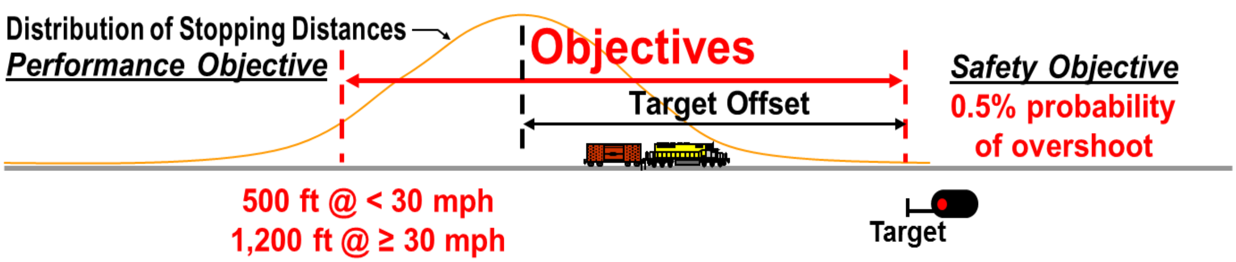
U.S. Department of Transportation

Federal Railroad Administration

Research on Methods for Enhancing Positive Train Control Freight Braking Algorithms

Office of Research, Development
and Technology
Washington, DC 20590



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13. ABSTRACT (Maximum 200 words)

The Federal Railroad Administration (FRA) sponsored a research project, executed by Transportation Technology Center, Inc. (TTCI) to investigate methods for enhancing the data used by Positive Train Control (PTC) freight braking algorithms and to improve the evaluation process of PTC freight braking algorithms. TTCI researched data available in Umler®, a system used by North American railroads for tracking and managing rail cars, and developed methods for using these data to estimate a brake force for a train that can be supplied to the PTC system on the locomotive. TTCI conducted and analyzed Monte Carlo simulations using these methods, and compared the results to current simulations. TTCI gathered track and operational data from railroads and used the data to create a weighted value for each simulated scenario by mapping railroad data into simulated scenarios. a weighted evaluation of the algorithm was produced and compared to non-weighted evaluation. Simulation results show improved safety performance of the algorithm and improved operational performance of the system when using the Umler®-calculated brake force. The results also show that the improvement in the safety and operational performance of the system is the greatest when using detailed information from each car to estimate the train brake force using the Umler® data.

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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)

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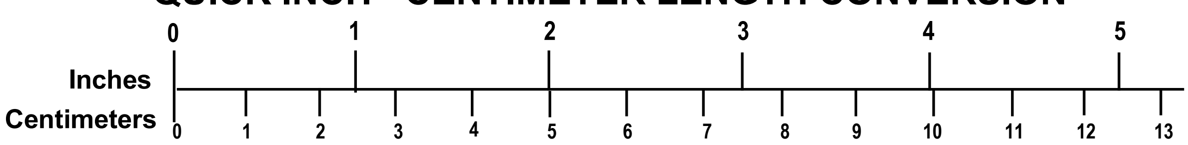
QUICK INCH - CENTIMETER LENGTH CONVERSION



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

Federal Railroad Administration (FRA) sponsored a research project, executed by Transportation Technology Center, Inc. (TTCI) to investigate methods for enhancing the data used by Positive Train Control (PTC) freight braking algorithms and the process by which PTC freight braking algorithms are evaluated. This work was performed between February 2013 and December 2014.

TTCI researched data fields available in Umler®, a system used by North American railroads for tracking and managing rail cars, to determine if a back-office process could use these data to calculate an estimated train brake force. This estimated brake force could then be supplied to the PTC onboard segment to provide the system with improved brake force information, improving the accuracy of PTC-enforced train stops. Two methods of calculating train brake force using data from Umler® were developed from this research: The first method used the consist information currently used for PTC along with a train type of unit, manifest, or intermodal, to calculate an estimated train break force. The second method used detailed information on a car-by-car basis to calculate an estimated train break force. Monte Carlo simulations were executed using both methods along with the current method of calculating train brake force with summary consist data available to the onboard system.

Results from these simulations show that there is a general increase in the probability of a train stopping short of the target, which improves the safety performance of the algorithm, and a general decrease in the distance a train stops short of the target, which improves the operational performance of the system, when using the Umler®-calculated brake force. The results also indicate that the improvement in the safety and operational performances of the system is the greatest when using the detailed information from each car to estimate the train brake force using the Umler® data.

TTCI manually measured the brake shoe force on a range of railroad vehicles and compared the measurement results with the estimated train brake force using car data from Umler®. Brake force values from these measurements show that the estimated train brake force calculated using car data from Umler®, for this data set, results in a reasonable brake force estimate.

TTCI worked with two freight railroads to gather track and operational data. These data were then used to develop weighted values for simulated scenarios as part of a Monte Carlo process. This determined that some scenarios are much more common than others, which resulted in high weighted values for these scenarios.

The Monte Carlo simulations were evaluated using the weighted values developed in this study and compared to the results without the weighted values. Results from the comparison show the overall probability of stopping short of the target was higher at 99.86 percent, without using weighted values, to 99.71 percent, using weighted values. This indicates that the overall probability of the simulated train stopping short of the target is not greatly affected by the weighting process. However, there are differences when looking at individual train types, which may lead to insights about the braking algorithm performance.

From an operational performance perspective, the braking algorithm was evaluated using the probability of trains stopping greater than 500 feet short of the target, when operating at less than 30 mph, and greater than 1,200 feet short of the target, when operating at 30 mph or above. The comparison indicates there was a significant decrease in the probability of trains stopping greater

than 500 feet short of the target when operating under 30 mph with the weighted evaluation. This indicates that the braking algorithm performs better, from an operational standpoint, on trains in scenarios that are more frequently encountered, when operating at less than 30 mph. For scenarios with trains operating at 30 mph or above, there was a general increase in the probability of trains stopping greater than 1,200 feet short of the target with the weighted evaluation. This indicates that the braking algorithm performs better, from an operational standpoint, on trains in scenarios that are less frequently encountered, when operating at speeds of 30 mph or greater. Overall, the weighted evaluation gives a different view of how a PTC enforcement braking algorithm is performing and provides some insight on how the current Monte Carlo scenarios relate to railroad operational data.

1. Introduction

The Federal Railroad Administration (FRA) sponsored a research project, executed by Transportation Technology Center, Inc. (TTCI), to investigate methods for enhancing the data used by Positive Train Control (PTC) freight braking algorithms and the process by which PTC freight braking algorithms are evaluated. Existing methods for evaluating PTC braking algorithms were developed using Monte Carlo simulation techniques, and methods for improving the performance of PTC braking algorithms were identified, simulated and tested. This project expanded on these methods, to determine how the algorithms could be improved with better data, and how the evaluation process could be improved by weighting the scenarios investigated in the Monte Carlo methodology according to their frequency in actual freight railroad operations.

1.1 Background

PTC is an emerging train control technology intended to enhance safety. The underlying concept of the technology is that movement authorities and speed restrictions are transmitted digitally to the controlling locomotive of each train. The locomotive monitors the train's location with respect to its authority and speed limits, and then automatically applies brakes to prevent the train from violating any limit in the event of human failure.

Enforcement braking is an event of last recourse when the locomotive engineer has failed to, or is unable to, take adequate action, after being warned by the PTC system. In PTC applications to date, the enforcement braking system consists of a full-service brake application, which can be followed by an emergency brake application, if needed, in trains that have emergency brake functionality enabled.

A standard methodology was established by which any PTC enforcement algorithm could be evaluated to demonstrate that it meets certain design objectives, such as safety and performance measures. The Monte Carlo simulation techniques were used to statistically evaluate the performance characteristics of the enforcement algorithm as well as small samples of field testing used to validate the results achieved from the simulation modeling process. This methodology is now being used to verify the performance of production-level enforcement algorithms within the industry, to provide better safety and performance data for the system, with reduced time and costs associated with lengthy field testing processes that have traditionally been required.

1.2 Objectives

The objectives of this project are presented below.

1.2.1 *Use of Umler® Data*

The first objective was to evaluate potential improvements in the safety and performance of the PTC braking algorithm and to improve the accuracy of the train brake force estimate through the use of Umler®[1] data.

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[1] Umler® is a registered trademark of Railinc Corp.

1.2.2 *Weighted Evaluation*

The second objective was to assess the methodology for evaluating enforcement algorithms from the current approach. The current methodology assumed every scenario simulated has the same probability of being seen in revenue service, to a weighted evaluation. However, each scenario has a different probability determined by how commonly that scenario is encountered in revenue service. The data used from this evaluation presented a clearer picture of how the algorithm will perform in revenue service.

1.3 Overall Approach

The Umler® fields and database were reviewed to identify fields to help determine car brake force. Then a methodology was developed to calculate the brake force for each car using the data available. The simulation process was modified so this brake force could be provided to the braking algorithm. Simulations were then run using the Monte Carlo variations for three different cases; a base case, which uses the Interoperable Electronic Train Management System (I-ETMS®[2]) braking algorithm with an onboard brake force calculation; an Umler® train information case, which uses an average brake force per train type derived from Umler® data; and, an Umler® car information case, which uses a brake force calculated at a car level using Umler® data. Analyses showed there is potential benefit by using data from Umler®.

For the weighted evaluation, operational and track data from the railroads were used to modify the evaluation methodology to a weighted scenario approach. The current methodology weights every scenario in the simulation test matrix the same during the analysis of the Monte Carlo simulations. This study was used to apply weighting, using data received from the railroads, to each of the scenarios during the analysis process to evaluate the enforcement algorithm. Results from using the weighted evaluation approach were compared against results from the current evaluation process.

1.4 Scope

The scope of this project focused on the use of individual car Umler® data and developing a weighted evaluation methodology to enhance PTC freight braking.

1.4.1 *Use of Umler® Data*

The scope of this task focused on developing and simulating methods for improving the brake force supplied to the algorithm using data from Umler®, to calculate the predicted stopping distance of a freight train more accurately. These results were compared to the Monte Carlo simulations with the same algorithm using a nominal brake force calculation based on car type.

The scope of this task also included data collection on freight railroad cars. The information collected included; measured brake shoe force, brake valve(s) types, stenciled car information, empty-load cars, brake rigging type, and other visual inspections. The collected data was used to support the method developed to calculate brake force based on information in Umler®.

[2] I-ETMS® is a registered trademark of Wabtec Corporation

1.4.2 *Weighted Evaluation*

The scope of this task was to develop a weighted evaluation methodology during the analysis of the Monte Carlo simulations. The weighted evaluation was produced using operational and track data from the railroads. A weighted value was generated for all the scenarios simulated in the Monte Carlo test matrix, based on the frequency that scenario was encountered in the operational and track data. These weighted values were then used during the analysis of the simulation results and compared to the current process.

1.5 Organization of the Report

This report is organized in four major sections. Section 1 is the introduction, which includes background information and discusses the project's objectives, scope, and overall approach. Section 2 is a detailed description of using Umler® data for estimating train brake force, a breakdown of the work completed, and results. Section 3 is a detailed description of the weighted PTC braking enforcement algorithm evaluation, a breakdown of the work completed, and the results. Section 4 provides a brief summary of conclusions.

2. Use of Umler® Data for Estimating Train Brake Force

The braking enforcement function of the PTC system is critical in ensuring that trains comply with movement authorities and speed limits. There are a number of parameters that can affect the braking distance of a freight train and it is not practical, or even possible, to provide the onboard system with all of the information required to predict the stopping distance with absolute certainty. Currently, the braking algorithm estimates the train brake force using the information it is supplied for the consist, which includes trailing tonnage, number of loaded cars, number of empty cars, number and position of locomotives, train length, and number of axles.

This project explores the concept of using Umler® data to calculate the brake force for the train and provide the locomotive onboard computer with the calculated brake force to be used in the braking enforcement algorithm. The analysis of the enforcement algorithm, using this force in the stopping distance predictions, is compared to the current method to show potential improvements.

2.1 Umler® Data Research

The Umler® system is an electronic resource that contains information for more than two million pieces of equipment used for North American rail transportation. Railroads and equipment owners provide equipment information includes: internal and external dimensions, capacities, light weight and load limit, build date and re-build date, and many other specific characteristics of the freight cars. The data in Umler® was studied and a number of fields were identified as applicable for calculating the brake force. A description of these fields is provided in Section 2.1.1 and the method of calculating the brake force using these fields is outlined in Section 2.1.2.

2.1.1 *Umler® Fields Related to Break Force*

Five fields that pertain to the braking characteristics of cars were identified in the Umler® data. These fields are:

1. Build date/rebuild date
2. Tare weight
3. Gross rail load (GRL)
4. Empty-load equipped
5. Car type

The build date/rebuild date field gives information about the Association of American Railroads (AAR) braking system specifications placed in the car when it was built or last rebuilt. These specifications include minimum and maximum net brake ratios for the freight equipment.

The tare weight, GRL and the minimum and maximum net brake ratios are used to determine the brake force range for the specific car in question.

The empty-load equipped and car type fields can be used to further define the brake force range for the specific car in question.

2.1.2 *Brake Force Calculation using Umler® Fields*

The information used to calculate brake force using the Umler® approach includes a combination of train consist information and data from the Umler® database. Below is a list of car data that is used in the brake force calculation, followed by a description of how the data is used to calculate the brake force.

6. Back Office Consist Information
   - Number of loaded and empty cars
   - Train type
   - Number of axles
7. Umler® Database
   - Empty-load equipped
   - Build date or rebuild date
   - Gross rail load (GRL)
   - Tare weight
   - Car type

For the methodology described below, it is assumed that the data fields used from Umler® would be available to the railroads and data within these fields are up-to-date and valid. If data is missing in Umler® or data in Umler® is not available to railroads, then additional assumptions may need to be used for those cars, which could result in these methods being more conservative than current methods of calculating brake force.

Umler® Brake Force Calculation using Train Type Information

The method developed for calculating brake force using Umler® data, on a train type level, uses a lookup table of empty and loaded car brake forces, based on train type. This method for calculating brake force uses the back office consist information, which includes: train type, trailing tonnage, number of loaded cars, number of empty cars, number and position of locomotives, train length, and number of axles with the brake force values, per train type, calculated from Umler®.

Table 1 shows the nominal brake force values for each train type calculated using the Umler® data. These values were calculated by identifying the cars in Umler® that fit into each train type and then calculating a brake force for each of the cars, in each train type, based on the calculation described in Section 2.1.2, subsection Umler® Brake Force Calculation using Car Information, and then using that data to produce a nominal empty brake force and a nominal loaded brake force per train type.

Table 1. Nominal Umler® Brake Force Calulation using Train Type

Train Type	Nominal Loaded Car Brake Shoe Force per Axle (lbs) at 64 psi BCP	Nominal Empty Car Brake Shoe Force per Axle (lbs) at 64 psi BCP
Unit Freight	$\frac{0.093 * W_{CARS}}{N_{AXLES}}$	4962
Unit Aluminum Coal	$\frac{0.11 * W_{CARS}}{N_{AXLES}}$	3975
Manifest Freight	5870	5044
Intermodal Freight	6895	3746

In Table 1, W_{CARS} is the total GRL (gross rail load) of the cars in the consist and N_{AXLES} is the total number of car axles in the consist.

Umler® Brake Force Calculation using Car Information

The method developed for calculating brake force using Umler® data, on a car level, includes calculating a minimum and maximum brake force for the car based on the car's build date, GRL, tare weight, and car type. Table 2 shows the two different maximum brake force values that are calculated based on the car's build date and car type. The maximum brake force calculations are calculated from the AAR specifications for maximum net brake ratio at the time the car was built. Maximum force #1 is the maximum brake force the car can have when fully loaded and maximum force #2 is the maximum brake force the car can have when empty. The lesser of the two values is used for the maximum brake force for that car, assuming the car is not empty-load device equipped.

Table 2. Maximum Brake Force Calculations for Umler® Method

Build/Re-Build Date	Car Type	Maximum Force #1	Maximum Force #2
1998 and Earlier	All Car Types	GRL * 0.1286	Tare Weight * 0.3857
From 1999 to 2003	All Car Types	GRL * 0.13	Tare Weight * 0.38
2004 and After	All Car Types	GRL * 0.14	Tare Weight * 0.32

Table 3 shows the minimum brake force calculation based on the car's build date and car type. The minimum brake force calculation is based on the AAR specification for the minimum net brake ratio at the time the car was built. The calculated minimum brake force also assumes a net brake ratio 1 percent less than the AAR specified minimum net brake ratio (e.g., 7.5 percent net brake ratio if the AAR specification was 8.5 percent) to account for degradation of the braking system over time [1].

Table 3. Minimum Brake Force Calculations for Umler® Method

Build/Re-Build Date	Car Type	Minimum Force
1998 and Earlier	All Car Types	GRL * 0.07
From 1999 to 2002	Intermodal (TOFC)	GRL * 0.10
From 1999 to 2002	General Freight and Unit	GRL * 0.075
2003 and After	All Car Types	GRL * 0.10

Next, a check is made to see if the car is equipped with an empty-load device. This is done by looking at the empty-load equipped field in the Umler® database. A check is also made to determine if the minimum calculated brake force is larger than the maximum calculated brake force. If this is the case, then the car must be empty-load device equipped. If the car is determined to have an empty-load device, whether from the Umler® database or the check with the minimum and maximum brake forces, then the brake force is calculated using the formula below.

$$\textit{If car has Empty Load Device}:$$

$$\textit{Brake Force} = \frac{(\textit{Maximum Force } \#1 + \textit{Minimum Force})}{2} \qquad \#1$$

The maximum brake force for the fully loaded position can be used in this case because the car is equipped with an empty-load device, which lowers the brake force when in the empty position, so there is no concern of exceeding the maximum brake force in the empty position. The Umler® brake force calculated if the car is empty-load equipped is the average of the maximum and minimum brake force for the car. Consist information is then used to determine if the car is loaded or empty. If the car is loaded then the empty-load brake force calculated in the above formula is used for that car. If the car is empty then the empty-load brake force calculated in the above formula is divided by 2. There are a variety of empty-load devices in service that limit the brake force of the car, when in the empty position, to 40-60 percent of the loaded brake force. For this study, it was assumed that all cars equipped with an empty-load device, are equipped with a 50 percent empty-load device. If more information on the type of empty-load device was available in Umler®, then a better prediction could be made.

If the car is not equipped with an empty-load device, then the brake force is calculated by using the average of the maximum and minimum brake force for the car, with the maximum brake force being the lesser of maximum force #1 and maximum force #2. The same force is used whether the car is loaded or empty. The formula for calculating brake force for cars not equipped with an empty-load device is shown below.

$$\textit{If car does not have an Empty Load Device}:,$$

$$\textit{Brake Force} = \frac{(\textit{Maximum Force} + \textit{Minimum Force})}{2} \qquad \#2$$

$$\textit{where Maximum Force is equal to the lesser of Maximum Force } \#1 \textit{ and Maximum Force } \#2$$

Whether the car is equipped with an empty-load device or not, the above calculations assume the brake force for the car is the average of the maximum and minimum brake force for that car. For this project, the average was used to approximate the brake force, but if additional information was available within Umler®, then a more accurate brake force could be calculated for each car. This additional information could include:

8. Actual specifications the car was built to
   - Loaded brake force ratio
   - Empty brake force ratio
9. Brake force measurements from actual car or another car within the same series of cars
10. Empty-load device type, if equipped
   - 40 percent, 50 percent, or 60 percent empty-load device

2.2 Simulations using Data from Umler®

The simulation methodology used was the Monte Carlo process that was developed and documented in Task Order 242 [2]. The simulation testing makes use of a set of computer software tools to employ a Monte Carlo simulation process that results 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 on the basis of 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 enforcement algorithm.

The simulation process for this project was modified to include the capability of calculating the brake force using the consist information for each simulation and providing the enforcement algorithm the calculated brake force to use in the predictive stopping distance calculations.

2.2.1 *Overview of Simulation Testing Process*

The simulation testing process is intended to evaluate the enforcement algorithm over a full range of operating scenarios that the system is expected to encounter and considering 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 of which represents a potential operating scenario for the system to encounter. Each 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. The full Monte Carlo test matrix consists of 4,262 scenarios and a subset of 1,528 scenarios was used in this study.

Multiple braking enforcement simulations were run for each test scenario. The values of the parameters that can have a significant effect on train stopping distance were randomly selected for each simulation from distributions that represent the practical range of values for the given parameter.

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. For this project, each test scenario contained 100 individual simulations, each representing a potential specific instance of the test scenario.

For each individual simulation test, the brake force was calculated for the train, either from the onboard calculation or from one of the Umler® calculations, and provided to the algorithm. The train was simulated approaching the target at the defined initial speed, the enforcement algorithm triggered a brake application to prevent a violation of the stop target, and the response of the train was simulated. The result of each individual simulation represents a single possible stopping location for the given test scenario with the given enforcement algorithm. The aggregate result of the simulations for the entire test scenario then defines the distribution of possible outcomes. This data was analyzed to determine the safety and performance characteristics of the enforcement algorithm for the given test scenario. These characteristics can then be analyzed together to quantify the overall safety and performance characteristics of the enforcement algorithm.

2.2.2 *Simulation Testing Tools*

The simulation testing tools used for this project are the same that were developed for Task Order 242 [2]. A description of the tools is provided below as well as illustrated in Figure 1:

11. The Simulation Model, the Train Operations and Energy Simulator (TOES™), is 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.
12. The test controller/logger (TCL) is a 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.
13. The enforcement algorithm under evaluation is the PTC braking enforcement algorithm, implemented as a standalone software application incorporating a common interface to the simulation test components to receive train status and command brake enforcement applications.

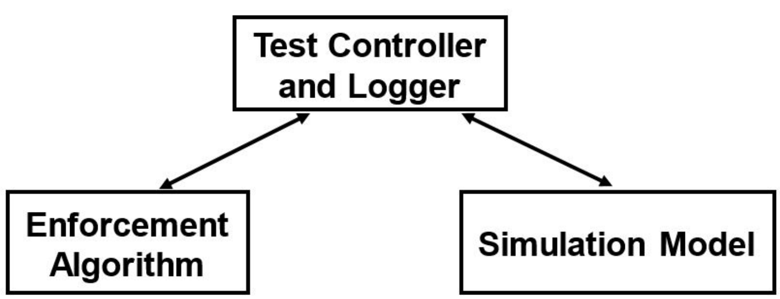

Figure 1. Simulation Software Tools

2.2.3 *Test Matrix Used*

The test matrix used for this project is a subset of the full test matrix that was defined in Task Order 242 [2]. A subset was used to reduce the total number of simulations that needed to be performed for this study, while still maintaining a large enough sample of the different train types to quantify any potential improvement from using brake force calculated with Umler® data.

The train consists included in the simulation test matrix represent a range of nominal train consists that are regularly and frequently run by the railroads. Each consist is made up of an arrangement of nominal cars, each with a given load. The specific car characteristics that affect braking performance are set to nominal values, which are then varied in the Monte Carlo simulation process. The following three groups of train consists were used in the simulations:

- Unit freight—Trains consisting entirely of a single car type that are typically all loaded to capacity or empty. These are typically bulk commodity trains, such as coal or grain trains.
- Manifest freight—Trains consisting of a mix of car types and loads.
- Intermodal freight—Trains consisting entirely of intermodal cars that are typically all loaded or empty, although the weight of the loads varies considerably.

For each train type, a range of train makeups, train lengths, train loading conditions, and locomotive arrangements were identified. For both the manifest freight and intermodal trains, a pseudo-random process for generating train makeup and car loading was developed. Train make-ups developed from Task Order 242 [2] were used for this project. Table 4 summarizes the consists used for each of the three train types.

Table 4 - Train Consist Parameters for Simulation Testing

	Unit Freight	**Manifest Freight**	**Intermodal Freight**
Train Makeup	Homogenous makeup of: • Aluminum hoppers • Steel hoppers • Covered hoppers • Tank cars • Refrigerated box cars • Multi-levels (vehicular flat cars)	Pseudo-random mix of: • Box cars • Covered hoppers • Gondolas • Flat cars • Open-top hoppers • Aluminum coal gondolas • Tank cars • TOFC/COFC flats • Multi-level cars (vehicular flats cars)	Pseudo-random mix of: • Single-platform intermodal well cars • Three-pack intermodal well cars • Five-pack intermodal well cars
Train Length	• 100 cars • 135 cars	• 40 cars • 100 cars • 150 cars • 200 cars	• Short (~ 5,000 ft) • Medium (~ 7,500 ft) • Long (~ 10,000 ft)
Train Loading Condition	• Fully loaded • Fully empty	Pseudo-random loading from historical consist data	• Loaded with pseudo-random loading from historical consist data • Empty with pseudo-random loading from historical consist data
Locomotive Arrangement	• Head end (100-car trains only) • Head and rear (100-car and 135-car trains) • Head, mid, and rear (135-car trains only)	• Head end (40-car and 100-car trains) • Head and rear (100-car, 150-car, and 200-car trains)	• Head end (short and medium trains) • Head and rear (short, medium, and long trains)

		• Head, mid, and rear (150-car and 200-car trains)	• Head, mid, and rear (long trains only)

2.2.4 *Simulation Testing*

Simulation testing was completed three times applying three different brake force calculations for the enforcement algorithm to use in the stopping prediction calculations. The base case brake force is an onboard brake calculation from the current I-ETMS enforcement algorithm; the Umler® train type brake force calculation is the brake force calculated by using Umler® and train type information; and the Umler® car type brake force calculation is the brake force that uses Umler® and individual car information. All three simulation sets used the same test matrix made up of consists shown in Table 4. Section 2.2.5 provides a comparison of the results from the simulations.

Base Case Simulations

These simulations were executed by allowing the onboard system to calculate the brake force for the consist based on the back office consist information it receives for each simulation. This is the brake force that the enforcement algorithm currently uses.

Umler® Train Type Simulations

These simulations were executed by providing the brake algorithm the brake force calculated using the back office consist information and the Umler® brake force data per train type, as described in Section 2.1.2, subsection Umler® Brake Force Calculation using Train Type Information. Every simulation in the test matrix was provided the calculated brake force for the consist used in that simulation.

Umler® Car Type Simulations

These simulations were executed by providing the brake algorithm the brake force calculated using the back office consist information, individual car information, and the Umler® brake force data per car type, as described in Section 2.1.2, subsection Umler® Brake Force Calculation using Car Type Information. Every simulation in the test matrix was provided the calculated brake force for the consist used in that simulation.

2.2.5 *Comparison of Brake Force Calculation Methods*

To evaluate the potential improvement with each method of brake force calculation, the resulting safety and performance metrics using each method were compared. The safety metric is the probability the train stops short of the target. The performance metric is the probability that the train stops within 500 feet of the target if the train is traveling less than 30 mph and within 1200 feet of the target if the train is traveling at 30 mph or more. Table 5 shows these results for the three different sets of simulations. This table includes the probability of stopping short of the target, the probability of stopping short of the performance metric at speeds less than 30 mph, and the probability of stopping short of the performance metric at speeds of 30 mph and more.

Table 5. Results for Base Case and Umler® Simulations

	Probability of Stopping short of Target	Probability of Stopping Short of Performance Metric <30mph	Probability of Stopping Short of Performance Metric >=30mph
Intermodal Base	99.97%	18.08%	15.99%
Intermodal Umler® Train	99.97%	18.07%	15.09%
Intermodal Umler® Car	99.99%	18.12%	15.67%
Manifest Base	99.98%	18.02%	20.30%
Manifest Umler® Train	99.97%	17.27%	17.04%
Manifest Umler® Car	99.95%	17.19%	15.59%
Unit Base	99.60%	14.24%	18.23%
Unit Umler® Train	99.97%	13.96%	13.29%
Unit Umler® Car	99.99%	13.90%	13.21%

Table 5 shows that there is a general increase in the algorithm performance, both from an increase in the probability of stopping short of the target and a general decrease in stopping short of the performance metric, when using the Umler® calculated brake force. This is more pronounced when using the individual car brake force Umler® calculation over the train type Umler® calculation.

There is more benefit from the Umler® calculations, using either the individual car brake force calculation or the train type brake force calculation, seen in the unit train type, which includes unit coal, unit covered hopper, unit multi-level, unit refrigerated box car, and unit tank car trains. These different unit train car types are combined when calculating the brake force for the unit train type. However, there can be significant differences in brake force between these different unit train car types. Since these unit train car types are not all the same, the result is an average brake force for unit trains that is significantly greater than the brake force on some of the unit train car types and significantly lower than the brake force on other unit train car types.

This is shown in the more detailed simulation results by comparing the enforcement locations for the simulations run using the Umler® train type brake force method and for the simulations using the Umler® car brake force method. The enforcement location for three of the unit trains (steel coal, covered hopper, and tank) is further from the target when using the brake force calculation based on the individual cars, because they all have a lower brake force value per car than the average brake force per car calculated using all unit train car types. The opposite is seen for the other three unit trains (aluminum coal, refrigerated box, and multi-level) because they all have a higher brake force value per car than the average brake force per car calculated using all unit train car types.

Using the Umler® brake force calculation for the individual cars also decreased the number of overruns observed in the simulations to 9, compared with 23 observed when using the Umler® brake force calculation for the train type. Both Umler® calculated brake force methods resulted in a reduction in the number of overruns for the unit train simulations from the base case algorithm, which resulted in 277 overruns. Reductions in overruns were predominantly on the unit steel coal, unit covered hopper and unit tank trains, all of which enforced further away from the target when using the Umler® brake force calculation for train types compared to the base case, and enforced even further away from the target when using the Umler® brake force calculations with individual car information. From this observation, it appears the average brake force calculated using Umler® data, results in a better estimation of the actual brake force than what is currently being used in the base case.

Similar results can be seen with the manifest and intermodal trains, as all of the cars within those trains are not built the same, but the brake force for cars used in manifest and intermodal trains do not vary as much as what is seen in the different unit train car types.

Another potential benefit from using the Umler® brake force calculations is a potential reduction in the target offset used. The probability of stopping short of the target using Umler® brake force calculations, train type or car type, shows that a reduction in the target offset may be possible, as all of the probabilities are at least 99.95 percent, which is greater than the established minimum of 99.5 percent.

2.3 Brake Shoe Force Measurements of Freight Cars

The brake shoe force on a limited number of freight cars was measured using the equipment described in Section 2.3.1 and data collection methods described in Section 2.3.2.

2.3.1 *Equipment Used*

Finding an accurate and efficient method to measure the force applied to a wheel by the brakes requires specialized equipment and processes. Inter Swiss Ltd. has a product that uses eight button cell load sensors (one per wheel) to collect simultaneous brake force readings on stationary cars. Their product, called JIM SHOE™[3], is a brake force measurement system that uses sensors to replace the brake shoes to accurately measure the force applied by the brakes to each wheel. Each JIM SHOE™ contains a load cell that records the force readings and transmits it wirelessly to a hand-held device for review. When the brakes are applied, the load cell is pressed against the wheel and it measures a force value. A Brake-O Lator™[4] Single Car Air Test device (BOL™) was used to activate the brakes. The BOL uses an independent air supply to charge the brake pipe and the auxiliary and emergency reservoirs to 90 psi and simulate the braking action of a train car. The BOL™ provides both brake pipe and brake cylinder pressure readings throughout the testing.

Each set of JIM SHOE™ contains a spare load cell that could be used to replace any sensor that ceases recording data. The handheld device (Panasonic Toughbook Tablet) is equipped for various forms of data collection, included a pre-programmed process and continuous recording for up to an hour.

Through this project, TTCI acquired this equipment from Inter Swiss Ltd. and worked with them to receive on-site training for the proper use of both the JIM SHOE™ and the BOL™. TTCI also worked with Inter Swiss Ltd. to provide feedback, which led to a few useful upgrades to the handheld device for the JIM SHOE™, and to receive repairs on the equipment when issues arose.

[3] JIM SHOE™ is a trademark of Inter Swiss Ltd.

[4] Brake-O Lator™ (BOL) is a trademark of Inter Swiss Ltd.

2.3.2 *Test Setup and Data Collection*

For the testing conducted at the Transportation Technology Center (TTC), several types of cars were chosen, based on availability. These included box cars, flat cars, and hoppers. Each car was isolated from the consist, the brake shoes were replaced with JIM SHOE™ sensors, and the BOL™ was used to charge the brake pipe pressure to 90 psi, which also charges the auxiliary reservoir on the car to 90 psi. After exercising the brakes to ensure there were no issues with the braking system on the car and verifying that the brake pipe was in the fully charged state, a value was recorded for each brake cell as the zero for the test. The brake pipe pressure was then dropped to 50 psi at a full service rate to simulate a full service application. This brake pipe reduction is enough for the brake cylinder pressure to reach equalization with the auxiliary reservoir on the car. As the brake pipe pressure is reduced the auxiliary reservoir transfers air into the car's brake cylinder via a control valve. The volume ratio between the auxiliary reservoir and the brake cylinder is approximately 2.5 to 1, so for 1 psi transferred from the auxiliary reservoir, the brake cylinder increases by 2.5 psi. The control value allows for this transfer of pressure until both the auxiliary reservoir and brake cylinder are at the same pressure. This equalization pressure occurs at a brake reduction of approximately 25.7 psi, from 90 psi brake pipe pressure, resulting in 64.3 psi in the auxiliary reservoir (90-25.7) and 64.25 psi in the brake cylinder (25.7 * 2.5). The car should be at its full service brake force once the brake cylinder has reached an equalization pressure of approximately 64.3 psi. Before a reading was recorded, the brake rigging was rapped with hammers, per AAR *Manual of Standards and Recommended Practices* Standard S-401 [3]. This rapping simulates travel over track and the jostling that occurs as the brakes apply when the car is moving. After readings were recorded for the full service brake shoe force, the brake pipe pressure was dropped to 0 psi at an emergency rate to simulate an emergency application. The brake rigging was again rapped before the emergency brake shoe force readings were recorded. This process was repeated twice for each car.

Full service and emergency brake shoe force was recorded for each wheel, as well as information about each car such as: car mark, date built/rebuilt, tare and loaded weight, number of axles and trucks, service valve and emergency valve type, whether the car was empty-load device equipped, type of brake shoes, car length, and axle journal size. Ambient temperature, pressure, and weather conditions were also recorded. Brake pipe and brake cylinder pressure readings were noted for the fully charged, full service, and emergency service states for each test. Brake shoe force and pressure readings were recorded both directly by the handheld device connected to the JIM SHOE™ and manually by the engineers running the test. For cars equipped with an empty-load device, the car was tested in the empty position and then shims were used to activate the device, simulating the loaded position, and the test was repeated. A test implementation plan (TIP) was created for this testing.

Similar testing was completed on a set of intermodal freight cars at a railroad yard. For this testing, the cars remained coupled and hand brakes and skates were used to prevent car movement. The brake pipe for the car under test was isolated from the other cars and connected to the BOL™, and the brake shoes were replaced by the JIM SHOE™. The same process described above was used to apply the brakes and record the data. A separate TIP was created for the brake force measurement testing at the railroad yard.

2.3.3 *Data Analysis*

Data was collected from 57 cars; 10 cars were equipped with an empty-load device and 47 cars were not. Table 6 shows data from the JIM SHOE™ measurements on the cars without an empty-load device, as well as the minimum and maximum brake shoe force calculation using the Umler® brake shoe force calculation for individual cars. Umler® data for these cars was pulled from the Umler® database using the documented car markings during the testing, and the data was used to calculate the minimum and maximum brake shoe force for these cars.

Table 6. JIM SHOE™ Measurements

Test Car Number	Average Measured Brake Shoe Force for Full Service Application (lbs.)	Umler® Minimum Brake Force Calculation (lbs.)	Umler® Maximum Brake Force Calculation (lbs.)
1	24411	18410	33787
2	24310	15400	24145
3	27991	15400	24955
4	20597	18410	24376
5	19559	15400	23451
6	24000	15400	28292
7	29160	18410	29737
8	25058	18410	24338
9	22544	18410	25958
10	22632	18410	25765
11	24684	18410	24415
12	22348	18410	24338
13	33956[1]	18410	23451
14	23822	18410	25958
15	24671	18410	25842
16	28356	18410	24145
17	26128	18410	24685
18	18599	18410	23721
19	15043	18410	23913
20	18103	18410	23798
21	22491	18410	23991
22	26181	15400	28292
23	25361	18410	27616
24	20088	15400	25842
25	23647	15410[2]	26305[2]
26	25281	18410	23798
27	25090	18410	25880
28	28466	15372[2]	26343[2]
29	29188	18410	33710
30	30424	18410	33556
31	20919	15400	28292
32	25720	18410	33363
33	24569	15680[2]	28806[2]

Test Car Number	Average Measured Brake Shoe Force for Full Service Application (lbs.)	Umler® Minimum Brake Force Calculation (lbs.)	Umler® Maximum Brake Force Calculation (lbs.)
34	16739[1]	18410	24955
35	24822	18410	32360
36	20015	18410	25610
37	20694	18410	25803
38	24153	18410	25148
39	24259	18410	24993
40	18271	18410	25456
41	19460	15400	28292
42	20928	15400	28292
43	23622	15400[2]	28292[2]
44	21366	15400	28292
45	15722	18410	23721
46	24436	18410	23913
47	24554	15400	28292

[1]Brake cylinder pressure build up for both full service and emergency applications were incorrect for these cars

[2]Stenciled data was used to calculate maximum and minimum brake force because data was not found in Umler® - possible reasons for this include (a) the stenciled car id was recorded incorrectly (b) the stenciled car id was unreadable or (c) the car was removed from service and the Umler® record was deleted.

As indicated in the first footnote in Table 6 and from test logs described in Section 2.3.2, it was observed for test car 13 that the full service brake cylinder pressure built up to 77.7 psi instead of the expected 64 psi, causing the measured brake force for this car to be higher than expected. For test car 34, the brake cylinder pressure built up to 72 psi for a full service brake set, which is higher than the expected 64 psi, but the measured brake force was still lower than expected. The observations from these two cars indicate that repair work is needed on test car 16’s braking system and test car 34’s braking system.

Figure 2 shows a graphical representation of the minimum and maximum brake force calculated from the Umler® data, as well as the nominal Umler® calculated brake force and the measured brake force for each car tested in Table 6.

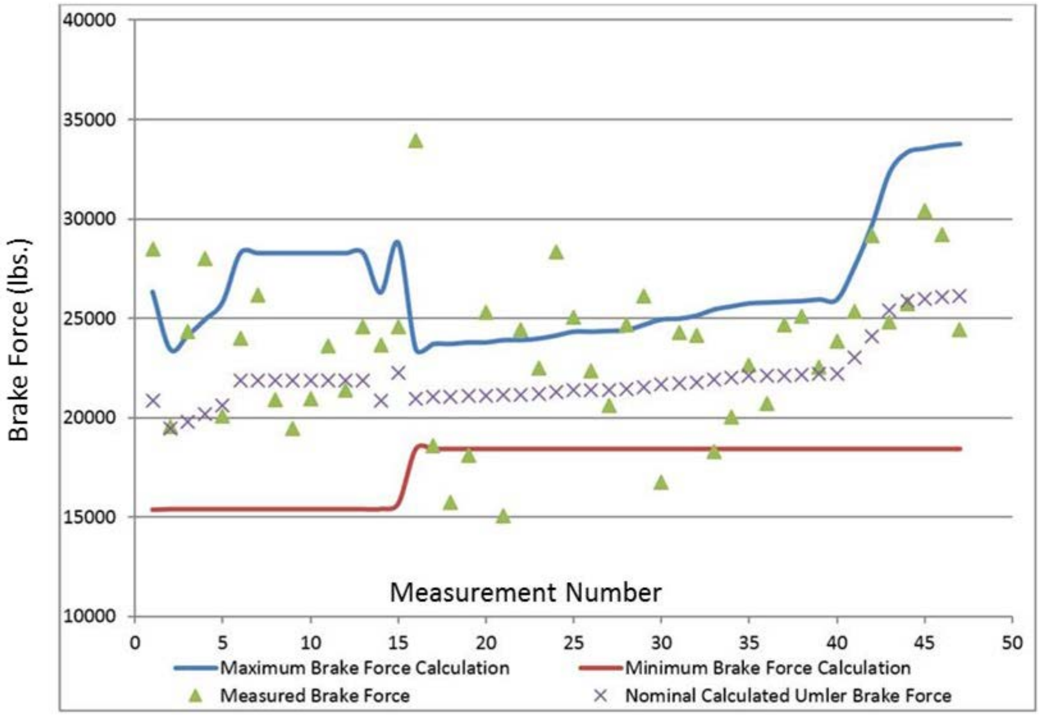

Figure 2. Brake Force Measurements Versus Umler® Brake Force Calculations for Cars without Empty-Load Devices

As shown in Figure 2, the measured brake shoe force falls between the minimum and maximum brake force calculations for the majority of the cars tested. For this sample set, the actual measured values are distributed around the Umler® calculated value, with the majority larger than the calculated value. While the available sample size is not large enough to make a general conclusion about the total population of cars, it appears, from those measured, that the method developed provides a reasonable estimation of the actual brake force.

Table 7 shows JIM SHOE measurement data on the cars that were equipped with an empty-load device. Each car was tested in the empty position and then shims were used to simulate the empty-load device in the loaded position and the car was retested. Umler® data for each of the cars was used to calculate a minimum and maximum brake force, for both the empty and loaded position.

Table 7. JIM SHOE™ Measurements for Empty-Load Equipped Cars

Test Car Number	Average Measured Wheel Force for Full Service Application (lbs.)	Umler® Minimum Brake Force Calculation (lbs.)	Umler® Maximum Brake Force Calculation (lbs.)
1 – Empty	13,740	14,300	20,020
1 – Loaded	18,980[1]	28,600	40,040
2 – Empty	14,731	14,300	20,020
2 – Loaded	27,915	28,600	40,040
3 – Empty	14,826	14,300	20,020
3 – Loaded	28,849	28,600	40,040

Test Car Number	Average Measured Wheel Force for Full Service Application (lbs.)	Umler® Minimum Brake Force Calculation (lbs.)	Umler® Maximum Brake Force Calculation (lbs.)
4 – Empty	13,330	14,300	20,020
4 – Loaded	25,352	28,600	40,040
5 – Empty	15,074	14,300	20,020
5 – Loaded	28,961	28,600	40,040
6 – Empty	14,903	14,300	20,020
6 – Loaded	28,261	28,600	40,040
7 – Empty	15,596	14,300	20,020
7 – Loaded	30,344	28,600	40,040
8 – Empty	12,652	14,300	20,020
8 – Loaded	24,862	28,600	40,040
9 – Empty	13,958	14,300	20,020
9 – Loaded	28,003	28,600	40,040
10 – Empty	16,005	14,300	20,020
10 – Loaded	15,955[1]	28,600	40,040

[1]Empty-load device was not fully defeated by the use of shims, so loaded full service brake force measurement is not accurate.

As indicated in the footnote in Table 7 and from test logs described in Section 2.3.2, it was observed for test car 1 that during the loaded brake force measurement test the brake cylinder pressure built up to 45 psi instead of the expected 64 psi resulting in a lower brake force measurement than expected. During this test the empty load device was partially activated as the brake cylinder pressure did increase from the empty test, which resulted in a brake cylinder pressure of 32 psi, but the empty load device was not totally activated. For test car 10, the brake cylinder build up for both the empty and loaded cases was 32 psi, indicating that the empty load device was activated during the loaded brake force test. It is assumed that the shims did not work as intended for these cars and that if they had an actual load on them that the brake cylinder pressure would have built up to the expected 64 psi.

Figure 3 shows a graphical representation of the minimum and maximum brake force calculated from the Umler® data, as well as the nominal Umler® calculated brake force and the measured brake force for each car tested in Table 7.

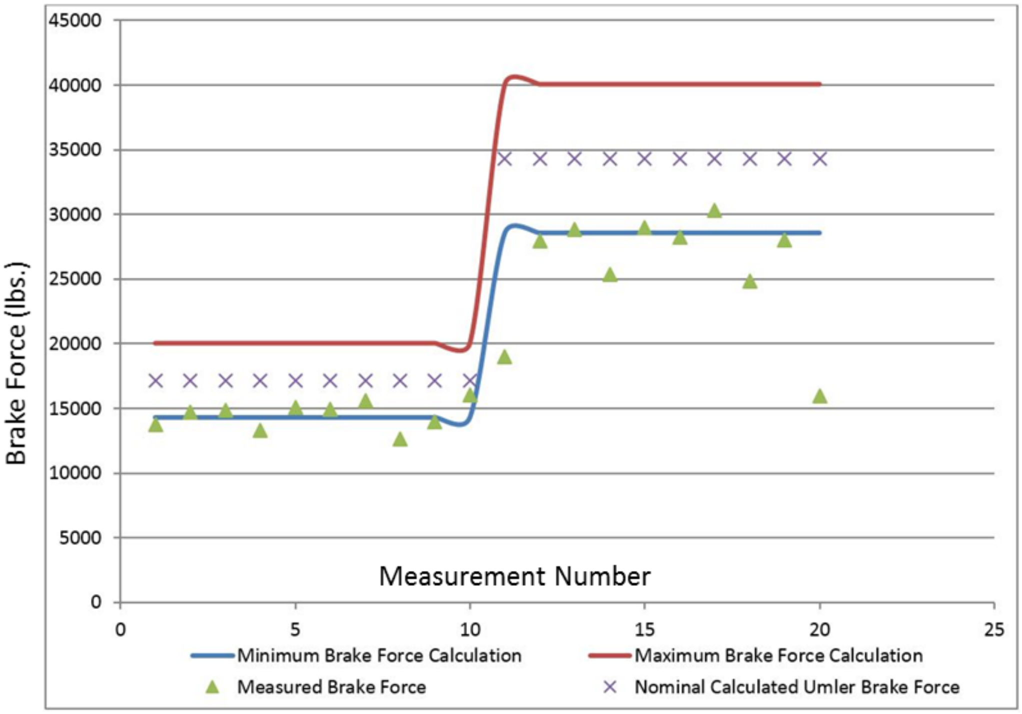

Figure 3. Brake Force Measurements Versus Umler® Brake Force Calculations for Cars with Empty-Load Devices

From Figure 3, it appears that the set of cars tested were built towards the minimum end of the allowable brake shoe force, but with the small sample of empty-load equipped cars tested, this cannot be assumed to apply to the entire population of cars with empty-load devices.

Overall, a larger data set for both empty load equipped and non-empty load equipped, what includes cars built from multiple time periods, would have been ideal to further support the calculations developed in this project, but with over one million cars in revenue service spread throughout the North America railroads, it was not practical to gather enough data for this study.

2.4 Summary

The brake shoe force calculated using Umler® data uses the average of the minimum and maximum brake shoe force values for that car, based on the net brake ratio specifications that were in place when the car was built. The brake shoe force calculated based on train type uses the averages for every car within each train type to best fit a nominal loaded and empty brake shoe force for each train type. The brake shoe force calculation using individual car information uses specific data from Umler® for that car to calculate a nominal loaded and empty brake shoe force. Both Umler® brake shoe force calculations assume that all of the needed data is available to the railroads for the purpose of calculating this brake shoe force. As mentioned earlier, if data is missing in Umler® or data in Umler® is not available to the railroads, then some conservative assumptions may be needed that would reduce the benefit gained by using these methods.

Using Umler® data to calculate the brake shoe force for the consist, using either a train type or an individual car basis, shows some improvement in the overall safety of the enforcement algorithm, especially in the unit train types. The Umler® brake force calculations reduced the number of overruns in the unit simulations, from 277 overruns with the base case, to 23 overruns using data based on train type, and 9 overruns using data based on individual car type.

JIM SHOE™ measurements of brake force on freight cars showed that the measured brake shoe force falls within, or close to, the minimum and maximum brake shoe force values. The JIM SHOE™ measurements combined with the results from the simulations using the Umler® data suggest that calculating the brake shoe force using Umler® data produces a reasonable nominal value for use in PTC enforcement algorithms. The nominal Umler® brake force values, when used in the enforcement algorithm, improve upon the safety objective of the algorithm without negatively impacting the performance objective of the algorithm.

In summary, the Umler® brake force calculations outlined in this project could be used in an enforcement algorithm, to calculate a nominal brake force for the consists that improves upon the current brake force calculation that is being calculated on board with summary consist information.

3. Weighted PTC Braking Enforcement Algorithm Evaluation

In Task Order 242 [2], the PTC braking enforcement algorithm evaluation assumed all scenarios in the Monte Carlo simulation matrix were weighted equally during the analysis of the data. Because some operational scenarios are more likely to occur than others, there is the potential for less common scenarios to artificially skew the overall results. This project included a research effort to gather operational and track data from the railroads to analyze and create a weighted value for each of the scenarios simulated. Then, the weighted values were used during the evaluation of the algorithm to ensure the overall results are more representative of current operations in revenue service.

3.1 Overview of Current Enforcement Algorithm Evaluation Methodology

The enforcement algorithm evaluation methodology, developed in Task Order 242 [2], includes the analysis of the results of simulation testing to quantify the safety and performance of the enforcement algorithm, using a limited set of field testing to support the results of the simulations. In order to provide meaningful results from the evaluation, two key parameters were identified that describe the safety and performance characteristics of the enforcement algorithm:

1. Probability of Target Overshoot - The probability that a given train overshoots the target stopping location for a given test scenario, with 99 percent confidence. This is the primary output of the analysis, as it demonstrates whether or not the enforcement algorithm under evaluation meets the safety objective of the system.
2. Probability of Excessive Target Undershoot — The probability that a given train undershoots the target stopping location by more than:
    - 500 feet, if the initial train speed at enforcement is < 30 mph
    - 1,200 feet, if the initial train speed at enforcement is ≥ 30 mph

    This provides an indication of the operational impact of the enforcement algorithm. Ultimately, the operational impact is defined by whether the enforcement algorithm forces the train crew to slow the train earlier than they would otherwise, and what impact that has on other trains on the network as a whole. The probability of excessive target undershoot provides an indication of the operational impact that can be analyzed for each scenario individually and for all of the scenarios combined.

These parameters are determined for each test scenario from the results of the simulation tests. A two-phase analysis methodology is employed, with the first phase being an exploratory data analysis (EDA) where data augmentation and validation, data consistency checking, and data cleanup is performed. The second phase being the specific statistical analysis, where the probabilities for the above parameters are estimated.

3.2 Description of Weighted Evaluation Methodology

The weighted evaluation of the enforcement algorithm uses the same results from the simulation tests as the current enforcement algorithm evaluation. The weighted evaluation methodology is applied to the results in the specific statistical analysis phase, where the probabilities for the target overshoot and the excessive target undershoot are estimated. Each scenario is given a weighted value depending on the probability of that scenario existing in revenue service, relative to the other scenarios. In the weighted evaluation methodology, scenarios that have a higher probability have a higher influence in the overall results of the analysis.

3.3 Track Data for Weighted Evaluation

This task in the weighted evaluation study looked at track data from the railroads to determine how the actual revenue track profiles fit within the simulated tracks in the Monte Carlo test matrix. The track data from the railroads are used to create probabilities of a train being on one of the track grades used in the simulations. Table 8 breaks the simulated tracks into bins and shows the grade ranges for the real track data used in each bin. The subsections below detail the data used from the railroads, the data processing methods, and the analysis and results of the data.

Table 8. Simulated Track Grade Bins

	2.8% Decline	**2.2% Decline**	**1.7% Decline**	**1.1% Decline**	**0.5% Decline**	**Flat**	**0.5% Incline**	**1.5% Incline**
Railroad Track Data	< -2.2%	< -1.7% >= -2.2%	> -1.1% >= -1.7%	< -0.5% >= -1.1%	< -0.25% >= -0.5%	<= 0.25% >= -0.25%	> 0.25% <= 0.5%	> 0.5%

3.3.1 *Data Overview*

TTCI worked with two Class I railroads in collecting all mainline track data information, from each railroad, for the weighted evaluation study. Data was received in multiple formats to determine the best data source for this study. The final format used was raw subdivision data that contained at least the following information:

1. Grade
    a. Beginning and ending milepost data for every grade change
2. Mileposts
3. Milepost length
    a. Track footage between mileposts
4. Subdivision information
    a. Name and line information

The data was provided by the railroads in Microsoft Access and Excel formats and loaded into a Structured Query Language (SQL) database for processing and analysis.

3.3.2 *Data Processing*

The first step in data processing was to identify any subdivisions or any lines within a subdivision that did not have valid data or was missing data for grades, mileposts, or milepost lengths. Data was considered invalid for subdivisions or lines that only had one grade value for the whole subdivision. Subdivisions were excluded from the study if any of the information was missing, because complete data is needed for calculating the average grade moving through the subdivision. Next, remaining subdivisions with 25 miles of track were discarded. This step was taken to eliminate connecting lines and focus on the major subdivisions within the railroad data.

The remaining data was used for the study and included 37,015 route miles (74,030 track miles when considering both directions along the route), which includes data from the subdivisions in each direction.

3.3.3 *Data Analysis*

In the SQL database, a point with track footage and grade information was created every 100 feet for the 37,015 miles of track used in this study. The 100 feet track footage and grade points were created for each direction in each subdivision. This was done using the track data information provided by the railroads and a statistical analysis tool called R[5]. R is a free software environment for data manipulation, data calculations, statistical computing, and graphical display. For purposes of data integrity, R was connected to the SQL database through an Open Database Connectivity (ODBC) package and the track data in SQL was imported directly to R. A program was developed using the R language that created a point that included milepost information every 100 feet in each of the subdivisions used for this study. The same ODBC package was used to create a table in SQL and write the data that included milepost information every 100 feet back to the SQL database.

Then, the resulting 100-foot "mileposts" were matched to the milepost and grade data for their subdivisions. The grades for each 100-foot milepost were extrapolated using the known grade values and track footage between given milepost value pairs from the railroad track data.

Next, relative elevation of 4,600 feet was assigned to the lowest (starting) milepost for each line in each subdivision. A relative elevation was used for plotting purposes and to calculate average grades. The choice of 4,600 feet was arbitrary, as the true data of interest for this study is the actual grade information, not the actual elevation. Again, R was used to calculate an elevation value for each of the 100-foot mileposts. The data containing the grade information for each point was imported into R using the ODBC connection to the SQL database. The relative elevation was calculated for every point and the results were pushed back to the SQL database and saved.

SQL was then used to calculate average grade every two miles, approximated at 10,500 feet, for each of the 100-foot mileposts. This was done by starting at the first 100-foot milepost on a line and calculating the average grade from that point to 10,500 feet in front of that point, then moving to the next 100-foot milepost and repeating until the end of the line is reached. The two mile average grade represents the average grade the train would travel over during a 2-mile penalty enforcement stop. Actual stopping distances are a function of speed, grade, and consist type, but for this study a 2-mile distance was used as a representative value for all stops.

After computing grades and relative elevations for every 100-foot milepost, histograms and elevation/grade profile plots could be readily generated for each line using the graphical display functions of R. For this analysis, the plots were generated programmatically in R by once again reading the SQL database through an ODBC connection. An example histogram and elevation plot is shown in Figure 4.

[5] R, https://www.r-project.org

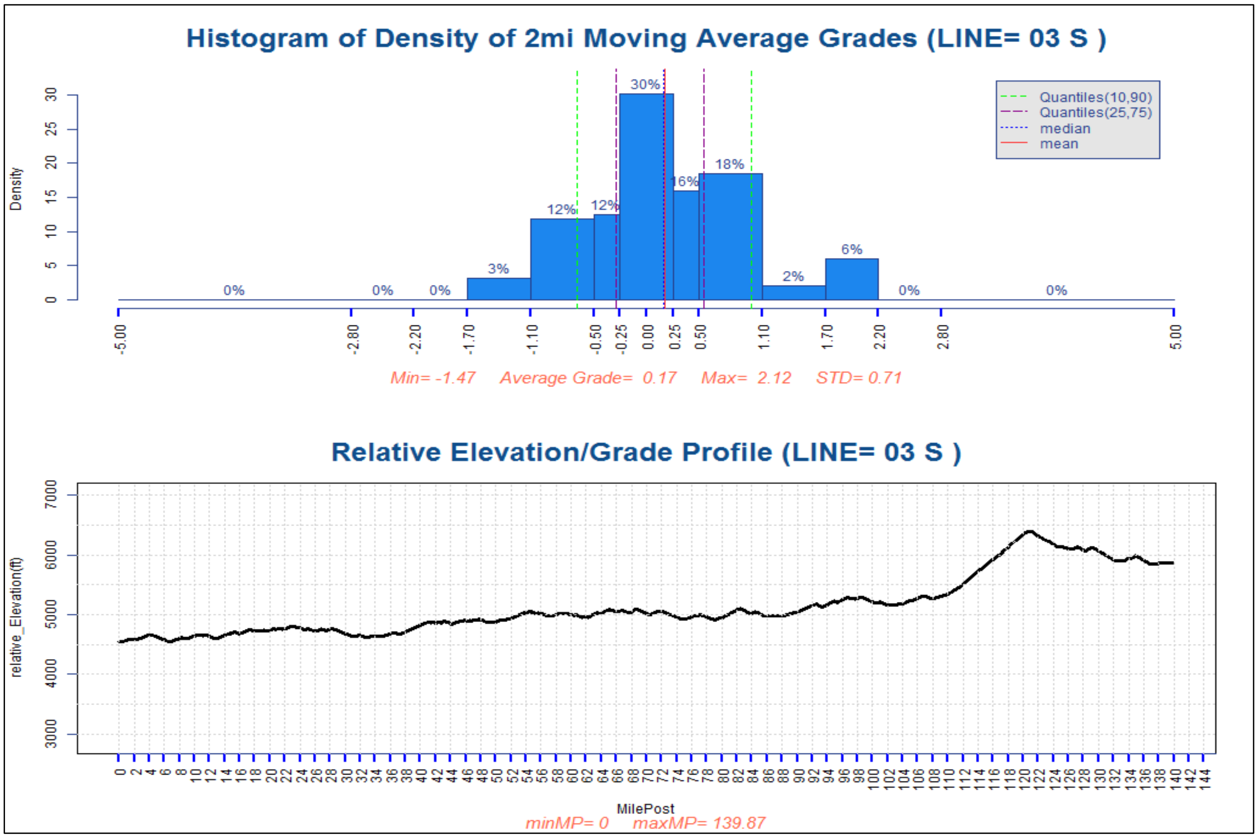

Figure 4. Example Histogram and Plot from R

The histogram in Figure 4 shows the results of moving through this line in the left to right direction on the elevation plot. A similar histogram is developed for the right to left direction, and if both histograms are combined, the results are very close to symmetrical around the center bin. The reason it is not perfectly symmetrical is that in each direction the starting point is either at the beginning of the line, lower milepost value, or the end of the line, higher milepost value, and the 100-foot mileposts are created based on those starting locations, so the 100-foot mileposts are not exactly the same in each direction. The bins for the histogram were set at -5, -2.8, -2.2, -1.7, -1.1, -0.5, -0.25, 0.25, 0.5, 1.1, 1.7, 2.2, 2.8, 5. A similar histogram and plot was produced for each line, in each direction, and an overall tally of each grade bin shown in Table 9 was computed for all of the track data, to give a frequency count for each of the bins. Each plot includes the minimum grade, maximum grade, average grade for the entire subdivision, and standard deviation, as well as the starting and ending milepost information. A handful of lines were used to spot check the results from R by doing the same process manually in Microsoft Excel and comparing the results.

The frequency of each track bin in Table 8 was used as well as train operational data from Section 3.4 to determine the probability each train type would run on each of the simulated track files. Table 9 illustrates these probabilities.

Table 9. Simulated Track Probabilities

	2.8% Decline	2.2% Decline	1.7% Decline	1.1% Decline	0.5% Decline	Flat	0.5% Incline	1.5% Incline	Total
General Freight	0.06%	0.23%	1.04%	7.55%	10.21%	61.84%	10.21%	8.87%	100%
Intermodal Freight	0.06%	0.23%	1.04%	7.54%	10.25%	61.79%	10.24%	8.86%	100%
Unit Freight	0.06%	0.23%	1.04%	7.54%	10.20%	61.87%	10.20%	8.87%	100%

Previously these track grades were weighted equally during the analysis of the Monte Carlo simulation results, but as Table 9 shows, the data from the railroads show over 80 percent of the trains operating on the two miles of simulated track have average grades between +0.5 percent and -0.5 percent. This data is used with the study described in Section 3.4 to break down each of these train types into each of the consist types and lengths used in the Monte Carlo simulation test matrix.

3.4 Operational Data for Weighted Evaluation

The major goal of this exercise was to gather operational data from the railroads and determine how that data fits in with the intermodal consist, manifest consist, and unit consist train types used in the simulation test matrix. TTCI's scenarios and consist data, shown in Table 10, Table 11, and Table 12were used to create break points for the lengths of each of the consists used in the simulation test matrix. This provided a length range for each of the consists used in the simulations that could be compared with the operational data to determine how the operational data fits within the consists used in the simulations. The breakdown of train lengths for each consist simulated is shown in Table 13, Table 14, and Table 15.

Table 10. Data for Intermodal Consists used in Simulations

Train Type	Length	Load Condition	Power Configuration
Intermodal	Short Medium Long Very Long	Empty Loaded	HE – Head End Power DE – Head-Tail Power DM – Head-Mid-Tail Power

Table 11. Data for Manifest Consists used in Simulations

Train Type	Number of Cars	Load Condition	Power Configuration
Manifest	0 3 10 40 100 150 200	Empty Loaded	HE – Head End Power DE – Head-Tail Power DM – Head-Mid-Tail Power

Table 12. Data for Unit Consists used in Simulations

Train Type	Number of Cars	Load Condition	Unit Type	Power Configuration
Unit	100 135 200 260	Empty Loaded	Coal Covered Hopper Multi-Level Refrigerated Boxcars Tank	HE – Head End Power DE – Head-Tail Power DM – Head-Mid-Tail Power

Table 13. Intermodal Consist Train Lengths

Train Type	Train Length (feet)
Intermodal Small	< 6695
Intermodal Medium	>= 6695 and < 9414
Intermodal Long	>= 9414 and < 13341
Intermodal Very Long	>= 13341

Table 14. Manifest Consist Train Lengths

Train Type	Train Length (feet)
Manifest 0	< 206
Manifest 3	>= 206 and < 484
Manifest 10	>= 484 and < 1178
Manifest 40	>= 1178 and < 4414
Manifest 100	>= 4414 and < 7815
Manifest 150	>= 7815 and < 9634
Manifest 200	>= 9634

Table 15. Unit Consist Train Lengths

Train Type	Train Length (feet)
Unit 100 Coal Steal	< 6608
Unit 135 Coal Steal	>= 6608 and < 9410
Unit 200 Coal Steal	>= 9410 and < 12950
Unit 260 Coal Steal	>= 12950
Unit 100 Coal Aluminum	< 6094
Unit 135 Coal Aluminum	>= 6094 and < 8677
Unit 200 Coal Aluminum	>= 8677 and < 11944
Unit 260 Coal Aluminum	>= 11944
Unit 100 Covered Hopper	< 7304
Unit 135 Covered Hopper	>= 7304
Unit 100 Multi-Level	< 11396
Unit 135 Multi-Level	>= 11396
Unit 100 Refrigerated Box	< 10211
Unit 135 Refrigerated Box	>= 10211
Unit 100 Tank	< 5431
Unit 135 Tank	>= 5431

3.4.1 *Operational Data from the Railroads*

TTCI worked with the same railroads that provided track data to collect operational data for the weighted evaluation study. Data was received in multiple formats and analyzed multiple ways to determine the best data source for this study. The final format used for this study had to include operational data collected over a 1-year period that included:

1. Train type including number of trains for each type
   a. Intermodal freight
   b. Manifest freight
   c. Unit freight broken down into the following categories if possible
      - Coal
      - Grain
      - Tank
      - Multi-level
      - Bulk commodity
      - Other
2. Average train length per train type
3. Standard deviation of train length per train type

Data Overview

Both railroads provided data to TTCI in Microsoft Excel spreadsheets, but one railroad had the operational data by subdivision and the other railroad had operational data across the whole network.

For the data received on a subdivision level, the operational data was matched to the track data, from Section 3.3, for that subdivision, and an analysis was performed per subdivision to create a frequency table that fits the railroad's operational and track data into the different simulated train consist and track grade combinations. All the frequency tables, from each subdivision, were combined to determine the weighted value for each simulated train consist and track grade combination for this railroad.

A similar approach was used for the data received across the whole network, with the operational data, in this case, being used across the entire track data set, from Section 3.3, to create a frequency table that fits the railroad's operational and track data into the different simulated train consist and track grade combinations. The frequency table was used to determine the weighted value for each simulated train consist and track grade combination for this railroad.

The resulting operational data results from both railroads were combined to produce the weighted values for each train consist and track grade combination simulated in the Monte Carlo test matrix.

Data Processing

For both railroads, the operational data was separated into three train types: unit freight, intermodal freight, and manifest freight. Each train type included information on the count of trains, the average length of the train, and the standard deviation of the train length.

For manifest freight and intermodal freight, the trains for each train type were combined to give a total number of trains within that train type and an overall average train length and standard deviation of the train length for that train type. Table 16 shows an example of how multiple trains within a train type were combined.

Table 16. Example of Combining Similar Trains within a Train Type to get Overall Average and Standard Deviation of Train Length

Intermodal Trains	Average Length (feet)	Standard Deviation (feet)	Count of Trains	Weighted Average Length (feet)	Weighted Standard Deviation (feet)
Intermodal - 1	7,000	1,500	120	840,000	180,000
Intermodal - 2	6,200	2,000	100	620,000	200,000
Intermodal - 3	6,500	1,000	80	520,000	80,000
Total	**6,600**	**1,533.33**	**300**	**1,980,000**	**460,000**

The weighted average length and standard deviation for train length shown in Table 16 were calculated by taking the average train length and standard deviation of the train length and multiplying it by the count of trains. The overall average train length was then calculated by summing the weighted averages and dividing by the total number of trains (1,980,000/300 = 6,600) and the overall standard deviation of train length was calculated by summing the weighted standard deviations and dividing by the total number of trains (460,000/300 = 1,533.33).

For unit trains, the trains were broken down to individual unit train types, and then consists for each individual unit train type were combined to give a total number of trains within that unit train type and an overall average train length and standard deviation of the train length for that unit train type using the same process as shown in Table 16.

Data Analysis

The average train lengths and standard deviations for unit, intermodal, and manifest trains were used to determine how the railroads operational data is categorized into one of the simulated train consists, described in Table 13, Table 14, and Table 15 . The operational and track data were used to create frequency tables showing how the railroads data best fits within the simulated track grade and consist combinations. A count of each simulated consist was needed to populate the frequency table. This was created by using the average train lengths and standard deviations for each train type and building 100,000 consists from their distributions. The type of distribution received from the railroads was not known, but it was assumed normal and three different normal distribution types were used to create the consists: Normal (left-skewed), standard normal, and normal (right-skewed). The 100,000 consists were then combined with the track data, for that subdivision, to create the frequency tables for each distribution type.

The frequency table created for each subdivision provided information on how the operational and track data, from that subdivision, best fits within the simulated train consist and track grade combinations. All the frequency tables, from each subdivision and each distribution type, were combined to create the overall weighted values for each of the scenarios simulated in the Monte Carlo test matrix.

Table 17, Table 18, and Table 19 show the probabilities for each consist type and track grade combination using the Normal (right-skewed) distribution. Some scenarios had smaller than a 0.01 percent, 1 in 10,000 trains, probability of being operated in revenue services, but was limited to no smaller than 0.01 percent. Values that were greater than 0.01 percent were proportionally lowered to maintain an overall value of 100 percent for all of the scenarios.

Table 17. Intermodal Consist Type and Track Grade Probabilities using Normal (right-skewed) Distribution

BATCH_NAME	2.8% Decline	2.2% Decline	1.7% Decline	1.1% Decline	0.5% Decline	Flat	0.5% Incline	1.5% Incline	Total
Int_ShortDE	0.02	0.08	0.37	2.67	3.63	21.91	3.63	3.14	**35.45**
Int_ShortHE	0.02	0.08	0.37	2.67	3.63	21.91	3.63	3.14	**35.45**
Int_MediumDE	0.01	0.03	0.12	0.88	1.19	7.2	1.19	1.03	**11.65**
Int_MediumHE	0.01	0.03	0.12	0.88	1.19	7.2	1.19	1.03	**11.65**
Int_LongDE	0.01	0.01	0.03	0.21	0.28	1.69	0.28	0.24	**2.75**
Int_LongDM	0.01	0.01	0.03	0.21	0.28	1.69	0.28	0.24	**2.75**
Int_VryLngDM	0.01	0.01	0.01	0.02	0.03	0.17	0.03	0.02	**0.3**
Total	**0.09**	**0.25**	**1.05**	**7.54**	**10.23**	**61.77**	**10.23**	**8.84**	**100**

Table 18. Unit Consist Type and Track Grade Probabilities using Normal (right-skewed) Distribution

BATCH_NAME	2.2% Decline	1.7% Decline	1.1% Decline	0.5% Decline	Flat	0.5% Incline	1.5% Incline	Total
Unit 100 Coal Steel	0.02	0.09	0.66	0.89	5.39	0.89	0.78	**8.72**
Unit 100 Hopper	0.05	0.19	1.35	1.82	11	1.82	1.58	**17.81**
Unit 100 Coal Alum.	0.03	0.09	0.68	0.92	5.54	0.92	0.8	**8.98**
Unit 100 Multi-Level	0.06	0.21	1.51	2.03	12.32	2.04	1.76	**19.93**
Unit 100 Box	0.06	0.2	1.47	1.99	12.04	1.99	1.72	**19.47**
Unit 100 Tank	0.04	0.16	1.16	1.56	9.45	1.56	1.35	**15.28**
Unit 135 Coal Steel	0.01	0.01	0.09	0.12	0.72	0.12	0.1	**1.17**
Unit 135 Hopper	0.01	0.02	0.16	0.22	1.3	0.22	0.19	**2.12**
Unit 135 Coal Alum.	0.01	0.01	0.07	0.1	0.61	0.1	0.09	**0.99**
Unit 135 Multi-Level	0.01	0.01	0.01	0.01	0.01	0.01	0.01	**0.07**
Unit 135 Box	0.01	0.01	0.03	0.05	0.29	0.05	0.04	**0.48**
Unit 135 Tank	0.01	0.05	0.35	0.48	2.89	0.48	0.41	**4.67**
Unit 200 Coal Steel	0.01	0.01	0.01	0.01	0.04	0.01	0.01	**0.1**
Unit 200 Coal Alum.	0.01	0.01	0.01	0.01	0.01	0.01	0.01	**0.07**
Unit 260 Coal Steel	0.01	0.01	0.01	0.01	0.01	0.01	0.01	**0.07**
Unit 260 Coal Alum.	0.01	0.01	0.01	0.01	0.01	0.01	0.01	**0.07**
Total	**0.36**	**1.09**	**7.58**	**10.23**	**61.63**	**10.24**	**8.87**	**100**

Table 19 – Manifest Consist Type and Track Grade Probabilities using Normal (right-skewed) Distribution

BATCH NAME	2.8% Decline	2.2% Decline	1.7% Decline	1.1% Decline	0.5% Decline	Flat	0.5% Incline	1.5% Incline	Total
Man_000HE	0.01	0.01	0.01	0.02	0.03	0.16	0.03	0.02	**0.29**
Man_003HE	0.01	0.01	0.01	0.07	0.1	0.6	0.1	0.09	**0.99**
Man_010HE	0.01	0.02	0.09	0.66	0.89	5.38	0.89	0.77	**8.71**
Man_040HE	0.03	0.11	0.51	3.71	5	30.3	5.01	4.36	**49.03**
Man_100DE	0.01	0.04	0.2	1.45	1.96	11.87	1.96	1.7	**19.19**
Man_100HE	0.01	0.04	0.2	1.45	1.96	11.87	1.96	1.7	**19.19**
Man_150DE	0.01	0.01	0.01	0.08	0.11	0.69	0.11	0.1	**1.12**
Man_150DM	0.01	0.01	0.01	0.08	0.11	0.69	0.11	0.1	**1.12**
Man_200DE	0.01	0.01	0.01	0.01	0.02	0.09	0.02	0.01	**0.18**
Man_200DM	0.01	0.01	0.01	0.01	0.02	0.09	0.02	0.01	**0.18**
Total	**0.12**	**0.27**	**1.06**	**7.54**	**10.2**	**61.74**	**10.21**	**8.86**	**100**

Looking at the resulting data in Table 17, Table 18, and Table 19, some large total values can be seen in certain simulated consists. With the intermodal consists, a weighted value of over 70 percent exists in the intermodal small trains, which consist of trains less than 6,695 feet. In the unit consists, a weighted value of over 90 percent exists for all unit 100-car consists. In the manifest consists a weighted value of over 77 percent exists in the manifest 40-car and 100-car consists, which includes trains between the length of 1,178 feet and 7,815 feet. Future consideration of adding additional simulated consists in these areas will reduce the weighted value in these simulated consists and the results will not be so heavily weighted in these areas.

Similar tables were created for the standard normal and normal (left-skewed) distributions. The tables for each distribution were used to analyze the simulation results with the weighted values created by each of the distributions. The results are provided in Section 3.5.

3.5 Simulation Analysis using Weight Evaluation

The following tables show the results of the simulation analysis using weighted values from each distribution type as well as the simulation analysis using the non-weighted values. Table 20 shows results with the brake algorithm emergency brake backup function disabled and Table 21 shows results with the brake algorithm emergency brake backup function enabled.

Table 20. Analysis for Simulations with Emergency Brake Backup Disabled

Train Type	Distribution	Short of Stop Target	Short of Performance Target < 30mph	Short of Performance Target >= 30mph
Intermodal	Non-Weighted	99.99%	28.30%	40.20%
Intermodal	Right Skewed	99.99%	2.95%	44.95%
Intermodal	Standard Normal	99.99%	2.90%	44.92%
Intermodal	Left Skewed	99.99%	2.69%	44.23%
Unit	Non-Weighted	99.99%	27.62%	43.82%
Unit	Right Skewed	99.99%	4.87%	48.44%
Unit	Standard Normal	99.99%	4.86%	48.32%
Unit	Left Skewed	99.99%	4.84%	48.10%

Train Type	Distribution	Short of Stop Target	Short of Performance Target < 30mph	Short of Performance Target >= 30mph
Manifest[1]	Non-Weighted	99.97%	32.17%	43.75%
Manifest[1]	Right Skewed	99.90%	4.68%	35.76%
Manifest[1]	Standard Normal	99.90%	4.57%	35.98%
Manifest[1]	Left Skewed	99.91%	4.67%	36.68%
Combined[1]	Non-Weighted	99.99%	29.47%	42.48%
Combined[1]	Right Skewed	99.94%	3.89%	37.21%
Combined[1]	Standard Normal	99.94%	3.80%	37.27%
Combined[1]	Left Skewed	99.94%	3.91%	37.67%

[1]Manifest simulations for 10-car, 3-car, and light locomotives were not run, because of changes being made to how short trains are simulated – Analysis was done without those simulations

Table 21. Analysis for Simulations with Emergency Brake Backup Enabled

Train Type	Distribution	Short of Stop Target	Short of Performance Target < 30mph	Short of Performance Target >= 30mph
Intermodal	Non-Weighted	99.96%	18.20%	14.94%
Intermodal	Right Skewed	99.93%	0.51%	20.43%
Intermodal	Standard Normal	99.93%	0.51%	20.75%
Intermodal	Left Skewed	99.94%	0.53%	21.52%
Unit	Non-Weighted	99.66%	14.77%	18.39%
Unit	Right Skewed	99.39%	1.05%	20.07%
Unit	Standard Normal	99.39%	1.06%	20.09%
Unit	Left Skewed	99.39%	1.07%	20.14%
Manifest[1]	Non-Weighted	99.90%	17.86%	19.54%
Manifest[1]	Right Skewed	99.74%	0.69%	21.19%
Manifest[1]	Standard Normal	99.75%	0.71%	21.27%
Manifest[1]	Left Skewed	99.76%	0.73%	21.42%
Combined[1]	Non-Weighted	99.86%	17.10%	17.53%
Combined[1]	Right Skewed	99.71%	0.81%	20.60%
Combined[1]	Standard Normal	99.71%	0.81%	20.68%
Combined[1]	Left Skewed	99.72%	0.83%	20.85%

[1]Manifest simulations for 10-car, 3-car, and light locomotives were not run, because of changes being made to how short trains are simulated – Analysis was done without those simulations

One of the biggest differences observed in Table 20 and Table 21 is in stopping short of the performance objective when the speed is less than 30 mph. For all consist types, with emergency brake backup enabled or disabled, there was a significant reduction in the probability of stopping shorter than 500 feet from the target when the speed is less than 30 mph. This indicates that the simulations that stop within the 500 foot objective are more heavily concentrated in the higher weighted scenarios. Looking further into this, with data from Table 17, Table 18, and Table 19, there is a weighted value of over 80 percent for simulations run on the following tracks: 0.5 percent decline, flat, and 0.5 percent incline. The majority of the simulations with speeds less than 30 mph on these tracks are run with a speed of 10 mph. Future considerations of adding additional speeds for these tracks will spread the weighted value over multiple speeds instead of being heavily weighted on 10 mph.

From Table 21, it can also be observed that stopping short of the target, for the unit train types drops from 99.66 percent to 99.39 percent, which is below the target value of 99.5 percent probability of stopping short of the target. This shows that the overruns in the unit simulations must be in cases that have a higher weighted value. Looking at the simulation results, it was found that over 70 percent of the overruns in the unit train type occur on track grades of 0.5 percent decline, flat, and 0.5 percent incline, which are the grades with the highest weighted values. About 32 percent of the above overruns also occur in the unit train 100-car consists, which are the unit consists with the highest weighted value. Looking further into the data, it was further found that 98 percent of the overruns in the unit simulations occur with steel coal, covered hopper, or tank trains. As discussed in the Umler® study in Section 2, these train types were shown to have lower brake force than the other three unit train types. There are a number of ways the overruns in these areas can be reduced, to meet the 99.5 percent probability of stopping short of the target and they include:

1. Using a lower brake force average, in the algorithm, for unit trains
    - This could have a negative impact on the performance of the algorithm, as all unit trains will be enforced earlier
2. Add additional safety target offset to account for the overruns
    - This could have a negative impact on the performance for any scenario that has the safety target offset increased
3. Create additional train types instead of lumping all unit trains into one train type
    - This could improve the safety and performance, as the average brake force would be calculated on fewer train types with less variability
4. Use an off-board brake force calculation – Umler®
    - In Section 2 it was shown that a brake force calculated from Umler® reduced the number of overruns without negatively impacting the performance of the algorithm
5. Use of an adaptive brake force algorithm
    - An adaptive algorithm would be able to adjust to brake force calculation errors as well as other factors that contribute to braking such as coefficient of friction, brake rigging, wet rail, and others. This could have significant benefit in the safety and performance of a braking algorithm.

3.6 Summary

For the weighted evaluation study, operational and track data was gathered from two Class I railroads. The track data consisted of the entire mainline track from each railroad and the operational data consisted of consist information collected over a 1-year period.

The track data was evaluated to find the 2-mile average grade every 100 feet throughout the mainline and each 2-mile average grade was assigned to one of the simulated track files. This produced a frequency table of how often a simulated track grade was seen in the railroad data, based on the 2-mile averages. This frequency table was used with operational data to create weighted values for the simulated consist type and track grade combinations.

The operational data was used to determine how the railroad data best fits within the different train consists that are used in the simulations. The average train lengths and standard deviation of train lengths, per train type, were used to determine how the operational data from the railroads fits within the simulated train consists.

By combining the operation and track data, frequency tables were created for all of the train consist and track grade combinations that are used in the Monte Carlo simulation matrix. The frequency tables were used to create a weighted value for each scenario that was used in the analysis of the simulation results.

From the frequency tables and results of the weighted evaluation, it was observed that there are some areas in the Monte Carlo simulation matrix that could be expanded upon in the future, such as adding additional consist lengths and train speeds in certain areas. It was also observed that some of the scenarios simulated had less than a 1in 10,000 likelihood of being encountered in revenue service. These scenarios could be modified or eliminated in the future, as well.

The weighted evaluation also showed a decrease in the probability of meeting the safety objective for the unit trains to 99.39 percent, which is below the target of 99.5 percent. Looking at the simulation results, almost all of the overruns in the unit simulations came from the three train types with lower overall brake force; steel coal, covered hopper, and tank, but the overruns were also observed in areas with a higher probability of being encountered in revenue service. There are a number of ways that the overruns could be addressed including, using a lower average brake force for all unit consists, using a brake force calculated from Umler® data, or using an adaptive brake force algorithm.

Overall the weighted evaluation gives additional insight on how revenue service operations best fit within the simulated test matrix and an analysis on the safety and performance of the algorithm with the scenarios weighted from the railroad data.

4. Conclusion

The research of Umler® data fields resulted in two methods for estimating train brake force using data from Umler®. The first method used the current PTC consist information along with a train type to estimate brake force for the train. The second method used detailed information for each car in the train to estimate brake force for the train. Monte Carlo simulations, using these two methods, show that there is a general increase in the probability of stopping short of the target, which improves the safety performance of the algorithm, and a general decrease in stopping overly short of the target, which improves the operational performance of the system when using the estimated brake force calculations from Umler® versus letting the PTC system calculate brake force onboard with less detailed consist information.

The weighted evaluation study gave an overview of the track and operations over the track for two Class I railroads. Using data from this study, the railroads' operations were mapped to the scenarios that are currently in the Monte Carlo test matrix and each scenario was given a weighted value using this mapping. The Monte Carlo simulations were then evaluated using the weighted value of each scenario to figure out the probability of stopping short of the target and the probability of stopping within 500 feet of the target if simulated at less than 30 mph or the probability of stopping within 1,200 feet of the target if simulated at 30 mph or greater.

Results from the comparison show the overall probability of stopping short of the target went from 99.86 percent, without using weighted values, to 99.71 percent, using weighted values. This shows that the overall probability of the algorithm stopping short of the target is not greatly affected by the weighting process. However, there were differences when looking at individual train types, which may lead to insights about the braking algorithm performance and where improvements could be made. The Monte Carlo simulations evaluated using the weighted values also show that there was a significant improvement in the performance of the algorithm being evaluated in the scenarios where the train was operated at less than 30 mph, and a slight drop in performance in the scenarios where the train was operated at 30 mph or greater. This may indicate that future considerations of performance improvements could show concentrated on trains operating at 30 mph or greater.

The weighted evaluation study also gave some insight on how the current Monte Carlo simulations fit within the combined railroad operational data received from the two railroads. The results of the weighted values created for each scenario could show that a majority of the railroad operations mapped to only a few consists in each train type. Consideration should be given to adding additional scenarios in these areas to ensure certain scenarios are not weighted too high, and proper resolution is available in the more frequent operating scenarios.

5. References

1. Carlson, F. (October 2002) "Body-mounted Brake Rigging." *Technology Digest* TD-02-022. Association of American Railroads, Transportation Technology Center, Inc., Pueblo, CO.
2. Brosseau, J., Moore Ede, B., Pate, S., Wiley, RB, Drapa, J., (October 2009) *Development of an Operationally Efficient PTC Braking Enforcement Algorithm for Freight Trains*, DOT-FRA-ORD-13/34, U.S. Department of Transportation, Federal Railroad Administration, Office of Policy and Development, Washington, D.C. Available: https://www.fra.dot.gov/eLib/details/L04712#p1_z5_gD_kdrapa
3. Association of American Railroads. *AAR Manual of Standards and Recommended Practices*. Section E. Standard S-401 "Brake Design Requirements." Washington, DC. Adopted: 1964; Last Revised: 2011.

Abbreviations and Acronyms

AAR	Association of American Railroads
BOL™	Brake-O-Later
EDA	Exploratory Data Analysis
FRA	Federal Railroad Administration
GRL	Gross Rail Load
I-ETMS®	Interoperable Electronic Train Management System
ODBC	Open Database Connectivity
PTC	Positive Train Control
SQL	Structured Query Language
TCL	Test Controller/Logger
TIP	Test Implementation Plan
TOES™	Train Operations and Energy Simulator
TTC	Transportation Technology Center
TTCI	Transportation Technology Center, Inc.
UMLER®	Universal Machine Language Equipment Register