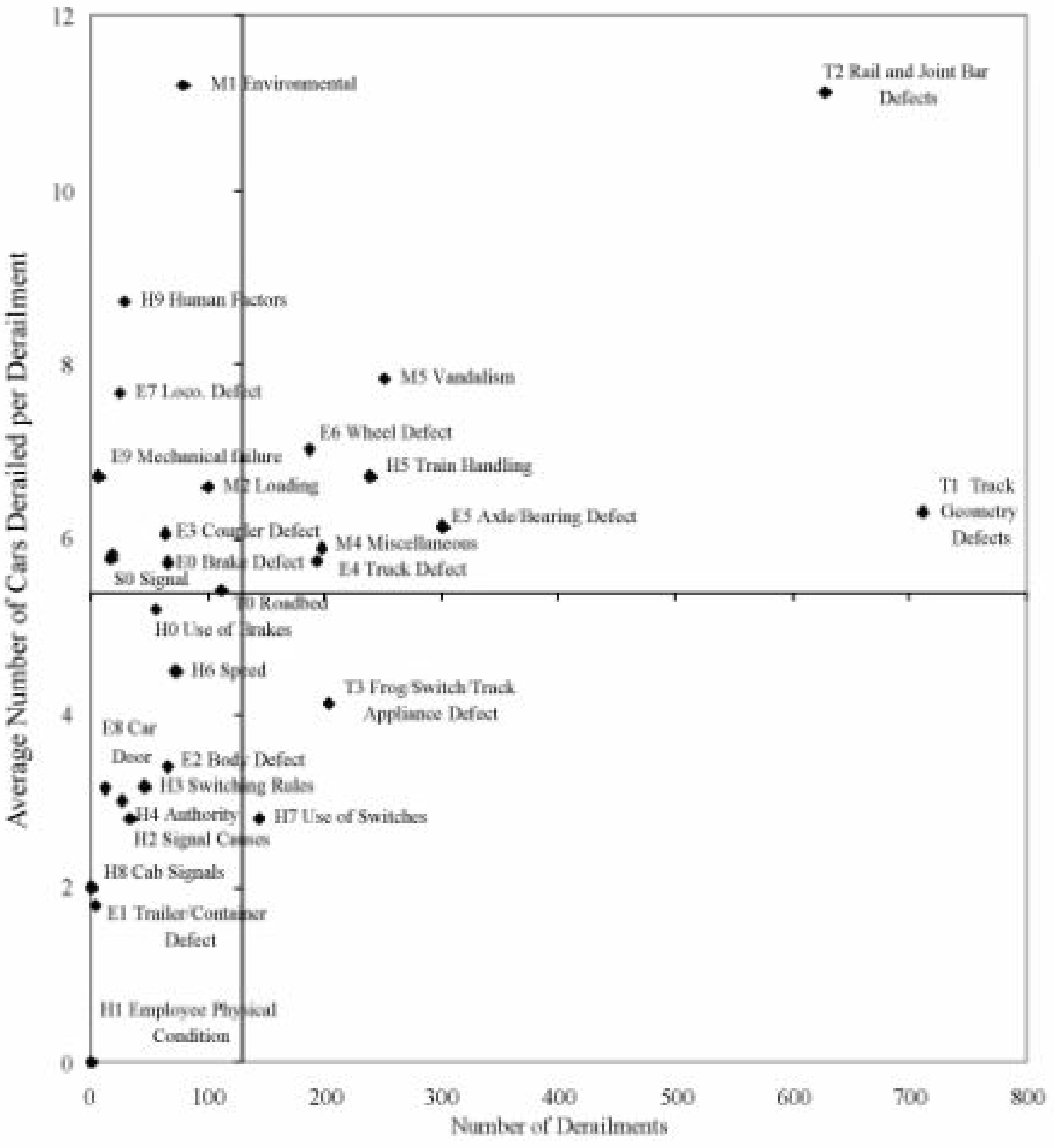


Figure 3 is divided into four quadrants by vertical and horizontal lines that represent the average value of the two variables with respect to the *X* and *Y* axes, respectively. The vertical line represents the average frequency of accidents for all recorded causes combined, and the horizontal line is the average number of cars derailed due to each cause. Causes above or below these lines are, by definition, above or below average for the respective axis.

The four quadrants in Figure 3 are of differing interest. The causes in the lower left quadrant are of least interest because they uncommon, low consequence events. The causes in the upper left quadrant are infrequent but above average in consequence. Although these are of interest, their low frequency means that it is more difficult to predict how consistently these causes will lead to events with significant consequences, and that sufficient data to isolate contributing factors may be difficult to develop. The causes in the lower right are of secondary interest. Although they are generally of low consequence, their high frequency makes them a source of some concern.

The causes in the upper right quadrant are most interesting and pose the greatest risk because they are both more frequent and more severe than average. The FRA cause code "Rail and joint bar defects" is one of the causes in the upper right quadrant, and in fact, is clearly the highest consequence, high frequency cause of accidents. Analysis of this cause in more detail reveals that most of the accidents accounted for by this code are due to broken rails. Based on these results we undertook a more detailed analysis of the factors contributing to the occurrence of broken rail derailments.

Broken Rails

Most broken rails do not result in derailments. Instead the break is detected, usually by the track circuit system or by track inspectors, and repaired (on several North American railroads these detected broken rails are referred to as "service failures"). Broken rail derailments appear to be correlated with the occurrence of service failures (Dick 2001). Therefore predicting the occurrence of service failures has a potential safety benefit because it could enable railroads to allocate broken rail prevention measures, detection technology or inspection efforts, more effectively (Orringer et al. 1999, Palese & Wright 2000, Palese & Zarembski 2001). Furthermore, understanding the factors correlated with service failure occurrence could help identify contributing causal factors, thereby enabling better preventive measures. The objective of the second phase of this research was to develop a probabilistic model to predict the circumstances that were most likely to lead to the occurrence of a service failure.

Model Form and Data Set

Ideally, the model we developed would enable the user to input values for the relevant parameters at a specific location on the railroad and determine a measure of the probability of a service failure there. The output of the model is an index value between 0 and 1, with 0 indicating the lowest probability of service failure and 1 representing the highest. Since a probability is the desired output and there are only two possible outcomes, service failure or no service failure, at each location, the model can be constructed as a discrete choice model.

A discrete choice model, such as the logit model, fits an appropriate equation to the data and uses this equation to score each location relative to a threshold value, above which failure is predicted to occur. The logit model then uses a logistic distribution to consider the uncertainty and error in the estimated score and threshold value, and determine the probability that the score is above the threshold value. The calculated probability is then used as an estimate of the service failure probability at that particular location.

In order to fit a discrete choice logit model, two sets of data were required; one to characterize locations where service failures occurred and a second set of data to characterize locations where service failures had not occurred. Development of these data began with information the Burlington Northern and Santa Fe Railway, a major North American freight railroad, had developed containing detailed information on the date, location and type of 1,903 service failures that had occurred over a recent two-year interval. These data were supplemented with engineering and operational data pertaining to each service failure location. A new dependent variable was created and assigned the value "1" for each of these records signifying that a service failure had occurred there.

The second set of data was created with records for locations where no service failure occurred during the same interval. An approximately equal-sized set of data was developed by selecting a random sample of locations from the railroad and assembling identical information as had been developed for the service failure locations. The dependent variable for these records was assigned a value of "0".

Ultimately, we developed a test database comprising 3,676 records with complete service failure and descriptive parameter information. Based on a univariate analysis of the service failure data and review of literature on the circumstances of rail defect growth and broken rail occurrence (Reiff 1997, Clark 2000, Lawrence et al. 2000), track structure and dynamic effects (Hay 1982, Selig & Waters 1994, American Railway Engineering and Maintenance-of-Way Association 2000), and the fracture mechanics of rail (Orringer & Bush 1982, Lawrence 2000) the following parameters were selected to be considered in the multi-variate service failure model:

- Rail Age
- Rail Weight
- Degree of curve
- Speed
- Average Tons Per Car
- Average Dynamic Tons Per Car
- Percent Grade
- Annual Gross Tonnage
- Annual Wheel Passes
- Insulated Joints
- Mainline Turnouts

All of the parameters are continuous variables except the last two, insulated joints and mainline turnouts, which are both discrete. These were assigned a value of "1" if present at a location, and "0" if not.

Model Development

The service failure probability model was developed using Statistical Analysis Software (SAS) and the LOGISTIC procedure. The LOGISTIC procedure fit a discrete choice logit model to the test database. Stepwise regression was used to determine the most relevant parameters and combinations of parameters (two-factor interaction terms) for inclusion in the model. The stepwise regression procedure uses an iterative process to select variables on the basis of their ability to explain the variance in the input data. The model conducts a "goodness of fit" test for each step and adds or subtracts variables or combinations of variables until the addition of another parameter does not significantly improve the fit. At this point the last version of the model is considered the "best" and the resultant parameters, coefficients, and functional relationships comprise the final model.

Retrospective and Prospective Models

Development of the service failure model was a two step process. First the model was fit to the test database described above. Recall that this database comprised 3,676 locations, approximately half of which experienced a service failure during the two-year period encompassed, and the other half were a random sample of locations that did not. Because the model is making predictions about the past, we termed it the "retrospective model". This version of the model is used primarily to assess the accuracy of the model's predictions with respect to the test database.

The second step of the process is development of a "prospective model". It is modified from the retrospective model by adjusting a constant term to reflect the actual average service failure probability over whatever portion of a railroad system is of interest. Once this adjustment is made, the prospective model can be used to calculate the annual probability of a service failure at particular locations, or along any portion of track that is of interest.

Retrospective Service Failure Model

The following retrospective service failure probability model was developed using the LOGISTIC procedure:

$$p_{SF2} = e^U / (1+e^U)$$

Where:

p_{SF2} = probability that a service failure occurred at a particular point during the study interval

$U = Z + Y$

$Z = -4.569$, model specific constant, (discussed below)

$Y = 0.059A + 0.025AC - 0.00008A^2C^2 + 5.101T/S + 217.9W/S - 3861.6W^2/S^2 + 0.897(2N-1) - 1.108P/S$

A = rail age in years

C = degree of curvature (= 0 for tangent)

T = annual traffic in million gross tons (MGT)

S = rail weight in pounds

$W = 4T/L$ = annual number of wheel passes (millions)

$P = L(1 + V/100)$ = dynamic wheel load

N = 1 if at turnout, 0 if not at turnout

L = tons per car

V = track speed

The fitted model includes a model-specific constant or intercept term, Z, that is related to the average service failure probability. Recall that the retrospective model is fit to a data set in which approximately half of the records were for locations that experienced service failures. The average service failure probability on an actual system would be far lower, so this term would be adjusted to reflect this (see discussion of prospective model below).

Interpretation of Model Terms

The service failure probability model contains terms that describe different effects and relationships between service failure probability, infrastructure characteristics and traffic characteristics.

The first term in the model, $0.059A$, reflects the effect of rail age. As rail age increases, service failure probability increases. This result is consistent with extensive industry experience. Older rail is likely to have carried more tonnage, experienced more thermal stress cycles and may have been manufactured using processes that allowed more flaws in the rail. A recent study of rail failures on Railtrack in Great Britain (Sawley & Reiff 2000) supports the importance of this parameter.

The second and third terms in the model, $0.025AC - 0.00008A^2C^2$, reflect the interaction between rail age and degree of curve. As either rail age or degree of curve increases, service failure probability is predicted to increase. Since the interaction between rail age and curvature is multiplicative, the model indicates that in terms of service failure probability, higher degree (sharper) curves are more sensitive to the effects of rail age, and vice versa.

The fourth term in the model, $5.101T/S$, reflects the effect of annual traffic (MGT) normalized by rail weight. As annual gross tonnage increases, service failure probability increases. However, the form of the interaction with rail weight indicates that the increase in service failure probability associated with a unit increase in annual traffic is greater on segments of track with relatively light rail.

The fifth and sixth terms in the model, $217.9W/S - 3861.6W^2/S^2$, describe the effect of annual wheel passes or load cycles normalized by rail weight. Service failure probability increases as the number of wheel passes or load cycles increases. However just as with gross tonnage, the increase in service failure probability associated with a unit increase in the annual number of wheel passes is greater on segments of track with relatively light rail. This is probably due to the fact that lighter rail experiences more stress under a given load than heavier rail. Thus, the amount of crack growth per fatigue cycle is greater in lighter rail than heavier rail.

It is interesting that the model includes terms that describe annual traffic in terms of gross tonnage and the number of wheel passes. The relationship between annual traffic and service failure probability is a function of both the total amount of load applied to a section of rail and the number of times the load is applied. This relationship is consistent with fracture mechanics models of fatigue crack growth in rails that depend on both the applied stress and the number of load cycles (Lawrence 2000).

The seventh term in the model, $0.897(2N-1)$, describes the effects of mainline turnouts. Since $N = 1$ near a turnout, the presence of a turnout increases the probability of a service failure. There are several possible explanations related to inferences about rail stress. Turnouts may tend to anchor the track structure thereby causing greater thermal stress cycling as the nearby rail expands and contracts. Also, to the extent that turnouts tend to be associated with locations where trains slow down, stop or start, rails in these locations may tend to experience more traction-induced stresses.

The final term in the model, $-1.108P/S$, describes the effect of dynamic load on service failure probability. The term is negative indicating that as dynamic load increases, service failure probability decreases. This is an unexpected result and is the opposite of what was suggested by a single variable analysis conducted prior to development of the multi-variate model. However, the relative effect of this term is weak. For example at an annual tonnage level of 50 MGT, on 136 lb. rail, in tangent track, varying the annual wheel passes between the highest and lowest possible values changes p_{SF2} by approximately 0.17. Under the same conditions, varying the dynamic load term between its extreme values only changes p_{SF2} by 0.03. In the stepwise regression this term was the final term added to the model (Table 1) and has the least predictive ability of the included terms (as indicated by the low chi-squared value). Thus we do not think that this term represents an actual physical relationship. The regression model development procedure may have included this term in the model to capture additional, unexplained variance resulting from various effects, and possibly to balance over-predictions of service failure probability caused by the linear nature of other effects in the model.

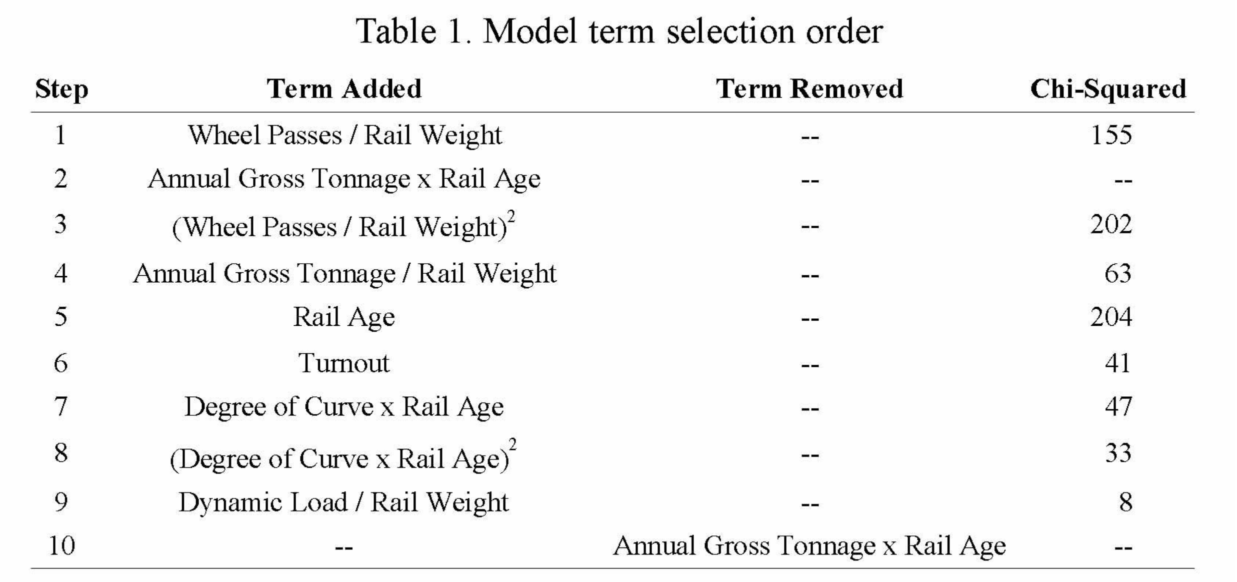


Table 1. Model term selection order

Step	Term Added	Term Removed	Chi-Squared
1	Wheel Passes / Rail Weight	--	155
2	Annual Gross Tonnage x Rail Age	--	--
3	(Wheel Passes / Rail Weight)^2	--	202
4	Annual Gross Tonnage / Rail Weight	--	63
5	Rail Age	--	204
6	Turnout	--	41
7	Degree of Curve x Rail Age	--	47
8	(Degree of Curve x Rail Age)^2	--	33
9	Dynamic Load / Rail Weight	--	8
10	--	Annual Gross Tonnage x Rail Age	--

Table 1 also indicates that during the stepwise regression process, an interaction term between rail age and annual gross tonnage was initially included in the model. By multiplying rail age by annual gross tonnage, the term estimated the effect of cumulative tonnage. Although the cumulative tonnage effect was initially significant, as more detailed terms describing the effects of rail age, turnouts and curvature were added to the model, the cumulative tonnage effect became less significant and was finally removed from the model. Thus, the variance in service failure probability that was initially explained by cumulative tonnage in a model with two terms could be better explained by a model with more terms and a combination of effects involving other variables. It is also interesting which parameters did not appear in the final model. The effects of grade, speed, average wheel load and insulated joints were not found to significantly improve the predictive ability of the model and were not included.

Retrospective Service Failure Model Performance

We used two methods to evaluate the ability of the retrospective model to predict locations where service failures occurred. The first calculates a “goodness of fit” statistic for the model based on the service failure probability (p_{SF2}) computed for each of the records in the input data. If the model completely accounted for all of the sources of variance, one would expect $p_{SF2} = 1$ at all of the service failure locations and $p_{SF2} = 0$ at all of the locations where service failures did not occur. In this case the summation of p_{SF2} over all service failure locations should equal the total number of service failures and the summation of 1- p_{SF2} over all locations where service failures did not occur should equal the total number of locations where service failures did not occur. It is highly unlikely that all sources of variance will have been accounted for by any statistical model. Therefore, when the summations are computed for actual values of p_{SF2}, they will correctly account for only a percentage of the total. This percentage reflects the "goodness of fit" or the amount of variance explained by the retrospective model (Ben-Akiva & Lerman 1985). Using this approach, the goodness-of-fit statistic is calculated using the expression below, where n_{sf} is the actual number of locations where service failures occurred, and n_{nosf} is the number of locations where they did not.

Goodness of fit = $\left(\sum_{n_{sf}} p_{SF2} + \sum_{n_{nosf}} 1\text{-}p_{SF2} \right) / (n_{sf} + n_{nosf})$

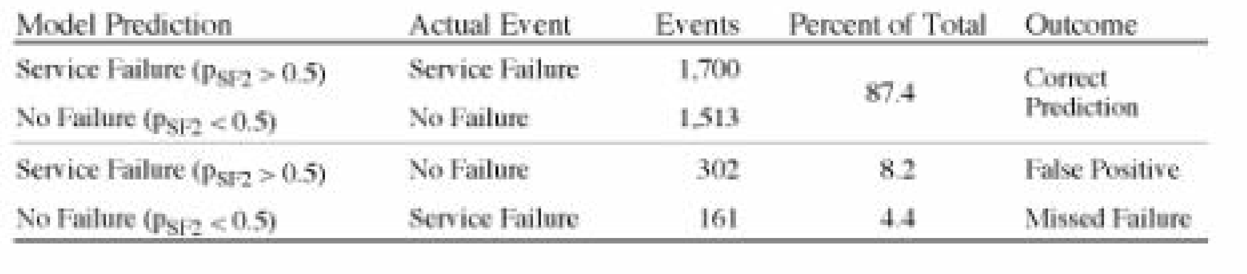
= (1,507 + 1,462) / (1,861 + 1,815)

= 0.808

Based on this analysis, the retrospective model accounted for 80.8 percent of the variance in the service failure data.

The second method we used to evaluate the performance of the model is to compare the value of p_{SF2} to the event that actually occurred at that location. The decision criteria, or threshold value, for service failure prediction was a p_{SF2} value of 0.5. If p_{SF2} was less than 0.5, it was classified as predicting “no failure” and if it was greater than 0.5 it was classified as predicting a service failure. 87.4 percent of these predictions were correct (Table 2). Of the incorrect predictions, there were twice as many false positives than missed service failures. This indicates that the model is somewhat conservative as it is more likely to provide a false positive than miss a service failure.

Table 2. Results of goodness-of-fit test for a threshold value of p_{SF2}=0.5



Model Prediction	Actual Event	Events	Percent of Total	Outcome
Service Failure ($p_{SF2} > 0.5$)	Service Failure	1,700	87.4	Correct Prediction
No Failure ($p_{SF2} < 0.5$)	No Failure	1,513		
Service Failure ($p_{SF2} > 0.5$)	No Failure	302	8.2	False Positive
No Failure ($p_{SF2} < 0.5$)	Service Failure	161	4.4	Missed Failure

These two evaluations indicate that the model had a reasonably high level of accuracy in predicting the occurrence of service failures in the database from which it was developed. The next steps in assessing the model's accuracy would be to apply it to data for a subsequent time period on the same railroad, and to apply it to data from a different railroad.

Prospective Service Failure Model

As explained above, in order to use the model to predict the annual probability of a service failure at a particular location, the retrospective model must be transformed into a prospective model. This transformation is accomplished by adjusting the value of the model specific constant, Z, to reflect the average service failure probability across the entire system of interest. There were 1,861 service failures in the test database over a two-year period for which complete records were available. The probability that one of these service failures falls into any given segment of track is a function of the length of the segment. To capture as much detail as possible, and to avoid the use of average values over a segment that may introduce additional variance, the segments should be kept relatively short. The maximum resolution in the data available for most of the parameters of interest was 0.01 miles (16.09 m). The total system represented by the database was approximately 23,750 miles of mainline. Thus, there were 2,375,000 segments 0.01 miles in length. Given this value, the average probability that a service failure is found in any one of those segments over a two-year period is approximately 0.00078. This probability can be converted into a new model-specific constant, Z*, through the use of the log-odds operator (McCullagh & Nelder 1989):

$$Z^* = Z + \ln [p_{SFavg} / (1 – p_{SFavg})]$$

$$= -4.569 + \ln [0.00078 / (1 – 0.00078)]$$

$$= -11.763$$

This new model specific constant, Z*, adjusts the scale of the probability calculated by the prospective service failure model so that the model predicts service failures at a rate that is comparable to the actual observed rate.

The retrospective model described above calculated the probability of a service failure over a two-year period. This can be converted to an annual probability simply by dividing by two when transforming the U-score into a probability. Once these two adjustments are made, the annual service failure probability for any 0.01 mile segment on the system can be calculated with the prospective service failure model. The prospective service failure probability model has the following form:

$p_{SF} = e^{U} / [\ 2(1+e^{U})\ ]$

Where:

p_{SF} = annual probability of a service failure in the 0.01-mile segment of interest

$U = Z^{*} + Y$

$Z^{*} = -11.763$, prospective model specific constant, described above
(all other terms and variables are the same as defined previously)

Service Failure Probability and Expected Service Failures per Mile

Cursory review of the annual service failure probabilities calculated by the prospective model might suggest that are too low. However, the probability is based on a segment of track that is only 0.01 miles in length. The calculated probability is approximately equal to the expected number of service failures per year in that 0.01 mile segment. Annual service failures per mile is a metric more typically used by North American railroads, so it is useful to calculate a per-mile rate by multiplying p_{SF} by 100.

$SF/MI/YR = 100e^{U} / [\ 2(1+e^{U})\ ]$

Where:

SF/MI/YR = expected service failure rate on segment of interest (service failures per mile per year)

This rate can be applied to a segment of track of any length as long as the values of the parameters in the service failure model remain constant along the section of the track. A service failure rate of 2 SF/MI/YR indicates that for every mile of track for which the rate applies, two service failures are expected to occur. If the track section to which this rate applied is 0.5 miles in length, then one service failure is expected along this length and if the section is two miles in length, four service failures are expected along the two-mile length. Note that in all three cases the service failure rate, 2 SF/MI/YR, is the same but the number of service failures expected in a section of track is a linear function of the length of the section. The number of service failures expected in a given section of track where the service failure rate is constant can be calculated by multiplying the length of the section by the service failure rate.

Example of Service Failure Model Application

The following example illustrates how the prospective service failure model can be used to obtain a measure of service failure probability and rate. A hypothetical 1.5-mile, single track portion of a railroad mainline is illustrated in Figure 4 and the relevant parameters are presented in Table 3. The segment has been broken into several sub-segments over which the input parameters are constant.

Figure 4. Schematic of hypothetical section of mainline track

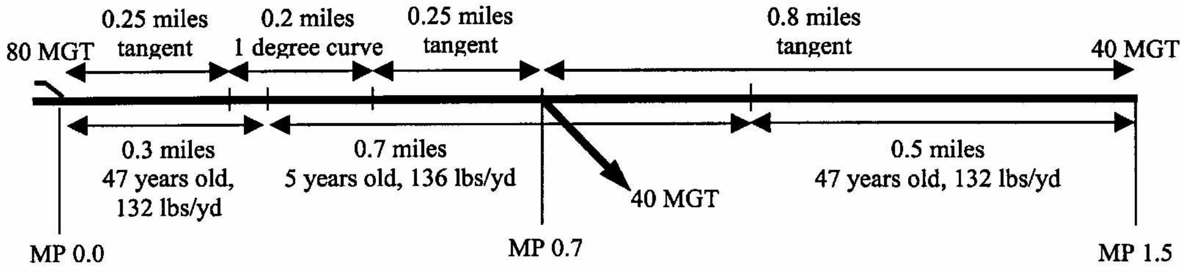
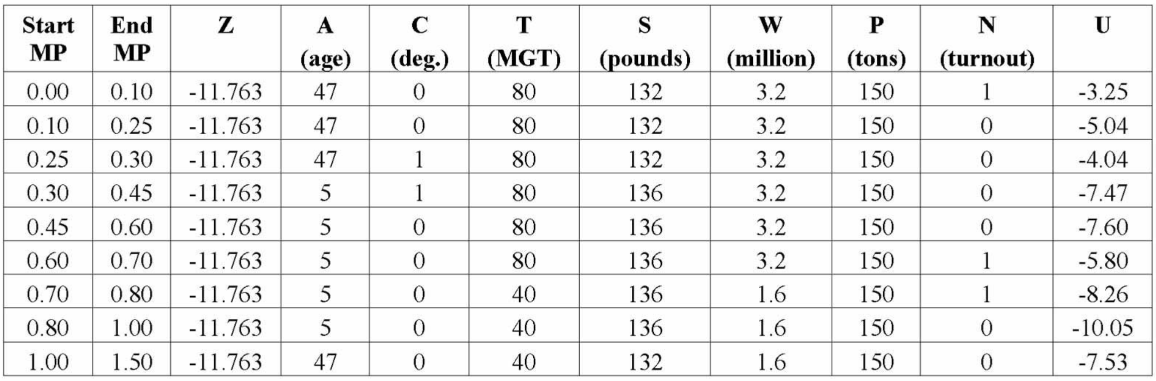


Table 3. Input parameters for hypothetical section of mainline track



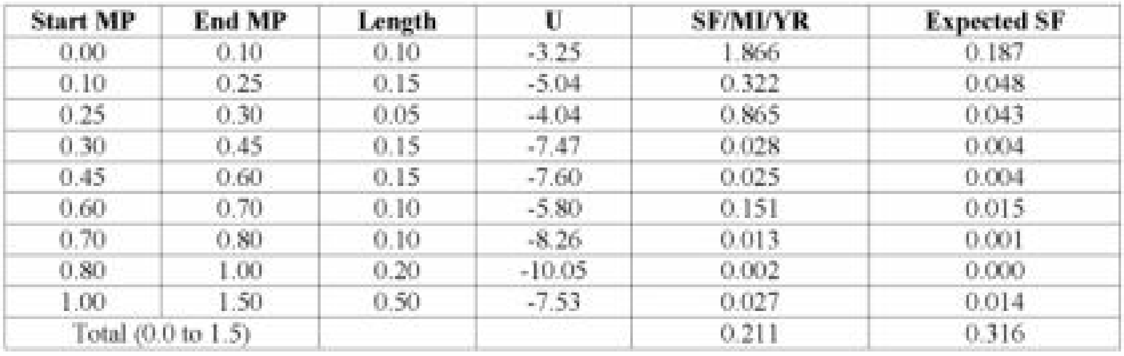
Start MP	End MP	Z	A (age)	C (deg.)	T (MGT)	S (pounds)	W (million)	P (tons)	N (turnout)	U
0.00	0.10	-11.763	47	0	80	132	3.2	150	1	-3.25
0.10	0.25	-11.763	47	0	80	132	3.2	150	0	-5.04
0.25	0.30	-11.763	47	1	80	132	3.2	150	0	-4.04
0.30	0.45	-11.763	5	1	80	136	3.2	150	0	-7.47
0.45	0.60	-11.763	5	0	80	136	3.2	150	0	-7.60
0.60	0.70	-11.763	5	0	80	136	3.2	150	1	-5.80
0.70	0.80	-11.763	5	0	40	136	1.6	150	1	-8.26
0.80	1.00	-11.763	5	0	40	136	1.6	150	0	-10.05
1.00	1.50	-11.763	47	0	40	132	1.6	150	0	-7.53

Some of the rail in the segment of interest is 47 years old and weighs 132 pounds per yard. The remaining rail is five years old and weighs 136 pounds per yard. Mainline turnouts are located at mile zero and also at mile 0.7 where another mainline connects to the line under study. A one degree curve is located between mile 0.25 and mile 0.45. Track speed on the segment is 50 miles per hour. The annual traffic is 80 million gross tons between mile 0.0 and mile 0.7. At mile 0.7, 40 million gross tons is routed on the connecting mainline with the remaining 40 million gross tons being routed on the segment under consideration between mile 0.7 and 1.5. The average gross rail load is 100 tons in the eastbound direction and 80 tons in the westbound direction for a maximum of 100 tons. The dynamic load computes to 150 tons per car, and the annual traffic of 80 MGT and 100-ton average per car results in an estimated 3.2 million wheel passes.

The U-score was calculated for each portion of the segment of interest and then transformed into an estimate of service failure rate. The estimated service failure rate (service failures per mile per year) for each sub-segment is summarized in Table 4 and presented graphically in Figure 5. Multiplying the service failure rate on each sub-segment by the actual length of each sub-segment provides an estimate of the expected number of service failures on an annual basis per mile in that sub-segment. Summing all of the individual sub-segment values provides an estimate of the expected number of service failures per year on all 1.5 miles of the segment of interest. In this case, the expected number of service failures for the segment is 0.316.

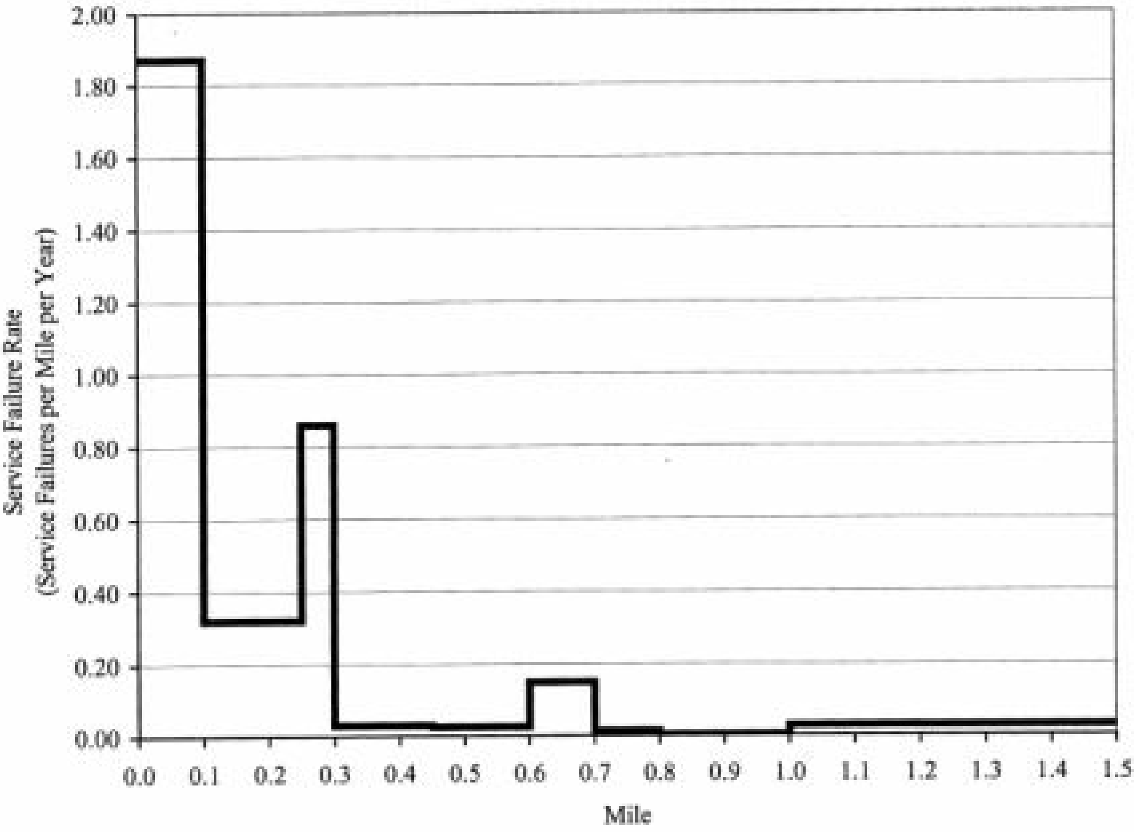
The service failure profile in Figure 5 highlights how interactions between the various parameters affects service failure rate. Between mile 0 and 0.1, the rail is relatively old and a turnout is present. The combination of these two factors results in a relatively high predicted service failure rate. At mile 0.1, the service failure rate drops as the rail is no longer close enough to the turnout to be subject to its effects. Between mile 0.1 and 0.25, the

Table 4. Service failure probabilities along hypothetical track section.



Start MP	End MP	Length	U	SF/MI/YR	Expected SF
0.00	0.10	0.10	-3.25	1.866	0.187
0.10	0.25	0.15	-5.04	0.322	0.048
0.25	0.30	0.05	-4.04	0.865	0.043
0.30	0.45	0.15	-7.47	0.028	0.004
0.45	0.60	0.15	-7.60	0.025	0.004
0.60	0.70	0.10	-5.80	0.151	0.015
0.70	0.80	0.10	-8.26	0.013	0.001
0.80	1.00	0.20	-10.05	0.002	0.000
1.00	1.50	0.50	-7.53	0.027	0.014
Total (0.0 to 1.5)				0.211	0.316

Figure 5. Graphical representation of service failure probability along hypothetical track section



track is tangent but the old rail produces a higher service failure rate than on the segment between mile 0.45 and 0.6 where the track is tangent but the rail is relatively new. This difference in service failure rate illustrates the importance of rail age. Under the traffic conditions in this example, the age difference of 42 years results in a service failure rate that is 16 times higher on the older section of rail. At mile 0.25, the track transitions from tangent to a one degree curve and the service failure rate increases approximately three times. When compared to mile 0.45, where the new rail transitions from curve to tangent and the service failure rate only increases by a factor of 1.5, the increase in service failure rate at mile 0.25 is large. This is due to the interaction of rail age and curvature that makes the old rail on this sub-section of track sensitive to curvature. At mile 0.3, the rail on the one degree curve changes from rail that is 47 years old to rail that is 5 years old. Since new rail is less sensitive to the effects of curvature, the service failure rate drops from 0.86 to 0.03 service failures per mile per year. Since there is one half the traffic between mile 0.7 and 1.5 than there is between mile 0.0 and 1.5, the service failure rate is lower between mile 0.7 and 1.5 than between mile 0.0 and 0.7.

Conclusions

We conducted a risk analysis that showed that broken rails are the leading cause of accidents in which large numbers of cars are derailed, and that the conditions of such accidents are correlated with conditions that can lead to a release of dangerous goods. Detection of broken rails and prevention of these derailments has important potential safety benefits. Furthermore, there are service quality and reliability benefits if the incidence of broken rails can be reduced. Improving the ability to predict the conditions that can lead to broken rails can help railroads allocate inspection, detection and preventive resources more efficiently, thereby enhancing safety and reducing service interruptions due to broken rails.

We developed a statistical model that provides probabilistic estimates of the likelihood of service failure occurrence based on engineering and operational input parameters. Although further validation needs to be conducted, the service failure prediction model described here shows promise of being able to provide improved ability to predict the occurrence of broken rails. If the requisite data for a railway system can be systematically developed in a consistent, easily accessed, electronic format, the model described in this paper can be applied to any portion of the system to generate probabilistic estimates of service failure probability. If the data include appropriate geographical information, then the service failure model presented here could be incorporated into a geographic information system that would generate service failure and broken rail derailment profiles automatically from railway databases.

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