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Projecting the Energy Reduction Benefits of MPL NatureBlend Locomotive Wheel Flange Lubricant to Specific Railroad Profiles

DECEMBER 2020

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Introduction and Objectives

This report is an addendum building upon a previous study entitled "Analysis of the Energy Reduction Benefits of MPL NatureBlend™ Locomotive Wheel Flange Lubricant." That study was specific to the results at TTCI. This report documents a model and tool which has been developed to project TTCI results to a sample profile for a specific railroad.

Tests conducted at TTCI are undertaken with tight controls. However, "real world" conditions are different than the TTCI environment. It is common to characterize TTCI tests as being somewhat optimistic, due to attributes that do not necessarily reflect a railroad's network and train profile. This model quantifies some of those attributes with the objective of projecting from the TTCI data to specific scenarios of interest to a railroad.

Description of the Energy Savings Tool

The model is a calculation engine with several modules reflecting various aspects of the projection factors. In some cases, the equations were derived from fitted curves (curve fitting regressions) with the TTCI data. In other cases, the calculation logic is simpler (e.g. multiplication factors), however, these factors have been derived from, or supported with the TTCI data.

The attributes, and therefore, the inputs to the model are:

- Train-miles – a reflection of the railroad's network, weighted by train traffic:
    - Grade profile: uphill versus flat versus downhill
    - Tangent versus curve profile
- Train length
- The installation prevalence of NatureBlend™ applicators and sticks.

The *methodology* section of this report provides details about the tool and its inputs.

Velocity Benefits

Apart from the energy savings, which is the main purpose of this tool, ancillary velocity benefits of NatureBlend™ are recognized. By using NatureBlend™ , trains realize the most energy savings in the midrange of throttle positions, due to the reduction of the coefficient of friction. We have seen that there is a small velocity benefit for trains operating in T8 in addition to energy savings, so a separate calculator was developed to estimate the velocity improvements. This is also described in the *methodology* section.

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Railroad Profile Examples and Projections

Here we provide three cases of how the inputs to the model translate to estimated savings. These examples will undoubtedly differ from a particular railroad's perspective on their specific profiles. They do not reflect a particular named railroad. The intent of this tool is for railroads to provide their own inputs to obtain estimates.

Each of the example summaries on the following pages show hypothetical values of the inputs to the tool, in each category, along with the estimated savings.

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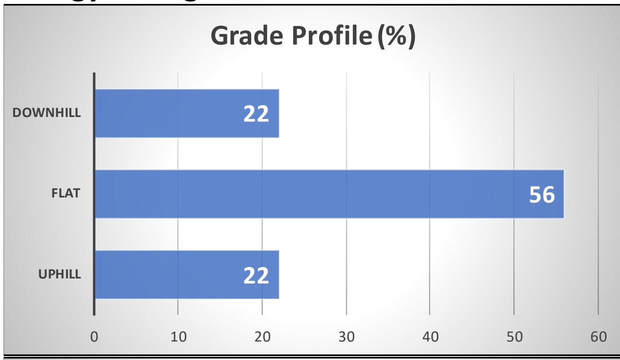
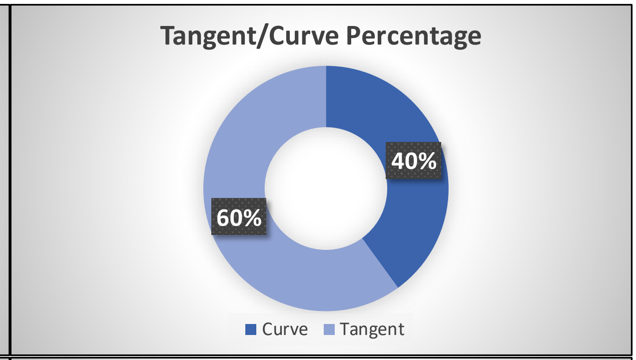
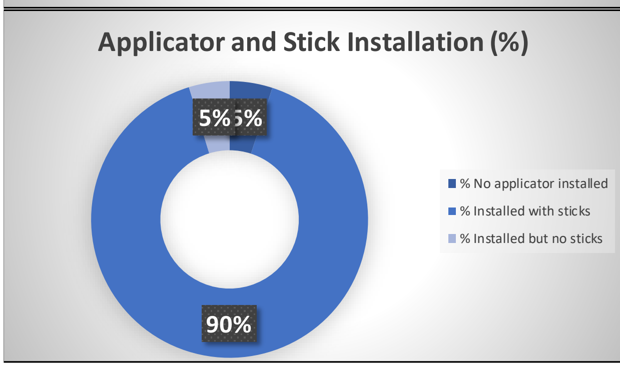
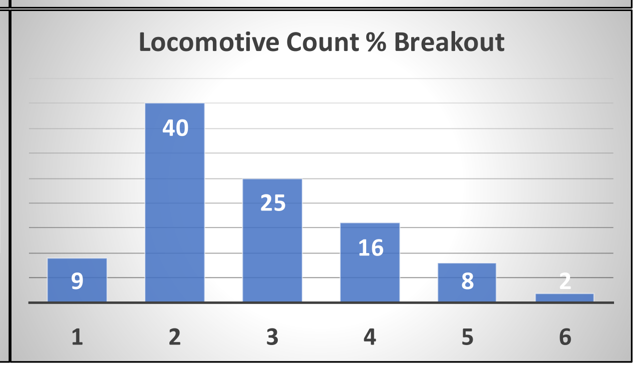
Example One: An Eastern Railroad

Energy Savings









Train Length	
Feet	Equivalent Cars
6800	94

Total % Savings
2.6

Velocity Benefit

Throttle Profile	
% Time in T8	20
% Time in Idle/DB	40

% Velocity Improvement
0.14

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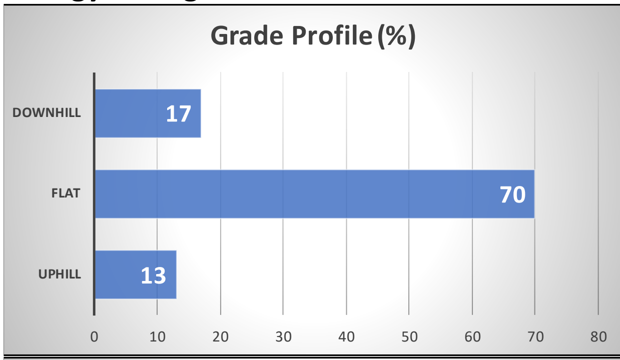
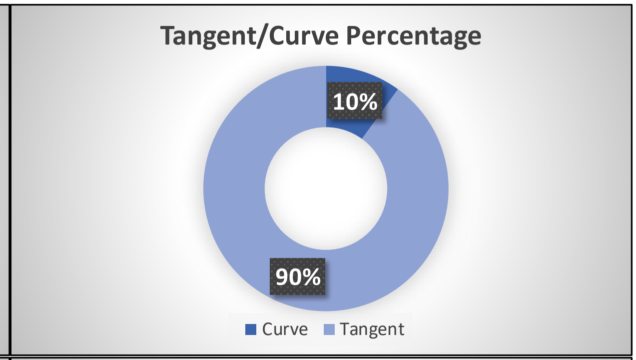
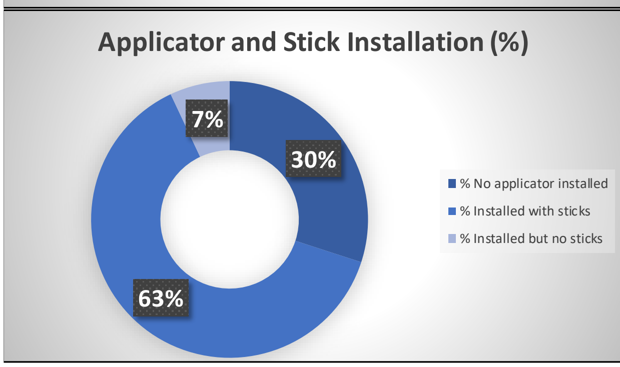
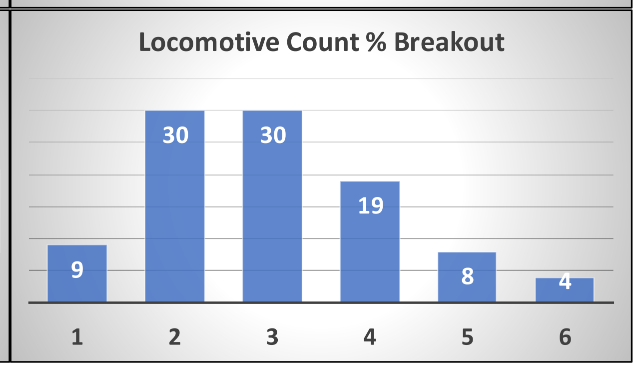
Example Two: Western Railroad

Energy Savings









Train Length

Feet	Equivalent Cars
9000	125

Total % Savings
2.2

Velocity Benefit

Throttle Profile

% Time in T8	15
% Time in Idle/DB	40

% Velocity Improvement
0.11

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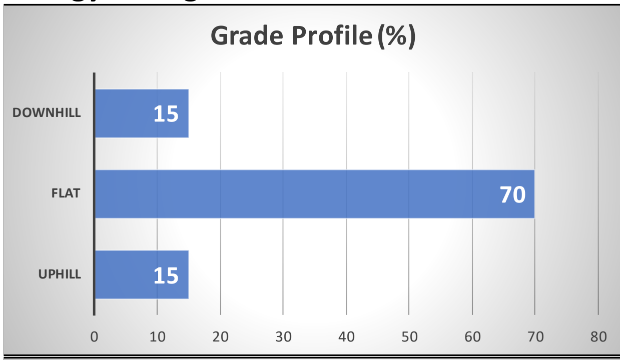
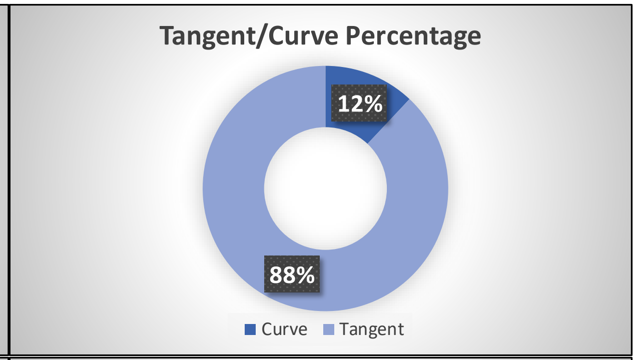
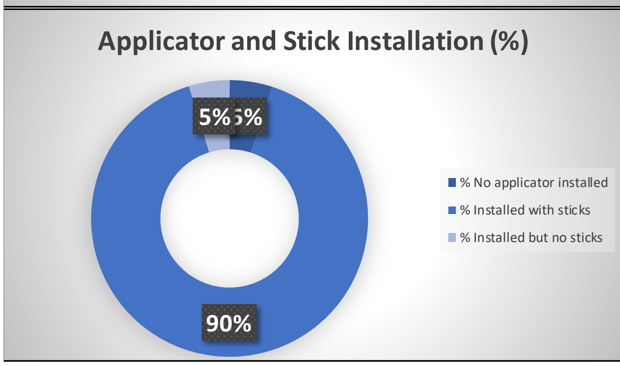
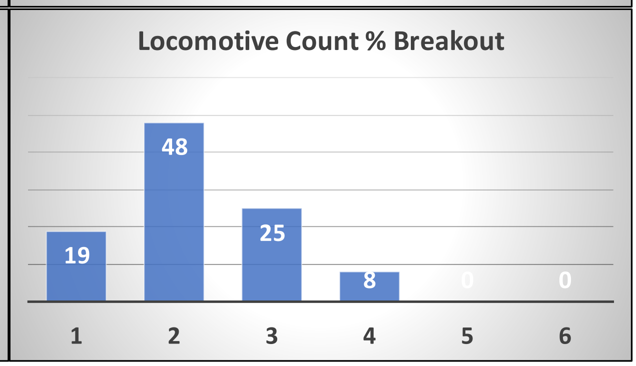
Example Three: Northern Railroad

Energy Savings









Train Length

Feet	Equivalent Cars
8100	113

Total % Savings
2.4

Velocity Benefit

Throttle Profile

% Time in T8	40
% Time in Idle/DB	40

% Velocity Improvement
0.29

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Methodology

To best understand how this model works, one should read the original report to learn about the TTCI tests, the data, and the approach we have taken for analysis.

Model Overview

Figure 1 contains a schematic of the model, showing the inputs, calculations, and outputs. The model can be considered to have modules that account for three types of projection factors: train mile profile; train length; and the installation prevalence of NatureBlend™. The sections following the schematic describe how the calculation logic for each module was derived.

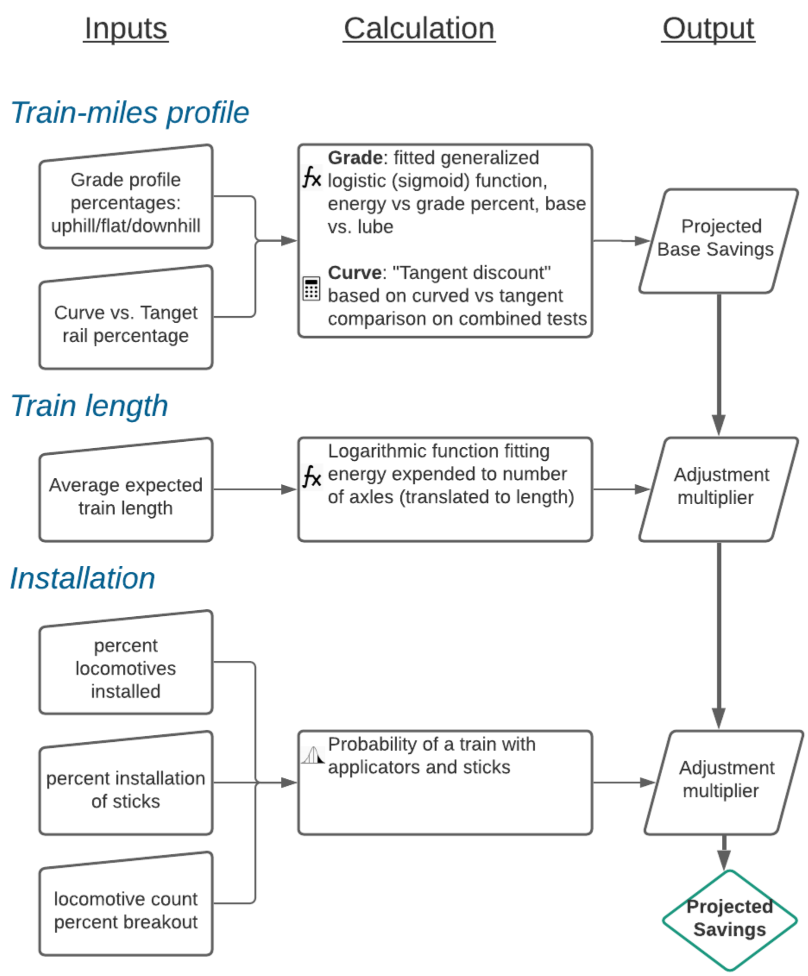

Figure 1- Model Overview

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Train-miles Profile

The major factors in projecting TTCI results to a railroad network relate to the differences in track curvature and grade changes. The two test loops have unique profiles with respect to elevation as well as tangent versus curved rail, and these profiles are different than those seen in a typical network. In the case of curvature, the loops are, of necessity, much curvier than a typical system network.

Grade Profiles

Those variations in elevation and curvature is what allows us to extrapolate to other profiles. For the grade projections, the philosophy in making these extrapolations followed these principles:

- In the spirit of the original analysis, the tests should be pooled to take advantage of the larger set of information and variation in the attributes of the tests.
- We should rely on a mathematical function with parameters estimated from the data to be able to input any grade percent and produce a prediction of the difference between the lubricating and base condition.
- The function should serve to smooth out irregularities and interpolate.

Figure 2 depicts the average raw energy curves for the two tests, showing how it relates to grade percent.

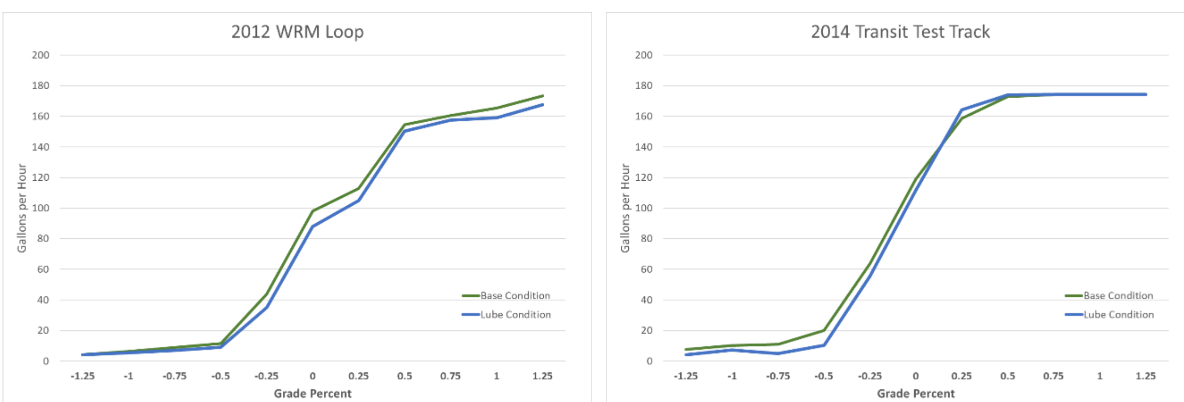

Figure 2- Energy Curves by Grade

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An S-shape (sigmoidal) curve[1] was fit to the combined data and produced the smoothed shape seen in figure 3, for both base and lube conditions. The estimated values of this function are used to produce the calculations of savings.

To make the provision of inputs simple, for the proceeding examples we created three simple groupings: uphill; flat; and downhill, based on cutoff definitions of grade percent. But this model is flexible enough to define more granular breakouts of these definitions.

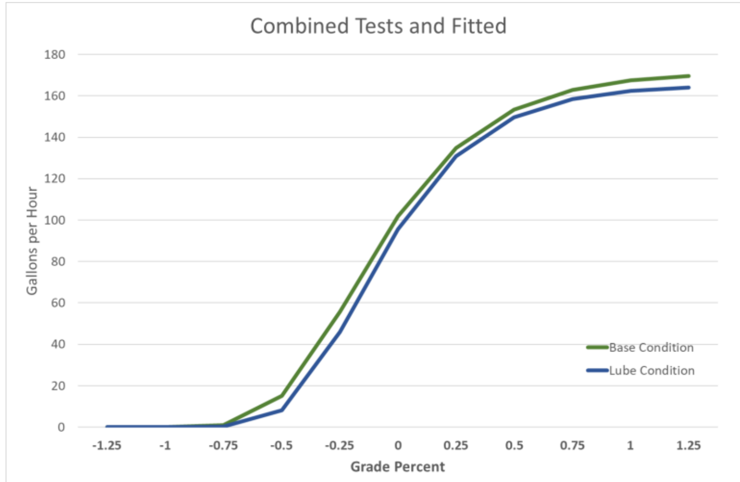

Figure 3- Fitted curves to combined tests

Curvature Profiles

For curvature profiles it is commonly hypothesized that the savings benefit is higher on curves, due to the flange lubrication impact on the coefficient of friction. Thus, in this particular calculation of the model, we apply a so-called "tangent discount" – the idea being that savings on tangent rail would be reduced by a percentage.

A postulated value of the tangent discount is 25%. While judgmental inputs into the model such as this can be valid, we desired to support this value with analysis.

The primary support analysis was a regression model built on the one-second measurement data (see the original report for details on this data) on electrical energy. Two of the regressors were the curvature degrees: one for base runs and the other for lube runs. This allows us to quantify the impact on energy of each degree of curvature, for each condition. There were two variations of the calculation of this discount factor based on the model parameter estimates: 18.4% and 18.1%.

As a second support point, we isolated portions of track where trains were running at T8 and classified the segments as curved or straight. Recall that at the highest throttle position (T8), the energy benefits give way to velocity benefits. We saw about an 18.2% discount factor on velocity. This value coincides nicely with the energy analysis.

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[1] Many functional forms were tested. We settled on logistic function based on best fit and simplicity.
$f(grade) = \frac{L}{1+e^{-k(grade-reference\ grade)}}$ where L and k are estimated parameters.

We examined whether this tangent discount might differ by grade. That is, might the discount be deeper for flat rail versus uphill? We could find no evidence for this difference. Nevertheless, the calculation engine can accommodate differential discounts by grade should data be found to support it.

Train Length

Train length is another difference between the TTCI tests and trains operating on networks. Both TTCI tests ran with 30 cars (120 axles), whereas operating trains can exceed 100 cars. Our projection method extrapolates to trains of a given length by taking advantage of data produced by contrasting test circumstances: conditioning; dry; lube; and dry-down. We benefited in having two rounds of dry-down laps, one with three laps following the lubrication, and another with eight laps. This allows us to simulate train lengths of greater than 30 cars, as we treat each subsequent lap as an additional 30 cars in a "virtual train".

We computed the total energy for each lap and counted the cumulative passing axles (as a proxy for length) in this virtual train, resetting the count when lubrication would begin again. Because there is variation of electrical energy (as expected) even within a particular condition, we fitted a function to quantify the relationship between axles and energy. This function has a diminishing returns feature[2] and serves to smooth out variations.

Figure 4 how this function produces the relationship between train length in cars and energy savings. Savings, before applying any projection factors, for TTCI is shown as 30 cars highlighted with the red box on the axis. The curve extrapolates out to trains of increasing length.

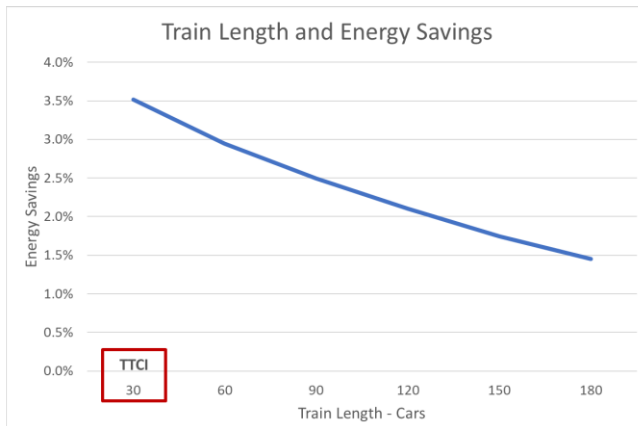

Figure 4- Train Length and Energy Savings

Using an estimated mathematical function with parameter values allows us to enter any length to produce an energy estimate, which we contrast with the test train of 30 cars. There is logic to convert from feet, or number of cars, to axles as the input variable. The output is a discount factor (multiplier) which is used to adjust the base savings estimate for train length.

One cautionary note about this approach is that oftentimes functions like these do not perform well beyond the range of data upon which they were estimate. For example, using this function to estimate the retentive benefits beyond the applying train may break down.

The calculation tool allows for overriding and adjusting the fitted model parameters. Such overrides should be supported by data or experience.

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[2] Though other functional forms had better fit, the simplicity of a natural logarithmic function had great appeal, while still fitting well.
$f(axles) = \alpha + \beta ln(axles)$ where α and β are estimated parameters.

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Applicator and Stick Installation

At TTCI four applicators with sticks were installed (axles three and four) in each of two locomotives for a total of eight sticks. We need to account for the fact that this may not be the same installation scheme for real trains. For an expected deployment we account for assumptions about:

- the percentage of locomotives with applicators installed;
- the percentage of applicators with sticks;
- the breakout of locomotive counts for trains.

This last point is important. One might assume that with, say, an 80% installation rate, that energy savings across all trains might be discounted by that amount. But the probability of having applying sticks on any given train is higher, due to train consists with multiple locomotives.

We employ probability math[3] with a combination of a joint probability of applicator and stick installation percentages combined with the breakout percentages of the locomotive counts (this is a probability union). This produces a final probability that a particular train will have applicators with sticks, and this factor can be used to project to all train traffic.

Finally, we apply an adjustment factor to account for the possibility that a consist may not have the full eight sticks as did the TTCI runs.

[3] $P(utilized) = \sum_1^N Q_L(1 - \left(1 - \left(P(applicator) * P(stick)\right)\right)^L)$

Where

Q = percent of trains with L locomotives

P(applicator) = percent of locomotives with applicators installed

P(stick) = precent of applicators with sticks

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Velocity Benefit Calculation

As mentioned in the introduction section, we saw an ancillary velocity benefit in the highest throttle position – notch 8. Once a train gets to throttle 8, there are still benefits from NatureBlend™. While energy usage by time is a constant, the reduced friction allows for quicker acceleration and slower deceleration. Since trains in T8 are often below track speed, this allows for increased overall velocity, as well as a corresponding energy savings. If a train is traveling one percent faster in a given notch, it is saving one percent in fuel because of reduced transit time.

We isolated data from sections of track that were mostly straight and where the locomotives were operating in notch 8. This can be seen in figure 5.

We calculated the velocity difference between the base and lube conditions to be about 1.2%. That is, at the maximum throttle position, the same amount of energy is expended for base and for lube, but the lube condition results in a slight increase in velocity.

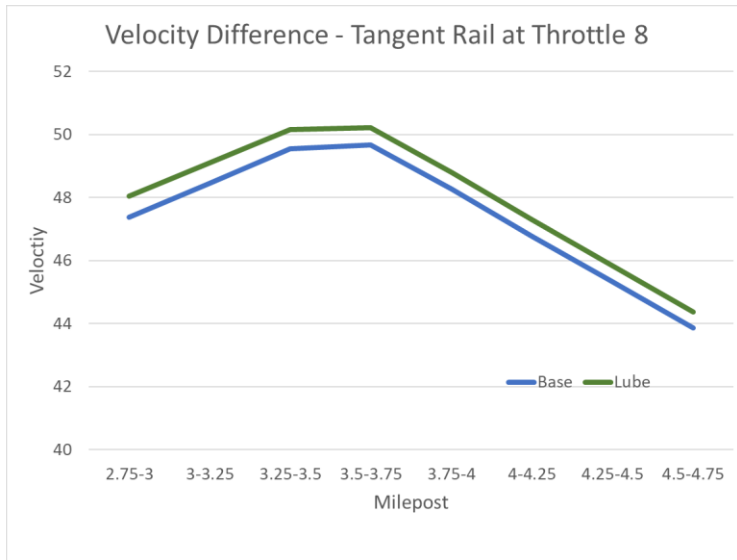

Figure 5- Velocity Difference at Throttle Position 8

Of course, no trip runs at 100% in at the highest throttle position, so we have the percent of time operating in T8 as an input to the calculator. Furthermore, any velocity improvement is diminished if the train gets to a certain point earlier only to spend time in idle (or use dynamic braking). Therefore, there is a deduction component to the calculator to subtract out any velocity benefits that are countered by increased idle time. This is the second component of the calculator.

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Using the Tool

Consultants from First Analytics can work with any railroad to analyze their particular inputs and profiles with the model. Within reason, there can be a modest amount of structural customization, such as the definition of grade, how tangent discounts are applied and at what magnitudes, etc.

Judgmental considerations with respect to some of the model parameters and calculations are possible if justified. We take the approach that such modifications should be supported by data or experience.

There are limitations as to the model's capabilities. Since it is based on data, attempts to use it to produce estimates for contexts not seen in the data (either in terms of the range of values of the data, or data elements or attributes that do not exist), typically are not reliable, or even possible.

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About the Producers of this Report

First Analytics is an analytical consulting firm with a focus on advanced analytics, statistical modeling, and machine learning.   Spanning multiple industries, we leverage the most up-to-date analytical tools to help businesses improve and optimize operations. Our team is comprised of statisticians, data scientists, and industrial engineers, most with graduate degrees.

Though we are broad in our use of analytics in various industries and many use cases, we have considerable experience in rail.