INERTIAL TRACTIVE EFFORT AS AN EXPLANATORY VARIABLE IN THE ANALYSIS OF LOCOMOTIVE FUEL SAVINGS

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SUMMARY

The purpose of the work presented has been the development of an explanatory variable that characterizes train handling effects, allowing for the identification of changes in locomotive fuel consumption over a given territory (for example in response to Top of Rail Friction Modifier (TORFM) application) with improved confidence. To generate the explanatory variable, the concept of Inertial Tractive Effort (ITE) was developed. Given the total instantaneous tractive effort (TE) dispatched by a locomotive consist to overcome all sources of resistance, ITE is an estimate of the portion spent overcoming inertial resistance to generate acceleration.

Integrating ITE over time yields cumulative ITE (cITE), which is in essence an estimate of total energy spent on acceleration versus a train travelling at constant speed over the same territory. Analysis of data collected in revenue service on several Union Pacific coal routes has shown that cITE acts as an explanatory variable, effectively mitigating variability in the data and allowing for an improved confidence when analyzing the impacts of other variables such as TORFM application. With the incorporation of cITE as an explanatory variable in a multi-variable regression of locomotive fuel data collected over five months of revenue service operation on Union Pacific, the statistical power of the underlying model was improved to yield a P-value of 0.028 versus 0.202 otherwise (the corresponding fuel savings associated with TORFM application were estimated at 6.4%). The approach represents a novel and useful mechanism to handle fuel data variability, with the potential to underpin a broad range of analyses.

INTRODUCTION

Locomotive fuel consumption represents a substantial operating cost in North American Heavy Haul [1-7]. This motivates the exploration and implementation of technologies with the capacity to generate verifiable fuel savings, with one such technology being train mounted application of Top of Rail Friction Modifier (TORFM) [2-10].

Analysis of locomotive fuel savings with statistical confidence is made challenging by substantial variability in the data. Among numerous sources of variability, train handling has generally been observed as a major contributing factor [4]. Operator behaviour including acceleration / deceleration and corresponding time-in-notch patterns can produce variations in fuel consumption over the same territory that overwhelm the differences generated by (for example) TORFM application.

The purpose of the work presented has been the development of an explanatory variable that characterizes train handling effects, allowing for the analysis of TORFM impacts with improved confidence. To generate this explanatory variable, the concept of Inertial Tractive Effort (ITE) was developed. Given the total instantaneous tractive effort (TE) dispatched by a locomotive consist to overcome all sources of resistance, ITE is an estimate of the portion spent overcoming inertial resistance to generate acceleration.

Estimating instantaneous ITE is non-trivial, requiring algorithmic analysis of relatively large volumes of heterogeneous locomotive event recorder data sets. By integrating ITE over the duration of a given run, Cumulative Inertial Tractive Effort (cITE) can be calculated. This cumulative value represents an estimate of net energy spent through locomotive tractive effort in acceleration/deceleration. It is important to note that calculation of ITE and cITE ignores regenerative work (i.e. work done by the environment on the system while the locomotive is not dispatching tractive effort), and as such yields a different result than would be obtained through a simple force balance and integration of mechanical work over the entire run. Aspects of train handling (e.g. excess energy spent through extraneous acceleration/deceleration) are then reflected in the magnitude of cITE for a given run.

NOTATION

F_i	Locomotive fuel consumed
β_j	Linear regression coefficient
x_{ij}	Explanatory variable in linear regression
ε_i	Unobserved random variable
m	Lumped estimate of train mass
v(t)	Lumped estimate of train speed
a(t)	Lumped estimate of train acceleration
α	Low-pass filter parameter
s(t)	Speed as measured by event recorder
k	Discrete sampling instant
$R_{tangent}$	Rolling resistance in tangent track
R_{curves}	Resistance due to curves
R_{grade}	Resistance due to grade
R_{wind}	Resistance due to wind
TE	Tractive Effort
ITE	Inertial Tractive Effort
cITE	Cumulative Inertial Tractive Effort

LOCOMOTIVE FUEL DATA AND VARIABILITY

As mentioned above, locomotive fuel data (i.e. fuel consumed by nominally similar trains over a given territory) is notoriously variable due to a range of factors including the train itself, environmental inputs and operator behaviour (i.e. train handling).

Given the introduction of an intentional change in operating conditions (e.g. the application of TORFM), it is consequently challenging to obtain a statistically significant measure of resulting changes in fuel consumption.

One common approach to managing variability is the use of multi-variable regression. For example, a linear model of the form shown in equation (1) might be constructed.

$$(1) \quad F_i = \beta_1 x_{i1} + \beta_2 x_{i2} + ... + \beta_n x_{in} + \varepsilon_i$$

Here F_i are the fuel measurements (measured variable), x_1, x_2, …, x_n are the explanatory variables, β_1, β_2, … β_n, are the coefficients of the explanatory variable (to be solved for) and ε_i is an “unobserved” random variable that adds noise (uncertainty) to the measured values (F_i). The explanatory variables would include all measured variables that are believed to have an impact or potential impact on fuel consumption, including the change that is being evaluated.

Explanatory variables can be continuous (e.g. train length, temperature, …), discrete (on/off) or constant. As an example, when evaluating Top of Rail Friction Modifier (TORFM) application, a discrete explanatory variable x_{TOR} might be introduced, and assigned a value of x_{TOR}=0 under baseline conditions and x_{TOR}=1 when TOR FM is applied. Typically a constant explanatory variable (x_c=1) is also included to allow for a non-zero intercept (β_c) in the model.

When the model is solved (e.g. using multivariable linear regression), the result will be the series of coefficients β_1, β_2, … β_n that indicate the degree to which each explanatory variable affects fuel consumption, as well as residual variation (represented above as ε_i). The strength of correlation between explanatory variables and the measured variable can also be reported. Referring to the example explanatory variable x_{TOR}, the corresponding coefficient β_{TOR} would represent the change in fuel consumption due to TORFM application.

Due to the large inherent variability in locomotive fuel consumption, the residual variation following this type of regression tends to be quite large and it is difficult to measure the effects of a given change with statistical confidence. Normally a p-value is reported to indicate the statistical power of the model in explaining fuel consumption, with $p < 0.05$ used as a threshold for statistical significance. Statistical power also tends to improve with the number of measurements collected, i.e. the large variability in fuel consumption is often handled by taking large numbers of sample measurements.

In the work described here, a linear model was constructed (initially in the absence of cumulative Inertial Tractive Effort as a factor) using the explanatory variables listed and described in Table 1.

Factor (Explanatory Variable)	**Description**
TOR status	TORFM On, Following, None, or Unknown.
TOR follow distance	If following a TOR train, number of trains behind TOR On train.
Month-Year	Accounts for seasonality (month within year) and overall trend (year-to-year)
Month-Year * TOR status	Effect of TOR on average litres by month and year
Grade score sum	Grade score for a run. Effect of more "ups and downs" on average litres used
Departing loco count	Accounts for more average litres used if more locomotives running
Total tonnes	Accounts for more average litres used if tonnage higher
Total tonnes * TOR status	Effect of TOR status on average litres used may vary by tonnes
Employee effect	Estimates different average litres used for each employee
Run CRC7 effect	Estimates different average litres used for each run (crc7 pair)
TOR status by Employee and Run	Effect of TOR on average litres used is employee- and run-specific
Total tonnes by Employee and Run	Effect of tonnes on average litres used is employee- and run-specific

Table 1: Explanatory variables used in a linear model for locomotive fuel consumption, not including cumulative Inertial Tractive Effort.

When using this approach, the detection of statistically meaningful changes in fuel consumption (i.e. a p-value <0.05) with the application of TORFM was challenging, despite the collection of a relatively large data set. The specific results of the regression are reported in the "Results" section below.

EXPLANATORY VARIABLE DEVELOPMENT

In order to improve the ability to detect meaningful changes in the presence of significant variability, cumulative Inertial Tractive Effort (cITE) was developed as an additional explanatory variable.

Figure 1 provides a conceptual illustration of ITE. Referring to the upper portion of the figure consider a train moving at constant speed, v, through a given territory. Employing a highly simplified model of the train as a lumped mass, m, the force corresponding to tractive effort (F_{TE}) required to maintain the constant forward velocity will be a function of the total train resistance comprising terms due to rolling resistance ($R_{tangent}$), curving resistance (R_{curves}), grade resistance (R_{grade}) and wind resistance (R_{wind}).

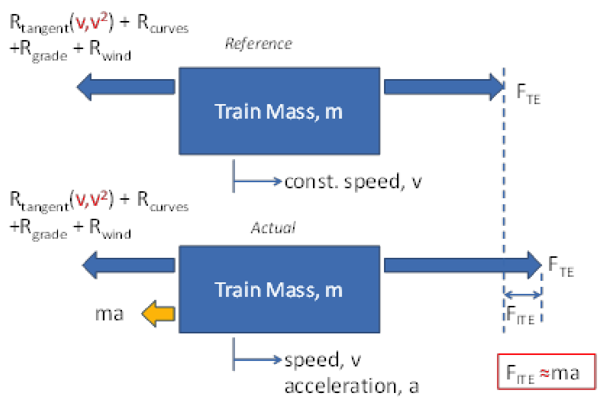

Figure 1: Conceptual Illustration of Inertial Tractive Effort (ITE).

Looking now at the lower portion of Figure 1, if the same train (at the same location, traveling at the same instantaneous velocity, v) were in addition to undergo an acceleration a(t), the required overall tractive effort (F_{TE}) would include an incremental "inertial" tractive effort required to generate the acceleration. This would correspond to the inertial force F_{ITE}, and would be approximately equal to the train mass multiplied by the acceleration.

As long as throttle is being applied (F_{TE}>0), the corresponding ITE would result in an incremental usage of locomotive fuel. If there is no throttle being applied (and in the absence of regenerative behaviour), instantaneous acceleration would not have an impact on instantaneous fuel usage.

From a conceptual standpoint, Inertial Tractive Effort (ITE) is then calculated as:

(2) $ITE(t) \approx m*a(t)$ (when $TE(t) > 0$)

(3) $ITE(t) \approx 0$ (otherwise)

Treating the product of ITE(t) and v(t) as inertial tractive power, cumulative ITE is then given as:

(4) $cITE = \int ITE(t)*v(t)dt$

MEASUREMENT AND CALCULATION

In practical terms, cITE must be calculated based on discrete-value, discrete-time locomotive event recorder data (typically sampled in 1 second intervals). Prior to calculating the value of cITE for a given run, locomotive event recorder data must be obtained for the given track segment, and on occasion converted to a standard format (locomotive event recorder data formats are, in general, heterogeneous).

Once locomotive event recorder data is obtained runs are calculated between crew change points with start / end speeds of zero. If one or both of the start / end speeds are not zero, the run is not comparable and is discarded from the data set.

Because of the discrete-value, discrete-time nature of the raw locomotive event recorder speed data, direct calculation of acceleration values can produce erratic results. As such, event recorder speed data s(t) is smoothed and used to calculate speed v(t) and acceleration a(t) of the (simplified) train at each 1-second sampling interval. This is done using the following discrete- time filters, with the filter parameter α chosen to reject noise from the discretized data while producing a stable result in the calculated value of cITE.

(5) $v_k = \alpha s_k + (1-\alpha)v_{k-1}$

(6) $a_k = \alpha(s_k - s_{k-1}) + (1-\alpha)a_{k-1}$

For each 1-second (post-filtered) interval of event recorder data, ITE is then calculated as:

(7) $ITE_k \approx m*a_k$ (when $TE > 0$)

(8) $ITE_k \approx 0$ (otherwise)

The condition TE > 0 is enforced by examining locomotive notch settings. ITE is set equal to zero when locomotive notch settings correspond to Dynamic Brake (DB) activity or Idle, calculated as $m*a_k$ otherwise.

Given the calculation of ITE_k and smoothed (filtered) speed v_k, the Inertial Tractive Power at each sampling interval is then given by ITE_k*v_k.

The total Inertial Tractive Energy (estimated by the value of cITE) over the run can then be found by integrating the Inertial Tractive Power. With 1-second sampling intervals, cITE is given as:

(9) $cITE = \int ITE(t)*v(t)dt = \sum ITE_k*v_k$

The value of cITE for each run can then be stored and utilized as an explanatory variable for the purposes of regression and identification of the impacts of various parameter changes (such as the use of TORFM) on locomotive fuel consumption.

RESULTS

As noted above, a preparatory step in the calculation of cITE involves the generation of filtered values of velocity and acceleration. The relationship between the selected value of the filter parameter, α, and the calculated value of cITE for a sample collection of train runs obtained from revenue service operation on Union Pacific Coal Routes is shown in Figure 2. As shown, selection of α=0.2 tends to produce a relatively stable cITE value (i.e. relatively insensitive to changes in the value of α). A value of α=0.2 is used in all subsequent values reported in this paper.

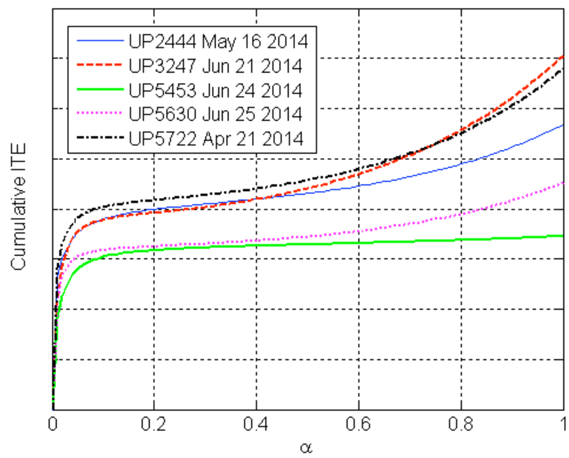

Figure 2: Relationship between the selection of α (discrete time filter parameter) and calculated value of cITE for a collection of train runs.

The relationship between train handling (in particular acceleration / deceleration profiles and the calculated value of cITE is shown in Figure 3.

The upper plot in the figure shows cITE versus elapsed distance for two train runs over the same route, with the final value of cITE (occurring at the complete elapsed distance) corresponding to the single value that would be reported for the run. The lower plot shows reported speed versus elapsed distance for the same two runs.

As shown, significant acceleration events tend to produce a generally persistent increase in the value of cITE. The run indicated by the red trace includes significantly more variation in speed versus the run indicated in blue (i.e. includes more substantial activity in the form of acceleration / deceleration events) and results in a larger corresponding value of cITE (i.e. larger estimate of energy spent on train handling in the form of acceleration over the duration of the run).

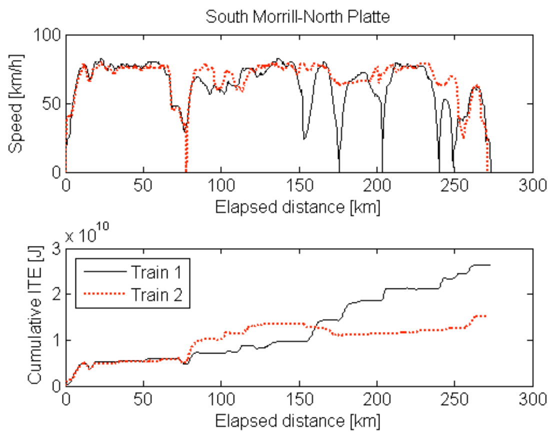

Figure 3: Example plots of speed versus distance (lower plot) and cumulative ITE (upper plot) for two train runs on the same territory. As shown, cumulative ITE increases with energy spent in acceleration / deceleration, providing an explanatory variable for train handling

Table 2 provides a summary of the explanatory variables used in a linear model of locomotive fuel consumption that includes cITE. This can be compared to the factors listed in Table 1, for the linear model that does not include cITE. As shown, in the work presented cITE was incorporated in a number of factors, including cITE, cITE * TOR status and cITE * Total tonnes. This allows for variations in the dependence of locomotive fuel consumption on TORFM application and trailing tonnage to vary with cITE within the overall model.

Both of the models described (i.e. constructed using the factors shown in tables 1 and 2) were used to carry out multi-variable linear regressions on locomotive fuel consumption data collected from revenue service traffic on Union Pacific's North American coal route. Following is a description of data collected, and results of the regressions.

Factor (Explanatory Variable)	**Description**
TOR status	TOR On, Following, None, or Unknown.
TOR follow distance	If following a TOR train, number of trains behind TOR On train.
Month-Year	Accounts for seasonality (month within year) and overall trend (year-to-year)
Departing loco count	Accounts for more average litres used if more locomotives running
Total tonnes	Accounts for more average litres used if tonnage higher
Total tonnes * TOR status	Effect of TOR status on average litres used may vary by tonnes
cITE	Effect of cITE on average litres used
cITE * TOR status	Effect of TOR status on average litres used may vary by cITE
cITE * Total tonnes	Effect of tonnes on average litres used may vary by cITE
Run CRC7 effect	Estimates different average litres used for each run (crc7 pair)
Total tonnes by Run	Effect of tonnes on average litres used is employee- and run-specific

Table 2: Explanatory variables used in a linear model for locomotive fuel consumption that includes cumulative Inertial Tractive Effort (cITE).

Locomotive event recorder and fuel usage data was collected over a 5 month period from revenue service traffic operating on Union Pacific's coal network in Nebraska and Kansas. Table 3 provides a summary of route segments from which data was collected, as well as the number of train runs from each segment for which valid cITE values could be generated.

Route Segment	Segment Length (km)	Number of Runs with Valid cITE Data
Coff_McAll_Pars (Coffeeville, McAllester Parsons)	253-288	15
FtWorth_McAlester (Fort Worth McAllester)	269-304	3
KC_JC (Kansas City to Jefferson City)	246-261	3
Mary_KC (Marysville to Kansas City)	235-258	7
NP_Mary (North Platte to Marysville)	400-408	74
SM_NP (South Morrill to North Platte)	272-282	40
FtWorth_Hearne_Tay_Halsted (Fort Worth, Hearne, Tay, Halsted)	230-238	11
KC_Coff_Pars (Kansas City Coffeeville Parsons)	182-222	4

Table 3: Union Pacific revenue service coal routes, lengths and number of train runs collected with valid cITE data.

Traffic consisted of heavy haul (130 tonne gross weight) vehicles operating on standard gauge (1435mm) North American track, with rail cross sections of 67kg/m or heavier (standard an premium rail quality), with concrete or wood ties on standard North American ballast and sub-ballast track structure.

As noted in Tables 1 and 2, the factor denoted TOR Status indicates whether or not TORFM was applied for each train run, using the system described below.

AutoPilot™ Train Mounted Top of Rail Friction Control

Train mounted TORFM was delivered via commercial (L.B. Foster AutoPilot) train mounted application systems operating on a fleet of UP coal cars, mounted in revenue service cars located immediately behind the last lead locomotive (for the purpose of drawing power and air supplies). Figure 4 shows the application equipment mounted under the slope plates of the coal car, and Figure 5 shows the application nozzle applying friction modifier to the top of rail.

Train location, direction, speed, and current track segment were determined via GPS, with a PLC based control system used to apply KELTRACK water based friction modifier at appropriate specific application rates (mL/km), depending on route segments. The system is self-controlling (requires no operator intervention or involvement). Friction modifier is applied to both rails over the entire route when applying. The system has the capability of varying application rate by territory or curvature if needed. These systems have been in revenue service on Union Pacific for more than four years.

System health as well as maintenance planning is facilitated by Remote Performance Monitoring of the equipment performance [11,12].

Figure 4: AutoPilot TORFM equipment mounted on a coal car

Fig 5: Friction Modifier Spray Application Nozzles

Fuel Usage Results

As noted above, locomotive event recorder data was collected over a 5 month period from revenue service coal trains operating on Union Pacific's coal network in Nebraska and Kansas (with route segments as shown in Table 3). Event recorder file parameters (collected at 1 Hz) included Date, Time, Speed, Distance, Tractive Effort and Locomotive Notch Setting among others.

Separately, locomotive fuel usage data had been calculated and archived by Union Pacific on a per-segment basis along with information including train length, trailing tonnage, etc. This archive was used to generate fuel usage data files corresponding to the same segments noted above, during the 5 month period of interest.

Post-processing software (writing in the Python programming language) was used to match event recorder data files with Union Pacific fuel usage records based on date and time of departure and locomotive identifier. Data from both files was then merged to establish a database of records containing information sufficient to calculate and apply cITE in the analysis of fuel usage under baseline and TORFM conditions.

Before calculating values of ITE and cITE for each matched set of records, smoothed values of velocity and acceleration were generated using the low-pass filter shown in equations (5) and (6) with the filter parameter, α=0.2. Subsequently ITE and cITE were calculated as shown in equations (7) through (9). Velocity and acceleration smoothing, as well as calculation of ITE and cITE, were also carried out using software developed in the Python programming language, motivated by its efficiency in handling large files containing data represented in text (comma separated value) format. For perspective, typical individual locomotive event recorder data files for a single route segment were 60-80MB in size.

Prior to introducing and adopting ITE and cITE in the analysis, a multi-variable linear regression had been applied using a model implementing the explanatory variables (factors) listed in Table 1. Referring to Table 4, the results of the regression when applied to the 5 month Union Pacific data set estimated the impact of TORFM application on locomotive fuel usage as -100.0 L/trip, with a p-value of 0.202 (not statistically significant). As described earlier in the paper, detecting a change in fuel usage with statistical confidence was made challenging by substantial residual variability with the application of this first model.

Model	Estimated change in Fuel usage with TORFM application L (%)	P-value
Initial model (see Table 1)	-100.0 (3.3%)	0.202
Model incorporating cITE (see Table 2)	-192.9 (6.4%)	0.028

Table 4: Estimated changes in fuel usage with application of TORFM, and statistical confidence (P-value).

Subsequently, a multi-variable linear regression was performed using a model implementing the explanatory variables listed in Table 2. In specific, the latter model incorporated cITE. When applying the model incorporating cITE to a 1,000 record sample data set, the explanatory power was seen to improve with R^2 increasing from 0.702 to 0.758. Referring again to Table 4, regression of the complete data set estimated the impact of top of rail friction modifier application on locomotive fuel usage as -192.9 L/trip, with a p-value of 0.028. This represents a fuel savings of 6.4%, versus average values under baseline (non TORFM applying) trains. The latter result can be assessed as statistically significant, and demonstrates the explanatory power of cITE given a limited data set.

CONCLUSIONS

Integrating ITE over time yields cumulative ITE (cITE), which is in essence an estimate of total energy spent on acceleration versus a train travelling at constant speed over the same territory. Analysis of data collected in revenue service on several Union Pacific coal routes has shown that cITE acts as an explanatory variable, effectively mitigating variability in the data and allowing for an improved confidence when analyzing the impacts of other variables such as TORFM application. With the incorporation of cITE as an explanatory variable in a multi-variable regression of locomotive fuel consumption data collected over five months of revenue service operation on Union Pacific, the statistical power of the underlying model was improved to yield a P-value of 0.028 versus 0.202 otherwise (the corresponding fuel savings associated with TORFM application were estimated at 6.4%).The approach represents a novel and useful mechanism to handle fuel data variability, with the potential to underpin a broad range of analyses.

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