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Analysis of the Practical Implementation of an Adaptive Braking Enforcement Algorithm

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14. ABSTRACT
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METRIC/ENGLISH CONVERSION FACTORS

ENGLISH TO METRIC

LENGTH (APPROXIMATE)

1 inch (in)	=	2.5 centimeters (cm)
1 foot (ft)	=	30 centimeters (cm)
1 yard (yd)	=	0.9 meter (m)
1 mile (mi)	=	1.6 kilometers (km)

AREA (APPROXIMATE)

1 square inch (sq in, in^2)	=	6.5 square centimeters (cm^2)
1 square foot (sq ft, ft^2)	=	0.09 square meter (m^2)
1 square yard (sq yd, yd^2)	=	0.8 square meter (m^2)
1 square mile (sq mi, mi^2)	=	2.6 square kilometers (km^2)
1 acre = 0.4 hectare (he)	=	4,000 square meters (m^2)

MASS - WEIGHT (APPROXIMATE)

1 ounce (oz)	=	28 grams (gm)
1 pound (lb)	=	0.45 kilogram (kg)
1 short ton = 2,000 pounds (lb)	=	0.9 tonne (t)

VOLUME (APPROXIMATE)

1 teaspoon (tsp)	=	5 milliliters (ml)
1 tablespoon (tbsp)	=	15 milliliters (ml)
1 fluid ounce (fl oz)	=	30 milliliters (ml)
1 cup (c)	=	0.24 liter (l)
1 pint (pt)	=	0.47 liter (l)
1 quart (qt)	=	0.96 liter (l)
1 gallon (gal)	=	3.8 liters (l)
1 cubic foot (cu ft, ft^3)	=	0.03 cubic meter (m^3)
1 cubic yard (cu yd, yd^3)	=	0.76 cubic meter (m^3)

TEMPERATURE (EXACT)

[(x-32)(5/9)] °F = y °C

METRIC TO ENGLISH

LENGTH (APPROXIMATE)

1 millimeter (mm)	=	0.04 inch (in)
1 centimeter (cm)	=	0.4 inch (in)
1 meter (m)	=	3.3 feet (ft)
1 meter (m)	=	1.1 yards (yd)
1 kilometer (km)	=	0.6 mile (mi)

AREA (APPROXIMATE)

1 square centimeter (cm^2)	=	0.16 square inch (sq in, in^2)
1 square meter (m^2)	=	1.2 square yards (sq yd, yd^2)
1 square kilometer (km^2)	=	0.4 square mile (sq mi, mi^2)
10,000 square meters (m^2)	=	1 hectare (ha) = 2.5 acres

MASS - WEIGHT (APPROXIMATE)

1 gram (gm)	=	0.036 ounce (oz)
1 kilogram (kg)	=	2.2 pounds (lb)
1 tonne (t)	=	1,000 kilograms (kg)
	=	1.1 short tons

VOLUME (APPROXIMATE)

1 milliliter (ml)	=	0.03 fluid ounce (fl oz)
1 liter (l)	=	2.1 pints (pt)
1 liter (l)	=	1.06 quarts (qt)
1 liter (l)	=	0.26 gallon (gal)
1 cubic meter (m^3)	=	36 cubic feet (cu ft, ft^3)
1 cubic meter (m^3)	=	1.3 cubic yards (cu yd, yd^3)

TEMPERATURE (EXACT)

[(9/5) y + 32] °C = x °F

QUICK INCH - CENTIMETER LENGTH CONVERSION

Inches	0			1			2			3		4		5
Centimeters	0	1	2	3	4	5	6	7	8	9	10	11	12	13

QUICK FAHRENHEIT - CELSIUS TEMPERATURE CONVERSIO

°F	-40°	-22°	-4°	14°	32°	50°	68°	86°	104°	122°	140°	158°	176°	194°	212°
°C	-40°	-30°	-20°	-10°	0°	10°	20°	30°	40°	50°	60°	70°	80°	90°	100°

For more exact and or other conversion factors, see NIST Miscellaneous Publication 286, Units of Weights and Measures. Price $2.50 SD Catalog No. C13 10286

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Executive Summary

Researchers at Transportation Technology Center, Inc. (TTCI) evaluated proposed adaptive braking enforcement algorithm processes for freight trains to identify potential risks that may be introduced by the use of an adaptive braking enforcement algorithm. Two main hazards, relating to the prediction of stopping distance, were identified when using an adaptive braking enforcement algorithm. The first hazard identified was the inaccurate estimation of train braking characteristics during an adaptive calculation. The second was a change in conditions affecting the train stopping distance after an adaptive calculation has been made, such as a change in ambient pressure, ambient temperature, the coefficient of friction (COF) between the brake shoe and the wheel, train brake pipe pressure leakage, speed accuracy, track grade profile accuracy, and brake pipe pressure sensor accuracy. Researchers identified methods of evaluating these hazards and when production adaptive braking enforcement algorithms are available for evaluation, they can be analyzed through simulations with minor updates to the simulation methodology.

Researchers conducted a sensitivity analysis for the hazard where conditions change after an adaptive calculation has been made. Findings showed that changes in the COF between the brake shoe and wheel had the greatest influence on train stopping distance, followed by changes in train brake pipe pressure leakage. Other factors such as ambient pressure and temperature and track grade errors also influenced train stopping distance, but to a lesser degree.

After gaining insights on the potential risks, the research team evaluated numerous scenarios using Monte Carlo stop distance simulations to generate representative distributions of stopping locations relative to a target for both a nonadaptive algorithm and an adaptive algorithm. The team used these distributions to determine if there was an increased risk of overrunning a target when using an adaptive algorithm in cases where conditions change after the adaptive calculation has been made.

A comparison of the distributions of stopping location relative to a target showed that the adaptive algorithm distribution always had a wider range, meaning there was the potential for more extreme outliers with adaptive algorithms, albeit with low probability of occurrence. Comparing the standard deviation of the distributions of stopping location relative to a target showed that adaptive algorithm distributions can have a smaller standard deviation than the nonadaptive distributions in scenarios where train consists have a wide range of variation. The team saw this in some of the scenarios with longer manifest freight trains. In other scenarios with less variation in the train consist, such as a unit coal train consist, the adaptive algorithm distributions had larger standard deviations than nonadaptive algorithms.

The Monte Carlo analysis assumed that the distribution types and ranges for parameters that can change after an adaptive calculation had been made were the same as the distribution types and ranges for these parameters more generally (in other words, there were no constraints on the amount a parameter could change following the adaptive calculation). This assumption resulted in the most conservative results, but the authors recommend future work to determine if these distributions should be constrained and how those constraints would affect the adaptive stopping distance distribution profiles.

The research team recommends adaptive braking enforcement algorithm calculations and performance be tested initially through simulations and, once proven in the simulation environment, with field testing.

1. Introduction

This report describes analyses performed to support the practical implementation of an adaptive predictive braking enforcement algorithm for freight train Positive Train Control (PTC) applications. TTCI engineers identified potential hazards associated with the use of an adaptive braking enforcement algorithm, quantified risks, and determined potential risk reduction strategies. This report describes the work performed to address the potential causes of safety hazards that differ between conventional (nonadaptive) braking enforcement algorithms and the proposed adaptive braking enforcement algorithms, to support a safety case for implementing the adaptive braking enforcement algorithm.

1.1 Background

One of the primary issues with PTC braking enforcement algorithms contributing to operational inefficiencies is the reliance on assumed values for parameters that are not known by the braking enforcement algorithm. Adaptive braking enforcement algorithms have the potential to improve the accuracy of the stopping distance prediction by measuring key performance characteristics of the train and adapting the algorithm to predict the stopping distance based on these characteristics, rather than relying on the assumed values. The concept of using adaptive functions was investigated in previous Federal Railroad Administration (FRA) research projects [1]. At the conclusion of these projects, adaptive functions were defined to improve the accuracy of the following parameters used by the braking enforcement algorithm:

- Brake pipe propagation time – defined as the time from when the penalty air brake application is initiated to when the brakes have reached full-service brake force on all of the cars in the train.
- Brake efficiency – defined as the full-service brake force for the train.

Although there are several other parameters for which the enforcement algorithm has assumed values, the brake pipe propagation time and brake efficiency adaptive functions represent the most significant parameters that can be practically measured. These two adaptive routines also compensate for various other parameters that can vary from the assumed values in the enforcement algorithm. For example, the adaptive brake efficiency function not only corrects for potential errors in the assumed train brake force but can also compensate for errors in the assumed values for the number of operable brakes, train weight, and the number of loaded and empty cars.

During the previous research on adaptive braking enforcement algorithms, these concepts were developed and implemented in a test application, followed by simulation and field testing, which demonstrated significant improvements when using the adaptive functions as compared with conventional (nonadaptive) techniques.

The previous work on the adaptive functions did not include any study to consider potential hazards introduced with use of the adaptive calculations and the effects of these hazards. This project examined these hazards to determine if they can be mitigated to help create a safety case for implementing adaptive functions into a braking enforcement algorithm.

1.2 Objectives

The objective of this project was to conduct a safety analysis to support the practical implementation of adaptive braking enforcement algorithms in PTC applications. Specifically, this included:

- Conducting a safety analysis to identify risks associated with using adaptive braking enforcement algorithms as compared to conventional (nonadaptive) methods
- Quantifying the risks identified
- Identifying potential mitigations for risks

1.3 Overall Approach

The general flow of the work performed:

- Create a project advisory group (AG) with representatives from FRA, Class I freight railroads, shortline railroads, and commuter/passenger railroads.
- Using adaptive braking functions from previous FRA research, conduct a safety analysis to identify the risks associated with using adaptive braking enforcement algorithms as compared to conventional (nonadaptive) methods.
  - Run Train Operations and Energy Management (TOES™) sensitivity braking simulations with predetermined parameters using flat distributions.
  - Conduct a 2k design of experiment to quantify potential risks.
  - Run Monte Carlo simulations using TOES for train types identified to have greatest risk from changes to initial train braking parameters.
- Theorize mitigation concepts where possible.
- Develop final report and propose next steps.

1.4 Scope

The scope of this project included tasks to identify potential hazards associated with the use of an adaptive braking enforcement algorithm, quantify risks, and determine potential mitigation strategies. Specifically, this project addressed the potential causes of safety hazards that differ between conventional (nonadaptive) braking enforcement algorithms and the proposed adaptive braking enforcement algorithms, to support a safety case for implementing the adaptive braking enforcement algorithm in freight operations. The scope of this project did not include any implementation of mitigations or field testing.

1.5 Organization of the Report

This document has been organized into three sections. Section 2, Adaptive Braking Enforcement Algorithms, describes the differences between the nonadaptive and adaptive braking algorithms as well as simulation testing and testing process. Section 3, Identification of Potential Hazards Associated with Adaptive Braking Enforcement Algorithms, gives and overview of potential hazards and describes methods and simulation tools used by the researchers to determine these hazards. Section 4, Proposed Methodology for Evaluating Adaptive Braking Enforcement Algorithms, describes how the current Monte Carlo braking simulation process could be utilized for further testing of the nonadaptive braking algorithm. This section also describes the modifications to the current Monte Carlo simulation process that will be required for future testing. The Conclusion summarizes the findings about the nonadaptive braking algorithm by the researchers as well as recommends further future simulation testing of the nonadaptive braking algorithm.

2. Adaptive Braking Enforcement Algorithms

The adaptive braking enforcement algorithm approaches in this analysis used two methods to tune the braking enforcement algorithm inputs: adaptive brake propagation time and adaptive brake efficiency. Brake propagation time is the amount of time it takes from the onset of a brake application until the brakes are applied throughout the train. Brake efficiency is the amount of brake force applied by the train once train brakes are fully applied. Both brake propagation time and brake efficiency are influenced by mechanical and environmental factors.

2.1 Differences between Nonadaptive Braking Enforcement Algorithms and Adaptive Braking Enforcement Algorithms

Conventional nonadaptive braking enforcement algorithms rely on summary train consist information to make assumptions about train braking characteristics. Those assumptions are used, along with track profile information under and ahead of the train and current train status (e.g., speed, tractive effort, and air brake settings), to estimate the stopping distance and determine if a warning or brake enforcement is needed. The main assumptions made for a given train include how long it will take to apply the brakes and how much brake force is applied. Train consist information used for these assumptions includes:

- Locomotive information for each locomotive in the train consist:
    - Length, weight, position in train, run status, horsepower
- Number of loaded and empty railcars
- Number of axles
- Trailing tonnage
- Train length
- Train type
- Back office brake force (optional)

North American freight operations include a pool of over 1 million freight cars that are interchangeable between the railroads. The mechanical equipment that relates to brake propagation and brake efficiency can vary among cars based on the date a railcar was built or rebuilt and the railcar characteristics. With the vast number of interchange cars and the limitations of the summary information supplied to the braking enforcement algorithm, there are many different train makeups with different braking characteristics that are possible, given the summary train consist information provided. Typically, the assumptions for brake propagation time and brake efficiency are tailored toward the poorer performing trains within a train type to make sure there is a high probability of stopping trains short of a target. With these assumptions, trains with better braking performance will be forced to apply brakes earlier than necessary and stop further short of the target stopping location.

Besides train makeup, the stopping distance of a train can vary on the basis of conditions of the train at the time of a brake enforcement such as ambient pressure and temperature, COF between the brake shoe and the wheel, train brake pipe pressure leakage, speed accuracy, track grade profile accuracy, and brake pipe pressure sensor accuracy. These conditions can change over time and/or geographical location and can cause the actual stopping distance of a train to be shorter or longer than the predicted stopping location. Typically, this variance in train stopping performance is handled through a target offset using the summary train consist information provided and current in-route train data such as speed, grade, tractive effort, and brake settings. Figure 1 gives an overview of a sample scenario with the predicted stopping profile and target offset for a given train consist.

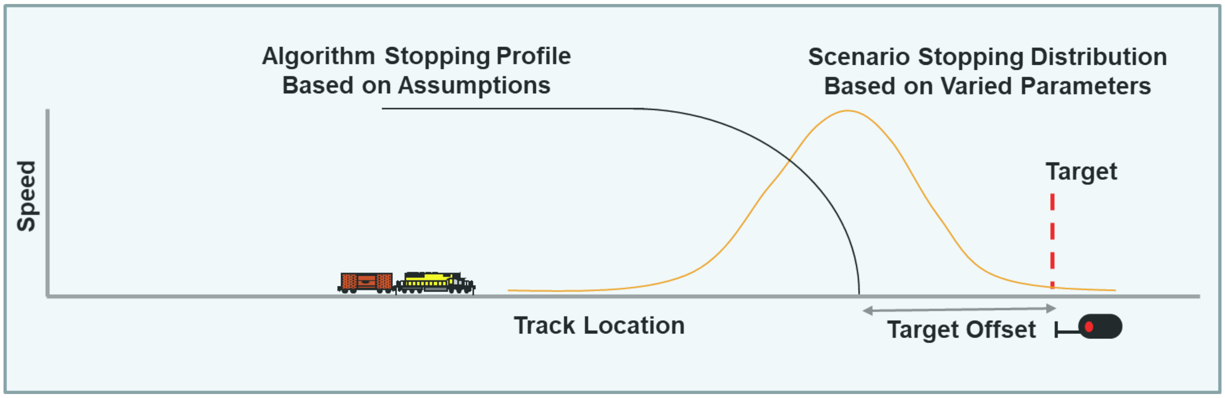

Figure 1. Stopping Profile and Target Offset

If a train consist matches the onboard brake propagation and brake efficiency assumptions, then the actual stopping location of the train would fall within the stopping distribution shown in Figure 1. If the train consist braking characteristics are better than the onboard assumptions, then the stopping profile in Figure 1 would be shifted to the left, which would result in stops further from the target for those train consists. Better braking characteristics in a train consist make the nonadaptive braking enforcement algorithm more conservative.

A method for reducing conservatism from current nonadaptive braking enforcement algorithms is to use an adaptive braking enforcement algorithm that uses brake sets from the train to gain information about the braking characteristics of the train. Once a brake set is made and the adaptive braking enforcement algorithm successfully calculates new values for brake propagation time and/or brake efficiency, the assumptions for the train are updated and used for future stopping predictions. Taking the example of a train with better-than-assumed braking characteristics, in a nonadaptive braking enforcement algorithm the stopping distribution would be shifted to the left in Figure 1, but in an adaptive braking enforcement algorithm the enforcement point could be delayed on the basis of the updated assumptions for the braking characteristics of the train, bringing the stopping distribution back to the right, eliminating some of the conservatism. By using information gathered from a train brake set, the adaptive braking enforcement algorithm also accounts for the other conditions for the train at that time such as ambient pressure and temperature, COF between the brake shoe and wheel, train brake pipe pressure leakage, speed accuracy, track grade profile accuracy, and brake pipe pressure sensor accuracy. In the near term, accounting for these conditions improve the adaptive braking enforcement algorithm stopping prediction of the train and will result in a tighter stopping distribution, but over time these conditions can change, causing the stopping distribution to grow.

2.2 Overview of Simulation Testing for Nonadaptive Braking Enforcement Algorithms

This section provides an overview of the simulation process, consisting of background information that originally appeared in the final report from previous FRA-funded braking enforcement algorithm research. [1]

The simulation testing component of the braking enforcement algorithm evaluation methodology uses a set of computer software tools to employ a Monte Carlo simulation process, resulting in a set of output data that can be analyzed to identify the statistical probability and confidence that the algorithm will meet the specified safety and performance criteria. The Monte Carlo method involves running large numbers of simulations with inputs to the simulations randomly assigned using the practical and physical distributions and limits that define the system. Because of the wide range of parameters that affect the stopping distance of a freight train and the interdependence of these parameters, a deterministic evaluation is not feasible, making the Monte Carlo simulation process the preferred method of evaluating the braking enforcement algorithm.

2.2.1 Overview of Simulation Testing Process

The simulation testing process is intended to evaluate the braking enforcement algorithm over the full range of operating scenarios the system is expected to encounter and consider the practical variability of the parameters that can have a significant effect on the stopping distance of the train. The simulations are organized into test scenarios, each representing a potential operating scenario for the system to encounter. The test scenario is defined by the nominal train consist, the nominal track profile, the initial speed and location of the train, and the target stopping position. These scenarios have been created to effectively cover the wide range of operations that are run daily in revenue service, as well as account for the less common extreme cases, such as steep track grades, higher speeds, and specialized train consist makeups.

Multiple braking enforcement simulations are run for each test scenario. The values of the parameters that can have a significant effect on train stopping distance are randomly selected for each simulation from distributions that represent the practical range of values for the given parameter. In some cases, the distribution of values for a parameter is affected by the value randomly selected for a different, related parameter.

The test scenarios that make up the complete simulation test matrix are intended to include the boundary operating conditions and represent the full range of conditions that can be experienced. To make the simulation process more efficient, the test scenarios are organized into batches that are executed together. A batch could contain any number of test scenarios, each representing a different nominal operating scenario, and each test scenario could contain any number of individual simulations, each representing a potential specific instance of the test scenario. Figure 2 illustrates the relationship between batches, test scenarios, and simulations.

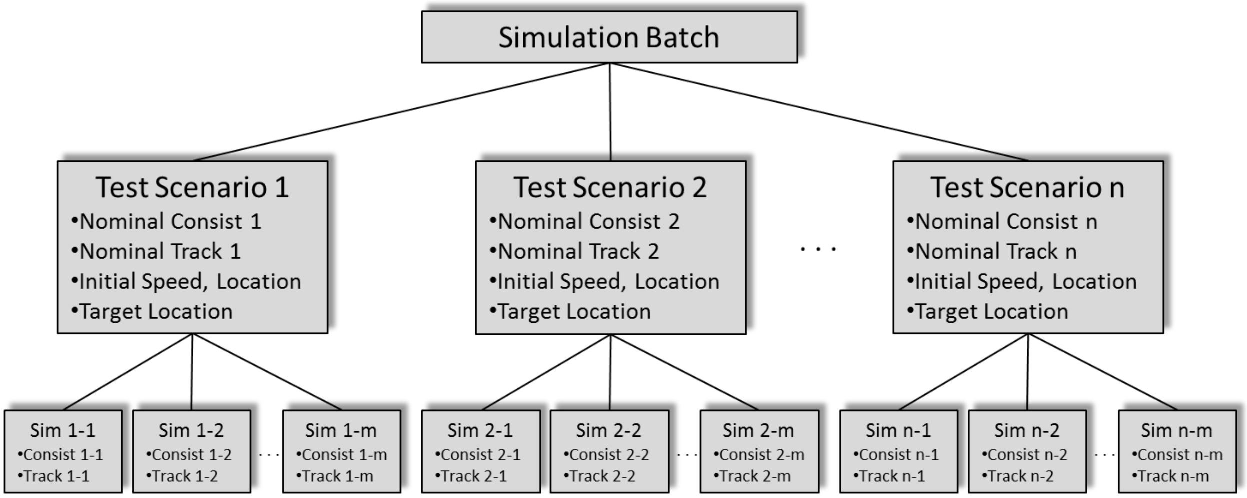

Figure 2. Organization of Simulations

For each individual simulation test, the train consist is modeled approaching the target at the defined initial speed, the braking enforcement algorithm triggers a brake application to prevent a violation of the stop target, and the response of the train is modeled. The result of the individual simulation represents a single possible stopping location for the given test scenario with the given braking enforcement algorithm. The aggregate result of the simulations for the entire test scenario then defines the distribution of possible outcomes. This data is analyzed to determine the safety and performance characteristics of the braking enforcement algorithm for the given test scenario. These characteristics can then be analyzed together to quantify the overall safety and performance characteristics of the braking enforcement algorithm.

2.2.2 Simulation Testing Tools

The simulation testing portion of the braking enforcement algorithm evaluation methodology requires the following three components, as Figure 3 illustrates:

- A proven, validated train action simulation model that accurately models the response of a given train under given conditions, with the ability to modify train, track, and environmental characteristics that can affect the stopping distance of the train
- A test controller/logger (TCL) software application that can generate the simulation inputs to the model from input provided by the user, run large batches of simulations using Monte Carlo simulation techniques, and log the required output
- The braking enforcement algorithm under evaluation, implemented as a standalone software application incorporating a common interface to the simulation test components to receive train status and command brake enforcement applications

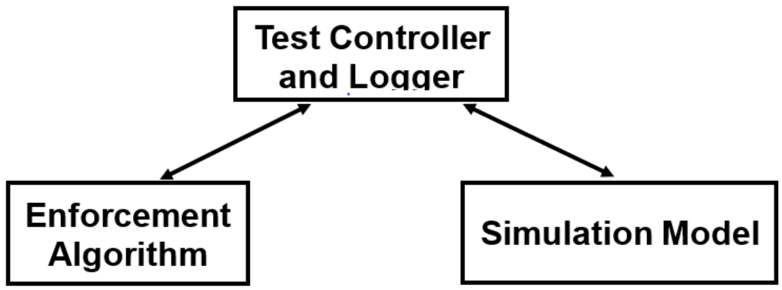

Figure 3. Simulation Testing Components

2.2.2.1 Simulation Model

To model any given braking enforcement scenario, the chosen simulation model must accurately model the response of the train to given inputs, be capable of modeling the specific characteristics of each component of each railcar within the train consist and the specific characteristics of the track, and be capable of reporting train status data at regular, frequent intervals. Therefore, TOES was the simulation model selected for braking enforcement algorithm evaluation. TOES is a longitudinal train dynamics model developed by the Association of American Railroads that models the status of every railcar in a given train consist at every time step of the simulation. Railcar status data includes location, velocity, acceleration, forces acting on the car, and brake system component status.

The model allows the user to enter specific characteristics for each railcar in the train consist, including car weights and dimensions, aerodynamic properties, truck characteristics, coupler and draft gear characteristics, and brake system components and characteristics. This flexibility allows the user to model essentially any currently used freight railcar and arrange the railcars into any train consist desired. The model also allows the user to enter track characteristics that affect the longitudinal motion of the train, i.e., track grade and curve, allowing any section of track to be modeled. Finally, the model allows the user to enter environmental conditions that can affect the longitudinal motion of the train, such as ambient temperature and the COF between the wheels and brake shoes. The TOES model allows the user to enter train handling commands, such as throttle and brake settings, at any time step in the simulation and models how the train reacts to these commands.

The components that make up the TOES model include some of the most accurate and proven models currently available to the railroad industry. These include a variety of draft gear models, multiplatform cars, an aerodynamic drag routine, and a variety of user-customizable car components. TOES also includes a theoretical fluid dynamics model of the air brake system. This model has been shown to be a significant improvement over similar models empirically derived from test data. The air brake model within TOES can simulate the automatic and independent air brakes, a range of brake valve and brake shoe types, any length of brake pipe, brake cylinder dimensions, and reservoir volumes.

2.2.2.2 TCL Software

A custom software application was necessary to manage the vast number of simulations required to generate the necessary statistical significance for the safety and performance of the enforcement algorithm over the entire range of potential operating scenarios. To support the industry in the development and testing of a safe and operationally efficient braking enforcement algorithm, TTCI developed (using internal research and development funds) a TCL software application with the capability to generate and execute thousands of braking enforcement simulations using a Monte Carlo method, using operating scenarios and parameter variation distributions entered by the user.

The TCL application performs the following three major functions:

- Generation of random simulation inputs
- Execution of individual simulations
- Logging of output data

To generate simulation input data, the user sets up a batch of test scenarios to be evaluated. The user selects a train consist and track profile and enters the initial train speed and location, as well as the target stopping location for each test scenario in the batch.

The train consists are defined by the user by selecting the desired railcars and arranging them in the desired order. Each railcar is defined by the nominal components and characteristics of the railcar and the potential variation of these components and characteristics, also defined by the user. The variation of the railcar components and characteristics can be represented by a variety of distributions, allowing the user to define the variability of a given parameter to match its actual, real-world variation. The user also defines the potential variation of environmental characteristics and the variation because of errors in reported data, such as track characteristics, train speed, and location.

The user selects how many simulations the TCL software will run for each test scenario in the Monte Carlo process. The TCL software then generates the simulation input data for each simulation within each test scenario by randomly selecting values for the variable parameters from the input distributions defined by the user.

Once the simulation input data is generated, the user can run the batch through the TCL software. The TCL application runs each simulation for each test scenario individually in the simulation model by advancing the train toward the target at a given speed. At each second of simulation time, the simulation model reports train status data to the TCL, which is then passed along to the braking enforcement algorithm. When the braking enforcement algorithm predicts an impending target overrun, it sends a command to initiate a penalty brake enforcement to the TCL application, which executes the penalty in the simulation model. The TCL continues to advance the simulation until the train is stopped. The braking enforcement algorithm can also send a command to initiate an emergency brake enforcement, which TCL then executes in the simulation model.

Once the train has stopped, the simulation is complete, and the TCL software logs the output data in a database for post-process analysis.

2.2.2.3 Interface to Braking Enforcement Algorithm

The intent of the braking enforcement algorithm evaluation methodology is that it can be applied to evaluate any braking enforcement algorithm for any North American freight PTC implementation. As such, the methodology treats the software implementation of the braking enforcement algorithm as a black box that communicates with the simulation testing components over an open communications interface. A document that details the communications process and protocols was prepared for use by developers of braking enforcement algorithm software to be evaluated using the methodology.

To allow for the most flexibility in the test setup, the interface was designed with communications over transmission control protocol/internet protocol (TCP/IP). This allows for the braking enforcement algorithm to be implemented as an executable software application running on the same machine as the TCL software, as a virtual machine with a separate IP address, but operating on the same hardware as the TCL software, or as software running on separate hardware that communicates over TCP/IP.

The interface was also designed with flexibility for initializing the simulation test process, to allow for more efficient execution of the simulations. The TCL software can execute the braking enforcement algorithm software directly, if it is run on the same machine as the TCL software. Alternatively, a braking enforcement algorithm initialization module was developed that sends an initialization message to the braking enforcement algorithm software, indicating that the previous simulation is complete, and the new simulation is beginning. This allows the braking enforcement algorithm software to re-initialize internal parameters, etc., for the new simulation.

To ease the integration of an untested braking enforcement algorithm with the TCL software setup, a protocol test application was developed. The protocol test application replicates the communications to and from the TCL software with the current protocols, but without the additional functionality of the TCL software. This allows the developer of the braking enforcement algorithm software to test its communications interface and debug any issues locally, resulting in reduced time and cost associated with the integration process. The source code for the protocol test application is also available, to support the development of the interface on the braking enforcement algorithm side without releasing the proprietary TCL software source code. [1]

2.3 Simulation Modifications for Adaptive Braking Enforcement Algorithms

Two modifications to TCL were made to support running simulations for adaptive braking enforcement algorithms.

The first modification was to allow a user to build a scenario that includes a user-specified number of simulations in which each simulation uses the same train consist, where parameters within the consist are not modified from simulation to simulation. This option is necessary for evaluating adaptive braking enforcement algorithms because the assumption is that a train consist will not be modified once the train has been assembled and adaptive calculations have been made. With this option, Monte Carlo simulations can be run where the train consist is held constant, but the other parameters that can change are varied on the basis of their distribution types and ranges.

The second modification runs the adaptive simulations for the first simulation in a scenario and stores the adaptive values calculated by the algorithm for brake propagation time and brake efficiency. The other simulations for that scenario are then executed using the adaptive values calculated in the first simulation. This change was necessary to run simulations where conditions such as ambient pressure and temperature, COF between the brake shoe and wheel, train brake pipe pressure leakage, speed accuracy, and/or track grade profile accuracy had changed since the adaptive values were calculated and evaluate how these changes affected the stopping location of the train.

3. Identification of Potential Hazards Associated with Adaptive Braking Enforcement Algorithms

Two main hazards were identified with using train brake sets to update the braking characteristics of the train: The miscalculation of the braking characteristic values in the adaptive braking enforcement algorithm and the potential change in conditions after an adaptive calculation has been made.

3.1 Miscalculation of Adaptive Values

Hazards introduced from a miscalculation of either brake propagation time or brake efficiency or both could result in an unsafe outcome. For example, if the algorithm calculates a brake propagation time that is faster than the actual train brake propagation time or brake efficiency that is greater than the actual train brake efficiency, the stopping distribution shown in Figure 1 could end up shifted further to the right, increasing the probability of a train to overrun the target. The following subsections describe considerations for calculating adaptive values.

3.1.1 Brake Propagation Time

For trains operating with head-end power, the adaptive braking enforcement algorithm must accurately determine the time of the initiation of a brake application and the amount of brake pipe pressure reduction, as well as accurately monitor head-end and end-of-train brake pipe pressure throughout the brake application. From this data, the adaptive braking enforcement algorithm calculates the estimated brake propagation time for a full-service brake application. If the calculation is performed on a brake application with a brake pipe pressure reduction less than a full-service application, the adaptive routine must extrapolate to determine the propagation time for a full-service application.

Often trains are operated with distributed power, which allows a brake application to be applied simultaneously by the locomotives distributed throughout the train. For trains operating with distributed power, the adaptive braking enforcement algorithm depends on the ability to apply a head-end-only brake application with the rear locomotive reporting end-of-train brake pipe pressure. Alternatively, a new method of calculating brake propagation time without monitoring the end-of-train brake pipe pressure could be developed and implemented. After the brake pipe propagation time calculation is made for the head-end only application, a further calculation is required to account for the brake propagation time for the distributed power train.

Comprehensive simulation and testing of a brake propagation time adaptive routine can be used to verify the accuracy and potential for miscalculation. Braking enforcement algorithms that implement a brake propagation time adaptive routine can be evaluated through the current Monte Carlo simulation process with a few updates to the data recorded for each simulation. To evaluate this specific functionality, the algorithm must output the calculated brake propagation time for each simulation, and TCL can be used to record the actual brake propagation time for the simulation using data from TOES. The two values can be compared to analyze the accuracy of the adaptive braking enforcement algorithm in calculating the brake propagation time. Initial development and evaluation could make use of simulations until confidence is gained in the process, followed by testing on actual trains.

Additional mitigations for potential adaptive brake propagation time miscalculations:

- Determine the worst-case and best-case brake propagation values for the given train consist and verify that any value calculated by the algorithm falls within the range of possible values defined by the worst case and best case.
- Make smaller adjustments from the assumed value, as opposed to simply accepting the calculated value. Further adjustments can be made as more brake applications are made after verifying that data from the previous brake sets are consistent.

3.1.2 Brake Efficiency

To calculate brake efficiency, the train must be moving with a brake application in place for a sufficient time duration to collect data for the adaptive algorithm. The algorithm must accurately account for the variety of forces acting on the train to calculate the force from the train brakes.

Similar to the brake propagation time, comprehensive simulation and testing of a brake efficiency adaptive routine can be used to verify the accuracy and potential for miscalculation. Braking enforcement algorithms that implement a brake efficiency routine can be evaluated through the existing Monte Carlo simulation process with updates to the outputs of the simulations. The algorithm must output the calculated brake efficiency, which can be compared to the actual train brake efficiency used in the simulation. Initial development and evaluation could make use of simulations until confidence is gained in the process, followed by testing on actual trains.

As with the brake propagation time routine, additional mitigations for potential adaptive brake efficiency miscalculations include the following:

- Determine the worst-case and best-case brake efficiency values for the given train consist and verify that any value calculated by the algorithm falls within the range of possible values defined by the worst case and best case.
- Make smaller adjustments from the assumed value, as opposed to simply accepting the calculated value. Further adjustments can be made as more brake applications are made after verifying that data from the previous brake sets are consistent.

3.2 Change in Conditions after Adaptive Values Have Been Calculated

The second hazard identified was a change in conditions, such as ambient pressure and temperature, COF between the brake shoe and wheel, train brake pipe pressure leakage, speed accuracy, and/or track grade profile accuracy after adaptive values have been calculated. Typically, braking enforcement algorithms handle the uncertainty of these (and other) conditions through the addition of a target offset. With adaptive braking enforcement algorithms, these conditions influence the adaptive values calculated during a brake set and changes in these conditions after adaptive values have been calculated and stored will affect the braking characteristics of the train. The more time elapsed and distance traveled after the adaptive values are calculated, the greater the potential for conditions to change. For this reason, additional research into how these conditions affect the stopping distance of a train was conducted through a sensitivity analysis, an expanded design of experiment for the sensitivity analysis, and Monte Carlo simulations of select scenarios.

3.2.1 Sensitivity Analysis

The sensitivity analysis started with identifying parameters used in the current Monte Carlo process that can change throughout a train trip, as opposed to those that can vary from one train consist to another, but do not change for a given train consist throughout a single trip. Below is a list of parameters used in the current Monte Carlo process that can change after the adaptive values are calculated:

- Ambient pressure
- Ambient temperature
- COF between brake shoe and wheel
- Brake pipe pressure leakage
- Speed reporting error
- Train position reporting error
- Brake pipe pressure sensor error
- Track grade error

Speed reporting error, brake pipe pressure sensor error, and train position reporting error were excluded from this study. These three parameters were not considered for this study for various reasons, but primarily because when each of them is considered in isolation, they have less influence on the train stopping distance than the other parameters.

A portion of the speed reporting error comes from calibration error on the locomotive tachometer, which on the same locomotive should change very little over time. Other speed reporting errors can come from GPS readings, but previous experience with modeling brake algorithms, the speed reporting error, in isolation, has a small effect on train stopping distance.

The train position reporting error has a range of approximately plus or minus 11 feet, which results in a small influence on train stopping distance.

The brake pipe pressure sensor errors are due to calibration errors on the locomotive brake pipe pressure sensors and calibration errors on the end-of-train brake pipe pressure sensors. It is expected that the calibration errors for a given train consist will change very little over time, and from previous experience the influence of this parameter on stopping distance will be minimal.

The remaining five parameters were evaluated further through TOES simulations, a targeted design of experiment, and limited Monte Carlo analysis.

3.2.1.1 TOES Simulations

An analysis was performed using simulations, including scenarios with different speed and grade combinations across unit, intermodal, and mixed manifest freight trains. The purpose of this analysis was to investigate the interaction of the parameters that influence stopping distance with an emphasis on parameters set toward their extremes. To limit the number of simulations and raise the probability a parameter would be selected toward the outer limits of its range, parameters that have a normal Gaussian distribution type were modified to a flat distribution type with the range extending to the four standard deviation points. Only a single train consist makeup was used for each scenario and that exact train consist was used for every simulation within a scenario. Using the new distribution types and ranges, 100 simulations were created and executed for each scenario.

The analysis of the parameters selected for each simulation shows that the extremes of each parameter were present, but there were not enough simulations created to get cases where all of the parameters were at their extremes in different combinations at the same time. The results of these simulations did provide useful data and trends, indicating which parameters had the most influence on stopping distance.

One identified trend was that the longest stopping distance for each scenario commonly had the COF parameter toward the low extreme. Other parameters ranged up and down for these simulations, indicating that their influence on stopping distance was less than the COF parameter.

Another trend was identified when looking at the stopping distance for simulations with similar COF values. For these simulations, longer stopping distances commonly had ambient temperature and brake pipe pressure leakage toward their low extreme, indicating that after the COF parameter, these two would be considered the next dominant parameters.

Looking beyond these trends with this dataset was difficult because of the limited similar parameter combinations.

3.2.1.2 Design of Experiment

Knowing the parameters and extreme values of interest, a design of experiment was created to test the extreme levels in combinations that might have been missed from the previous Monte Carlo simulations that used a flat distribution. The full factorial 2k design of experiment was selected to ensure all combinations of the five parameters, set to their high and low values, would be simulated. Simulations were run for 612 scenarios (combination of train consists, speeds, and grade) at all combinations of factors at high and low levels. Using the five parameters of interest, all in combination of high and low levels resulted in 32 (2^5) permutations per scenario. Each permutation was set up in TCL by selecting the exact value desired for each parameter and then running a simulation for each scenario for that permutation before moving onto the next and repeating the process. Table 1 shows the high and low levels for each factor that was considered in the model analysis. Table 2 shows the different permutations for the full factorial 2k design of experiment.

Table 1. Factor Levels for Simulation and Design of Experiment Modeling

Parameter	Setting
Ambient Pressure (High)	14.7
Ambient Pressure (Low)	8.7
Ambient Temperature (High)	97.3
Ambient Temperature (Low)	10.9
Brake Pipe Pressure Leakage (High)	5.82
Brake Pipe Pressure Leakage (Low)	0.1
Coefficient of Friction (High)	26.68
Coefficient of Friction (Low)	-26.68
Grade Error (High)	0.05
Grade Error (Low)	-0.05

Table 2. Design of Experiment Parameter Permutations

Run Order	Ambient Pressure (psi)	Ambient Temperature (°F)	Brake Pipe Leakage Rate (psi/m)	Shoe/Wheel COF (% from nominal)	Track Grade Error (% from nominal)
1	8.7	10.9	0.1	-26.68	-0.05
2	14.7	10.9	0.1	-26.68	-0.05
3	8.7	97.3	0.1	-26.68	-0.05
4	14.7	97.3	0.1	-26.68	-0.05
5	8.7	10.9	5.82	-26.68	-0.05
6	14.7	10.9	5.82	-26.68	-0.05
7	8.7	97.3	5.82	-26.68	-0.05
8	14.7	97.3	5.82	-26.68	-0.05
9	8.7	10.9	0.1	26.68	-0.05
10	14.7	10.9	0.1	26.68	-0.05
11	8.7	97.3	0.1	26.68	-0.05
12	14.7	97.3	0.1	26.68	-0.05
13	8.7	10.9	5.82	26.68	-0.05
14	14.7	10.9	5.82	26.68	-0.05
15	8.7	97.3	5.82	26.68	-0.05
16	14.7	97.3	5.82	26.68	-0.05
17	8.7	10.9	0.1	-26.68	0.05
18	14.7	10.9	0.1	-26.68	0.05
19	8.7	97.3	0.1	-26.68	0.05
20	14.7	97.3	0.1	-26.68	0.05
21	8.7	10.9	5.82	-26.68	0.05
22	14.7	10.9	5.82	-26.68	0.05
23	8.7	97.3	5.82	-26.68	0.05
24	14.7	97.3	5.82	-26.68	0.05
25	8.7	10.9	0.1	26.68	0.05
26	14.7	10.9	0.1	26.68	0.05
27	8.7	97.3	0.1	26.68	0.05
28	14.7	97.3	0.1	26.68	0.05
29	8.7	10.9	5.82	26.68	0.05
301	14.7	10.9	5.82	26.68	0.05
31	8.7	97.3	5.82	26.68	0.05
32	14.7	97.3	5.82	26.68	0.051

Simulation results from the design of experiment were analyzed using Minitab statistical software. The simulations were grouped by train type, speed, and grade for this analysis. This grouping was selected based on similar analysis completed on target offsets, in previous braking enforcement algorithm modeling efforts, which also used stop distance simulations. The end goal of this analysis was to provide models or regression equations that could be used to estimate the change in stopping distance by modifying parameters from known values to values of interest to show how the change in parameters after an adaptive calculation is made can change the stopping distance. Analysis of the effects of each parameter from one of the simulation groupings is shown in Figure 4. This figure shows for each factor how the stopping distance would change from the nominal stopping distance, using a value change of that factor. Also, the steepness of the line indicates the amount of influence on stopping distance that factor has. Figure 4 shows that the stopping distance of a train would increase if the pressure increased, the temperature decreased, the brake pipe pressure leakage decreased, COF decreased, or grade error decreased.

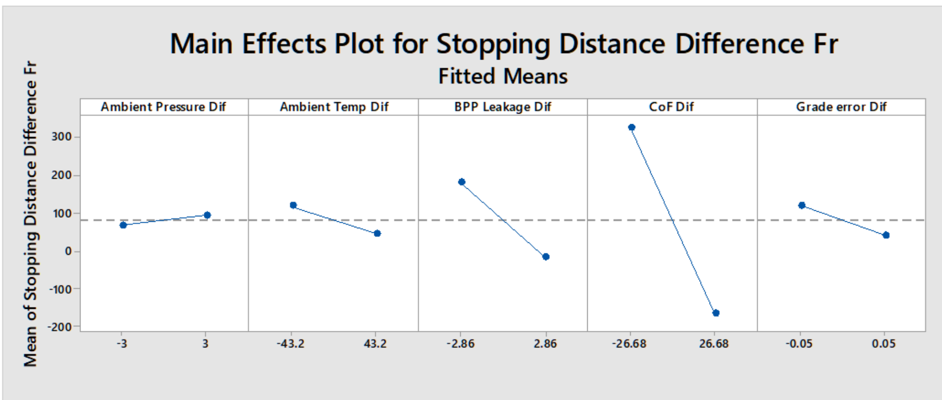

Figure 4. Typical Parameter Effects Plot Result for Simulation Grouping

The design of experiment Minitab analysis results provided a pareto chart for each group; Figure 5 shows a typical result. The chart shows the ranking of the standardized effects for each factor. Factors with a larger standardized effect number had a stronger effect on the change of stopping distance from nominal. When looking at the sum of standardized effects overall for all different speeds and grades, change in COF had, by far, the strongest effect, followed by brake pipe pressure leakage change, ambient temperature change, and grade error change. Ambient pressure was sometimes significant, but not as strong an effect.

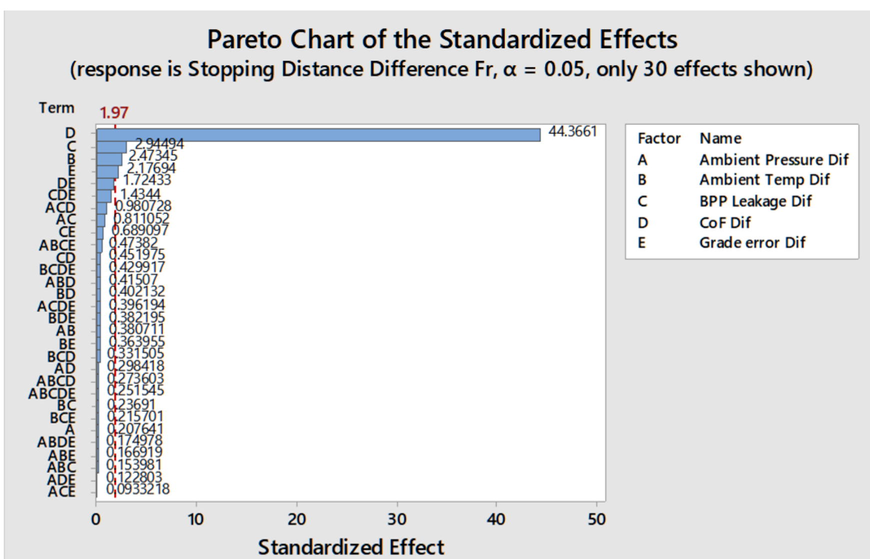

Figure 5. Typical Pareto Chart of Standardized Effects

Using the data from the design of experiment, Minitab was used to create regression equations for each grouping that included coefficients for each pareto value deemed relevant for that grouping. These equations were intended to estimate the change in stopping distance caused by changes in parameters. For most of the equations created by Minitab there was a constant value associated with the equation, meaning that if none of the parameters had changed, the equation would still be estimating a change in stopping distance. Because of this result, some additional simulations were run in TOES for each of the factors using additional intermediate points instead of extreme settings only. This smaller set of simulations showed that changing the COF and the change in brake pipe pressure leakage for longer trains did not change the stopping distance with a linear relationship. The nonlinearity of these variables violates the fundamental assumption of linearity put forth by the design of experiment. Therefore, any regression equation coefficients (slopes) obtained through the design of experiment may not be correct if the accompanying variable does not have a linear relationship with the change in stopping distance. However, the coefficients developed in the equations could still be used to calculate an approximate change in stopping distance and the results for relative strength and significance of factors still stand with the COF being, by far, the most significant factor, followed by brake pipe pressure leakage.

Being able to estimate the change in stopping distance on the basis of the change in a parameter or parameters could be useful for adaptive braking enforcement algorithms if methods are available for monitoring the parameters of interest. In the absence of monitoring these parameters, which is the current case for nonadaptive braking enforcement algorithms, this data could still prove useful in understanding how far parameters need to change to negatively affect the stopping distance difference.

3.2.1.3 Limited Monte Carlo Simulations for Specific Groupings in Design of Experiment

The Monte Carlo process was used to see how the distribution of stopping locations relative to a target location would change when using an adaptive algorithm. Monte Carlo stopping distance simulations were run on a limited number of scenarios, and the results were used to create stopping distance distributions. The stopping distributions were then analyzed to estimate the distribution of stopping locations relative to a target location for a nonadaptive braking enforcement algorithm and an adaptive braking enforcement algorithm. The process is first explained for a single train consist within a single scenario and then is expanded to include the full range of potential train consists that can be seen within the scenario.

For a single train consist, an example scenario of a 100-car manifest freight train on level track, operating at 50 mph, was chosen. Normally, in the Monte Carlo process, a scenario would consist of 100 simulations, but for this study the number of simulations was increased to 2,000 to define the stopping distance distribution more accurately. All simulations were built using the same train consist, while only parameters identified as being able to change following an adaptive calculation were varied for each simulation using the Monte Carlo process. Stop distance simulations were executed and the results from the simulations were analyzed in MATLAB to create the histogram shown in Figure 6, which shows the stopping distance distribution for this nonadaptive braking enforcement algorithm scenario and single train consist.

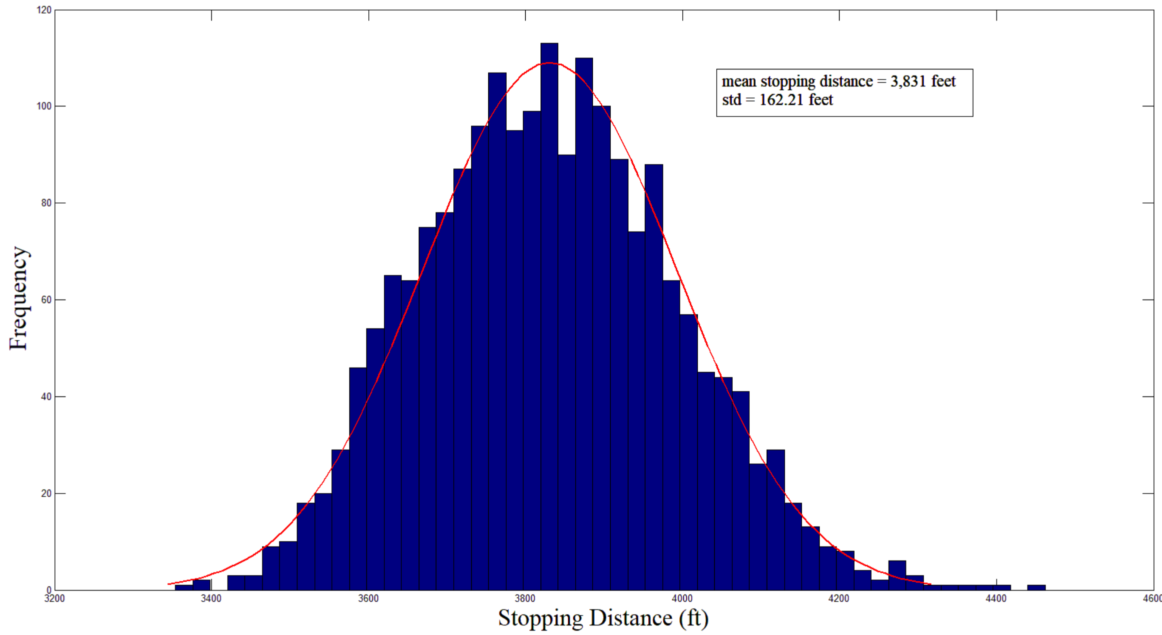

Figure 6. Stopping Distance Distribution for a Nonadaptive Braking Enforcement Algorithm (Single Train Consist)

If a nonadaptive braking enforcement algorithm is used in this scenario, the location where the algorithm applies the penalty brake enforcement would be the same for all simulations, as the nonadaptive braking enforcement algorithm would have the same inputs for each simulation within the scenario. Assuming the nonadaptive braking enforcement algorithm nominally predicts the stopping distance to be the mean of the stopping distance distribution (with no target offset applied), the stopping location relative to the target for any individual simulation would be the difference between the stopping distance for that simulation and the mean stopping distance (where a negative value indicates a train stopping short of the target and a positive value indicates a train stopping beyond the target). Applying this to the stopping distance distribution in Figure 6 resulted in the distribution of assumed stopping locations relative to the target shown in Figure 7. As expected, the shape of the stopping distance distribution and the distribution of stopping locations relative to the target were the same for a nonadaptive braking enforcement algorithm, with the only difference being the values on the independent axis.

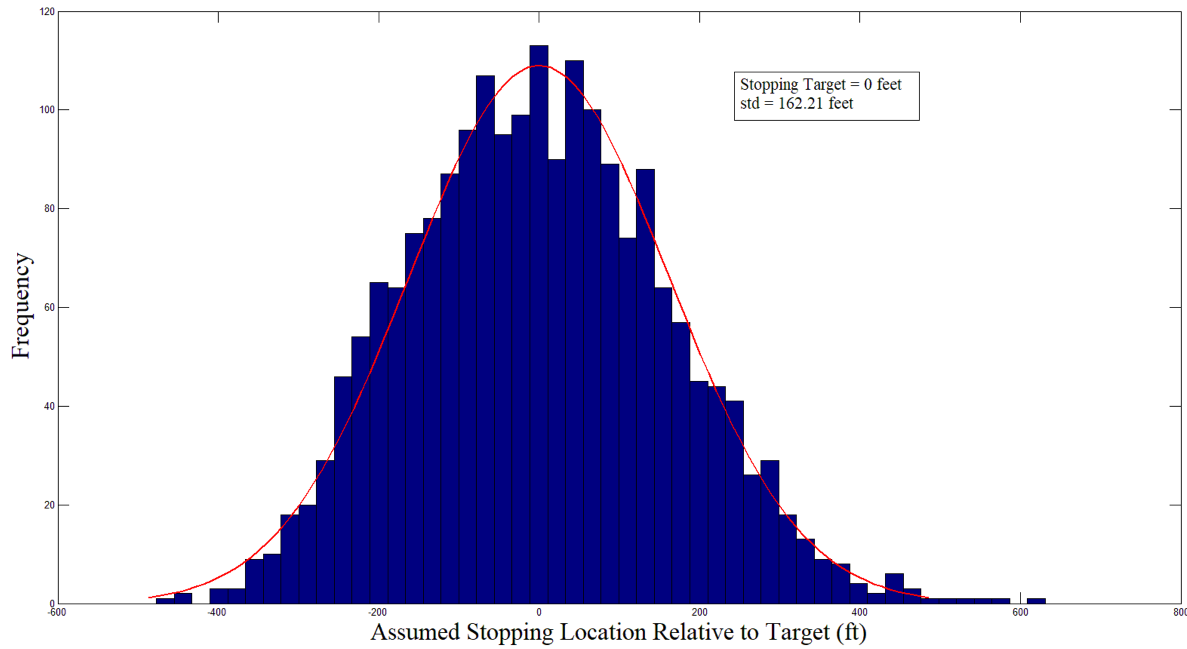

Figure 7. Distribution of Stopping Locations Relative to the Target for a Nonadaptive Braking Enforcement Algorithm (Single Train Consist)

To create a distribution of stopping locations relative to the target that would be representative of an adaptive braking enforcement algorithm, it was assumed that the adaptive braking enforcement algorithm would update the estimated braking characteristics for the train such that the predicted stopping distance would equal the stopping distance from the simulation used to update the braking characteristics (with no target offset applied). In this case, the stopping location relative to the target for any individual simulation would be the difference between the stopping distance for that simulation and the stopping distance for the simulation used to update the braking characteristics using the adaptive algorithm (again, a negative value indicates a train stopping short of the target and a positive value indicates a train stopping beyond the target). Therefore, if a single simulation is chosen as representative of the conditions when the adaptive braking enforcement algorithm updates the braking characteristics, the other Monte Carlo simulations can be used to determine the stopping location relative to the target for cases where changes to the conditions occur after the adaptive calculations are performed.

This analysis assumes that the distribution types and ranges for parameters that can change after an adaptive calculation has been made are the same as the distribution types and ranges for these parameters more generally (in other words, there were no constraints on the amount a parameter could change following the adaptive calculation). It is reasonable to expect that, for at least some of these parameters, the distribution of potential values would be more tightly grouped around the measured value. Therefore, the assumption is considered to be conservative, but further research is needed to determine if the distribution types and ranges should be constrained and how those constraints would affect the distribution of stopping locations relative to the target for the adaptive braking enforcement algorithm analysis.

Using these assumptions, a MATLAB program was developed and implemented to step through each of the simulations, using the stopping distance from that simulation as the predicted stopping distance for the adaptive braking enforcement algorithm and the other simulations as representative of stopping distances with changes to the conditions after the adaptive calculations have been made. For each simulation selected as the adaptive simulation, the program calculated the stopping location relative to the target for all other simulations, generating 2,000 stopping locations for each simulation selected as the adaptive simulation. Therefore, a total of 4 million stopping locations were generated from the 2,000 stopping distance simulations. Figure 8 shows the resulting histogram, with the histogram from Figure 6 shown above for easy comparison.

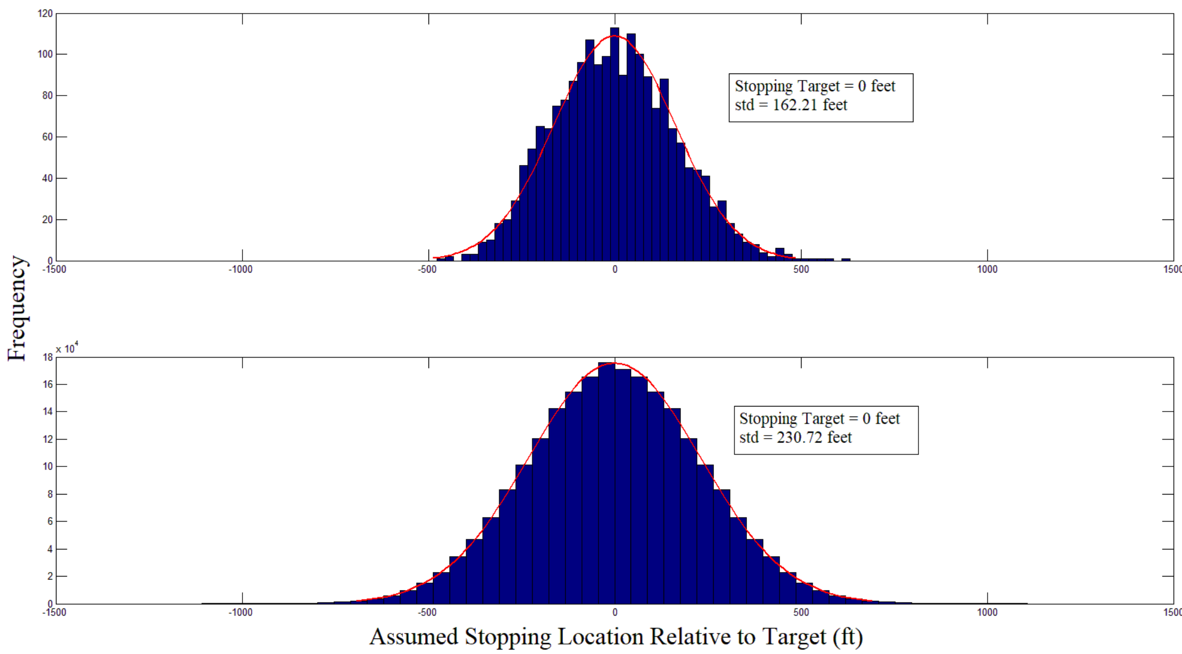

Figure 8. Comparison of Distributions of Stopping Locations Relative to the Target for Nonadaptive and Adaptive Braking Enforcement Algorithms (Single Train Consist)

Figure 8 shows that, for a single train consist, the stopping distribution was wider for the adaptive algorithm compared to the nonadaptive algorithm, which was expected because adaptive algorithms take into account the current conditions at the time of the adaptive calculations, which creates a larger potential change in conditions after the adaptive calculations have been made, due to the assumption that the distributions of potential values are not constrained.

This method was expanded to look at the full range of train consists that can exist within the scenario, as opposed to a single train consist, as described above. The same scenario of a 100-car manifest freight train on level track, operating at 50 mph, was used. Figure 9 shows the histogram of stopping distances for these simulations a nonadaptive braking enforcement algorithm.

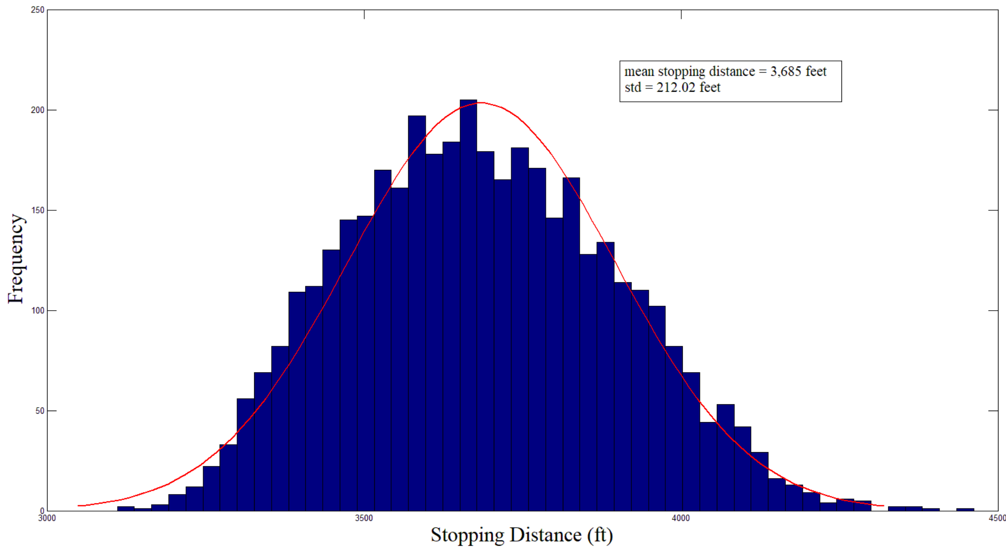

Figure 9. Stopping Distance Distribution for a Nonadaptive Braking Enforcement Algorithm

The same method was used to determine the distribution of stopping locations relative to the target representative of the nonadaptive braking enforcement algorithm, and the MATLAB program was again used to generate distribution of stopping locations relative to the target representative of the adaptive braking enforcement algorithm. Figure 10 shows the resulting distributions of stopping locations relative to the target for both the nonadaptive and adaptive braking enforcement algorithms.

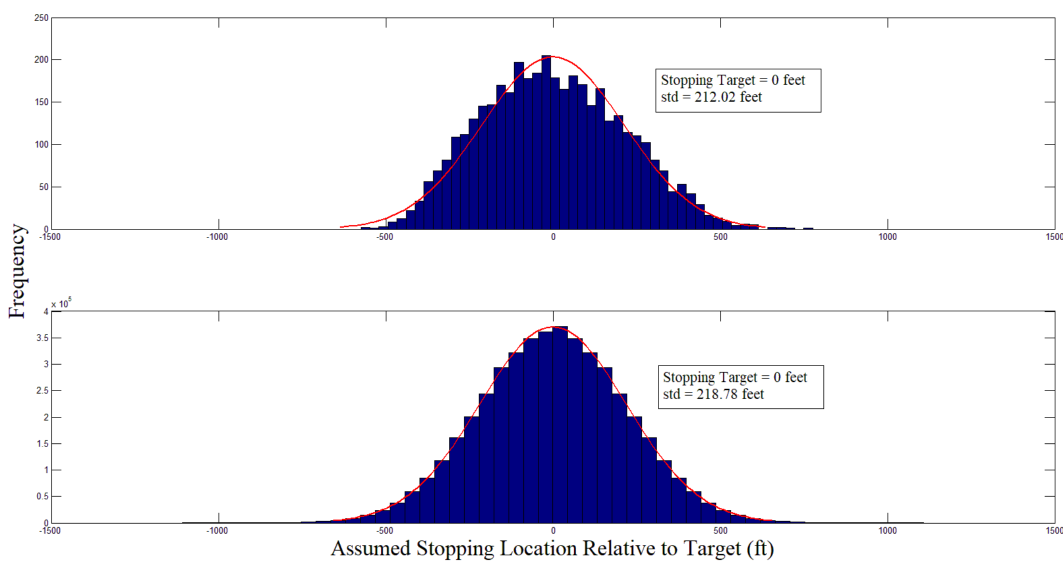

Figure 10. Comparison of Distributions of Stopping Locations Relative to the Target for Nonadaptive and Adaptive Braking Enforcement Algorithms

Figure 10 shows that the distribution of stopping locations relative to the target was still slightly wider for the adaptive braking enforcement algorithm, but the standard deviation for the adaptive braking enforcement algorithm was closer to the standard deviation of the nonadaptive algorithm.

The process was completed on a variety of 100-car manifest freight trains and 100-car unit freight trains on flat grade at varying speeds. The results showed that the range of the distribution of stopping locations relative to the target was always larger for the adaptive braking enforcement algorithm distribution, meaning there was a chance for more extreme outliers, albeit at a low probability of occurrence. The standard deviation for the distribution of stopping locations relative to the target was larger for the adaptive braking enforcement algorithm distribution in some cases and the nonadaptive braking enforcement algorithm distribution in others. Looking further into the scenarios, the standard deviation was larger for the nonadaptive algorithm distributions in scenarios where there was a wider variation of varied parameters within a train consist – for example, in longer manifest freight trains. Scenarios where the variation in parameters was narrower – for example, in unit freight trains, tended to result in a larger standard deviation for the adaptive braking enforcement algorithm distribution.

Adaptive braking enforcement algorithms may need to account for the larger range in stopping location relative to the target and the difference in standard deviation, especially for cases where the standard deviation may be larger. It is recommended that a modified Monte Carlo analysis be used to evaluate adaptive braking enforcement algorithms, along with some level of field testing, to help support the safety case for using an adaptive braking enforcement algorithm.

3.3 Risk Reduction Methods

The two main hazards identified in this project are inaccurate estimations for braking characteristics of a train during an adaptive calculation and conditions that can affect train braking distance changing after an adaptive calculation is made, such as changes in ambient pressure and temperature, COF between the brake shoe and wheel, train brake pipe pressure leakage, speed accuracy, and/or track grade profile accuracy.

The following concepts may be used to limit the risk of inaccurate estimations for braking characteristics of a train during an adaptive calculation:

- Account for known errors or variances in input data.
- Make smaller incremental changes to braking characteristic values as more is learned about the train consist.
- Bound the minimum and maximum expected values for a train consist and compare calculated values to limits.
- Trending multiple brake sets before updating values

The following ideas may be used to reduce risk associated with conditions changing after an adaptive calculation has been made:

- Develop methods to monitor parameters, record parameter values at the time of adaptive calculation, and modify stopping distance prediction based on the change in parameters.
- Develop an uncertainty value that grows with train run time, since adaptive calculations have been made or transition adaptive calculations back toward original assumed values as time from adaptive calculations increases.

- Develop new target offsets used for adaptive braking enforcement algorithms that could help mitigate this risk.
- Evaluate whether the emergency brake backup can compensate for the risk associated with a change in conditions.

Ultimately, whatever risk mitigations are used, adaptive braking enforcement algorithms should go through an evaluation using Monte Carlo simulations to demonstrate safety and performance metrics.

4. Proposed Methodology for Evaluating Adaptive Braking Enforcement Algorithms

4.1 Evaluation of the Accuracy of Adaptive Calculations

The current Monte Carlo process can be leveraged to run a wide range of simulations that can be used to evaluate the accuracy of a braking enforcement algorithm in calculating adaptive values. The simulation tools can be modified to record the brake propagation time and brake efficiency values calculated by the adaptive braking enforcement algorithm and compare against the actual values used in the TOES simulation. Initial evaluation can be completed solely with simulations until adaptive performance is considered sufficient, and then limited field testing is recommended to supplement simulation testing.

4.2 Monte Carlo Simulations to Evaluate Adaptive Braking Enforcement Algorithm Performance

For evaluating adaptive braking enforcement algorithms through Monte Carlo simulations, the current Monte Carlo simulation process will need to be updated per the following:

- Review parameter distribution types and ranges and research the extent that each parameter can change, given the value for the parameter was recently calculated by an adaptive braking enforcement algorithm. Using this information, develop the parameter distribution types and ranges representing the potential change for a train that has parameters updated based on adaptive calculations.
- Modify the simulation process to use each of the 100 simulations normally created for a scenario as a simulation to calculate adaptive values and then create 100 simulations for each one based on the parameter distribution types and ranges representing the potential change, as defined above. This results in 100 simulations for each of the original simulations in a scenario, for a total of 10,000 simulations per scenario.

Simulation results would still be analyzed to report the probability of stopping a train short of the target with the adaptive braking enforcement algorithm, and performance results would be compared to the nonadaptive braking enforcement algorithm.

5. Conclusion

Adaptive braking enforcement algorithms have the potential to improve the accuracy of the predicted stopping distance of a train, allowing trains to stop closer to the target stopping locations. However, modifying the assumed braking characteristics in real time as the train is operating creates potential hazards that must be considered. Hazards that influence the predicted stopping distance identified in this project are (a) inaccurate braking characteristic calculations made by the adaptive braking enforcement algorithm and (b) changes in conditions that can affect train braking distance after the adaptive calculations have been made.

For the first hazard (inaccurate braking characteristic calculations), analysis that compares adaptive calculated values to the actual (or simulated) values for a train over a broad range of scenarios and conditions can increase confidence in the performance of the adaptive braking enforcement algorithm in performing the adaptive calculations. Existing Monte Carlo simulation processes can be employed to perform this analysis, followed by limited field testing with actual equipment. With a sufficient confidence in a particular braking enforcement algorithm in performing these calculations, the risk associated with this hazard can be managed.

For the second hazard (changes in conditions that can affect train braking distance after the adaptive calculations have been made), modifications to the current Monte Carlo simulation process can be made to evaluate the performance of the adaptive braking enforcement algorithm that considers the potential change in conditions. The analysis performed in this project indicates that the distribution of stopping locations relative to the target for an adaptive braking enforcement algorithm can be narrower than a nonadaptive braking enforcement algorithm (for scenarios where there is wide train consist variation, e.g., manifest freight), but can also be wider than a nonadaptive braking enforcement algorithm (for scenarios where there is less train consist variation, e.g., unit freight).

However, this analysis is conservative in that it assumes the distribution types and ranges for parameters that can change after an adaptive calculation has been made are the same as the distribution types and ranges for these parameters more generally (in other words, there were no constraints on the amount a parameter could change following the adaptive calculation). It is reasonable to expect that, for at least some of these parameters, the distribution of potential values would be more tightly grouped around the measured value. The research team recommends that further research examine the extent that each parameter can change, given that the value for the parameter was recently calculated by an adaptive braking enforcement algorithm. The team also recommends that the Monte Carlo process be modified both to incorporate these distributions and to perform simulations where adaptive values are calculated, and then the full range of potential conditions (including potential changes to parameter values) can be simulated for each simulation where adaptive calculations are performed.

The team recommends that adaptive braking enforcement algorithms be evaluated through a Monte Carlo simulation methodology to evaluate against these hazards and report the safety and performance statistics of such algorithms.

6. References

1. Federal Railroad Administration. (October 2009). Development of an Operationally Efficient PTC Braking Enforcement Algorithm for Freight Trains [DOT/FRA/ORD-13/34]. Washington, DC: U.S. Department of Transportation.

Abbreviations and Acronyms

ACRONYM	EXPLANATION
AG	Advisory Group
BPP	Brake Pipe Pressure
COF	Coefficient of Friction
FRA	Federal Railroad Administration
IP	Internet Protocol
PTC	Positive Train Control
TCP/IP	Transmission Control Protocol/Internet Protocol
TCL	Test Controller Logger
TOES™	Train Operations and Energy Management
TTCI	Transportation Technology Center, Inc.