A Framework for Evaluating Cost-Effectiveness of Accident Prevention Strategies under Uncertainty

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ABSTRACT

Rational allocation of resources to reduce train accident occurrence in the most cost-effective manner is important for the rail industry and government. Accident prevention strategies, individually and in combination, may result in different safety benefits and corresponding implementation costs. An appropriate assessment of the cost-effectiveness of accident prevention strategies is an important step to evaluate, develop and prioritize safety improvement investments. Both the safety benefit and implementation cost of a strategy may be subject to uncertainty at the time of decision making. However, little prior research has considered the effect of uncertainty in evaluating the cost-effectiveness of train accident prevention strategies. Properly accounting for this uncertainty can improve the efficient allocation of safety resources. This paper presents a framework to conduct an uncertainty-based cost-benefit analysis. The types and sources of uncertainty are identified and statistical models are developed to quantify the effect of uncertainty. The results can aid the rail industry and government to develop more cost-effective strategies to maximize safety given limited resources.

1. INTRODUCTION

Train accidents may result in damage to infrastructure and rolling stock, service disruptions, casualties and harm the environment. Accordingly, improving train operating safety has long been a high priority in the rail industry and government. There are a variety of accident prevention strategies to reduce accident occurrence. These strategies, individually and in combination, have safety benefits and implementation costs. Assessment of the benefit and cost of each strategy is important for determining the optimal strategies to invest and the level of implementation. Both the benefits and costs may be subject to uncertainty at the time of decision making. Therefore, the evaluation and comparison of different accident prevention strategies should be based on an appropriate assessment of the uncertainty. Otherwise, it may result in an inefficient allocation of limited resources for safety improvement. Despite its importance, little prior work has been developed to quantify the effect of uncertainty in the cost-benefit analysis of train accident prevention strategies.

In this paper, we develop a quantitative framework to evaluate cost-effectiveness of accident prevention strategies under uncertainty. First, we identify and explain the various sources of uncertainty in train accident analysis. Then, we develop analytical techniques to quantify the uncertainty using broken rail prevention as an example. Finally, we discuss the implications of the analysis to train safety policy and practices.

2. Framework for Evaluating Cost-Effectiveness of Accident Prevention Strategies

The safety benefit of an accident prevention strategy can be measured by the level of reduced accident risk. In this study, accident risk is defined as the product of car derailment frequency and the corresponding average consequence of a derailment (Equation 1). Car derailment frequency is a product of car derailment rate and traffic exposure (*1-5*).

$$R = Z \times M \times D \tag{1}$$

where:
R = accident risk
Z = car derailment rate
M = traffic exposure
D = average consequence of a car derailment

Car derailment rate is a critical metric to measure railroad transportation safety performance. It is defined as the number of cars derailed normalized by some measure of traffic exposure, i.e. gross ton-miles, car-miles or train-miles. Car derailment rates are affected by FRA track class (*1, 2, 6, 7*), type of track and railroad (*2*), train length (*8, 9*), method of operation (*7, 10*) and traffic density (*7*). The consequence of a car derailment may also vary widely depending on the conditions of infrastructure and rolling stock, accident causes, operational characteristics, type of traffic, environment, population in the accident location and many other factors. If a car derailment results in a hazardous materials release, the general accident risk model can be extended by adding a series of possible consequences and associated probabilities. The safety benefit of an accident prevention strategy is calculated as the difference between the accident risk with and without implementation of the strategy (Equation 2).

$$B = R_b - R_a \tag{2}$$

Where:
B = safety benefit of an accident prevention strategy
R_b = accident risk before a prevention strategy is implemented (baseline risk)
R_a = accident risk after a prevention strategy is implemented

Any accident prevention strategy has an implementation cost. The total implementation cost may vary depending on which strategies are selected and their level of usage. When both the safety benefit and cost are evaluated in monetary terms, it is appropriate to assess the net present value (NPV) of different strategies to compare their cost-effectiveness. The NPV is calculated as the sum of the safety benefit minus the associated cost, over the time span they are expected to accrue. The monetary savings of the benefit and cost of implementation are discounted to constant (year 0) dollars.

$$NPV=\sum_{i=0}^{Y}\frac{B_i - C_i}{(1+d)^i} \tag{3}$$

Where:

B_i = safety benefit in year i
C_i = implementation cost in year i
d = discount rate
i = year

Given traffic exposure *M*, the NPV of an accident prevention strategy can be calculated using Equation 4:

$$NPV=\sum_{i=0}^{Y}\frac{(Z_{bi}D_{bi}-Z_{ai}D_{ai})M_i-C_i}{(1+d)^i} \quad (4)$$

Where:

Z_{bi} = car derailment rate before an accident prevention strategy is implemented
Z_{ai} = car derailment rate after an accident prevention strategy is implemented
D_{bi} = average consequence before an accident prevention strategy is implemented
D_{ai} = average consequence after an accident prevention strategy is implemented
M_i = traffic exposure
C_i = implementation cost in year i
d = discount rate

It is noted that different accident prevention strategies may differently affect car derailment rate and the average consequence of a car derailment. *Ceteris paribus*, the reduction in the accident risk can be estimated as a product of the derailment rate of accident causes that are preventable by a strategy and the corresponding average consequence cost (Equation 5).

$$Z_{bi}D_{bi}-Z_{ai}D_{ai}=\sum_{c}Z_{ci}D_{ci} \quad (5)$$

Where:

Z_{ci} = accident-cause-specific car derailment rate that are preventable by the strategy
D_{ci} = average damage cost per derailment due to that accident cause
c = accident cause

Equation 5 is based on the assumption that different accident causes are independent of one another. For example, the safety benefit of broken rail prevention focuses on the reduction of broken-rail-caused derailments, without accounting for the possible reduction of non-broken-rail-related causes attributable to improved rail condition. Further research is needed to better understand what the possible interactive effects are, how to quantify them, and their effects on accident rate estimation and policy evaluation. Based on Equations 1 to 4, the NPV of an accident prevention strategy can be estimated as:

$$NPV=\sum_{i=0}^{Y}\frac{\sum_{c} Z_{c_i} D_{c_i} M_i - C_i}{(1+d)^i} \tag{6}$$

Equation 6 shows that the cost-effectiveness of an accident prevention strategy is affected by accident-cause-specific car derailment rate that is preventable by the strategy, derailment damage cost, traffic exposure, implementation cost of the strategy, and discount rate. Each of these factors may be subject to uncertainty at the time of decision making. The input uncertainty contributes to the uncertainty in the NPV estimation. The objective of this research is to develop a framework to identify and quantify the uncertainty, in order to assist in making informed-decisions related to railroad safety. In the remaining sections, we first introduce the types and sources of uncertainty. Next, we discuss methods to analyze the uncertainty propagation. We then use broken rail prevention as an example to explain how the analytical framework can be applied to evaluate an accident prevention strategy. Finally, we discuss the policy implications of the results.

3. TYPE AND SOURCE OF UNCERTAINTY

There are two basic types of uncertainty - aleatory and epistemic uncertainty (*11-14*). Aleatory uncertainty, also called stochastic uncertainty or random uncertainty, is an inherent variation associated with a phenomenon or process. By contrast, epistemic uncertainty is derived from lack of knowledge of the system or the environment (*11-14*). In the context of rail transportation safety analysis, each variable may be subject to these uncertainties. For example, the frequency of train accident occurrence is assumed to follow a Poisson distribution (*15-18*). Correspondingly, the actual number of accidents to occur is a random variable. The aleatory uncertainty is inherent and cannot be reduced by more information and/or accurate measurements.

Although the actual number of accidents is random, its mean value can be estimated using statistical methods. For instance, Poisson regression or negative binomial regression models are commonly used to estimate the mean accident count (*15-18*). The discrepancy between the estimated mean and the "true" mean represents the second type of uncertainty called epistemic uncertainty, resulting from uncertainties with the variable, model formulation or decisions. Epistemic uncertainty is commonly derived from statistical inference based on sample data.

It is neither feasible nor practical to analyze all possible sources of uncertainty. In this study, we focus on analyzing the aleatory uncertainty (stochastic uncertainty) associated with freight-train derailment frequency and severity. For example, the objective might be to evaluate the cost-effectiveness of a broken rail prevention strategy over the next 20 years. In each year, the number of broken-rail-caused car derailments is a random variable, and the consequence of each car derailment is also random, depending on accident circumstances. The uncertainty of accident probability and severity affects the estimation of cost-effectiveness of an accident prevention strategy. Consequently, there is a need to understand the distribution of NPV based on the information available at the time of decision making. The comparison and prioritization of multiple accident prevention strategies should account for the uncertainty. We will explain the policy implications of uncertainty analysis in more detail in the remaining sections.

4. METHODOLOGY

A common method for uncertainty analysis is Monte Carlo simulation. It provides an easier and practical way to analyze the uncertainty in complex problems and has been used in various fields, including physics (*21*), engineering (*22-24*), statistics (*25*), public health (*26*) and finance (*27*). In railroad engineering, Monte Carlo simulation has been used to predict track/rail degradation process (*28, 29*). There are four basic steps to perform a Monte Carlo simulation:

1) Develop the parametric relationship between the input and output variables
2) Generate random input values from a pre-defined probability distribution
3) Calculate the output value based on each simulated input value and repeat for a large number of runs
4) Analyze the distribution of the output for all runs

So far, we have introduced the methodologies for evaluating the cost-effectiveness of accident prevention strategies under uncertainty. In the second half of this paper, we illustrate the application of the methodology and its implications to train safety policy using broken rail prevention as an example. The methodology can be adapted to various other accident prevention strategies.

5. CASE STUDY: BROKEN RAIL PREVENTION

In terms of preventing accident causes to reduce car derailment rate, it is first necessary to identify the distribution of derailment frequency by accident cause. The data used throughout this study are from the Federal Railroad Administration's (FRA) Rail Equipment Accident (REA) database. This database contains information regarding all accidents that exceed a monetary threshold of damage to on-track equipment, signals, track, track structures, and roadbed. The reporting threshold is periodically adjusted for inflation, and has increased from $7,700 in 2006 to $9,400 in 2011 (*30*). This paper focuses on Class I freight railroads (operating revenue exceeding $378.8 million in 2009), which accounted for approximately 68% of U.S. railroad route miles, 97% of total ton-miles transported and 94% of the total freight rail revenue (*31*). Broken rails are the most common accident causes, accounting for approximately 23% of car derailments on Class I mainlines from 2001 to 2010 (Figure 1) (*32*). Broken rail prevention appears to be a promising accident prevention strategy, so it is used here as an example to illustrate the methodology for analyzing the cost-effectiveness of an accident prevention strategy under uncertainty.

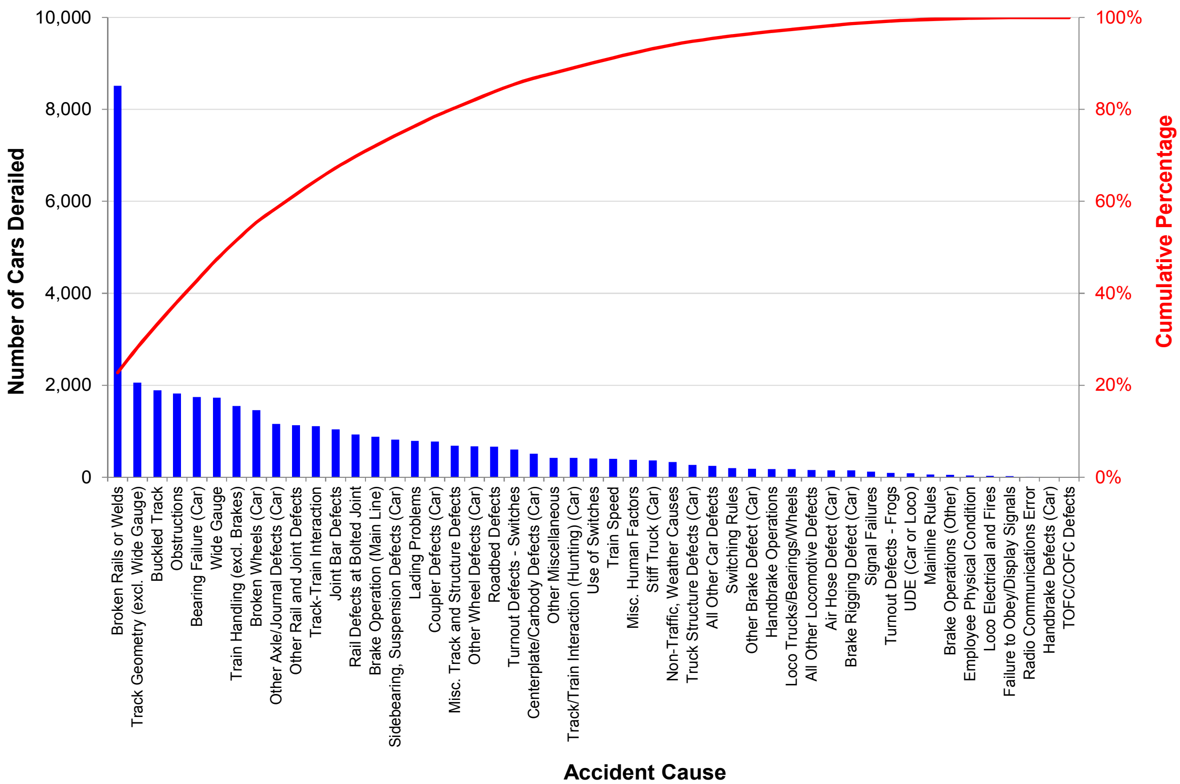


FIGURE 1 Car derailment by accident cause,
FRA-reportable freight-train derailments on Class I mainlines, 2001 to 2010

Next, we explain the analytical procedures to perform an uncertainty-based assessment of the cost-effectiveness broken rail prevention.

5.1 Scope

In terms of broken rail prevention, we focus on broken-rail-caused derailments on Class I mainlines. We do not consider the possible reduction of non-broken-rail-caused accidents, attributable to improved rail condition. Furthermore, a number of technologies or operating practices can prevent broken rails. In this study, we analyze the overall effect of broken rail prevention strategies, without accounting for a specific broken rail prevention measure. Future analysis can be developed to analyze the variability of cost-effectiveness for different broken rail prevention measures, such as rail grinding, increased inspection frequency or an advanced rail inspection technology.

5.2 Safety Benefit of Broken Rail Prevention

The safety benefit of broken rail prevention is defined as the reduced broken-rail-caused car derailment rate multiplied by the corresponding derailment damage cost. An infrastructure index (MOW-RCR) was developed from components of the AAR Railroad Cost Recovery Index (AAR-RCR) using the methodology developed by Grimes and Barkan (*33, 34*). MOW-RCR was used to adjust car derailment costs at various years in terms of base year prices. Finally, the car derailment damage cost was multiplied by a factor of 1.65 to account for other loss and damage, wreck clearing, and unreported property damage costs that are not included in the FRA-reported costs (*35*).

5.2.1 Broken-Rail-Caused Car Derailment Rate

It is assumed that the number of broken-rail-caused car derailments for a given traffic exposure follows a Poisson distribution:

$$P(Y=k)=\frac{\lambda^k}{k!}e^{-\lambda} \tag{7}$$

The Poisson mean, λ, is assumed to follow a gamma distribution (*15-18*):

$$P(\lambda=m)=\frac{\left(\frac{\phi}{\mu}\right)^{\phi}}{\Gamma(\phi)}m^{\phi-1}e^{-\left(\frac{\phi}{\mu}\right)m} \tag{8}$$

It can be proved that the marginal distribution of broken-rail-caused derailment count follows a negative binomial distribution (*36*):

$$\int Poi(y\mid\lambda)Gamma(\lambda\mid\phi,\mu)d\lambda=\frac{\Gamma(y+\phi)}{y!\Gamma(\phi)}\left(\frac{\phi}{\phi+\mu}\right)^{\phi}\left(\frac{\mu}{\phi+\mu}\right)^{y} \tag{9}$$

$$\mu=\exp\left(\sum_{p=0}^{k}\beta_p X_p\right)M \tag{10}$$

Where:

μ = expected car derailment count
β_p = p^{th} parameter coefficient
X_p = p^{th} explanatory variable
M = traffic exposure (e.g., gross ton-miles)
ϕ = gamma parameter (also called inverse dispersion parameter)

Equation 9 and 10 represent the widely used Poisson-gamma (negative binomial) regression model for estimating accident rates (*15-18, 36*). In this paper, we use annual rail maintenance cost per track mile as an explanatory variable to estimate FRA-reportable broken-rail-caused car derailment rate on Class I mainlines. Data from five U.S. Class I railroads (BNSF, UP, NS, CSX and KCS) from 2002 to 2008 were used to develop the model. The expected car derailment rate, μ, is a function of annual rail maintenance cost per track mile:

$$\mu=\exp(-0.1868-0.3356C)M \quad (11)$$

where:
C = annual rail maintenance cost per track mile (thousand dollars)

The overall goodness-of-fit of the model is evaluated by *Deviance*, which asymptotically follows a chi-square distribution (*37*). Based on this criterion, the model exhibits an overall good fit (P = 0.28 > 0.05).

TABLE 1 Broken-Rail-Caused Car Derailment Rate

Parameter	Estimate	Standard Error	95% Confidence Limits		Pr > ChiSq
Intercept	-0.1868	0.3053	-0.7852	0.4115	0.5405
Annual Rail Maintenance Cost per Track Mile ($ 000)	-0.3356	0.1101	-0.5514	-0.1198	0.0023
Dispersion Parameter (1/Φ)	0.3682	0.0857	0.2333	0.5811	

Deviance=37.2 (Degree of Freedom =33)
P = 0.28 > 0.05

Table 1 shows that the expected broken-rail-caused car derailment rate declines as rail maintenance increases, given all else being equal. The probability of a given number of broken-rail-caused car derailments can be estimated using Equation 12:

$$P(y)=\frac{\Gamma(y+2.7159)}{y!\Gamma(2.7159)}\left(\frac{2.7159}{2.7159+\exp(-0.1868-0.3356C)M}\right)^{2.7159}\left(\frac{\exp(-0.1868-0.3356C)M}{2.7159+\exp(-0.1868-0.3356C)M}\right)^{y} \quad (12)$$

Figure 2 shows the distribution of annual total number of broken-rail-caused car derailments on Class I mainlines assuming that annual rail maintenance cost (*C*) is $2,000/track-mile or $4,000/track-mile. It is also assumed that annual traffic exposure (*M*) is 3,446 billion gross ton-miles. It shows that the higher the rail maintenance cost, the smaller the mean and variance of car derailments.

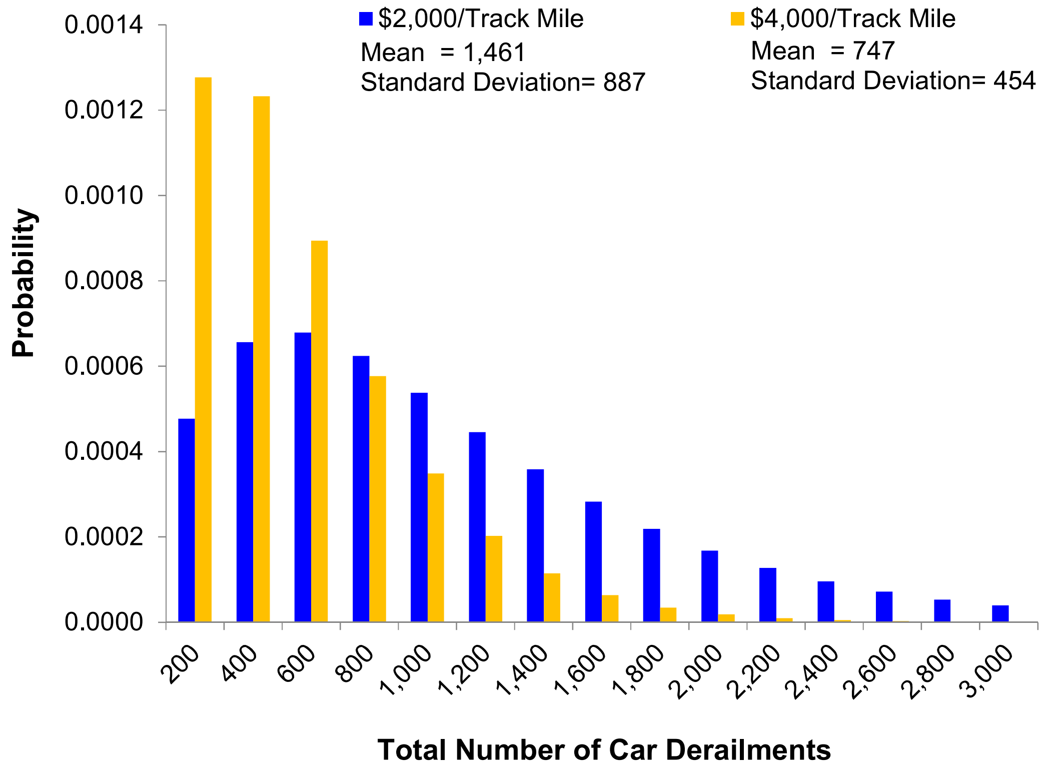


FIGURE 2 Probability distribution of broken-rail-caused car derailments on Class I mainlines by annual rail maintenance cost (only part of the distribution is displayed here)

5.2.2 Derailment Damage Cost

Track and equipment damage costs of train accidents are recorded in the FRA's REA database. Broken-rail-caused car derailment damage cost was fitted by common distributions (Beta, Normal, Logistic, Weibull, Gamma). The goodness-of-fit of a distribution is evaluated by Kolmogorov-Smirnov (K-S) test (*38*). A curve-fitting software *EasyFit* was used to perform the K-S test for each selected distribution, and rank the relevant distributions by their test values. The "best-fit" of the average broken-rail-caused car derailment cost follows a Weibull distribution:

$$P(D \leq d)=1-\exp\left(-\left(\frac{d}{\beta}\right)^{\alpha}\right) \qquad (13)$$

Where:

$P(D \leq d)$ = probability that FRA-reportable track and equipment cost does not exceed d ($)

α, β = parameters of the Weibull distribution (α=1.3483 ; β=41,459)

Figure 3 shows the fitted distribution of FRA-reportable broken-rail-caused track and equipment cost per car derailment. The average cost is $38,026, with a standard deviation of $28,505. The derailment cost may be affected by derailment speed, car type, track condition and many other factors. The variance in derailment cost contributes, in part, to the uncertainty in estimating the safety benefit of accident prevention strategies.

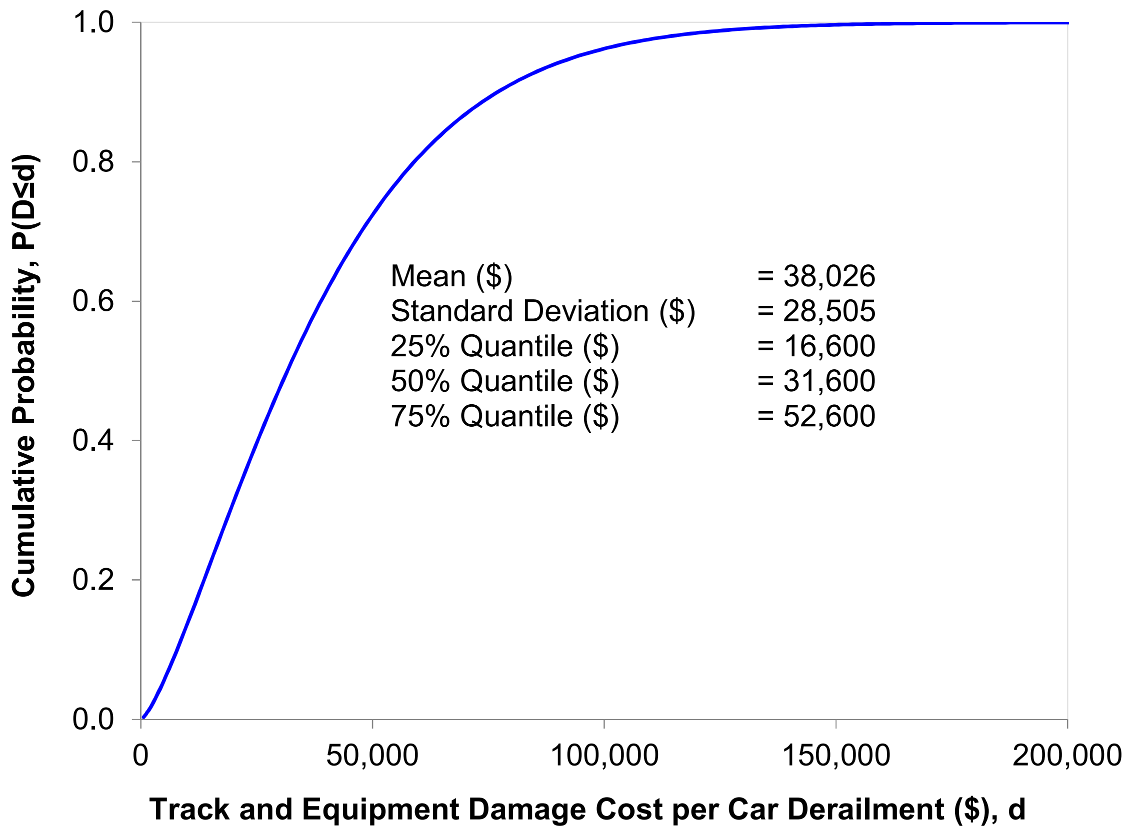


FIGURE 3 Fitted distribution of track and equipment cost per derailed car due to broken rails on class I mainlines

5.2.3 Uncertainty-Based Cost-Benefit Analysis

A Monte Carlo simulation model is developed to analyze the effect of uncertainty on the cost-effectiveness of broken rail prevention. First, the number of broken-rail-caused car derailments is randomly generated from a negative binomial distribution with and without the implementation of broken rail prevention, respectively (Equation 12). For each car derailment, the average FRA-reportable track and equipment damage cost is randomly generated from a Weibull distribution (Equation 13) and multiplied by 1.65 to account for other non-FRA-reportable damage costs (*34*). The following input variables are assumed:

- A broken rail prevention measure increases annual rail maintenance cost from $2,000 to $4,000 per track mile
- annual traffic exposure is 3,446 billion gross ton-miles

- 160,240 track miles on Class I mainlines
- 20 years study period
- 5% annual discount rate

The analytical process of a Monte Carlo simulation in train accident analysis is presented in Figure 4.

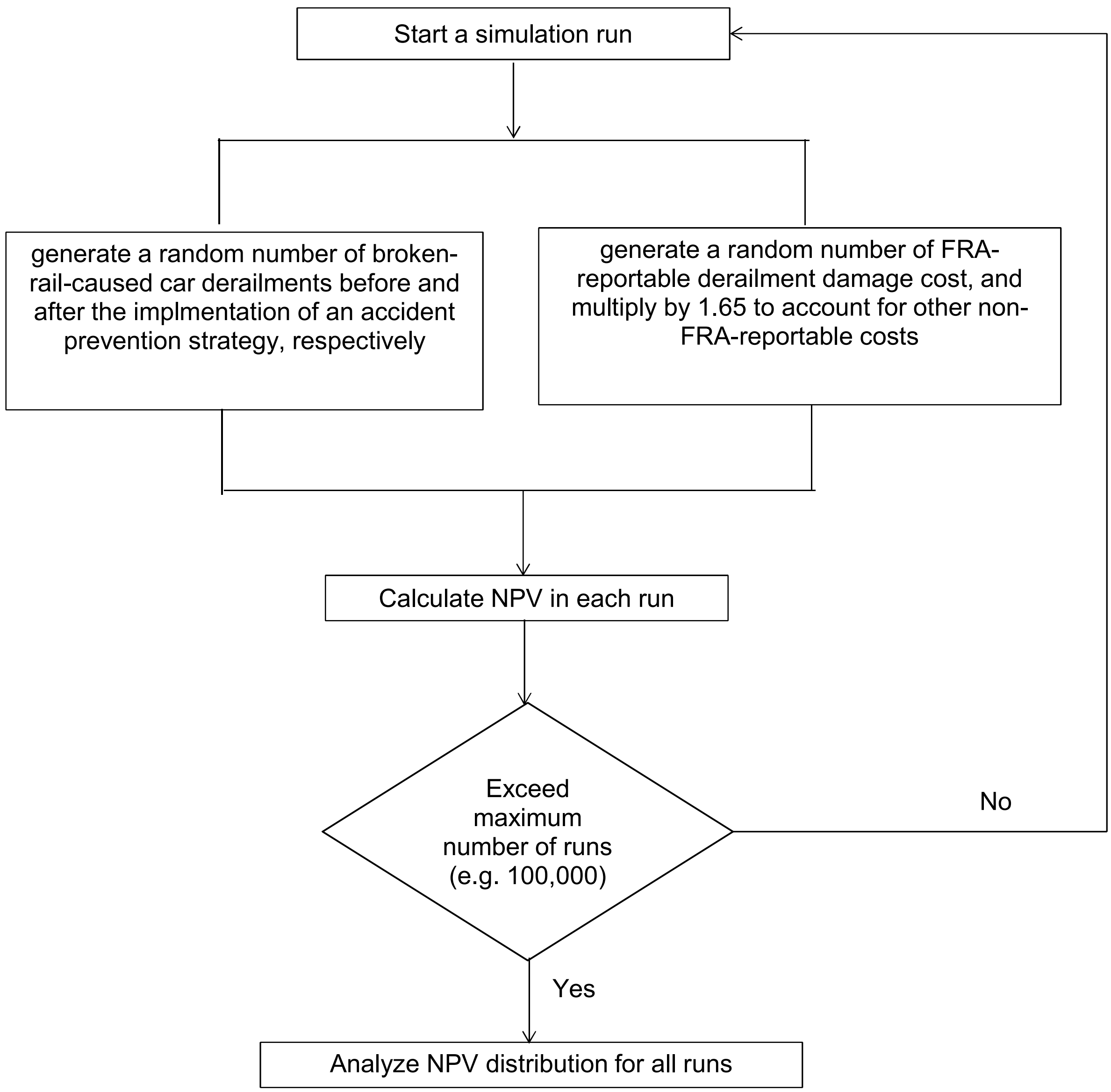
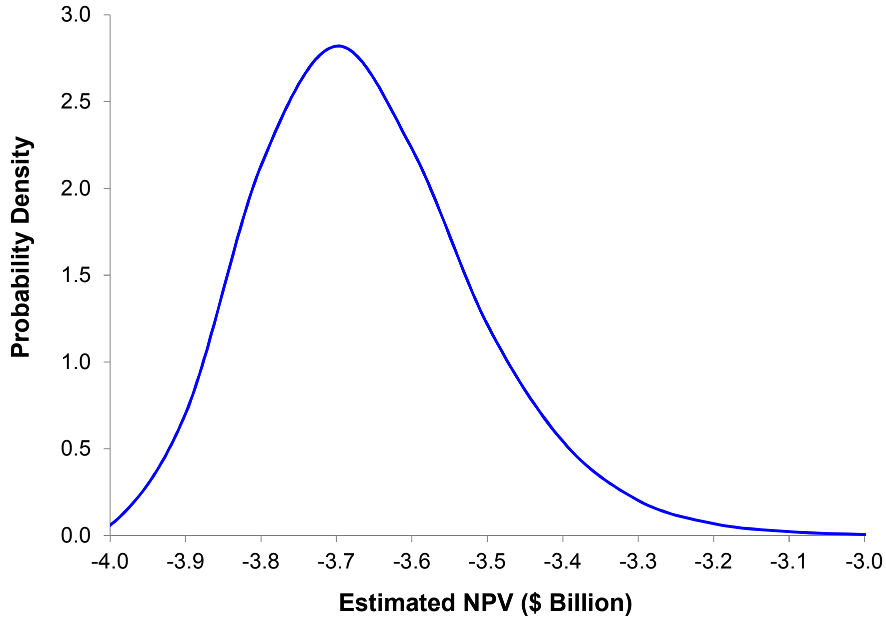


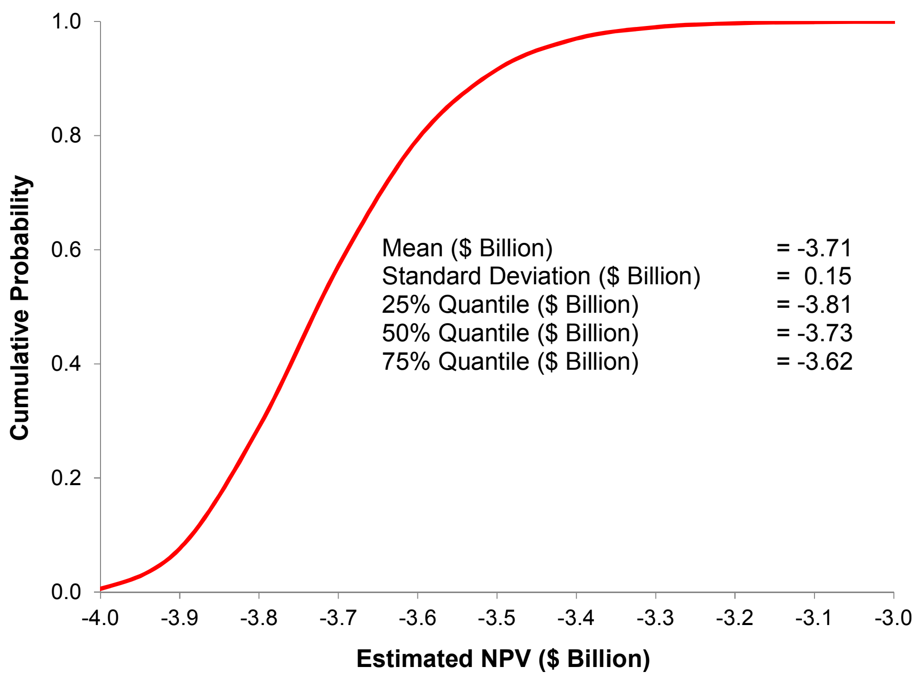
FIGURE 4 Monte Carlo simulation for evaluating the NPV of accident prevention strategies

5.2.4 NPV Distribution

The NPV distribution using Monte Carlo simulation is presented in Figure 5:



(a)



(b)

FIGURE 5 Estimated NPV distribution of broken rail prevention, (a) probability density function, (b) cumulative distribution function

The results above should be interpreted with caution. Due to data constraints, not all possible benefits and costs of broken rail prevention strategies are considered. For example, we do not consider the reduction of casualties due to broken rail prevention. When all these and other factors are taken into account, the estimated NPV and the corresponding conclusion may change. When more data become available, the Monte Carlo simulation model can be adapted to account for these changes.

6. Discussion

6.1 Uncertainty in the estimation of NPV

The principal proposition of this paper is to treat the estimated NPV as a random variable, rather than a single-point value. Many traditional approaches compare accident prevention alternatives solely based on estimates of their mean. In such an analysis the accident prevention strategy with a higher estimated NPV may be chosen. However, the NPV is estimated based on information from multiple sources that are generally subject to uncertainty. Therefore, the estimated NPV may differ from the actual NPV. This discrepancy reflects the uncertainty in evaluating cost-effectiveness of accident prevention strategies. One common measure of the uncertainty is variance, representing the spread of possible values around the mean.

For example, consider two accident prevention strategies with different NPV distributions denoted as NPV1 and NPV2 (Figure 6). The two distributions have the same mean (average) value, but NPV2 has lower variance (uncertainty). Assuming that the decision-maker is risk-averse, the second alternative would be chosen. In the more realistic case in which both the mean and variance of the NPV distributions differ, which one is preferred will depend on the risk sensitivity of the decision-maker and possible non-linearities in the utility function associated with NPV.

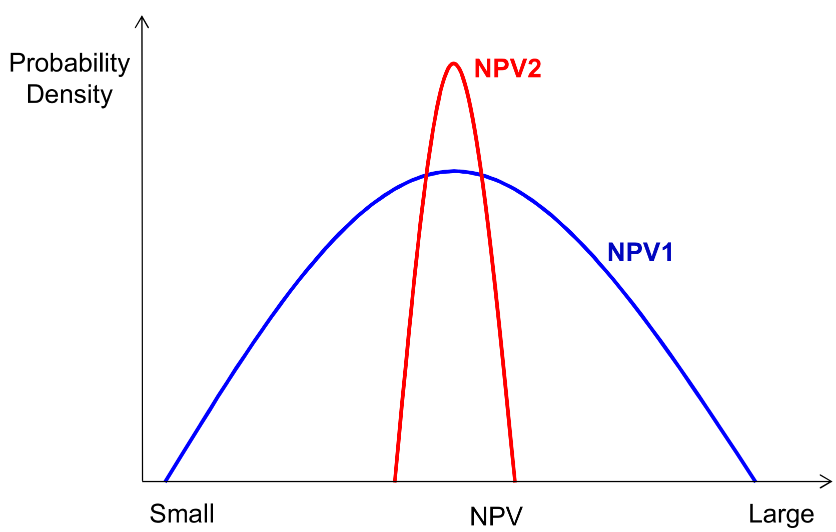


FIGURE 6 Comparison of two hypothetical NPV distributions

Although new in the rail industry, uncertainty-based cost-benefit analysis is receiving increasing interest in various fields. Graham (1981) developed an economic model to analyze the uncertainties in the cost-benefit analysis (*39*). Thompson and Graham (1996) accounted for the uncertainty in the cost-benefit analysis in the public health-related decisions (*40*). Yokomizo et al. (2011) analyzed optimal decisions under uncertainty in the cost-benefit analysis in biological research (*41*). Hauer (2012) discussed the application of uncertainty-based cost-benefit analysis in highway safety research and quantified the value of research in reducing the uncertainty (*42*). The methodology developed in this paper could potentially be used to facilitate a better-informed decision making related to train safety.

6.2 Comparison of different accident prevention strategies

When NPV distributions differ in both mean and variance, decision-making should account for the effect of each (Fig. 7). For illustration, we consider two broken rail measures:

Option A: Increase annual rail maintenance cost from $2,000 to $4,000 per track mile
Option B: Increase annual rail maintenance cost from $2,000 to $6,000 per track mile

Using Monte Carlo simulation, the distribution of two broken rail prevention measures are presented below:

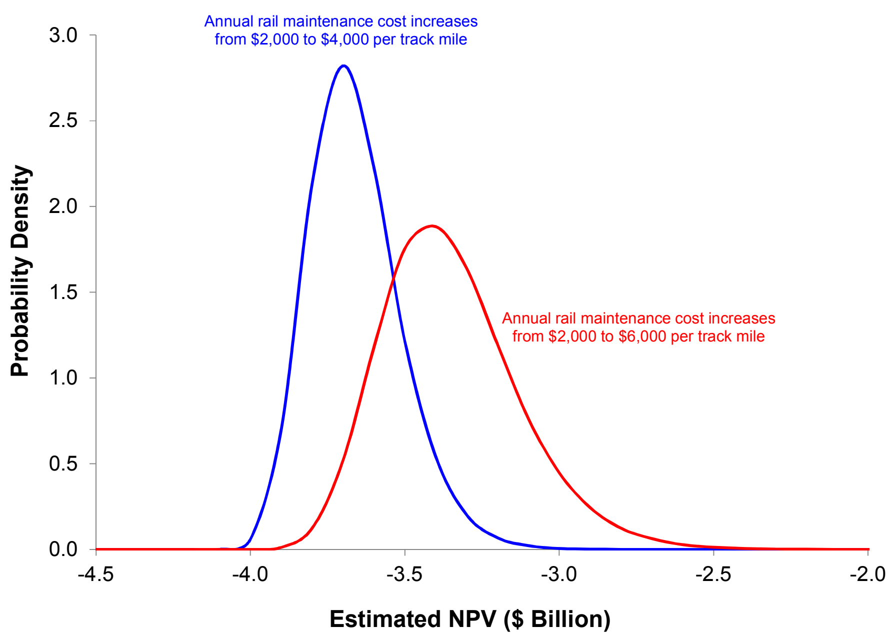


FIGURE 7 NPV distribution by annual rail maintenance cost

Option B has a greater increase in the rail maintenance cost, thus it results in a greater mean of estimated NPV. However, there is more uncertainty associated with option B (the NPV distribution has a larger variance). Which option is more favorable depends on the decision maker's utility and trade-off between the mean and variance. Define a decision variable C, which accounts for both the mean and variance of a NPV distribution.

$$C = \lambda\mu - (1-\lambda)\sigma \tag{14}$$

Where:
C = decision variable
λ = trade-off between the mean and variance ($0 \le \lambda \le 1$)
μ = mean of NPV distribution
σ = standard deviation (square root of variance) of NPV distribution

The trade-off parameter λ ($0 \le \lambda \le 1$) reflects the decision maker's trade-off between the mean and variance. When $\lambda=1$, the mean NPV will be the only criterion for comparing risk reduction alternatives, and the risk reduction strategy with the higher mean will be chosen. When $\lambda=0$, the risk reduction strategy with a lower variance (uncertainty) will be chosen. For any values of λ between 0 and 1, the decision is based on both the mean and variance.

For example, the mean and variance of NPV distribution for option A and option B are estimated using Monte Carlo simulation:

	Option A	Option B
Mean (μ)	$ -3.71 billion	$ -3.40 billion
Standard deviation (σ)	$ 0.15 billion	$ 0.22 billion

For illustration, it is assumed that $\lambda=0.8$. Using Equation (14),

$C_A = 0.8\times(-3.71) - (1-0.8)\times0.15 = -3.00$
$C_B = 0.8\times(-3.40) - (1-0.8)\times0.22 = -2.76$
Because $C_B > C_A$, option B is chosen.

However, if $\lambda=0.05$, Using Equation (14),
$C_A = 0.05\times(-3.71) - (1-0.05)\times0.15 = -0.328$
$C_B = 0.05\times(-3.40) - (1-0.05)\times0.22 = -0.379$
Because $C_A > C_B$, option A is chosen.

The analysis indicates that, in the presence of uncertainty, the decision is affected by the trade-off between the mean and variance. Accounting for the uncertainty in the cost-benefit analysis could potentially facilitate development of robust safety improvement decisions.

7. CONCLUSIONS

This paper develops a quantitative framework to account for the uncertainty in the cost-effectiveness analysis of accident prevention strategies. A Monte Carlo simulation model is developed to estimate the distribution of NPV based on the probability distribution of broken-rail-caused car derailments and derailment damage cost, respectively. The model provides a practical way to quantify uncertainty propagation in train accident analysis. The potential application of this model is to analyze and compare different accident prevention strategies. Compared to the traditional single-point estimation of the NPV, understanding the distribution of NPV provides additional information regarding its range and variability that may aid decision makers to develop better-informed train safety policy.

8. FUTURE RESEARCH

The next step of this research is to apply the model to other accident prevention strategies, such as detection of mechanical failures using wayside detection technologies or improving operating practices to reduce human errors. The comparison and integration of different accident prevention strategies enables the development of an optimal portfolio of strategies to reduce train accident risk in the most efficient manner. In addition, more advanced simulation methods, such as importance sampling, will be developed to improve computational efficiency.

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