QUANTITATIVE ANALYSIS OF FACTORS AFFECTING RAILROAD ACCIDENT PROBABILITY AND SEVERITY

BY

ROBERT THOMAS ANDERSON

B.A., DePauw University, 2001
B.S., University of Illinois at Urbana-Champaign, 2003

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ABSTRACT

The research presented in this thesis describes methodologies developed to quantify railroad accident and derailment probability and severity. Analysis of Federal Railroad Administration (FRA) track class-specific accident and derailment rates indicates two to three orders of magnitude difference between the lowest and highest track classes. Segment-specific derailment rates were calculated for a Class I railroad and theoretical methodologies to determine the optimal segment length for a given level of confidence in the estimated derailment rate were evaluated. A parametric Empirical Bayes analysis is used to adjust observed estimates of the derailment rate based on traffic volume and characteristics of similar track segments. Models are developed for calculating point-of-derailment probabilities and positional derailment probabilities for cars within a derailed train consist. Results are dependent upon such factors as accident cause, train length, and train speed. Lastly, an example risk calculation analyzes the effect of different operating practices on total derailment risk for freight trains and cars.

To Elizabeth

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CHAPTER 1: INTRODUCTION

The research in this thesis addresses the question of the risk of derailment associated with the shipment of freight trains and freight cars by rail. The goal is to present methodologies to determine the probability and severity of derailment for freight trains and freight cars as affected by train length, train speed, track class, accident cause, and position of cars in trains. Chapters 2 and 3 present updated Federal Railroad Administration (FRA) track class-specific derailment rates and methodologies for determining the level of confidence with estimated rates. Chapters 4 and 5 present methodologies for estimating position-dependent derailment probabilities for freight cars within a derailed train consist and analyze derailment probability and severity as affected by various operating practices. Chapter 6 summarizes the research and presents some suggestions for further research. Below are summaries of each of the four main chapters.

Chapter 2:

Annual safety statistics published by the Federal Railroad Administration (FRA) provide train accident counts for various groupings (e.g. railroad, accident type, cause, track type and class, train length, and speed). However, transportation risk analysis often requires more detailed accident rate statistics for specific combinations of these groupings. The statistics presented here enable more precise determination of the probability that Class I and non-Class I railroad freight trains will be involved in an accident on various classes of mainline track.

The increase in overall accident rate between 1997 and 2001 can be largely attributed to the increase in yard accidents. During this time, the mainline derailment rate for Class I freight trains remained nearly constant. Track class-specific derailment rates for Class I mainline freight trains show two orders of magnitude difference between the lowest and highest FRA track classes. Depending on the risk analysis question being addressed, accounting for these differences in rates will often be important in developing an accurate estimate of risk over the length of a route or at particular locations along a route. A sensitivity analysis suggests that the distribution of freight train-miles by FRA track class may have changed since a study conducted by the Association of American Railroads (AAR) in the early 1990s. More up-to-date estimates of track class-specific accident rates would require new data on this distribution.

Chapter 3:

This chapter examines track class-specific and segment-specific derailment rates on the BNSF Railway. The level of uncertainty in such rates and the optimal segment length is shown to be largely a function of the number of observed derailments. A parametric Empirical Bayes methodology was used to adjust the observed derailment rates based on the traffic volume and the characteristics of similar track segments. The results were incorporated into a Geographic Information System, enabling visual identification of derailment probability along the BNSF mainline track network.

Chapter 4:

This chapter examines the relationship between position-in-train and derailment probability for Class I railroad freight trains derailed on mainline track in the United States. The severity of derailment is shown to be a function of train speed, the number of cars following the point-of-derailment, and the accident cause. The conditional derailment probability of cars in derailed freight trains is shown to be dependent on the train length, train speed, and positioning within the consist. Results show that cars positioned near the front and rear of a train have the lowest probability of being derailed and that the probability of derailment tends to increase for all positions as train length decreases or train speed is increased.

Chapter 5:

Statistical analyses and modeling techniques were used to develop derailment probabilities for freight trains and freight cars operating on North American railroads. Knowing the expected frequency of derailment and the conditional probabilities of derailment for individual cars enables estimation of the derailment risk as it is affected by train length, operating speed, and positioning of cars in the consist. These results can be used to quantify the benefit in terms of reduced accident probability and severity of various changes in railroad operating and safety practices.

CHAPTER 2: ACCIDENT RATES

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2.1 Introduction

Accident rates are an essential element in conducting hazardous materials transportation risk assessment. Rail shipment of hazardous materials is of particular interest to chemical shippers and railroads because of the large volume shipped by rail and the safety and liability consequences of a major accident. Consequently, the ability to conduct accurate risk analysis for rail transport is important. Risk analysts are fortunate to have comprehensive accident data available for rail transportation from the Federal Railroad Administration (FRA, 2003a). However, the aggregated accident rate statistics published by FRA do not provide sufficient resolution for many risk analysis calculations, so more detailed analyses are required.

Risk analysis for the shipment of hazardous materials railcars involves estimation of the probability that a train transporting hazardous materials will be involved in an accident, the conditional probability that a hazardous materials car will be derailed and exposed to damage, and the conditional probability that the derailed car will release its contents (CCPS, 1995). Accurate assessment of the risk for a particular hazardous materials shipment requires detailed information on the railroad and trackage that it will traverse.

In this paper we analyze data from the FRA Office of Safety (FRA, 2003a) to develop better resolution estimates of accident rates pertinent to risk analysis. Train accident rates for the ten-year period 1992-2001 were calculated that distinguish mainline and yard track operations, Class I and non-Class I railroads, and different FRA track classes.

2.2 Train Accident Rates

The overall train accident rate is defined as the total number of independent accidents (usually excluding highway-rail grade crossing accidents) per million total train-miles. Although trends in train accident rate can be useful, they are also potentially misleading if the effects of different variables are averaged together thus masking the various factors that affect the probability of a train being involved in an accident. As an example, the mainline derailment rate for Class I freight trains, arguably the most important in terms of the risk associated with the transportation of hazardous materials by rail, has shown little variation over the last decade despite the overall increase in accident rate between 1997 and 2001 (FRA, 2003a-c; Figure 2.1).

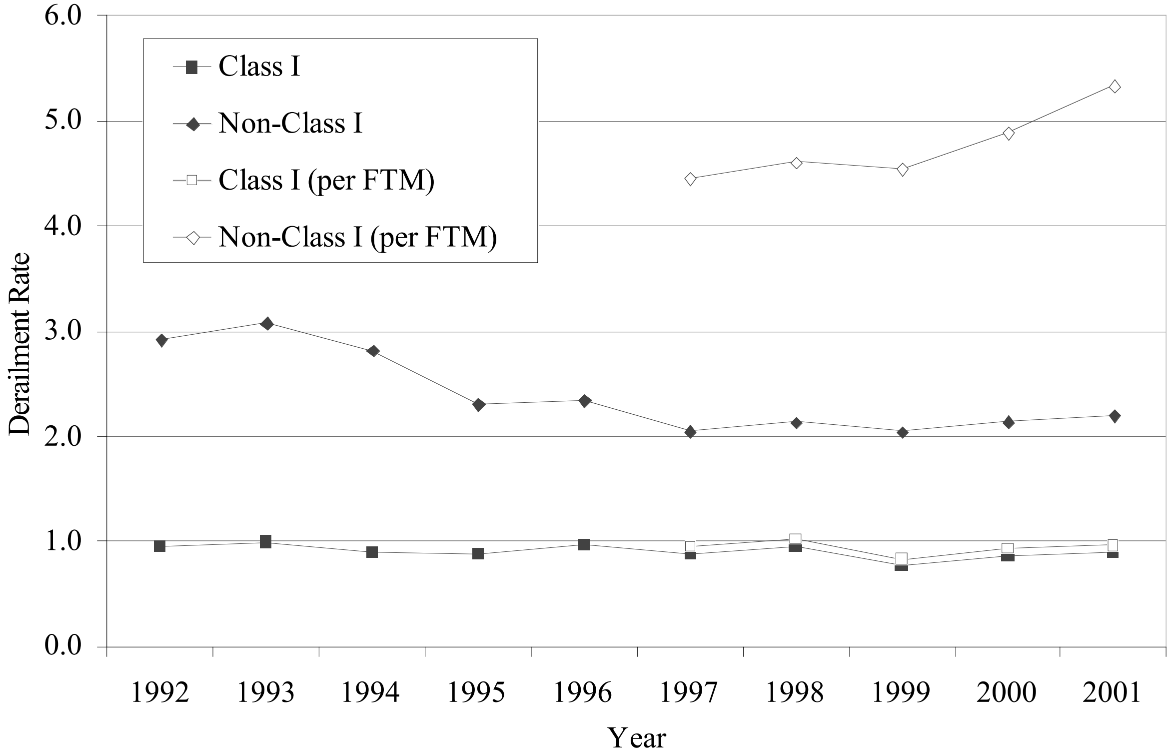

Figure 2.1 Mainline Freight Derailment Rate for Class I and Non-Class I Railroads[1]

2.2.1 Mainline and Yard Accident Rate

Annual accident rates for yard and "other" track (mainline, siding, and industry) are calculated by the FRA (FRA, 2003b). The yard accident rate is defined as the number of accidents occurring on yard track divided by yard-switching train-miles. The accident rate for "other" track is defined as the number of accidents on non-yard trackage, divided by the difference between total train-miles and yard-switching train-miles. The majority of accidents on "other" track occurs on mainline track; thus the mainline accident rate uses the denominator for "other" track to calculate the mainline rate.

Between the years 1997-2001, the accident rate for yard track increased 27% (6.2% average annual increase), while that of mainline track increased 11.8% (3.3% average annual

[1] Derailment rates for solid data points are calculated as derailments per million non-yard-switching train-miles while the derailment rates for open data points are calculated as derailments per million freight train-miles (FTM).

increase) (FRA, 2003c). The rail industry has been concerned about this increase in overall accident rate, but it should be noted that most of the change is due to the increase in yard accidents. Although a matter of concern, yard accidents typically occur at low speed and are two to five times less likely to lead to a release if a hazardous materials car is involved (Barkan et al., 2003). Subsequent to the completion of these analyses, complete data for 2002 became available that indicated a reduction in both the number of accidents and accident rate for both mainline and yard operations (FRA, 2003c).

2.2.2 Derailment Rates on Mainline and Yard Track

Derailments, collisions, highway-rail grade crossing accidents, and other accident types are all components of the overall accident rate. Of particular importance to hazardous materials risk assessment is the derailment rate, due to the frequency of occurrence and severity of consequences in terms of cars derailed and release probability (Barkan et al., 2003). In 2001, of the 32 train consists that had hazardous materials released, derailments accounted for 28 (87.5%) of the accidents and 51 of the 57 cars that released (FRA, 2003b).

The mainline and yard derailment rates are calculated with the same denominator values as above, using the number of derailments on mainline and yard track in the numerator. The mainline derailment rate changed from 1.16 derailments per million train-miles in 1997 to 1.21 in 2001 (a total increase of 4.4%), while the yard derailment rate increased 38.9%, from 9.43 in 1997 to 13.10 in 2001 (FRA, 2003c).

2.2.3 Mainline Derailment Rates for Class I and non-Class I Railroad Freight Trains

Accident rates also vary among railroads and are different for Class I railroads (gross annual revenues ≥ \$266.7 million) and non-Class I railroads (< \$266.7 million) (Barkan et al., 2003; AAR, 2002). While hazardous materials frequently travel relatively short distances on non-Class I railroads, the majority of this traffic is on Class I railroads. In 2001, over 83% of all trains carrying hazardous materials and involved in an accident, and 93% of all hazardous materials cars that released their contents, were on Class I freight railroads (FRA, 2003b).

Table 2.1 FRA Accident/Incident Report Database Field Codes

FRA Field Name	Description	
JOINTCD	Joint code: Used to distinguish between multiple reports	
TRKCLAS	FRA Track Class: X, 1-9[2]	Maximum Speed (mph)
	X & 1	10
	2	25
	3	40
	4	60
	5	80
	6	110[3]
TYPE	Type of accident/incident	
	1. Derailment	7. Highway-rail crossing (HRC)
	2. Head on collision	8. Railroad grade crossing
	3. Rear end collision	9. Obstruction
	4. Side collision	10. Explosion-detonation
	5. Raking collision	11. Fire/violent rupture
	6. Broken train collision	12./13. Other impacts/Other
TYPEQ	Type of consist: e.g. Freight train has a value of 1	
TYPRR	Railroad type: Distinguishes between railroad groups (e.g. Class I Railroads have a value of 1)	
RR3	Railroad responsible for track maintenance (track owner)	
INCDTNO3	Incident number of track owner	
YEAR4, MONTH,DAY	Date (4-digit year, 2-digit month and day) of incident	
STCNTY	Alpha-numeric state and county code of incident location	
ACCAUSE	Accident cause code on 'jointcd' 1 report	
ACCTRK	Track type code on 'jointcd' 1 report	
ACCTRKCL	FRA track class on 'jointcd' 1 report	

[2] While there are higher track classes now in service (7,8,&9), these are primarily for high-speed passenger train operations.

[3] Although FRA track safety standards allow speeds up to 110 mph on class 6 track, FRA traffic control regulations limit train speeds to less than 80 mph on most U.S. trackage.

There are two problems when trying to determine the number of accidents for Class I and non-Class I railroads. The first is due to the consolidation of railroads during the interval considered in this research, which complicates trend comparisons. The FRA combines information reported by predecessor railroads in order to make a more valid comparison of major railroad systems (FRA, 2003b; FRA, 2004). Due to the unavailability of the current FRA list of consolidated railroads, we used the railroad type variable to separate the two groups (Table 2.1). However, comparison showed the differences between the two approaches to be small as many of the railroads that were consolidated into Class I railroads during the time period analyzed were already Class I railroads. The difference between the two approaches was estimated to be approximately 2% when looking specifically at mainline freight train accident reports.

The second problem is due to the possibility that more than one train consist or railroad may be involved in an individual accident. The FRA created the "joint code" field to assist in counting accidents when multiple reports are filed for an individual accident (Table 2.1). For accidents involving multiple railroads and/or consists, only one railroad accident report will be filed with a joint code of "1." All other railroads involved will have one report filed with a joint code of "2," with all other reports (for any additional consists) receiving a joint code of "3." Therefore, the number of independent accidents for all railroads can be determined by counting only those accident reports with a joint code of "1." The number of independent accidents for one specific railroad can be determined by counting the railroad's accident reports having a joint code of "1" or "2." When distinguishing between railroad groups; however, a more advanced method is needed to determine the number of independent accidents.

2.2.3.1 Assigning Unique Accident Identification Numbers to Determine Accident Counts

Development of accurate statistics from the FRA data requires an understanding of the database and use of appropriate methodology to extract the proper, relevant information. In this section we describe our method to link reports corresponding to the same accident by assigning a unique accident number that will be the same across all linked reports. Use of this method allows one to accurately determine the number of independent accidents among any group of consists being considered. In addition we provide quantitative estimates of the effect of different approaches so that other investigators can adjust their data accordingly, depending on which method they choose.

By comparing report identifications for the track owner to date and location information, using "joint code" variables as checks, we assigned unique numbers to individual accidents for the ten years of data analyzed (Table 2.1). Using this technique, there were 27,850 assigned accident numbers (corresponding to the number of accident reports having a joint code of "1") for the 34,061 reports filed with FRA over the ten years 1992-2001. Once a unique accident number has been assigned to each report, the task of calculating the number of independent accidents for a particular consist group of interest is greatly simplified. Using this approach, there were 4,600 derailments in which there was at least one Class I freight train derailed on mainline track, and 1,803 for non-Class I railroads.

An alternative method of analyzing reports with a joint code of "1" is simpler, but somewhat underestimates the number of accidents when distinguishing between freight train derailments of Class I and non-Class I railroads. Using this method, there were 4,461 Class I and 1,729 non-Class I mainline freight train derailments over the ten-year period (an error of 3-4% less than the actual accident counts as determined using the method above). A second alternative approach analyzes reports with a joint code of "1" or "2." Although this approach double counts some accidents, the net accident counts are much closer to the actual accident counts (with an error of less than 0.5% for both railroad groups). Future analyses that use these two approaches should recognize the limitations of the two "joint code" methods and factor the error into accident count and rate estimations.

2.2.3.2 Derailment Rate Calculations

In addition to accident counts, care must be taken in interpreting the exposure data provided by FRA that are used as the denominator in the calculation of accident rates. Beginning in 1997, FRA began distinguishing between passenger and freight train-miles (prior to this they only distinguished between locomotive and motor train-miles). This change is an improvement but must be accounted for when comparing derailment rate trends over intervals prior to 1997.

The calculated derailment rates for 1992-2001 (solid points in Figure 2.1) use the older approach in which the difference between total and yard-switching train-miles is used as the denominator. By contrast, the rates calculated for the years 1997-2001 (open points) use the more relevant data on freight train-miles as the denominator to calculate the mainline freight train derailment rates.

The difference between the rate calculations is due to the inclusion of passenger (and other) train-miles in the denominator of the former, but not the latter approach. For Class I railroads, the difference between the two rates is minimal because passenger train-miles are only a small portion of their total (~6%). However, the derailment rate changes considerably for the non-Class I railroads because passenger train-miles account for about half their total mileage (FRA, 2003a). The result of this difference is that while the Class I derailment rates are similar in both calculations (~7% difference), the non-Class I freight train derailment rates are more than two times higher when only freight train-miles are used as the denominator.

Both approaches are included here as the former allows for relative comparison of the years prior to 1997 that do not have freight train-miles for both railroad groups. The latter approach uses the more appropriate denominator value for rate calculation, as it is a better metric of exposure for mainline freight trains. Using AAR data (AAR, 2002), it is possible to compare derailment rates in terms of freight train-miles for Class I freight railroads for years prior to 1997. The difference in calculated rates is small because the AAR-reported freight train-miles are nearly the same as those reported by the FRA for Class I railroads (usually varying by less than 2% and most likely attributable to the consolidation problem mentioned above).

The mainline derailment rate for non-Class I freight trains is as much as five times higher than Class I freight trains and increased over the five-year period considered, while the Class I derailment rate is virtually unchanged since 1997 (Figure 2.1). The difference in rates between Class I and non-Class I railroads probably reflects the general difference in the distribution of FRA track class between the two railroad types.

2.3 Track Class-Specific Mainline Derailment Rates

The FRA divides track into seven "classes" commonly used by Class I freight railroads. The higher the FRA track class, the higher the maximum permissible speed (Table 2.1). Track class is not specifically intended as a metric for prediction of derailment probability and there are a variety of potential confounding factors that affect its reliability for this role. Furthermore, there is not a direct causal relationship between FRA track class criteria and derailment probability. However, FRA track classes do specify certain attributes related to track quality, with higher classes having more stringent requirements (CCPS, 1995). Because of its universal use by railroads in the United States, and in the absence of a better set of causal parameters for track quality, it is reasonable to consider track class as a proxy variable for statistical estimation of derailment probability.

Track class-specific estimates of derailment rate were first developed by Nayak et al. (1983) in the early 1980s. These estimates are now two decades old and were developed before most of the railroad safety improvements that followed economic deregulation (Gallamore, 1999; Dennis, 2002). Consequently, the AAR conducted a study in the early 1990s that developed more up-to-date estimates for these rates using data collected in the late 1980s and early 1990s. More recently the Surface Transportation Board (STB) used the results from the unpublished AAR study and additional data from the mid-to-late 1990s as a basis to develop updated derailment (and other accident) rate estimates (STB, 2002). All of these analyses found a clear statistical relationship between FRA track class and derailment rate.

The analysis presented in the following section attempts to update these track class-specific mainline derailment rate estimates for Class I railroad freight trains, and provides an assessment of their current reliability.

2.3.1 Derailment Counts

For the ten year period analyzed, there were 4,600 accidents classified as derailments in which one or more Class I railroad freight trains derailed on mainline track. Due to the relatively small number of accidents occurring on excepted (X) class track or on class 6 track, accidents on class X track are combined with class 1, and accidents on class 6 track are combined with class 5 (as in previous studies). Eighteen accidents could not be assigned to a specific track class group due to incomplete or contradictory track class information for the accident. Table 2.2 shows the distribution of the 4,582 derailments among the five FRA track class groups and includes the eighteen unassigned accidents in the total. These values were used as the numerators for derailment rate calculations.

Table 2.2 Estimated Accident Rates by FRA Track Class (95% Confidence Interval in Parentheses); 1992-2001 Class I Mainline Freight Train Accidents (Derailments only)

FRA Track Class	X & 1	2	3	4	5 & 6	Total[4]
Number of Derailments	671	921	1,136	1,522	332	4,600
Number of Derailed Cars	3,708	7,218	10,809	15,045	2,869	39,747
Average Number of Cars Derailed per Derailment	5.5	7.8	9.5	9.9	8.6	8.6
Average Speed (mph)	8.7	17.7	26.3	33.6	37.0	25.2
Train-Mile Percentage[5]	0.3	3.3	12.1	61.8	22.6	100
Freight Train-Miles (Millions)	13.8	152.0	557.5	2,847.5	1,041.3	4,612
Derailments per Million Freight Train-Miles	48.54 (±3.67)	6.06 (±0.39)	2.04 (±0.12)	0.53 (±0.03)	0.32 (±0.03)	1.00 (±0.03)
Car-Mile Percentage[2]	0.3	3.2	11.6	63.1	21.9	100
Freight Car-Miles (Billions)	0.9	9.9	36.0	196.0	68.0	310.9
Derailments per Billion Freight Car-Miles	720.1 (±54.5)	92.7 (±6.0)	31.5 (±1.8)	7.8 (±0.4)	4.9 (±0.5)	14.8 (±0.4)
Cars Derailed per Billion Freight Car-Miles	3,979 (±128)	726 (±16.8)	300 (±5.7)	77 (±1.2)	42 (±1.5)	128 (±1.3)
Estimated Average Train Length	67.4	65.4	64.6	68.8	65.3	67.4

2.3.2 Train-Mile and Car-Mile Denominator Data

Exposure data for Class I railroad freight car-miles and freight train-miles, from the AAR (AAR, 2002), were used as the denominator values in calculating derailment rates. Although the values for freight train-miles published by the AAR differ slightly from those reported by the FRA, the AAR data are used in the calculations because freight car-mileage is not available from the FRA. Derailment rates per car-mile may provide more accurate

[4] Includes those accidents and cars derailed for which track class was indeterminable and may be larger than the total across track class categories.
[5] Individual values of train- and car-mile percentages have been rounded.

derailment probabilities for longer trains and will be useful in future work when calculating separate derailment rates broken down by cause group (STB, 2002). The AAR does not routinely collect mileage data broken down by FRA track class, so the distributions must be estimated.

The distribution of train- and car-miles among FRA track classes used in the STB report was based on the AAR study mentioned above. The AAR survey included data for five Class I railroads accounting for more than 70% of all Class I traffic. The distribution of traffic is given in terms of percentages of total train- and car-miles (Table 2.2). These percentages are then multiplied by the total freight train- and car-miles over the ten year period to give estimated values of the traffic distribution for each FRA track class. Use of these percentages assumes that the traffic distribution by track class has not changed substantially over the past decade, an assumption we address later in this paper.

2.3.3 Derailment Rates

The current derailment rates for Class I freight trains on mainline track are estimated by dividing the total number of derailments on each track class by the estimated proportion of total train- and car-miles (Table 2.2). The train derailment rates and 95% confidence intervals are presented in terms of million freight train-miles and billion freight car-miles. The (1-α)100% confidence interval for the point estimate of the derailment rate for the i^{th} track class, R_i, is calculated as follows (assuming a normal distribution):

$$R_i \pm z_{\alpha/2}\, \sigma_{Ri}$$

where: $\alpha = 0.05$, $z_{\alpha/2} = 1.96$;

$\sigma_{Ri} = [(R_i)(1- R_i)/m_i]^{1/2}$;

$R_i = x_i/m_i$;

x_i = the number of derailments;

m_i = the number of train- or car-miles.

The results indicate that over the entire ten-year period, higher track classes have lower derailment rates and that there is no overlap in the 95% confidence intervals for any of the track class groups (Table 2.2).

2.3.3.1 Uncertainty Errors

These derailment rates are subject to error and some uncertainty. Sources for error include the estimation methods used to develop the distribution of traffic across track classes in the original study, subsequent changes in the track class traffic distribution percentages, unaccounted variance in track quality within track classes, and temporal variability that may have occurred over the ten-year period.

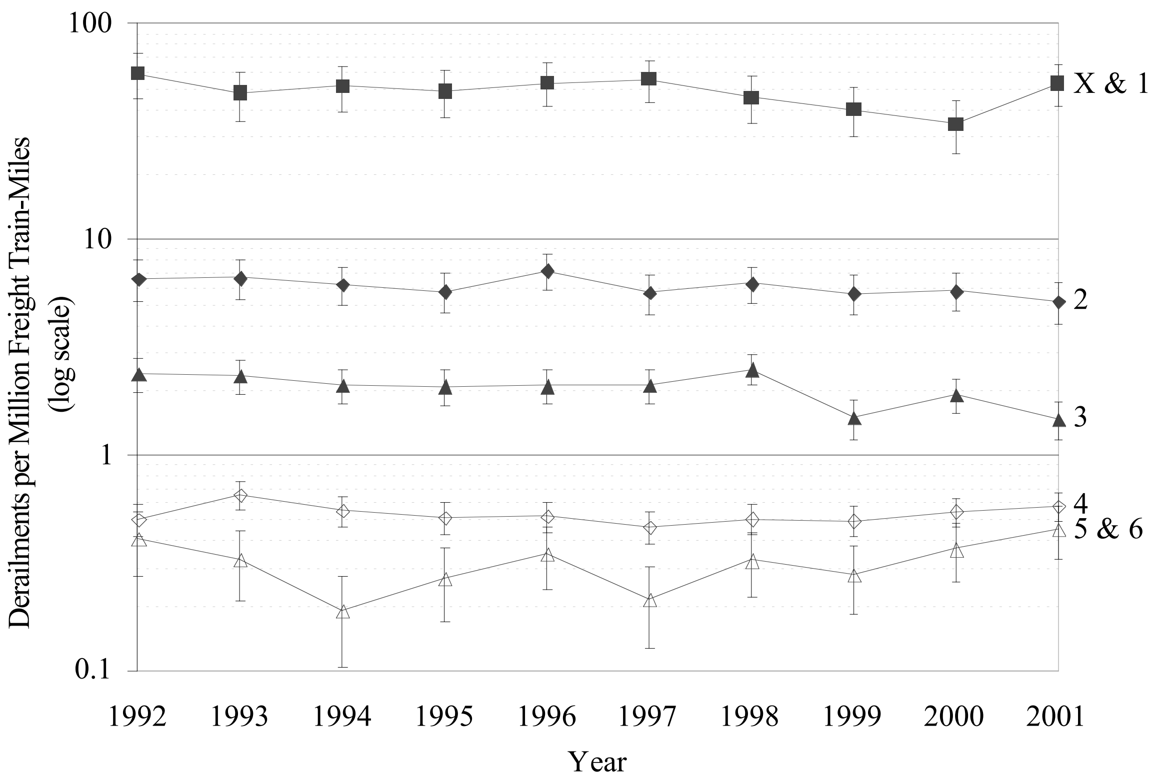

Figure 2.2 Derailment Rate by Track Class with 95% Confidence Interval Error Bars; 1992-2001 Class I Mainline Freight Derailments

2.3.3.1.1 Annual Variation

Yearly derailment rates were calculated to investigate whether the change in the number of derailments each year was proportional to the changes in traffic that occurred between 1992 and 2001 (Figure 2.2). The largest variations in year-to-year rates were for the two track class groups: X & 1 and 5 & 6. For both groups, the numerator values are quite small for any given year and the denominator values for class X and 1 track are also small, resulting in substantial year-to-year variation in derailment rate estimates. Based on the assumption that the distribution of traffic by track class has remained unchanged since the 1992 AAR study, the following patterns are evident over the last five years:

- The derailment rates appear to be rising on higher track classes (4 and higher);
- The derailment rates appear to be falling for lower track classes (3 and lower), excluding the large increase from 2000-2001 for the X & 1 class track group (due to an additional 27 accidents); and
- The 95% confidence interval for class 4 track overlaps the interval for class 5 & 6 track in some years.

2.3.3.1.2 Track Class Traffic Percentages

The STB analysis and our own (Table 2.2 & Figure 2.2) assumed that the distribution of traffic over the five track class groups had not changed since 1992. This assumption may explain the yearly variation and the apparent increase in derailment rate on higher track classes, but it may be incorrect. The number of derailments is recorded annually in the FRA database, but the traffic distribution data that comprise the denominator are estimated and thus introduce uncertainty. Consequently, we considered some of the possible reasons the traffic distribution may have changed.

2.3.3.2 Traffic Changes Over the Past Ten Years

Class I railroads have sold off or abandoned over 15,000 miles of road and 23,000 miles of track between 1992 and 2001, much of this to non-Class I railroads (AAR, 2002). Sale or abandonment of light density, low speed lines by Class I railroads has the effect of increasing Class I railroads' average track class. Evidence of this can be found in two aspects of the data: changes in the distribution of accidents among track classes, and the changes in operational data observed over the past decade.

While total train-miles increased for both groups of railroads over the ten-year period, yard-switching train-miles decreased for Class I railroads and increased for non-Class I railroads (FRA, 2003a). It may be that line sales have shifted yard trackage and operation from Class I railroads to non-Class I railroads. Because yard operation is low speed in nature, it is usually maintained at one of the lower FRA track classes. As the distribution of Class I railroad trackage shifts toward higher FRA track classes, the relative percentage of Class I traffic will tend to shift as well.

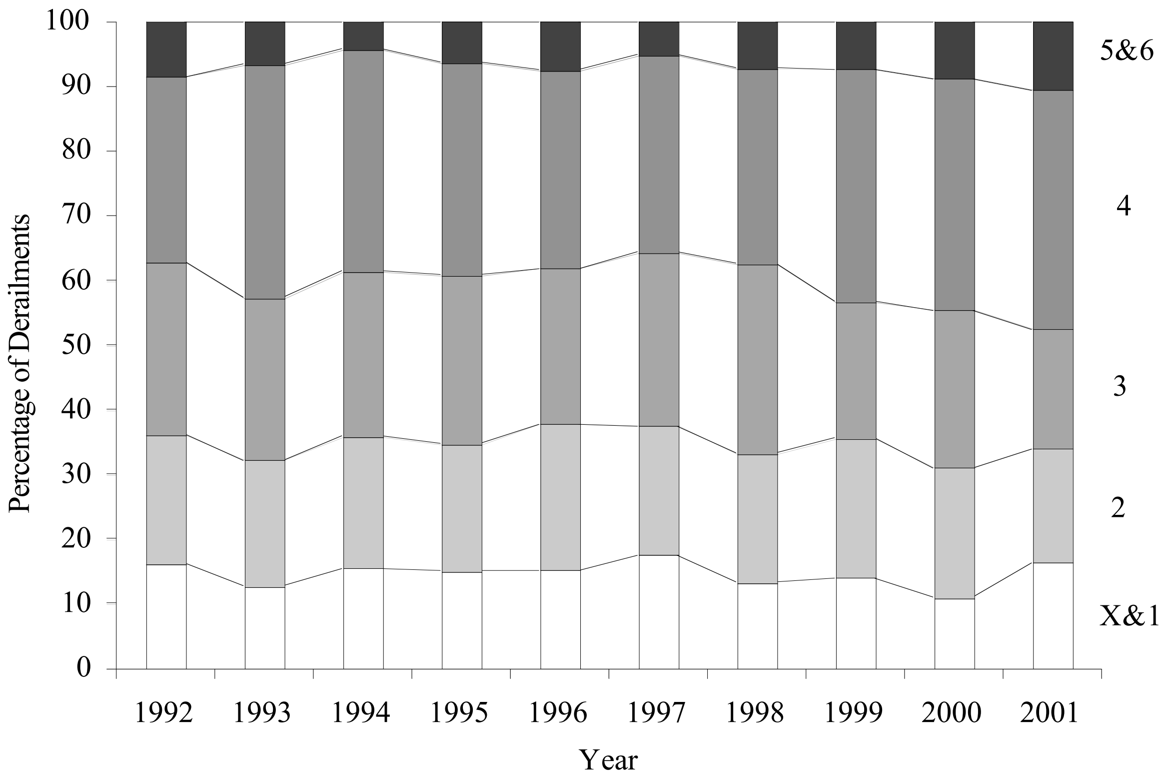

Figure 2.3 Percentage of Derailments by Track Class; 1992-2001 Class I Mainline Freight Derailments

Looking at the percentage of derailments by track class for each of the ten years analyzed, it can be seen that there was little change for any of the five track class groupings between 1992 and 1997 (Figure 2.3). After 1997, the proportion of derailments on class 4 and higher track increased 12% while the proportion of derailments on class 3 track decreased 8.5% (with only a small decrease of 3.5% for class 2 and lower track). The reason for the increase in the relative number of derailments on higher class track may be due to an increase in the amount of traffic over these classes of track in 2001 compared to 1997.

During the 1990s Class I railroads invested heavily in mainline trackage in order to accommodate higher tonnage, upgrade capacity, increase operating speed, and enhance railroad track safety performance (AAR, 2002; Dennis, 2002; Grimes unpublished data). Increasing speed (and capacity) was necessary to meet the demand of intermodal customers, the fastest growing segment of railroad traffic (up 35% from 1992 to 2001) (AAR, 2002). The higher speed requirements lead directly to a need for higher FRA track classes on mainline trackage. The growth in freight, particularly intermodal traffic, combined with expansion of higher FRA track classes on mainlines, would have the effect of shifting the relative proportion of train- and car-miles toward the upper FRA classes.

This postulated shift in track class and traffic may explain the increase in the number of derailments on class 4 and higher track between 1997 and 2001. Using the distribution of traffic by track class based on early 1990s data would thus understate the percentage of traffic on higher track classes in recent years, resulting in over-estimated derailment rates for these track classes. In the absence of more up-to-date data on traffic distribution by track class, we conducted a sensitivity analysis on the estimated derailment rates with variations on the assumed distribution of traffic among FRA track classes.

2.3.3.3 Sensitivity Analysis

We assumed that the estimates of train-mile distribution percentages for specific track classes developed by AAR in 1992 were representative for the years 1992-1994. We calculated a derailment rate for each track class for the three-year interval using the number of derailments, the total freight train-miles, and the estimated traffic percentages for each track class from the AAR study (Table 2.3). Under the assumption that Class I mainline freight derailment rates have changed little over the ten years analyzed (Figure 2.1), we used the number of derailments in the three-year period 1999-2001 to back-calculate the number of train-miles corresponding to constant derailment rates. The estimated total, summed across the five track class groups, was less than 2.5% different from the actual number of train-miles during this interval. The estimated traffic distribution percentages are calculated and compared to the values from the AAR survey. Derailment rates for 1999-2001 using these estimated train-mile percentages were also calculated (Table 2.3).

Table 2.3 Sensitivity Analysis Results Comparing Derailment Rates and Traffic Percentages between 1992-1994 and 1999-2001

FRA Track Class	X & 1	2	3	4	5 & 6	Total[6]
1992-1994						
Number of Derailments	195	264	341	438	85	1,333
Freight Train-Miles (Millions) *(AAR Train-Mile Percentages)*	3.71 (0.3%)	40.8 (3.3%)	149.6 (12.1%)	764.2 (61.8%)	279.5 (22.6%)	1,236.6
Derailment Rate	52.56	6.47	2.28	0.57	0.30	1.08
1999-2001						
Number of Derailments	190	272	295	501	124	1,384
Derailment Rate *(Using AAR Train-Mile Percentages)*	42.39	5.52	1.63	0.54	0.37	0.93
Estimated Freight Train-Miles[7] (Millions)	3.61	42.0	129.4	874.1	407.7	1,494[8]
Estimated Percentage of Train-Miles	0.25%	2.89%	8.88%	60.00%	27.98%	100%
Derailment Rate *(Using Estimated Train-Mile Percentages)*	51.26	6.31	2.22	0.56	0.30	0.93
Percent Difference Between Train-Mile Distribution Percentages	-17.3%	-12.6%	-26.6%	-2.9%	+23.8%	

The sensitivity analysis suggests that:

- The largest differences in train-mile percentages are for class 3 track which decreased nearly 27%, and class 5 & 6 track which increased about 24%;

[6] Includes those accidents for which track class was indeterminable and may be larger than the total across track class categories.

[7] Assumes constant derailment rates between 1992-1994 and 1999-2001.

[8] Total train-miles summed across track classes: 1,456,924 thousand (error of 2.5%).

- Derailment rates increased for those track classes having lower estimated train-mile percentages (all except class 5 & 6 track), while the rate decreased for class 5 & 6 track; and
- The derailment rates calculated for the period 1999-2001 are within the 95% confidence intervals of the ten-year rates calculated using the AAR train-mile percentages for all track classes except class 3 track.

These observations are consistent with a shift in traffic towards higher track class in the past decade. The actual track class-specific derailment rates probably lie in-between the rates presented in Table 2.2 and the rates calculated using the estimated train-miles percentages (Table 2.3). A better estimate of the current derailment rate would require a new survey of traffic distribution among FRA track classes.

2.4 Other Mainline Accident Rates

While derailments account for a majority of derailed cars and hazardous materials releases, collisions, highway-rail grade crossing (HRC) accidents, and other accidents can also derail and/or damage cars and cause a hazardous materials release. Table 4 includes data for mainline accidents for Class I railroad freight trains that were not identified as derailments and gives accident rates for each of three categories: collisions (FRA #2-6,8), HRC accidents (FRA #7), and other accidents (FRA #9-13) (Table 2.1). In the collision category, 16 accidents could not be assigned to a specific track class as the value was either blank or differed between accident reports for the same accident.

Also calculated are accident statistics for non-Class I railroad freight trains on mainline track (Table 2.4). Accident rates for non-Class I railroads were calculated using the number of accidents occurring between 1997 and 2001 and freight train-mileage data from the FRA for the same years (FRA, 2003a). While the number of accidents over the ten-year period are broken down by track class, the five-year accident rates are combined across all track classes because there is no basis to estimate traffic data on different track classes for non-Class I railroads. While the Class I derailment rate is about one-fifth that of non-Class I railroads, the rates for other types of accidents only differ by about a factor of two (Tables 2.2 & 2.4).

Table 2.4 Estimated Accident Rates by FRA Track Class (95% Confidence Interval in Parentheses); 1992-2001 Class I Mainline Freight Train Accidents (Non-Derailments) and 1992-2001 Non-Class I Mainline Freight Train Accidents

Class I Railroads[9]

FRA Track Class	X & 1	2	3	4	5 & 6	Total[10]
Collisions[11]	36	47	75	132	36	342
Rate	2.60	0.31	0.13	0.05	0.03	0.07
	(±0.85)	(±0.09)	(±0.03)	(±0.01)	(±0.01)	(±0.01)
Cars Derailed	143	196	533	923	328	2,126
HRC[12] Accidents	9	46	222	616	114	1,009
Rate	0.65	0.30	0.40	0.22	0.11	0.22
	(±0.43)	(±0.09)	(±0.05)	(±0.02)	(±0.02)	(±0.01)
Cars Derailed	1	48	259	662	191	1,161
Other Accidents	42	58	100	223	77	500
Rate	3.04	0.38	0.18	0.08	0.07	0.11
	(±0.92)	(±0.10)	(±0.04)	(±0.01)	(±0.02)	(±0.01)
Cars Derailed	132	74	113	241	116	676

Non-Class I RRs[13]

FRA Track Class	X &1	2	3	4	5 & 6	Total
Derailments	569	773	342	98	2	1,803
Rate	n/a	n/a	n/a	n/a	n/a	4.79
						(±0.32)
Cars Derailed	2,816	4,765	2,925	975	5	11,591
Collisions	12	16	24	15	1	73
Rate	n/a	n/a	n/a	n/a	n/a	0.18
						(±0.06)
Cars Derailed	19	13	81	38	1	170
HRC Accidents	8	55	46	33	0	142
Rate	n/a	n/a	n/a	n/a	n/a	0.41
						(±0.09)
Cars Derailed	2	91	116	31	0	240
Other Accidents	19	17	17	8	1	64
Rate	n/a	n/a	n/a	n/a	n/a	0.23
						(±0.07)
Cars Derailed	47	11	21	0	0	79

[9] Accident rates in terms of train-miles are given; car derailment rates for class I railroads can be calculated by dividing the number of cars derailed by the appropriate number of car-miles from Table 2.2

[10] Includes those accidents and cars derailed for which track class was indeterminable and may be larger than the total across track class categories.

[11] Includes collisions at railroad grade crossings.

[12] Highway-Rail grade Crossing.

[13] Rates use accidents and freight train-miles for the years 1997-2001.

2.5 Estimated Car Derailment Rates

The train accident rates can be used to estimate the probability that a freight train will be involved in an accident. However, for some risk analyses it is more useful to know the probability that a particular car will derail.

The FRA data permit development of track class-specific statistics for the number of cars derailed for each track class, as well as the average number of cars derailed per accident. Exposure by track class is calculated using previously determined traffic percentages and current total car-mile data from AAR (AAR, 2002; STB, 2002). The individual car derailment rate is calculated by dividing the number of cars derailed by the estimated number of freight car-miles for each track class, and is not necessarily dependent on the number of independent accidents. To account for all derailed cars on a particular track class, the number of cars derailed was summed across all accident reports that had a valid track class entry, regardless of whether the track class values were in agreement across reports from the same accident. The car derailment rate can also be estimated by multiplying the average number of cars derailed per accident by the number of accidents per billion freight car-miles. Both methods calculate the estimated number of cars derailed per billion freight car-miles. While the number of cars derailed on each track class is given for both Class I and non-Class I railroads, car derailment rates for non-Class I railroads cannot be determined because car-mile data are not available (Tables 2.2 & 2.4).

Operating speeds are generally higher on higher class track and there is a positive linear relationship between speed and the number of cars derailed (Barkan et al., 2003). While derailments on higher class track tend to derail more cars per accident, the net result is that higher track classes still have lower individual car derailment rates due to the lower probability of being involved in a derailment (Table 2.2).

2.6 Estimated Release Probability of a Hazardous Materials Car

The other key element in the rail risk probability calculation is the likelihood that a hazardous materials car involved in an accident will be damaged or derailed, and suffers a release. We considered the hypothesis that hazardous materials cars that derail on higher track classes might have a higher probability of releasing because of higher operating speeds (Barkan et al., 2003).

Table 2.5 Hazardous Materials Derailment and Release Statistics; 1992-2001 Class I Mainline Freight Trains

Class I Railroads

FRA Track Class	**X & 1**	**2**	**3**	**4**	**5 & 6**	**Total**
Derailments						
Consists with 1+ Hazmat Car Derailed	78	112	174	281	64	710
Hazmat Cars Derailed	230	409	619	1,034	197	2,492
Average Hazmat Cars Derailed	2.9	3.7	3.6	3.7	3.1	3.5
Consists with 1+ Hazmat Car Released	5	19	40	60	14	138
Hazmat Cars Released	6	37	87	116	27	273
Average Hazmat Cars Released	1.2	1.9	2.2	1.9	1.9	2.0
Average Release Rate	2.5	10.5	10.1	12.7	13.1	10.6
Collisions						
Consists with 1+ Hazmat Car Derailed	4	6	11	20	10	52
Hazmat Cars Derailed	4	18	35	64	28	150
Average Hazmat Cars Derailed	1.0	3.0	3.2	3.2	2.8	2.9
Consists with 1+ Hazmat Car Released	0	2	4	3	2	11
Hazmat Cars Released	0	2	4	5	5	16
Average Hazmat Cars Released	0.0	1.0	1.0	1.7	2.5	1.5
Average Release Rate	0.0	12.5	24.6	8.3	9.2	11.6
HRC Accidents						
Consists with 1+ Hazmat Car Derailed	1	0	5	12	4	22
Hazmat Cars Derailed	1	0	9	32	12	54
Average Hazmat Cars Derailed	1.0	0.0	1.8	2.7	3.0	2.5
Consists with 1+ Hazmat Car Released	0	0	1	4	1	6
Hazmat Cars Released	0	0	1	5	2	8
Average Hazmat Cars Released	0.0	0.0	1.0	1.3	2.0	1.3
Average Release Rate	0.0	0.0	6.7	25.0	25.0	19.7
Other Accidents						
Consists with 1+ Hazmat Car Derailed	2	3	3	6	2	16
Hazmat Cars Derailed	5	11	9	11	5	41
Average Hazmat Cars Derailed	2.5	3.7	3.0	1.8	2.5	2.6
Consists with 1+ Hazmat Car Released	0	1	0	1	1	3
Hazmat Cars Released	0	1	0	1	3	5
Average Hazmat Cars Released	0.0	1.0	0.0	1.0	3.0	1.7
Average Release Rate	0.0	33.3	0.0	16.7	37.5	17.2

For the ten years analyzed, there were 710 Class I railroad mainline freight trains derailed that had at least one hazardous materials car derailed (Table 2.5). Of the 2,492 hazardous materials cars derailed, 273 released their contents (none on class X or class 6 track) (Table 2.5). While the release rate on class 1 track was substantially lower than on the higher track classes, the release rate for classes 4 and 5 was not substantially higher than for classes 2 and 3 track, with an average of approximately 10%. Comparing the average speed of derailment (Table 2.2) to the maximum operating speeds permitted on different track classes (Table 2.1), it is evident that many accidents occur below track speed, especially on the higher track classes (CCPS, 1995). This may explain the small differences between the release rates on the lower track classes (2 and 3) and class 4 and higher track.

Table 2.6 Hazardous Materials Derailment and Release Statistics; 1992-2001 Non-Class I Mainline Freight Trains

Non-Class I Railroads

FRA Track Class	**X & 1**	**2**	**3**	**4**	**5 & 6**	**Total**
Derailments						
Consists with 1+ Hazmat Car Derailed	54	72	52	21	0	199
Hazmat Cars Derailed	227	208	145	98	0	678
Average Hazmat Cars Derailed	4.2	2.9	2.8	4.7	0.0	3.4
Consists with 1+ Hazmat Car Released	6	9	13	5	0	33
Hazmat Cars Released	14	15	18	26	0	73
Average Hazmat Cars Released	2.3	1.7	1.4	5.2	0.0	2.2
Average Release Rate	8.3	6.8	15.2	13.8	0.0	10.1
Collisions, HRC Accidents, & Other Accidents[14]						
Consists with 1+ Hazmat Car Derailed	6	4	4	3	0	17
Hazmat Cars Derailed	11	7	5	9	0	32
Average Hazmat Cars Derailed	1.8	1.8	1.3	3.0	0.0	1.9
Consists with 1+ Hazmat Car Released	1	0	0	0	0	1
Hazmat Cars Released	2	0	0	0	0	2
Average Hazmat Cars Released	2.0	0.0	0.0	0.0	0.0	2.0
Average Release Rate	16. 7	0.0	0.0	0.0	0.0	5.9

The majority of derailed hazardous materials cars and hazardous materials releases are due to derailments, accounting for 346 of the 377 (92%) hazardous materials cars that

[14] These three accident groups are lumped together as only one accident (other category) resulted in a hazmat release.

released on Class I and non-Class I railroads (Tables 2.5 & 2.6). The majority of releases occur on Class I railroads, which generally operate at higher speeds than non-Class I railroads. It is thus interesting to note that the total derailment-caused release rates for Class I and non-Class I railroads are similar (Tables 2.5 & 2.6).

2.7 Example Risk Calculation

To illustrate how these rates can be applied to risk assessment of hazardous materials transportation, consider the following simple example: a Class I railroad is interested in understanding the risk associated with operating a freight train carrying hazardous materials from Point A to Point B. The route is 1,000 miles long with 65% class 4 track and 35% class 5. The probability that this train will be involved in a derailment can be calculated as follows:

$$\Pr(der) = \sum_{i=1}^{n} R_i m_i$$

where R_i is the derailment rate per mile for class i track and m_i is the mileage traversed on class i track.

For the example considered, using the derailment rates in Table 2.2, the following derailment probability is calculated:

$\Pr(der) = (0.53\text{x}10^{-6} \text{ x } 650) + (0.32\text{x}10^{-6} \text{ x } 350) = 4.6\text{x}10^{-4}$, or a little less than 1 in 2,000.

Consider that the train has 100 cars, and the shipper wants to know the probability that a particular car will derail while enroute from A to B. From the derailment rates in Table 1.2, the following derailment probabilities are calculated:

$\Pr(der) = (7.8\text{x}10^{-9} \text{ x } 650 \text{ x } 100) + (4.9\text{x}10^{-9} \text{ x } 350 \text{ x } 100) = 6.8\text{x}10^{-4}$, or a little more than 1 in 1,500 that the train will be involved in a derailment.

As shown in this example, longer than average trains will have higher car-mile train derailment probabilities. For trains longer than about 67 cars, the risk analyst may choose to use the car-mile train derailment rate for a more accurate accident probability (Table 2.2).

Further, Pr(*der*) = ($77\text{x}10^{-9}$ x 650) + ($42\text{x}10^{-9}$ x 350) = $6.5\text{x}10^{-5}$, or a little less than 1 in 15,000 chance that a particular car will be derailed. Thus, an individual car would have a 10% (conditional) probability of derailing given that the 100-car train is involved in a derailment. Extending this example to other train lengths would show the inverse relationship between train length and the conditional probability of an individual car being derailed.

This probability, when combined with the conditional probability of hazardous materials cars releasing, given they are derailed, can be used to quantify the risk associated with one train of hazardous materials over this particular line. The same approach can be adapted to other questions regarding whatever cars or trains are of interest.

2.8 Conclusions

Rail transportation risk analysis relies on the accurate estimation of accident rates. In hazardous materials transportation, the derailment rate for mainline freight trains is the rate most applicable since this is where the majority of exposure occurs. The results presented in this paper provide updated track class-specific accident rate estimates for Class I and non-Class I railroads.

The importance of using more precise estimates of derailment rate is illustrated by the following comparison. The average mainline derailment rate for Class I railroads over the period 1992-2001 was approximately 1 per million freight train miles (Figure 2.1). However, much of the U.S. mainline trackage over which the bulk of rail freight is shipped is FRA class 4 or 5 track with estimated derailment rates of 0.53 and 0.32 derailments per million train-miles, respectively (Table 2.2). Estimating risk along segments with class 4 or 5 track based on the average mainline rates would potentially overstate the risk by a factor of 2 or 3. Conversely, the risk along a segment of class 2 track would potentially be understated by a factor of 6 (Table 2.2).

Future work aims to extend this analysis to provide more detailed analyses of other derailment factors including accident cause, train speed, length, and position in train. These factors are also important in calculating the conditional probabilities of particular cars within the consist being derailed. Categorization of accidents into those correlated with the number of train-miles versus car-miles operated will enable better understanding of how specific derailment prevention measures will affect risk (Barkan et al., 2003; STB, 2002; Dick et al., 2003). Combining these derailment rates with up-to-date information on railcar performance in accidents will permit the risk analyst to calculate the probability of a hazardous materials release for any particular shipment or rail line segment.

CHAPTER 3: DERAILMENT RATES ON THE BNSF RAILWAY

3.1 Introduction

In this chapter, I extend and expand on the work presented in the preceding chapter by developing segment-specific derailment rates for a Class I railroad, the BNSF Railway. Development of such rates requires two principal types of information, data on accidents (the numerator) and data on traffic volume (the denominator). Five years of accident data (1999-2003) provided by BNSF were used to perform these analyses. These data include FRA-reportable accidents as well as those falling below the FRA reporting threshold. BNSF also provided traffic density information (million gross tons, MGT) for the majority of their mainline track network, broken down into segments whose length ranged from thousandths of a mile to several hundred miles, with an average of about 6.5 miles per segment. The goals of these analyses are to calculate segment-specific derailment rates and determine the optimum segment length required to achieve a desired level of confidence in the estimated derailment rate.

A parametric Empirical Bayes method (Nembhard & Young, 1995) was used to normalize segment-specific derailment rates to network-wide rates based on the amount of traffic data. This approach incorporates knowledge surrounding track class-specific derailment rates into the calculation of segment-specific derailment rates. The aim is to achieve as accurate an estimate possible of the rate based on an understanding of similar track segments. The end product will include the derailment rates in tabular format as well as in an interactive Geographic Information System (GIS) map that will enable visual identification of derailment probability levels at different locations in the system. The objective is an analytical and graphical system enabling system-wide characterization of derailment probabilities.

3.2 BNSF Accident and Traffic Databases

Data extracted from the BNSF accident database were used to determine derailment counts. The raw data were extracted by BNSF into *.list (flat) files that were later manually imported into Excel for analysis. The variables from the BNSF accident database that are needed for this analysis are listed in Table 3.1.

The data were analyzed and accident counts were calculated by accident type and year (Table 3.2). Nearly two-thirds of accidents are classified as derailments, the majority of which occurred on non-mainline trackage (i.e. yard trackage). On average, about 45% of all derailments exceeded the monetary damage reporting threshold set by the Federal Railroad Administration. For the years 1999-2001, the threshold was set at $6,600; for 2002 and 2003 (and "until further notice"), the threshold was set at $6,700 (CFR, 2004). The number of FRA-reportable mainline derailments in the BNSF accident database is very close to the number for BNSF in the FRA database.

Table 3.1 BNSF Accident Database Variables

Variable Name	Description	Attributes
ACDNT_YR	Accident Year	1999-2003
DIV_NME	Division Name	
SDIV_NME	Subdivision Name	
FRA_RPT_	FRA Reportable	Y or N
MP_NBR	Milepost Number	To the nearest tenth of a mile
FRA_TRK_	FRA Track Class	X, 1-6
ACDNT_CA	FRA Accident Cause	
CROSS_12	Track Type	Mainline Track = 1
INCD_TYP	Incident Type	Derailment = 1
LN_SEG	Line Segment Number	

Table 3.2 BNSF Accident Counts; 1999-2003

Year	1999	2000	2001	2002	2003	Total
Accidents	3,630	4,087	4,060	3,802	3,865	19,444
Derailments	2,307	2,605	2,769	2,471	2,473	12,625
Mainline Derailments	332	360	389	294	311	1,686
FRA-Reportable	140	164	177	138	126	745
Non-FRA-Reportable	192	196	212	156	185	941
Percent Reportable	42.2%	45.6%	45.5%	46.9%	40.5%	44.2%

When the derailments are further analyzed by FRA track class, there is a trend toward a higher percentage of FRA-reportable accidents on higher track classes (Table 3.3). The effect is likely due to higher operating speeds and the consequent greater likelihood that an accident will result in damages exceeding the FRA reporting threshold (Barkan et al., 2003).

Table 3.3 BNSF Mainline Derailment Count (FRA-Reportable, R, & Total, T) by FRA Track Class

Track Class	R/T	1999	2000	2001	2002	2003	Total	Percent FRA-Reportable
	R	19	25	37	26	26	133	
1	T	87	95	100	77	98	457	29%
	R	27	23	27	24	23	124	
2	T	51	63	59	47	55	275	45%
	R	22	35	31	24	27	139	
3	T	49	65	69	48	47	278	50%
	R	63	66	71	51	41	292	
4	T	116	110	140	97	88	551	53%
	R	9	15	11	13	9	57	
5	T	28	24	15	25	19	111	51%
	R	140	164	177	138	126	745	
Total[15]	T	332	360	389	294	311	1,686	44%

Traffic data were provided by BNSF for each year from 1999 to 2003. The traffic density data for each particular segment were separated by traffic type (freight or passenger) and direction (East and West). Analysis of the traffic data indicated that approximately one-third of all mainline trackage was multiple main track. Roughly 20-30% of multiple main track had traffic in one direction that exceeded the traffic in the other direction by more than 20 MGT.

For the years 1999 to 2001, track segments having multiple mainline tracks were not separated into individual records. The total traffic in millions of gross tons (MGT) over a particular segment was given along with the track mileage for each mainline track (for up to 4 tracks). In 2002 and 2003, the traffic data were separated for track segments having multiple mainline tracks. For these two years, BNSF generally divided the total traffic over a particular segment equally among the tracks. However, this is unlikely to be correct as BNSF generally practices “right-hand running” in which traffic in a given direction will run on the right-hand track, and there are several track segments in which traffic in one direction is substantially greater than the opposite direction. Consequently, there remains some uncertainty regarding the exact amount of traffic on some track segments.

The traffic data also contained freight train speed values that were used to derive FRA track class for each segment based on the maximum permitted freight speeds for each track class (Table 3.4). Gross ton-miles (GTM) of freight traffic were calculated for each segment

[15] Totals include derailments on class X track, class 6 track, or for which track class was not given.

in the database by multiplying the total freight MGT (in both the East & West directions) by the mileage for each track segment (Table 3.4)[16]. The calculated values were then summed for all five years by track class. The corresponding traffic percentages for each track class are similar to those determined by the AAR in the early 1990's (Treichel & Barkan, 1993). The sensitivity to these percentages in calculating derailment rates will be discussed later in the chapter.

Table 3.4 BNSF Traffic Distribution by Track Class

Track Class	1	2	3	4	5	Total[17]
Maximum Freight Train Speed (mph)	10	25	40	60	80	-
Gross Ton-Miles (millions)	5,009	66,384	282,762	2,973,183	1,317,834	4,645,171
Percent of Total GTM	0.1%	1.4%	6.1 %	64.0%	28.4%	100%

AAR's *Analysis of Class I Railroads* (AAR, 1999-2003a) provides annual operating statistics for all Class I railroads, including BNSF, in terms of freight train-miles (FTM), freight car-miles (FCM), and gross ton-miles (Table 3.5). The total gross ton-miles calculated from the BNSF traffic data (Table 3.4) were within 4% of the total value given by the AAR (Table 3.5).

Table 3.5 AAR Traffic Data for BNSF Railway

Line Item	1999	2000	2001	2002	2003	Total
650. Freight Train-Miles (millions)	146.1	145.7	146.2	145.2	153.2	736.4
658. Freight Car-Miles (millions)	8,989.9	8,751.1	9,437.8	9,178.9	9,515.2	45,873.0
704. Gross Ton-Miles (billions)	957.1	960.4	982.1	958.9	1,002.9	4,861.3
Average Train Length (cars)	61.5	60.1	64.6	63.2	62.1	62.3
Average Train Weight (tons)	6,551	6,592	6,718	6,602	6,547	6,602
Average Car Weight (tons)	106.5	109.7	104.1	104.5	105.4	106.0

[16] Some segments in the traffic data had negative values for track mileage as the ending milepost number was less than the beginning milepost number; the traffic on these segments were thus excluded from the total traffic volume.
[17] Excludes 32,061 million GTM (0.7%) that were unable to be categorized by track class due to missing speed information.

3.3 Track Class-Specific Derailment Rates

Track class-specific derailment rates (Table 3.6) are calculated by dividing the total number of derailments on each track class (Table 3.3) by the portion of total traffic for each track class. The denominator was calculated by multiplying the traffic distribution percentages (Table 3.4) by the total traffic (GTM, FCM, FTM) from the AAR (Table 3.5). The same traffic distribution percentages are used for all three exposure metrics; this assumes that there is no difference in average car weight (tons per car) or average train length (cars per train) between track classes. Although more specificity would be desirable, the BNSF traffic data only provides traffic in million gross tons. The previous estimates by the AAR (Treichel & Barkan, 1993), in which track class-specific traffic volumes in other exposure metrics (i.e. train-miles and car-miles) were estimated, showed similar percentages between the three exposure metrics, indicating similar train lengths and car weights between the track classes.

Table 3.6 BNSF Derailment Rates by Track Class; 1999-2003

Track Class	1	2	3	4	5	Total
Derailment Rate Per Billion GTM	87.2	3.96	0.94	0.18	0.08	0.35
(95% Conf. Int.)	(79.4,95.6)	(3.50,4.45)	(0.83, 1.06)	(0.16,0.19)	(0.07,0.10)	(0.33,0.36)
Derailment Rate Per Billion FCM	9,240	419	99.6	18.8	8.53	36.8
(95% Conf. Int.)	(8,412-10,127)	(371,472)	(88.2,112)	(17.2,20.4)	(7.02,10.3)	(35.0,38.6)
Derailment Rate Per Million FTM	576	26.1	6.20	1.17	0.53	2.29
(95% Conf. Int.)	(524,631)	(23.1,29.4)	(5.49,6.98)	(1.07,1.27)	(0.44,0.64)	(2.18,2.40)

3.3.1 Confidence Intervals

Confidence intervals around the estimated derailment rates (Table 3.6) were calculated following the procedures developed by Nicholson (1987) in which the confidence limits for the "underlying true accident rate" (UTAR) are estimated assuming that accident counts follow a Poisson distribution. The lower (λ_L) and upper (λ_U) limits for the UTAR, λ, are as follows:

$$\lambda_L = \frac{\chi^2(1-\alpha \mid \nu = 2Y_i)}{2D_i} \ \& \ \lambda_U = \frac{\chi^2(\alpha \mid \nu = 2Y_i + 2)}{2D_i}; \qquad \text{(Eq. 3.1)}$$

where (1-2α) is the level of confidence, ν is the degrees of freedom for the χ^2 distribution, Y_i is the number of observed derailments and D_i is the traffic volume on the i^{th} track class (modified from Nicholson, 1987). This method is better suited for calculating confidence intervals for accident rates because the point estimate approach shown previously (§2.3.3) tends to overstate the accuracy of the estimates (particularly for the lower track classes which have much larger variances, as will be discussed later).

3.3.2 Uncertainty of Results

Because the "true" derailment rate is unknown and since there can be substantial variation in the quality of track both within and between different track classes, there is uncertainty in the estimated rates. One potential source of uncertainty is the denominator due to the estimation of the percentage of traffic among each track class.

Davis (2000) presents a methodology for estimating accident rates while accounting for traffic-volume estimation error. In that case, the error is due to sampling a short duration of traffic counts in order to estimate total (annual) traffic. In the research described here, the error is not due to small sample size, but rather several uncertainties regarding how to apportion the total traffic for each track class.

Sensitivity of the estimated track class-specific derailment rates to the traffic distribution percentages was analyzed by comparing FRA-reportable derailment rates calculated using the estimated traffic distribution percentages (Table 3.4, repeated here) to those calculated using the traffic distribution percentages from the AAR study (Treichel & Barkan, 1993) (Table 3.7). The derailment rates (in terms of FCM and FTM) for all Class I railroads from Table 2.2 are also repeated here for comparison to those for BNSF.

Table 3.7 Sensitivity of FRA-Reportable BNSF Mainline Derailment Rate to Traffic Distribution Percentages

Track Class	1	2	3	4	5	Total
Traffic Distribution Percentages (GTM, FCM, FTM)	0.1%	1.4%	6.1%	64.0%	28.4%	100%
AAR GTM Percentages	0.25%	2.39%	11.26%	62.92%	23.18%	100%
AAR FCM Percentages	0.27%	2.55%	11.62%	63.54%	22.03%	100%
AAR FTM Percentages	0.27%	2.73%	12.13%	62.13%	22.74%	100%
Derailments per Billion GTM	25.4	1.78	0.47	0.094	0.041	0.15
Rates using AAR Percentages	10.8	1.07	0.25	0.095	0.051	0.15
Derailments per Billion FCM	2,689	189	49.8	9.95	4.38	16.2
Rates using AAR Percentages	1,092	106	26.1	10.0	5.64	16.2
Rates from Table 2.2	720.1	92.7	31.5	7.8	4.9	14.8
Derailments per Million FTM	168	11.8	3.10	0.62	0.27	1.01
Rates using AAR Percentages	68.1	6.18	1.56	0.64	0.34	1.01
Rates from Table 2.2	48.54	6.06	2.04	0.53	0.32	1.00

The derailment rates calculated for BNSF using the AAR percentages are generally slightly higher than those for all Class I railroads (Table 3.7). One possible reason for the difference may be due to the time period used for the calculation. The BNSF rates are calculated using data from 1999-2003 while the rates for all Class I railroads were calculated using data from 1992-2001.

Comparison between the rates using the percentages derived from the BNSF traffic data to those rates calculated using the AAR percentages shows that the rates are similar for class 4 & 5 track, while there are relatively larger differences for class 3 and lower track. These are due to the large (relative) differences in the traffic distribution percentages for these track classes (e.g. halving the traffic distribution percentage doubles the derailment rate). This results in substantially higher estimated derailment rates for these track classes.

It is also important to note that the derived track class values in the traffic data can, at best, only represent the track class for a majority of the track for a particular segment. There is bound to be variation in the quality of track and operating speed within the segment. The estimated confidence intervals (Table 3.6) do not take into account the large possible variation in the true amount of traffic over each track class.

The FRA recently developed a set of objective track quality indices (TQIs) from measured track geometry data that can quantitatively describe the relative condition of quality within each track class (El-Sibaie & Zhang, 2004). The TQIs were found to correlate well with Federal Track Safety Standards (used to classify track by class) and the results showed three distinct TQI ranges for each track class. Using track class for categorizing track quality is, at best, a proxy for a better, quantitative measure of the quality of track (e.g. TQIs). While the FRA TQI results illustrate the variation of track quality within track classes, track class remains the most broadly applicable metric for track quality and previous results have found a clear statistical relationship between track class and derailment rates (Nayak et al., 1983; Treichel & Barkan, 1993; Anderson & Barkan, 2004).

3.4 Segment-Specific Derailment Rates

The next step of the analysis involved matching derailments in the accident database to segments in the traffic data (i.e. calculating segment-specific derailment rates). One shortcoming of the accident data is the lack of data on which main track the derailment occurred in segments having multiple main track. Due to the differences in beginning and ending milepost (BMP and EMP) values between multiple main track in the 2002 and 2003 traffic data, the traffic data for these segments were not able to be combined into one record (as in data for 1999-2001). In the absence of specific information on which track the derailment occurred, it was necessary to first determine the number of possible track segments in the traffic data to which a derailment in the accident database could be assigned. The number of records in the traffic database that matched line segment and milepost information in the derailment record was counted; the derailment was then assigned a value of the inverse of the number of matching segments. Segment derailment counts are thus obtained by summing the values that were assigned to each derailment.

The following data (Table 3.8), extracted from the accident and traffic databases, illustrate this method. A 2003 derailment on line segment 7200 at milepost 459 was recorded as having occurred on class 3 track. In the 2003 traffic data, there are two main tracks between MP 457 and MP 460.283 each having a recorded freight train speed of 50 mph (indicating class 4 track). The derailment is thus assigned a value of ½ representing the inverse of the number of matching segments (1/SEG). Each matching track segment is thus assigned ½ of the derailment (DER).

Table 3.8 Derailment—Segment Matching Example

Accident Database

LN_SEG	MP_NBR	FRA_TRK	SEG	1/SEG
7200	459	3	2	0.5

Traffic Database

LINE SEGMENT	BMP	EMP	TRACK NUMBER	FREIGHT SPEED	DER
7200	457	460.283	1	50	0.5
7200	457	460.283	2	50	0.5

Ideally, the accident and traffic databases would both contain the necessary information needed to assign a derailment to the correct track on which it occurred. In the absence of such data, the next best alternative would assign the derailment based on the proportion of traffic on each track, with tracks having more traffic assigned a higher proportion of the derailment. The traffic density over multiple main track segments; however, is nearly always shown as being equally distributed among each track. As mentioned above, this is unlikely to be correct in many instances. This is a limitation of the available data; the method chosen is an attempt to overcome this by assuming that each track has an equal likelihood of derailment.

Of the 21,061 segment records in the five years of traffic data, 94% of these observed no derailments. Seventy-four percent of all mainline derailments were able to be assigned to a particular line segment in the traffic data (Table 3.9a). Most of the remaining 26% of derailments occurred on line segments that did not have traffic data available. Derailments recorded as derailing on lower track classes were less likely to be assigned to a particular segment in the traffic data.

Table 3.9a Segment-Assigned Derailment Counts by Track Class; 1999-2003

	Recorded Track Class in Accident Data					
Derived Track Class in Traffic Data	1	2	3	4	5	Total[18]
1	**13**	2	0	0	0	15
2	56	**78**	13	1	0	148
3	37	34	**91**	12	0	174
4	105	64.5	104	**415**	16	707.5
5	26	7.5	13	66	**91**	206.5
Total Assigned Derailments	237	186	221	494	107	1,251
Total Derailments (Table 3.3)	457	275	278	551	111	1,686
Percent Assigned	51.9%	67.6%	79.5%	89.7%	96.4%	74.2%

Table 3.9b Segment-Assigned Derailment Counts by Track Class; 1999-2003 (2003 Track Data)

	Recorded Track Class in Accident Data					
Derived Track Class in Traffic Data	1	2	3	4	5	Total[18]
1	**11**	6	1	0	0	18
2	55	**75**	19	6	0	155
3	31	41	**97**	17	0	186
4	95.5	57	94	**410**	19	678.5
5	27.5	6	14	66	**88**	204.5
Total Assigned Derailments[19]	221	186	225	499	107	1,244
Total Derailments (Table 3.3)	457	275	278	551	111	1,686
Percent Assigned	48.4%	67.6%	80.9%	90.6%	96.4%	73.8%

[18] Totals include those derailments that were recorded as derailing on class X track, on class 6 track, or did not have a value for track class.

[19] Totals include those derailments that were assigned to segments with missing speed values.

Perfect assignment of derailments in the accident database to the track information in the traffic database would be indicated by zeros for all values not along the diagonal. However, there is the tendency for derailments on lower track classes to be assigned to segments in the traffic data with higher derived track class values (e.g. 106 of the derailments on class 2 track were assigned to class 3 or higher track). This indicates that the given value of track class in the accident data is generally lower than the segment track class derived from given track speed values presented in the traffic data. This suggests that there are portions of track within a given segment that have a lower class rating than that of the majority of the segment (for example, curves with lower allowable operating speeds or sections of track having temporary slow orders imposed).

Using only the most current track information (2003), derailments and traffic data for all five-years were also apportioned to the segments within the 2003 traffic database. There were 6,277 segment records in the 2003 data, 3,947 of which were single main track segments. 80% of the total number of segments observed no derailments. Nearly 74% of derailments were able to be assigned to segments in the 2003 track data (Table 3.9b). The similarity in numbers in Tables 3.9a and 3.9b indicate that there has not been much change in the track segments for which traffic data are maintained (only the manner in which it is recorded for multiple main track segments).

Once the derailments were assigned to segments in the traffic database, segment-specific derailment rates were calculated by dividing the number of derailments by the total GTM for each segment. The average and standard deviation of the segment-specific derailment rates were also calculated for each track class (Table 3.10a). The track class-specific derailment rates calculated by dividing the total number of derailments by total GTM are considerably lower than those calculated by averaging the segment-specific derailment rates for each track class (Table 3.10a). The large standard deviations illustrate the large variation in derailment rates within track classes.

When using track data from 2003, there are substantial differences, particularly on class 3 track. While the number of assigned derailments and gross ton-miles are similar, the average and standard deviation of the derailment rate are much higher when using 2003 track data (Table 3.10b). This was due to a single derailment in 2000 that was matched to a track segment having four main tracks of length 0.937 miles that had approximately 0.067 MGTM over the five-year period (for a resulting derailment rate of 3,753 derailments per BGTM). The summation of the four of these rates leads to the large average derailment rate for class 3 track and the resulting variance. Even though the majority of segments record zero derailments, the inclusion of segments having low traffic volumes and high derailment rates shifts the average upward. This may suggest that a weighted average should be used; this is equivalent to dividing the total derailments by the total GTM for each track class (i.e. $\frac{\sum (w_i \cdot Y_i / D_i)}{\sum (w_i)}$; where the weights, w_i, are equal to the traffic volume, D_i). A parametric Empirical Bayes analysis, to be described later in this chapter, will be used to adjust the low traffic volume—high derailment rate segments towards the lower average derailment rate.

Table 3.10a Segment-Specific Derailment Rates by Track Class; 1999-2003

Track Class	1	2	3	4	5	Total
Derailments*	15	148	174	707.5	206.5	1,251
Gross Ton-Miles (billions)	5.009	66.38	282.8	2,973	1,318	4,645
Derailments per Billion GTM	3.00	2.23	0.615	0.238	0.157	0.269
Average	18.6	9.15	1.70	0.615	0.283	2.04
Standard Deviation	138	119	14.7	8.59	3.45	45.4

Table 3.10b Segment-Specific Derailment Rates by Track Class; 1999-2003 (2003 Track Data)

Track Class	1	2	3	4	5	Total
Derailments*	18	155	186	678.5	204.5	1,244
Gross Ton-Miles (billions)	4.266	73.54	293.3	2927	1332	4,631
Derailments per Billion GTM	4.22	2.11	0.634	0.232	0.153	0.269
Average	21.0	14.5	18.8	0.788	0.262	4.94
Standard Deviation	82.3	186	255	11.9	1.44	112

*Fractional values are due to the need to assign a portion of some derailments to different tracks on multiple main segments.

3.4.1 Optimal Segment Length

Segment-specific derailment rates can vary considerably around the average value for similar track as indicated by the large standard deviations (Tables 3.10a&b). An additional source of uncertainty is the value of the numerator; one additional derailment over a particular segment can change the calculated derailment rate considerably, especially for lines where traffic density is light. In the analogous case of estimating highway accident rates, Okamoto & Koshi (1989) expressed the problem as follows, "occurrence of a traffic accident in a road segment is a stochastic event and an observed accident rate in a segment contains a certain magnitude of random error." The probability of a derailment on a given track segment is a function of the following segment characteristics: 1) the "true," unknown, derailment rate, 2) the traffic density (million gross-tons), and 3) the segment length. Increases in any of these variables also increases the calculated derailment probability for a given track section.

Traffic density is generally known for a given track section and while the derailment rate is not known, it can be assumed to be a function of the quality of track that does not vary with changes in either the traffic density or the length of segment chosen (assuming homogenous quality of the track section being segmented)[20]. Therefore, increasing the segment length will increase the likelihood of a derailment having occurred over the segment. "Random errors of accident rates can be smaller with longer segments but the set of longer segments may lose its explanatory power" to distinguish between high and low-accident locations (Okamoto & Koshi, 1989). The question addressed here pertains to the optimal length of segment for a certain level of confidence in the accident rate estimate.

Nicholson (1987) finds that "statistical reliability considerations indicate that five years is probably the optimum time period" upon which to base an estimate of the UTAR. His conclusions are based on an analysis of the variation in the confidence interval with variation in the time period chosen (where accident rates are estimated in terms of accidents per unit time). This conclusion is not easily extended to traffic based derailment rates due to the different choices for the unit of exposure. Nicholson further states that the precision of the UTAR estimate is increased (i.e. the "width of the confidence interval, as a proportion of the UTAR" decreases) as the length of segment is increased. This "error ratio" approach was also studied on Japan's Tokyo-Kobe Expressway and measures the relative magnitude of the error between the observed and true accident rate (Okamoto & Koshi, 1989). For instance, let $x_1 = (\hat{\lambda} - \lambda_L)/\hat{\lambda}$, $x_2 = (\lambda_U - \hat{\lambda})/\hat{\lambda}$, $x_3 = (\lambda_U - \lambda_L)/\hat{\lambda}$, where x_1, x_2, and x_3 are "error ratios," $\hat{\lambda}$ is the estimated derailment rate, and λ_L & λ_U are the confidence limits defined previously in Eq. 3.1. Clearly, all three error ratios are independent of exposure (i.e. gross ton-miles, D), and only depend on the number of derailments observed over a given segment (Figure 3.1).

[20] This assumption of a linear relationship between traffic volume and derailment occurrence (i.e. a linear "safety performance function") may not be entirely accurate (Hauer, 1997; Qin et al., 2004).

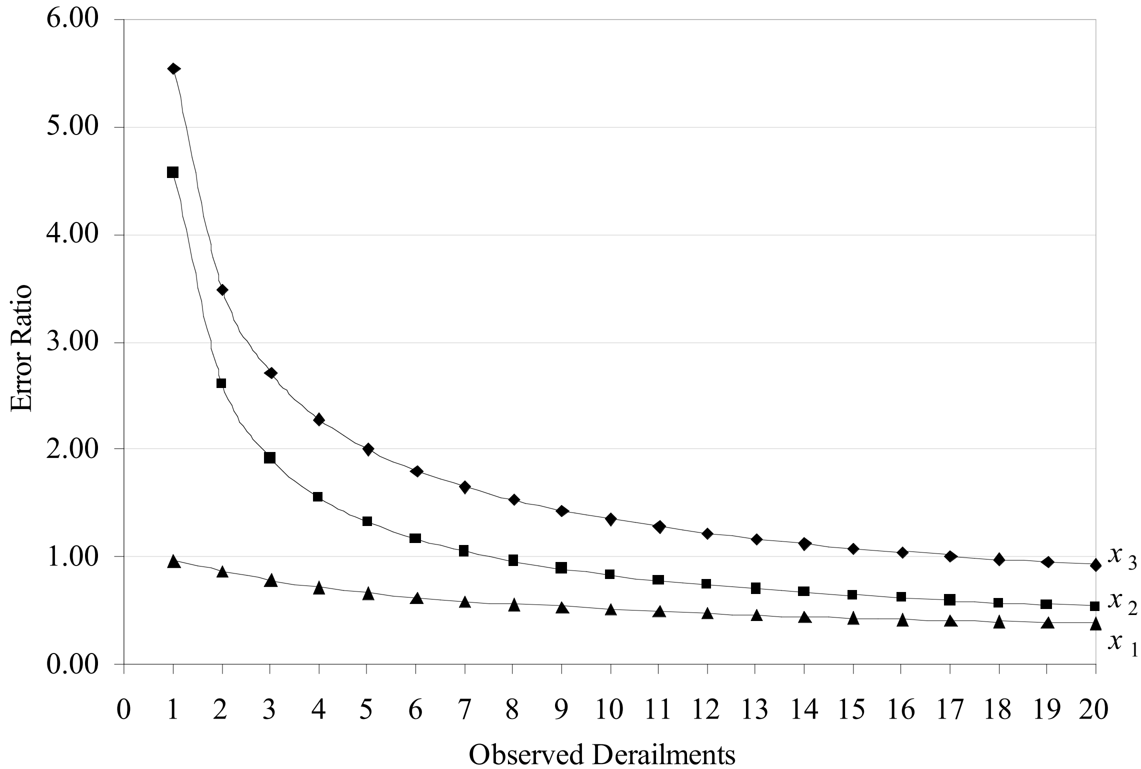

Figure 3.1 Error Ratios (x_1, x_2, and x_3) of Accident Rate Estimates; 95% Confidence Level

As the number of derailments is increased, the value of each error ratio decreases. Also, the value of each error ratio approaches infinity as the observed number of derailments approaches zero (also, note that $x_1 + x_2 = x_3$). For segments in which there are no observed derailments, the upper value of the derailment rate estimate will decrease in proportion to the increase in traffic volume (i.e. $\lambda_U = 3.69/D$).

3.4.1.1 Deterministic Approach to Finding Desired Segment Length

Assume now that a given section of track of length L is known to have a traffic density of T million gross tons (MGT) and a derailment rate of λ derailments per billion gross ton-miles. A deterministic approach to ascertain the optimal segment length, l, would be based on the desired level of accuracy of the observed derailment rate over each segment. Thus, $l \approx (1000Y)/\lambda T \leq L$, where Y is the number of derailments predicted to occur on each segment (the conversion factor of 1000 converts MGT to billion gross-tons).

For instance, if the desired level of accuracy is such that x_3=2, then 5 derailments would need to be observed over each segment (Figure 3.1). The segment length necessary to observe 5 derailments decreases as the traffic density or derailment rate increases (Figure 3.2). For example, a track section with a traffic density of 100 MGT believed to have a derailment rate of 5 derailments per billion gross ton-miles (BGTM), would be predicted to record 5 derailments on each 10-mile segment (or every BGTM). For a track believed to have the same derailment rate that carries 25 MGT, the segment length would quadruple to 40 miles for the same level of exposure (i.e. 1 BGTM).

3.4.1.2 Probabilistic Approach to Finding Desired Segment Length

A more stochastic approach might determine the desired segment length in probabilistic terms based an assumed derailment rate for the section and the known traffic density. The probability of observing k accidents over a segment with a given derailment rate λ is as follows: $\Pr(Y = k \mid \lambda \cdot D) = \frac{e^{-\lambda \cdot D}(\lambda \cdot D)^k}{k!}$, $k \in \{0,1,2,...\}$ where D is the number of gross ton-miles. For a given segment with derailment rate λ and traffic density T, the probability of derailment can be plotted for various segment lengths (Figure 3.3). Holding the derailment rate and traffic density constant, the mean of the (Poisson) distribution is proportional to the segment length. In other words, the probability of observing at least k derailments increases as the segment length is increased.

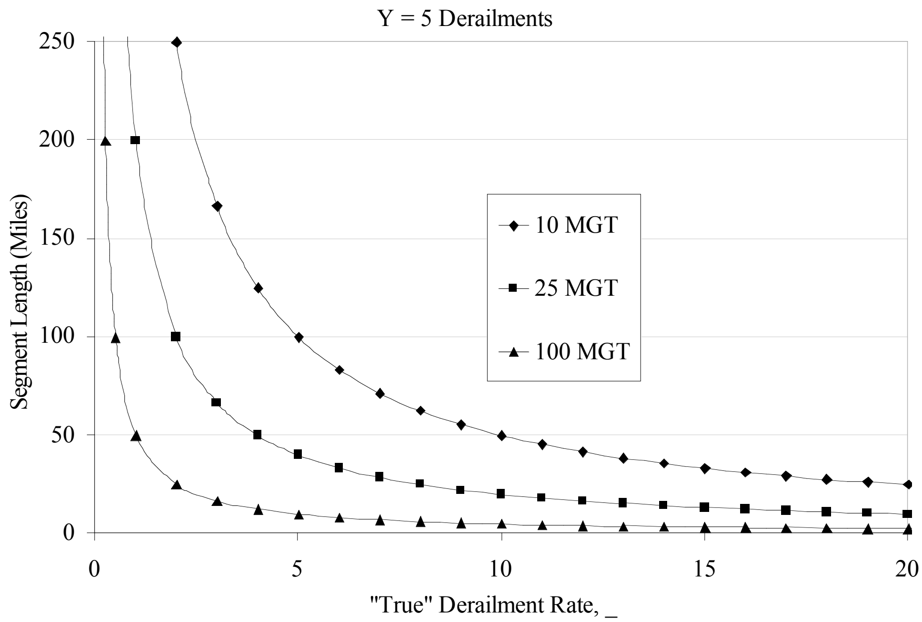

Figure 3.2 Segment Lengths by Derailment Rate and Traffic Density (Deterministic Approach: Y = 5 Derailments)

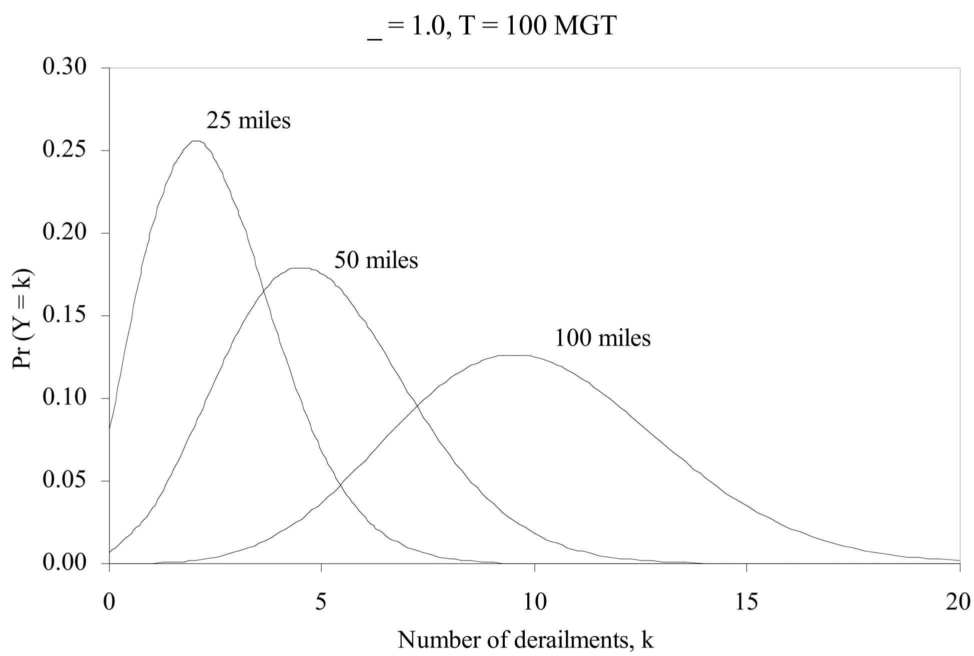

Figure 3.3 Probability of Derailment by Segment Length (for given Traffic Density, T = 100 MGT, and Derailment Rate, λ = 1.0 Derailments per BGTM)

3.4.1.3 Empirical Example

One line segment in the data was chosen to illustrate the increased level of certainty in the derailment rate estimate that can be achieved by increasing the segment length. There were 43 derailments[21] recorded between 1999 and 2003 on line segment #1025, which averaged about 18 MGT each year. The segment begins at milepost 7.3 and ends at milepost 283.3 with a total length of 276 miles.

For purposes of illustration, the segment was divided into 32, 16, 8, 4, 2, and 1 segments of length 8.625, 17.25, 34.5, 69, 138, and 276 miles, respectively. Derailment rates and corresponding confidence intervals and error ratios were calculated for each segment (Table 3.11). The traffic volume was determined using a weighted average approach in which the average MGT over each segment was multiplied by the segment length (miles) to derive the number of gross ton-miles.

As segment length was increased, there were three effects: 1) the number of segments observing zero derailments decreased, 2) the upper confidence limit decreased for zero-derailment segments (as traffic volume increased), and 3) the width of the confidence intervals decreased (Table 3.11).

The decrease in width of the confidence interval, or error interval, is evident by the average interval width over each segment division. Similarly, an averaged error ratio was obtained by dividing the average error interval by the average derailment rate (about 1.66 for every division level but the 276 mile segment). Both the average error interval and the averaged error ratio decrease as the segment length is increased (Figure 3.4).

[21] One derailment in the accident database was unable to be assigned to the segment in the traffic data as its milepost value (7.1) was below the beginning milepost value for the segment.

Table 3.11 Derailment Rates on Line Segment #1025; 1999-2003

Miles	BMP	EMP	Derailments	MGTM[22]	Derailment Rate	λ_L	λ_U	$\lambda_U - \lambda_L$	x_3
17.25	7.30	24.54	4	2,073	1.930	0.53	4.94	4.42	2.29
	24.55	41.79	7	2,082	3.362	1.35	6.93	5.58	1.66
	41.80	59.04	1	1,915	0.522	0.01	2.91	2.90	5.55
	59.05	76.29	5	1,512	3.307	1.07	7.72	6.64	2.01
	76.30	93.54	1	1,470	0.680	0.02	3.79	3.77	5.55
	93.55	110.79	5	1,471	3.399	1.10	7.93	6.83	2.01
	110.80	128.04	3	1,487	2.017	0.42	5.89	5.48	2.72
	128.05	145.29	4	1,486	2.692	0.73	6.89	6.16	2.29
	145.30	162.54	0	1,473	0.000	0.00	2.50	2.50	N/A
	162.55	179.79	0	1,435	0.000	0.00	2.57	2.57	N/A
	179.80	197.04	0	1,342	0.000	0.00	2.75	2.75	N/A
	197.05	214.29	1	1,278	0.782	0.02	4.36	4.34	5.55
	214.30	231.54	0	1,339	0.000	0.00	2.75	2.75	N/A
	231.55	248.79	6	1,390	4.316	1.58	9.39	7.81	1.81
	248.80	266.04	3	1,322	2.269	0.47	6.63	6.16	2.72
	266.05	283.34	2	1,429	1.400	0.17	5.06	4.89	3.49
34.5	7.30	41.79	11	4,158	2.645	1.32	4.73	3.41	1.29
	41.80	76.29	6	3,485	1.722	0.63	3.75	3.12	1.81
	76.30	110.79	6	2,945	2.037	0.75	4.43	3.69	1.81
	110.80	145.29	7	2,971	2.356	0.95	4.85	3.91	1.66
	145.30	179.79	0	2,901	0.000	0.00	1.27	1.27	N/A
	179.80	214.29	1	2,612	0.383	0.01	2.13	2.12	5.55
	214.30	248.79	6	2,746	2.185	0.80	4.76	3.95	1.81
	248.80	283.34	5	2,713	1.843	0.60	4.30	3.70	2.01
69	7.30	76.29	17	7,640	2.225	1.30	3.56	2.27	1.02
	76.30	145.29	13	5,921	2.195	1.17	3.75	2.59	1.18
	145.30	214.29	1	5,465	0.183	0.00	1.02	1.01	5.55
	214.30	283.34	11	5,435	2.024	1.01	3.62	2.61	1.29
138	7.30	145.29	30	13,563	2.212	1.49	3.16	1.67	0.75
	145.30	283.34	12	10,909	1.100	0.57	1.92	1.35	1.23
276	7.30	283.34	42	24,305	1.728	1.25	2.34	1.09	0.63

The narrowing of confidence intervals is due to two things: 1) longer segments recorded more derailments, and 2) longer segments recorded higher levels of traffic volume. Both of these contributed to less uncertainty in the derailment rate estimates on longer segments. Similar trends could be observed by extending this analysis to other line segments.

[22] The summation of traffic volumes for each division level will vary slightly as the values have been estimated using a weighted average approach discussed above.

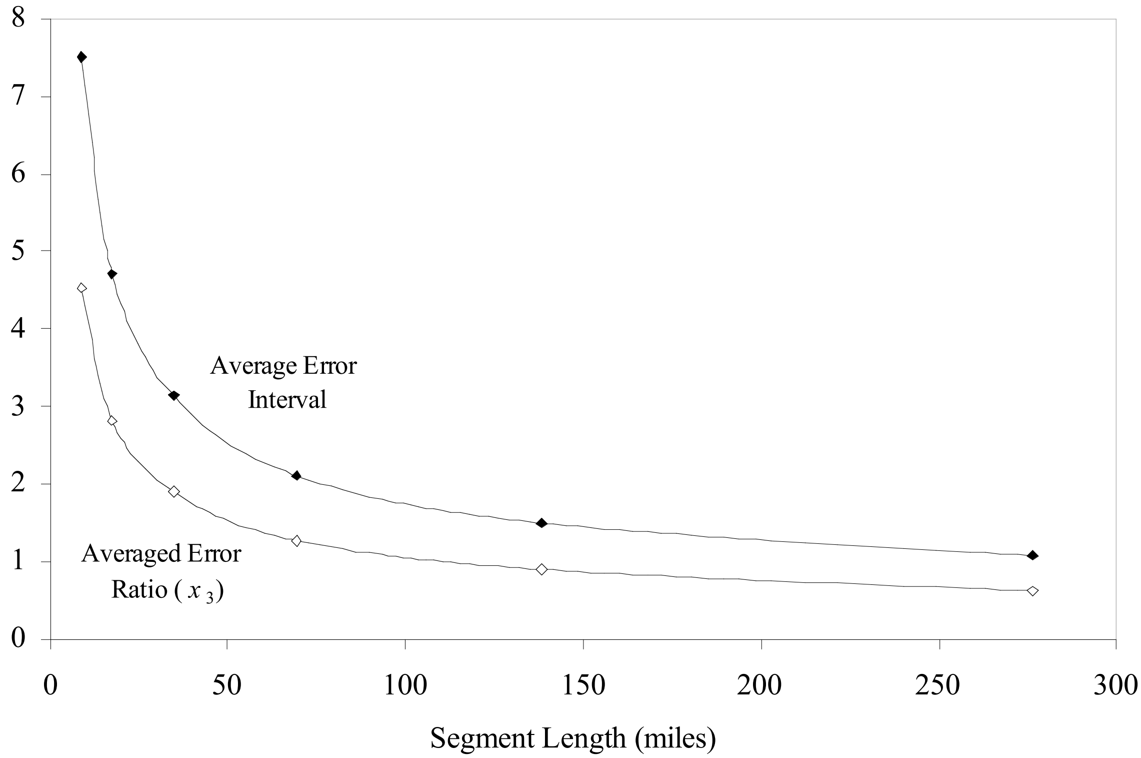

Figure 3.4 Average Width of Confidence Interval by Segment Length

3.5 Parametric Empirical Bayesian Analysis

One potential problem with segment-specific accident rates is that there may be a limited accident-history on low-density (or high-quality) track. While five years of accident data have been analyzed, no derailments occurred on the majority of segments during that time period. Several other segments, having very small volumes of traffic, recorded a single derailment. It would be naïve to be confident that the derailment rate for the former case is zero, and just as naïve to be confident that the derailment rate in the latter case would be as large as that estimated using the low traffic volumes. The main benefit of the empirical Bayes methodology presented by Nembhard & Young (1995) is that it "strikes a balance between the aggregate & segment-specific methods" while "maintaining continuity between the two estimation philosophies," thus "gaining the advantages of each while minimizing their drawbacks." This model is appropriate for "systems where the goal is to simultaneously estimate multiple Poisson process rates for items with similar but nonidentical rates" (Nembhard &Young, 1995).

The following section describes the parametric Empirical Bayes (PEB) method as it is applied to railroad derailment rates (adapted from Nembhard & Young, 1995). Let λ_i be the derailment rate per billion gross ton-miles (or any other appropriate exposure metric) for the i^{th} track segment. Let Y_i represent the number of observed derailments and D_i represent the number of gross ton-miles (GTM, in billions) over the i^{th} track segment. As previously discussed, the conditional probability of observing Y_i derailments given a traffic volume of D_i billion GTM and an underlying derailment rate of λ_i derailments per billion GTM, is as follows: $\Pr(Y_i = k \mid \lambda_i \cdot D_i) = \frac{e^{-\lambda_i \cdot D_i}(\lambda_i \cdot D_i)^k}{k!}$, $k \in \{0,1,2,...\}$. The maximum likelihood estimate (MLE) of λ_i is the observed rate $R_i = Y_i / D_i$.

The Bayesian estimator uses the objective data known about all segments to infer the subjective prior probability distribution (Nembhard & Young, 1995). The prior distribution is inferred by examining the observed rates R_i on all track segments and the Bayesian estimator adjusts the observed rate based on the amount of traffic over the particular segment (with substantial adjustment for low volume segments). The gamma distribution (with parameters α & β) is used for the prior probability distribution. The posterior distribution is the gamma distribution with parameters $\alpha' = \alpha + Y_i$ and $\beta' = 1/(D_i + \beta^{-1})$. The adjusted mean for λ_i is thus: $\lambda_i' = \frac{\alpha + Y_i}{D_i + \beta^{-1}}$. Note that the adjusted rate approaches the observed rate when D_i is large and approaches the prior mean ($\alpha \cdot \beta$) when D_i (& Y_i) is small.

Nembhard & Young (1995) present two approaches to estimating the gamma prior parameters: maximum likelihood estimation (MLE) and a moment estimator method in which the observed moments are set equal to the expected moments. Using the simpler, latter approach, the Bayesian estimate of accident rate is thus: $\hat{\lambda}_i = \frac{Y_i + \hat{\alpha}}{D_i + \hat{\beta}^{-1}}$; (Eq. 3.2)

where $\hat{\alpha} = \frac{\overline{R}^2}{s_R^2 - \overline{R}\frac{\sum D_i^{-1}}{n}}$, $\hat{\beta} = \frac{s_R^2 - \overline{R}\frac{\sum D_i^{-1}}{n}}{\overline{R}}$, $\overline{R}$ is the sample mean and s_R^2 is the sample variance of the observed accident rates for all track segments (i = 1, 2,..., n).

In this analysis, the total track segment population was divided into five sub-samples or "reference populations" (Hauer, 1986) based on FRA track class. The moment matching method did not produce valid results as the gamma prior parameter estimates for all but class 4 track (and all track classes combined) were less than zero. This occurred because: $s_R^2 < \overline{R}\frac{\sum D_i^{-1}}{n}$. The results are independent of the scale of the exposure metric chosen (i.e. GTM, MGTM, or BGTM). As such, the MLE method was used to estimate parameter estimates.

The MLE method maximizes the marginal likelihood (or log-likelihood) across all segments. The log-likelihood to be maximized is:

$$L(\alpha,\beta) = \sum_{j=1}^{n}[\Psi(\alpha + Y_j) - (\alpha + Y_j)\cdot\log(D_j + 1/\beta)] - n\Psi(\alpha) - n\alpha\log(\beta)\,; \qquad \text{(Eq. 3.3)}$$

where $\Psi(\cdot)$ is the log-gamma function (Nembhard & Young, 1995). The parameter estimates were determined by numerical iteration using the SOLVER tool in Excel. The log-likelihood equation was maximized for each track class with the constraint that both α and β had to be positive.

The iterations for class 5 track produced values of α that tended toward infinity and values of β that tended toward zero; the prior mean (α·β) tended toward 0.157 and the maximized likelihood tended toward -589. In order to derive practical values of the parameter estimates, the value of β was determined by using a power function extrapolation of the results for class 2, 3 and 4 track (using the estimated prior mean as the independent variable). The value of parameter α was then derived by dividing the prior mean (α·β) by the derived value of β. The resulting likelihood was within 2% of the maximum likelihood (Table 3.12a).

Estimates for the Bayesian parameters were also determined using the 2003 track data (Table 3.12b). The results for class 5 track had to again be approximated using extrapolated results for class 2, 3 and 4 track. The prior means are similar to those estimated in Table 3.12a and do not show the discrepancy in derailment rate on class 3 track as observed in the average rates. The estimates for parameters α and β varied somewhat between the two approaches; however, both showed the same trends: as track class was increased, α increased and β decreased and the prior means, α·β, also decreased (Tables 3.12a&b).

Table 3.12a Parametric Empirical Bayes Analysis Parameters

Track Class	1	2	3	4	5	Total
Average Derailment Rate (per Billion GTM)	18.6	9.15	1.70	0.615	0.283	2.04
L(α, β)	8.16	-2.84	-244	-1705	-598	-2856
α	0.047	0.200	0.566	0.923	1.26	0.804
β	284	17.6	1.22	0.272	0.124	0.362
β^{-1}	0.0035	0.057	0.818	3.68	7.97	2.76
α·β	13.3	3.51	0.692	0.251	0.157	0.291

Table 3.12b Parametric Empirical Bayes Analysis Parameters (2003 Track Data)

Track Class	1	2	3	4	5	Total
Average Derailment Rate (per Billion GTM)	21.0	14.5	18.8	0.788	0.262	4.94
L(α, β)	10.3	-11.3	-237	-1,650	-603	-2,797
α	0.470	0.504	0.605	1.52	1.59	0.918
β	19.5	6.50	1.31	0.166	0.096	0.349
β^{-1}	0.051	0.154	0.763	6.01	10.4	2.86
α·β	9.18	3.28	0.794	0.252	0.154	0.321

Unlike results using the moment method, the prior means are consistently lower than the average derailment rates (Tables 3.12a&b) and become increasingly closer to the values calculated by dividing the total derailments by the total GTM (Tables 3.10a&b) for higher class track. To consider how these parameters will affect the adjusted derailment rates, rewrite Eq. 3.2 in the following manner: $\hat{\lambda} = \left(\frac{Y}{D}\right)\left(\frac{\beta \cdot D}{\beta \cdot D + 1}\right) + \left(\frac{\alpha \cdot \beta}{\beta \cdot D + 1}\right)$. For a given traffic volume, *D*, the PEB adjusted derailment rate is a simple linear translation of the observed derailment rate. For a given number of observed derailments, *Y*, the PEB adjusted derailment rate is a nonlinear function of the observed derailment rate (Figure 3.5). The observed and adjusted rates are equal when $D = Y/\alpha\beta$ (i.e. when the derailment rate is equal to the prior mean, α·β). As traffic volume is increased, the adjusted rate tends to the observed rate. As the number of derailments is increased, the PEB adjustment parameters become less influential and the PEB adjusted rate tends to the observed derailment rate. For segments observing zero derailments, the adjusted rate decreases nonlinearly with increases in traffic volume (and is equal to the prior mean when D=0).

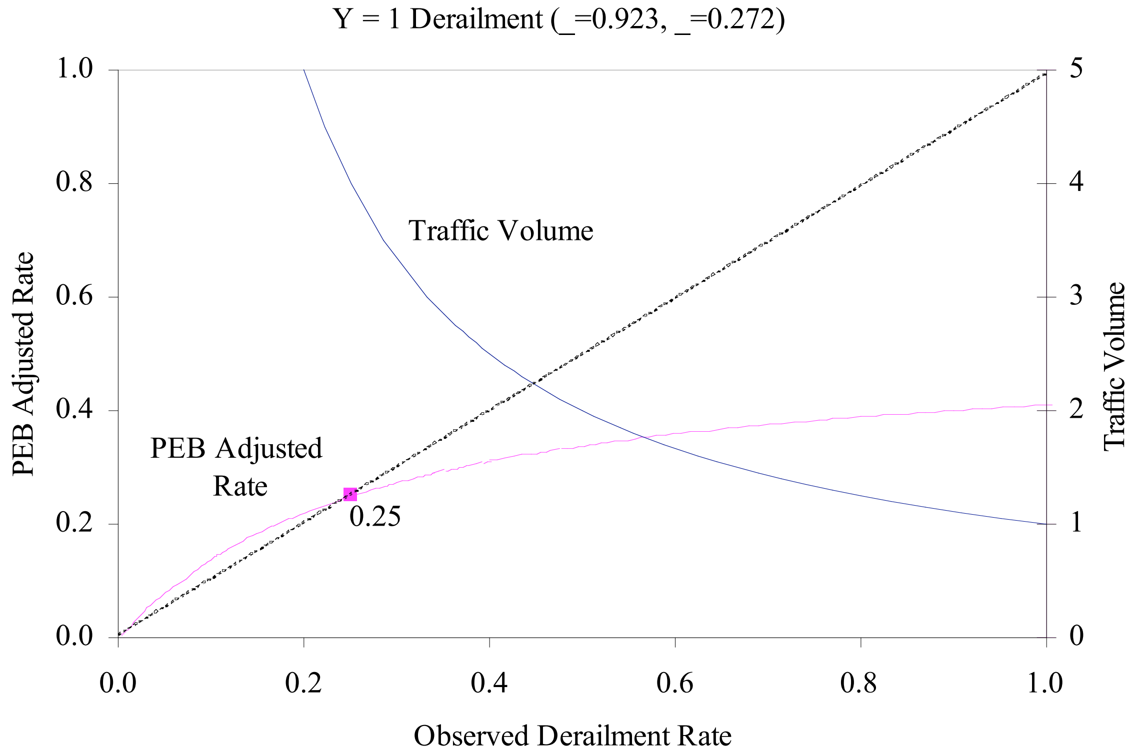

Figure 3.5 PEB Adjusted Derailment Rates (Y = 1 Derailment, Class 4 Track)

3.6 GIS Analysis

The next phase of the analysis involved the use of a Geographic Information System (GIS). In the GIS database provided by BNSF, there were 913 track segments over the BNSF network. The database included track sections having multiple mainline track segments. Comparison of the mileage values with the beginning and ending milepost information revealed that several mileage values were largely incorrect (on the low side). If uncorrected, this would lead to much larger incorrect derailment rates. To remedy this problem, a new mileage value was calculated as the difference between the ending and beginning milepost numbers. Once corrected, the average length of segment was 28 miles. Track class values were already specified within the GIS table for each segment, so no derivation was needed.

3.6.1 Determination of Segment-Specific Derailment Rates

The same approaches as described above (§3.4) were taken to assign derailments and traffic data information to the track segments in the GIS database table. When adding all the derailments that were matched to the GIS track information, approximately two-thirds of the total number of derailments were able to be correctly assigned (Table 3.13). The unassigned derailments are again mostly attributed to the lack of segment information in the GIS database. While a similar trend was observed for the percentage of derailments assigned to segments in the GIS database (i.e. higher track classes had better assignment), there were more derailments assigned to segments having lower values of track class in the GIS data. Derailments assigned to class 3 or lower track accounted for 54% of all assigned derailments in the GIS database (Table 3.13), while they only accounted for 27% of the assigned derailments discussed above (Table 3.9a).

Segment-specific derailment rates were calculated for each track segment in the GIS database and average derailment rates were calculated for each track class (Table 3.14). The values calculated by dividing the total derailments by the traffic volume on each track class were again considerably lower than the actual average. The average derailment rate for class 5 track was also estimated to be higher than the rate for class 4 track (Table 3.14). The standard deviations of the estimated derailment rates were much lower than those presented earlier (Table 3.9). This is likely due to the longer length of segments in the GIS database and possibly due to the given track class values in the GIS database.

Table 3.13 GIS Segment-Assigned Derailment Counts by Track Class; 1999-2003

	Recorded Track Class in Accident Data					
Track Class in GIS Table	1	2	3	4	5	Total[23]
1	**53.00**	43.25	26.00	22.00	3.00	147.25
2	40.67	**40.58**	32.50	57.33	2.00	173.08
3	46.50	43.83	**84.92**	111.33	9.25	296.83
4	46.33	29.33	54.33	**209.83**	22.33	364.17
5	21.50	10.00	15.25	51.50	**57.42**	158.67
Total Assigned Derailments	208	167	213	452	94	1,140
Total Derailments (Table 3.3)	457	275	278	551	111	1,686
Percent Assigned	45.5%	60.7%	76.6%	82.0%	84.7%	67.6%

After calculating each segment-specific derailment rate in the GIS database, the PEB estimation methodology was applied to the rates in the GIS data. MLE was again used to determine parameter estimates (Table 3.15).

[23] Totals include those derailments that were recorded as derailing on class X track, on class 6 track, or did not have a value for track class.

Table 3.14 GIS Segment-Specific Derailment Rates by Track Class; 1999-2003

Track Class	1	2	3	4	5	Total
Derailments	147.25	173.08	296.83	364.17	158.67	1,140
Gross Ton-Miles (billions)	120.9	458.2	815.8	1,943	848.6	4,186
Derailments per Billion GTM	1.218	0.378	0.364	0.187	0.187	0.272
Average	10.9	5.33	1.77	0.308	0.808	3.46
Standard Deviation	46	23	13	0.89	2.5	23

Table 3.15 PEB Parameter Estimates for Segments in GIS Database

Track Class	1	2	3	4	5	Total
Average Derailment Rate (per Billion GTM)	10.9	5.33	1.77	0.308	0.808	3.46
$L(\alpha, \beta)$	-37.6	-226	-553	-949	-416	-2314
α	0.399	0.489	1.88	1.88	2.29	0.639
β	19.6	3.10	0.246	0.120	0.110	1.01
β^{-1}	0.051	0.323	4.07	8.32	9.07	0.985
$\alpha \cdot \beta$	7.82	1.52	0.461	0.226	0.252	0.649

3.6.2 Linking Tabulated Results to GIS Shapefile

Once the derailment rates were calculated (in Excel), the tabular results (including derailment counts, traffic volumes, and derailment rates) were linked to the GIS data file (shapefile) of the BNSF track network using ESRI's ArcGIS. This involved creating a comma delimited (*.csv) file which was then added to the data layer in the GIS software. The added file was joined to the GIS shapefile table based on a unique 'OBJECTID' variable in both tables. New fields were added to GIS shapefile data for the number of derailments, traffic density (MGT), and the estimated derailment rates. The values for each new field were calculated by assigning the corresponding values from the joined *.csv file for each segment. Once the values were calculated, the joins were removed and the tabulated results were permanently integrated into the GIS shapefile table.

Once the results were combined with the GIS shapefile, various layers were added to the GIS map to show different attributes of the BNSF track network, including: track class, traffic density (MGT), number of derailments, and derailment rate. A second layer was added for the number of derailments, normalizing the value by the segment length, thus calculating per track-mile derailment rates. Each layer was symbolized (by width and color shade) based on the values for each attribute and then exported to *.pdf format at high resolution. Three of these exported figures are included here: traffic density (Figure 3.6), number of derailments (Figure 3.7), and derailment rates (Figure 3.8).

3.6.3 Segments of Particular Interest

After the analysis had been completed, it was evident that one particular segment had an unusually large number of derailments. Line segment #1025 is in the River subdivision of the Springfield (East) division between mileposts 7.3 and 283.3 (St. Louis, MO to Memphis, TN). In the GIS database, the track is single main and is labeled as class 3 track. As mentioned previously, there were 43 derailments over this 276 mile stretch of track over the five-year period analyzed. Of the 42 derailments[24] assigned to the GIS database, 17 were reported to the FRA, 7 of these were in 2003. This line recorded about 16-20 MGT per year for a total of about 90 MGT over the five-year period. The total exposure for this line was estimated to be about 24.5 billion gross ton-miles over the five-year period, producing an estimated derailment rate of about 1.7 derailments per billion GTM. While several other segments had a higher derailment rate, most of those rates were based on only a few derailments.

Another line segment of interest was #147 in the Bellwood subdivision of the Nebraska division, between milepost 24.9 and 66.4. This 41.5 mile stretch of single main track recorded 14 derailments over five years (9 in 2003) and had about 6.35 MGT of total traffic (no traffic data were given for 2002). An estimated derailment rate of 53 derailments per billion GTM was calculated, indicating that this segment has a particularly high risk of derailment. None of these derailments; however, were severe enough to require reporting to FRA. Of the nine derailments in 2003, six of these were reported as derailing on class 2 track and three were reported as derailing on class 1 track.

[24] A single derailment was unable to be assigned to the segment due to a milepost value (7.1) that was lower than the beginning milepost in the GIS database.

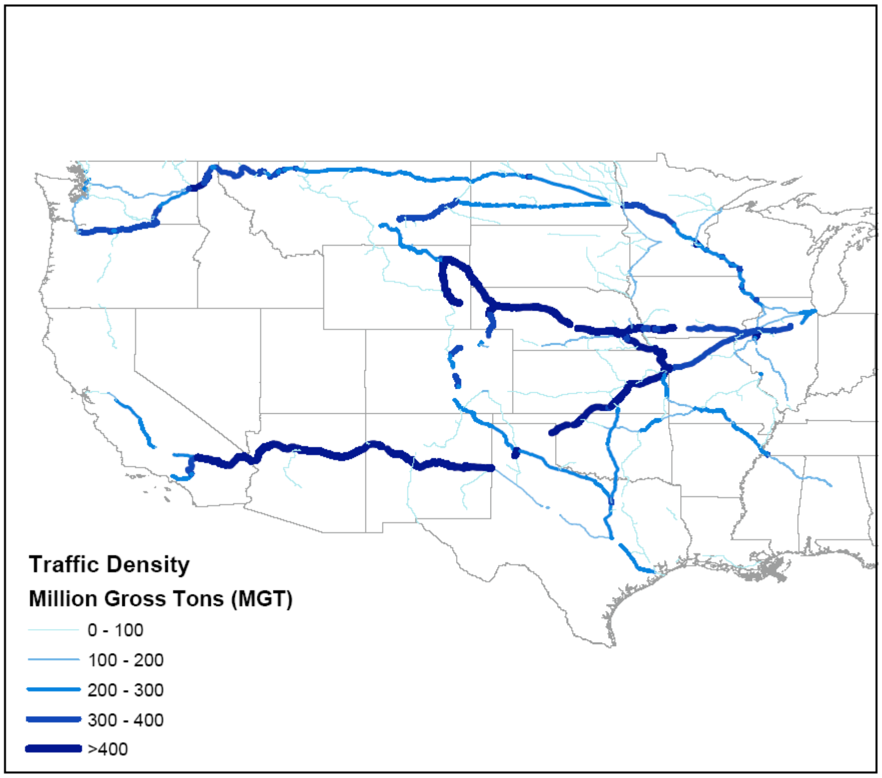

Figure 3.6 BNSF 5-Year Traffic Density (1999-2003)

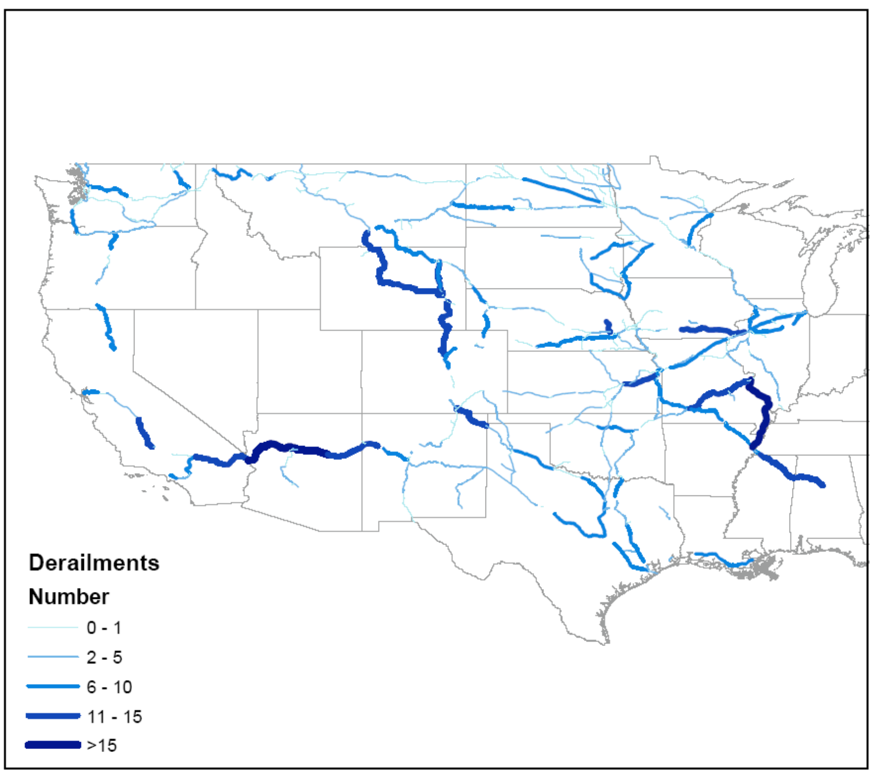

Figure 3.7 BNSF Mainline Derailments (1999-2003)

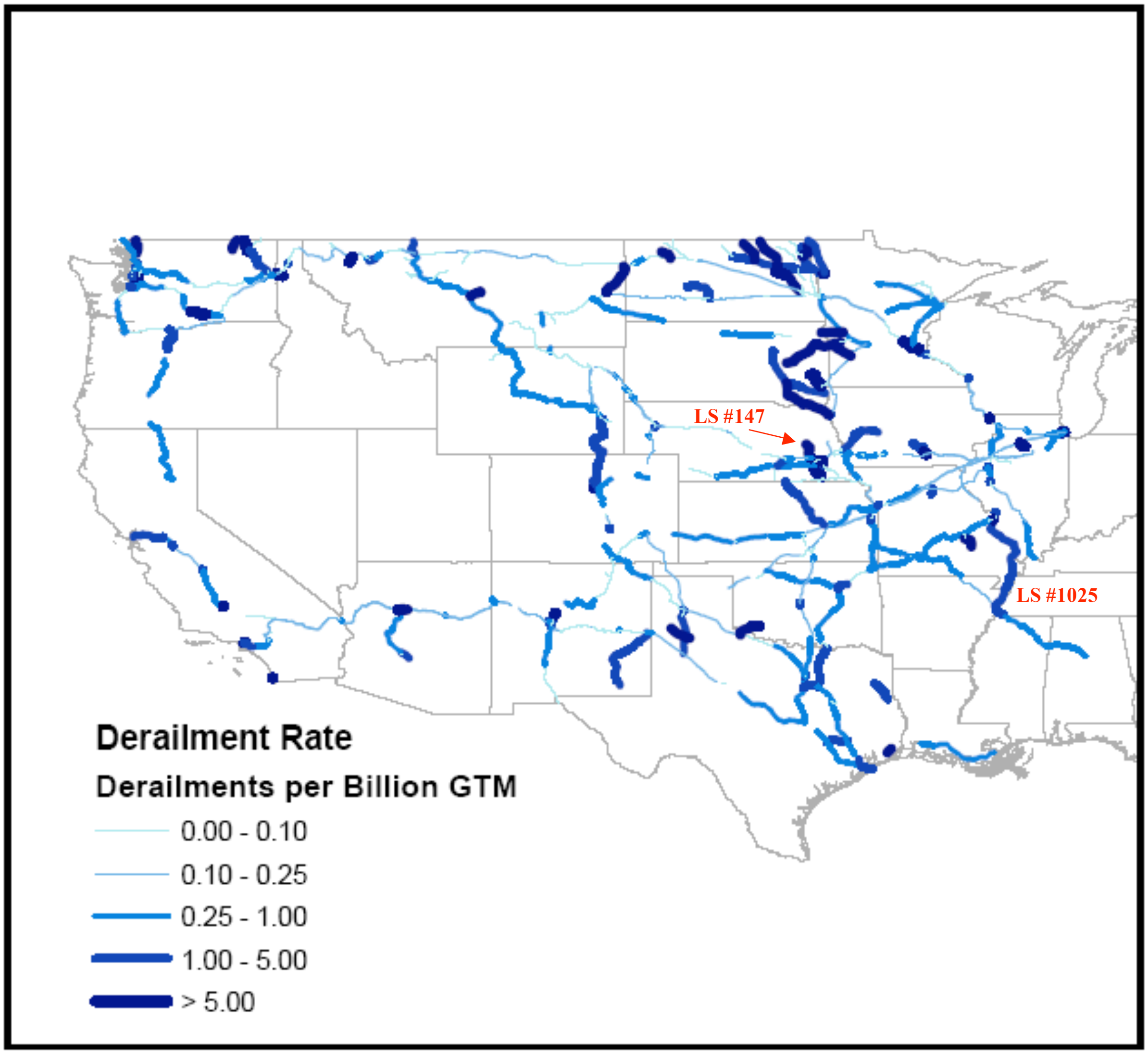

Figure 3.8 Mainline Derailment Rates on the BNSF Railway (1999-2003)

3.7 Conclusions

In this chapter, both track class-specific and segment-specific derailment rates were calculated for the BNSF Railway. Track class-specific derailment rates were shown to vary both within and between segments with three orders of magnitude difference between rates on class 1 and class 5 track. Segment-specific derailment rates were determined by matching accident records to segmented traffic data. The average derailment rates by track class were shown to have very large variances and a parametric Empirical Bayes method was used to adjust each segment's derailment rate based on the average derailment rates for each track class.

The question of optimal segment length needed for a certain level of confidence was shown to be a function of the number of observed derailments and traffic volume. As segment length was increased on a particular line segment, the average width of the confidence intervals decreased. The optimal length of segment needed for a certain level of confidence is largely up to the risk analyst.

After completing these analyses, the results were incorporated into a GIS database and layers were added for traffic density, number of derailments, and derailment rate. The resulting maps provide the end-user with an interactive, visual identification of potentially hazardous locations.

CHAPTER 4: DERAILMENT PROBABILITIES

Currently being prepared for submission to Accident Analysis & Prevention for publication.

4.1 Introduction

The purpose of this research is to better understand the dynamics of a train derailment by analyzing critical parameters that can be used to predict accident severity and to determine the derailment probability of individual cars within a derailed train consist. English et al. (1999) summarize the nature of railroad accidents in terms that are applicable to the current research:

> Rail vehicle derailments and impacts are dynamic events that involve conversion of large amounts of kinetic energy through dissipation by friction, absorption through structural deformation, momentum transfer and conversion to potential energy. These processes involve interactions of a vehicle with its environment and lead to the development of substantial forces. The structural response and gross motion of a rail vehicle are extensively interrelated.

In this paper, we test the hypothesis that the severity of derailment is dependent upon the amount of kinetic energy in the portion of the train consist behind the point-of-derailment (POD). We also hypothesize that the probability that a particular car will derail is primarily a function of two other probability distributions, namely, the point-of-derailment (POD) probabilities for various accident causes and the distribution of derailment severities (as measured by number of cars derailed) for various train lengths, speeds, and accident causes.

Previous studies have analyzed train derailment dynamics through the use of simulation models (Yang et al., 1972, 1973; Coppens et al., 1988; Birk et al., 1990). Potential risk reduction strategies were studied by analyzing the effects of train speed, train length, accident cause, and car positioning on the probability and severity of derailment (Nayak et al., 1983; Saccomanno & El-Hage, 1989, 1991; Thompson et al., 1992).

4.1.1 Literature Review

In the early 1970s, a research team from Pullman-Standard developed an analytical simulation model to determine the influence of various factors on derailment severity (Yang et al., 1972, 1973). The model numerically solved nonlinear equations of motion coupled with constraint equations for derailed and non-derailed cars. The model included the effects of ground friction, mating coupler moment, and brake retarding force to determine the number of cars derailed based on the position of the first car derailed. Results from the simulation showed that as the number of cars following the point-of-derailment (POD) increased, so did the number of cars derailed. They found a similar result for train velocity, and proposed that the effect was related to the amount of kinetic energy in the train.

Nayak et al. (1983) developed statistical techniques for assessing the risk of transporting hazardous materials by rail. Besides estimating track class-specific derailment rates and conditional hazardous materials release rates, they also developed analytical equations for estimating the number of cars derailed for mainline and yard derailments. The analysis explored the effects of track type and class, accident type and cause, train speed, and exposure. Results showed that longer and heavier trains have a higher probability of an accident per mile of travel than a shorter, lighter one.

In the late 1980s, a group of Canadian engineers, seeking to extend the Pullman model, developed a new derailment accident computer simulation model (DERACS) that allowed for coupler failure and independent car motion, simulating the dynamic interaction of cars in a derailment (Coppens et al., 1988; Birk et al., 1990). The DERACS sub-model DERAIL could be used to predict the number of cars derailed in an accident based on such inputs as train speed, number of cars, ground friction, and braking rate.

Saccomanno & El-Hage (1989, 1991) analyzed six years of Canadian train accident data to develop potential marshaling and buffering strategies to minimize the likelihood of derailing special dangerous commodity cars when involved in a derailment. They developed a procedure to predict the derailment potential for different positions in the train, under the assumption that the number of cars involved in a derailment is a function of train operating speed, the cause of derailment, and the number of cars following the point-of-derailment. For each cause of derailment, they found that the mean number of cars derailed increased exponentially with both train operating speed and “residual train length” (i.e. the number of cars following the POD).

Woodward (1989) also discussed the potential reduction in the probability of derailment for hazardous materials cars by separation of such cars throughout a train consist.

The effectiveness of separation was shown to be a function of train length, the number of hazardous materials cars, and the size of accident (number of cars derailed).

Similar research by Thompson et al. (1992) also looked at the placement of hazardous materials cars in train consists. Analysis of accident data found the "rear quarter to be statistically the 'safest' location in a mainline freight train [accident]". The research also confirmed that, on average, more cars derailed in longer trains and trains traveling at higher speeds. The study also considered the separation of hazardous materials within the train consist (as opposed to coupling or blocking cars together in groups) as a means to lower the risk associated with having a hazmat release, or the mixture of incompatible commodities.

4.1.2 Advancements to Previous Research

The first objective of this research is to develop a simple analytical equation to test the hypothesis that the severity of derailment (measured by the number of cars derailed) can be predicted by knowing the amount of kinetic energy in the (trailing) portion of the train consist behind the POD. We will also present methodology to assign point-of-derailment probabilities for various train lengths and accident causes. We then present a model that combines the predicted derailment probabilities with POD probabilities to estimate the conditional derailment probabilities for railcars in a derailed train consist.

Of the analytical models available in the literature, the geometric model developed by Saccomanno & El-Hage (1989, 1991) is the most robust in its capacity to both estimate the severity of derailment and calculate the probability of derailment for individual cars. The equation they used to model the mean number of cars derailed; however, was presented incorrectly. The second objective of this research is to develop a corrected version of that model and update the parameter estimates in the geometric model for a more focused group of accident causes than were previously considered. We then test the validity of both models by comparing predicted derailment probabilities to empirical derailment probabilities.

Our analyses focused on mainline derailments of Class I railroad freight trains operating in the United States over the ten-year interval 1992-2001. Class I railroads account for the majority of mainline railroad operation in the U.S. and their safety performance has been quite stable over this interval (Anderson & Barkan, 2004). We used accident data collected by the Federal Railroad Administration (FRA) in the Railroad Accident/Incident Reporting System (RAIRS) database (FRA, 2003a).

4.2 Position-in-Train of Derailed Cars

Each accident record in the FRA database contains information regarding the total number of vehicles (locomotives, freight cars, cabooses, etc.) and the number of each that derailed. Throughout this paper, the generic use of "cars" refers to all vehicles (including railcars and locomotives), unless specifically stated otherwise. Also recorded in the database is the position-in-train of the car first derailed. Assuming that cars derail sequentially behind the first car derailed, these data make it possible to determine the position-in-train of each derailed car for each accident. Throughout this paper, we use the terminology "point-of-derailment" to represent both the position-in-train of the car first derailed and the point along the track just ahead of the first car derailed (such that the number of cars behind the point-of-derailment includes the car first derailed). During the ten-year period analyzed, there were 4,661 accident reports classified as mainline derailments of Class I railroad freight trains. Of these, there were 157 reports considered unusable for this portion of the analysis due to one or more of the following reasons:

- Blank or zero values for the position-in-train of the first car derailed;
- Zero values for total number of cars or total number of cars derailed; and/or
- The computed position of the last car derailed exceeded the consist length.

The 4,504 remaining accident reports accounted for 38,608 derailed cars.

4.2.1 Position of First Car Derailed

We developed frequency and cumulative distributions for the position-in-train of the first car derailed (Figure 4.1). The first vehicle (generally the lead locomotive) in the train is most frequently the first to derail and the point-of-derailment (POD) of one-quarter of all derailments is within the first ten positions of the train. This high frequency of derailments might simply be due to a preponderance of short trains, but this is not the case. Over 98% of all train consists analyzed had train lengths greater than ten cars and 90% were longer than 30 cars (Figure 4.2). The large percentage of derailments with the POD near the front of the train can be largely explained by the cause of the accident. The data were analyzed for all accident causes combined (ALL) as well as for the fifteen most frequent accident cause groups (Appendix A). The remaining cause groups were lumped together in four broad categories (Equipment—EO, Human-Factor—HO, Track—TO, Signal—01S). Grade crossing collisions (02M) are categorized by FRA as a distinct accident (type 7), and are thus excluded from these analyses as only accidents designated as derailments (type 1) have been analyzed. Nearly half of all derailments are due to track-related causes, many of which (especially broken rail or welds) tend to derail the lead locomotive (FRA, 2003b). Other accident cause groups showing similar tendencies include: other miscellaneous (05M), use of switches (09H), and obstructions (01M) (Figure 4.3).

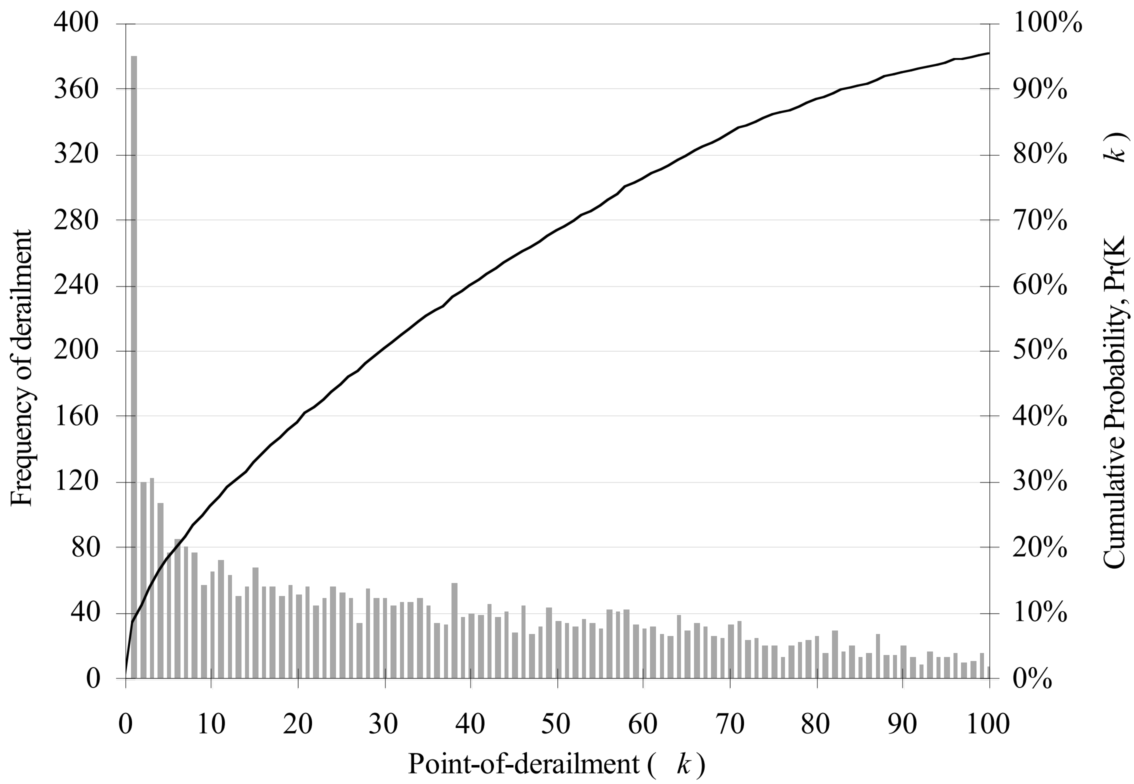

Figure 4.1 Frequency and Cumulative Distribution of Position of First Car Derailed (All Accident Causes)

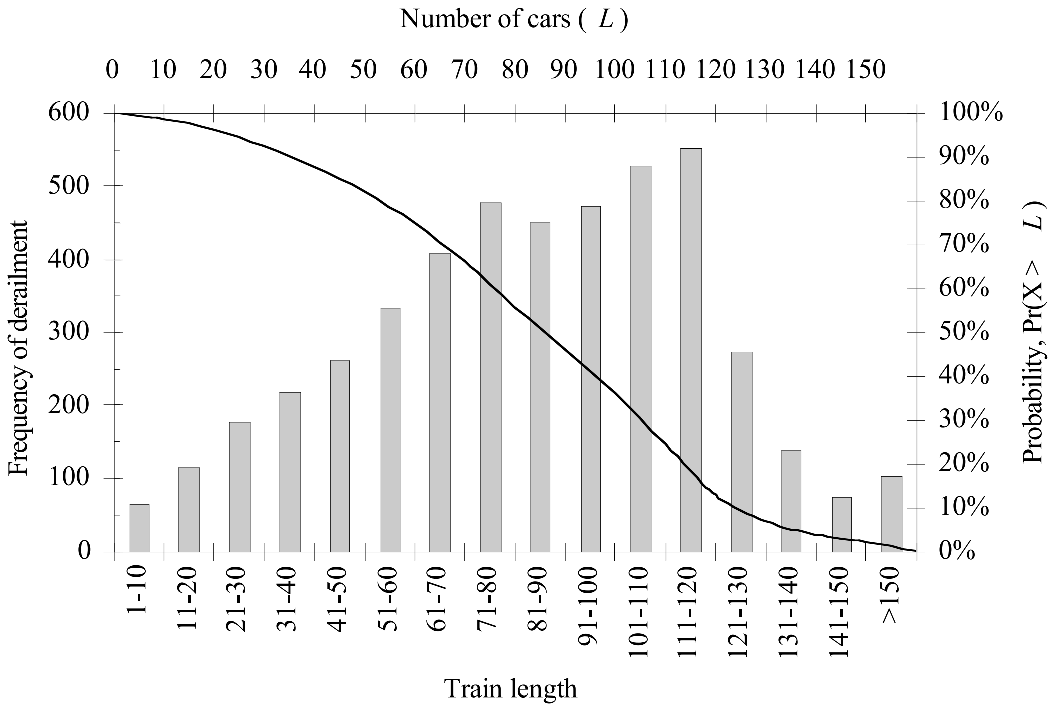

Figure 4.2 Frequency and Negative Cumulative Distribution of Train Length for Derailed Class I Railroad Freight Trains (All Accident Causes)

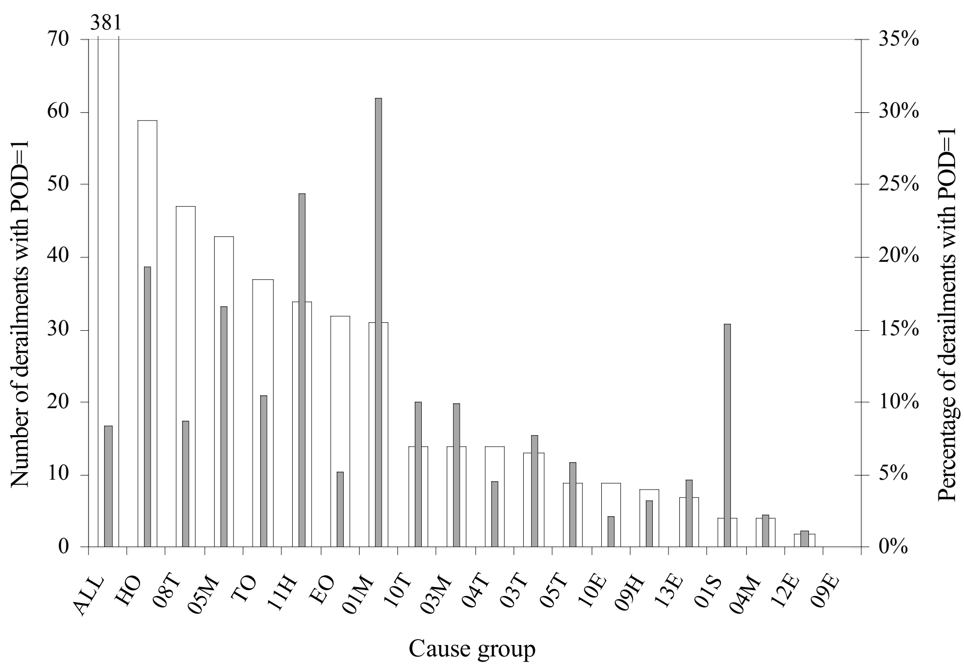

Figure 4.3 Frequency Distribution of Front-of-Train Derailments (POD=1) by Accident Cause Group (Ranked by Number of Derailments with POD=1)

4.2.1.1 Decile Approach to Assign POD Probabilities

Saccomanno & El-Hage (1989, 1991) analyzed the POD (normalized by train length), and found that train length had no significant effect while the cause of derailment did. They divided each train in their dataset into ten segments or "deciles" and determined the decile in which the POD occurred. They calculated normalized POD probabilities by decile group for seven broad accident cause groups.

We used this method for the top fifteen accident cause groups (and other lumped categories) and conducted chi-square analyses to determine whether POD and position-in-train were independent. We also calculated the Z-statistic and corresponding P-value for the null hypothesis that the estimated POD probability is independent for the first decile. The results (Table 4.1) show which accident causes are more likely to have cars at the front of the train derail first in a derailment. These include several track causes (08T, 03T, & 10T), some human factor causes (09H and 11H), as well as some miscellaneous causes (01M and 05M). That these causes tend to occur near the front of the train is not surprising because they all involve some element of track or operations that will cause a derailment when the train first encounters it, i.e. broken rail, misaligned switch, or obstruction on the track, etc.

4.2.1.2. Distribution Fitting Approach to Assign POD Probabilities

Identification of accident causes that are biased toward front-of-train PODs is also possible using graphical techniques. Figure 4.4 plots the cumulative distribution of normalized POD for various cause groups. Those accident cause distributions that closely follow the uniform distribution (i.e. slope = 1) exhibit little-to-no relationship between the (normalized) POD and the position-in-train e.g. bearing failures (10E). The distributions for accident causes that diverge from the uniform distribution indicate that the point-of-derailment is related to the position-in-train. For example, a steep slope (>> 1) at the lower percentiles of normalized POD indicates that a large proportion of derailments initiate at the front of the train e.g. obstructions (01M) and broken rail or welds (08T). Derailments caused by truck hunting (20E), grouped here within 'All Other Equipment Causes' due to a limited number of derailments (53), often initiated at the rear of the train (with one-half of all such derailments initiating in the last quartile of the train).

Table 4.1 Test Statistics for Point-of-Derailment Probabilities (Decile Approach)

		$\chi^2_{cr} = 16.92$		$Z_{cr} = 1.64$	
Cause Group	N	χ^2	P	Z	P
All Accident Causes (ALL)	4,504	494.95	<0.001	21.98	<0.001
Broken Rail or Welds (08T)	540	177.81	<0.001	12.19	<0.001
Bearing Failures (10E)	413	10.08	0.344	0.71	0.240
Track Geometry (excl. Wide Gage) (04T)	306	12.50	0.187	0.27	0.395
Other Miscellaneous (05M)	259	91.77	<0.001	8.93	<0.001
Train Handling (excl. Brakes) (09H)	246	35.30	<0.001	3.49	<0.001
Track-Train Interaction (04M)	178	8.63	0.472	0.05	0.480
Broken Wheels (12E)	171	8.71	0.465	1.30	0.097
Wide Gage (03T)	167	42.40	<0.001	5.49	<0.001
Buckled Track (05T)	154	13.40	0.145	0.70	0.242
Other Wheel Defects (13E)	150	11.33	0.254	0.54	0.293
Lading Problems (03M)	140	16.71	0.053	2.25	0.012
Turnout Defects—Switches (10T)	139	52.87	<0.001	6.25	<0.001
Use of Switches (11H)	139	100.64	<0.001	9.36	<0.001
Sidebearing Suspension Defects (09E)	106	9.47	0.395	1.81	0.035
Obstructions (01M)	100	153.40	<0.001	12.00	<0.001
All Other Equipment Causes (EO)	614	98.08	<0.001	9.63	<0.001
All Other Human-Factor Causes (HO)	305	121.98	<0.001	10.78	<0.001
All Other Track Causes (TO)	351	98.20	<0.001	9.59	<0.001
All Signal Failures (01S)	26	14.00	0.122	2.88	0.002

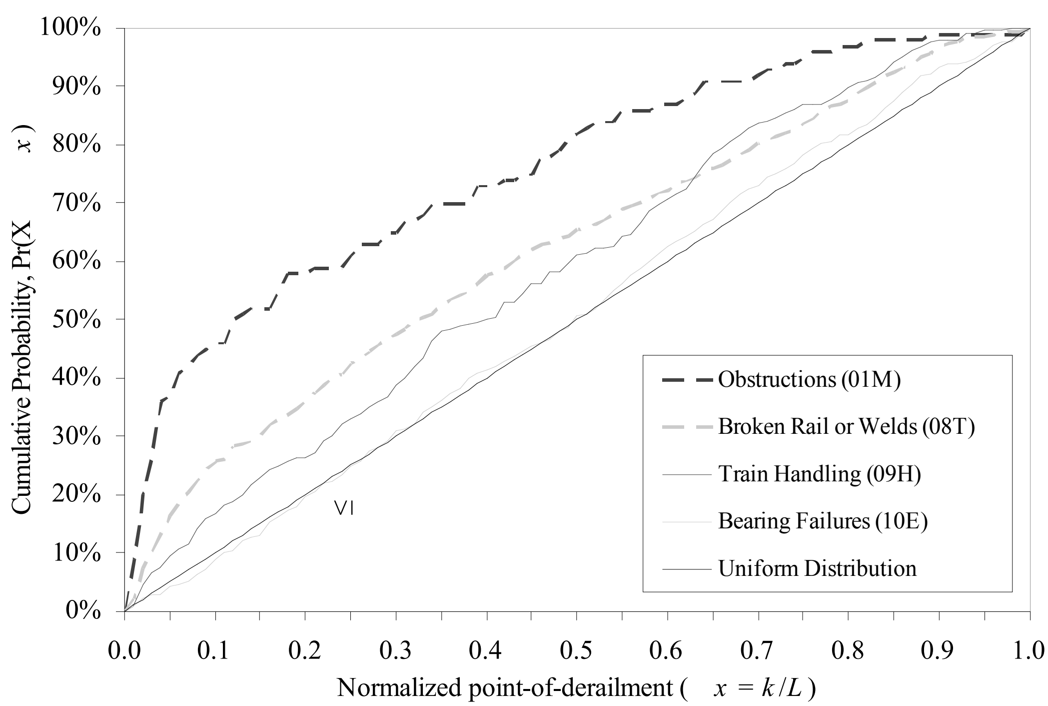

Figure 4.4 Cumulative Distribution Probabilities for the Normalized Point-of-Derailment (Various Accident Causes)

After determining the cumulative distribution function (CDF) for the normalized point-of-derailment probabilities for each accident cause, we fit the data to a standard probability distribution to achieve a more continuous representation of the actual POD probabilities. As the NPOD random variable has a finite range of (0:1], the Beta distribution was used to model NPOD probabilities (Appendix B). Using the Beta distribution allows for a smooth, continuous, and probably more realistic depiction of the NPOD probabilities (as opposed to using decile values). The parameter estimates (α and β) were determined by minimizing the error sum of squares (SSE) between the percentages of the cumulative Beta distribution and the observed CDF (using 1 percent increments in NPOD) (Table 4.2).

Table 4.2 Beta Distribution Parameter Estimates for Point-of-Derailment Probabilities

Cause Group	N	α	β	RMSerr
All Accident Causes (ALL)	4,504	0.722	0.906	0.0107
Broken Rail or Welds (08T)	540	0.635	1.039	0.0112
Bearing Failures (10E)	413	1.109	1.154	0.0072
Track Geometry (excl. Wide Gage) (04T)	306	1.034	0.883	0.0167
Other Miscellaneous (05M)	259	0.630	0.952	0.0246
Train Handling (excl. Brakes) (09H)	246	0.962	1.348	0.0163
Track-Train Interaction (04M)	178	1.056	0.979	0.0151
Broken Wheels (12E)	171	1.118	1.085	0.0119
Wide Gage (03T)	167	0.685	0.986	0.0202
Buckled Track (05T)	154	1.006	0.806	0.0233
Other Wheel Defects (13E)	150	1.252	1.248	0.0218
Lading Problems (03M)	140	0.810	0.835	0.0218
Turnout Defects—Switches (10T)	139	0.649	0.974	0.0343
Use of Switches (11H)	139	0.360	0.607	0.0225
Sidebearing Suspension Defects (09E)	106	1.352	1.032	0.0148
Obstructions (01M)	100	0.403	1.257	0.0209
All Other Equipment Causes (EO)	614	0.643	0.790	0.0099
All Other Human-Factor Causes (HO)	305	0.507	0.813	0.0098
All Other Track Causes (TO)	351	0.569	0.814	0.0139
All Signal Failures (01S)	26	0.610	0.773	0.0408

Those accident causes that had alpha and beta parameters near one indicate a uniform distribution of NPOD probability for the entire train length. Those with $\alpha < 1$ (and $\beta > 1$) tend to initiate at the front. Those with $\beta < 1$ (and $\alpha > 1$) tend to initiate at the rear. Those with $\alpha < 1$ and $\beta < 1$ tend to initiate at the front or rear of the train. Those with $\beta > 1$ and $\alpha > 1$ tend to initiate in the middle. The tendency for these generalizations becomes more apparent as the parameter estimates deviate from unity. The root-mean-squared error (RMSerr) measures the goodness-of-fit of the modeled POD distribution probabilities.

The probability density function (PDF) for the Beta distribution can be determined by discretizing the cumulative Beta distribution for various train lengths. The POD probability for a car in the k^{th} position of a train can be determined as follows:

$P_p(k) = P(x = k/L) = F(k/L) - F(\{k-1\}/L)$, where L is the train length, x is the normalized POD, and $F(\cdot)$ is the cumulative probability operator. The POD probabilities for all cars in the consist thus sums to 1, with $F(0) = 0$ and $F(1) = 1$. Figure 4.5 shows the POD probabilities (using the estimated Beta distribution parameters) for 100-car trains susceptible to broken rail or weld-caused derailments.

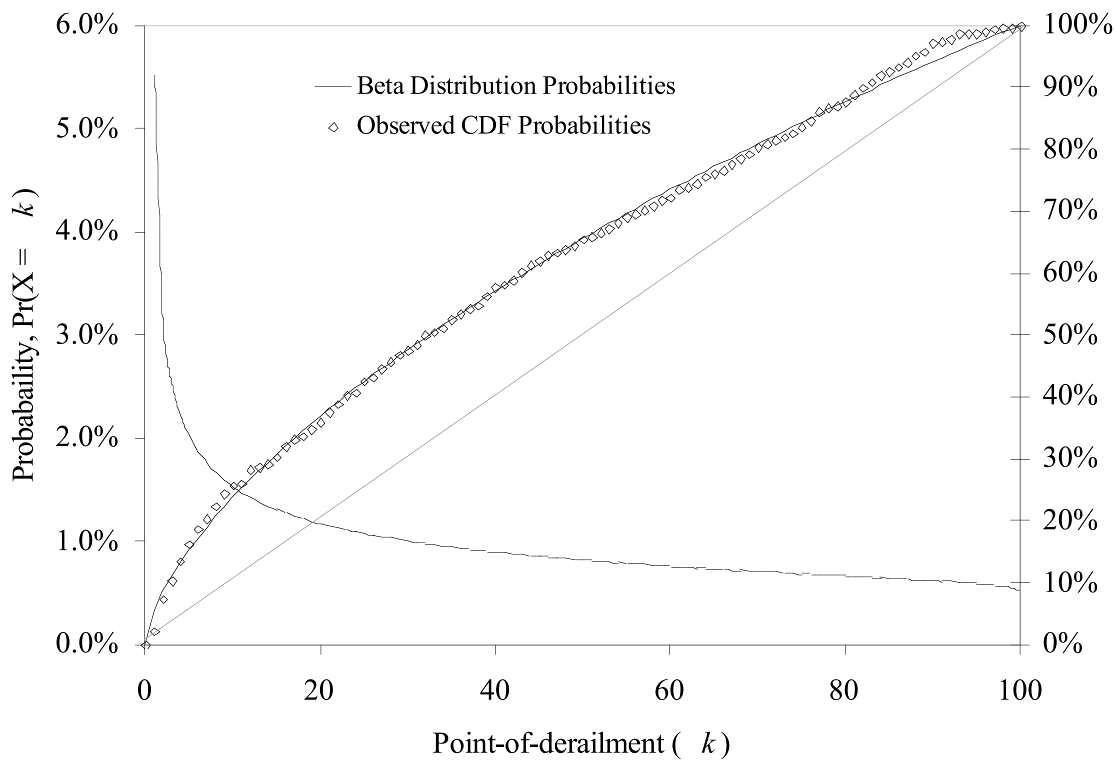

Figure 4.5 Beta Distribution Point-of-Derailment Probabilities
(Broken Rail or Weld-Caused Derailments: α=0.635 & β=1.039, Discretized for L=100)

4.2.2 Number of Cars Derailed

Having developed a model for POD probabilities using the Beta distribution, the second distribution needed to model derailment probabilities is that of the severity of derailment. For all accident causes combined, the modal number of cars derailed is one, decreasing exponentially thereafter with about eight cars derailing on average (Figure 4.6). This distribution is not the same for all accident causes or accident speeds (Barkan et al., 2003). For instance, derailments caused by broken rail or welds tend to derail more than twice as many cars, on average, than bearing-failure-caused derailments.

Bearing-failure-caused derailments frequently occur at higher speeds (due to overheated journals), but one-car derailments were most frequent at all speeds. Due to the installation of trackside warning detectors, such as hot-box (bearing) detectors and dragging equipment detectors, or emergency brake applications caused by broken air-lines, single-car derailments caused by burnt-off journals are frequently discovered before a pile-up occurs.

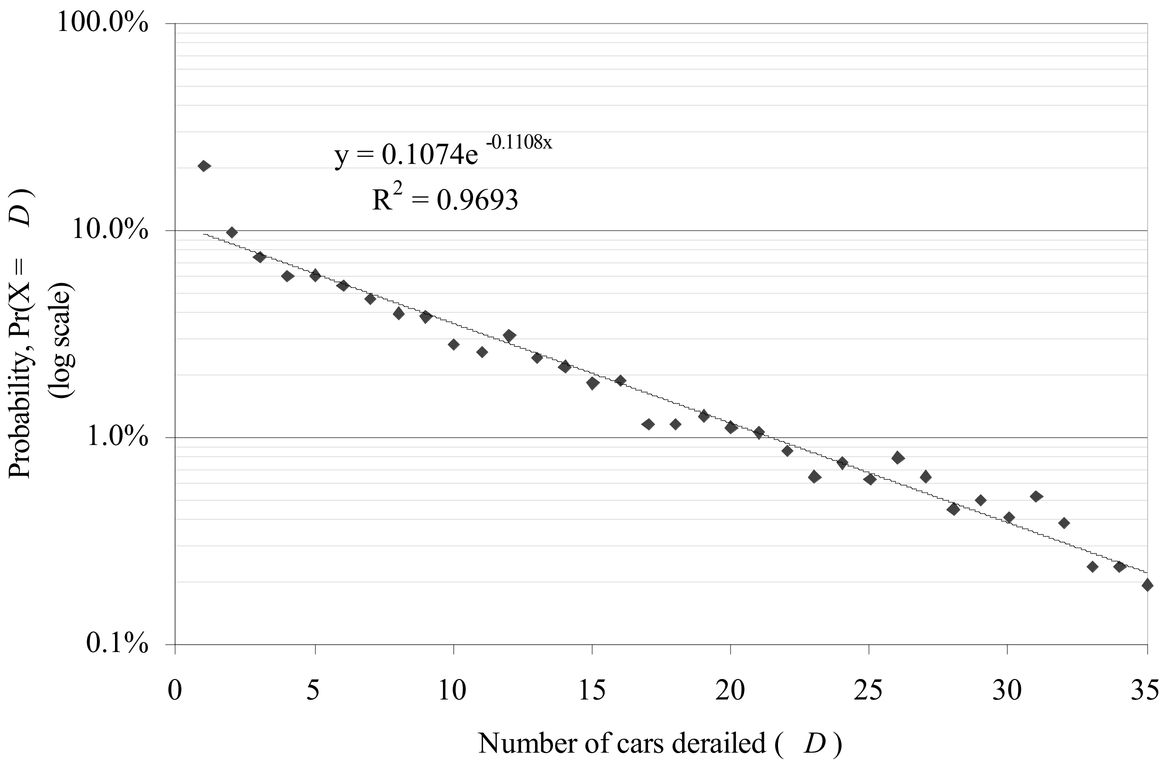

Figure 4.6 Probability Distribution of Number of Cars Derailed (All Accident Causes, All Train Speeds)

The substantial difference (Z=25.3, P<0.001) between the actual percentage of one-car derailments (20.6%) and that predicted by the exponential line-of-best fit for all accident causes combined indicates the different process that governs single-car derailments as opposed to multi-car derailments (Figure 4.6). Consequently, single-car derailments were not included in the subsequent analyses on derailment severity and probability.

Several equipment-related accident causes are particularly prone to cause single-car derailments. These include the following accident cause groups: bearing failures (10E), broken wheels (12E), lading problems (03M), sidebearing suspension defects (09E), and other wheel defects (13E) (Figure 4.7).

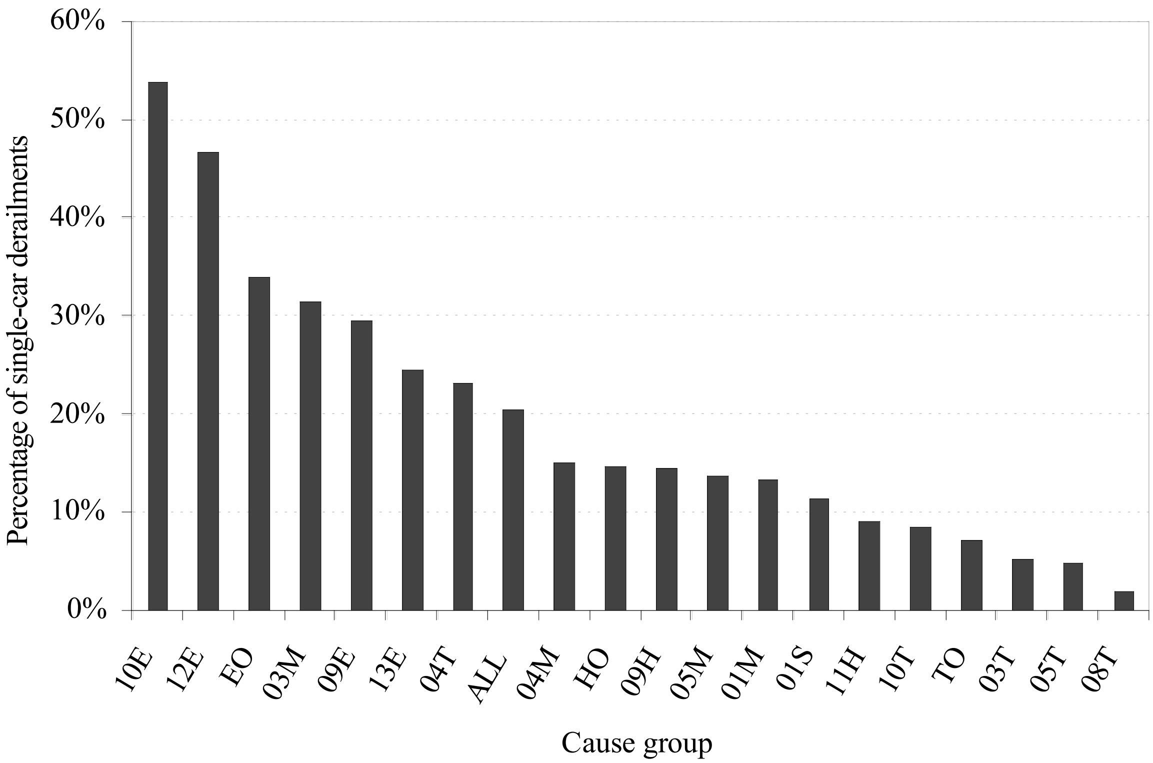

Figure 4.7 Frequency of Single-Car Derailments by Accident Cause Group (Ranked by Percentage)

4.2.3 Position of Derailed Cars

Derailment frequency is a combination of three interrelated distributions: train length, POD probability, and number of cars derailed. The derailment frequency for each position is obtained by counting the number of times a car in each position derailed (summed for all consist lengths). While the car in the first position is the one that most commonly derails first, the car in the eleventh position is derailed most frequently (Figure 4.8).

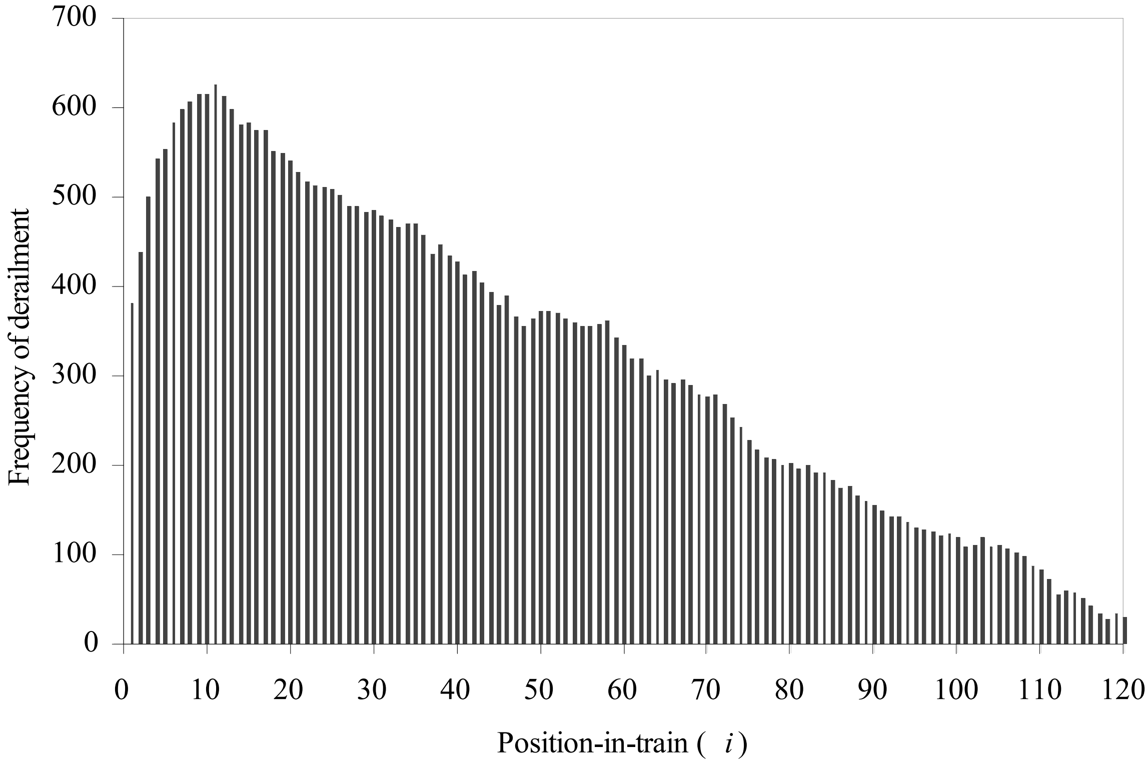

Figure 4.8 Frequency of Derailment by Absolute Position-in-Train (All Accident Causes, All Train Speeds)

There is a steady decline in derailment frequency for positions behind the eleventh car (Figure 4.8). This trend is due in part to the decreasing number of trains having at least i cars (Figure 4.2); as well as the number of cars derailed as a function of the POD. The probability that a car will derail is the summation of the probabilities that the car will either be the first car derailed, or that it will be a "victim" in the block of cars behind the POD that are subsequently derailed. In the two sections to follow, we present analytical equations for predicting the number of cars derailed based on the point-of-derailment and combine the predicted values with the POD probability distribution to derive conditional derailment probabilities for car positions within a derailed train consist.

4.3 Estimation of the Number of Cars Derailed

In this section, we attempt to determine the best analytical model for estimating the severity of derailment in terms of the number of cars derailed. Various factors considered include: accident cause, train speed, total and residual train length, and train mass.

Prior work by Yang et al. (1972, 1973) simulated the effects of several different variables (including speed and residual train length) on the severity of derailment; however, no analytical equations were developed to predict the number of cars derailed as a function of these variables. Nayak et al. (1983) presented an equation for estimating the number of cars derailed as a function of the square root of train speed. The coefficient of the model was estimated for various types of track and accident causes.

Saccomanno & El-Hage (1989, 1991) combined the effects of accident cause, train speed, and residual train length into a single equation based on a truncated geometric distribution for estimating the mean number of cars derailed (Appendix C). The parameters in the model (Eq. C.4) were estimated for seven broad cause categories and the differences in derailment severity between accident causes were determined by allowing the parameter *a* to vary, while using the same values for speed (*b*) and residual train length (*c*) for all accident causes.

4.3.1 Nonlinear Regression Analyses

In order to test the hypothesis that the severity of derailment is a function of the amount of (trailing) kinetic energy behind the POD, we used the following nonlinear equation for estimating the number of cars derailed: $D = a \cdot S^b \cdot L_r^c$, where D is the estimated number of cars derailed, S is train speed, and L_r is residual train length. Adding an intercept term to the equation only slightly improved the level of significance and was thus excluded for parsimony. Although residual train length is not a mass variable, it is related to the residual tonnage by a factor equivalent to the average tonnage per car. Previous studies have found a clear relationship between residual train length and number of cars derailed. In the absence of data on the tonnage for each car in the train consist, residual train length is considered to be a reasonable proxy variable for residual train mass. For our hypothesis to be correct, we would expect estimates of parameter *b* to be near 2 and those for parameter *c* to be near 1 (as kinetic energy is proportional to mass and velocity squared, i.e. $E_k = ½mv^2$).

The three parameters *a*, *b*, and *c* are estimated using nonlinear regression techniques available in the SAS software package (Appendix D). As discussed above, single-car derailments are the function of an altogether different process than the kinematic behavior of pile-ups, and therefore were not included in these analyses. The remaining 3,515 accident reports, also having valid values for residual train length and speeds greater than zero, were analyzed. The regressions were first run for several of the top accident cause groups allowing all three parameters to vary; the values for parameter *b* ranged from 0.34 to 0.93 and the values for parameter *c* ranged from 0.21 to 0.83. The average values (weighted by the number of accidents for each cause group) were determined to be 0.63 for parameter *b* and 0.42 for parameter *c*. For simplicity, both parameters were set to 0.5 and the regressions were re-run, accounting for the difference in cars derailed with the parameter *a*. By doing so, the severity of derailments can be compared for different accident cause groups without substantial loss in significance level (e.g. for all accident causes combined, the R^2 value was 0.376 compared to 0.387 when allowing all three parameters to vary; for broken rail or welds, the R^2 was 0.619 compared to 0.655 when all three parameters were estimated).

Table 4.3 Nonlinear Regression Results for Estimating Number of Cars Derailed (All consists)

Cause Group	N	$\overline{D}$	*a*	s_a[25]	F	P	R^2
All Accident Causes (ALL)	3,515	10.6	0.347	0.004	2,116.68	<0.001	0.376
Broken Rail or Welds (08T)	526	14.4	0.428	0.007	849.62	<0.001	0.619
Bearing Failures (10E)	187	12.2	0.327	0.012	124.98	<0.001	0.403
Track Geometry (excl. Wide Gage) (04T)	232	7.9	0.298	0.014	52.21	<0.001	0.185
Other Miscellaneous (05M)	221	12.1	0.376	0.017	103.71	<0.001	0.321
Train Handling (excl. Brakes) (09H)	208	9.8	0.331	0.016	47.17	<0.001	0.186
Track-Train Interaction (04M)	150	7.5	0.297	0.015	41.66	<0.001	0.220
Broken Wheels (12E)	88	14.8	0.419	0.025	65.60	<0.001	0.433
Wide Gage (03T)	158	9.4	0.426	0.016	120.77	<0.001	0.436
Buckled Track (05T)	145	12.8	0.383	0.014	122.27	<0.001	0.461
Other Wheel Defects (13E)	113	7.7	0.220	0.017	18.44	<0.001	0.142
Lading Problems (03M)	93	9.6	0.324	0.021	57.71	<0.001	0.388
Turnout Defects—Switches (10T)	126	6.5	0.265	0.017	43.79	<0.001	0.261
Use of Switches (11H)	126	4.9	0.258	0.015	27.84	<0.001	0.183
Sidebearing Suspension Defects (09E)	74	7.8	0.307	0.023	21.79	<0.001	0.232
Obstructions (01M)	72	14.1	0.361	0.029	32.49	<0.001	0.317
All Other Equipment Causes	401	9.3	0.261	0.010	89.10	<0.001	0.183
All Other Human-Factor Causes	248	8.3	0.315	0.018	86.16	<0.001	0.259
All Other Track Causes	324	13.1	0.401	0.011	348.87	<0.001	0.520
All Signal Failures (01S)	23	8.8	0.298	0.038	25.16	<0.001	0.545

[25] Standard deviation of estimate for parameter *a*

The average severity of derailment, $\overline{D}$, ranged from 4.9 cars to 14.4 cars derailed. In general, those accident causes that were more severe also had larger values for parameter *a*, ranging from a low of 0.220 (other wheel defects) to a high of 0.428 (broken rail or welds). The latter would be expected to derail nearly twice as many cars in a derailment as the former. While regressions against either train speed or residual train length only account for 10-20% of the variation in number of cars derailed (Saccomanno & El-Hage, 1989), regression against both variables can account for more than 50% of the variation in the number of cars derailed for certain accident causes e.g. broken rails or welds (08T). The level of significance (R^2), however, can vary considerably for different accident cause groups. It should also be noted that due to the exclusion of one-car derailments from the regressions, the estimated number of cars derailed may be considerably higher for those accident causes that frequently derail one car.

4.3.2 Tonnage and Energy Effects

The results described above suggest that severity of derailment may be more dependent on the square root of train speed (rather than the square of train speed as would be expected if the number of cars derailed is proportional to the kinetic energy of the train); however, the mass of the cars following the POD was only approximated by using L_r. In this section, we try to determine whether residual tonnage (i.e. tonnage of all cars following the POD) may be a better predictor in determining the number of cars derailed.

We use two different approaches in determining the effect of residual tonnage on derailment severity. The first approach analyzes only fully-loaded consists (i.e. no empty freight cars) and the second approach uses a sample of mixed consists with two different assumptions regarding the placement of empty and loaded freight cars throughout the train.

4.3.2.1 Fully-Loaded Consists

We first analyzed a sample of fully-loaded train consists in order to reduce the variance due to uncertainty regarding placement of empty and loaded cars. Also excluded were trains with mid-train and rear-end locomotives, passenger cars, or cabooses. By analyzing only fully-loaded consists with head-end locomotives, it was possible to make more accurate estimates of the tonnage values for each freight car.

The weight of road locomotives commonly used in U.S. mainline freight operations ranges from 390,000 to about 432,000 pounds (Kratville, 1997; GE, 2004). We assumed that the average locomotive weight for the time interval studied was 200 tons. We also assumed that the "trailing" tonnage values given in the FRA data (i.e. gross tonnage, excluding the weight of all power units) were evenly distributed among the freight cars in the train. This assumption is reasonable considering that cars in fully-loaded unit trains are typically fairly consistent in size and weight. Accident reports that had an average tonnage per loaded freight car below 50 tons and above 150 tons were also excluded to ensure that accident reports included in the analysis had reasonable values for the tonnages of loaded freight cars. It was also assumed in this analysis that cars derail sequentially following the first car derailed.

A total of 829 derailment reports met the above criteria. A sub-sample of derailments caused by broken rail or welds was also analyzed. Nonlinear regression results from these two analyses with estimates for all three parameters are shown in Table 4.4. Model 1 uses residual train length (L_r) as the variable in the prediction equation and Model 2 replaces L_r with residual tonnage (T_r) in the equation (Appendix D). As might be expected, there is little difference in the significance level between using residual train length and residual tonnage, as the tonnage was assumed to be evenly distributed among all freight cars. However, the fully-loaded consist regression results for all accidents combined and broken rail or welds have a higher level of significance (R^2) than the regression results for all consists (allowing all three parameters to vary). This is likely due to the better approximations of tonnage values of freight cars in the consist. The estimates for *b* and *c* parameters are both approximately 0.5. The estimate for parameter *a* differs by about a factor of 10 (i.e. $(T_r/L_r)^c \approx 100^{0.5}=10$).

Table 4.4 Nonlinear Regression Results for Estimating Number of Cars Derailed (Sample of Fully-Loaded & Mixed Consists)

Fully-Loaded Consists

Cause Group	N	Model	*a*	*b*	*c*	F	P	R^2
All Accident Causes (ALL)	829	1	0.183	0.663	0.567	444.97	<0.001	0.519
		2	0.011	0.745	0.547	538.52	<0.001	0.566
Broken Rail or Welds (08T)	176	1	0.108	0.873	0.546	296.61	<0.001	0.774
		2	0.014	0.871	0.482	264.69	<0.001	0.754

Mixed Consists

Cause Group	N	Model	*a*	*b*	*c*	F	P	R^2
Broken Rail or Welds (08T)	160	1	0.313	0.650	0.440	130.55	<0.001	0.625
		2a	0.030	0.730	0.456	133.58	<0.001	0.630
		2b	0.103	0.731	0.314	103.14	<.0001	0.568

4.3.2.2 Mixed Consists

In the second approach we used a sample of trains that were derailed due to broken rail or welds and had loaded as well as empty freight cars (still holding to all other conditions described above). In order to assign tonnage values to freight cars, we ran the nonlinear regressions with two different assumptions for the placement of empty and loaded freight cars in the consist. The first set (Model 2a) assumed that the empty and loaded freight cars were evenly mixed within the consist and we distributed the total tonnage (excluding locomotive tonnage) amongst all freight cars (loaded and empty). The second set (Model 2b) assumed that the loaded freight cars were placed behind the locomotives and ahead of the empty freight cars—consistent with recommended train makeup practices (CCPS, 1995). As such, the second sample will have lower residual tonnage values. While this assumption follows recommended train makeup procedures (to reduce longitudinal in-train forces), it is not always be practical for efficient yard classification operations.

The results from these regressions are also shown in Table 4.4. From these results, we observe the following:

- The model based on the first assumption (2a) is just slightly more significant than the model using residual train length (1);
- The model based on the second assumption (2b) is less significant than the other two models (1 & 2a);
- The mixed consist model results are less significant than those for fully-loaded consists.

From these results, we cannot conclude which variable is the best predictor of derailment severity. The fully-loaded consist regression results indicate that the model is more accurate when freight car weights are more accurately known. However with mixed consists, it is not possible to determine the exact relationship in estimating the number of cars derailed without knowing the exact placement and tonnage of each freight car within the consist.

4.3.3 Residual Analysis

We plotted the residuals between the observed number of cars derailed and the expected number of cars derailed using the results from the nonlinear regressions against the independent variables and the expected number of cars derailed. The residual plots against the independent variables (train speed and residual train length) exhibited some heteroscedasticity of the residuals, but were generally scattered throughout the range of the independent variable (Figures 4.9a & 4.9b). The residual plot against the expected values for the number of cars derailed; however, showed notable heteroscedasticity in the variance (Figure 4.9c), indicating a violation of the assumption of constant variance. Since the dataset has been restricted to derailments in which at least two cars derailed, the minimum residual value for any expected value of cars derailed is equal to two minus the expected value. This can be viewed as a "line" (with slope = -1 and intercept = 2), which acts as a lower bound to the residual value (Figure 4.9). Both a logarithmic and a square root transformation of the dependent variable were unable to correct the unequal variance in the regressed model and Iteratively Reweighted Least Squares (IRLS) regression was also unable to remove the heteroscedasticity from the model.

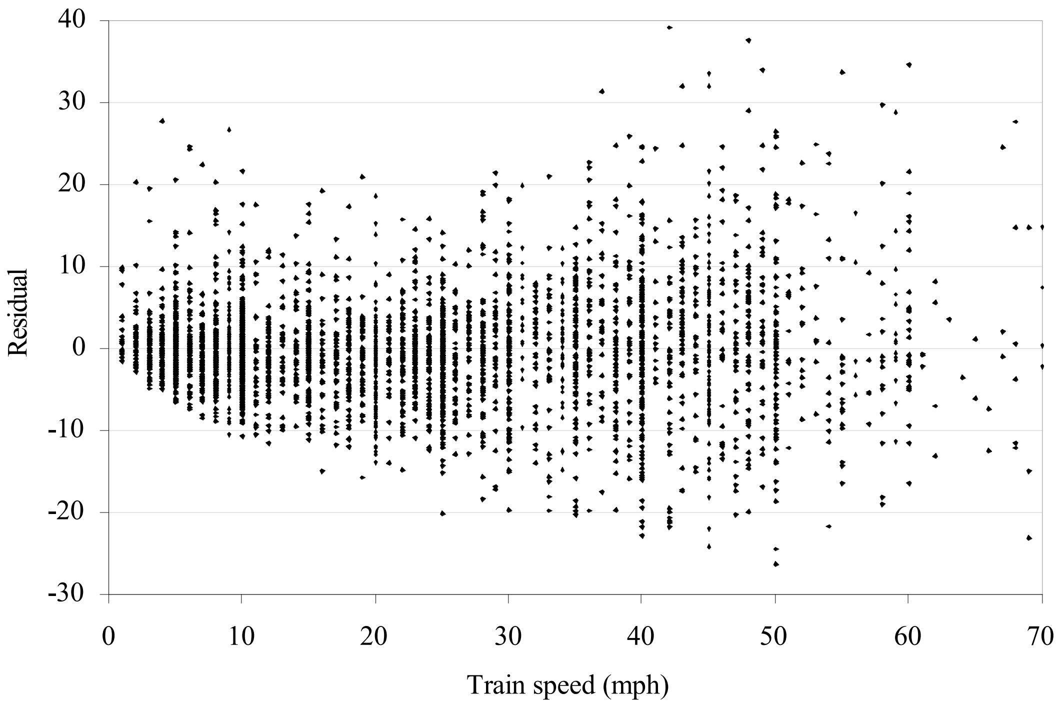

Figure 4.9a Residual Analysis for Independent Variables (Train Speed) (Nonlinear Regression Results, All Accident Causes)

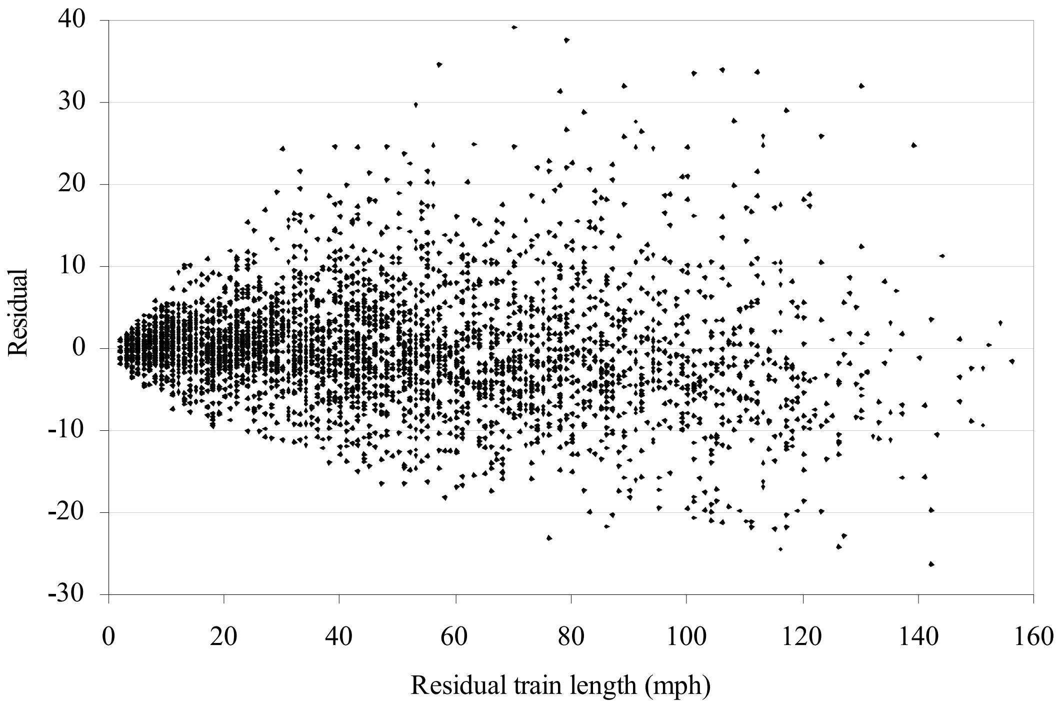

Figure 4.9b Residual Analysis for Independent Variables (Residual Train Length) (Nonlinear Regression Results, All Accident Causes)

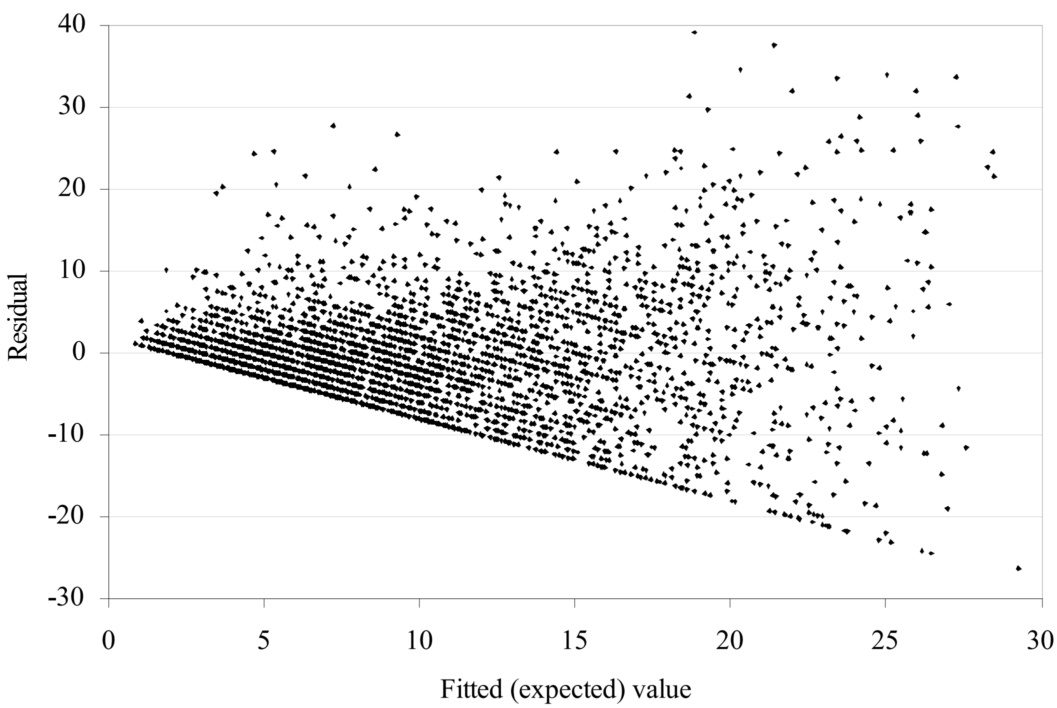

Figure 4.9c Residual Analysis for Expected Number of Cars Derailed (Nonlinear Regression Results, All Accident Causes)

While this heteroscedasticity may be inherent to the model chosen and the nature of derailments, it may also be further evidence that derailments are complex, dynamic events and the use of two or three variables from the FRA data are not able to completely predict derailment severity. As shown in Yang et al. (1972, 1973), there are several factors that can affect the severity of derailment such as brake retarding force and ground friction, that are not recorded in the FRA data and cannot be included into one simple analytical equation.

4.4 Probabilities of Derailment

The following section seeks to determine the conditional probabilities of derailment for cars in a derailed train consist. There are three goals in this section:

1. Test the hypothesis that derailment probability can be determined by knowing the point-of-derailment probabilities and estimated derailment severity.
2. Present the correct equation for the mean number of cars derailed in the geometric model of Saccomanno & El-Hage (1989, 1991) and update the parameter estimates.
3. Compare the results from both models and check the validity of the two approaches using FRA accident data.

4.4.1. Reverse Summation Model

As previously stated, the probability of derailment for a car in a given position is the summation of the probabilities that the car of interest will either be the first to derail, or that it will be a "victim" in the block of cars following the POD. We developed the following analytical method to predict the conditional probability of derailment for a car in the i^{th} position: $P_d(i) = \sum_{k=i}^{j} P_p(k)$; where the point-of-derailment probabilities, $P_p(k)$, are summed in reverse order (i.e. $k = i \rightarrow j$ with $1 \leq j \leq i$) from the car of interest ($k = i$) to the front-most car position that, if derailed first, would also derail the car of interest ($j = k \ni (k + D - 1) \geq i$), and D is the estimated number of cars derailed (rounded up to the next integer). Using the updated point-of-derailment probabilities (Table 4.2) and the nonlinear regression parameters (Table 4.3), we plotted the conditional derailment probabilities for derailments for all accident causes combined (Figure 4.10). The cumulative POD probabilities are represented by dashed lines for each train length.

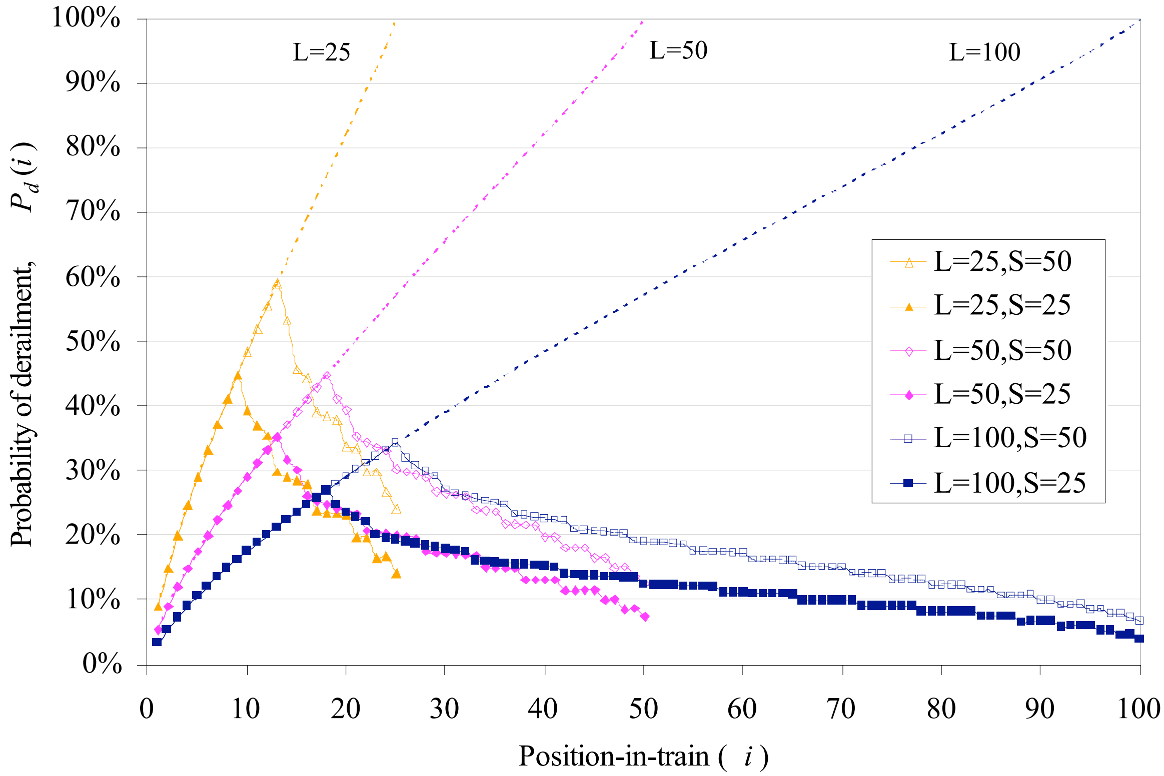

Figure 4.10 Conditional Derailment Probabilities for Various Train Lengths and Train Speeds (Reverse Summation Model, All Accident Causes)

Figure 4.10 indicates the following:

- The derailment probabilities for cars at the front of the consist are equal to the cumulative summation of the POD probabilities (dashed lines) and those at different speeds overlap up to the car with the highest probability of derailment at the lower speed;
- The car with the highest probability of derailment is the last car expected to derail when the car in the first position (lead locomotive) is first to derail (i.e. $k = 1$);
- There is a steep decrease in derailment probability following the car with the highest probability of derailment (for accident causes in which cars at the front of the train have the highest likelihood of being first to derail);
- As train length decreases or train speed increases, the probability of derailment for cars in the rear and mid-sections of the train increases.

4.4.2 Geometric Model

The only other technique for determining the conditional probability of derailment that we are aware is that of Saccomanno & El-Hage (1989, 1991). Their equation (Eq. C.1) combines two probabilities: 1) the probability of a derailment initiating at the k^{th} position, $P_p(k)$, and 2) the probability of derailing x cars, $P(x)$, based on the point-of-derailment for a given train length. They used a geometric distribution model (doubly truncated to account for the finite number of possible cars derailed) to develop probabilistic estimates of the number of cars derailed. An increase in either the train speed or the residual train length was found to increase the number of cars derailed for all accident causes (i.e. as S or L_r increase, Z & p decrease, and D increases). This model is similar to the reverse summation model, with the exception that the number of cars derailed is represented by a probability distribution, $P(x)$.

The model first presented by Saccomanno & El-Hage (1989) differed from the model they presented in 1991. Neither model appeared to be correct as both equations presented for the mean of the doubly truncated geometric distribution (DTGD) led to values outside the range of possible cars derailed. Between the two equations they presented, the 1989 equation (Eq. C.5a) was more nearly correct and is presented here so that comparison can be made to the actual equation for the mean of the DTGD (derived in App. C). The corrected equation (Eq. C.5b) ensures that the number of cars derailed lies in the range $[1, L_r]$ for all $0 < p < 1$.

Using Eq. C.5b, we applied nonlinear regression techniques to the FRA data to estimate the response function parameters a, b, and c (Eq. C.4) for all accident causes combined (App. D). The results showed that the value estimated for parameter c was not statistically different than 0 (at the 95% confidence level) while the value for parameter b was estimated to be -0.946 (standard error = 0.033). Thus, we assigned a value of 0 to parameter c and a value of -1 to parameter b when running the regressions for several of the top accident cause groups. The effect of residual train length is thus entirely accounted for in Eqs. C.2 and C.5b (i.e. p is independent of k for a given train length and accident cause, simplifying calculations). While the values for the parameters are different than those presented by Saccomanno & El-Hage (1989, 1991), the same patterns are exhibited (i.e. as speed or residual train length is increased, the mean number of cars derailed also increases, and those accident causes with the lower values for parameter a tend to be more severe in nature). If residual train length is replaced with residual tonnage in the response function

(Eq. C.4), similar results as above (§4.3.2) are obtained, with no clear benefit from using tonnage values in the model.

Table 4.5 Response Function Parameter Estimates for Geometric Model

Cause Group	N	*a*	s_a	F	P	R^2
All Accident Causes (ALL)	3,515	0.556	0.016	1134.12	<0.001	0.392
Broken Rail or Welds (08T)	526	0.236	0.028	457.00	<0.001	0.636
Bearing Failures (10E)	187	0.690	0.054	71.19	<0.001	0.436
Track Geometry (excl. Wide Gage) (04T)	232	0.857	0.072	24.65	<0.001	0.177
Other Miscellaneous (05M)	221	0.457	0.075	56.41	<0.001	0.341
Train Handling (excl. Brakes) (09H)	208	0.549	0.072	24.42	<0.001	0.192
Track-Train Interaction (04M)	150	0.815	0.081	19.26	<0.001	0.208
Broken Wheels (12E)	88	0.134	0.122	35.08	<0.001	0.452
Wide Gage (03T)	158	0.094	0.066	50.63	<0.001	0.395
Buckled Track (05T)	145	0.506	0.069	62.53	<0.001	0.468
Other Wheel Defects (13E)	113	1.222	0.095	14.53	<0.001	0.209
Lading Problems (03M)	93	0.697	0.108	33.27	<0.001	0.425
Turnout Defects—Switches (10T)	126	0.833	0.091	13.39	<0.001	0.179
Use of Switches (11H)	126	0.743	0.079	16.93	<0.001	0.216
Sidebearing Suspension Defects (09E)	74	0.785	0.124	9.87	<0.001	0.218
Obstructions (01M)	72	0.482	0.129	17.43	<0.001	0.336
All Other Equipment Causes (EO)	401	0.998	0.058	43.71	<0.001	0.180
All Other Human-Factor Causes (HO)	248	0.653	0.083	55.62	<0.001	0.312
All Other Track Causes (TO)	324	0.387	0.049	165.42	<0.001	0.508
All Signal Failures (01S)	23	0.786	0.170	12.84	<0.001	0.562

As mentioned above (§4.2.1.1), the approach taken by Saccomanno & El-Hage was to apply POD probabilities in deciles to determine derailment probabilities. This approach produces artificial "kinks" in the derailment probability curve every tenth of the train. Using the continuous POD probabilities from Table 4.2, and the corrected coefficients for parameter *a* in the response function (Table 4.5), we plotted the conditional derailment probabilities for all accident causes combined (Figure 4.11).

Comparing the results using the geometric model with the reverse summation model presented above (§4.4.1), we observe similar tendencies in the derailment probabilities for various train lengths and speeds. However, two clear differences between the models are evident:

- The derailment probabilities estimated by the geometric model are much lower than those determined by the reverse summation model.

- The derailment probability curve using the geometric model is smoother, without the large discontinuity at the position of the car with the highest probability of derailment.

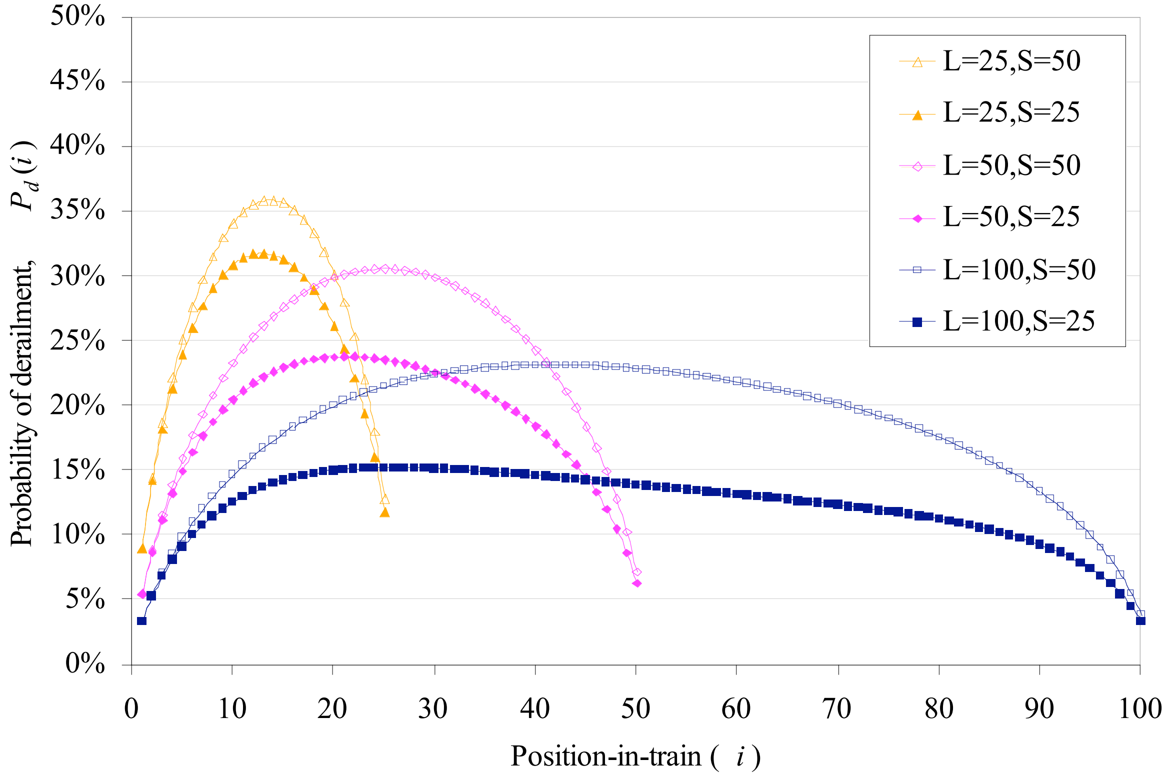

Figure 4.11 Conditional Derailment Probabilities for Various Train Lengths and Train Speeds (Geometric Model, All Accident Causes)

4.4.3 Empirical Validity

We tested both models using positional derailment frequencies (Figure 4.8) to determine position-dependent derailment probabilities. The denominator used for the conditional probability of derailment for the car in the i^{th} position of a derailed train is the number of derailed trains that had at least *i* cars in the train consist. In order to make valid comparisons, we restricted each set of analyses to train consists having approximately the same number of cars. First, we calculated empirical derailment probabilities for train lengths of about 25, 50, and 100 cars (20-30, 45-55, and 95-105 cars respectively), without separation by the speed of derailment. The empirical results are compared to the geometric model (Figure 4.12a) and reverse summation model (Figure 4.12b) for the same train lengths at a speed of 23 mph—corresponding to the average derailment speed for each length group.

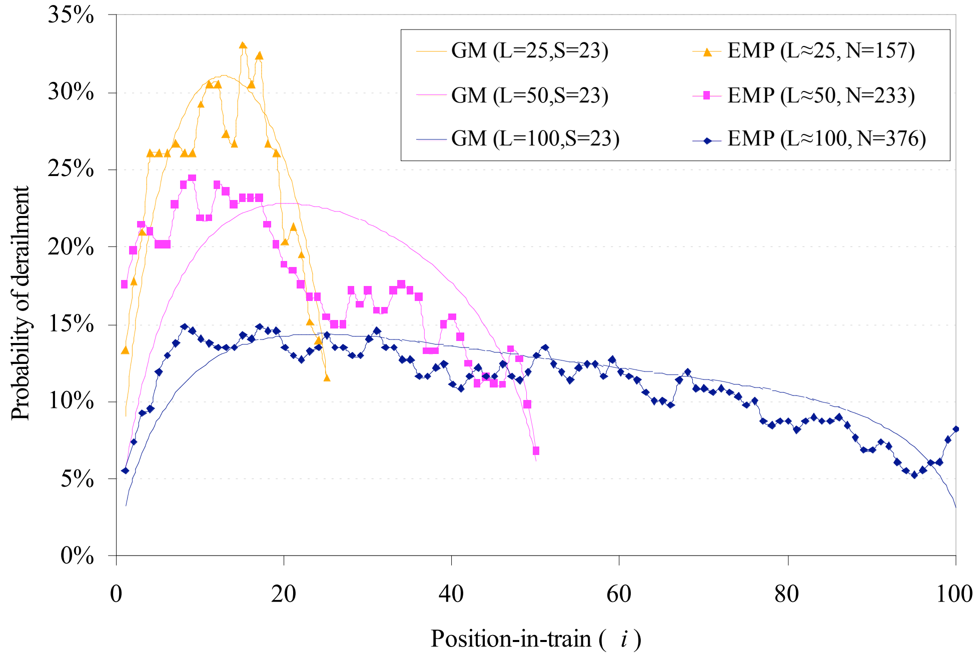

Figure 4.12a Conditional Derailment Probabilities for Various Train Lengths (Comparison of Empirical Results (EMP) and Geometric Model (GM), All Accident Causes)

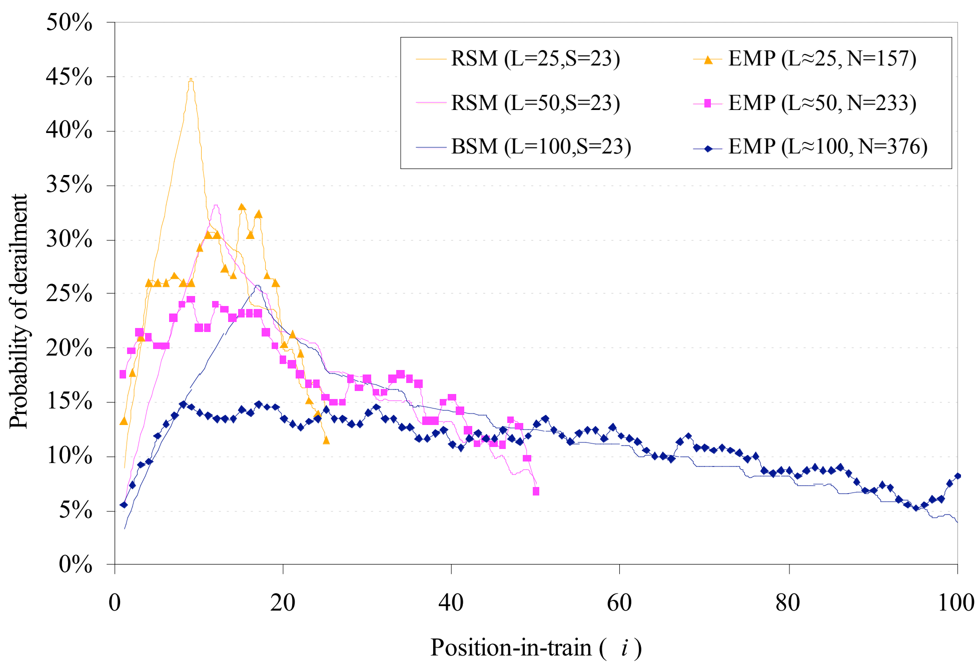

Figure 4.12b Conditional Derailment Probabilities for Various Train Lengths (Comparison of Empirical Results (EMP) and Reverse Summation Model (RSM), All Accident Causes)

The geometric model appears to be more consistent with the empirical results than the reverse summation model (especially for train lengths of 25 and 100 cars). While both models are observed to show similar trends, the "spike" in the reverse summation model tends to over-estimate the derailment probabilities for cars within that region.

Next, we calculated empirical derailment probabilities for train consists that were about 100 cars long in length (90 to 110 cars) for all accident causes, separated into two groups—those that occurred at speeds less than 25 mph and those that occurred at speeds of 25 mph or greater. The results are compared to the derailment probabilities predicted by the geometric model (Figure 4.13a) and the reverse summation model (Figure 4.13b) for 100-car trains. The average speed of derailment for each speed range (12 and 38 mph) is used in the two models.

In order to gain some insight into the difference in derailment probabilities for different accident causes, we also analyzed two cause groups having two different derailment mechanisms—broken rail or welds (08T) and bearing failures (10E). Again, trains of lengths between 90 and 110 cars were analyzed for the two cause groups. The average speed of derailment for those due to broken rail or welds was 24 mph while the average speed of derailment was 34 mph for those due to bearing failures. The empirical results are again compared to the results from the geometric model (Figure 4.14a) and reverse summation model (Figure 4.14b) using the respective average derailment speed (24 and 34 mph) in the models for each accident cause.

We computed the chi-square statistic (i.e. $\chi^2 = \sum \frac{(observed - expected)^2}{expected}$) and root-mean-squared-error (RMSerr) for each comparison in order to determine the goodness-of-fit between the predicted (or expected) values from both models and the empirical (or observed) values. The results (Table 4.6) are inconclusive as to which model is better suited to modeling derailment probabilities. For the 50-car comparison and the comparison for two accident cause groups, the reverse summation model is statistically a better fit to the empirical results. For all other cases considered, the geometric model had lower χ^2 and RMSerr values (Table 4.6).

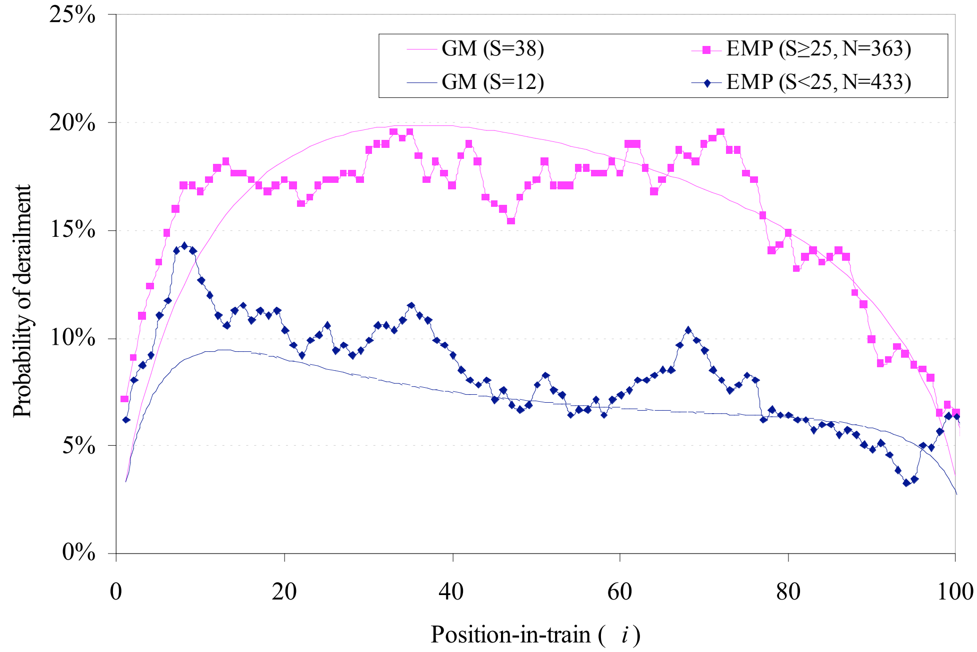

Figure 4.13a Conditional Derailment Probabilities for Various Train Speeds (Comparison of Empirical Results (EMP) and Geometric Model (GM), All Accident Causes)

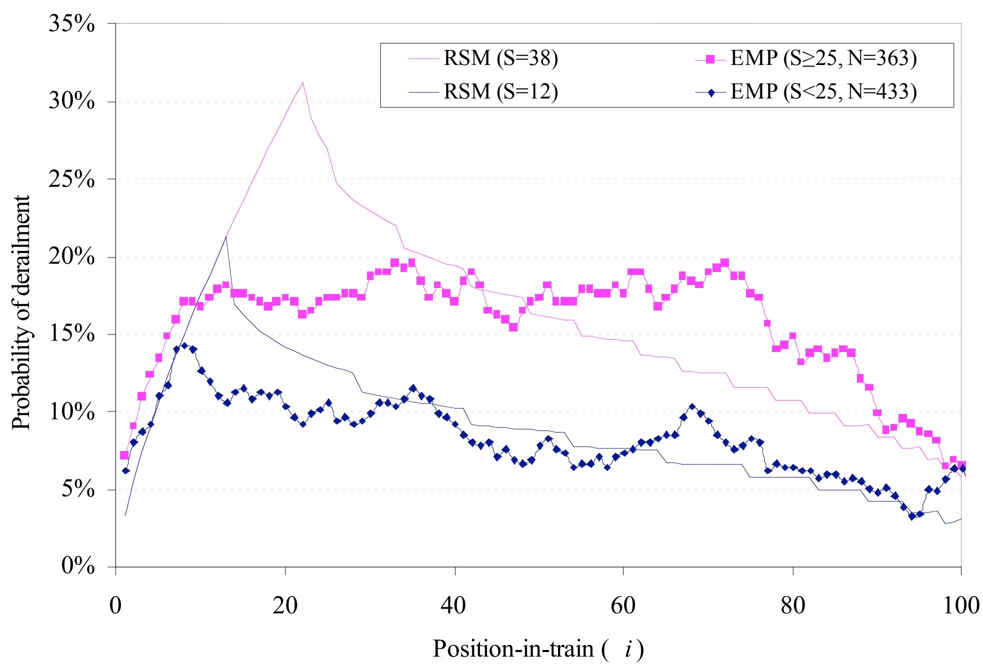

Figure 4.13b Conditional Derailment Probabilities for Various Train Speeds (Comparison of Empirical Results (EMP) and Reverse Summation Model (RSM), All Accident Causes)

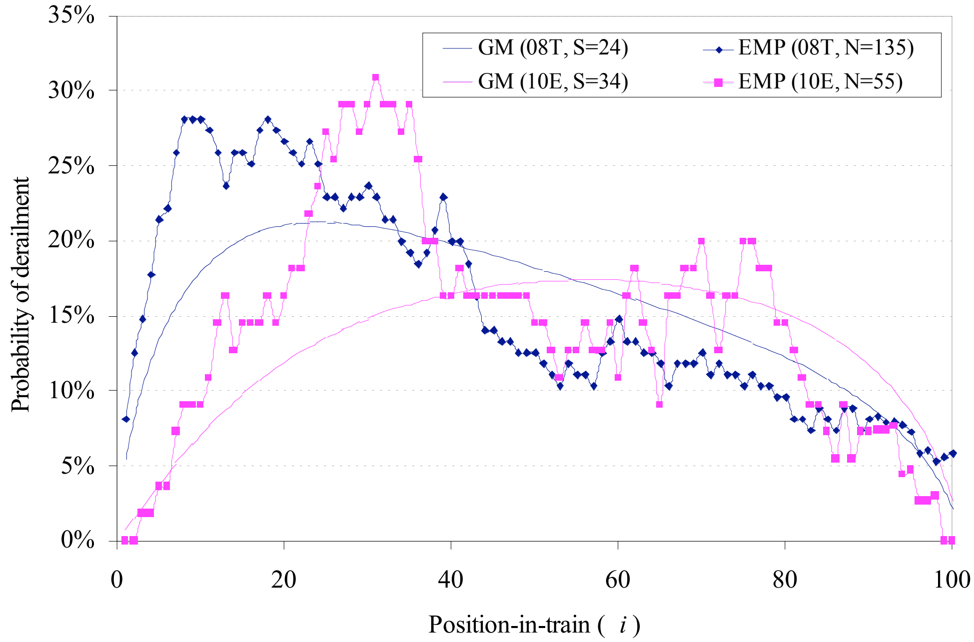

Figure 4.14a Conditional Derailment Probabilities for Various Derailment Causes (Comparison of Empirical Results (EMP) and Geometric Model (GM) for Broken Rail or Welds (08T) and Bearing Failures (10E))

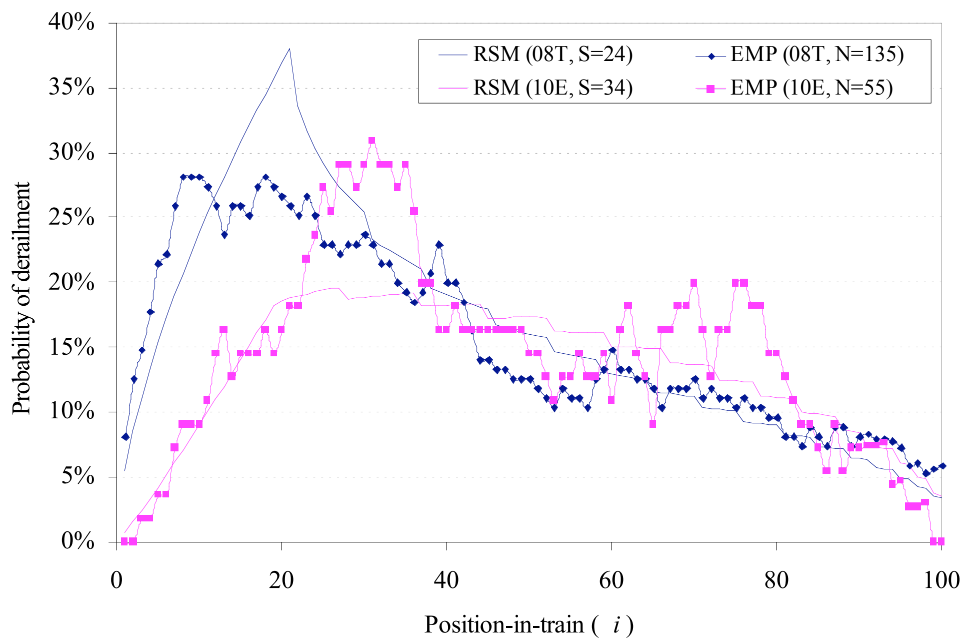

Figure 4.14b Conditional Derailment Probabilities for Various Derailment Causes (Comparison of Empirical Results (EMP) and Reverse Summation Model (RSM) for Broken Rail or Welds (08T) and Bearing Failures (10E))

Table 4.6 Goodness-of-Fit Statistics for Empirical and Model Probability Distributions

	Observed			Expected			GOF	
Accident Cause	Train Length	N	Average Speed	Model	Train Length	Speed	χ^2	RMSerr
All Accident Causes (ALL)	95-105	376	23.2	GM	100	23	0.308	0.0156
	95-105	376	23.2	RSM	100	23	0.729	0.0355
	45-55	233	22.3	GM	50	23	0.943	0.0491
	45-55	233	22.3	RSM	50	23	0.731	0.0425
	20-30	157	22.6	GM	25	23	0.097	0.0282
	20-30	157	22.6	RSM	25	23	0.320	0.0657
	90-100	433	12.2	GM	100	12	0.566	0.0197

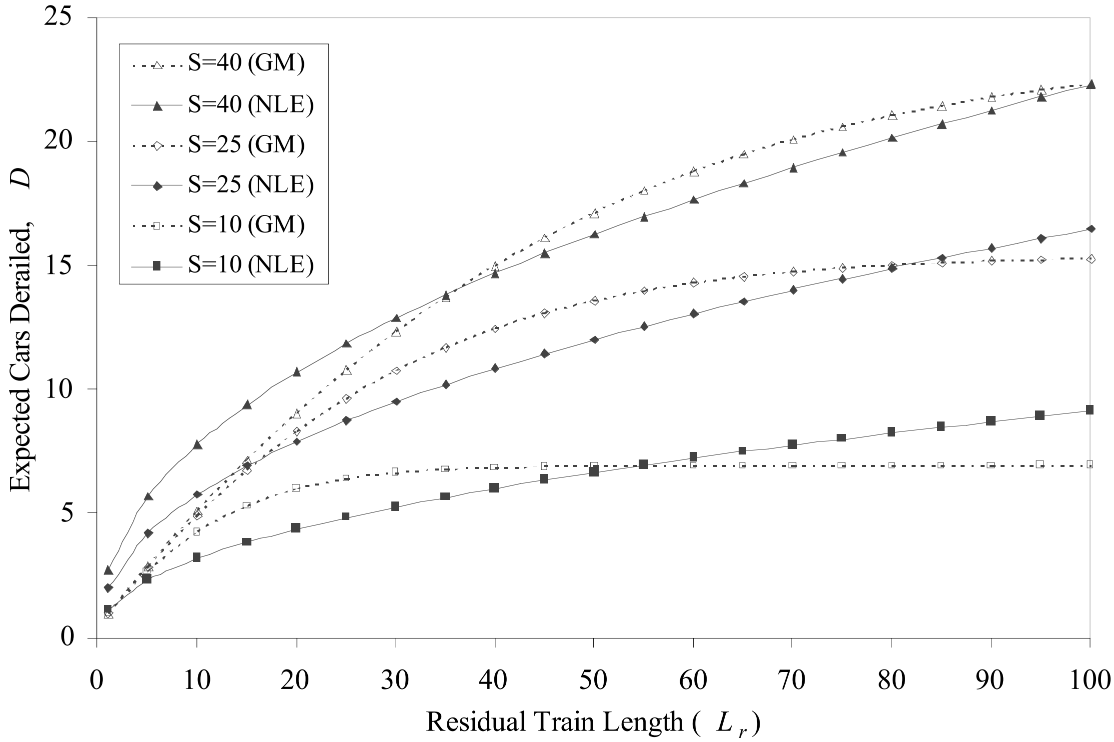

Figure 4.15 Comparison of Expected Cars Derailed Between Geometric Model (GM) and Nonlinear Equation (NLE) at Various Speeds (S)

4.5 Conclusions

In this paper, we have tested the hypothesis that the probability of derailment for individual freight cars is a combination of two other probability distributions—namely the point-of-derailment probabilities and the severity of derailment. We also tested the hypothesis that the severity of derailment can be predicted by knowing the amount of (trailing) kinetic energy behind the POD.

The point-of-derailment probability distribution was modeled using the Beta distribution for various accident cause groups. Doing so allowed for a more continuous representation of the probability distribution for any train length.

While the severity of derailment was clearly shown to be related to both the speed of derailment and the number (or mass) of cars trailing the POD, the regression analyses indicated that the relationship may not be directly proportional, but rather, dependent upon the square root of train speed and mass. This may be due to absorption of energy that occurs as each car entering the derailment block is derailed and subjected to the derailment forces.

Two models were then derived to estimate positional derailment probabilities. The reverse summation model and the geometric model both combine the point-of-derailment probabilities and severity of derailment to estimate the probability of derailment for cars within a derailed train. The validity of both models was tested by comparison to empirical data from the FRA.

Incorporation of these models into probabilistic models of train accident risk will allow the risk analyst to determine the probability of derailment for freight cars shipped by rail. The models presented in this paper can be used to develop quantitative estimates of derailment probabilities for hazardous materials cars and with additional information, release probability and ultimate risk. These models also enable sensitivity analyses of various changes in railroad operating practices to assess the effectiveness of various options to reduce risk.

Our analyses have shown that more cars can be expected to derail as train speed or the number of cars behind the point-of-derailment is increased. As a large number of derailments initiate at the front of the train, this also implies that longer trains tend to derail more cars. The severity of derailment is also largely affected by the cause of derailment. Cars positioned near the front or rear of trains generally have the lowest probability of being derailed in a derailment; as train speed is increased or train length is decreased, the probability of derailment for all positions tends to increase. Cars placed within the middle sections of the train tend to have the highest probability of being derailed in a derailment.

These results would suggest that placement of safety-critical cars at the front or rear of longer freight trains (with possible speed restrictions) will lower the probability that the car of interest will be derailed in a derailment. However, train dynamics effects and yard classification requirements will often impose constraints on the extent to which this can be practiced.

CHAPTER 5: DERAILMENT RISK

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5.1 Introduction

The purpose of this research is to quantify the benefits in reduced derailment risk that can be achieved through various changes in railroad operating practices. We will consider the effects of train speed and train length on the probability of derailment for individual cars within a train consist. The probability that a train will be involved in a derailment is a function of the quality of track, the length of train, and the exposure in terms of miles traveled. The probability of derailment for individual cars within a derailed train consist is a function of the point-of-derailment (POD), train length, train speed, and the accident cause. Changes to any of these parameters can alter the risk level of particular shipments.

We will present methodologies to model the derailment potential to train consists and individual cars within the train. We will then present a derailment risk calculation for a specific shipping scenario, showing the effect of train length, train speed, and positioning on the overall derailment potential for various cars within the train consist.

The following analyses used accident data collected by the Federal Railroad Administration (FRA) in the Railroad Accident/Incident Reporting System (RAIRS) database (FRA, 2003a). This paper will focus on derailments of Class I railroad freight trains on mainline track that occurred in the ten-year period, 1992 to 2001.

5.2 Speed & Track Class Effects

It has been shown that the speed at which a derailment occurs can be a predictive measure of the severity of derailment (Nayak et al., 1983; Barkan et al., 2003). To better understand the effect of speed on derailment severity, the accidents in our analysis are grouped by train speed, FRA track class, and number of cars derailed (Table 5.1). Track class is representative of track quality and minimum standards are specified by regulation for each class.

Table 5.1 Derailed Train Counts by Train Speed, Track Class, and Number of Cars Derailed

Speed (mph)	FRA Track Class	Cars Derailed 1-5	6-10	11-15	16-20	21-25	>25	Total	Total Cars Derailed	Average Cars Derailed
1-10	X/1	353	154	55	11	4	2	583	3,230	5.6
	2	138	63	14	6	3	2	228	1,314	5.8
	3	128	44	13	2	6	2	199	1,033	5.2
	4	150	42	12	3	1	3	216	1,032	4.8
	5/6	41	7	3	0	0	0	51	189	3.7
	Total	815	312	98	22	14	9	1,285	6,845	5.3
11-25	X/1	44	29	2	1	1	0	79	391	4.9
	2	260	187	112	32	18	12	622	4,853	7.8
	3	162	75	30	22	5	3	300	1,925	6.4
	4	149	74	44	17	5	4	294	2,027	6.9
	5/6	25	15	8	1	0	0	49	291	5.9
	Total	643	381	196	73	29	19	1,348	9,503	7.0
26-40	X/1	3	0	1	0	0	0	4	25	6.3
	2	25	8	12	8	4	6	63	739	11.7
	3	186	88	85	61	45	63	529	6,344	12.0
	4	163	59	66	44	28	31	394	4,032	10.2
	5/6	37	13	8	8	3	2	71	515	7.3
	Total	414	169	172	121	80	102	1,062	11,663	11.0
>40	X/1	2	0	0	1	1	0	4	44	11.0
	2	1	1	1	0	0	5	8	299	37.4
	3	42	11	11	17	9	17	107	1,444	13.5
	4	275	67	69	55	42	109	621	7,720	12.4
	5/6	74	18	16	15	7	24	158	1,717	10.9
	Total	394	97	98	89	59	155	890	11,251	12.5
Total	X/1	408	184	58	13	6	2	671	3,690	5.5
	2	429	259	139	46	25	25	923	7,205	7.8
	3	530	218	139	102	65	86	1,140	10,746	9.4
	4	752	243	191	120	77	151	1,534	14,811	9.7
	5/6	182	54	35	24	10	28	333	2,712	8.1
	Total	2,309	962	564	306	183	292	4,661	39,747	8.5

** Note: Totals include those accident reports for which values of speed, track class, or total cars derailed were either zero or blank. **

The seven FRA track classes and associated freight train speed restrictions are as follows:

MAXIMUM SPEED	FRA TRACK CLASS X/1	2	3	4	5	6
mph	10	25	40	60	80	110
km/h	16	40	64	97	129	177

The speed groups are associated with the maximum speed distinctions between levels of track class and are: 1-10, 11-25, 26-40, & >40 mph. The majority of freight trains are operated at speeds below 60 mph and there are few accidents at speeds above this; therefore, accidents occurring at speeds above 60 mph were grouped with those occurring at speeds between 41 and 60 mph. Due to the relatively small number of accidents occurring on excepted and class 6 track, accidents on class X track are combined with class 1 track and accidents on class 6 track are combined with class 5 track. The accidents are further divided into five bins based on the total number of cars derailed, as follows: 1-5, 6-10, 11-15, 16-20, 20-25, & >25 cars derailed.

For the ten-year study period, there were 4,661 train accident reports for Class I railroad freight train derailments on mainline track[26]. The average speed of derailment was 24.8 mph. The following observations can be made regarding Table 5.1:

- Nearly half of all derailed train consists have five or fewer cars derailed.
- Only 6.3% of all trains derailed more than 25 cars; 90% of these were at speeds greater than 25 mph.
- One-third of all trains were derailed on class 4 track and nearly 25% derailed on class 3 track[27].
- 265 trains (5.7% of total) derailed at speeds exceeding the maximum allowable operating speed for the track class on which it was derailed. While the largest portion of these were low consequence derailments (1-5 cars derailed), these accidents still accounted for nearly 3,000 derailed cars.

While it is apparent that more cars are derailed, on average, at higher speeds, it is not clear that more cars are derailed, on average, on higher track classes. This may be due to the fact that many of the derailments on higher class track occur at less than normal track speed or may be due to the differences in derailment severity for different accident causes, which is likely correlated with track quality (class).

5.3 Train Length Effects

The likelihood that a train will be involved in an accident is a function of both train-miles (TM) and car-miles (CM) operated (ADL, 1996). Car-mile related causes are those for which the likelihood of an accident is proportional to the number of car-miles operated.

[26] Of these, 66 have a speed of zero and 45 have zero cars derailed (11 have both) and 15 do not have a value for track class.
[27] Approximately 70% off all traffic is carried over these two track classes for Class I railroads (Anderson & Barkan, 2004).

These include most equipment failures for which accident likelihood is directly proportional to the number of components (e.g. bearing failure) and also include most track component failures for which accident likelihood is proportional to the number of load cycles imposed on the track (e.g. broken rails or welds). Train-mile related causes are those for which accident likelihood is proportional to the number of train-miles operated. These include most human error failures for which accident likelihood is independent of train length and depends only on exposure (e.g. grade crossing collisions).

Each FRA accident cause code has been grouped into 51 groups of related causes that share similar causal mechanisms based on a scheme developed for the IIRSTF hazardous materials risk model (ADL, 1996) and included in a 2001 unpublished report of the Association of American Railroads. Each cause group is categorized as either a CM or TM caused accident group. The probability that an accident will occur is then a summation of the number of train-miles multiplied by the train-mile accident rate and the number of car-miles multiplied by the car-mile accident rate. Thus, it follows that longer trains have an increased likelihood of having an accident due to a larger number of car-miles of exposure.

In 2001, the average number of cars per freight train of Class I freight railroads was 68.5 cars (AAR, 2003b). In the same year, the average length of derailed Class I freight trains was 78.6 cars (FRA, 2003a). These two statistics are consistent with the hypothesis that longer trains have a higher likelihood of derailment. Shorter trains may have a lower risk of derailment; however, more trains must be operated to ship the same number of cars. In light of the trade-off between car-mile and train-mile-caused derailments, there may be an optimal train length to minimize derailment occurrence.

5.4 Positions of Derailed Cars

The first vehicle (lead locomotive) in the freight train is most frequently the first to derail. In one-quarter of all derailments, the point-of-derailment (POD) is located within the first ten positions of the train. Over 98% of all train consists analyzed had train lengths greater than ten cars. The large percentage of derailments with cars near the front of the train being first to derail is primarily due to the large proportion of track-related causes, many of which tend to derail the lead locomotive (FRA, 2003a).

The relationship between point-of-derailment (normalized by train length, NPOD) and position-in-train indicates that a large proportion of derailments initiate at the front of the train (Figure 5.1). This is often the case for track-caused derailments. We modeled NPOD probabilities by regression of the data against the beta distribution with parameters, α and β. The modeled NPOD distribution uses the beta distribution parameters that minimize the error sum of squares between the data and the beta distribution percentages. This allows for a smooth, continuous description of NPOD probabilities. The POD probabilities for various positions and train lengths can then be determined by discretizing the cumulative beta distribution.

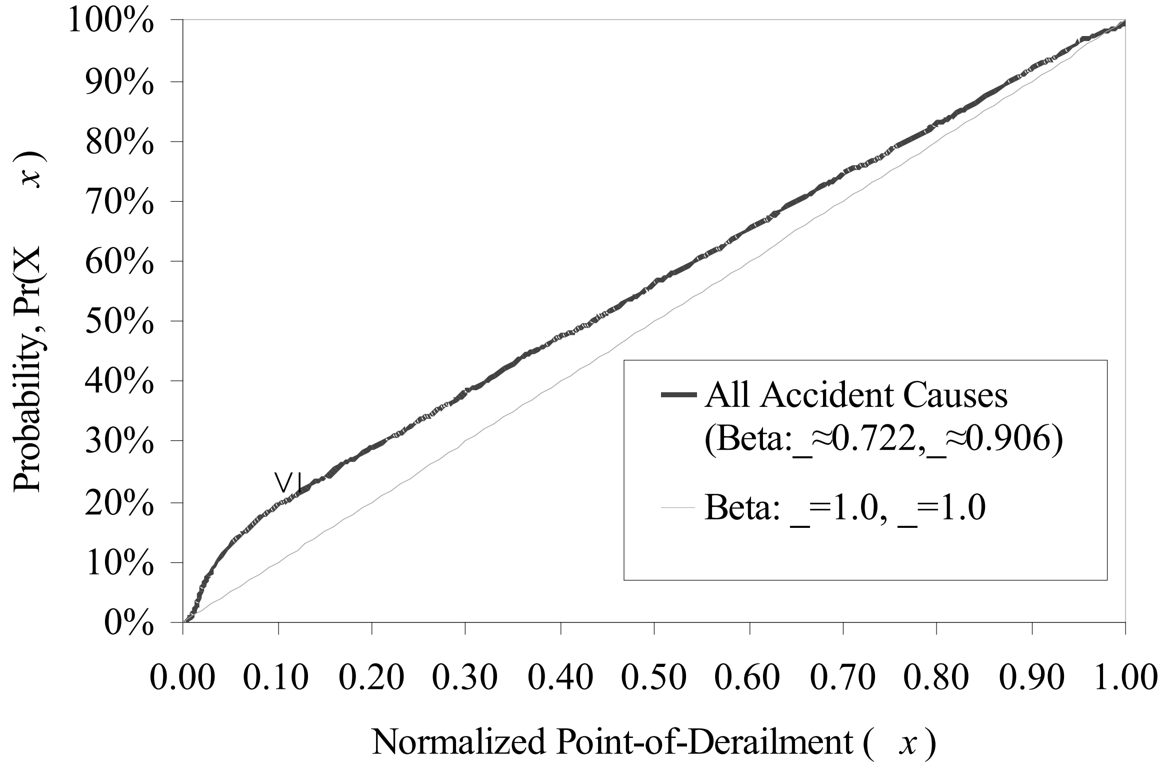

Figure 5.1 Point-of-Derailment Probabilities

The frequency of derailment for each position in the train (Figure 5.2) is obtained by counting the number of times vehicles in each position derailed (for all consist lengths). Although the first position most commonly derails first, it is not the position most frequently derailed. In absolute terms, the car in the eleventh position is derailed most frequently.

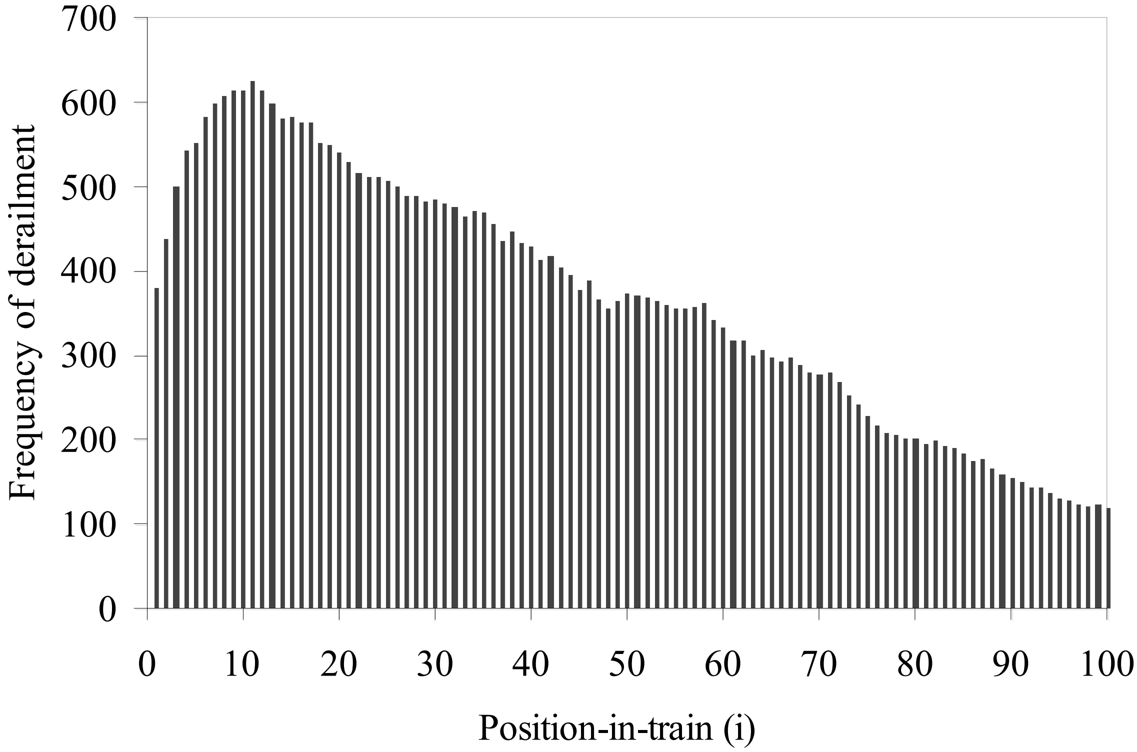

Figure 5.2 Frequency of Derailment by Position-in-Train

5.5 Severity of Derailment

For all accident causes combined, the modal number of cars derailed is one, decreasing exponentially thereafter with about eight cars derailing on average. This distribution is not the same for all accident causes or accident speeds. For example, derailments caused by broken rail or welds tend to derail more than twice as many cars, on average, than bearing failure-caused derailments (Barkan et al., 2003).

We have developed an analytical model for estimating the severity of derailment in terms of the number of cars derailed. Various factors considered include: accident cause, train speed, and residual train length (i.e. the number of cars behind the POD).

Prior work by Yang et al. (1972, 1973) analyzed the effects of several different variables on the severity of derailment. No explicit equations were given, but the relationships between the variables and the number of cars derailed were determined by varying the parameters in the simulation model and observing the change in derailment severity. Nayak et al. (1983) presented an equation for estimating the number of cars derailed as a function of the square root of train speed.

Saccomanno & El-Hage (1989, 1991) combined the effects of accident cause, train speed, and residual train length into a single equation based on a truncated geometric distribution for estimating the mean number of cars derailed (Appendix C). Our investigations indicate that the equation for the mean of the truncated geometric distribution presented by Saccomanno & El-Hage was incorrect. The correct equation presented here (Eq. C.5b) ensures that the number of cars derailed lies within the range $[1, L_r]$ where L_r is residual train length.

Using the correct equation for the mean of the truncated geometric distribution (Eq. C.5b), we used nonlinear regression techniques to estimate the parameters of the response function (Eq. C.4) for all accident causes combined. The value for parameter *a* was estimated to be 0.68 with a standard error of 0.18. The results showed that the value estimated for parameter *c* was not statistically different than 0 (at the 95% confidence level) while the value for parameter *b* was estimated to be -0.95 with a standard error of 0.03. If parameter *c* is assigned a value of 0, the effect of residual train length is entirely accounted for by Eq. C.5 (i.e. the logistic function *p* remains constant for all positions). This model was able to account for 40% of the variation in the number of cars derailed when all accident causes are combined. If accidents are separated by cause group, the model accounts for more than 60% of the variation for certain accident causes (Anderson & Barkan, unpublished—Ch. 4). The geometric model predicts that the number of cars derailed increases asymptotically with increases in the number of cars behind the POD and train speed (Figure 5.3).

5.6 Probabilities of Derailment

In the following section, we consider the conditional probabilities of derailment for cars in a derailed train consist. The only analytical technique for determining the conditional probability of derailment that we are aware of is that of Saccomanno & El-Hage (1989, 1991). Their equation (Eq. C.1) combines two probabilities: 1) the probability of a derailment initiating at the k^{th} position and 2) the probability of derailing *x* cars based on the point-of-derailment for a given train length.

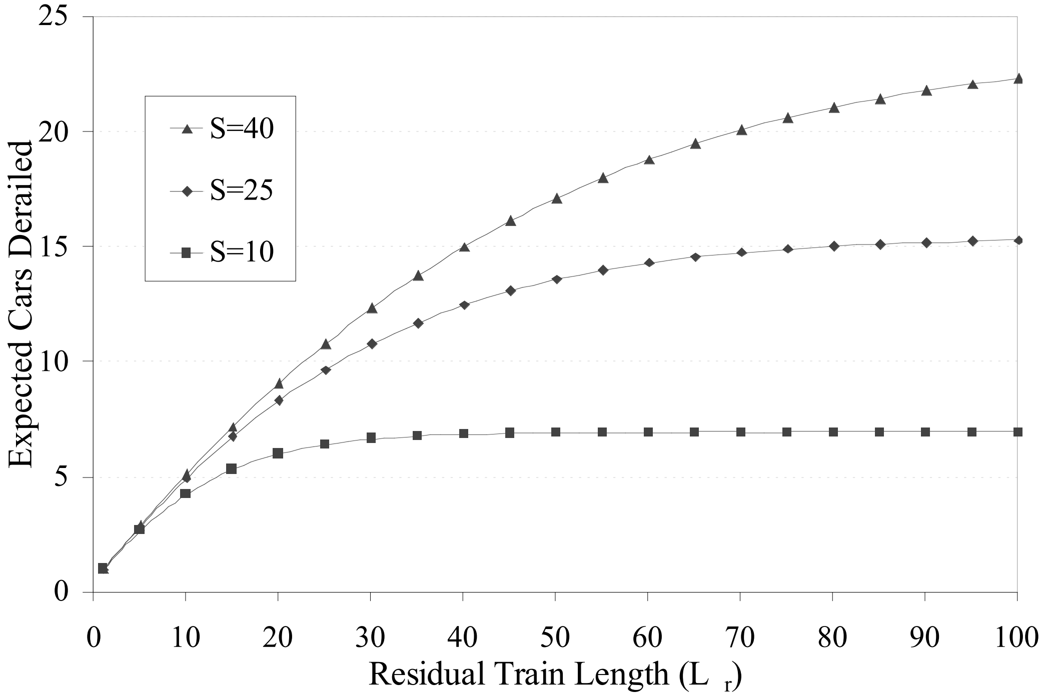

Figure 5.3 Cars Derailed by Residual Train Length & Speed (S)

Using the POD probabilities derived from Figure 5.1, and the parameters for the response function given above, we calculated the conditional derailment probabilities for all accident causes combined for different train lengths at 25 and 50 mph (Figure 5.4). The following observations can be made regarding this figure:

- The lowest derailment probabilities occur in the front and rear sections of the train
- As train length decreases or train speed increases, the probability of derailment increases for all positions (except $i = 1$), and most notably for those in the middle.

5.6.1 Empirical Validity

If we analyze the relative position of derailed cars (absolute position normalized by train length), the derailment probability is the number of cars derailed divided by the total number of cars derailed within the quantile of interest (Figure 5.5).

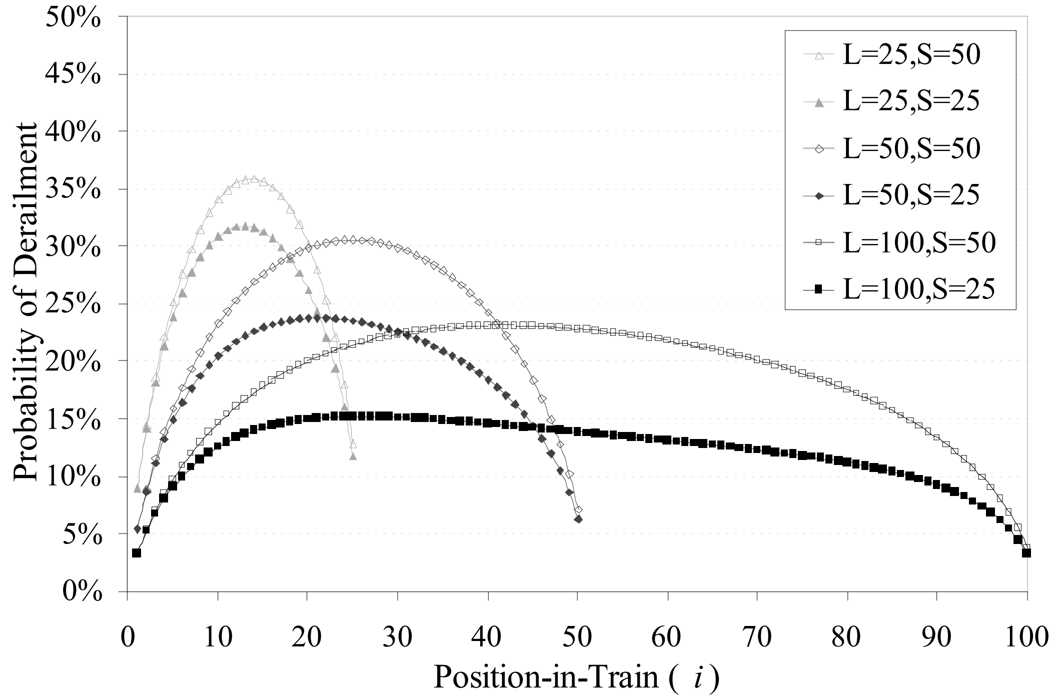

Figure 5.4 Derailment Probabilities by Position, Length (L) & Speed (S)

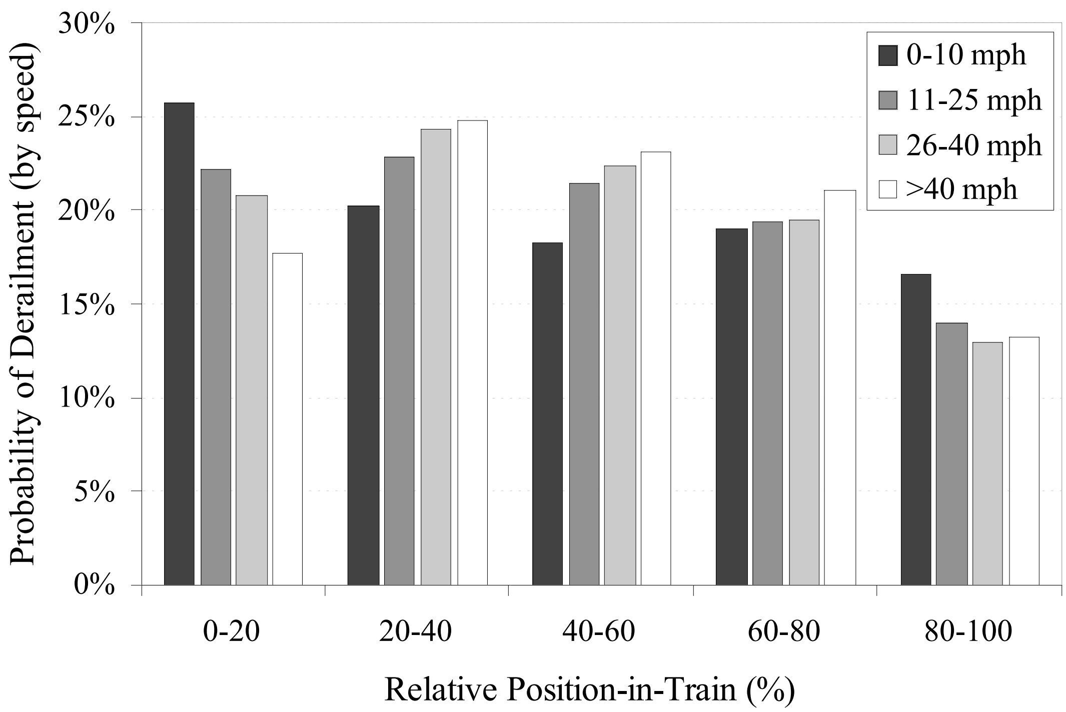

Figure 5.5 Derailment Probabilities by Relative Position-in-Train

Derailment probabilities by relative position sum to 100% (unlike those by absolute position, Figure 5.4). In general, cars within the second quintile have the highest probability of derailment while cars in the last quintile of the train have the lowest derailment probability. As train speed increases, the probability of derailment for cars in the front of train decreases in response to the increase in derailment probability for the second and third quintiles of the train.

5.7 Risk Sensitivity

In this section, we consider the effects of different operating practices on derailment probabilities. This analysis considers the shipment of one-thousand cars a distance of 1,000 miles over class 4 track. If train length is reduced, more train shipments will be required to haul the same number of cars—increasing the exposure to having an individual train consist derail. If train speed is increased, the expected derailment severity also increases. We consider the sensitivity to train length (25, 50, 100, 125, & 200 cars) and operating speed (25 & 50 mph) on the probability of derailment for various cars within the consist.

For class 4 track, estimated derailment rates are 7.8 derailments per billion freight car-miles (FCM) or 0.53 derailments per million freight train-miles (FTM) (Anderson & Barkan, 2004). Using the grouping scheme mentioned above, approximately 75% of all Class I derailments can be classified as car-mile caused, while 25% are classified as train-mile caused[28]. Using these percentages, the corresponding derailment rates are 5.9 and 0.13 per billion FCM and million FTM, respectively.

The probability that an individual train of length L traveling on class 4 track a distance of M miles is involved in a derailment, $P_1(der)$, is as follows:

$$P_1(der) = 1 - e^{-M[5.9x10^{-9}(L) + 0.13x10^{-6}]} \quad \text{(Eq. 5.1a)}$$

For $P_1(der) << 1$, Eq. 5.1a can be simplified to the following:

[28] There is a slight tendency for a larger proportion of car-mile caused derailments on higher track classes (likely due to higher operating speeds).

$$P_1(der) = M[5.9x10^{-9}(L) + 0.13x10^{-6}] \quad \text{(Eq. 5.1b)}$$

The probability that one or more of S train shipments (with the same characteristics, i.e. train length and shipping distance) is involved in a derailment, $P_S(der)$, is as follows:

$$P_S(der) = 1 - [1 - P_1(der)]^S \quad \text{(Eq. 5.2)}$$

The portion of $P_1(der)$ due to train-mile causes is constant for all train lengths, while the portion of $P_S(der)$ due to car-mile causes is approximately constant for all train lengths[29]. For the scenario considered of 1,000 cars shipped 1,000 miles, $P_{1\text{-}TM}(der) = 0.13\text{x}10^{-3}$ and $P_{S\text{-}CM}(der) \approx 5.9\text{x}10^{-3}$. Therefore, $P_1(der)$ is directly proportional to train length while $P_S(der)$ decreases asymptotically with increases in train length (Table 5.2).

Table 5.2 Probability of Derailment by Train Length

Train Length, L	Train Shipments, S	$P_1(der)$ (x 10^{-3})	$P_S(der)$ (x 10^{-3})
25	40	0.278	11.040
50	20	0.425	8.466
100	10	0.720	7.177
125	8	0.868	6.919
200	5	1.310	6.533

We observe that longer trains have an increased likelihood of being involved in a derailment. For a fixed number of cars; however, fewer train shipments are required for longer trains, thereby decreasing the overall risk that one or more trains will be involved in a derailment.

The risk of derailment for a car in the i^{th} position is a combination of the probability of derailment for the train consist, $P_1(der)$, and the conditional derailment probability for the car in a derailed consist, $P(i|der)$. For S train shipments, the probability of derailment for a car in the i^{th} position, $P_S(i)$, is as follows[30]:

$$P_S(i) = 1 - [1 - P_1(der) \cdot P(i \mid der)]^S \quad \text{(Eq. 5.3)}$$

[29] As $P_1(der) \ll 1$, $P_S(der) \approx S \cdot P_1(der)$; therefore, $S{\cdot}M[5.9\text{x}10^{-9}(L)]$ is constant for all train lengths as $S{\cdot}L$ = 1,000 cars.

[30] As $P_1(der) \ll 1$, $P_S(i) \approx P_S(der) \cdot P(i|der)$.

Using the results from above, we calculated $P(i|der)$ for the first, tenth, and last car for each of the five consist lengths at 25 and 50 mph, as well as for the position with highest derailment probability (Table 5.3).

Table 5.3 Conditional Derailment Probabilities by Length & Speed

Case No.	Train Length	Speed (mph)	$P(i\|der)$ i=1	i=10	i=L	$i=i_{max}$	i_{max}
0	25	25	9.07%	30.9%	11.78%	31.8%	13
1	25	50	9.07%	34.1%	12.87%	35.9%	14
2	50	25	5.49%	20.5%	6.31%	23.8%	21
3	50	50	5.49%	23.3%	7.18%	30.6%	25
4	100	25	3.33%	12.6%	3.31%	15.2%	26
5	100	50	3.33%	14.7%	3.84%	23.1%	42
6	125	25	2.83%	10.7%	2.69%	12.9%	26
7	125	50	2.83%	12.5%	3.12%	20.3%	47
8	200	25	2.02%	7.6%	1.75%	9.2%	26
9	200	50	2.02%	8.9%	2.02%	14.8%	51

From these results, we observe:

- The probability that the first car derails is simply the probability that the POD=1; this probability decreases with increased train length and is unaffected by speed.
- For i=10 and i=L (the last car), the probability of derailment is 13-17% higher at 50 mph than at 25 mph for each train length.
- The position with highest derailment probability (i_{max}) increases asymptotically with increased train speed and train length.
- Cars positioned in the middle sections of the train have the highest probabilities of derailment while the front and rear sections of a train have the lowest probabilities of derailment.

Applying Eq. 5.3 to the results in Tables 5.2 & 5.3, we derived derailment probabilities for each of the ten cases for each car position (Figure 5.6). For a given speed and car position, there appears to be a significant reduction in derailment probability as train length is increased up to 100-car trains and is largely due to the lower probability of derailment, $P_S(der)$. As train length is further increased to 125 and 200 cars, the reduction becomes much smaller. Again, for a given position and train length, the increase in risk by shipment at 50 mph is 13-17% higher than at 25 mph.

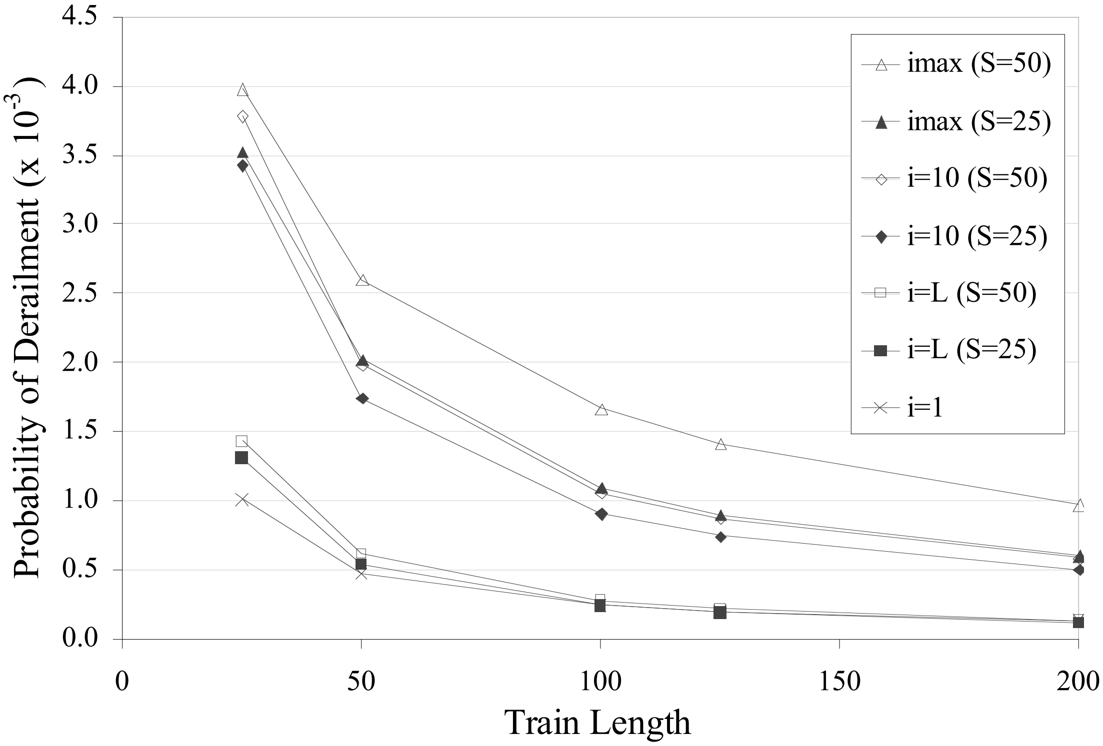

Figure 5.6 Derailment Risk by Length (L), Speed (S), & Position (i)

5.8 Conclusions

In this paper, we have examined the probabilities of derailment for freight trains and freight cars as affected by train length, train speed, and positioning of cars within the consist.

The probability of derailment for a single train is largely a function of track class, distance traveled, and train length. While a shorter train will have a lower probability of derailment, shipments of longer trains will have a lower probability that one or more trains will be derailed (for a fixed quantity of cars shipped).

The probability that a particular car will be derailed in a derailment is largely a function of train length, train speed, and positioning within the consist. More cars can be expected to derail with increases in train speed and residual train length. Cars positioned near the front or rear of a train have the lowest probability of being derailed in a derailment. As train length is decreased or train speed is increased, the conditional probability of derailment increases for all cars within the train consist.

As with any effective risk reduction option, the expected benefits from any changes in railroad operating practices must be compared with the costs associated with lowering the risk of derailment. For example, if train speed is reduced, the risk of derailment is lowered at the expense of increasing shipment time and possibly reducing traffic throughput. Physical constraints, such as siding lengths, may control the length of trains that can shipped over particular corridors. Other constraints, such as train handling procedures and train make-up regulations, may also affect the placement of cars within the consist. These and all other operational constraints must be considered before any change in operating procedure is implemented to reduce derailment risk. The optimal cost-effective configuration would allow for the necessary throughput at the lowest possible risk level.

CHAPTER 6: CONCLUSIONS

6.1 Research Summary

The research presented in this thesis addresses the question of risk of derailment to freight trains and freight cars in mainline freight operations. The probability of derailment for a freight train is a function of the number of cars in the train, the track on which the train is operating, and the distance it travels. Longer trains have an increased likelihood of derailment.

Track class-specific and segment-specific derailment rates were calculated for the BNSF Railway. The segment-specific rates were shown to vary substantially for track segments having the same track class value. The level of confidence in the estimated segment-specific derailment rates was shown to be largely a function of the number of observed derailments over the section. As segment length was increased, the number of segments observing zero derailments decreased, the average width of the confidence interval decreased, and the uncertainty surrounding an estimated derailment rate also decreased. A parametric Empirical Bayesian analysis was used to adjust the estimated rates based on knowledge of similar track segments.

The probability that a particular car in a derailed train consist will be derailed is a function of the train length, the speed of derailment, the derailment cause, the point-of-derailment, and the position-in-train of the car of interest. While severity of derailment is related to the amount of kinetic energy in the train, it is not directly proportional and appears to be dependent on the square root of train speed and train mass. This may be due to the interaction between cars and absorption of energy that occurs as each car following the point-of derailment is subjected to the possibility of being derailed.

The geometric model presented by Saccomanno & El-Hage (1989, 1991) was corrected and updated parameter estimates were developed, enabling the risk analyst to determine the probability of derailment for various train lengths, speeds, and accident causes. Combined with train derailment probabilities, these models can be used to determine the overall risk of derailment for freight cars as affected by various railroad operating practices.

6.2 Future Research

An alternative technique to simply calculating segment-specific accident rates is to use a multivariate statistical model (generalized linear accident model, GLAM) to predict the expected number of derailments based on several variables (or covariates) that are specific to each segment. For example, traffic flow (gross ton-miles) would be an independent variable in some function that relates the number of derailments to traffic flow and other variables. Other variables to be considered could include: track class (or some other measure of track quality, TQIs for example), grade, curvature, environmental conditions (temperature & weather), soil conditions, etc. Potential models including the Poisson and negative binomial distribution models are described by Wood (2002). For instance, the single flow model, $\mu = \beta_0 x^{\beta_1}$, models the true mean number of accidents as a function of traffic flow, x, with the two parameters, β_0 & β_1, determined from GLAM regression assuming the accidents are Poisson (or negative binomial) distributed about the mean value, μ. Hauer (1992) describes how to apply the multivariate regression method to an Empirical Bayes methodology and Wood (2002, 2005) describes a methodology to establish goodness-of-fit criteria and calculate confidence and prediction intervals for GLAM predictions.

A more thorough analysis would also look at time dependent variations in predicted accident rates. This could occur due to possible track upgrades, changes in traffic volume or train makeup, or any other changes that may have occurred during the time interval studied. Hauer (1992) discusses possible scenarios why a time-series multivariate approach may better estimate the likelihood of an accident along a particular segment.

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Appendix A – FRA Cause Code Groups[31,32]

Cause Group	Description	CM/TM	FRA Cause Codes										
01T	Roadbed Defects	CM	T001	T099									
02T	Non-Traffic, Weather Causes	TM	T002	T401	T402	T403							
03T	Wide Gauge	CM	T110	T111	T112	T113							
04T	Track Geometry (excl. Wide Gauge)	CM	T101	T102	T103	T104	T105	T106	T107	T108	T199		
05T	Buckled Track	CM	T109										
06T	Rail Defects at Bolted Joint	CM	T201	T211									
07T	Joint Bar Defects	CM	T213	T214	T215	T216							
08T	Broken Rails or Welds	CM	T202	T203	T204	T207	T208	T210	T212	T218	T219	T220	T221
09T	Other Rail and Joint Defects	CM	T299										
10T	Turnout Defects - Switches	CM	T307	T308	T309	T310	T311	T312	T313	T314	T315	T319	
11T	Turnout Defects - Frogs	CM	T304	T316	T317	T318							
12T	Misc. Track and Structure Defects	CM	T205	T206	T217	T222	T301	T302	T303	T305	T306	T399	T499
			S001	S002	S003	S004	S005	S006	S007	S008	S009	S010	S011
01S	Signal Failures	TM	S012	S013	S099								
01E	Air Hose Defect (Car)	CM	E00C										
02E	Brake Rigging Defect (Car)	CM	E07C										
03E	Handbrake Defects (Car)	CM	E08C	E0HC									
04E	UDE (Car or Loco)	CM	E05C	E05L									
05E	Other Brake Defect (Car)	CM	E01C	E02C	E03C	E04C	E06C	E09C					
06E	Centerplate/Carbody Defects (Car)	CM	E20C	E21C	E22C	E23C	E24C	E25C	E26C	E27C	E29C		
07E	Coupler Defects (Car)	CM	E30C	E31C	E32C	E33C	E34C	E35C	E36C	E37C	E39C		
08E	Truck Structure Defects (Car)	CM	E44C	E45C									
09E	Sidebearing, Suspension Defects (Car)	CM	E40C	E41C	E42C	E43C	E47C	E48C					
10E	Bearing Failure (Car)	CM	E52C	E53C									
11E	Other Axle/Journal Defects (Car)	CM	E51C	E54C	E55C	E59C							
12E	Broken Wheels (Car)	CM	E60C	E61C	E62C	E63C	E6AC						
13E	Other Wheel Defects (Car)	CM	E64C	E65C	E66C	E67C	E68C	E69C					
14E	TOFC/COFC Defects	CM	E11C	E12C	E13C	E19C							
			E07L	E40L	E41L	E42L	E43L	E44L	E45L	E46L	E47L	E48L	E4TL
			E49L	E51L	E52L	E53L	E54L	E55L	E59L	E60L	E61L	E62L	E63L
15E	Loco Trucks/Bearings/Wheels	CM	E64L	E65L	E66L	E67L	E68L	E6AL	E69L	E70L	E77L		
16E	Loco Electrical and Fires	CM	E71L	E72L	E73L	E74L	E76L						
			E00L	E01L	E02L	E03L	E04L	E06L	E08L	E0HL	E09L	E20L	E21L
			E22L	E23L	E24L	E25L	E26L	E27L	E29L	E30L	E31L	E32L	E33L
17E	All Other Locomotive Defects	CM	E34L	E35L	E36L	E37L	E39L	E79L	E99L				
18E	All Other Car Defects	CM	E49C	E80C	E81C	E82C	E83C	E84C	E85C	E86C	E89C	E99C	
19E	Stiff Truck (Car)	CM	E46C										
20E	Track/Train Interaction (Hunting) (Car)	CM	E4TC										
21E	Current Collection Equipment (Loco)	CM	E75L										
			H510	H511	H512	H513	H514	H515	H516	H517	H518	H519	H520
01H	Brake Operation (Main Line)	TM	H521	H525	H526								
02H	Handbrake Operations	TM	H017	H018	H019	H020	H021	H022	H025	M504			
03H	Brake Operations (Other)	TM	H008	H099									
04H	Employee Physical Condition	TM	H101	H102	H103	H104	H199						
			H201	H202	H203	H204	H205	H206	H207	H208	H209	H215	H216
05H	Failure to Obey/Display Signals	TM	H217	H299									
06H	Radio Communications Error	TM	H210	H211	H212	H405							
			H301	H302	H303	H304	H305	H306	H307	H308	H309	H310	H311
07H	Switching Rules	TM	H312	H313	H314	H315	H399						
08H	Mainline Rules	TM	H401	H402	H403	H404	H406	H499					
			H501	H502	H503	H504	H505	H506	H507	H508	H509	H522	H523
09H	Train Handling (excl. Brakes)	TM	H524	H599									
10H	Train Speed	TM	H601	H602	H603	H604	H605	H606	H699				
11H	Use of Switches	TM	H701	H702	H703	H704	H705	H799					
12H	Misc. Human Factors	TM	H821	H822	H823	H824	H899	H991	H992	H993	H994	H995	H999
01M	Obstructions	TM	M101	M102	M103	M104	M105	M199	M402	M403	M404		
02M	Grade Crossing Collisions	TM	M301	M302	M303	M304	M305	M306	M307	M399			
03M	Lading Problems	CM	M201	M202	M203	M204	M205	M206	M207	M299	M409	M410	
04M	Track-Train Interaction	CM	M405										
05M	Other Miscellaneous	TM	M401	M406	M407	M408	M501	M502	M503	M505	M599		

31 Car-mile (CM) related accident causes are those for which accident likelihood is considered to be proportional to the number of car-miles operated (i.e. failure is a function of the number of imposed loading cycles). Train-mile (TM) related accident causes are those for which accident likelihood is considered to be proportional to the number of train-miles operated (i.e. accident likelihood is independent of train length).

32 This list does not include FRA cause codes added in May, 2004.

Appendix B – Beta Distribution Background[33]

Shape Parameters: α > 0, β > 0
Range: $0 \le x \le 1$
Mean: $\alpha/(\alpha+\beta)$

Probability Density Function:

$$f(x) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)}$$; where $B(\alpha, \beta)$ is the Beta Function:

$$B(\alpha,\beta) = \int_0^1 u^{\alpha-1}(1-u)^{\beta-1}\,du\,.$$

OR

$$f(x) = \frac{d}{dx}F(x)\,.$$

Cumulative Density Function**:

$$F(x) = \frac{B_z(\alpha,\beta)}{B(\alpha,\beta)}$$; where $B_z(\alpha, \beta)$ is the Incomplete Beta Function[34]:

$$B_z(\alpha,\beta) = \int_0^z u^{\alpha-1}(1-u)^{\beta-1}\,du\,.$$

OR

$$F(x) = \int_0^x f(u)du\,.$$

**Note: In Excel: $F(x)$ = BETADIST(x,α,β,a,b); where $a \le x \le b$.

[33] See Evans et al., 2000.
[34] Eric W. Weisstein. "Incomplete Beta Function." From *MathWorld*--A Wolfram Web Resource. http://mathworld.wolfram.com/IncompleteBetaFunction.html.

Appendix C – Geometric Model Equations

$$P_d(i) = \sum_{k=1}^{i} \{P_p(k) \times \sum_{x=i-k+1}^{L_r} P(x)\} \quad \text{(Eq. C.1)}$$

where: $P_d(i)$ = conditional probability of derailment for car in i^{th} position of a train
$P_p(k)$ = point-of-derailment probability for the k^{th} position of a train
$P(x)$ = probability of derailing x cars in a train derailment
$x = i - k + 1$ = number of cars between the POD (k) and the car of interest (i)
$L_r = L - k + 1$ = residual train length (i.e. number of cars following the POD)
L = train length (i.e. number of vehicles in the train consist)

$$P(x) = \frac{p(1-p)^{x-1}}{1-(1-p)^{L_r}} \quad \text{(Eq. C.2)}$$

where: p = logistic function of continuous "success" probability

$$p = \frac{e^Z}{(1+e^Z)} \quad \text{(Eq. C.3)}$$

where: Z = response function based on the cause of derailment (C_d), train speed (S), and residual train length (L_r)

$$Z = a \mid C_d + b \times \ln(S) + c \times \ln(L_r) \quad \text{(Eq. C.4)}$$

where: parameters a, b, & c are estimated using maximum likelihood techniques and a is dependent upon the cause of derailment ($a|C_d$)

$$D = \frac{1}{p[1-(1-p)^{L_r}]} \quad \text{(Eq. C.5a)}$$

where: D = the mean (estimated) number of cars derailed (*incorrect equation*)

Derivation of the mean of the doubly truncated geometric distribution:
Let $q = 1 - p$ and $0 < p < 1$.

$$D = \sum_{x=1}^{L_r} x \cdot P(x) = \sum_{x=1}^{L_r} x \cdot \frac{(1-q) \cdot q^{x-1}}{1-q^{L_r}} = \left(\frac{1-q}{1-q^{L_r}}\right) \cdot \sum_{x=1}^{L_r} x \cdot q^{x-1}$$

$$= \left(\frac{1-q}{1-q^{L_r}}\right) \cdot \left(\frac{1-(L_r+1) \cdot q^{L_r} + L_r \cdot q^{L_r+1}}{(1-q)^2}\right) = \frac{1-(L_r+1) \cdot q^{L_r} + L_r \cdot q^{L_r+1}}{(1-q)(1-q^{L_r})} \quad \text{(Eq. C.5b)}$$

$$= \frac{1-(1+p \cdot L_r)(1-p)^{L_r}}{p[1-(1-p)^{L_r}]} = \frac{1}{p} - \frac{L_r(1-p)^{L_r}}{1-(1-p)^{L_r}}$$

where: $\sum_{x=1}^{L_r} x \cdot q^{x-1}$ is the Arithmetic-Geometric Series (Jeffrey, 2004).

Appendix D – SAS Code

Glossary of terms:

`derailed`: number of cars derailed
`trnspd`: train speed (mph)
`reslen`: residual train length
`reston`: residual tonnage
`cause_group`: accident cause group

`**`: power operator

Nonlinear Regressions (§4.3)

```
proc nlin data=file;
parms a=0.2
b=0.5
c=0.5;
model derailed = a*trnspd**b*reslen**c;
by cause_group;
run;

proc nlin data=file;
parms a=0.02
b=0.5
c=0.5;
model derailed = a*trnspd**b*reston**c;
by cause_group;
run;
```

Geometric Model (§4.4.2)

```
proc nlin data=file;
parms a=1
b=-1
c=0;
z=(a+b*log(trnspd)+c*log(reslen));
p=exp(z)/(1+exp(z));
model derailed = (1/p)-((reslen*((1-p)**reslen))/(1-((1-p)**reslen)));
by cause_group;
run;
```

Appendix E – Memo on Hazardous Materials Release Rates

To: Chris Barkan

From: Robert Anderson

Date: September 5, 2003

Re: Hazardous Materials Release Rates

Professor Barkan,

I analyzed the Federal Railroad Administration (FRA) accident database for the ten-year interval 1992-2001. There were 1,074 accidents on mainline track in which one or more hazardous materials cars were damaged or derailed. Of these, 199 accidents had hazardous materials released with the majority (126) of these accidents having only one hazmat car release its contents. Of the 3,596 hazmat cars that were damaged or derailed, 384 released their contents. The average proportion of damaged or derailed hazmat cars that released contents was 10.6%. The following table shows the breakdown of the 1,074 accidents by the number of hazmat cars damaged or derailed and the number of hazmat cars released.

# of Hazmat Cars Dam/Der	Number of Hazardous Materials Cars Released								Total Accidents		Total Hazmat Cars	
	0	1	2	3	4	5	6	>6	w/ Release	Total	Released	Dam/Der
1	394	43	-	-	-	-	-	-	43	437	43	437
2	173	32	9	-	-	-	-	-	41	214	50	428
3	83	12	8	5	-	-	-	-	25	108	43	324
4	72	9	5	3	2	-	-	-	19	91	36	364
5	44	7	2	1	0	1	-	-	11	55	19	275
6	27	4	2	3	1	2	1	-	13	40	37	240
7	17	2	5	0	0	0	0	0	7	24	12	168
8	14	2	4	0	2	0	0	0	8	22	18	176
9	9	4	0	2	1	1	1	0	9	18	25	162
10	11	1	0	0	0	1	1	0	3	14	12	140
11	6	1	1	0	0	0	0	0	2	8	3	88
12	4	0	1	0	0	0	0	0	1	5	2	60
13	6	0	0	0	0	0	1	0	1	7	6	91
14	4	0	0	0	0	0	0	0	0	4	0	56
15	1	0	0	0	0	0	0	0	0	1	0	15
16	0	1	0	1	0	0	0	1	3	3	20	48
17	0	1	0	0	0	0	0	1	2	2	14	34
18	3	2	0	0	0	0	0	1	3	6	20	108
19	1	1	0	0	0	0	0	0	1	2	1	38
20	1	1	0	0	0	0	0	0	1	2	1	40
>20	5	3	0	0	1	0	1	1	6	11	22	304
Total	875	126	37	15	7	5	5	4	199	1074	384	3596

The four accidents that had more than 6 hazmat cars released are as follows:

Accident	Train Length	Train Speed (mph)	Cars Derailed	Hazmat Cars Damaged/Derailed	Hazmat Cars Released	FRA Accident Cause
1	116	39	32	18	18	M505
2	83	48	34	16	16	M505
3	79	52	24	17	13	E4TC
4	109	40	30	23	9	E24C

The two accidents with FRA cause code 'M505' are listed as 'other miscellaneous' causes that were under investigation. 'E4TC' is a truck hunting caused accident and 'E24C' is an accident caused by the center plate disengaging from the truck (car off center).

On average, 9.8 cars were derailed in accidents in which no hazmat car released its contents versus the 16.5 average number of cars derailed in which there was a hazardous materials release. The average speed of accidents in which no hazmat was released was 24.9 mph while the average speed of accidents in which there was a hazmat release was 33.2 mph.

Please let me know if I can be of any further assistance on this.