



# Integrated risk reduction framework to improve railway hazardous materials transportation safety



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## HIGHLIGHTS

- An integrated framework is developed to optimize risk reduction.
- A negative binomial regression model is developed to analyze accident-cause-specific railcar derailment probability.
- A Pareto-optimality technique is applied to determine the lowest risk given any level of resource.
- A multi-attribute decision model is developed to determine the optimal amount of investment for risk reduction.
- The models could aid the government and rail industry in developing cost-efficient risk reduction policy and practice.

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## ABSTRACT

Rail transportation plays a critical role to safely and efficiently transport hazardous materials. A number of strategies have been implemented or are being developed to reduce the risk of hazardous materials release from train accidents. Each of these risk reduction strategies has its safety benefit and corresponding implementation cost. However, the cost effectiveness of the integration of different risk reduction strategies is not well understood. Meanwhile, there has been growing interest in the U.S. rail industry and government to best allocate resources for improving hazardous materials transportation safety. This paper presents an optimization model that considers the combination of two types of risk reduction strategies, broken rail prevention and tank car safety design enhancement. A Pareto-optimality technique is used to maximize risk reduction at a given level of investment. The framework presented in this paper can be adapted to address a broader set of risk reduction strategies and is intended to assist decision makers for local, regional and system-wide risk management of rail hazardous materials transportation.

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## 1. Introduction

There are approximately two million annual rail carloads of hazardous materials (hazmat) in North America [1]. Although the majority of these shipments (99.996% in 2011) safely reach their destinations [1], the potential severe consequence of a hazmat release incident remains a major safety concern to the rail industry, government and public in the U.S. For example, the consequent release of chlorine gas from a train collision in Graniteville, South Carolina in January 2005 resulted in 9 fatalities, hundreds of injuries, an evacuation of about 5400 people and economic loss exceeding \$6.9 million [2]. There has been growing interest

and intensifying regulatory requirement in the U.S. to improve the safety of railway hazmat transportation. Improvements have focused on enhancing packaging and tank car safety design [3–9], deploying wayside defect detection technologies [10–13], upgrading track infrastructure [14–16], routing [17–22], reducing train speed [22] and improving emergency response practices [23]. Each strategy has a direct effect on the hazmat release risk, and different strategies may also have interactive effects.

However, how to optimize the integration of different risk reduction strategies in the most cost-efficient manner is not well understood. In order to facilitate a risk-based decision, this paper develops an integrated risk reduction framework, accounting for the cost-effectiveness of an individual risk reduction strategy, their interactive effects and optimal integration. The paper is structured as follows. First, we formulate hazmat risk management as a multi-attribute decision analysis problem. Then, we develop a Pareto-optimality approach to determine the lowest risk that can be achieved at a specific level of investment. Understanding the risk-and-cost relationship leads to development of a decision

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model to determine the “optimal” investment. To illustrate the methodology, we analyze cost-effectiveness of broken rail prevention, tank car safety design enhancement and their optimal combination under budgetary constraint. Although the model implementation is based on U.S. data, the methodology may be adapted to the rail systems in other regions.

## 2. Multi-attribute decision model for hazmat transportation risk management

Hazmat transportation risk management can be formulated as a multi-attribute decision problem. It is assumed that certain risk reduction strategies are implemented to reduce the baseline risk ( $R_0$ ) to a lower level ( $R$ ). The associated implementation cost is  $I$ . Given a specific investment  $I_i$ , there is an optimal combination of risk reduction strategies so as to achieve the lowest risk. Let  $R^*(I_i)$  define the lowest risk given investment  $I_i$ . For a rational decision making, additional investment should not worsen the system safety, that is:

$$\text{If } I_j > I_i, \text{ then } R^*(I_j) \leq R^*(I_i) \quad (1)$$

In Eq. (1), the equality holds when the additional investment ( $I_j - I_i$ ) does not result in additional safety benefit. Fig. 1 illustrates the relationship between  $R^*(I)$  and  $I$ . This relationship is called Pareto-optimality in economics [24]. In the context of hazmat risk management, Pareto-optimality means that the safety cannot be further improved without additional investment. When Pareto-optimality is used in a multi-attribute decision analysis model, the “optimal” investment ( $I^{**}$ ) and the corresponding risk ( $R^{**}$ ) can be determined.

In decision analysis, the value function is a general approach to account for the decision maker’s preference and trade-off between multiple attributes (such as the risk and cost) [25]. The linear form of value function has been used in previous studies and it has practical convenience [26,27]. A value function  $V(R,I)$  is defined based on the risk and corresponding investment to reduce the baseline risk to a lower level of risk.

$$V(R, I) = W_R R + W_I I \quad (2)$$

where  $V(R,I)$  = value function of risk and investment,  $R$  = proportion of baseline risk ( $R=100\%$  for baseline risk),  $I$  = investment for reducing the baseline risk ( $R_0$ ) to a lower level of risk  $R$ ,  $W_R$  = first-order partial derivative of the value function with respect to risk,  $W_I$  = first-order partial derivative of the value function with respect to investment.

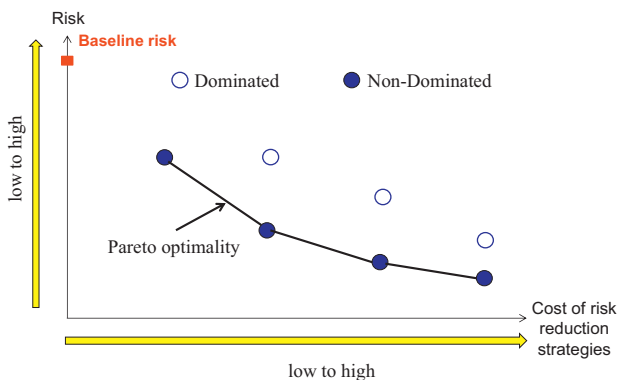


Fig. 1. Schematic illustration of Pareto-optimality in hazardous materials transportation risk management.

On the Pareto-optimality frontier, the minimum risk can be estimated as a function of investment, denoted as  $R=g(I)$ . Eq. (2) can be re-written as:

$$V(R, I) = W_R g(I) + W_I I \quad (3)$$

The optimal investment ( $I^{**}$ ) is determined by solving the following equation:

$$\frac{\partial V(R, I^{**})}{\partial I^{**}} = W_R \frac{\partial g(I^{**})}{\partial I^{**}} + W_I = 0 \quad (4)$$

Eq. (4) can be simplified as:

$$\frac{\partial g(I^{**})}{\partial I^{**}} = -\frac{W_I}{W_R} \quad (5)$$

If the optimal investment ( $I^{**}$ ) exceeds the budgetary constraint ( $I_{\max}$ ), the optimal decision may be either no investment ( $I^{**}=0$ ) or using all the budgets ( $I^{**}=I_{\max}$ ), depending on the value function. In order to optimize the allocation of investment, we need to estimate the safety effectiveness and cost of a risk reduction strategy. In the next section, we introduce a railway hazmat transportation risk model.

## 3. Railroad hazmat transportation risk analysis model

In rail transport of hazardous materials, risk is generally defined as a multiplication of derailment rate of a hazmat car, traffic exposure, conditional probability of release (CPR) of a derailed hazmat car and the consequence of a car release (Eq. (6)) [14,15,22,23,28,29].

$$R = Z \times M \times P \times C \quad (6)$$

where  $R$  = hazardous materials release risk (e.g., expected affected population),  $Z$  = hazmat car derailment rate per billion car-miles,  $M$  = traffic exposure (e.g., billion car-miles),  $P$  = CPR of a derailed hazmat car,  $C$  = consequence of a car release (e.g., number of people affected).

Hazmat car derailment rate is defined as the number of cars derailed by traffic exposure (e.g., train-miles, car-miles or ton-miles). Car derailment rates vary by track characteristics [28,30,31]. The CPR of a hazmat car reflects its safety performance. The majority of railroad hazardous materials shipments (72%) and the greatest quantity are in tank cars [1], thus tank car safety design analysis and improvement has been a priority in the U.S. rail industry and government. Treichel et al. developed a logistic regression model to estimate the CPR of a derailed tank car given its configuration [32]. Kawprasert and Barkan extended Treichel et al.’s model by accounting for derailment speed [14]. The consequences of a hazmat car release can be measured by several metrics, including property damage, disruption of service, environmental impact, human impact (e.g., number of people potentially exposed to a release), litigation or other types of impacts [22]. Among the consequence measures, population in the affected area of a release incident is often used [8,22,23]. The hazard exposure model provided in the U.S. Department of Transportation (U.S. DOT) Emergency Response Guidebook (ERG) can be used to estimate the affected area based on the material and scenario of release (fire, spill, daytime, nighttime) [33]. Once the affected area is determined, the number of people affected can be estimated by multiplying the affected area of each segment by the corresponding average population density. The assessment of release consequence could be performed using Geographical Information System (GIS) [22].

Fig. 2 illustrates two basic strategies to reduce tank car release risk: (1) reduce the likelihood of a hazmat release incident; (2) reduce release consequences. This study focuses on the former – reducing the likelihood of a hazmat release incident.

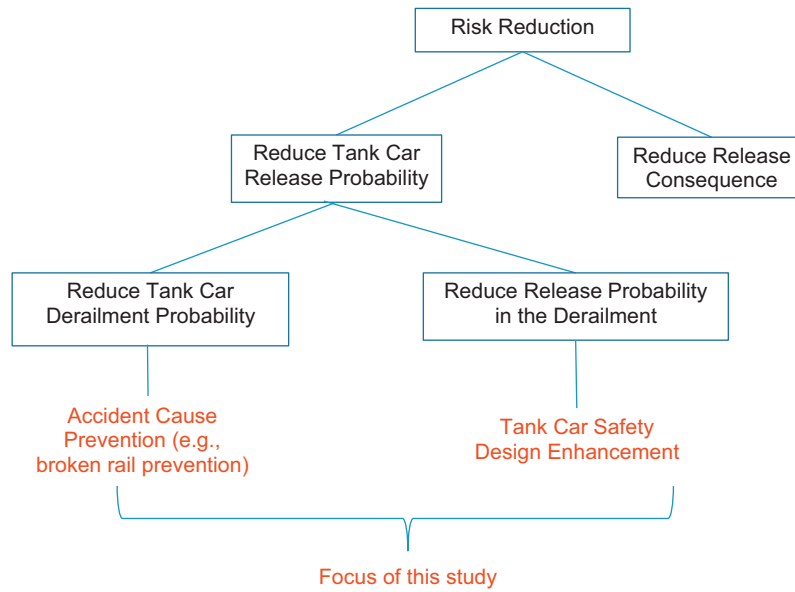


Fig. 2. Hierarchy of risk reduction strategies in this paper.

The strategies intended to mitigate the release consequences are beyond the scope of this paper. Reducing the likelihood of a hazmat car release incident (we use tank car as an example throughout this paper) can be achieved by reducing tank car derailment probability and/or reducing the CPR of a derailed tank car. For illustration, we consider two potential risk reduction strategies, broken rail prevention to reduce tank car derailment probability and tank car safety design enhancement to reduce its release probability after a car derailment occurs. The methodology could be adapted to various other risk reduction strategies.

In the next section, we analyze the cost-effectiveness of broken rail prevention and tank car safety design enhancement, respectively, for reducing hazmat release risk.

#### 4. Cost-effectiveness of risk reduction strategies

##### 4.1. Broken rail prevention

##### 4.1.1. Broken-rail-caused car derailment rate

Broken rails are among the most common and severe accident causes on U.S. railroads [34–36]. Due to relatively small sample of tank car derailment and release each year in the U.S. (e.g., 66 hazmat cars released in 2011 on U.S. railroads [1]), we use the number of all types of railcar derailment as a proxy to evaluate the safety effectiveness of broken rail prevention. This approach has been used in prior research assuming that the proportional reduction of hazmat car derailments is equal to the other types of railcars by broken rail prevention [22,28]. It is based on the fact that a broken rail could derail any type of railcar, regardless whether it is a hazmat car. It is assumed that the number of broken-rail-caused railcar derailments given traffic exposure follows a Poisson distribution:

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

Further, the Poisson mean ( $\lambda$ ) is assumed to follow a gamma distribution [37]:

$$p(l = m) = \frac{(h/m)^h}{\Gamma(h)} m^{h-1} e^{-(h/m)^h} \tag{8}$$

It can be proved that the marginal distribution of broken-rail-caused derailment count follows a negative binomial distribution [37]:

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

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

where  $\mu$  = expected broken-rail-caused car derailment count,  $\beta_p$  =  $p$ th parameter coefficient,  $X_p$  =  $p$ th explanatory variable,  $M$  = traffic exposure (e.g., gross ton-miles),  $\eta$  = gamma parameter (also called inverse dispersion parameter).

Eqs. (7)–(10) represent the widely used Poisson-gamma (negative binomial) regression model for estimating accident rates [37]. In this paper, we use annual rail maintenance (including rail repair and renewal) cost per track mile (adjusted to dollars in year 2008) as an explanatory variable to estimate the distribution of broken-rail-caused car derailments. The accident data are from the Rail Equipment Accident (REA) database from the Federal Railroad Administration (FRA) of U.S. Department of Transportation (U.S. DOT). The database contains information regarding all accidents that exceed a monetary threshold of damages to on-track equipment, signals, track, track structures, and roadbed [38]. This paper focuses on Class I freight railroads (each Class I railroad has 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 [39]. Annual rail maintenance cost and traffic exposure data are from Class I railroad’s annual report to the U.S. Surface Transportation Board [40]. Using the negative binomial regression model, the expected broken-rail-caused car derailment rate on Class I mainlines ( $Z_{br}$ ) is estimated as follows:

$$Z_{br} = \exp(-0.1868 - 0.3356C) \tag{11}$$

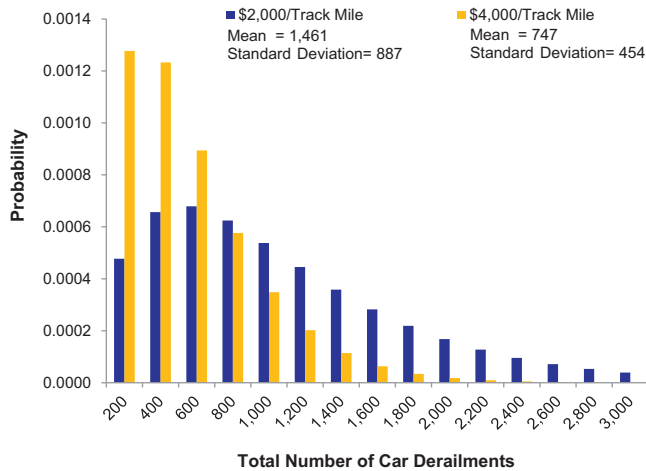
where  $Z_{br}$  = expected broken-rail-caused car derailment rate per billion gross ton-miles,  $C$  = annual rail maintenance cost per track-mile (thousand dollars) (1 ton-mile = 1459 kilogram-kilometer).

The goodness-of-fit of the regression model is evaluated by a statistic called Deviance, which asymptotically follows

**Table 1**  
Broken-rail-caused car derailment rate on U.S. Class I mainlines, 2002–2008.

| 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 (thousand dollars) | -0.3356  | 0.1101         | -0.5514               | -0.1198 | 0.0023     |
| Dispersion parameter ( $1/\eta$ )                              | 0.3682   | 0.0857         | 0.2333                | 0.5811  |            |

Deviance = 37.2 (degree of freedom = 33);  $P = 0.28 > 0.05$ .



**Fig. 3.** Probability distribution of annual number of broken-rail-caused car derailments by annual rail maintenance cost, U.S. Class I mainlines, annual traffic exposure is 3446 billion gross ton-miles (only a portion of the entire distribution is displayed).

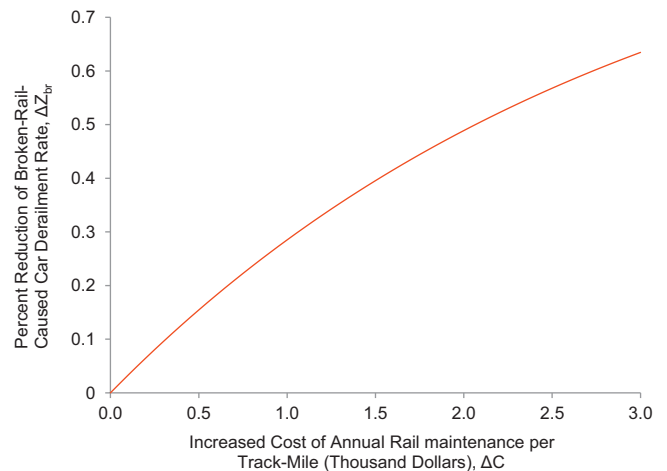
a Chi-squared distribution [37]. Based on this criterion, the model exhibits an overall acceptable fit, at 5% significance level (Deviance = 37.2, degree of freedom = 33,  $P = 0.28 > 0.05$ ). Appendix A presents the original data for the statistical analysis. In addition to normalizing annual rail maintenance cost per mile, some railroads may have the information regarding annual rail maintenance cost per tonnage. The two variables (cost per mile versus cost per ton) are highly correlated (Pearson correlation coefficient is 0.96), therefore using either one could fit the data well. Appendix B presents the model details when using rail maintenance cost per ton as the predictor variable in lieu of the cost per mile as shown in Table 1.

Table 1 shows that the expected broken-rail-caused car derailment rate declines when rail maintenance cost increases, all else being equal. The probability distribution of number of broken-rail-caused car derailments given traffic exposure and rail maintenance cost can be estimated using a negative binomial distribution:

$$P(y) = \frac{\Gamma(y + 2.7159)}{y! \Gamma(2.7159)} \left( \frac{2.7159}{2.7159 + \exp(-0.1868 - 0.3356C)M} \right)^{2.7159} \left( \frac{\exp(-0.1868 - 0.3356C)M}{2.7159 + \exp(-0.1868 - 0.3356C)M} \right)^y \quad (2.7159 \approx 1/0.3682) \quad (12)$$

where  $P(y)$  = probability that there are  $y$  broken-rail-caused car derailments given traffic  $M$ ,  $M$  = traffic exposure (billion gross ton-miles),  $C$  = annual rail maintenance cost per track-mile (thousand dollars) (1 mile = 1.609 kilometer; 1 ton-mile = 1459 kilogram-kilometer).

Fig. 3 shows the distribution of annual total number of broken-rail-caused car derailments assuming that annual rail maintenance cost ( $C$ ) is \$2000/track-mile or \$4000/track-mile, respectively, on the 160,240 track miles of U.S. Class I railroad mainlines [39]. It is also assumed that annual traffic exposure ( $M$ ) is 3446 billion gross ton-miles [39]. It shows that the higher the rail maintenance cost per track-mile, the smaller the expected number of broken-rail-caused car derailments given traffic exposure. It is probably because improved rail maintenance reduces rail failure rate, thereby reducing the probability of broken-rail-caused car derailments [41].



**Fig. 4.** Percent reduction of broken-rail-caused car derailment rate by increasing annual rail maintenance cost per track-mile.

The percent reduction of broken-rail-caused car derailment rate is an exponential function of additional rail maintenance cost (proof is in Appendix C):

$$\Delta Z_{br} = 1 - \exp(-0.3356\Delta C) \quad (13)$$

where  $\Delta Z_{br}$  = percent reduction of broken-rail-caused car derailment rate per billion ton-miles,  $\Delta C$  = increment of annual rail maintenance cost per track-mile (thousand dollars.)

The relationship between  $\Delta Z_{br}$  and  $\Delta C$  is illustrated in Fig. 4 using Eq. (13). It shows that when the investment for broken rail prevention increases to a certain level, the percent reduction of car derailment rate levels off.

This paper focuses on the overall effect of broken rail prevention, without accounting for a specific broken rail prevention technique. Further analysis is needed to analyze the variability of cost-effectiveness for different broken rail prevention techniques,

such as rail grinding or advanced rail defect detection technologies. Note that broken rails may not necessarily be the leading train accident cause in other nations. If so, the analysis herein should be properly modified to reflect the possible international difference in railway engineering and transportation.

#### 4.1.2. Proportion of broken-rail-caused car derailment ( $\lambda$ )

The analysis above is related to the percent reduction of broken-rail-caused car derailment by increasing rail maintenance cost. However, not all car derailments are caused by broken rails. In order to assess the effect of broken rail prevention on the overall accident rate due to all causes, we estimate the proportion of car derailments caused by broken rails versus other causes.

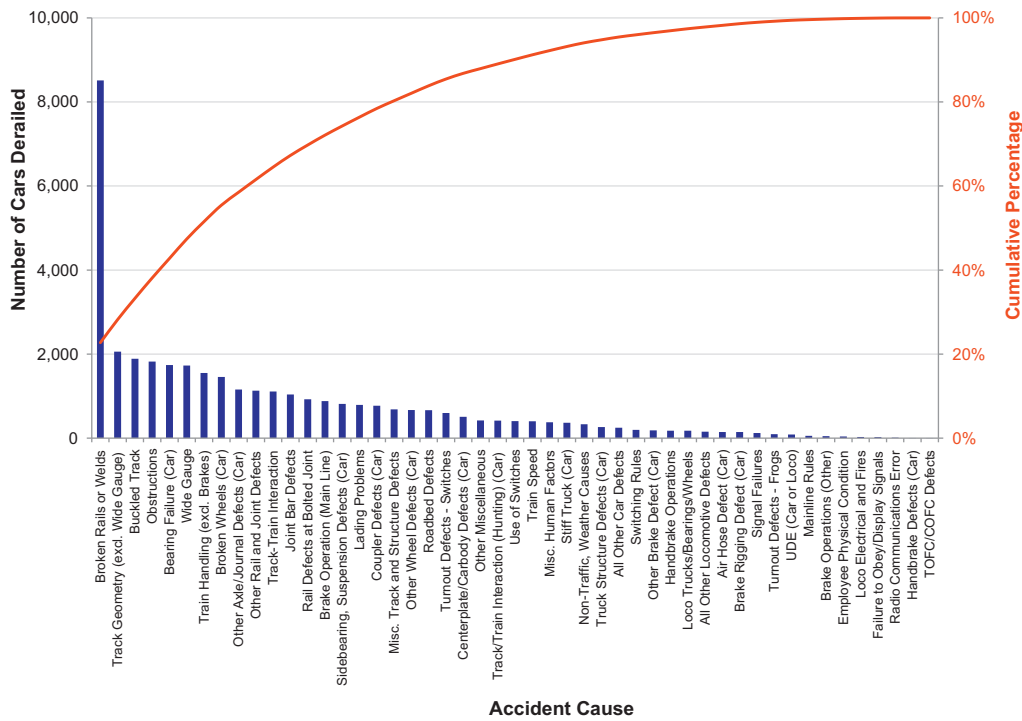


Fig. 5. Railcar derailment frequency by accident cause, Class I mainline freight-train derailments, 2001–2010 [42].

Fig. 5 shows the number of freight railcar derailment by primary accident cause for FRA-reportable freight-train derailments on Class I mainlines from 2001 to 2010. It shows that broken rails or welds accounted for 23% of railcars derailed.

The proportion of broken-rail-caused car derailment may vary by track characteristics. Each car derailment is caused by either broken rails or other causes. The probability that a car derailment is caused by broken rails can be estimated using a logistic regression model [42]:

$$P_{b|a} = \frac{\exp(\sum_k \beta_k X_k)}{1 + \exp(\sum_k \beta_k X_k)} \tag{14}$$

where  $P_{b|a}$  = probability that a car derailment is due to broken rails,  $\beta_k$  = parameter coefficient,  $X_k$  = explanatory variables associated with operating characteristics.

The following factors are considered herein. The selection of these variables is based on prior research [41–43], and communication with professionals in railway engineering.

- TrkClas (ordinal variable)
 

It represents FRA track class (1, 2, 3, 4 and 5). FRA track class is a proxy of railroad track quality by U.S. federal regulations. The higher the FRA track class, the greater the allowable maximum operating speed, and correspondingly more stringent engineering standards apply.
- MOO (dummy variable)
 

MOO = 1 indicates a signaled track territory; 0 otherwise.
- MGT (dummy variable)
 

It represents annual traffic density level on railroad tracks, measured in million gross tons (MGT). “MGT = 1” represents annual traffic density greater than 20 MGT (threshold for high-density track defined by the Associated of American Railroads (AAR) [39]), 0 otherwise.
- Season (dummy variable)
 

“Season = 1” represents a train derailment occurred in colder months between September and February, 0 otherwise.

Table 2 Statistical significance of explanatory variables.

| Variable | Chi-square | Pr > ChiSq |
|----------|------------|------------|
| TrkClas  | 1.21       | 0.8773     |
| MGT      | 3.79       | 0.0516     |
| MOO      | 24.38      | <0.0001    |
| Season   | 28.4       | <0.0001    |

Table 2 presents the significance of each variable using likelihood ratio (LR) test [37]. It shows that FRA track class (TrkClas) is not significant given the other variables. Traffic density (MGT) has a minor effect on the probability that a car derailment is caused by broken rails. Whereas, both method of operation (MOO) and climate (Season) are significant. Table 3 presents 95% confidence interval of estimated proportion of broken-rail-caused car derailments by track characteristics. It shows that a non-signaled track has a greater proportion of broken-rail-caused car derailments than a signaled track, probably due to the absence of track circuits to detect broken rails in non-signaled track territories. In addition, there is a greater probability that a car derailment is caused by broken rails during colder season (September to February), probably because of thermal contraction in rails [41].

#### 4.2. Tank car safety design improvement

##### 4.2.1. Release probability of a derailed tank car

An alternative risk reduction strategy is to reduce the release probability of a derailed tank car. Reduction of release probability can be achieved by improving tank car safety designs [3–9]. Treichel et al. [32] estimated the CPR and lading loss of a derailed tank car for almost any common or hypothetical configuration using a logistic regression. The model has been used by Barkan [7] and Saat [8] to optimize tank car safety design. Table 4 shows the CPR of two types of tank cars transporting ethanol, a common type of hazardous materials transported by rail in North America [1]. The enhanced tank car is thicker and has head protection. Thus, it is

**Table 3**

Estimated probability that a car derailment is due to broken rails, by method of operation, annual traffic density and season, Class I mainlines, 2001–2010.

| Method of operation | Annual traffic density | Season                | Mean   | 95% Confidence interval |             |
|---------------------|------------------------|-----------------------|--------|-------------------------|-------------|
|                     |                        |                       |        | Lower bound             | Upper bound |
| Non-signaled        | <20MGT                 | March to August       | 0.2862 | 0.2281                  | 0.3523      |
| Non-signaled        | <20MGT                 | September to February | 0.4779 | 0.4088                  | 0.5478      |
| Non-signaled        | ≥20MGT                 | March to August       | 0.2254 | 0.1689                  | 0.2943      |
| Non-signaled        | ≥20MGT                 | September to February | 0.3992 | 0.3245                  | 0.4789      |
| Signaled            | <20MGT                 | March to August       | 0.1455 | 0.1063                  | 0.1961      |
| Signaled            | <20MGT                 | September to February | 0.2799 | 0.2169                  | 0.3531      |
| Signaled            | ≥20MGT                 | March to August       | 0.1100 | 0.0858                  | 0.1400      |
| Signaled            | ≥20MGT                 | September to February | 0.2201 | 0.1833                  | 0.2619      |

Sample contains 6383 broken-rail-caused car derailments out of 27,516 cars derailed by all causes (including all types of empty or loaded railcars).

**Table 4**

Conditional probability of release by tank car safety design.

| Design   | Tank thickness (in.) | Shell thickness (in.) | Bottom fitting | Headshield          | Capacity (gal) | Conditional probability of release (CPR) |
|----------|----------------------|-----------------------|----------------|---------------------|----------------|--|
| Baseline | 0.4375               | 0.4375                | Yes            | None                | 32,000         | 0.2947                                   |
| Enhanced | 0.5000               | 0.4375                | Yes            | 0.5-in. half height | 31,186         | 0.2412                                   |

1 in. = 0.0254 m; 1 gallon = 3.785 l.

expected to have a lower release probability (0.2947 for baseline tank car versus 0.2412 for enhanced tank car).

Saat [8] developed a financial model to estimate the capital and operational cost for upgrading baseline tank car fleet. In this paper, we use this model to quantify the cost-effectiveness of tank car upgrade for risk reduction. The cost for upgrading baseline tank car fleet is estimated based on the following information in the U.S.:

- 29,013 ethanol baseline tank cars in the fleet [1];
- 317,370 tank car shipments annually [1];
- Average shipment distance is 926 miles [44];
- The capital cost is \$80,485 and \$84,494 (dollars in year 2008) for a baseline tank car and an enhanced tank car, respectively using Saat's model [8];
- Life cycle of a tank car is assumed to be 40 years [8];
- Annual discount rate is 5% [45].

Using Saat's model [8], the annualized cost over a 40-year period is approximately \$9.7 million if the entire ethanol baseline tank car fleet is replaced by the enhanced tank cars at once. Correspondingly, the average CPR is expected to reduce by 18.2% ( $[(0.2947 - 0.2412)/0.2947 = 18.2\%]$ ). It means that, on average, \$1 million annual investment for tank car fleet upgrade is expected to yield 1.9% reduction of release probability, all else being equal ( $18.2\%/9.7 = 1.9\%$ ). Therefore, the percent reduction of average release probability of baseline tank car fleet is a function of annual cost:

$$\Delta_{\text{CPR}} = \text{minimum}(1.9\% \times C, 18.2\%) \quad (15)$$

where  $\Delta_{\text{CPR}}$  = percent reduction of CPR of baseline tank car fleet,  $C$  = annual cost for upgrading baseline tank car fleet (million dollars).

Using Eq. (15), the relationship between percent CPR reduction and annual cost for tank car fleet upgrade is shown in Fig. 6.

## 5. Pareto-optimality between risk and cost

The analysis above shows the cost-effectiveness of different risk reduction strategies. The following optimization model is developed to determine the "optimal" portfolio of risk reduction strategies under budgetary constraints (derivation of the optimization model is in Appendix D).

*Objective function:*

$$\text{maximize } \left\{ -(1 - em) \left[ (1 - b) + \frac{P_u}{P_b} b \right] \right\} \quad (16)$$

*Subject to:*

$$-\frac{\ln(1 - e)}{0.3356} \times 160.240 + 9.7b \leq \text{Budget} \quad (17)$$

$$0 \leq e \leq 1 \quad (18)$$

$$0 \leq b \leq 1 \quad (19)$$

The objective function is to maximize the average percent risk reduction on the rail network. The decision variables are the proportion of broken-rail-caused car derailments that it is feasible to prevent ( $e$ ), and the proportion of tank car fleet to upgrade ( $b$ ). The first constraint is that total implementation cost cannot exceed the budget. The other constraints require that the decision variables are between 0 and 1.

We apply this optimization model to the 160,240 track miles on U.S. Class I mainline rail network [39]. On national average, 23% of car derailments are due to broken rails ( $\lambda = 0.23$ ) [36]. The CPR of a baseline and enhanced tank car are 0.2947 and 0.2412, respectively. A sensitivity analysis is conducted varying annual budget from \$0 to \$200 million, at an increment of \$2 million. Given the level of annual budget, the optimization model is solved by the software

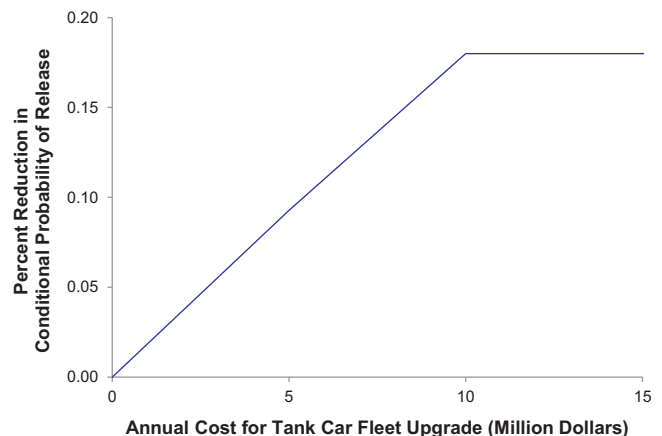


Fig. 6. Percent reduction of CPR by annual cost for upgrading tank car fleet.

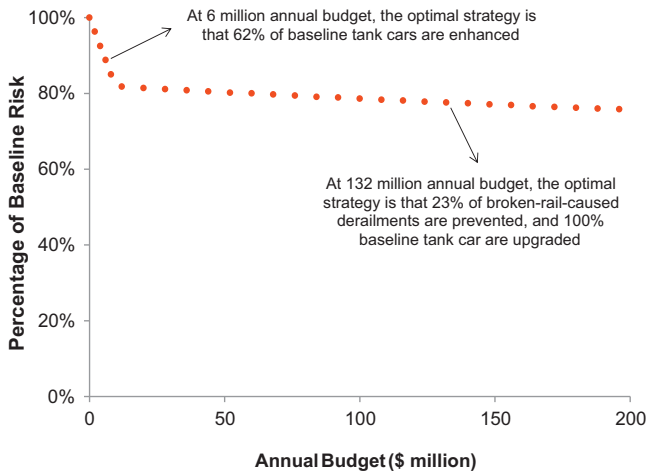


Fig. 7. Pareto-optimality of implementation of integrated risk reduction strategies.

called *General Algebraic Modeling System (GAMS)* using its built-in solver MINOS. The relationship between the minimum risk level and annual budget constructs a Pareto-optimality frontier (Fig. 7).

This paper aims to address “what strategies to invest” (objective) rather than “how to implement” (methods). For example, we estimate that 23% of broken-rail-caused car derailments should be prevented without specifying how to achieve this objective. The next step of this research is to develop an operational model to determine what technologies to implement and extent of implementation to prevent major accident causes.

### 6. Optimal investment

The risk-and-investment relationship in Fig. 7 is fitted by the following step-wise function:

$$R = g(I) = \begin{cases} 1 - 0.0184 \times I & \text{if } I \leq 9.7 \\ 0.8198 \exp(-0.0004 \times I) & \text{otherwise} \end{cases}$$

Recall the value function is  $V(R,I)=W_R R + W_I I$ . If maximum annual budget does not exceed \$9.7 million ( $I_{max} \leq 9.7$ ), it can be shown that the optimal investment ( $I^{**}$ ) is either \$0 or \$9.7 million, depending on the ratio of  $W_I$  to  $W_R$ , specifically,

$$\text{If } \frac{W_I}{W_R} > 0.0184, \quad I^{**} = 9.7$$

otherwise,  $I^{**} = 0$

If annual investment exceeds \$9.7 million, the risk decreases as an exponential function of investment. The optimal investment is determined by Eq. (5):

$$\frac{\partial g(I^{**})}{\partial I^{**}} = -\frac{W_I}{W_R}$$

$$g(I) = 0.8198 \exp(-0.0004 \times I) \text{ for } I > 9.7, \text{ thus,}$$

$$\frac{\partial g(I^{**})}{\partial I^{**}} = 0.8198 \exp(-0.0004 I^{**}) (-0.0004) = -\frac{W_I}{W_R} \quad (20)$$

Therefore,

$$I^{**} = \frac{\ln(W_I / (0.8198 \times 0.0004 W_R))}{-0.0004} \quad (21)$$

If  $I^{**}$  exceeds maximum allowable budget ( $I_{max}$ ), the optimal investment is either \$0, \$9.7 million or the maximum budget, depending on the value function. In the multi-attribute value function,  $W_I/W_R$  is numerically equal to the monetary value of one percent risk reduction. For example, if it is assumed that the decision maker is willing to invest 32 million dollars annually to achieve

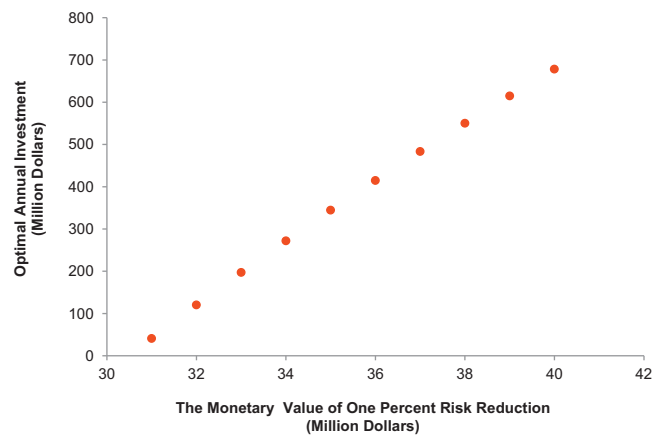


Fig. 8. Illustrative example of optimal investment by monetary value of one percent risk reduction.

1% baseline risk reduction, then  $W_I/W_R$  is equal to 0.000313 (1%/32). Using Eq. (21), the optimal investment ( $I^{**}$ ) is 120 million dollars. It means that the decision maker is willing to spend \$120 million annually to the rail network for safety improvement. Fig. 7 has shown that this investment, if used in the cost-efficient manner, is expected to reduce the baseline risk by approximately 22%. Fig. 8 shows that the optimal investment varies by the monetary value of one percent risk reduction. It illustrates that the greater monetary value per unit risk reduction, the more investment the decision maker is willing to spend for risk reduction.

### 7. Conclusion

This paper develops a framework model to optimize the integration of multiple risk reduction strategies to reduce the risk in the most cost-efficient manner. Broken rail prevention represents an accident prevention strategy to reduce tank car derailment probability, while tank car safety design enhancement affects the probability that a derailed car releases. The interactive effects among the risk reduction strategies are taken into account in evaluating the combined safety effectiveness of these strategies. The methodology presented in this paper is the first step of a larger integrated risk management framework under development. The method can be further developed and applied to a broader set of risk reduction strategies. It can be used to demonstrate how to properly analyze the integrated safety effectiveness of multiple approaches to reduce hazmat transportation risk.

### 8. Limitation of current study and future research

The intent of this research is to identify the strategic options for risk reduction, without detailing specific techniques or practices to achieve the safety goal of any specific risk reduction strategy. Future research is needed to better understand the relative cost-effectiveness of various risk reduction measures within the same strategy (for example, rail grinding versus rail inspection for broken rail prevention) under various operating conditions. Additionally, railroads need to prioritize the track segments to improve safety based on the trade-off between risk and cost, resource available, and operational characteristics. Implementation and prioritization of integrated risk reduction framework are based on extensive data. Each railroad should use their enterprise-specific data to optimize the allocation of risk reduction resources. An inter-industry collaboration between railroads, government, shippers and academia may advance the state-of-the-art in the risk management of hazardous materials transportation.

The next stage of this research is to implement integrated risk reduction strategies on representative hazardous materials routes.

When extending the analysis to a rail network involving multiple routes, network-specific optimization models can be developed to simultaneously determining the optimal routing and cost-efficient infrastructure and rolling stock improvement [46,47].

In addition to in-transit risk, the risk in the yard is also important [48,49]. Other risk reduction strategies, such as hazmat car marshaling, can be incorporated into the integrated risk reduction framework [50]. Ultimately, the risks of different modes of transportation will be evaluated and optimized to facilitate a risk-informed decision related to multi-modal transportation of hazardous materials [51].

A final note is that risk assessment addresses the probability and consequence of an event. The next stage of research is to understand how to make a sound decision based on risk analysis results. Some researchers considered risk aversion in the hazmat transportation risk management accounting for the decision maker's avoidance toward catastrophic consequences [52]. Use of utility (or disutility) model [53] might be useful in the group decision involving multiple stakeholders.

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### Appendix A. Data for negative binomial regression of broken-rail-caused car derailment rate

| Number of broken-rail-caused car derailments | Railroad indicator | Year | Annual rail maintenance cost per track-mile (\$) | Billion gross ton-miles |
|--|--------------------|------|--|-------------------------|
| 53   | A                  | 2002 | 2194   | 959                     |
| 334  | B                  | 2002 | 1729   | 469                     |
| 23   | C                  | 2002 | 1405   | 38                      |
| 35   | D                  | 2002 | 2443   | 373                     |
| 277  | E                  | 2002 | 2560   | 1086                    |
| 155  | A                  | 2003 | 2331   | 1003                    |
| 310  | B                  | 2003 | 2179   | 488                     |
| 37   | C                  | 2003 | 1019   | 37                      |
| 126  | D                  | 2003 | 2443   | 380                     |
| 449  | E                  | 2003 | 2395   | 1109                    |
| 270  | A                  | 2004 | 2614   | 1110                    |
| 165  | B                  | 2004 | 3636   | 510                     |
| 34   | C                  | 2004 | 711  | 44                      |
| 59   | D                  | 2004 | 2915   | 408                     |
| 280  | E                  | 2004 | 2434   | 1130                    |
| 200  | A                  | 2005 | 2609   | 1162                    |
| 148  | B                  | 2005 | 3421   | 504                     |
| 36   | C                  | 2005 | 535  | 54                      |
| 160  | D                  | 2005 | 3080   | 417                     |
| 352  | E                  | 2005 | 2751   | 1141                    |
| 316  | A                  | 2006 | 2986   | 1228                    |
| 237  | B                  | 2006 | 3560   | 513                     |
| 20   | C                  | 2006 | 880  | 56                      |
| 133  | D                  | 2006 | 3424   | 419                     |
| 134  | E                  | 2006 | 2991   | 1175                    |
| 77   | A                  | 2007 | 3031   | 1231                    |
| 219  | B                  | 2007 | 3618   | 496                     |
| 52   | C                  | 2007 | 1388   | 55                      |
| 153  | D                  | 2007 | 3397   | 401                     |
| 234  | E                  | 2007 | 3265   | 1155                    |
| 83   | A                  | 2008 | 3432   | 1237                    |
| 150  | B                  | 2008 | 4153   | 487                     |
| 53   | C                  | 2008 | 2773   | 54                      |
| 93   | D                  | 2008 | 2956   | 393                     |
| 155  | E                  | 2008 | 3224   | 1119                    |

**Table B1**

Broken-rail-caused car derailment rate on U.S. Class I mainlines, 2002–2008.

| Parameter  | Estimate | Standard error | 95% Confidence limits | Pr > ChiSq |        |
|--|----------|----------------|-----------------------|------------|--------|
| Intercept  | -0.0676  | 0.2859         | -0.6279               | 0.4928     | 0.8132 |
| Annual rail maintenance cost per million gross tons (thousand dollars) | -0.0056  | 0.0015         | -0.0086               | -0.0027    | 0.0002 |
| Dispersion parameter (1/η)   | 0.3307   | 0.0772         | 0.2093                | 0.5225     |        |

Deviance = 36.7 (degree of freedom = 33);  $P = 0.30 > 0.05$ .

### Appendix B. Negative binomial modeling of broken-rail-caused car derailment rate using rail maintenance cost per tonnage as the predictor variable

Compared to Table 1, using either rail maintenance cost per mile or rail maintenance cost per ton as the predictor variable would fit the data well, because of the significant correlation between these two variables (Pearson correlation coefficient is 0.96,  $P < 0.001$ ). Depending on the data available to the railroads, they may use the most appropriate predictor to estimate broken-rail-caused car derailment rate on their routes (Table B1).

### Appendix C. Proof of Eq. (13)

Let  $C_1$  and  $C_2$  represent annual rail maintenance cost per track mile (thousand dollars), respectively. It is assumed that  $C_2 > C_1$ . Let  $\Delta C = C_2 - C_1$ . The percent broken-rail-caused car derailment rate reduction is:

$$\Delta Z_{br} = \frac{Z_{br}(C_1) - Z_{br}(C_2)}{Z_{br}(C_1)} \quad (C.1)$$

From Eq. (11), broken-rail-caused car derailment rate is an exponential function of rail maintenance cost  $C$ :

$$Z_{br}(C_1) = \exp(-0.1868 - 0.3356C_1) \quad (C.2)$$

$$Z_{br}(C_2) = \exp(-0.1868 - 0.3356C_2) \quad (C.3)$$

From Eqs. (C.1)–(C.3),

$$\Delta Z_{br} = 1 - \exp[-0.3356(C_2 - C_1)] = 1 - \exp(-0.3356\Delta C)$$

So proof of Eq. (13) is completed.

### Appendix D. Derivation of optimization model (Eqs. (16) and (17))

Let  $\Delta R$  denote the percent risk reduction by preventing broken rails and enhancing tank car safety design. Let  $Z$ ,  $M$ ,  $C$  represent the national average car derailment rate per traffic exposure, traffic exposure and average release consequence, respectively. Let  $P_b$  and  $P_u$  represent the CPR of a baseline tank car and an enhanced tank car, respectively.

Broken rail prevention and tank car design enhancement affect tank car derailment rate and conditional probability of release, respectively. By definition, we have

$$\Delta R = \frac{ZMP_bC - Z_{new}MP_{new}C}{ZMP_bC} \quad (D.1)$$



It is assumed that the proportion of baseline tank car to upgrade is  $b$ , so the weighted average of CPR in the mixed tank car fleet (baseline tank car and enhanced tank car) is:

$$P_{\text{new}} = P_b(1 - b) + P_u b \quad (\text{D.2})$$

It is assumed that the proportion of broken-rail-caused car derailments that are feasible to prevent is  $e$ . In addition, the proportion of broken-rail-caused car derailments among all accident causes is  $m$ . Therefore, the overall tank car derailment rate after implementation of broken rail prevention is estimated as:

$$Z_{\text{new}} = Z(1 - em) \quad (\text{D.3})$$

From Eqs. (D.1)–(D.3),

$$\Delta R = \frac{ZMP_b C - Z(1 - em)[P_u b + P_b(1 - b)]MC}{ZMP_b C} \quad (\text{D.4})$$

Eq. (D.4) is simplified as:

$$\Delta R = 1 - (1 - em) \left[ (1 - b) + \frac{P_u}{P_b} b \right] \quad (\text{D.5})$$

To maximize percent risk reduction,

$$\text{Maximize } \left\{ 1 - (1 - em) \left[ (1 - b) + \frac{P_u}{P_b} b \right] \right\} \Leftrightarrow$$

$$\text{Maximize } \left\{ -(1 - em) \left[ (1 - b) + \frac{P_u}{P_b} b \right] \right\} \quad (\text{D.6})$$

From Eq. (13),  $\Delta Z_{\text{br}} = 1 - \exp(-0.3356\Delta C)$

Let  $\Delta Z_{\text{br}} = e$  (percent reduction of broken-rail-caused car derailment rate). So we have:

$$\Delta C = \frac{\ln(1 - e)}{-0.3356} \quad (\text{D.7})$$

$\Delta C$  is the increment of annual rail maintenance cost per track-mile, measured by thousand dollars. So total increment of annual rail maintenance cost over 160,240 track miles of U.S. Class I rail network is:

$$C_{\text{rail}} = \frac{\Delta C \times 160,240}{1000} \quad (\text{measured by million dollars}) \quad (\text{D.8})$$

Also, if the entire baseline tank car fleet is upgraded, the total annual cost is \$9.7 million. Assuming that the proportion of baseline tank car to upgrade is  $b$ , the corresponding cost is  $C_{\text{tank}} = 9.7b$ .

The total annual cost for broken rail prevention and tank car upgrade should not exceed the budget, that is:

$$C_{\text{rail}} + C_{\text{tank}} \leq \text{Budget} \quad (\text{D.9})$$

Eq. (D.9) is re-written as:

$$\frac{(\ln(1 - e)/(-0.3356)) \times 160,240}{1000} + 9.7b \leq \text{Budget} \quad (\text{D.10})$$

So the optimization model is derived.

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