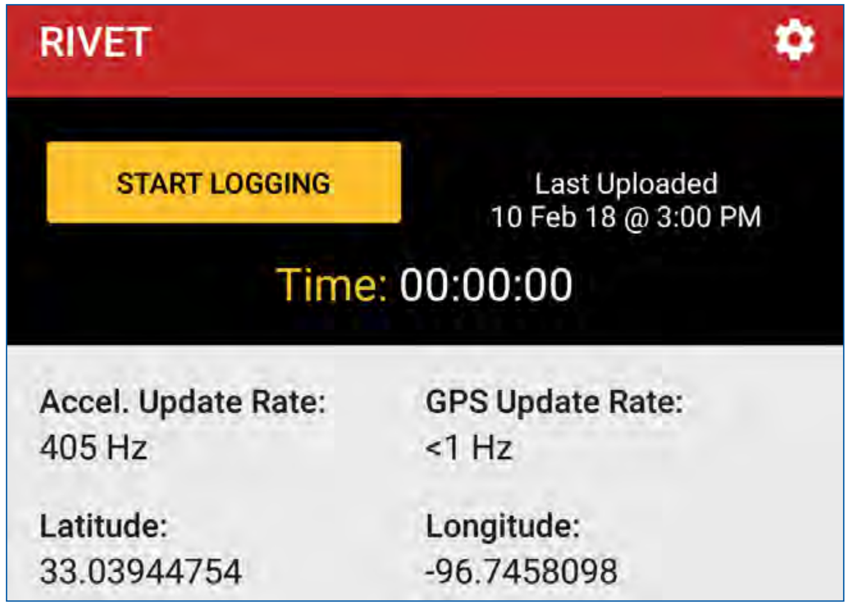
MOUNTAIN-PLAINS CONSORTIUM

MPC 21-446 | R. Bridgelall, P. Lu, D. Tolliver, N. Dhingra and B. Bhardwaj

BENEFIT COST ANALYSIS OF RAILROAD TRACK MONITORING USING SENSORS ONBOARD REVENUE SERVICE TRAINS



MOUNTAIN-PLAINS CONSORTIUM REGION 8

A University Transportation Center sponsored by the U.S. Department of Transportation serving the Mountain-Plains Region. Consortium members:

Colorado State University
North Dakota State University
South Dakota State University
University of Colorado Denver
University of Denver
University of Utah
Utah State University
University of Wyoming

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
MPC-549		

4. Title and Subtitle	5. Report Date
Benefit Cost Analysis of Railroad Track Monitoring Using Sensors Onboard Revenue Service Trains	December 2021
	6. Performing Organization Code
7. Author(s) Dr. Raj Bridgelall, Dr. Pan Lu, Dr. Denver Tolliver Neeraj Dhingra, Bhavana Bhardwaj	8. Performing Organization Report No. MPC 21-446
9. Performing Organization Name and Address North Dakota State University Upper Great Plains Transportation Institute 418 Quentin Burdick Building Fargo, ND 58102	10. Work Unit No. (TRAIS) 11. Contract or Grant No.
12. Sponsoring Agency Name and Address Mountain-Plains Consortium North Dakota State University PO Box 6050, Fargo, ND 58108	13. Type of Report and Period Covered Final Report 14. Sponsoring Agency Code

15. Supplementary Notes

Supported by a grant from the US DOT, University Transportation Centers Program

16. Abstract

Railroad accidents can cause economic harm that extends far beyond their own financial losses. As one of the most efficient modes of long-distance freight transportation, losses in line capacity and cargo due to accidents can disrupt the supply chain and lead to commodity shortages everywhere. Therefore, railroads are seeking affordable and effective safety technologies that can help to prevent accidents. However, uncertainties about the cost of those technologies and a general lack of knowledge about their potential performance are barriers to their adoption. This research applied several analytical techniques to gain insights about railroad accident characteristics and to assess the return on investment (ROI) from safety technology deployments. The techniques applied were exploratory data analysis (EDA), machine learning (ML), and benefit-cost analysis (BCA). The EDA revealed the trend that derailment accidents consistently approached 1,500 each year and that they accounted for more than 60% of the annual accidents. The EDA also revealed that the top three causes of accidents were human factors, track and roadbed problems, and mechanical failures. Annually, those causes on average accounted for 81% of the accidents. The ML revealed that derailment type accidents were statistically associated with lower track classes, non-signalized territories, and areas with restricted limits of movement authorization. The ML also revealed that derailments were typically the result of track and roadbed problems and generally not associated with human error. The BCA showed that achieving a positive ROI required railroads to seek additional ways to benefit from the deployed positive train control (PTC) system designed to reduce the risk of human-caused accidents. One such additional benefit could come from adding onboard sensors that can use the PTC network to communicate track and roadbed problems that increase derailment risks. Railroads can use the BCA models to evaluate the tradeoff in safety technology investments and payback period.

17. Key Word	18. Distribution Statement
data cleaning, exploratory data analysis, machine learning, railroad accident analysis, railroad financial losses, return on investment, sensor system price budget, technology payback period	Public distribution

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	61	n/a

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

Benefit Cost Analysis of Railroad Track Monitoring Using Sensors Onboard Revenue Service Trains

Dr. Raj Bridgelall
Assistant Professor/ Program Director
raj.bridgelall@ndsu.edu
ORCiD: 0000-0003-3743-6652

Dr. Pan Lu
Associate Professor/ Associate Research Fellow
pan.lu@ndsu.edu
ORCiD: 0000-0002-1640-3598

Dr. Denver D. Tolliver
Director
denver.tolliver@ndsu.edu
ORCiD: 0000-0002-8522-9394

Neeraj Dhingra
Research Assistant/Ph.D. Student
neeraj.dhingra@ndsu.edu
ORCiD: 0000-0002-4371-5685

Bhavana Bhardwaj
Research Assistant/ Ph.D. Student
bhavana.bhardwaj@ndsu.edu
ORCiD: 0000-0002-4379-1565

Department of Transportation, Logistic and Finance/College of Business
Mountain-Plains Consortium/Upper Great Plains Transportation Institute
North Dakota State University

December 2021

Acknowledgements

The authors extend their gratitude to the Mountain-Plains Consortium, the U.S. Department of Transportation, the Research and Innovative Technology Administration, and North Dakota State University for funding this research.

Disclaimer

ABSTRACT

Railroad accidents can cause economic harm that extends far beyond their own financial losses. As one of the most efficient modes of long-distance freight transportation, losses in line capacity and cargo due to accidents can disrupt the supply chain and lead to commodity shortages everywhere. Therefore, railroads are seeking affordable and effective safety technologies that can help to prevent accidents. However, uncertainties about the cost of those technologies and a general lack of knowledge about their potential performance are barriers to their adoption. This research applied several analytical techniques to gain insights about railroad accident characteristics and to assess the return on investment (ROI) from safety technology deployments. The techniques applied were exploratory data analysis (EDA), machine learning (ML), and benefit-cost analysis (BCA). The EDA revealed the trend that derailment accidents consistently approached 1,500 each year and that they accounted for more than 60% of the annual accidents. The EDA also revealed that the top three causes of accidents were human factors, track and roadbed problems, and mechanical failures. Annually, those causes on average accounted for 81% of the accidents. The ML revealed that derailment type accidents were statistically associated with lower track classes, non-signalized territories, and areas with restricted limits of movement authorization. The ML also revealed that derailments were typically the result of track and roadbed problems and generally not associated with human error. The BCA showed that achieving a positive ROI required railroads to seek additional ways to benefit from the deployed positive train control (PTC) system designed to reduce the risk of human-caused accidents. One such additional benefit could come from adding onboard sensors that can use the PTC network to communicate track and roadbed problems that increase derailment risks. Railroads can use the BCA models to evaluate the tradeoff in safety technology investments and payback period.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

The subsections below provide a background that motivated this research, the research objectives, and an overview of the report organization.

1.1 Background

Railroads are a critically important and efficient mode of long-distance transportation. Railroad freight movements complement those by trucks. Railroads move more than 40% of the long-distance freight volume in the United States (BTS, 2020). Whereas trucks dominate freight movements within a 500-mile band, railroads dominate freight movements beyond 1,000 miles (BTS, 2021). Based on data summarized from the freight analysis framework (FAF) of the Bureau of Transportation Statistics (BTS, 2021), Figure 1.1 shows the proportional distance distribution of ton-miles by freight mode. The trend shows that, from 750 to 2,000 miles, railroads account for the largest proportion of freight movements in ton-miles.

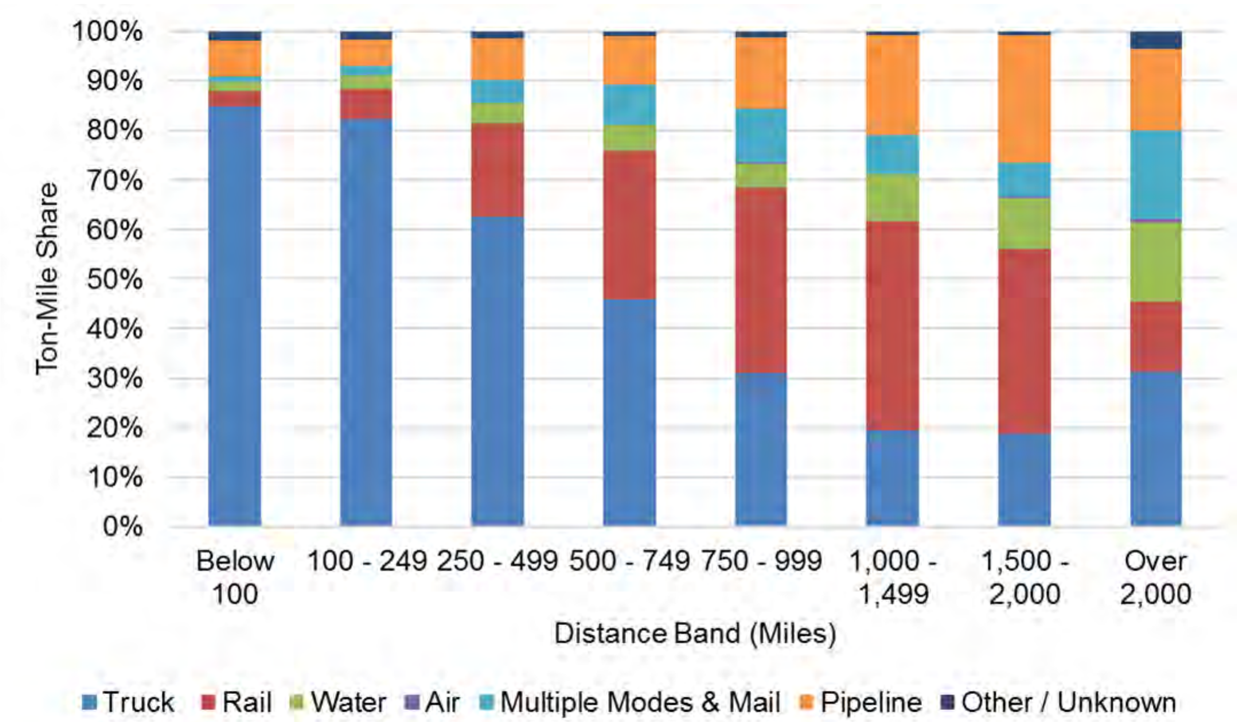


Figure 1.1 Distribution of distance traveled by freight mode

Figure 1.2 shows the trend in modal share for freight transportation in the United States (BTS, 2021). It is evident that since 1980 railroads have been steadily increasing their mode share.

The largest railroad network in North America, the Class I railroads, own and operate approximately 140,000 miles of maintenance-of-way (AAR, 2021). Figure 1.3 illustrates the North American spatial distribution of freight railroad traffic density in net tons (FRA, 2020). It is evident that, unlike roads, there are fewer alternative routes between point-to-point connections.

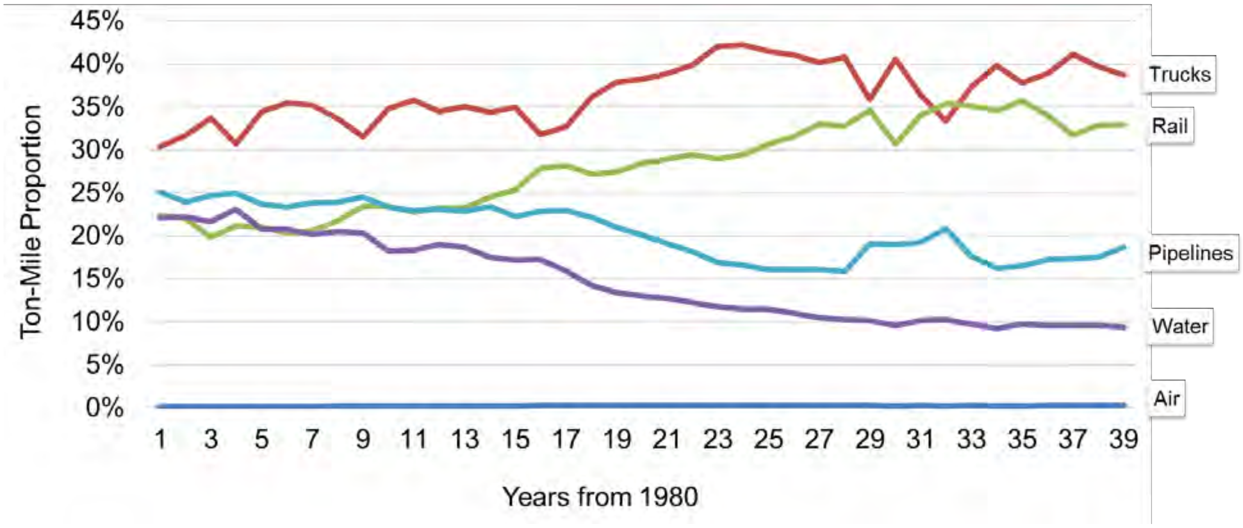


Figure 1.2 Trends in freight transportation modal share

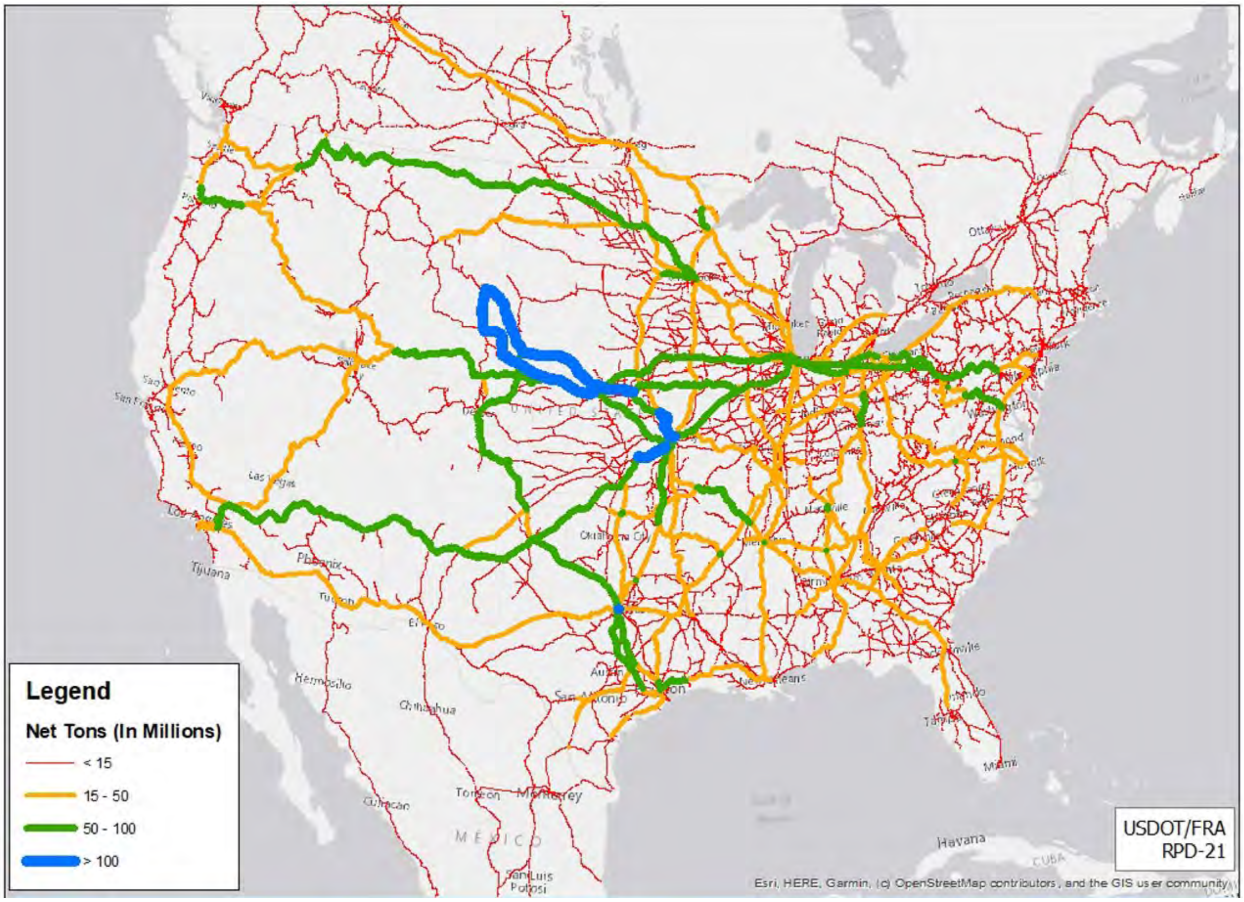


Figure 1.3 Extent of U.S. Class I railroads

Therefore, losses in line capacity due to accidents can result in significant supply chain disruption and economic harm. Data summarized from the Federal Railroad Administration (FRA) equipment accident database indicate that railroads incur more than 2,500 accidents each year (FRA, 2021). Hence, in addition to transport capacity losses in the network, railroad accidents cause financial losses, fatalities, injuries, and property damage.

1.2 Research Objectives

The **goal** of this research is to create models that railroads can use to inform investment decisions in safety technology. The main **objective** of this research is to conduct a benefit-cost analysis (BCA) to determine technology cost thresholds as a function of their potential return-on-investment (ROI). The general methodology is to:

1. Identify and clean a comprehensive database of railroad accidents
2. Assess the statistical trends of railroad accidents in terms of frequency, type, and cost
3. Identify factors associated with the dominant railroad accident type and cause
4. Assess solutions available to prevent most railroad accidents
5. Create a BCA model to help inform investment decisions in potential safety technology solutions

1.3 Organization of Content

The study begins with a literature review (Section 2) of key findings from relevant scholarly academic publications that examined accident causes and technology solutions. Next, the methods and results (Section 3) present the data sources and data cleaning (subsection 3.1); exploratory data analysis to visualize and gain insights into railroad accident trends (subsection 3.2); statistical modeling to understand key factors in accident type, cause, and financial losses (subsection 3.3); safety technologies deployed to reduce accident risk (subsection 3.4); and finally a BCA to inform technology deployment decisions (subsection 3.5). Section 4 discusses some of the limitations of this study and Section 5 concludes the work.

2. LITERATURE REVIEW

The literature review focused on two research areas: 1) accident contributor analysis, and 2) the assessment of safety-improvement technology solutions. The first category uses exploratory data analysis, data mining (DM), and ML techniques to produce insights into railroad accidents. The second category reviewed the performance assessments of various automated condition monitoring technologies and their effectiveness in reducing accident risks. These two categories of literature reviews help to highlight the potential for safety technology deployments to help prevent accidents.

2.1 Accident Contributor Analysis

Studies covering railroad maintenance and operations tend to outnumber those that cover railroad safety (Ghofrani, He, Goverde, & Liu, 2018). However, numerous studies applied ML and DM methods to reveal contributors of railroad accidents. For example, using ordered regression models, Dabbour et al. (2017) found that higher train and vehicle speeds were positively correlated with driver injury severity (Dabbour, Easa, & Haider, 2017). Using geospatial modeling techniques, Liu and Khattak (2017) found that gate violations were more highly associated with two-quadrant than with four-quadrant crossings (Liu & Khattak, 2017). Using random survival forest, Karamati et al. (2020) found that crash likelihood can decrease by 50% by adding audible alarm devices to crossings that already have gates and flashing lights (Keramati, Lu, Iranitalab, Pan, & Huang, 2020). Using extreme gradient boosting, Soleimani et al. (2019) identified highway rail-grade crossings that should be closed to prevent accidents (Soleimani, Mousa, Codjoe, & Leitner, 2019). By extracting and applying text mining methods to crash narrative data of railroad trespassing incidents, Wali et al. (2021) found that the use of headphones or cellphones was more likely to result in fatal injuries (Wali, Khattak, & Ahmad, 2021).

Liu et al. (2017) found that signalized tracks and those with higher class ratings and traffic density had fewer derailment type accidents (Liu, Saat, & Barkan, 2017). Wang et al. (2020) confirmed the expectation that the rate of derailments declined on tracks with fewer broken rails, irregular track geometry, and wheel-related equipment defects (Wang, Barkan, & Saat, 2020). Iranitalab and Khattak (2020) found that the random forest (RF) method outperformed others, such as logistic regression, Naïve Bayes, and support vector machine (SVM) in predicting the level of hazardous material (hazmat) releases (Iranitalab & Khattak, 2020). In a previous work, the authors compared the performance of multinomial logit (MNL), k-nearest neighbor (kNN), SVM, and RF to predict the crash severity of two-vehicle roadway crashes (Iranitalab & Khattak, 2017). They found that kNN and MNL performed best.

Researchers also used ML models to analyze other aspects of railroad operations (Ghofrani, He, Goverde, & Liu, 2018). Li et al. (2014) applied ML models to historical and real-time data of railroad maintenance needs to predict rules (Li, et al., 2014). Lasisi and Attoh-Okine (2019) predicted rail fatigue defects by using a combination of ensemble tree-based ML models (Lasisi & Attoh-Okine, 2019).

Text mining is emerging as another tool in accident analysis (Bala & Bhasin, 2018). Brown (2016) applied text mining to accident narratives in the FRA accident database to predict the cost of unusual railroad accidents (Brown, 2016). Williams and Betak (2019) found that the topic modeling techniques of latent semantic analysis (LSA) and latent Dirichlet allocation (LDA) were complementary in identifying the tractor-trailer trucks that are common in rail grade crossing (RGC) accidents (Williams & Betak, 2019). Soleimani et al. (2021) combined spatial analysis and text mining to identify RGCs that should be closed to prevent accidents (Soleimani, Leitner, & Codjoe, 2021).

There were also some general findings from comparing ML model performance. Olson et al. (2017) found that the performance benchmarking of ML models is subjective because of its high relevance to the target problem (Olson, Cava, Orzechowski, Urbanowicz, & Moore, 2017). Cook (2007) found that subjective performance ratings depend on the level of acceptable risk for a given application (Cook, 2007). Therefore, it becomes difficult to quantify levels of goodness unless one standardizes on a rating scheme such as the fuzzy academic grading system (Echauz & Vachtsevanos, 1995).

2.2 Assessment of Technology Solutions

Several studies evaluated the effectiveness of using onboard sensors to monitor the condition of railroad tracks (Chia, Bhardwaj, Lu, & Bridgelall, 2019). Lee et al. (2012) estimated track geometry from the lateral and vertical accelerations measured by an accelerometer mounted to the axle box and bogie of a high-speed train (Lee, Choi, Kim, Park, & Kim, 2012). With a similar goal, Mori et al. (2013) estimated track irregularities by sensing the car body dynamics with a battery-powered device (Mori, Sato, Ohno, Tsunashima, & Saito, 2013). Balouchi et al. (2020) found that their onboard track monitoring system provided good agreement with ground truth measurements (Balouchi, Bevan, & Formston, 2020).

As part of the Internet-of-Things (IoT) movement, more researchers have been evaluating the use of smartphones or smartphone-derived sensor technologies to measure car body dynamics (Fraga-Lamas, Fernández-Caramés, & Castedo, 2017). The deployment of positive train control (PTC) to enable connected trains has also increased its association with IoT (Brezulianu, et al., 2020). Paixão et al. (2019) found that smartphones can help to forecast derailment risk because of their ability to measure accelerations (Paixão, Fortunato, & Calçada, 2019). An effective sensor-based system can combine many types of sensors to detect a multitude of problems (Li, Luo, Cole, & Spiryagin, 2017). One method is to merge the data from multiple sensors by using a wireless sensor network (Hodge, O'Keefe, Weeks, & Moulds, 2014). Bridgelall & Tolliver (2020) showed how combining signals from numerous measurements across the same track segment can reduce the localization errors from GPS reception issues (Bridgelall & Tolliver, 2020).

Advancements in artificial intelligence (AI) technology subsets such as DM and ML have led to analysis of other signals, such as vibration, sound, and image sensors, to identify accident risks. Tsunashima (2019) found that applying ML to vibration signatures can help to detect track problems (Tsunashima, 2019). Farlik & Tabaszewski (2020) found that although neural networks trained on vibration signals can help to detect track problems, the approach can be sensitive to train speed (Firlik & Tabaszewski, 2020). Using SVM to analyze sound signals, Sun et al. (2020) found that the technique can be effective in predicting track switch condition (Sun, Cao, Xie, & Wen, 2020). In a similar work, Bukhsh et al. (2019) found that using tree-based classification models to predict switch maintenance needs can provide better interpretability than other methods (Bukhsh, Saeed, Stipanovic, & Doree, 2019). Sysyn et al. (2019) found that analyzing high-resolution images with ML models can be effective in detecting rail contact fatigue (Sysyn, Gerber, Nabochenko, Gruen, & Kluge, 2019). Lasisi and Attoh-Okine (2019) found that ensemble classification methods that use bagging and boosting techniques can be effective in the prediction of track defects (Lasisi & Attoh-Okine, 2019).

Although sensing and AI techniques can be effective in predicting track failures, surveys found there are still challenges to their adoption. Yet, there has been little analysis at the intersection of engineering and railroad decision-making about technology adoption. Beyond costs, there are still challenges in training, deskilling, and technology performance (Brooks, Groshong, Liu, Houpt, & Oman, 2017). In a review of emerging technologies and issues in local line inspections, Ren et al. (2021) found that smaller railroads are seeking more affordable track inspection technologies than currently exist (Ren, et al., 2021). In general, this literature review reveals the gap in model development that could help railroads trade off price, performance, and ROI for the adoption of automated onboard safety inspection technologies.

3. METHODS AND RESULTS

The overall approach of this study was to identify and clean data sources (Section 3.1), analyze the characteristics and extent of railroad accidents (Section 3.2), determine factors in accident causes and financial losses (Section 3.3), evaluate technology solutions available to help prevent railroad accidents (Section 3.4), and to develop a model to weigh the benefits and costs (Section 3.5) in adopting safety monitoring technologies.

3.1 Data

The next two subsections describe the data sources used in the analysis and the data cleaning methods to prepare the dataset for further analysis.

3.1.1 Data Sourcing

This research used the FRA equipment accident database that contained records of more than 26,000 accidents that occurred from January 1, 2009, to June 30, 2020 (FRA, 2011). Each record of the database contained 145 fields. This research also used the Topologically Integrated Geographic Encoding/Line (TIGER/Line™) shapefiles of U.S. counties from the U.S. Census Bureau to conduct spatial analysis (USCB, 2019). The data table associated with the TIGER shapefile contained 11 fields of descriptive and spatial data about each of the 3,108 continental U.S. counties.

3.1.2 Data Cleaning

Studies estimated that the use of dirty data costs the U.S. economy trillions of dollars every year (Ilyas & Chu, 2019). Data analysis techniques can also become useless when applying them to dirty data (Jesmeen, et al., 2018). There are a few common approaches to data cleaning, but every dataset has its own set of unique challenges that require custom approaches (Bridgelall, Lu, Tolliver, & Xu, 2018). Therefore, it is no surprise that data scientists spend 60% of their time on average cleaning and organizing data before further processing (Ilyas & Chu, 2019). The data cleaning methods used in this research involved the eight procedures summarized in Table 3.1.

Table 3.1 Data Cleaning Procedures

Procedure	Actions
Gap Pruning	Delete attributes with large gaps of missing values.
Correlation Filtering	Highly correlated attributes are redundant, so detect and remove those.
Feature Engineering	Combine attributes and categories to reveal new information.
Attribute Imputation	Apply various techniques to estimate or predict missing values.
Geospatial Repair	Spatially impute replacement values for erroneous geospatial coordinate entries.
Transformation	Reduce distribution bias due to the skews.
Normalization	Map all values to the [0, 1] range.
One-Hot-Encoding	Expand categories of variables to numerical features.

The *gap pruning* procedure removed attributes with large gaps of missing values, redundant variables, or irrelevant attributes. The *correlation filtering* procedure removed attributes that were highly redundant with other attributes. The *feature engineering* procedure relied on heuristics in creating data synergies by combining a few less useful variables. For example, converting the fixed fields indicating the hour, minute, and AM/PM to a continuous variable reduced the data complexity and interpretability without loss of information. Another example was that reducing the number of categories of the "CONSIST" field from 14 types to six ("freight," "passenger," "work train," "yard equipment," "cars" and "locomotives") yielded more sensible and cohesive categories that simplified the data analysis and enhanced the visualization of patterns. The *attribute imputation* procedure predicted missing values based on the mean, most frequent, or nearest neighbor in feature space (Abidin, Ismail, & Emran, 2018). It was important to fill missing values because some of the analytical techniques and mathematical methods used cannot work with missing values.

The *geospatial repair* procedure detected erroneous geospatial coordinates (latitude and longitude) based on their mismatch with the county of the accident location. Approximately 22% of the geospatial coordinates were not within the county of the accident. The systematic skew of coordinates toward the southeast was due to low-resolution data entry or rounding off the decimal coordinates of the geospatial coordinates. The repair procedure replaced erroneous coordinates with those of the nearest station if available, or with the TIGER shapefile centroid coordinates for the county where the accident occurred. Figure 3.1 illustrates the systematic error of the geospatial coordinate entries prior to the repair.

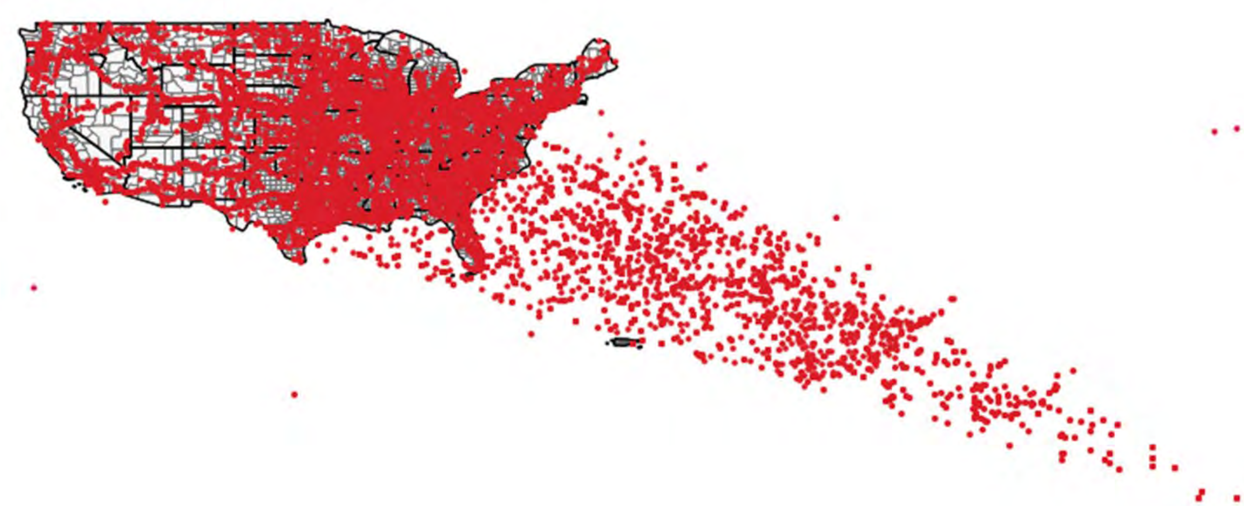


Figure 3.1 Systematic error in the geospatial coordinates of accident locations

The next set of operations helped to improve the performance of feature importance and feature ranking algorithms that used ML methods. The *transformation* procedure converted the values of highly skewed attribute distributions to reduce bias toward exceptionally large or exceedingly small values (Manning & Mullahy, 2001). The procedure used the shifted natural logarithm, LN($1 + x$), and value squaring to reduce right and left skews, respectively, of the feature distribution. The *normalization* procedure mapped all values of a continuous variable feature to the [0, 1] range. The mapping helped to improve the performance of ML models that applied gradient methods and to more easily interpret variable importance in linear regression models (Géron, 2017). The *one-hot-encoding* procedure expanded categorical variables to several binary variables that enabled the use of ML algorithms that do not operate directly with non-numerical data.

The workflow improved model generalization by removing outlier records to prevent bias from training on them. Table 3.2 summarizes the outlier removal algorithms compared and the hyperparameters selected to maximize performance. The receiver operating curve (ROC) metric and the associated area under the ROC curve (AUC) were the performance measures (Géron, 2017). The best performing algorithm was the local outlier factor with 20 nearest neighbors and 1% outliers.

Table 3.2 Outlier Removal Algorithm Selection

Algorithm	**Reference**	**Hyperparameters**	**AUC**
One class SVM	(Liu, Ting, & Zhou, 2012)	Nu: 1%, Kernel Coefficient: 0.01	0.881
One class SVM	(Liu, Ting, & Zhou, 2012)	Nu: 1%, Kernel Coefficient: 0.1	0.878
One class SVM	(Liu, Ting, & Zhou, 2012)	Nu: 10%, Kernel Coefficient: 0.01	0.879
Local Outlier Factor	(Breunig, Kriegel, Ng, & Sander, 2000)	C: 1%, Neighbors: 10, Euclidean	0.879
Local Outlier Factor	(Breunig, Kriegel, Ng, & Sander, 2000)	C: 1%, Neighbors: 20, Euclidean	0.882
Local Outlier Factor	(Breunig, Kriegel, Ng, & Sander, 2000)	C: 1%, Neighbors: 50, Euclidean	0.880
Isolation Forest	(Liu, Ting, & Zhou, 2012)	C: 0%	0.881
Isolation Forest	(Liu, Ting, & Zhou, 2012)	C: 1%	0.880
Isolation Forest	(Liu, Ting, & Zhou, 2012)	C: 5%	0.880
Covariance Estimator	(Rousseeuw & Driessen, 1999)	C: 1%	0.817

Table 3.3 lists the final set of variables after applying the various data cleaning methods. In summary, the data cleaning and transformation methods reduced the number of features from 145 to 38. The one-hot-encoding then increased the number of features used by the ML algorithms to 74. The dispersion column shown in the table indicates the amount of information spread for each attribute. The measures of dispersion for the categorical and non-categorical variables were the *entropy* and *coefficient of variation*, respectively.

Table 3.3 Data Variables Selected After Cleaning

Attribute	Dispersion	Type	Description
HC	0.672	Binary	Target attribute: 1 if the accident type was human caused
REGION	1.980	Categorical	FRA region code for accident location
LAT	0.133	Continuous	Cleaned latitude coordinate
LON	-0.129	Continuous	Cleaned longitude coordinate
CLASS_RR	0.818	Ordinal	Cleaned railroad class
MONTH	0.541	Ordinal	Incident month
DAY	0.557	Ordinal	Incident day
HR24	0.562	Continuous	Transformed time to fractional 24-hour
TEMP	0.382	Continuous	Temperature (degrees Fahrenheit)
VISION	1.130	Categorical	Visibility: {Dawn, Day, Dusk, Dark}
WEATHER	0.952	Categorical	Weather: {Clear, Cloudy, Rain, Fog, Sleet, Snow}
TRK_TYP	1.010	Categorical	Track Type: {Main, Yard, Siding, Industry}
TRK_CL	0.755	Ordinal	Track Class: {X as 0, 1 through 9}
CWR	1.280	Binary	1 if the rail type was continuously welded, 0 otherwise
SIG	1.855	Binary	1 if used signals to control train movements, 0 otherwise
MOVEx	1.120	Categorical	Movement: {Blocks, Control, Signal, Not Main, Restrict}
TRK_DEN_LG	1.027	Continuous	log(1+x) of annual track density in millions of gross tons
TONS_LG	0.846	Continuous	log(1+x) of gross tonnage, excluding power units
TRNSPD_LG	0.606	Continuous	log(1+x) of train speed in miles per hour (mph)
SPD_OVR	-1.335	Continuous	Difference between train speed and limit for track class
CONSIST	1.080	Categorical	Consist: {Freight, Locomotive, Cars, Work, Yard}
HUMANS	0.579	Continuous	Number of humans present on the train
HEADEND1	0.757	Ordinal	Number of headend locomotives
N_CARS	0.998	Ordinal	Total number of cars (sum of loaded + empty cars)
CARS_LD	0.766	Continuous	Proportion of the number of cars that were loaded (0 to 1)
CARS_HZMT	2.772	Continuous	Proportion of loaded cars carrying hazardous materials (0 to 1)
CARS	3.336	Ordinal	Number of cars carrying hazardous materials
CARSHZD	21.950	Continuous	Number of cars that released hazardous materials
ACC_TYPE	1.290	Categorical	The type of accident {derail, collide, obstruct, etc.}
CARSDMG	4.975	Continuous	Number of cars damaged or derailed
POSITON2	4.863	Continuous	Position of car on the train that caused the accident
EMPTYF2	2.926	Continuous	Number of empty freight cars that derailed
LOADF2	2.253	Continuous	Number of loaded freight cars that derailed
HEADEND2	3.340	Continuous	Number of headend locomotives that derailed
POS_CAR	0.923	Continuous	Relative position of the first involved car in the train
LOADED_1	0.929	Binary	Is first involved car loaded? Missing (22%, 6568)
ACCDMG	3.552	Continuous	Total reported damage in U.S. dollars
CASKLD	9.574	Continuous	Total killed for all involved railroads
CASINJ	20.339	Continuous	Total injured for all involved railroads

3.2 Exploratory Data Analysis

The next three sections applied EDA techniques to the FRA accident database to reveal trends in accident frequency, accident causes, accident types, and the annual financial losses from accidents.

3.2.1 Frequency of Railroad Accidents

The FRA classifies the causes of accidents into one of the following five categories (FRA, 2018):

1. **Mechanical** and electrical failures include those of axles, bearings, locomotive/truck components, wheels, and brakes

2. **Track**, roadbed, and structures that are defective such as poor track geometry, broken rail, inoperable switches/frogs, and settling roadbeds
3. **Human** factors in train operation such as poor throttling/braking, ignoring signals/rules/orders, or deficient performance due to drowsiness or illness
4. **Signal** and communications failures such as defective automatic stop device, power switch, radio, computer, and remote control
5. **Unknown** factors, which may include environmental conditions, loading procedures, or vandalism

The bar chart of Figure 3.2 summarizes the annual number of railroad accidents reported by cause. The temporal trend shows that, on average, railroads have been consistently involved in more than 2,500 accidents each year.

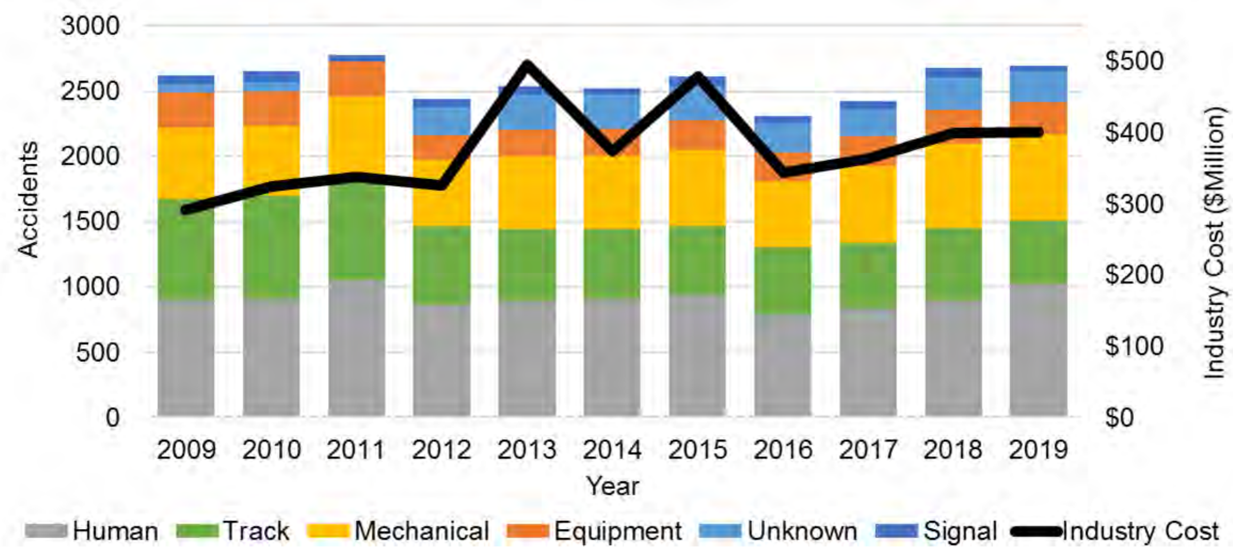


Figure 3.2 Frequency of railroad accidents by type and year, and industry cost

Each year, the number of human errors dominated accident causes, and they consistently approached 1,000 accidents. Track and roadbed problems were consistently the next dominant category of causes, followed by mechanical and equipment failures. Signal failures accounted for the fewest accidents each year. The FRA categorized accidents that did not fit into one of the known categories as miscellaneous. Overall, the trend in the number of accidents by accident cause has been consistent. Therefore, the number of accidents and their causes are likely to remain similar each year if the industry does nothing different to mitigate accident risk.

3.2.2 Types of Railroad Accidents

Different from causes, the FRA defined four categories of accident types. The categories are collisions, derailments, obstructions, and fire. Figure 3.3 is a visual summary of the four categories of FRA-defined accident types. Figure 3.4 summarizes the frequency of railroad accidents by type and year.

Figure 3.3 Accident types are a) Collisions, b) Fire, c) Derailments and d) Obstructions
Image Credit: a) (NBC Universal, 2017), b) (ABC News, 2016), c) (iStockphoto, 2021) d) (Wordsworth, 2020).

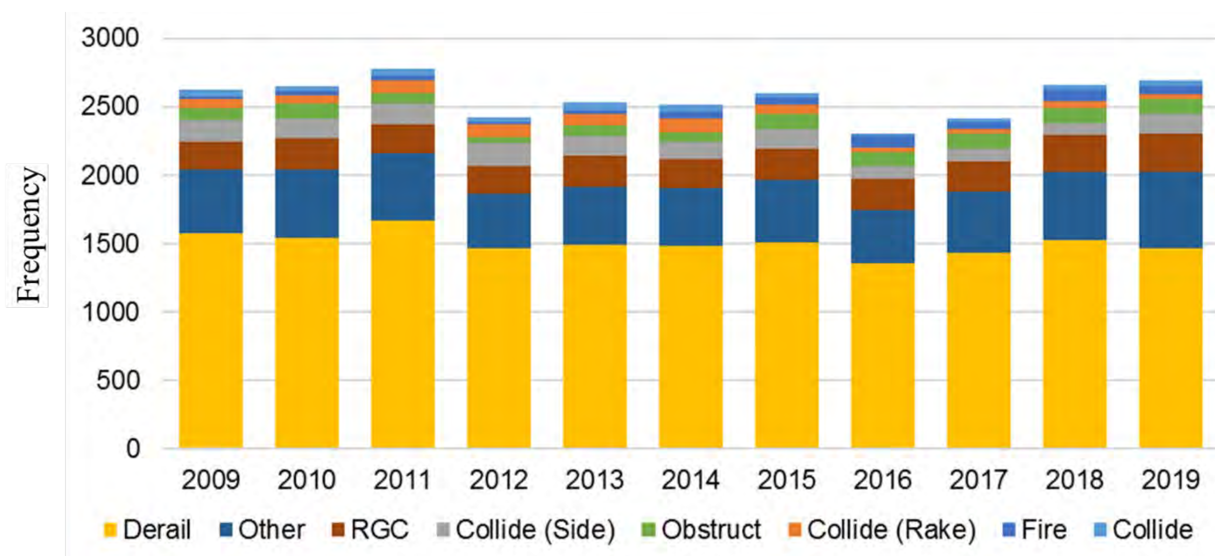


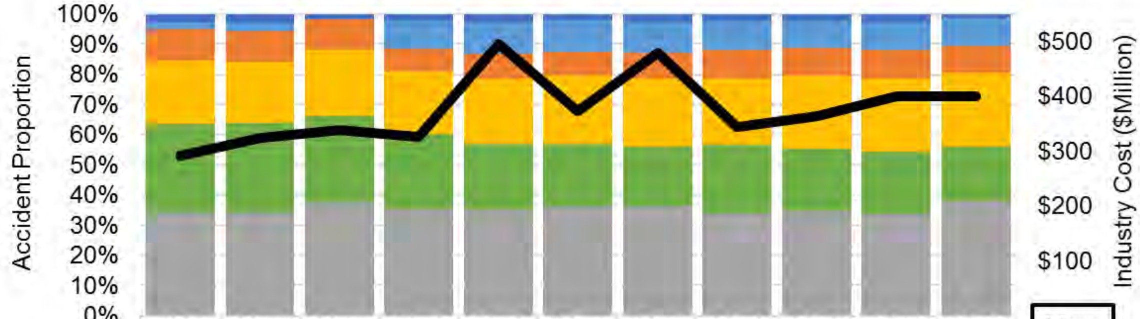
Figure 3.4 Railroad accident frequency by type and year

The FRA further subdivided the collision type accidents into the four categories of side, rake, front, and rail-grade crossing (RGC) collisions. Side collisions occur when one piece of equipment hits the side of another while moving in an orthogonal or angular direction. In contrast, rake collisions occur when one piece of equipment grazes the side of another while moving in the same or opposite direction. Front collisions occur when equipment rams into something while moving in the forward direction. Common accidents that resulted in fire were due to sparks and combustion created by oil or hazardous materials. The FRA also maintains a separate database of accidents involving RGCs.

The accident trend indicates that railroads are consistently incurring more than 1,500 derailment type accidents each year. Derailment type accidents consistently account for more than 60% of the annual accidents. Hence, solutions that can predict derailments will likely reward railroads with a larger return on their investment (Ghofrani, He, Goverde, & Liu, 2018).

3.2.3 Cost of Railroad Accidents

Figure 3.5 summarizes the proportion of accidents by cause each year. The line chart shows the trend in total monetary loss for the railroad industry. The cells at the bottom of Figure 3.5 break down the financial loss for each year by accident cause, and are shown in million-dollar units.



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean
Signal	69	81	51	60	68	53	74	58	61	72	40	2.4%
Unknown	61	72	0	218	270	262	258	219	209	247	241	7.4%
Equipment	276	263	275	188	208	201	230	219	227	255	245	9.1%
Mechanical	546	546	616	499	550	565	586	508	587	646	657	22.3%
Track	768	778	790	610	553	526	519	521	498	557	487	23.3%
Human	902	914	1047	861	893	915	945	785	838	897	1025	35.4%
Industry Cost	$291	$325	$338	$325	$495	$373	$479	$344	$364	$400	$401	$376M

Year

Human Track Mechanical Equipment Unknown Signal Industry Cost

Figure 3.5 Accident cause proportion by year and monetary loss

Overall, the trend in the number of accidents by accident cause has been consistent. On average, accidents due to human factors, track and roadbed problems, and mechanical failures account for 81% of the accidents. The top two accident causes (human factors and track/roadbed problems) account for more than half of all accidents. These results justify the focus on evaluating technology deployments that can help to reduce the risk of those accident causes.

The amount of monetary loss is generally proportional to the size of the railroad. Figure 3.6 summarizes the monetary loss by year for the top five Class I railroads in North America. The EDA results show that the largest (BNSF) and the second largest (UP) railroads together accounted for more than half of the industry's monetary loss from accidents.

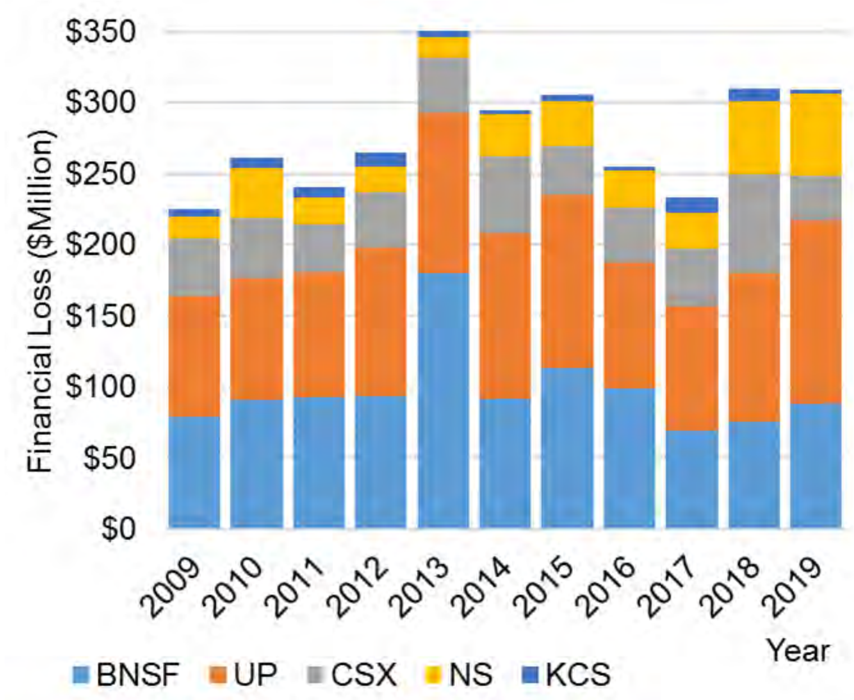


Figure 3.6 Monetary loss by year for the top five railroads in North America

3.3 Risk Factors of Railroad Accidents

Uncovering the risk factors associated with different railroad accident types and causes will help to focus on potentially high-impact technology applications that can minimize those risks. This section highlights how the AI methods of ML can build models to represent accident data and thereby reveal risk factors that are statistically significant. Section 3.1.1 discusses ML modeling that ranked factors associated with derailments, which are the dominant accident type. Section 3.3.2 discusses ML modeling that ranked factors associated with human-caused railroad accidents, which is the dominant accident cause. Section 3.3.3 discusses ML regression methods that ranked factors associated with financial losses from railroad accidents.

3.3.1 Factors in Derailment Type Accidents

This section describes the application of ML to rank features associated with derailment type accidents. Table 3.4 summarizes the unsupervised ML methods used, including references to their detailed theory of operations. All methods used normalized values for the attributes so their magnitudes could be comparable. Each method has strengths and weaknesses; hence, their rankings cannot be identical. However, when used together, some methods tended to compensate for the weaknesses of others (Wang, Khoshgoftaar, & Gao, 2010).

Table 3.4 Feature Ranking by Scoring Methods

Method	Description	Reference
ANOVA	Analysis of variance (ANOVA) measures the difference between average values of a feature in different classes of the target, based on the F distribution.	Agresti (2018) (Agresti, 2018)
Chi-Squared	Measures a dependency or association between the feature and the target class by using a chi-square statistic.	Wang et al. (2010) (Wang, Khoshgoftaar, & Gao, 2010)
Information Gain	The expected amount of entropy reduction. A decrease in entropy (uncertainty) based on the presence of other features will increase information.	Yu and Liu (2003) (Yu & Liu, 2003)
Gain Ratio	Reduces the bias of Information Gain toward features that have many values by taking the ratio of Information Gain to the intrinsic information (entropy) of the feature.	Quinlan (1986) (Quinlan, 1986)
Gini Decrease	A measure of the inequality among values of a frequency distribution based on their statistical dispersion. A value of zero and one represents perfect equality and inequality, respectively, of the distribution of a feature within each target class.	Han et al. (2016) (Han, Guo, & Yu, 2016)

Table 3.5 summarizes the ranking by each method for the top 30 features. All methods agree that track class (TRK_CL), signalized movement authority (MOVEx = Signal), speed excess, and signalized territory (SIG) are the most important features for distinguishing derailment from non-derailment type accidents. Table 3.6 lists the pairwise correlation of the rankings. The correlation coefficients ranged from 84.2% for the Gini and Chi-squared methods to 94.5% for the ANOVA and Chi-squared methods. The strong correlation is an indication that the methods generally agreed on the rank ordering, especially for the top 10 ranked attributes.

Figure 3.7 shows the probability distribution of the two accident types (derailment and non-derailment) for some of the highest-ranking features. Figure 3.7a and Figure 3.7b show the probability distribution and histogram, respectively, for the “track class” variable. Figure 3.7c and Figure 3.7d show the probability distribution for the “movement authorization” and “signalized territory” variables, respectively. The results indicate that although models can use those top variables to distinguish between derailment and non-derailment type accidents, the overlap in their distributions can lead to uncertainties. It is noteworthy that the distinction would be more statistically significant for Class I tracks because they have the highest frequency of accidents. Similarly, there is more distinguishability between the two accident types for non-signalized territories and when movements are within restricted limits.

Figure 3.8 is a box plot of the excess speed, categorized by the accident type. The results of the analysis indicate that accidents tend to be associated with speeds that are lower than the speed limits of the track classes where they occurred. However, there is a difference in both the mean and standard deviation (STD) of the speed limit for the two accident types. A student t-test indicated that the mean difference of 10 mph (16 kph) is statistically significant, based on a p-value of nearly zero. That is, derailment type accidents tend to be associated with speeds that are closer to the speed limit and with higher certainty than those of non-derailment type accidents. The box plot shows the mean and STD with solid vertical and horizontal lines, respectively. The line that extends to the x-axis indicates the median values. The solid box visualizes the range of values spanning from the first to the third quartiles.

The finding that derailments are more strongly associated with lower track classes makes sense because railroads classify those tracks as higher risk and, thus, lowered their speed limit. Similarly, the stronger association of derailments with non-signalized territories and restricted limits of movement authorizations also align with their higher risk association.

Table 3.5 Feature Importance Ranking

Feature	ANOVA	χ^2	Info. Gain	Gain Ratio	Gini
TRK_CL	1	2	4	3	2
MOVEx=Signal	2	3	3	1	4
SPD_OVR	3	1	7	11	3
SIG	4	4	5	2	5
HUMANS	5	7	6	10	6
TRK_TYP=Main	6	5	9	6	7
CWR	7	6	1	8	8
MOVEx=Not Main	8	11	11	9	11
LOCOS	9	9	10	12	9
CONSIST=Cars	10	8	14	4	12
TRK_TYP=Industry	11	10	12	7	14
TRK_TYP=Yard	12	16	2	18	16
TONS_LG	13	14	15	20	17
CARS_LD	14	18	13	19	13
CONSIST=Yard	15	15	18	17	19
N_CARS	16	12	28	16	10
MOVEx=Restrict	17	17	26	15	20
LAT	18	20	22	32	22
TEMP	19	22	24	30	21
TRK_TYP=Siding	20	21	25	13	24
VISION=Dark	21	24	21	24	25
CLASS_RR	22	13	30	14	15
TRK_DEN_LG	23	19	20	22	18
REGION=7.0	24	23	19	21	26
VISION=Day	25	31	29	35	27
REGION=8.0	26	26	27	23	28
REGION=6.0	27	27	23	28	29
REGION=2.0	28	28	33	25	30
TRNSPD_LG	29	25	37	5	1
REGION=3.0	30	29	31	31	31

Table 3.6 Correlation of Ranking Methods

Method A	Method B	Correlation
ANOVA	Chi-Squared	0.945
ANOVA	Info. Gain	0.897
Gain Ratio	Gini	0.843
Gini	Chi-Squared	0.842

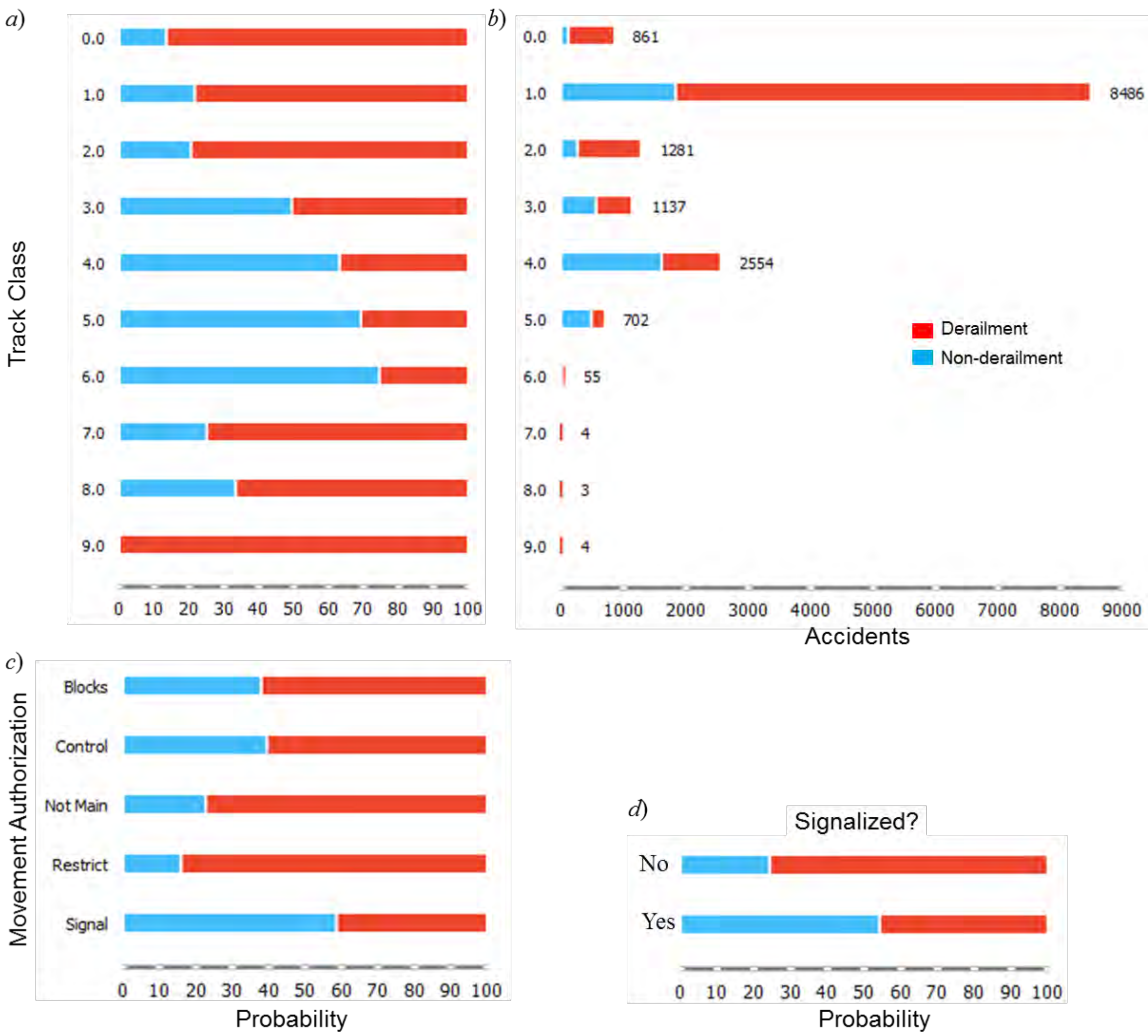


Figure 3.7 Class probability for the top two and fourth ranking attributes
Source: (Bridgelall & Tolliver, 2021)

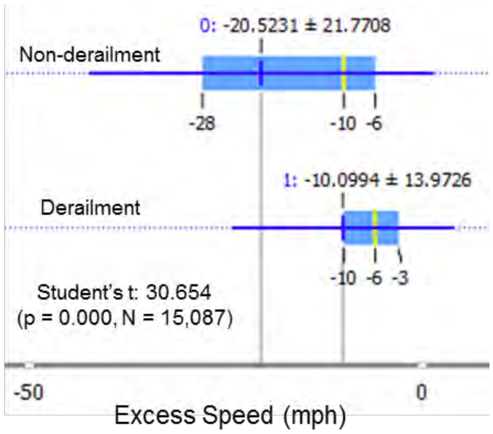


Figure 3.8 Distribution and statistics for excess speed
Source: (Bridgelall & Tolliver, 2021)

3.3.2 Factors in Human-Caused Accidents

Data mining the FRA equipment accident database showed that human error caused more than 35% of the accidents that occurred from 2009 to 2019 (Figure 3.9).

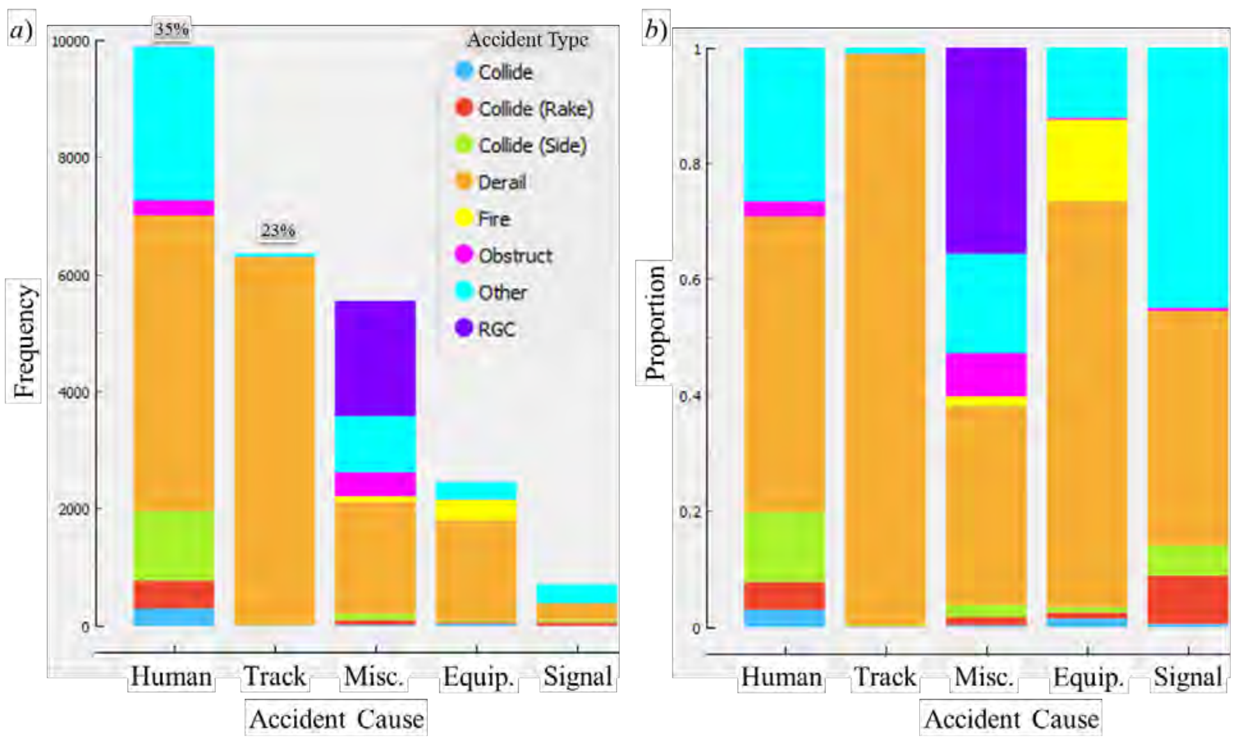


Figure 3.9 Accident cause a) frequency and b) proportion

Figure 3.9 shows that after human-caused accidents, the next dominant category was track and roadbed problems, which accounted for 23% of the accidents. Figure 3.9a and Figure 3.9b summarize the accident causes by frequency and proportion, respectively. The patterns indicate that derailment type accidents, which were dominant, accounted for approximately half of the human-caused accidents, but they accounted for nearly all the accidents due to track and roadbed problems.

The statistical association between derailment type and human-caused accidents is not easy to see in the bi-factor distribution charts because all accident causes were associated with some proportion of derailments. A *classification* ML model representation of the data provided further insights by ranking the features based on their contribution toward correctly predicting the target class of derailment from non-derailment type accidents. Each type of classification model has advantages and disadvantages. The best performing model depends on the nature of the dataset and the target variable. Table 3.7 summarizes the ML models built to represent the accident data and to provide insights. The table summarizes the theory of operations, the main hyperparameters tuned, and their key advantages and disadvantages. This research used four broad types of models, which included 11 different classification ML models of data representation.

Table 3.7 ML Models Built to Represent the Accident Data

Type	Model	Algorithm & Hyperparameters	Advantages and Disadvantages
Tree-Based Methods	Decision Tree (DT)	Recursive tree node splitting to maximize the purity of sub-trees. HP: Minimum number of instances in leaves (N), and minimum size of subsets (S).	A: Simple to interpret and to visualize. Works with non-numerical categorical attributes. D: Tends to overfit, resulting in low predictive power on new data.
	Random Forest (RF)	Build many full trees for voting. Each tree grows from a bootstrapped dataset and a random subset of attributes. HP: Number of trees (*N*) and minimum size of subsets (S).	A: Offers the simplicity and intuition of decision trees but with less tendency to overfit, therefore, improves generalization on unseen data. D: Incomplete trees diminish insights that full trees might otherwise provide.
	AdaBoost (AB)	Sequentially build improved shallow trees for voting. HP: Number of estimators (*N*), learning rate (*R*), boosting algorithm, and regression loss function.	A: Selects only those features that improve predictive power, hence, reducing the computational burden for datasets with very large dimensionality. Less sensitive to overfitting. D: Sensitive to the presence of outliers and data with high incoherence.
	Extreme Gradient Boost (XGB)	A highly configurable version of gradient boosting. HP: Number of estimators (N), learning rate (*R*), maximum tree depth (*S*), loss function.	A: Improved performance over gradient boosting and more efficient. D: Sensitive to hyperparameter selection; requires manual intervention to achieve the best configuration for a given dataset.
	Gradient Boost (GB)	Sequentially build improved models that fit the errors of previous models. HP: Number of estimators (N), learning rate (*R*), maximum tree depth (*S*), loss function.	A: Efficient and good performance on large datasets; inherently supports missing values. D: Sensitive to hyperparameter selection but has fewer to tune than extreme gradient boosting.
Statistical Models	*k*-Nearest Neighbors (*k*-NN)	Determine the class of an instance based on the majority class of its k nearest neighbors. HP: Number of neighbors (*k*), distance method.	A: Method simplicity. D: Sensitive to a skewed class distribution. The computational intensity grows exponentially with the number of instances and attributes.
	Naïve Bayes (NB)	Applies Bayes theorem to determine the class probability, given probabilities of the observations. HP: None	A: Fast and simple method. D: Poor performance when attributes are not independent.
Decision Boundaries	Logistic Regression (LR)	Establish a decision boundary by using a logistic function to maximally separate classes. HP: Regularization function and strength (C), and probability threshold.	A: Inherits many of the advantages of linear regression; precisions are easy to make. D: Sensitive to noise in the data such as outliers and incorrectly classified instances. Model fitting may fail to converge if there are many highly correlated features.
	Support Vector Machine (SVM)	Establish a decision boundary by finding a multidimensional hyperplane to maximally separate classes. HP: Kernel type, cost (C), and regression loss (ε)	A: High accuracy with low computational complexity. D: Sensitive to noisy data and multidimensional planes that lack clear boundaries.
Learned Functions	Stochastic Gradient Descent (SGD)	An optimization technique that fits a linear multivariate function to the data. It works best when all features are scaled. HP: Loss function, learning rate method and parameters.	A: An efficient technique on large datasets. D: Sensitive to feature scaling; many hyperparameters; and the true minima may not be achieved because the gradient is only an approximation.
	Artificial Neural Network (ANN)	A weighted multilayer linear network that represents a function. HP: Hidden layer neurons (N), solver type, regularization parameter (α), number of iterations (I).	A: Accuracy improves with use and feedback about classification accuracy. D: Requires many training examples to improve classification accuracy.

Feature ranking followed building all the ML models and selecting the best performing one, which was the extreme gradient boosting (XGB) algorithm. Figure 3.10 illustrates the results of feature ranking using the XGB algorithm.

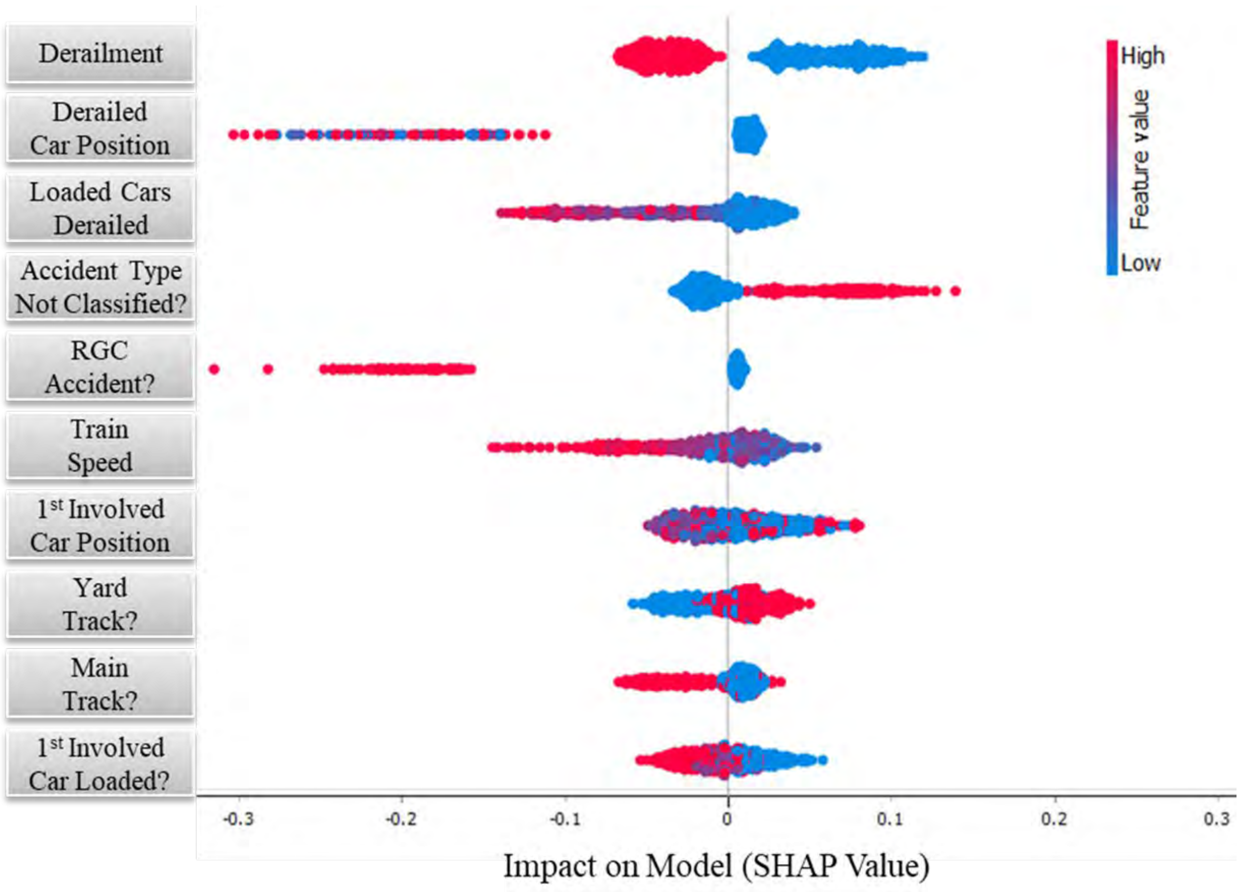


Figure 3.10 Factors that impact the prediction of human-caused railroad accidents

The Shapely (SHAP) value is a measure of how much a feature impacts the model's predictive performance (Štrumbelj & Kononenko, 2014). In this case, the predictive performance was the model's ability to distinguish between derailment and non-derailment type accidents. The SHAP value is

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!} [v(S \cup \{i\}) - v(S)] \tag{1}$$

where $|S|$ is the number of non-zero features from a subset of N features and $v(S)$ is the proportion of their collective contribution toward a prediction. Hence, the marginal contribution of feature $\{i\}$ is $v(S \cup \{i\}) - v(S)$.

Positive and negative impacts are SHAP values greater than or less than zero, respectively. The chart ordered the features by their global SHAP value on the vertical axis. The *local* SHAP value is the proportional impact of that feature for a given data instance. Each dot in the chart represents a data instance where the color code is its value relative to the mean value for that feature. The chart stacks dots within impact bins. Therefore, a thicker portion of a blob indicates that more data instances have that SHAP impact value than a value at a thinner portion of the blob.

A general rule of thumb for interpreting the chart is that it lists factors in the order of their *global* SHAP influence on the predicted outcome. The factor at the top of the chart ranks highest in influence. The relative amount of extension to the left or right of the zero vertical axis indicates the relative *local* influence of that factor on the predicted outcome. Values that extend to the right and left are associated with positive and negative predicted outcomes, respectively. The values associated with positive or negative influences are color coded on a continuous scale from zero to one with a mean value of 0.5.

The results indicate that, statistically, derailment type accidents are generally *not* associated with human-caused accidents because a low value for the binary feature "derailment" is associated with a positive impact and vice versa. This finding suggests that systems designed to identify derailment risks can complement those designed to prevent accidents due to human error. Another result of the SHAP analysis was that yard tracks are generally associated with human-caused accidents because mostly high values of the binary feature "Yard Track?" are associated with positive impacts. Similarly, mostly unloaded cars are associated with human-caused accidents.

3.3.3 Factors in Monetary Losses from Railroad Accidents

This section summarizes the analysis of 15 years of railroad accident data from 2003-2017 to produce insights about the major factors associated with financial losses from accidents. The first step was to represent the data with several different types of ML regression models and then to select the model that provided the least error in predicting financial loss. Subsequently, regression with the best predictive model revealed the ranking of factors based on their influence on the prediction accuracy for financial loss.

The models selected were based on their past performance on non-linear and highly imbalanced datasets. The regression models were random forest (RF), K-nearest neighbor (KNN), support vector machines (SVM), stochastic gradient boosting (SGB), extreme gradient boosting (XGB), and stepwise linear regression (SLR). Model training used cross-validation with 10 folds and three repeats to improve their generalization. Table 3.8 summarizes the theory of operations and the advantages and disadvantages of the *regression* ML models compared.

The performance metrics evaluated were the root-mean-squared error (RMSE), mean absolute error (MAE), and R-squared. R-squared represents the proportion of variability in the dependent variable explained by the variability in the set of independent variables. Hence, higher R-squared values are associated with better performing models. MAE reflects the average magnitude of the absolute error. Hence, a lower MAE value is associated with a better performing model. RMSE is the square root of the mean squared differences between predicted and actual values. If the error distribution is symmetric, then the RMSE is a more reliable metric than the MAE (Aggarwal, 2015).

To simplify the modeling, preliminary regression analysis revealed those variables that did not contribute to the prediction accuracy of monetary loss, so the workflow dropped those. Table 3.9

lists the final set of features used to build the regression model. The dependent variable was the accident damage (ACCDMG) amount in dollars.

Table 3.8 ML Regression Methods Compared

Method	Theory of Operation	Advantages (A) and Disadvantages (D)
k-Nearest Neighbor (KNN)	The predicted value is based on the average output of the *k* most similar instances within the entire dataset. The measure of similarity is often the Euclidean distance based on all the features.	A: no explicit training required. D: computationally intensive because of the repeated comparisons.
Random Forest (RF)	Bootstrapping and aggregation (bagging) is a fundamental operation of the RF method (Breiman, Bagging predictors, 1996). The algorithm builds an ensemble of trees by randomly sampling the same dataset with replacement. The trees are diverse because the algorithm uses a random subset of features for splitting each node. Unlike the boosting method that grows successive trees to reduce the errors made by previous trees, the trees grown by RF grow independently (Breiman, Random Forests, 2001). The predicted result is based on the majority vote of the ensemble.	A: robust against overfitting because of tree diversity and majority voting. D: harnessing the power of randomness and voting works best with large balanced datasets.
Stochastic Gradient Boosting (SGB)	Boosting combines the predictions of many weak learners in an ensemble (Schapire & Singer, 1998). Gradient boosting fits successive trees to the residuals of the previous trees in a manner that minimizes the residuals with each iteration. In this formulation, the gradient is the residual. The stochastic part is based on randomness incorporated into the boosting algorithm, such as randomly sampling the data to build trees (Friedman, 2002). The predicted value is a weighted sum of the individual weak learners.	A: Diversity of weak learners helps to prevent the overfitting tendencies of full decision trees. D: small datasets may not support the leverage of randomness and boosting.
Extreme Gradient Boosting (XGB)	The extreme in XGB refers to an extension of SGB that imposes additional controls to minimize tendencies toward overfitting (Mousa, Bakhit, Osman, & Ishak, 2018).	A: The algorithm was demonstrated to perform well in applications with noisy datasets (Chen & He, 2014). D: many hyperparameters to tune.
Support Vector Machine (SVM)	The algorithm seeks a decision boundary in multidimensional feature space that maximally separates the data (Mountrakis, Im, & Ogole, 2011).	A: tends to generalize well with limited training samples. D: high sensitivity to noisy datasets that lack clean feature space boundaries among the targets.
Stepwise Linear Regression (SLR)	Regresses multiple variables in many stages by successively adding and removing predictor variables in a linear regression to maximize predictive performance.	A: can reduce the feature set size. D: computationally intensive.

Table 3.10 summarizes the performance metric for each regression model. The XGB method provided the best predictive performance based on both the RMSE and R-squared metrics. The XGB model then explained the importance of each independent variable based on three metrics. The gain percentage was the relative amount of information gained by splitting the decision tree on that variable. Hence, relative variable importance was proportional to the gain percentage. Cover was an indicator of the relative number of observations associated with that variable

during the model building. Frequency was the proportional number of times that the model used that variable to generate trees.

Table 3.11 summarizes the feature importance ranking and Figure 3.11 provides a visualization based on the gain percentage. The results indicate that train weight (TONS) followed by train speed (TRNSPD) and track density (TRKDNSTY) are the principal factors associated with monetary loss. This result makes sense because accidents involving trains that carry more freight (value), travel faster (throughput), and use tracks with higher traffic (capacity) are most likely to result in higher financial losses.

Figure 3.12 shows the marginal effect of each variable on monetary loss for a range of values. The “yhat” variable is the monetary loss predicted for a range of values of the indicated independent variable while the XGB regression model maintains the values of the other variables at their mean value. Hence, the plots revealed the values of each independent variable where the monetary loss peaked. The results indicate that train weight and speed at approximately 20,000 tons and 105 mph, respectively, were associated with peak financial losses. Longer trains of 120-130 cars were also associated with peak financial losses; this finding agrees with the findings of other studies (Ii & Barkan, 2008).

Table 3.9 Variables of the Regression Models

Variable	Label	Description
IMO	Month	Month of incident
TIMEHR	Time of incident	Time of the incident in military format
CARS	Number of cars	Total number of cars carrying hazmat
TEMP	Temperature	In degrees Fahrenheit
TRNSPD	Speed of train	In miles per hour
TONS	Gross tonnage	The weight carried, excluding power units
TRKCLAS	FRA track class	Track class from 1 to 9, X
TRKDNSTY	Annual track density	Gross tonnage in millions
ACCDMG	Financial damage	Total reportable damage in dollars (dependent variable)
Precipitation	Weather condition	1 if conditions were either rainy, sleety, or snowy, 0 otherwise
Fog	Weather condition	1 if conditions were foggy, 0 otherwise

Table 3.10 Model Performance Evaluation

	MAE	RMSE	R-Squared
SGB	145,198.96	619,746.97	0.07
KNN	152,738.79	681,613.91	0.02
SVM	131,923.65	627,625.37	0.06
RF	143,636.45	610,262.40	0.12
XGB	132,698.43	606,608.90	0.13
SLR	153,611.97	621,920.75	0.06

Table 3.11 Feature Importance Ranking

Feature	**Gain (%)**	**Cover**	**Frequency**
TONS	0.5536	0.2618	0.4114
TRNSPD	0.2750	0.4069	0.2477
TRKDNSTY	0.0515	0.1816	0.1103
IMO11	0.0506	0.0034	0.0383
TIMEHR	0.0477	0.0158	0.0657
CARS	0.0065	0.0112	0.0303
TRKCLAS4	0.0050	0.0892	0.0563
IMO9	0.0043	0.0000	0.0003
IMO5	0.0041	0.0039	0.0177
TRKCLAS7	0.0011	0.0253	0.0140
TEMP	0.0006	0.0009	0.0080

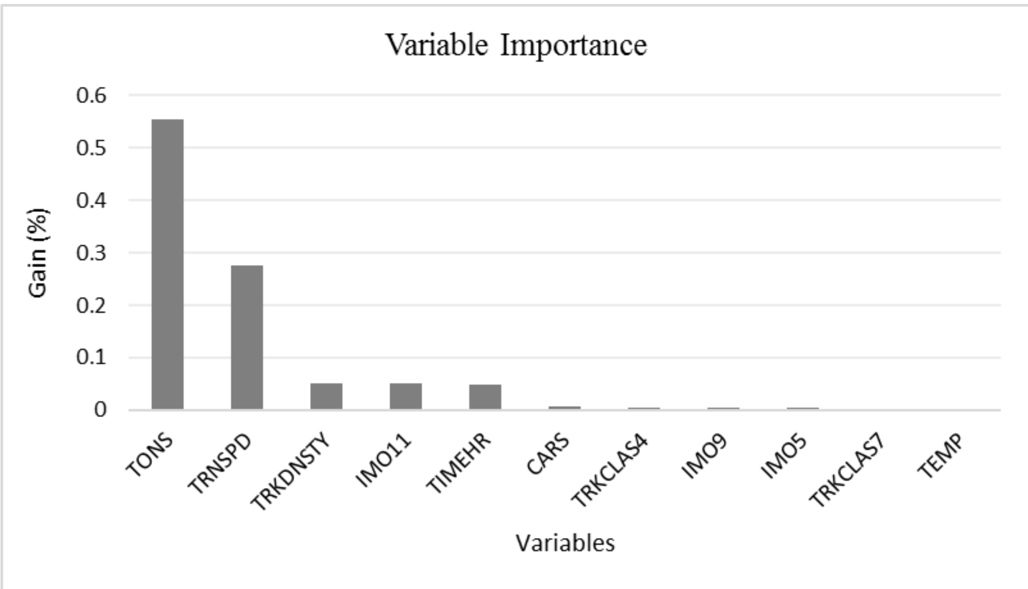


Figure 3.11 Feature importance ranking in monetary loss
Source: (Dhingra, Bridgelall, Lu, Szmerekovsky, & Bhardwaj, 2019)

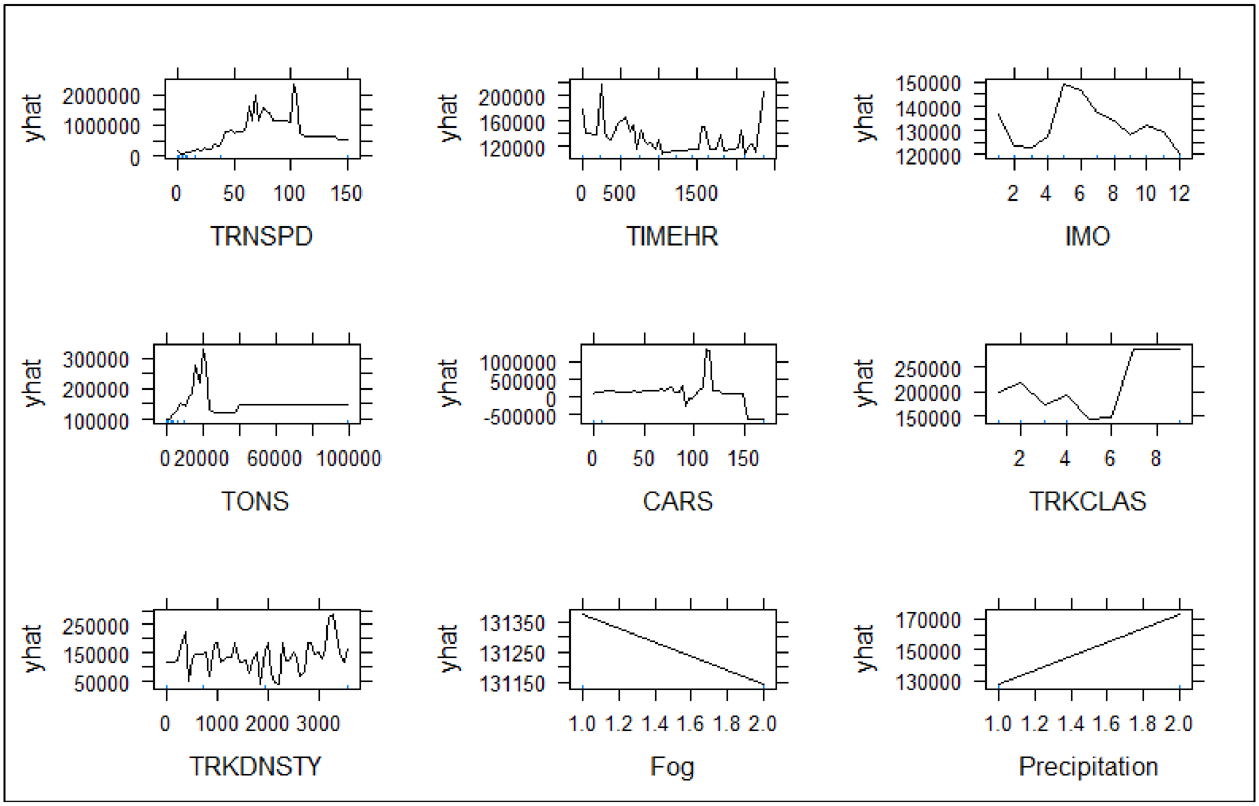


Figure 3.12 Marginal effect of factors in financial losses
Source: (Dhingra, Bridgelall, Lu, Szmerekovsky, & Bhardwaj, 2019)

The marginal effect showed that higher track classes were associated with peak financial losses, which agreed with other findings that crash risk increased with track class because the speed limit increases with track class (Liu, Barkan, & Saat, 2011). The model also suggested two temporal factors that influenced financial losses. The first was that financial loss tended to peak between 11 PM and 5 AM, which appears to correlate with other findings that fatigue (Filtness & Naweed, 2017) and lack of sleep (Naweed, Rainbird, & Chapman, 2015) were primary accident causes. The second factor was that financial losses tended to peak in the warmer months, which correlates with peaks in traffic due to harvest shipping and favorable track conditions.

3.3.4 Endnote

The following publications from this project provide more in-depth analytical details and theoretical expansions of the matter reported in this section:

Journal Article

1. Bridgelall, R., & Tolliver, D. (2021). “Railroad Accident Analysis Using Extreme Gradient Boosting.” *Accident Analysis and Prevention*, 156(2021). DOI: 10.1016/j.aap.2021.106126, 2021(106126).

Conference Proceedings

1. Dhingra, N., Bridgelall, R., Lu, P., Szmerekovsky, J., & Bhardwaj, B. (2020). “Ranking Risk Factors in Financial Losses from Railroad Incidents: A Machine Learning Approach.” In *61st Annual Transportation Research Forum*.
2. Dhingra, N., Bridgelall, R., Lu, P., Szmerekovsky, J., & Bhardwaj, B. (2019). “Using Data Mining Methods to Rank the Importance of Factors in Railroad Accidents.” In *Proceedings of the 98th Annual Meeting of the Transportation Research Board*. 19-01768, http://amonline.trb.org/
3. Dhingra, N., Bridgelall, R., Lu, P., & Bhardwaj, B. (2019, October). “Text Mining Railroad Accident Narratives for Identifying Contributors to Railroad Accidents and to Extend the Sustainability of Fixed Field Data.” *INFORMS Annual Conference*, Seattle, Washington.

3.4 Railroad Accident Prevention Technologies

The next two subsections discuss technologies designed to minimize the risk of the two dominant accident causes. Section 3.4.1 discusses PTC, which is designed to help prevent accidents due to human-error. Section 3.4.2 discusses evolving onboard track condition monitoring technologies, which aim to help prevent accidents due to track and roadbed problems.

3.4.1 PTC to Prevent Human-caused Accidents

PTC is a sensing and communication network designed to help prevent accidents caused by human error (GAO, 2010). The PTC system can sense and communicate the location, speed restrictions, and moving authority of trains. Therefore, the system should be able to prevent train collisions, derailments due to speeding or incorrect switch lining, and movements into unauthorized territories (Badugu & Movva, 2013). In theory, the system can take over and stop a train if the operator fails in their responsibilities (FRA, 2018). An analysis by the Government Accountability Office (GAO) in 2010 suggested that a PTC deployment could have prevented 49% of the accidents that occurred between 2000 and 2009.

The Rail Safety Improvement Act of 2008 (RSIA08) mandated PTC deployments for the major freight and passenger railroads in North America. The RSIA08 mandated the following installments:

1. Class I lines and those lines used to transport poisonous- or toxic-by-inhalation (PIH/TIH) materials
2. The main lines of any railroad that operates regularly scheduled intercity passenger or commuter rail

The above requirements resulted in an installation scope of 41 railroads consisting of seven Class I freight railroads, 30 commuter and intercity passenger railroads (Amtrak included), and four short line and terminal railroads (FRA, 2018). The FRA determined that the scope of deployment covered approximately 60,000 route miles of the 140,000-mile railroad network, and 20,000 locomotives. The federal mandate required the completion of PTC implementations by 2015, but the deadline had to be extended several times to accommodate deployment and interoperability issues (AAR, 2018). The first extension was to 2018 and the second was to 2020. The FRA had initially approved and certified 10 different types of PTC systems during the first extended implementation deadline year (FRA, 2018). However, only one of the seven U.S. Class I railroads achieved interoperability with some of their tenant railroad PTC deployments by that time (FRA, 2018). Yet, by the end of that year, only 29% of their tenant railroads achieved interoperability.

Figure 3.13 shows the implementation architecture of a typical PTC deployment (Bridgelall, King, Huang, Tolliver, & Lu, 2019).

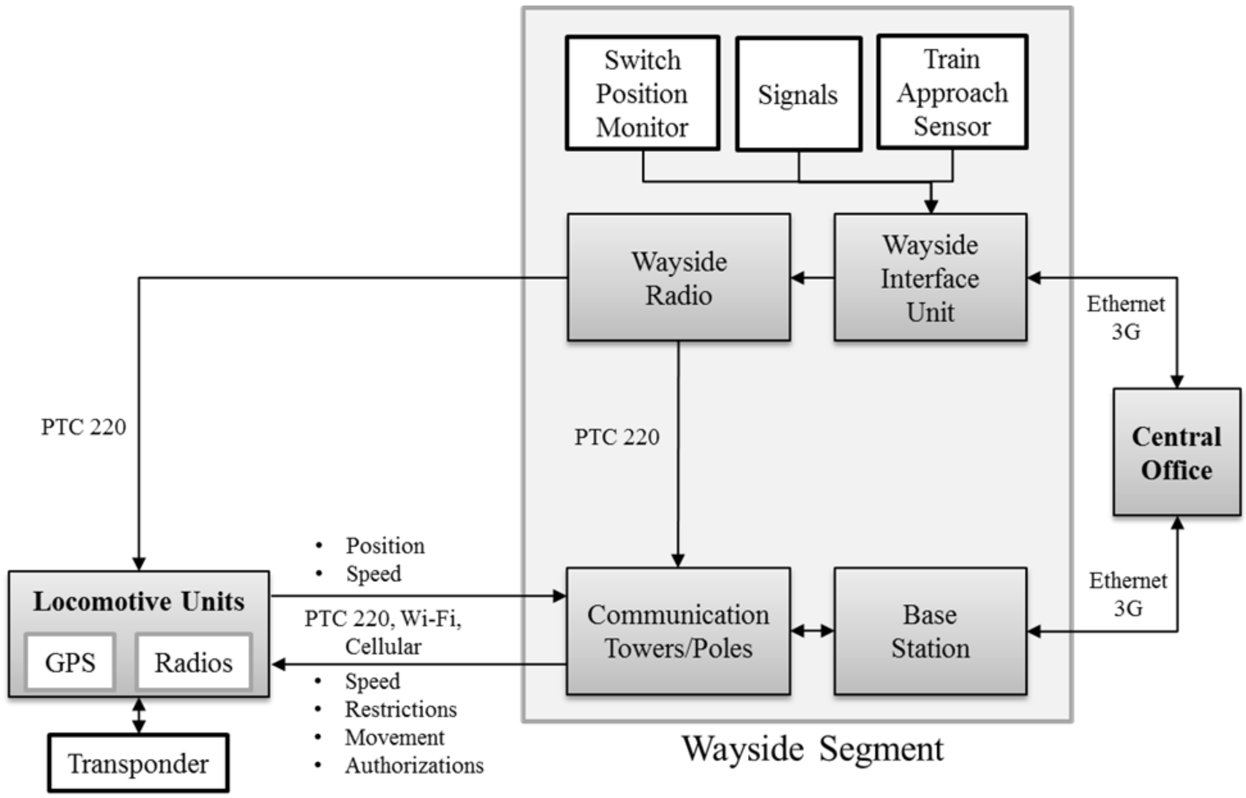


Figure 3.13 A typical PTC implementation architecture
Source: (Bridgelall, King, Huang, Tolliver, & Lu, 2019)

Figure 3.14 illustrates the architecture selected by BNSF Railway. The locomotive contains onboard computers to track the train and manage its speed. The wayside devices can monitor signals, detect switch positions, and track the condition of other systems. Wayside devices use radio towers to communicate with the train and the central office to authorize train movements.

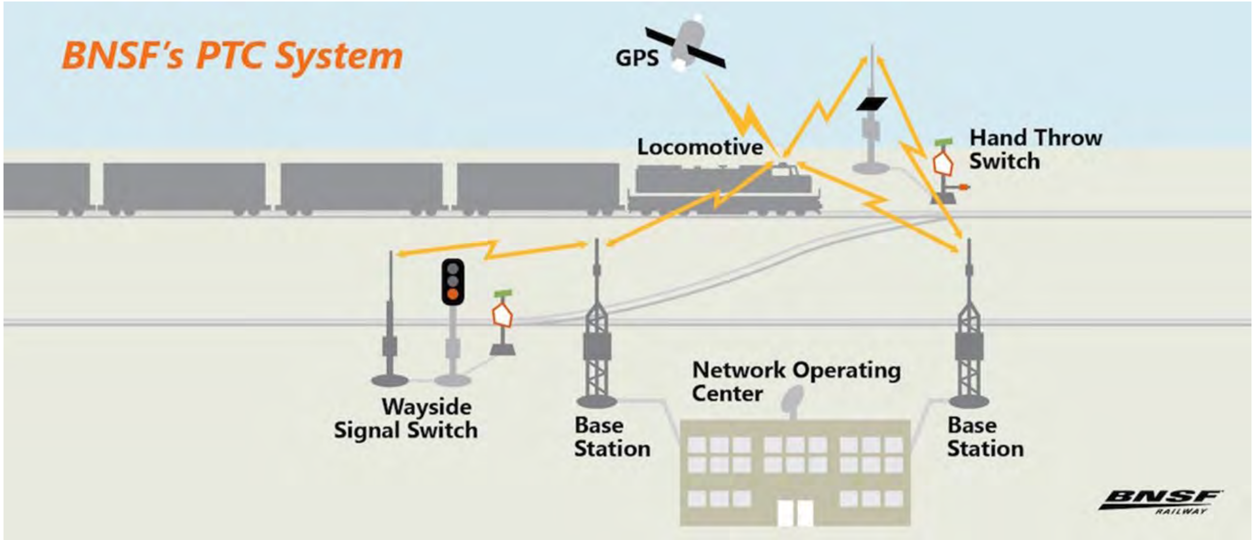


Figure 3.14 PTC system architecture by BNSF
Image Source: (Stagl, 2016)

The central office has computers and dispatching systems that respond to information from the train, wayside systems, and personnel. A typical PTC system has more than 20 technology components, each of which can fail for a variety of reasons.

The proprietary nature of initial PTC implementations and the rush to comply with the federal mandate resulted in a scarcity of data about the actual deployment costs. The lack of standards for PTC deployments also resulted in widely varying cost estimates. An FRA commissioned study in 2009 estimated that the PTC implementation over 20 years could cost between $10 billion and $13.8 billion (Roskind, 2009). A revised analysis by Peabody & Associates, Inc., in 2010 included other direct, indirect, and societal costs, which increased the estimate to $15.2 billion (L. E. Peabody & Associates, Inc., 2010). An estimate by a Canadian working group on rail safety found that average cost would be $192,000 per route mile (ACRS, 2016), or approximately $11.5 billion for the U.S. network. The USDOT estimated in 2018 that, excluding the Class I railroads, 37 other railroads would spend $4.2 billion to implement PTC (DeWeese, 2018). This brought the overall estimate to $15.7 billion (11.5 + 4.2), which agreed with the Peabody & Associates estimate. There were a few estimates of PTC maintenance costs. The FRA-commissioned study estimated that the annual maintenance cost would be approximately $860 million (Roskind, 2009). The American Public Transportation Association (APTA) estimated that the annual operating and maintenance costs for commuter railroads would be $100 million (DeWeese, 2018).

A limitation of PTC is that the system cannot prevent all types of accidents such as those involving rail-grade crossings and trespassers (Lobb, 2006). A report by the Congressional Research Service (CRS) found that those accidents PTC could prevent caused relatively few fatalities (Peters & Frittelli, 2018). However, the National Transportation Safety Board (NTSB) testified that PTC could have prevented 300 deaths between 1969 and 2018 (Sumwalt (III), 2018). The deployment of PTC also presents new cybersecurity challenges and risks of system failures (Zhang, Liu, & Holt, 2018).

3.4.2 Onboard Sensors to Detect Track and Roadbed Problems

This project created a generalized system architecture for connected trains called Railway Autonomous Inspection Localization System (RAILS). Figure 3.15 illustrates the concept of connected trains that carry sensors to detect and report potential track and roadbed problems (Bhardwaj, Bridgelall, Lu, Nygard, & Dhingra, 2020). The system suggests that low-cost energy harvesting sensors that contain accelerometers, gyroscopes, and GPS receivers can log and report the multidimensional motions of locomotives and railroad cars. The energy-harvesting sensor package (EHP) would contain low-cost sensors that are common in all smartphones. The EHP devices would include a micro-electro-mechanical (MEM) device that implements the accelerometers and gyroscopes, a global positioning system receiver, wireless communications such as Wi-Fi, Bluetooth, and RFID, and a microprocessor. The EHP would communicate the raw signal samples to a cloud-based system that would apply signal processing and artificial intelligence methods to detect and localize track irregularities.

Figure 3.16 illustrates the three types of movements that the EHP can detect to predict the type and severity of track and roadbed problems. Profile irregularities are vertical deviations from a flat surface. Alignment irregularities are lateral deviations from a straight line. Warp irregularities are uneven vertical displacements between the two rails that can cause rocking motion and lead to derailments.

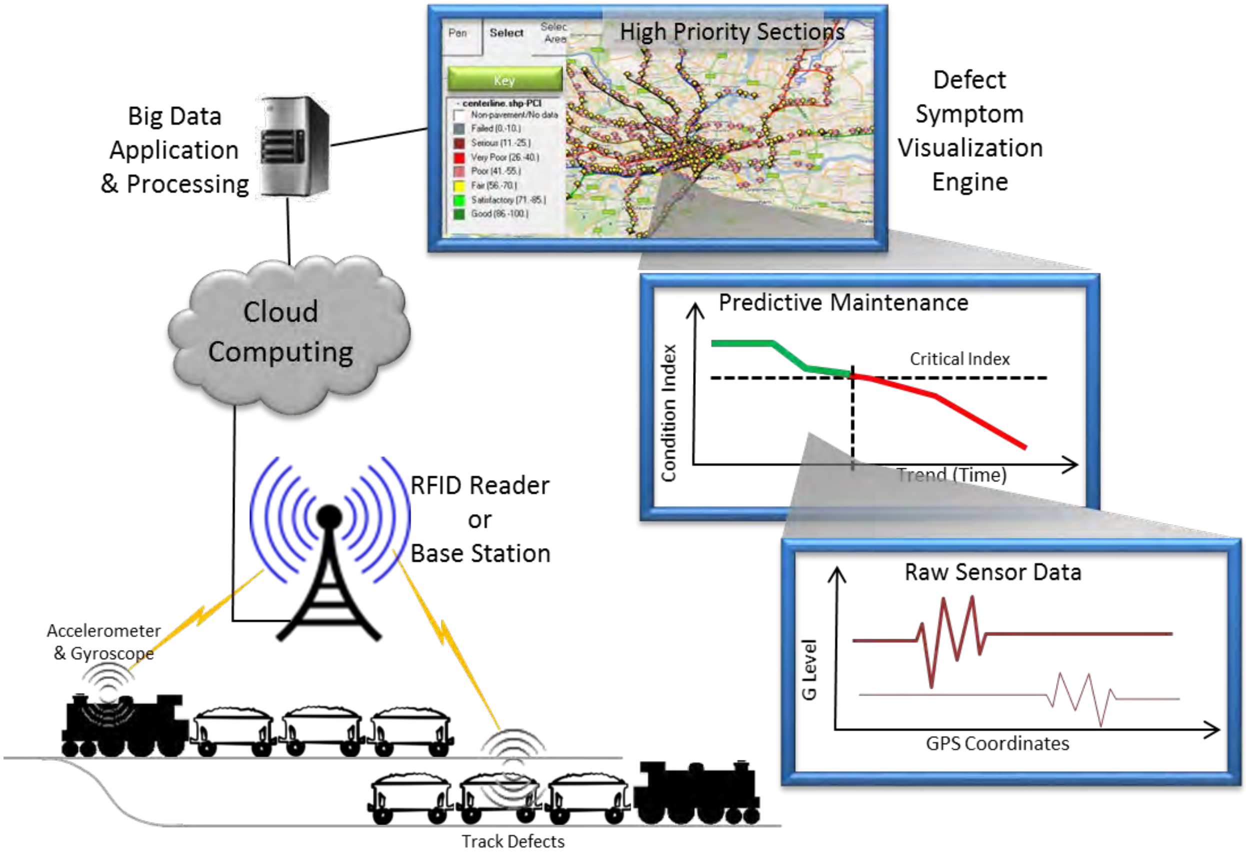


Figure 3.15 System architecture for connected trains

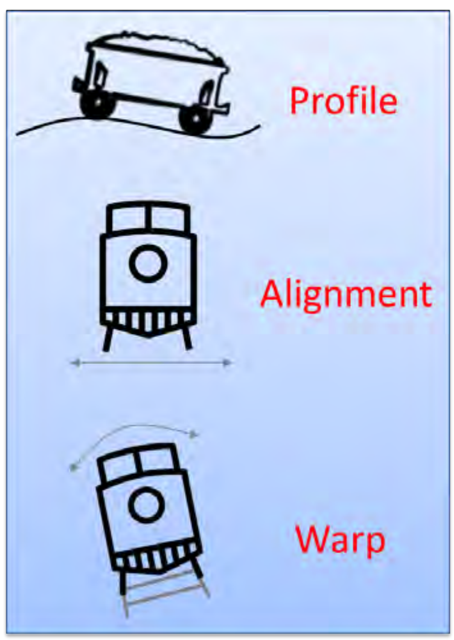


Figure 3.16 Movement detections due to track and roadbed problems

Figure 3.17 suggests how practitioners could integrate the onboard EHP within the existing PTC system to leverage the communication network and cloud-based platform. For instance, using the same communication pathways, locomotives can add accelerometer, gyroscope, GPS position, and speed data from the EHP.

The BCA incorporates the first-pass detection rate, P1, of any sensor-based system considered. P1 encapsulates the sensitivity and selectivity characteristics of any sensor-based system. Figure 3.18 illustrates how P1 relates to the system's ability to distinguish signal from noise. Figure 3.18a shows a first scenario for the distribution of signal and noise amplitudes and Figure 3.18b shows a second scenario. The error can be a false positive (FP) or a false negative (FN). An FP error is the erroneous detection of a signal; whereas, an FN error is a missed detection of a signal. The likelihood of an FP error is the area under the intersection of the red (noise) and blue (signal) curves, relative to the remaining area under the red curve. The likelihood of an FN error is the area under the intersection of the red and blue curves, relative to the remaining area under the blue curve. P1 is the area under the blue curve above the a_1 threshold. The first scenario shows that the signal amplitude is generally higher and more consistent than the noise amplitude, but there is still some overlap. Therefore, setting a threshold at a_1 will result in detecting signals without FP or FN errors half of the time. So P1 = 0.50 in the first scenario. The second scenario shows much more overlap between the signal and noise distributions. Therefore, both the FP and FN rates will be higher; whereas, the P1 rate (without FP or FN errors) will be lower. Reducing the threshold level to a_2 will increase the P1 rate but at the expense of higher FP and FN rates. Figure 3.19 plots the probability of detection as a function of P1 for three scenarios of scan frequency.

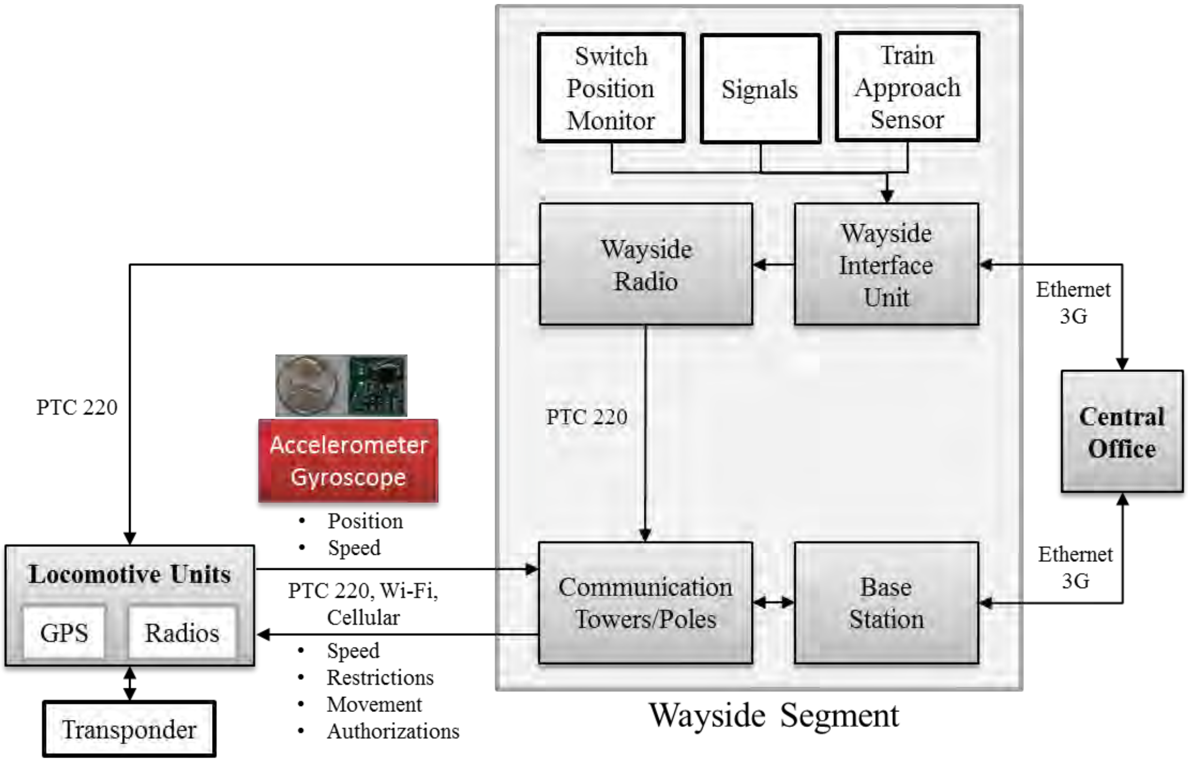


Figure 3.17 Integrating connected trains with the PTC system

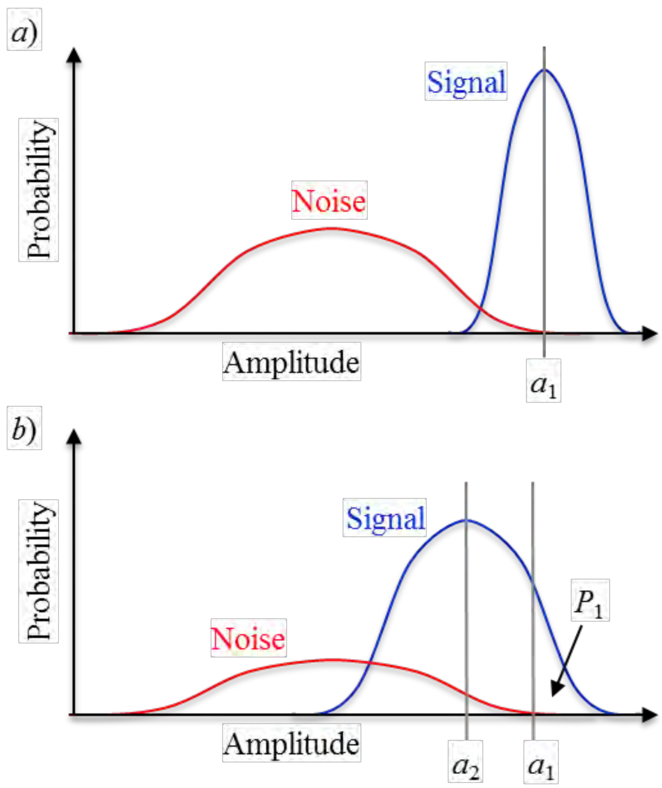


Figure 3.18 Characteristics that determine the first pass probability of a signal detector

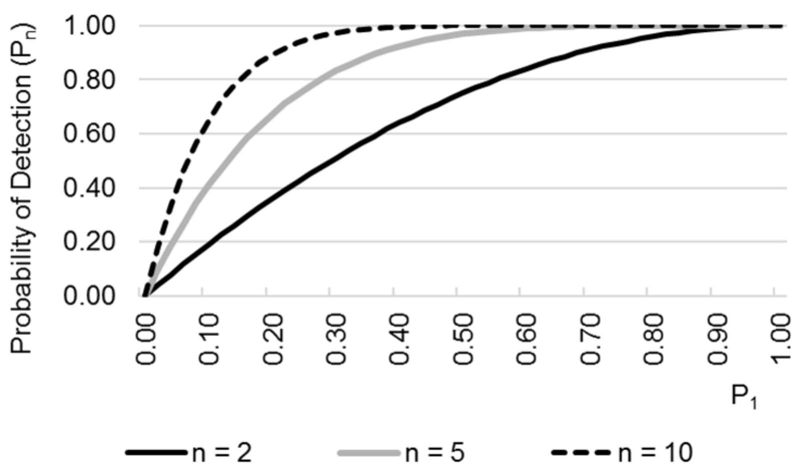


Figure 3.19 Probability of detection as a function of P1 for three scan frequencies

Figure 3.20 shows the typical flow of operations that onboard sensors must perform to take advantage of the increased probability of detecting track and roadbed problems with multiple passes of the sensors.

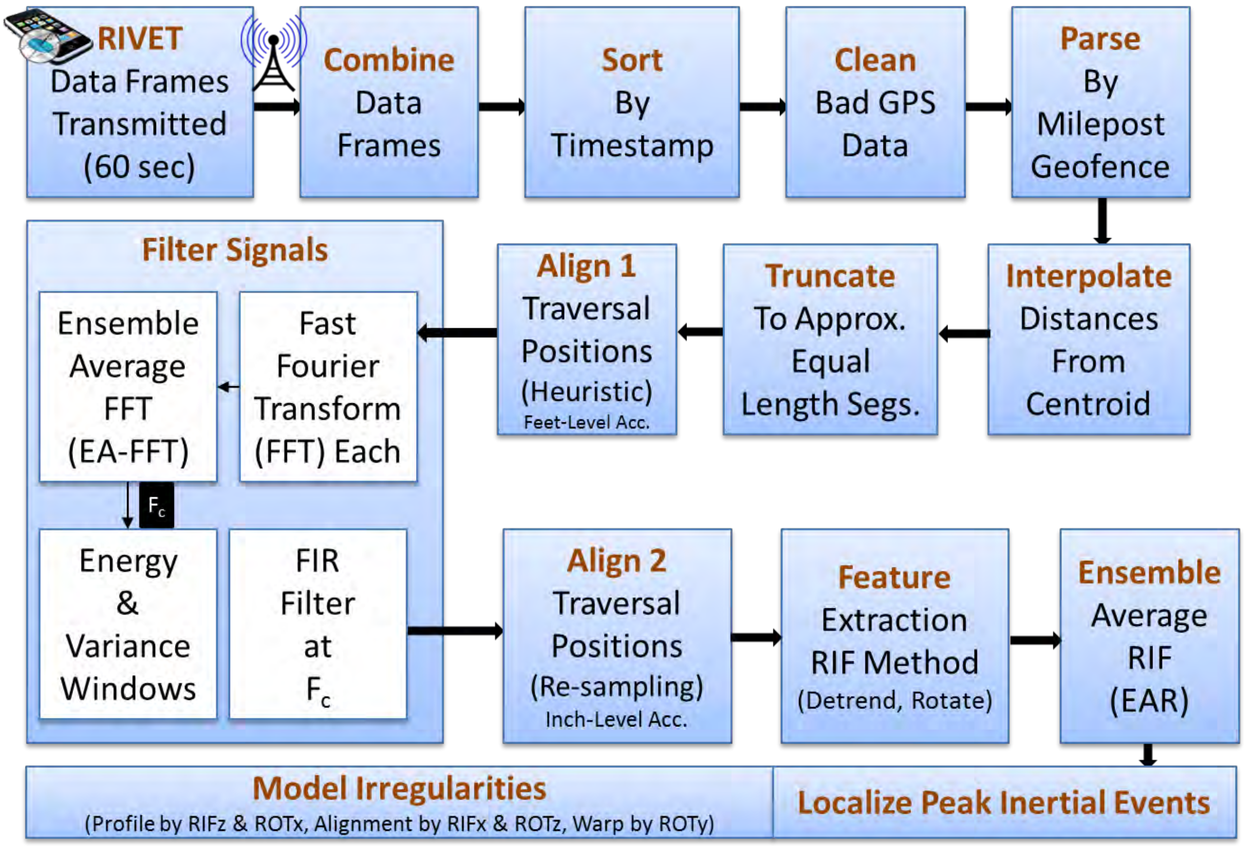


Figure 3.20 Theory of operations for onboard sensors

The cost and size of a sensor increases with the number of operations performed to clean the data and apply intelligence to detect the signals. This complexity affects the first pass detection rate P1. For example, filtering the signal to reduce the noise can allow for a lowering of the signal detection threshold, which in turn will increase the P1 rate.

As a case study, the Railroad Infrastructure & Vehicle Evaluation Technology (RIVET) system, shown in Figure 3.20, implements the onboard sensors and communications device by using a smartphone (Lu, Bridgelall, Tolliver, Chia, & Bhardwaj, 2019). The system then sends the data samples to a cloud-based platform for further processing. The cloud-based platform applies algorithms to sort, stitch, clean, parse, interpolate, truncate, align, and filter the data for accurate feature extraction and ensemble averaging. Another set of algorithms then localize peak inertial events to model the irregularities of the track and roadbed. Hence, the variable cost of the system is the onboard device; whereas, the fixed cost can be the software used on the cloud-based platform to localize and visualize problem areas across the railroad infrastructure.

3.4.3 Endnote

The following publications from this project provide more in-depth analytical details and theoretical expansions of the matter reported in this section:

Journal Articles

1. Bhardwaj, B., Bridgelall, R., Lu, P., & Dhingra, N. (2021). "Signal Feature Extraction and Combination to Enhance the Detection and Localization of Railroad Track Irregularities." *IEEE Sensors*, 21(5). DOI: 10.1109/JSEN.2020.3041652.
2. Bhardwaj, B., Bridgelall, R., Chia, L., Lu, P., & Dhingra, N. (2020). "Signal Filter Cut-off Frequency Determination to Enhance the Accuracy of Rail Track Irregularity Detection and Localization." *IEEE Sensors*, 20(3). DOI: 10.1109/JSEN.2019.2947656, pp. 1393-1399.
3. Bridgelall, R., Chia, L., Bhardwaj B., Lu, P., Tolliver, D., & Dhingra, N. (2019). "Enhancement of Signals from Connected Vehicles to Detect Roadway and Railway Anomalies." *Measurement Science and Technology*. DOI: 10.1088/1361-6501/ab5b54.
4. Chia, L., Bhardwaj, B., Lu, P., & Bridgelall, R. (2019). "Railroad Track Condition Monitoring Using Inertial Sensors and Digital Signal Processing: A Review." *IEEE Sensors Journal*, 19(1). DOI: 10.1109/JSEN.2018.2875600, pp. 25-33.

Conference Proceedings and Presentations

1. Bridgelall, R., & Tolliver, D. (2020). "Will IoT Technology Deployments Prevent Railroad Accidents?" In *Sensors Expo & Conference 2020*.
2. Bhardwaj, B., Bridgelall, R., Lu, P., Nygard, K., & Dhingra, N. (2020). "Architecture for an Intelligent Low-Cost Rail Track Condition Evaluation System." In *ASCE International Conference on Transportation & Development*. DOI: 10.1061/9780784483145.020.
3. Bhardwaj, B., Bridgelall, R., Lu, P., & Dhingra, N. (2020, January). "Signal Feature Extraction and Combination to Enhance the Detection and Localization of Railroad Track Irregularities." *The 99th Annual Meeting of the Transportation Research Board*, Washington, D.C.
4. Chia, L., Lu, P., Bhardwaj B., Bridgelall, R., Tolliver, D., & Dhingra, N. (2019). "Automatic Rail Track Surface Anomaly Detection with Smartphone Based Monitoring System." In *DEStech Transactions on Engineering and Technology Research*, pp. 168-172. DOI: 10.12783/dtetr/icicr2019/30565.
5. Bhavana, B., Bridgelall, R., Lu, P., & Dhingra, N. (2019, April). "Railroad Track Irregularities: Position Accuracy Assessments Using Low-Cost Sensors on a Hi-Rail Vehicle." *The 3rd Graduate Student Council (GSC) Annual Research Symposium*, Fargo, ND.
6. Bhavana, B., Bridgelall, R., Lu, P., & Dhingra, N. (2019). "Railroad Track Irregularities: Position Accuracy Assessments Using Low-Cost Sensors on a Hi-Rail Vehicle." In *Proceedings of the ASCE International Conference on Transportation & Development* (ICTD 2019). DOI: 10.1061/9780784482575.043.
7. Chia, L., Bhardwaj B., Bridgelall, R., Lu, P., Tolliver, D., & Dhingra, N. (2019). "Heuristic Methods of Inertial Signal Alignment to Detect and Locate Railtrack Anomalies." In *Proceedings of the 98th Annual Meeting of the Transportation Research Board*. 19-00229, http://amonline.trb.org/
8. Chia, L., Bhardwaj B., Bridgelall, R., Lu, P., Tolliver, D., & Dhingra, N. (2019). "Train Speed Estimation Using Low-Cost GPS Sensors." In *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2019*. International Society for Optics and Photonics (SPIE). DOI: 10.1117/12.2507020.

3.5 Benefit-Cost Analysis

The next two subsections evaluate the benefits and costs of the deployed PTC system and a price budget model for onboard sensor systems as a function of a return on their investments.

3.5.1 Benefit Cost Analysis of PTC

As a result of the RSIA08 federal mandate, the Class I railroads collectively invested $11.2 billion to comply with the federal law (GAO, 2010). Table 3.12 summarizes the amount that each Class I railroad reportedly spent on PTC deployments. This section analyzes the benefits from accident savings in proportion to the PTC deployment costs and as a function of the payback period.

Table 3.12 Sources for the Class I Railroad Stated Deployment Costs

Railroad	Cost ($B)	Source
Union Pacific Railroad	2.900	Company webpage on PTC (Union Pacific Railroad, 2018)
BNSF Railway	2.000	Company webpage on PTC (BNSF Railway, 2018)
CSX Transportation	2.400	CRS 2018 Report (Peters & Frittelli, 2018)
Norfolk Southern Railway	1.800	Company news webpage (Norfolk Southern Railway, 2017)
Canadian National Railway	1.400	Company press release (Canadian National Railway, 2018)
Kansas City Southern Railway	0.300	USDOT Report on Grant Distribution (DeWeese, 2018)
Canadian Pacific Railway	0.375	Canadian Working Group Report (ACRS, 2016).

Table 3.13 summarizes the monetary loss from PTC addressable (PTC-A) accidents for the five years prior to the first deadline year extension of 2018. The table shows that the coefficient of variation (CV) for the STD from the average number of accidents (AVG) was 5.8%, showing that the accident frequency was consistent. Therefore, the consistency justifies using an average value as the annual financial benefits in accident prevention. On average, PTC avoidable accidents accounted for 31.6% of the monetary loss from all accidents. Hence, if the PTC deployments were flawless, the average finance loss avoided (benefits) would have been approximately $92 million.

Table 3.13 Financial Losses from Human, Signaling, and Communication Errors

Year	Accidents	PTC-A	PTC-A (%)	TFL ($)	PTC-A FL ($)	PTC-A FL (%)
2013	1806	771	42.7	361,341,622	120,788,225	33.4
2014	1836	789	43.0	296,289,876	86,366,068	29.1
2015	1892	993	52.5	311,490,762	90,034,696	28.9
2016	1650	679	41.2	253,430,453	96,279,982	38.0
2017	1686	724	42.9	226,583,986	64,887,319	28.6
AVG	1774	791.2	44.6	289,827,340	91,671,258	31.6
STD	102.4	120.7		52,320,684	20,107,467	4.1
CV (%)	5.8	15.3				

The cumulative discounted net benefit or the return on the investment (*R*) is

$$R = \sum_{i=1}^{Y} \frac{B_i - C_i}{(1+r)^i} \tag{2}$$

The variables are the discount rate *r*, the future year index *i*, and the number of years *n* for payback. The analysis uses 7% and 3% discount rates that the FRA suggests for payback and sensitivity assessments (FRA, 2016). The analysis also uses a 15% rate of the initial investment for annual operating and maintenance costs, C_i based on previous studies (Roskind, 2009). The maintenance rate includes replacement parts for failed sensor systems. Manufacturer analysis of the integrated accelerometer types of sensors suggested for onboard condition monitoring found that under normal operating conditions of temperature and humidity, there is a 10% chance of failure after 15 years (NXP, 2007).

The following optimization problem solved for the *net* annual *average* benefits needed to achieve payback in *Y* years with a first investment of *I*:

$$\text{Minimize} \quad \sum_{i=1}^{Y} \frac{B_i - C_i}{(1+r)^i} - I = 0 \tag{3}$$

$$\text{Subject to} \quad \frac{B_i}{I} > 0, \forall i \tag{4}$$

$$\text{and} \quad Y = \{1, 2, \dots, 20\} \tag{5}$$

After computing the solution for B_i as a function of the payback period *Y*, solving a similar optimization problem yields the internal rate of return (IRR) *r* that satisfies

$$\sum_{i=1}^{Y} \frac{B_i - C_i - I}{(1+r)^i} = 0 \tag{6}$$

The benefit-cost-ratio (BCR) for a 10-year period is then

$$BCR = \sum_{i=1}^{10} \frac{B_i}{(1+r)^i} \Big/ I \tag{7}$$

Table 3.14 lists the additional annual net benefits as a proportion of the aggregate PTC investment that Class I railroads would need to achieve the desired payback period. The net benefits are in addition to the benefit from accident avoidance due to the PTC system. The table also lists the IRR and 10-year BCR as a function of the desired payback period using both the 3% and 7% discount rates. For example, at a 3% discount rate over 10 years, Class I railroads must collectively realize an added annual net benefit of 25.9% of the total PTC deployment cost for a return on their investment. The added net benefit that Class I railroads must realize increases to 28.4% when the discount rate is 7%.

Table 3.14 Results of the Benefit Cost Analysis

3% Discount				7% Discount		
Payback Years	Additional Net Benefits (%)	IRR (%)	10Yr BCR	Additional Net Benefits (%)	IRR (%)	10-Yr BCR
1	117.2	103.0	8.79	121.2	107.0	7.52
2	66.4	52.2	4.46	69.5	55.3	3.88
3	49.5	35.3	3.02	52.3	38.0	2.68
4	41.1	26.7	2.29	43.7	29.4	2.07
5	36.0	21.4	1.86	38.6	24.1	1.71
6	32.6	17.8	1.57	35.2	20.5	1.47
7	30.2	15.1	1.37	32.7	17.9	1.30
8	28.4	13.0	1.22	30.9	15.9	1.18
9	27.0	11.3	1.10	29.5	14.3	1.08
10	25.9	10.0	1.00	28.4	13.0	1.00
11	25.0	8.8	0.92	27.5	11.9	0.94
12	24.2	7.8	0.86	26.8	11.0	0.88
13	23.6	7.0	0.80	26.1	10.3	0.84
14	23.0	6.2	0.76	25.6	9.6	0.80
15	22.6	5.5	0.71	25.2	9.0	0.77
16	22.1	4.9	0.68	24.8	8.5	0.74
17	21.8	4.4	0.65	24.4	8.1	0.72
18	21.5	3.9	0.62	24.1	7.7	0.70
19	21.2	3.4	0.60	23.9	7.3	0.68
20	20.9	3.0	0.57	23.6	7.0	0.66

Figure 3.21 and Figure 3.22 plot the data in Table 3.14 for the 3% and 7% discount rates, respectively. The non-linear trends fit the power model

$$B = \alpha i^{-\beta} \tag{8}$$

where the estimated parameters are α and β. B is a placeholder for one of the three predicted variables and i is the index of the payback year.

Table 3.15 summarizes the parameter estimates and R^2 coefficient of determination for each model at the two discount rates. The high R^2 values show that the models are a good predictor of the benefit proportion needed as a function of the desired payback period. This analysis suggests that to realize a positive return on the PTC investments, railroads must seek additional means to benefit from the deployed system. Considering this, Congress requested that the FRA conduct a study to assess the potential for PTC technology to help prevent rail-grade crossing accidents (Peters & Frittelli, 2018). That is, the extensive communication network of the PTC deployment can accommodate additional sensors at rail-grade crossings to help with conflict avoidance between vehicles on tracks and oncoming trains. Other possible business benefits can come from leveraging the sensing and communication system to improve line capacity, equipment utilization, service reliability, fuel savings, and real-time diagnostics. As the communication network is now in place, another benefit can come from adding sensors to detect track and roadbed problems as discussed in Section 3.5.2.

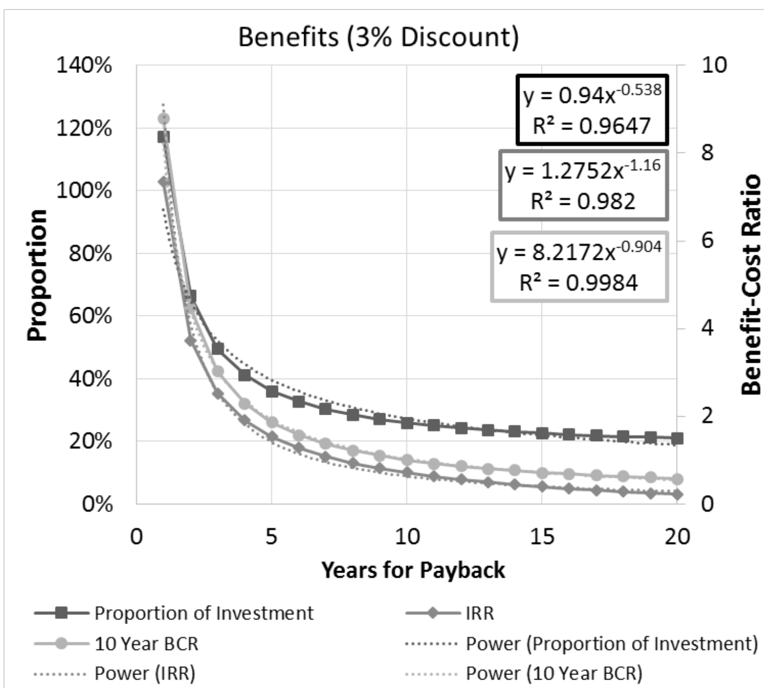


Figure 3.21 Benefit proportion as a function of payback year at a 3% discount rate
Source: (Bridgelall & Tolliver, 2020)

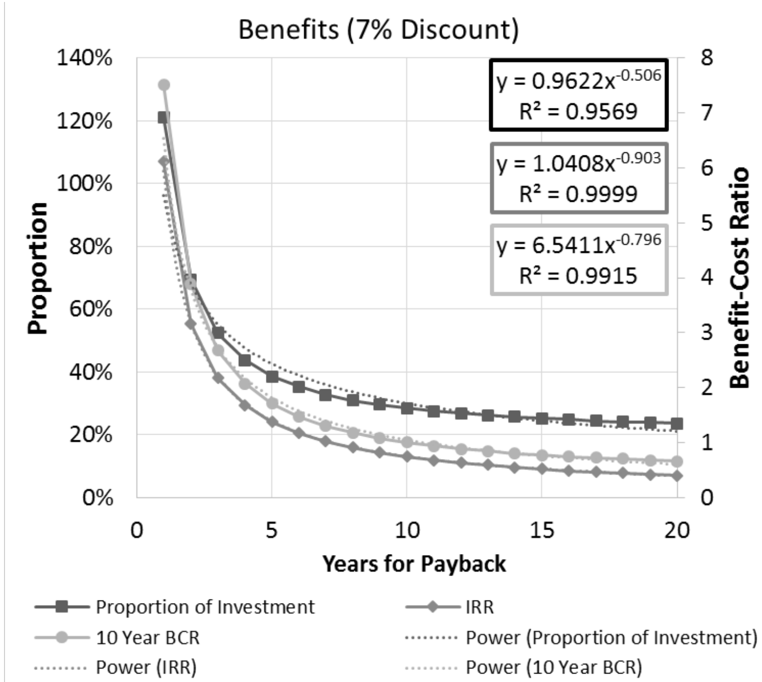


Figure 3.22 Benefit proportion as a function of payback year at a 7% discount rate
Source: (Bridgelall & Tolliver, 2020)

Table 3.15 Model Parameter Estimates

	Benefit Proportion			**IRR**			**BCR (10-Yr)**		
Discount Rate	α	β	R^2 (%)	α	β	R^2 (%)	α	β	R^2 (%)
3%	0.94	0.54	96.5	1.28	1.16	98.2	8.22	0.90	99.8
7%	0.96	0.51	95.7	1.04	0.90	99.9	6.54	0.80	99.2

3.5.2 Benefit Cost Analysis of Onboard Sensing

The BCA's main idea for onboard sensing equipment is to first determine a system price budget (SPB) as a function of the desired payback period in years. To generalize the analysis, the SPB should be a proportion of the average annual anticipated benefits (AAAB) that a railroad realized after deploying the system. As with PTC, benefits can extend beyond accident prevention alone. For example, consider that railroads can use the system to provide a real-time location function that can help their business optimize service and routing. In that case, they could add those as additional benefits anticipated because of higher operational efficiencies. Another potential use of the system is to measure ride quality and provide that as another piece of information customers can use to assess service quality. However, given the myriad of possible benefits, it is not within the scope of this analysis to determine a specific SPB.

The optimization problem of Equations (3) to (5) provides a framework to derive the proportional SPB as a function of the desired payback period in years. The solution is to replace the annual operating and maintenance costs (AOMC), C_i, with a proportion of the AAAB, B_i, such that $C_i = \gamma B_i$, and the SPB as the initial investment $I = \alpha B_i$. Doing so creates a generalized expression that does not require determination of a specific AAAB to solve for the proportion of SPB as a function of the payback period of Y years.

Figure 3.23 plots the solution where the vertical axis is the SPB as a factor of the AAAB. The calculations use two scenarios of AOMC of 15% and 25% of the SPB, both using a 7% discount rate. For example, if the AOMC is 25% of the SPB, allowing the SPB to be 2.5 times the AAAB, would realize a payback period of 10 years. If the AOMC drops to 15% of the SPB, then the SPB could increase to 3.5 times the AAAB. In general, the model shows that the SPB can increase as a logarithmic function with more time allowed to realize a return on the investment. The estimated logarithmic functions show that the high CV (R^2) provides good confidence of using the closed-form model of the data to simplify calculations.

The model coefficients depend on the AOMC as a proportion of the SPB as well as the discount rate. Therefore, railroads must solve the optimization problem to estimate parameters for the closed form model after determining both the AOMC as a proportion of SPB and the discount rate. The SPB can increase with the AAAB, keeping the ratio above 1.0 to accommodate the possibility for higher performance and more automated systems.

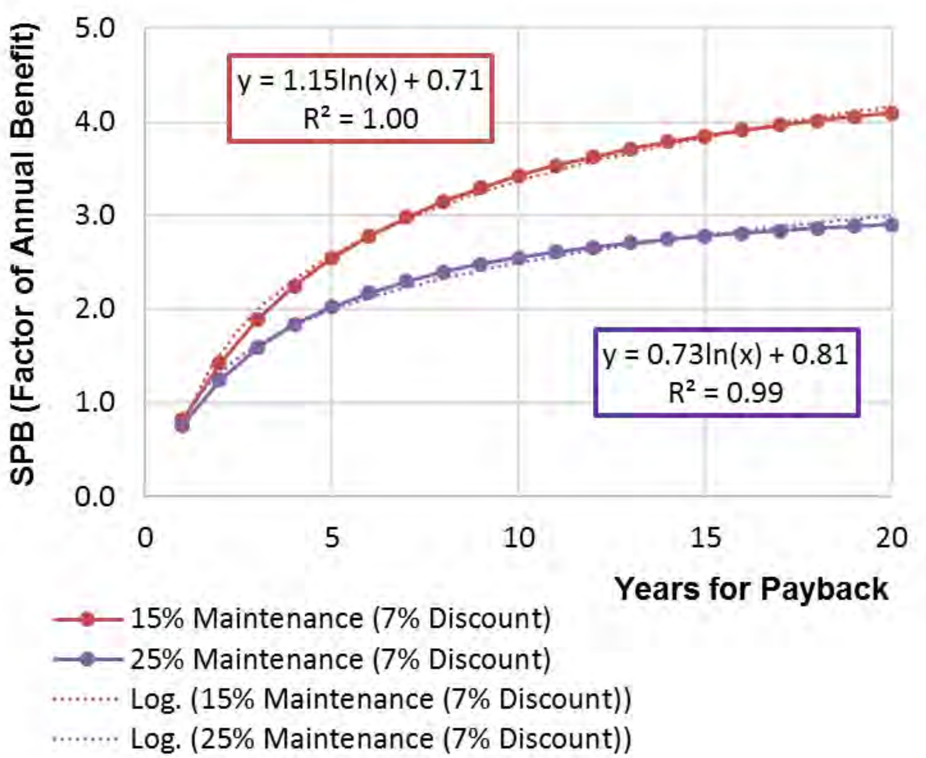


Figure 3.23 Factor of annual benefit as a function of payback years and maintenance cost

3.5.3 Endnote

The following publications from this project provide more in-depth analytical details and theoretical expansions of the matter reported in this section:

Journal Articles

1. Bridgelall, R., & Tolliver, D. (2022). "Budgeting the Adoption of Sensors on Connected Trains." *Transportation Planning and Technology*, 45(1). DOI: 10.1080/03081060.2021.2017205.
2. Bridgelall, R., & Tolliver, D. (2020). "Closed Form Models to Assess Railroad Technology Investments." *Transportation Planning and Technology*, 43(7). DOI: 10.1080/03081060.2020.1805541.
3. Bridgelall, R. & Tolliver, D. (2020). "A Cognitive Framework to Plan for the Future of Transportation." *Transportation Planning and Technology*, 43(3). DOI: 10.1080/03081060.2020.1735728.

Conference Proceeding

1. Bridgelall, R., King, B., Huang, Y., Tolliver, D., & Lu, P. (2019). "Sensor System Benefits and Costs in Positive Train Control." In *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2019*. International Society for Optics and Photonics (SPIE). DOI: 10.1117/12.2512882.

4. LIMITATIONS

The FRA stated it does not require railroads to report accidents with financial losses below $10,500. Therefore, the exploratory data analysis would not include statistics or reveal patterns that include such accidents. Similarly, the ML algorithms would not have trained on data from such accident types and may, therefore, show some bias toward more expensive accidents. Another limitation is that financial losses do not include costs beyond those incurred to repair equipment, systems, and structures. For example, railroads do not necessarily include the cost of cleanup, lost freight, societal damages, fatalities, injuries, and line closures in their reported monetary loss. Therefore, benefits associated only with the avoidance of direct financial losses reported may be underestimated. The BCA analysis also does not include any external benefits such as the removal of truck traffic and their associated emissions by shifting traffic to railroads. In summary, analysts using the FRA dataset should be aware of these limitations and their potential impact on the results of the benefit-cost analysis.

5. CONCLUSIONS

Freight railroads complement trucks by moving freight more efficiently across longer distances. Therefore, financial losses from accidents not only erode the profitability of railroads but such losses also create broader economic impact from reduced freight transport capacity. Analysis of the largest and most comprehensive railroad accident database, maintained by the Federal Railroad Administration (FRA), revealed that for more than a decade, railroads have been consistently losing revenue from accidents. On average, railroads have been involved in more than 2,500 accidents each year, which accounted for an average annual monetary loss of $376 million. Overall, the annual trend in accident volume and the proportion of accident causes have been consistent.

Regardless of their cause, there were four types of railroad accident: collisions, fire, derailments, and obstructions. Derailment type accidents were far more common than the other accident types. Exploratory data analysis (EDA) determined that derailment type accidents consistently account for more than 60% of the annual accidents. The trend in accident frequency by accident type showed that accidents consistently resulted in more than 1,500 derailments each year. Applying machine learning (ML) techniques to the accident database revealed that common factors in derailment type accidents were lower track classes, non-signalized territories, and areas with restricted limits of movement authorization. This suggests that railroads could focus technology deployments toward those higher-risk situations. Interestingly, the application of ML also revealed that derailment type accidents are generally not associated with human-caused accidents. Rather, derailments are typically the result of track and roadbed problems. Another finding was that yard tracks are generally associated with human-caused accidents.

The finding that human-caused accidents dominated is consistent with the federal mandate to deploy a positive train control (PTC) system to help reduce those risks. The other main finding was that the next dominant accident cause of track and roadbed problems typically resulted in derailment type accidents. Given that derailments were the most common accident type, railroads are keen to understand the benefits and costs of deploying onboard sensing technologies to help reduce those risks. Such solutions also have the potential to leverage the communication networks of the deployed PTC system to enable backend signal processing and analysis. Railroads can use the benefit-cost model developed in this research to help analyze the tradeoff between technology costs, their potential benefits in accident prevention, and the payback period with different discount rate scenarios.

6. REFERENCES

AAR. (2018). *Positive Train Control (PTC).* Washington, D.C.: Association of American Railroads (AAR).

AAR. (2021). *Freight Railroads & Climate Change.* Association of American Railroads (AAR). Retrieved from https://www.aar.org/wp-content/uploads/2021/02/AAR-Climate-Change-Report.pdf

ABC News. (2016, June 29). 3 Crew Members Missing in Texas Train Wreck. *ABC News*. Retrieved from https://abcnews.go.com/US/video/crew-members-missing-texas-train-wreck-40215976

Abidin, N., Ismail, A., & Emran, N. (2018). Performance Analysis Of Machine Learning Algorithms For Missing Value Imputation. *International Journal of Advanced Computer Science and Applications, 9*(6). doi:10.14569/IJACSA.2018.090660

ACRS. (2016). *Train Control Working Group Final Report.* Ottawa, Ontario: Transport Canada Advisory Council on Railway Safety (ACRS). Retrieved from https://www.tc.gc.ca/media/documents/railsafety/train-control-working-group-final-report.pdf

Aggarwal, C. C. (2015). *Data Mining.* New York, New York, United States of America: Springer International Publishing.

Agresti, A. (2018). *Statistical Methods for the Social Sciences* (5th ed.). Boston, Massachusetts, U.S.: Pearson.

Badugu, S., & Movva, A. (2013). Positive train control. *International Journal of Emerging Technology and Advanced Engineering, 3*(4), 304-307.

Bala, M., & Bhasin, A. (2018). A Review on Analysis of Railway Traffic Accident with Data Mining Techniques. *International Journal of Computer Sciences and Engineering, 6*(6), 1251-1256. doi:10.26438/IJCSE/V6I6.12511256

Balouchi, F., Bevan, A., & Formston, R. (2020). Development of railway track condition monitoring from multi-train in-service vehicles. *Vehicle System Dynamics*, 1-21. doi:10.1080/00423114.2020.1755045

Bhardwaj, B., Bridgelall, R., Lu, P., Nygard, K., & Dhingra, N. (2020). Architecture for an Intelligent Low-Cost Rail Track Condition Evaluation System. *International Conference on Transportation and Development 2020.* doi:10.1061/9780784483145.020

BNSF Railway. (2018, August 7). *Leading the Way in PTC*. (BNSF Railway) Retrieved August 7, 2018, from http://www.bnsf.com/in-the-community/safety-and-security/positive-train-control.html

Breiman, L. (1996). Bagging predictors. *Machine Learning archive, 24*(2), 123. doi:10.1023/A:1018054314350

Breiman, L. (2001). Random Forests. *Machine Learning archive, 45*(1), 5-32. doi:10.1023/A:1010933404324

Breunig, M., Kriegel, H.-P., Ng, R., & Sander, J. (2000). LOF: identifying density-based local outliers. *Proceedings of the 2000 ACM SIGMOD International Conference on Management of Data, 29*, pp. 93-104. doi:10.1145/335191.335388

Brezulianu, A., Aghion, C., Hagan, M., Geman, O., Chiuchisan, I., Balan, A.-L., . . . Balas, V. E. (2020). Active Control Parameters Monitoring for Freight Trains, Using Wireless Sensor Network Platform and and Internet of Things. *Processes, 8*(6), 639. doi:10.3390/pr8060639

Bridgelall, R., & Tolliver, D. (2020). Accuracy Enhancement of Anomaly Localization with Participatory Sensing Vehicles. *Sensors, 20*(2), 409. doi:10.3390/s20020409

Bridgelall, R., & Tolliver, D. (2020). Closed form models to assess railroad technology investments. *Transportation Planning and Technology, 43*(7), 639-650. doi:10.1080/03081060.2020.1805541

Bridgelall, R., & Tolliver, D. (2021). Railroad accident analysis using extreme gradient boosting. *Accident Analysis & Prevention, 156*, 106126-106126. doi:10.1016/J.AAP.2021.106126

Bridgelall, R., King, B., Huang, Y., Tolliver, D., & Lu, P. (2019). Sensor system benefits and costs in positive train control. *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2019, 10970*. doi:10.1117/12.2512882

Bridgelall, R., Lu, P., Tolliver, D., & Xu, T. (2018). Mining Connected Vehicle Data for Beneficial Patterns in Dubai Taxi Operations. *Journal of Advanced Transportation, 2018*, 1-8. doi:10.1155/2018/8963234

Brooks, J., Groshong, H., Liu, A., Houpt, P., & Oman, C. (2017). Survey of Future Railroad Operations and the Role of Automation. *Transportation Research Record, 2608*(2608), 10-18. doi:10.3141/2608-02

Brown, D. (2016). Text Mining the Contributors to Rail Accidents. *IEEE Transactions on Intelligent Transportation Systems, 17*(2), 346-355. doi:10.1109/TITS.2015.2472580

BTS. (2020, October 13). *Freight Facts and Figures*. Retrieved October 13, 2020, from Bureau of Transportation Statistics (BTS): https://www.bts.gov/product/freight-facts-and-figures

BTS. (2021, July 28). *National Transportation Statistics*. (B. o. (BTS), Producer, & United States Department of Transportation) Retrieved July 28, 2021, from U.S. Ton-Miles of Freight: https://www.bts.gov/content/us-ton-miles-freight

BTS. (2021, July 28). *Value, Tonnage, and Ton-Miles of Freight by Distance: 2015*. Retrieved from Bureau of Transportation Statistics (BTS): https://www.bts.gov/content/value-tonnage-and-ton-miles-freight-distance-2015

Bukhsh, Z., Saeed, A., Stipanovic, I., & Doree, A. (2019). Predictive maintenance using tree-based classification techniques: A case of railway switches. *Transportation Research Part C-emerging Technologies, 101*, 35-54. doi:10.1016/J.TRC.2019.02.001

Canadian National Railway. (2018, January 23). *CN targeting record C$3.2 billion capital program in 2018*. (Canadian National Railway) Retrieved August 7, 2018, from https://www.cn.ca/en/news/2018/01/pressrelease_20180123040328_1353/

Chen, T., & He, T. (2014). Higgs boson discovery with boosted trees. *HEPML'14 Proceedings of the 2014 International Conference on High-Energy Physics and Machine Learning - Volume 42*, (pp. 69-80). Retrieved from https://academic.microsoft.com/paper/2292355502

Chia, L., Bhardwaj, B., Lu, P., & Bridgelall, R. (2019). Railroad Track Condition Monitoring Using Inertial Sensors and Digital Signal Processing: A Review. *IEEE Sensors Journal, 19*(1), 25-33. doi:10.1109/JSEN.2018.2875600

Cook, N. (2007). Use and Misuse of the Receiver Operating Characteristic Curve in Risk Prediction. *Circulation, 115*(7), 928-935. doi:10.1161/CIRCULATIONAHA.106.672402

Dabbour, E., Easa, S., & Haider, M. (2017). Using fixed-parameter and random-parameter ordered regression models to identify significant factors that affect the severity of drivers' injuries in vehicle-train collisions. *Accident Analysis & Prevention, 107*, 20-30. doi:10.1016/J.AAP.2017.07.017

DeWeese, B. J. (2018). *Observations on Federal Funding Support for Positive Train Control Implementation.* United States Department of Transportation (USDOT), Office of Inspector General. Washington, D.C.: USDOT.

Dhingra, N., Bridgelall, R., Lu, P., Szmerekovsky, J., & Bhardwaj, B. (2019). Using Data Mining Methods to Rank the Importance of Factors in Railroad Accidents. *The 98th Annual Meeting of the Transportation Research Board. 19-01768.* Washington, D.C.: Transportation Research Board.

Echauz, J., & Vachtsevanos, G. (1995). Fuzzy Grading System. *IEEE Transactions on Education, 38*(2), 158-165. doi:10.1109/13.387218

Filtness, A., & Naweed, A. (2017). Causes, consequences and countermeasures to driver fatigue in the rail industry: The train driver perspective. *Applied Ergonomics, 60*, 12-21. doi:10.1016/J.APERGO.2016.10.009

Firlik, B., & Tabaszewski, M. (2020). Monitoring of the technical condition of tracks based on machine learning. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 234*(7), 702-708. doi:10.1177/0954409719866368

FRA. (2011). *Rail Equipment Accident/Incident Data File Structure and Field Input Specifications.* Washington, D.C.: Federal Railroad Administration (FRA). Retrieved November 25, 2020, from https://safetydata.fra.dot.gov/OfficeofSafety/publicsite/DownloadFStructure.aspx

FRA. (2016). *Benefit-Cost Analysis Guidance for Rail Projects.* Washington, D.C.: Federal Railroad Administration, U.S. Department of Transportation.

FRA. (2018, 11 27). *Accident Data as Reported by Railroads*. (Federal Railroad Administration (FRA) Office of Safety Analysis) Retrieved 11 27, 2018, from https://safetydata.fra.dot.gov/officeofsafety/publicsite/on_the_fly_download.aspx

FRA. (2018). *Federal Funding Support for Positive Train Control Implementation.* United States Department of Transportation, Office of Inspector General. Washington, D.C.: Federal Railroad Administration.

FRA. (2018, August 7). *PTC System Information*. (Federal Railroad Administration (FRA)) Retrieved August 7, 2018, from https://www.fra.dot.gov/Page/P0358

FRA. (2020, July 8). *Freight Rail Overview*. (United States Department of Transportation) Retrieved from Federal Railroad Administration (FRA): https://railroads.dot.gov/rail-network-development/freight-rail-overview

FRA. (2021, July 28). *Federal Railroad Administration*. Retrieved from Office of Safety Analysis: https://safetydata.fra.dot.gov/OfficeofSafety/default.aspx

Fraga-Lamas, P., Fernández-Caramés, T. M., & Castedo, L. (2017). Towards the Internet of Smart Trains: A Review on Industrial IOT-Connected Railways. *Sensors, 17*(6), 1457. doi:10.3390/s17061457

Friedman, J. (2002). Stochastic gradient boosting. *Computational Statistics & Data Analysis, 38*(4), 367-378. doi:10.1016/S0167-9473(01)00065-2

GAO. (2010). *Rail Safety: Federal Railroad Administration Should Report on Risks to the Successful Implementation of Mandated Safety Technology.* Washington, D.C.: Government Accountability Office.

Géron, A. (2017). *Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems* (2nd ed.). Sebastopol, California: O'Reilly Media.

Ghofrani, F., He, Q., Goverde, R., & Liu, X. (2018). Recent applications of big data analytics in railway transportation systems: A survey. *Transportation Research Part C-emerging Technologies*, *90*, 226-246. doi:10.1016/j.trc.2018.03.010

Han, H., Guo, X., & Yu, H. (2016). Variable Selection Using Mean Decrease Accuracy and Mean Decrease Gini Based on Random Forest. *The 7th IEEE International Conference on Software Engineering and Service Science (ICSESS)* (pp. 219-224). Institute of Electrical and Electronic Engineers (IEEE). doi:10.1109/ICSESS.2016.7883053

Hodge, V. J., O'Keefe, S., Weeks, M., & Moulds, A. (2014). Wireless Sensor Networks for Condition Monitoring in the Railway Industry: A Survey. *IEEE Transactions on Intelligent Transportation Systems, 16*(3), 1088-1106. doi:10.1109/TITS.2014.2366512

Ii, D., & Barkan, C. (2008). Relationship between Train Length and Accident Causes and Rates. *Transportation Research Record, 2043*(2043), 73-82. doi:10.3141/2043-09

Ilyas, I., & Chu, X. (2019). *Data Cleaning.* New York, NY: Association for Computing Machinery and Morgan & Claypool Publishers.

Iranitalab, A., & Khattak, A. (2017). Comparison of four statistical and machine learning methods for crash severity prediction. *Accident Analysis & Prevention, 108*, 27-36. doi:10.1016/J.AAP.2017.08.008

Iranitalab, A., & Khattak, A. (2020). Probabilistic classification of hazardous materials release events in train incidents and cargo tank truck crashes. *Reliability Engineering & System Safety, 199*, 106914. doi:10.1016/J.RESS.2020.106914

iStockphoto. (2021). *Train and Railroad Accident.*

Jesmeen, M. Z., Hossen, J., Sayeed, S., Ho, C., Tawsif, K., Rahman, A., & Arif, E. (2018). A Survey on Cleaning Dirty Data Using Machine Learning Paradigm for Big Data Analytics. *Indonesian Journal of Electrical Engineering and Computer Science, 10*(3), 1234-1243. doi:10.11591/IJEECS.V10.I3.PP1234-1243

Keramati, A., Lu, P., Iranitalab, A., Pan, D., & Huang, Y. (2020). A crash severity analysis at highway-rail grade crossings: The random survival forest method. *Accident Analysis & Prevention, 144*, 105683. doi:10.1016/J.AAP.2020.105683

L. E. Peabody & Associates, Inc. (2010). *Positive Train Control Benefits Analysis: Updated Statement of Total Benefits and Restatement of FRA Cost-Benefit Analysis Based on FRA Costs and Updated Benefits.* Alexandria, Virginia: The Chlorine Institute, INc.

Lasisi, A., & Attoh-Okine, N. (2019). Machine Learning Ensembles and Rail Defects Prediction: Multilayer Stacking Methodology. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 5*(4), 4019016. doi:10.1061/AJRUA6.0001024

Lasisi, A., & Attoh-Okine, N. (2019). Machine Learning Ensembles and Rail Defects Prediction: Multilayer Stacking Methodology. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 5*(4), 4019016. doi:10.1061/AJRUA6.0001024

Lee, J., Choi, S., Kim, S.-S., Park, C., & Kim, Y. (2012). A Mixed Filtering Approach for Track Condition Monitoring Using Accelerometers on the Axle Box and Bogie. *IEEE Transactions on Instrumentation and Measurement, 61*(3), 749-758. doi:10.1109/TIM.2011.2170377

Li, C., Luo, S., Cole, C., & Spiryagin, M. (2017). An Overview: Modern Techniques for Railway Vehicle On-Board Health Monitoring Systems. *Vehicle System Dynamics, 55*(7), 1045-1070. doi:10.1080/00423114.2017.1296963

Li, H., Parikh, D., He, Q., Qian, B., Li, Z., Fang, D., & Hampapur, A. (2014). Improving rail network velocity: A machine learning approach to predictive maintenance. *Transportation Research Part C-emerging Technologies, 45*, 17-26. doi:10.1016/j.trc.2014.04.013

Liu, F., Ting, K., & Zhou, Z.-H. (2012). Isolation-Based Anomaly Detection. *ACM Transactions on Knowledge Discovery From Data, 6*(1), 3. doi:10.1145/2133360.2133363

Liu, J., & Khattak, A. (2017). Gate-violation behavior at highway-rail grade crossings and the consequences: Using geo-Spatial modeling integrated with path analysis. *Accident Analysis & Prevention, 109*, 99-112. doi:10.1016/J.AAP.2017.10.010

Liu, X., Barkan, C., & Saat, M. (2011). Analysis of Derailments by Accident Cause: Evaluating Railroad Track Upgrades to Reduce Transportation Risk. *Transportation Research Record, 2261*(2261), 178-185. doi:10.3141/2261-21

Liu, X., Saat, M., & Barkan, C. (2017). Freight-train derailment rates for railroad safety and risk analysis. *Accident Analysis & Prevention, 98*, 1-9. doi:10.1016/j.aap.2016.09.012

Lobb, B. (2006). Trespassing on the tracks: a review of railway pedestrian safety research. *Journal of Safety Research, 37*(4), 359-365. doi:10.1016/j.jsr.2006.04.005

Lu, P., Bridgelall, R., Tolliver, D., Chia, L., & Bhardwaj, B. (2019). *Intelligent Transportation Systems Approach to Railroad Infrastructure Performance Evaluation: Track Surface Abnormality Identification with Smartphone-Based App.* Mountain-Plains Consortium. Fargo: North Dakota State University - Upper Great Plains Transportation Institute. Retrieved from https://www.ugpti.org/resources/reports/details.php?id=954

Manning, W., & Mullahy, J. (2001). Estimating log models: to transform or not to transform? *Journal of Health Economics, 20*(4), 461-494. doi:10.1016/S0167-6296(01)00086-8

Mori, H., Sato, Y., Ohno, H., Tsunashima, H., & Saito, Y. (2013). Development of Compact Size Onboard Device for Condition Monitoring of Railway Tracks. *Journal of Mechanical Systems for Transportation and Logistics, 6*(2), 142-149. doi:10.1299/jmtl.6.142

Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. *Isprs Journal of Photogrammetry and Remote Sensing, 66*(3), 247-259. doi:10.1016/J.ISPRSJPRS.2010.11.001

Mousa, S., Bakhit, P., Osman, O., & Ishak, S. (2018). A Comparative Analysis of Tree-Based Ensemble Methods for Detecting Imminent Lane Change Maneuvers in Connected Vehicle Environments:. *Transportation Research Record, 2672*(42), 268-279. doi:10.1177/0361198118780204

Naweed, A., Rainbird, S., & Chapman, J. (2015). Investigating the formal countermeasures and informal strategies used to mitigate SPAD risk in train driving. *Ergonomics, 58*(6), 883-896. doi:10.1080/00140139.2014.1001448

NBC Universal. (2017, March 31). 15 Survivors Seek $250M-Plus in Deadly Biloxi Train-Bus Crash. *NBC News*. Retrieved from https://www.nbcnews.com/news/us-news/15-survivors-seek-250m-plus-deadly-biloxi-train-bus-crash-n741431

Norfolk Southern Railway. (2017, March 30). *A Trip to the Moon for Today's Generation of Railroaders*. (Norfolk Southern Railway) Retrieved August 7, 2018, from http://www.nscorp.com/content/nscorp/en/bizns/a-trip-to-the-moonfortodaysgenerationofrailroaders.html

NXP. (2007). *Sensors Device Data.* NXP Semiconductor. Retrieved from https://www.nxp.com/docs/en/supporting-information/DL200.pdf

Olson, R., Cava, W., Orzechowski, P., Urbanowicz, R., & Moore, J. (2017). PMLB: a large benchmark suite for machine learning evaluation and comparison. *Biodata Mining, 10*(1), 1-13. doi:10.1186/S13040-017-0154-4

Paixão, A., Fortunato, E., & Calçada, R. (2019). Smartphone's Sensing Capabilities for On-Board Railway Track Monitoring: Structural Performance and Geometrical Degradation Assessment. *Advances in Civil Engineering, 2019*, 1-13. doi:10.1155/2019/1729153

Peters, J. C., & Frittelli, J. (2018). *Positive Train Control (PTC): Overview and Policy Issues.* Washington, D.C.: Congressional Research Service (CRS). Retrieved from https://www.everycrsreport.com/reports/R42637.html

Quinlan, J. (1986). Induction of Decision Trees. *Machine Learning, 1*(1), 81-106. doi:10.1023/A:1022643204877

Ren, Y., Lu, P., Ai, C., Gao, L., Qiu, S., & Tolliver, D. (2021). Review of Emerging Technologies and Issues in Rail and Track Inspection for Local Lines in the United States. *Journal of Transportation Engineering, Part A: Systems, 147*(10). doi:10.1061/JTEPBS.0000567

Roskind, F. D. (2009). *Positive Train Control Systems Economic Analysis.* United States Department of Transportation (USDOT), Federal Railroad Administration, Office of Safety Analysis. Washington, D.C.: USDOT.

Rousseeuw, P., & Driessen, K. (1999). A fast algorithm for the minimum covariance determinant estimator. *Technometrics, 41*(3), 212-223. doi:10.2307/1270566

Schapire, R., & Singer, Y. (1998). Improved boosting algorithms using confidence-rated predictions. *Proceedings of the eleventh annual conference on Computational learning theory, 37*, pp. 80-91. doi:10.1145/279943.279960

Soleimani, S., Leitner, M., & Codjoe, J. (2021). Applying machine learning, text mining, and spatial analysis techniques to develop a highway-railroad grade crossing consolidation model. *Accident Analysis & Prevention, 152*, 105985-105985. doi:10.1016/J.AAP.2021.105985

Soleimani, S., Mousa, S., Codjoe, J., & Leitner, M. (2019). A Comprehensive Railroad-Highway Grade Crossing Consolidation Model: A Machine Learning Approach. *Accident Analysis & Prevention, 128*, 65-77. doi:10.1016/J.AAP.2019.04.002

Stagl, J. (2016, June). With deadline anxiety and other worries behind them, railroads press forward with PTC. *Progressive Railroading*. Retrieved from https://www.progressiverailroading.com/csx_transportation/article.aspx?id=48471

Štrumbelj, E., & Kononenko, I. (2014). Explaining prediction models and individual predictions with feature contributions. *Knowledge and Information Systems, 41*(3), 647-665. doi:10.1007/S10115-013-0679-X

Sumwalt (III), R. L. (2018). *Testimony on Oversight of Positive Train Control Implementation in the United States.* Washington, DC: National Transportation Safety Board (NTSB). Retrieved from https://www.ntsb.gov/news/speeches/RSumwalt/Documents/sumwalt-20180215.pdf

Sun, Y., Cao, Y., Xie, G., & Wen, T. (2020). Condition Monitoring for Railway Point Machines Based on Sound Analysis and Support Vector Machine. *Chinese Journal of Electronics, 29*(4), 786-792. doi:10.1016/J.TRC.2019.02.001

Sysyn, M., Gerber, U., Nabochenko, O., Gruen, D., & Kluge, F. (2019). Prediction of Rail Contact Fatigue on Crossings Using Image Processing and Machine Learning Methods. *Urban Rail Transit, 5*(2), 123-132. doi:10.1007/S40864-019-0105-0

Tsunashima, H. (2019). Condition Monitoring of Railway Tracks from Car-Body Vibration Using a Machine Learning Technique. *Applied Sciences, 9*(13), 2734. doi:10.3390/app9132734

Union Pacific Railroad. (2018, August 7). *Positive Train Control*. (Union Pacific Railroad) Retrieved August 7, 2018, from https://www.up.com/media/media_kit/ptc/about-ptc/

USCB. (2019). *TIGER/Line Shapefiles Technical Documentation.* Washington, D.C.: United States Census Bureau (USCB). Retrieved from https://www2.census.gov/geo/tiger/TIGER2019/COUNTY/

Wali, B., Khattak, A. J., & Ahmad, N. (2021). Injury severity analysis of pedestrian and bicyclist trespassing crashes at non-crossings: A hybrid predictive text analytics and heterogeneity-based statistical modeling approach. *Accident Analysis & Prevention, 150*, 105835. doi:10.1016/j.aap.2020.105835

Wang, B., Barkan, C., & Saat, M. (2020). Quantitative Analysis of Changes in Freight Train Derailment Causes and Rates. *Journal of Transportation Engineering, Part A: Systems, 146*(11), 4020127. doi:10.1061/JTEPBS.0000453

Wang, H., Khoshgoftaar, T. M., & Gao, K. (2010). A Comparative Study of Filter-Based Feature Ranking Techniques. *2010 IEEE International Conference on Information Reuse & Integration.* Las Vegas, Nevada: Institue of Electrical and Electronic Engineers (IEEE). doi:10.1109/IRI.2010.5558966

Williams, T., & Betak, J. (2019). A Comparison of LSA and LDA for the Analysis of Railroad Accident Text. *Journal of Ubiquitous Systems and Pervasive Networks, 11*(1), 11-15. doi:10.5383/JUSPN.11.01.002

Wordsworth, N. (2020, 10 23). Keeping leaves – and trees – off the line. *Rail Insider*. Retrieved from https://railinsider.co.uk/2020/10/23/keeping-leaves-and-trees-off-the-line/

Yu, L., & Liu, H. (2003). Feature Selection for High-Dimensional Data: A Fast Correlation-Based Filter Solution. *The Twentieth International Conference on Machine Learning (ICML-2003)*, (pp. 856-863). Washington, D.C. Retrieved from https://www.aaai.org/Papers/ICML/2003/ICML03-111.pdf

Zhang, Z., Liu, X., & Holt, K. (2018). Positive Train Control (PTC) for railway safety in the United States: Policy developments and critical issues. *Utilities Policy, 51*(2018), 33-40.