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NSTSCE

National Surface Transportation Safety Center for Excellence

# Slippery Road Vehicle Early Warning System

## Method Augmentation

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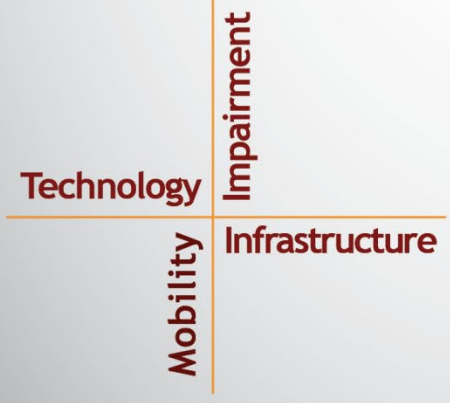


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## EXECUTIVE SUMMARY

Two prior projects conducted by the Virginia Tech Transportation Institute (VTTI) for the Federal Highway Administration (FWHA) demonstrated that small but statistically significant differences in vehicle wheel rotational rates can be used to quantify the changes in tire grip that occur when pavement conditions change due to road weather. The impetus for this work occurred when researchers noticed that a vehicle traveling along the Virginia Smart Roads required more rotations of the driving wheels to travel the same distance when climbing the road's 6% grade as compared to when traveling downhill over the same segment. This phenomenon was attributed to microslip that occurs at the pavement-tire interface.

Microslip occurs when the tread area deforms and only a portion of the tire's contact patch moves with respect to the pavement surface. In contrast, macroslip occurs when the entire contact patch moves with respect to the road surface. Advanced automotive safety systems such as anti-lock brakes, traction control, and stability control rely upon a vehicle's wheel speed sensors to detect macroslip for their operation.

The researchers hypothesized that microslip would vary predictably as road surface conditions changed and that the amount that occurred would be higher at the driving wheels where longitudinal forces at the tire-pavement interface are higher compared to the free-rolling wheels on the other axle. The first FHWA project was conducted to validate this concept and that the original equipment manufacturer (OEM) wheel speed sensors provided sufficient resolution for this determination. Experimental driving tests were conducted on the Smart Roads with a rear-wheel-drive (RWD) vehicle under a variety of different pavement conditions that included rain, snow, and ice. This testing established proof-of-concept by demonstrating that tire microslip increased where the pavement was covered with liquid or frozen water and well before onboard traction-related safety systems were activated. This work also showed that OEM wheel sensors were of sufficient resolution to determine statistically different microslip rates at the driving and free-rolling wheels. In recognition that longitudinal acceleration would likely confound the experimental results, testing was conducted at constant speeds and with consideration of road incline and wind.

A second FHWA-sponsored study was conducted to further explore the method in general and to further characterize confounding effects such as road incline and wind. Testing was done using both front-wheel-drive (FWD) and RWD vehicles on the Smart Roads and public roads. A major focus of this work was to investigate whether data sharing between vehicles (i.e., a connected vehicle scenario) traveling in opposite directions might be used to mitigate the confounding effects of road slope and wind. Also, the concept of a traction index (TI) was developed to provide a standard method for calculating the relationship between microslip at the driving and free-rolling wheels. This work showed that the "noise" that resulted from apparent vehicle acceleration (whether from throttle input or grade) and wind prevented accurate measurement of TI given the constraints of sensor resolution and other factors.

After completion of the aforementioned work, the research team developed the hypothesis that information available via the vehicle network other than wheel speeds—variables such as throttle position, fuel flow rate, vehicle speed, engine speed, and transmission gear—might be used to correct the calculated TI to account for the apparent acceleration confound that occurs during

speed changes, on inclines, and when longitudinal winds are present. This is the subject of the work reported herein.

Researchers scoped this work under the premise that the data already collected during previous testing could be used to test the hypothesis and that no new data collection would be conducted. After examining the relationships between TI and/or wheel sensor counts versus various independent variables indicative of vehicle dynamics, instantaneous fuel consumption rate (IFCR) and engine throttle position were chosen for further analysis. A variety of techniques were used to analyze the relationship between TI and the factors that might be used to correct TI for confounds introduced by road grade and wind. In the end, the research team was unable to demonstrate that basic TI calculated values could be corrected using vehicle dynamic data due to a variety of factors stemming from the unsuitability of the existing road friction dataset for the application intended.

Over the time spanned by the three VTTI studies, companies such as NIRA Dynamics have introduced commercial “virtual sensor” systems that use microslip and other vehicle variables as a basis for dynamic assessment of road friction. This system is now being offered in VW and Audi production vehicles. Also, vehicle data, including that which might be used to assess road weather, is now available commercially from companies such as Wego and others. The use of data from these sources provides opportunities for future research on the safety and environmental benefits of real-time assessment and sharing of road weather information.

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## LIST OF ABBREVIATIONS AND SYMBOLS

| | |
|---|---|
| ABS | anti-lock braking system |
| CAMP | Collision Avoidance Metrics Partnership |
| CAN | Controller Area Network |
| DAS | data acquisition system |
| ECU | electronic control unit |
| FHWA | Federal Highway Administration |
| FWD | front-wheel drive |
| GPS | Global Positioning System |
| Hz | hertz (cycles per second) |
| IFCR | instantaneous fuel consumption rate |
| IMU | inertial measurement unit |
| L/h | liters per hour |
| OEM | original equipment manufacturer |
| RWD | rear-wheel drive |
| TCS | traction control system |
| TI | traction index |
| VDOT | Virginia Department of Transportation |
| VTTI | Virginia Tech Transportation Institute |

# CHAPTER 1. INTRODUCTION

The adverse impact of weather on road conditions is a major contributing cause of vehicle crashes in the U.S. Recent data on traffic-related crashes in the U.S. show that the fatality rate for weather-related crashes is still at a high level, with more than 20% of all vehicle crashes occurring in adverse weather conditions, resulting in numerous deaths and injuries (over 400,000 injuries and around 5,000 deaths) on average per year.[1] Slick pavement surface is mentioned as a primary cause and a contributing cause of many of these adverse weather crashes, with nearly a quarter of these occurring on roads covered by snow or ice.[2] The total economic costs of weather-related crashes exceed $40 billion annually, with road maintenance agencies spending more than $2.3 billion on snow and ice control operations during the winter.[3,4]

Road friction develops at the contact patch between the tire and the pavement surface as the tire is driven or just freely rolls, and is drastically reduced by hydroplaning during heavy rain or in wintry conditions, such as e.g., snow, ice, etc.[5] A number of onboard safety systems engage in order to adjust the tire grip while driving. During hard braking, the anti-lock braking system (ABS) prevents the wheels from locking up in an effort to maximize traction and prevent tire sliding. Similarly, the traction control system (TCS) assists drivers in retaining control of the vehicle and keeping the vehicle safe on the road by minimizing wheel spin during acceleration.[6] Each of these systems, including electronic stability control (ESC), which controls the vehicle's stability by sensing and reducing the loss of traction, monitors vehicle dynamics at the pavement/tire interface. ESC also adjusts the throttle and steering systems to improve vehicle stability under typical driving conditions to optimize traction.[7]

Currently, ambient weather data from roadside weather stations and pavement sensors are used to predict roadway conditions, allowing for travel advisories to motorists and winter maintenance officials. However, there is the possibility that modern, onboard vehicle sensors could deliver real-time warnings of slippery road conditions by measuring tire slip before advanced safety systems activate.

## BACKGROUND

### Tire-Pavement Interaction

Typically, the wheel longitudinal or lateral displacement phenomenon, known as "slip," occurs because of the relative motion that develops between the tire and the road surface. There are two types of slip that occur at the tire-to-pavement interface, also referred to as the contact patch: microslip and macroslip. *Microslip*, or partial tire sliding, occurs when only a portion of the contact patch moves relative to the pavement and appears to increase when the coefficient of friction between the tire and pavement decreases. This means that the "static" and "sliding," or "dynamic," friction regions of the tire will expand or contract depending on the degree of slipperiness of the road surface, vehicle speed, and level of braking.[8] Microslip was quantified in real-time using data from the wheel-speed sensors available on all test vehicles. This information is used to calculate the traction index (TI) indicative of road condition prior to the macro-slip-exceeding threshold that triggers the vehicle's onboard safety systems.

*Macroslip*, on the other hand, takes place when the entire tire contact patch area moves with respect to the pavement's surface and generally may activate one or more of the vehicle's dynamic safety systems. Potential loss of control, which may result in a crash, could occur when the capabilities of these systems are exceeded due to hydroplaning, dirty roads, or the presence of ice.(5) During these slipping events, the force transfer between the tires and the pavement is mainly achieved through two types of friction: adhesive friction that depends on the tire and pavement microscale interaction, and hysteretic friction that depends on the tire and pavement surface condition. Additional information about the friction components can be found in Druta et al.(9)

The tire microslip concept is illustrated in Figure 1.

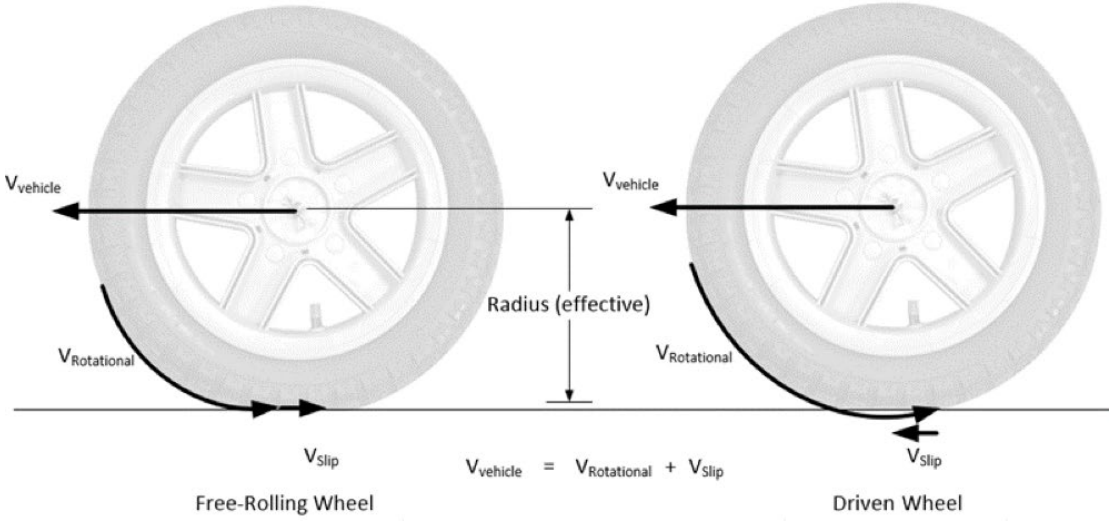



**Figure 1. Diagram. Vehicle-driven and free-rolling wheels and respective dynamic parameters.**

Considering the information provided above, a comparison of the relative rotational displacement (i.e., wheel sensor pulses) of the driven versus free-rolling wheels over a traveled road segment may provide an indication of the pavement surface's friction level. In a previous study, the ratio of the relative rotational displacement of the driven and free-rolling (or nondriven) wheels (i.e., speed sensor pulses) was calculated as a traction index (TI).(10) The TI values were computed using the total number of pulses acquired for road segments in a certain time interval. The wheel slip due to the road grade (i.e., incline) function of the speed gradient can also be determined to allow for evaluation of pavement surface slipperiness. However, for certain dry road inclines (i.e., road slopes larger than 3%) the calculated ratios of free-rolling divided by driven-wheel sensor pulses, which provide the TI that defines the surface condition, may be comparable to the TI values calculated for a wet, level road section. This confounding aspect may provide erroneous TI data when traveling on roads of different inclines and slipperiness levels.

However, a better approximation of the road slope can be achieved by analyzing other vehicle Controller Area Network (CAN) bus variables (e.g., engine rotating speed or throttle) in concert

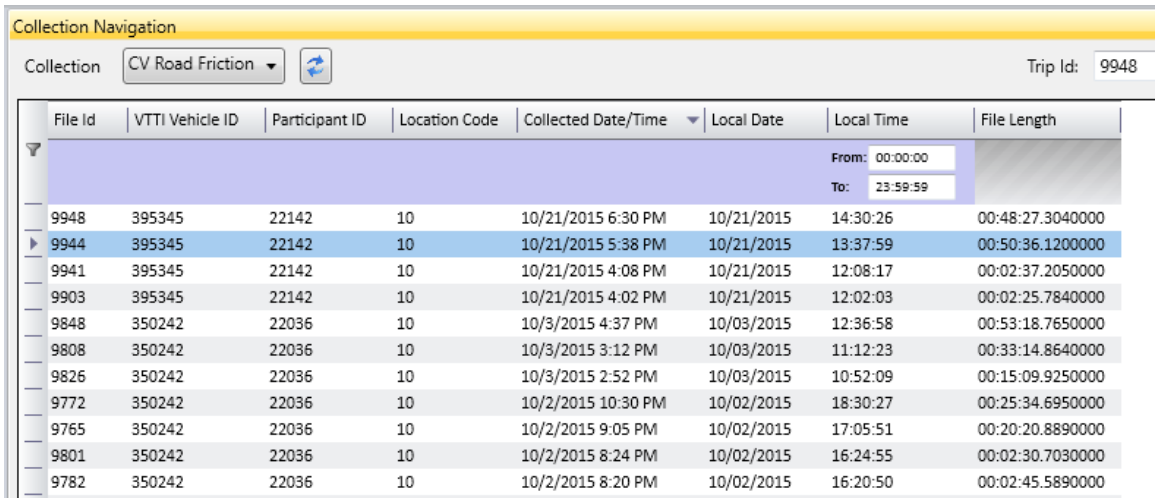
with the rotational displacement of the driven/free-rolling wheels. This approach can also differentiate between vehicles traveling in an uphill direction versus a downhill direction.

## OBJECTIVE AND SCOPE

The main objective of this research was to further analyze vehicle data collected under a previous study to try to address the identified confounds (e.g., slope) using available onboard vehicle sensors (i.e., fuel flow or throttle control).[10] Prior collected data covered multiple vehicles that were driven under various weather and speed scenarios. This investigation focused on utilizing targeted vehicle network variables, such as fuel consumption rate and applied throttle among others, to adjust the already validated tire microslip measurement estimates (i.e., TI) of road slipperiness. The approach attempted to compensate for confounding influences created by driving actions, such as acceleration and braking, steering, and road characteristics.

# CHAPTER 2. ROAD FRICTION DATABASE

During a previous Virginia Tech Transportation Institute (VTTI) research study, a road friction database was created using collected data that includes such information as speed and wheel sensor pulse from various vehicle platforms.[9] The data set includes front-wheel drive (FWD), rear-wheel drive (RWD), and all-wheel drive (AWD) vehicles of the same make (Chevrolet) but different models (Impala, Tahoe, Equinox). Data were collected by driving the vehicles at constant speeds ranging from 50 to 70 mph, without acceleration or braking, and involving only minor steering while on straight portions of roadway. Multiple variables (e.g., brake status, engine speed, etc.) were collected during driving sessions, and driving conditions included various sloped road sections and both dry and wet surfaces. The database includes searchable fields, such as Trip ID, Participant ID, Location, and others, as shown in Figure 2. A software program developed in-house was used to visualize and query collected data.




| File Id | VTTI Vehicle ID | Participant ID | Location Code | Collected Date/Time | Local Date | Local Time | File Length |
|---|---|---|---|---|---|---|---|
| 9948 | 395345 | 22142 | 10 | 10/21/2015 6:30 PM | 10/21/2015 | 14:30:26 | 00:48:27.3040000 |
| 9944 | 395345 | 22142 | 10 | 10/21/2015 5:38 PM | 10/21/2015 | 13:37:59 | 00:50:36.1200000 |
| 9941 | 395345 | 22142 | 10 | 10/21/2015 4:08 PM | 10/21/2015 | 12:08:17 | 00:02:37.2050000 |
| 9903 | 395345 | 22142 | 10 | 10/21/2015 4:02 PM | 10/21/2015 | 12:02:03 | 00:02:25.7840000 |
| 9848 | 350242 | 22036 | 10 | 10/3/2015 4:37 PM | 10/03/2015 | 12:36:58 | 00:53:18.7650000 |
| 9808 | 350242 | 22036 | 10 | 10/3/2015 3:12 PM | 10/03/2015 | 11:12:23 | 00:33:14.8640000 |
| 9826 | 350242 | 22036 | 10 | 10/3/2015 2:52 PM | 10/03/2015 | 10:52:09 | 00:15:09.9250000 |
| 9772 | 350242 | 22036 | 10 | 10/2/2015 10:30 PM | 10/02/2015 | 18:30:27 | 00:25:34.6950000 |
| 9765 | 350242 | 22036 | 10 | 10/2/2015 9:05 PM | 10/02/2015 | 17:05:51 | 00:20:20.8890000 |
| 9801 | 350242 | 22036 | 10 | 10/2/2015 8:24 PM | 10/02/2015 | 16:24:55 | 00:02:30.7030000 |
| 9782 | 350242 | 22036 | 10 | 10/2/2015 8:20 PM | 10/02/2015 | 16:20:50 | 00:02:45.5890000 |

**Figure 2. Screenshot. VTTI vehicle data.**

Once a file or trip is selected for analysis, collected and categorized variables can be accessed in a different pane for further data extraction and analysis. Figure 3 shows an example of collected variables and their properties. All variables are aligned by timestamp and were collected at different frequencies depending on project requirements.

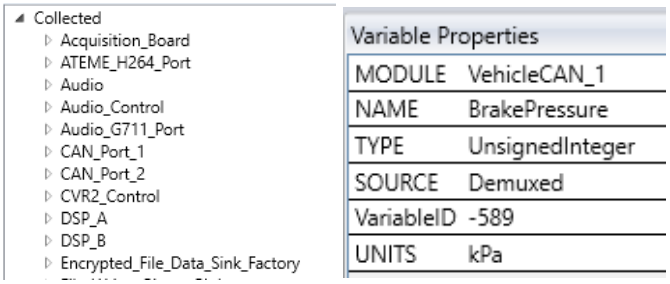



**Figure 3. Screenshot. Collected variables and variable properties description.**

## VARIABLE DESCRIPTION

Three variables were selected for analyses:

- **Wheel sensor pulse counts** – used for calculating the TI describing the state of the road surface (dry vs. wet). These pulses were averaged over certain road segments depending on their grade. Pulse resolution differed among vehicles, which is included in Table 1.
- **Instantaneous fuel consumption rate (IFCR)** – a measure of drivetrain effort used to differentiate between a vehicle cruising at constant speed and accelerating or traveling in an uphill or downhill direction. Sometimes IFCR values are low, nearly zero even, due to the vehicle coasting at different road inclines.
- **Throttle position** – also a measure of drivetrain effort and similar to IFCR. Throttle position was used to estimate changes in road grade.

Brief descriptions of these variables are provided as follows.

**Pulse counts** from the ABS wheel speed sensor provide information about wheel rotation rate (displacement with time). Typically, pulse counts vary for front and rear wheels and are affected by tire pressure, which affects the tire's rolling circumference. The pulses are measured by the wheel speed sensor that works in conjunction with the safety systems described above. Wheel speed sensor pulse counts were used to calculate TI (i.e., free-rolling wheel sensor pulse divided by driven-wheel sensor pulse counts), a dimensionless estimate of road surface condition.

**IFCR**, measured in liters/hour (L/h), is closely related to the tire rolling resistance (friction between tire and road), aerodynamic drag, speed, acceleration, and road incline. To maintain a constant speed on sloped roadways, IFCR decreases or increases when the vehicle slightly accelerates or decelerates uphill or downhill as a direct indication of engine/drivetrain effort. Data were collected from vehicles driven on road sections of different inclines at constant speed to study incline's effect on IFCR.

**Throttle position** data from the sensor (reported as a percentage) can also be used to correlate the vehicle's travel to either a downhill or an uphill direction. The throttle position is in direct connection to the accelerator pedal sensor and fuel injection system and helps ensure that the correct mixture of air and fuel is delivered to the engine. An example illustrating how IFCR and throttle position variables are reported is presented in the next section.

Of course, throttle position and IFCR vary depending on input received from either the driver or automated speed control system (e.g., cruise control).

## CHAPTER 3. METHODS

Data from the VTTI road friction database described above were used for this work. Table 1 lists the key vehicle network bus variables selected for extraction, storage, and data reduction. Selection was based on prior experience gained from testing in the two phases of a Federal Highway Administration (FHWA) project[9,10], as well as from discussions with experts in the automotive and information technology industries. Some of the listed variables, such as tire or road condition, were not acquired through the CAN bus but were constantly monitored throughout the driving sessions. As the table indicates, only wheel sensor pulses were measured at a high frequency (100 Hz), as very small granularity was required to process the TI, which was indicative of surface condition. Other variables were measured at lower frequencies (10 Hz), as they did not vary critically over short periods of time. ABS, ESC, and TCS were monitored to log their activity since their engagement during testing would confound normal TI calculations.

**Table 1. Vehicle experimental variables.**

| Variable | Type | Measurement Method/Sensor | Notes |
|---|---|---|---|
| Time | Control (via data acquisition system [DAS]) | NextGen (DAS) | Timestamp recorded by the portable test kit @ 100 Hz |
| Wheel driven/free-rolling pulse counter (left/right axle) | Dependent (upon vehicle sensor) | Vehicle network (ABS sensors) | Wheel rotational displacement measured for all four wheels independently |
| Wheel pulses per revolution driven and free-rolling axle | Dependent (upon vehicle sensor) | Vehicle network (speed sensor) | Per axle (numbers vary for different vehicles)<br>Impala: NA; Tahoe: 32/55<br>Malibu: 48/48 pulse per wheel revolution |
| Vehicle speed average per driven/free-rolling axle (horizontal, vertical) | Control (driver input) | Vehicle network (via DAS), GPS | Speed to be kept constant throughout each test trip |
| Vehicle acceleration (longitudinal) | Control (driver input) | Inertial measurement unit (IMU), CAN bus | Zero to light acceleration over test course |
| IFCR (L/h) | Dependent (vehicle parameter) | CAN (ECU) | Calculated based on fuel injection system parameters |
| Throttle position (%) | Engine sensor | CAN | Measured @ 10 Hz, throttle applied at engine not accelerator pedal |
| Tire pressure (psi) | Independent | Vehicle network (pressure sensor) | Monitored onboard @ 10 Hz |
| Weather condition | Independent | Handheld device and in-vehicle sensors | Monitored, recorded (temp., dew point, wind) |
| Road surface condition | Independent | Visual assessment (via DAS video) | Depending on weather conditions (or may be created using the Smart Roads weather system) |

| Variable | Type | Measurement Method/Sensor | Notes |
|---|---|---|---|
| Activation/status of vehicle safety systems (ABS, TCS) | Dependent (speed sensor) | On/off status from vehicle network | Monitored, recorded. Driving procedure adjusted to prevent activation |

The wheel speed sensors are an inductive or Hall Effect device that generates an electronic signal each time a tooth on the associated rotating reluctor ring passes. These signals are reported periodically on the vehicle network as a cumulative pulse count for each wheel. IFCR, wheel sensor pulses, and throttle position variables were extracted from the road friction database for two different vehicle platforms (i.e., FWD and RWD) and under specific road conditions (e.g., wet and sloped), weather conditions, and speed level. Table 2 shows a testing matrix listing the vehicles, road conditions, and speed that were used to collect the data.

**Table 2. Vehicle testing matrix.**

| Vehicle | Road Condition | Grade (slope) | Speed |
|---|---|---|---|
| Chevy Impala (FWD) | Dry, Wet, Snowy, Icy | 6% (Smart Road) | 35 mph |
| Chevy Tahoe (RWD) | | | |
| Chevy Malibu (FWD) | Dry & Wet | 8% (U.S. 460) | 60 mph |

Data of interest, such as wheel sensor pulses or IFCR, were retrieved by accessing the trips that occurred under specific weather and road conditions. For calculation purposes, as well as for reduction and analysis, the collected data were placed in Excel files, where metadata were created. Figure 4 shows an example of data reduction, where the variables (e.g., IFCR, throttle, speed) are synchronized by parameter timestamp.

| Avg Speed (**kph**) (CAN Bus) | Time (ms) | IFCR (l/h) (InstantFuelConsumpRate) | Time (ms) | Throttle Position (%) | Time (ms) |
|---|---|---|---|---|---|
| 97.125 | 1141404 | 3.95 | 1141404 | 16.078437 | 1141404 |
| 97.234375 | 1141504 | 4.775 | 1141504 | 16.078437 | 1141504 |
| 97.3125 | 1141603 | 3.975 | 1141603 | 16.078437 | 1141604 |
| 97.40625 | 1141704 | 3.975 | 1141704 | 16.078437 | 1141704 |
| 97.359375 | 1141803 | 4.65 | 1141803 | 16.078437 | 1141804 |
| 97.265625 | 1141903 | 3.875 | 1141903 | 16.078437 | 1141904 |
| 97.296875 | 1142004 | 3.95 | 1142004 | 15.68628 | 1142004 |
| 97.265625 | 1142103 | 4.675 | 1142103 | 15.294123 | 1142104 |
| 97.234375 | 1142204 | 3.675 | 1142204 | 14.901966 | 1142204 |
| 97.234375 | 1142304 | 3.6 | 1142304 | 14.117652 | 1142304 |
| 97.359375 | 1142403 | 4.3 | 1142403 | 13.725495 | 1142404 |
| 97.296875 | 1142504 | 3.475 | 1142504 | 13.333338 | 1142504 |
| 97.3125 | 1142604 | 3.375 | 1142604 | 13.333338 | 1142604 |
| 97.359375 | 1142703 | 4 | 1142703 | 12.549024 | 1142704 |

**Figure 4. Screenshot. Example of metadata compiled for IFCR and throttle position at 60 mph (97 km/h).**

## FINDINGS FROM PREVIOUS WORK

A higher TI is indicative of higher friction between the tire and pavement. In general, TI increases when traveling downhill at a constant speed since less torque is required at the driving wheels to maintain speed, which results in less tire microslip. A tailwind may also produce the same effect. Figure 5 shows observed TI values for various road weather conditions for vehicles traveling on a level road.

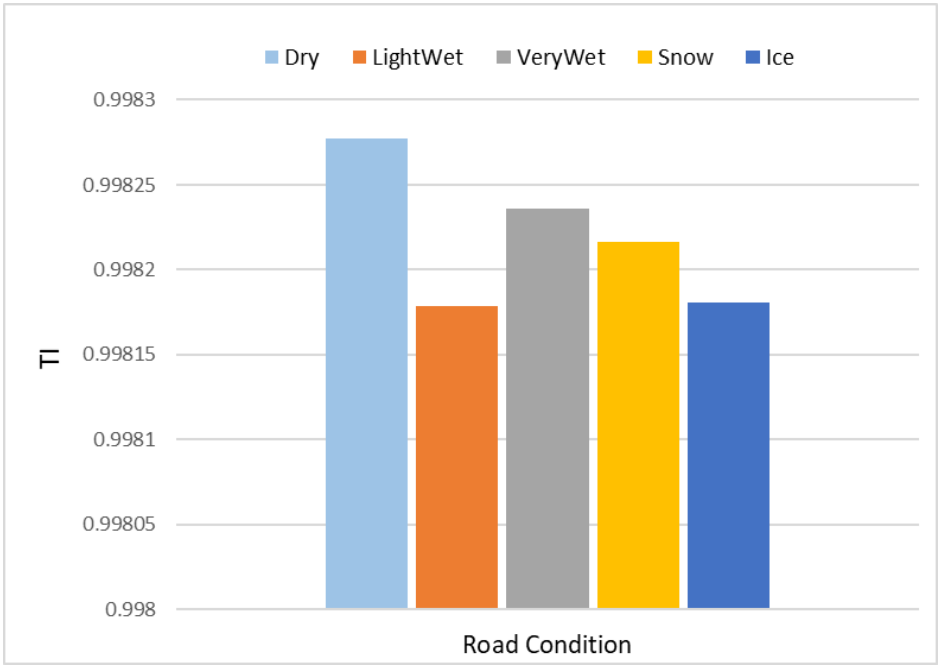



**Figure 5. Graph. Example of TI values for RWD on level road.**

As illustrated, the slipperiest road conditions were icy and lightly wet surfaces. This conforms with the literature in that road surfaces tend to be more slippery after a light rain or shortly after it starts raining than after a heavy downpour. The explanation resides in the fact that a thin layer of dirt/mud forms on the surface of a dirty road after a light rain, whereas all the impurities and deposits are washed away during a downpour. Moreover, a slightly wet road surface exhibits lower frictional coefficients than a cleaned wet pavement after a certain period of rain as dust and other contaminants mix with water, leading to a decrease in friction level.[(10)] However, TI values in this example are similar in magnitude, making it very difficult to clearly distinguish among various surface conditions. In certain cases, comparable TI values might indicate two possible scenarios: (1) a vehicle traveling uphill on a dry surface versus traveling on a level and wet surface at a certain speed; or (2) a vehicle traveling on a snow- or ice-covered level roadway versus traveling uphill on a wet surface. Road slope, and potentially longitudinal winds, may introduce significant confounds to determining tire grip using TI calculation. Therefore, it would be desirable to augment the basic TI calculation approach by applying a correction factor based on available data indicative of road grade and/or wind effects. The use of IFCR and/or throttle position data from the vehicle network are investigated herein as readily available factors that might be used to adjust TI calculations to compensate for these confounds.

## CHAPTER 4. RESULTS AND DISCUSSION

Table 3 shows IFCR and throttle position data collected on the Virginia Smart Roads Highway, including the steepest portion (6% grade), at 35 mph under varying road weather conditions. Table 4 illustrates the same data collected on U.S. 460, including a steep portion (8% grade), although sometimes varying speeds were necessitated for safe operation in traffic. The tables indicate increases in both variables' values as road slipperiness transitions from dry to rain to snow and ice. The largest increases of 36% and 20.6% were observed for IFCR on snow-covered surfaces in the uphill direction for both the FWD and RWD vehicles, whereas less than 15% increases were noted for wet and icy road conditions. Similarly, large increases, 27.7% and 9%, were noted in the downhill direction for both vehicle types on snow-covered roads, while increases ranging from 6% to 15% were seen on wet and icy surfaces, respectively. On level surfaces, IFCR increases ranged from around 5% on wet and icy surfaces to 12% on snow-covered roads.

The throttle position variable exhibited a similar trend, with the highest increases of 9% and 7.5% in the uphill and downhill directions in snow, followed by wet and icy conditions at around 5% for both FWD and RWD vehicles. On a level surface, a 7% increase was observed in snow only, while the rest of the values (wet and ice) were at 5% or less. Table 5 shows data from an FWD vehicle traveling uphill and downhill on a steeper slope at 60 mph. Both IFCR and throttle position also varied with the surface condition for the respective directions. Greater values were recorded for these variables due to a higher speed and road incline. Comparable increases, however, of around 8% were noted on the wet surface, indicating slight changes in the two variables as the slope increased by 33%.

**Table 3. Averaged IFCR and throttle values for FWD vehicle at 6% slope.**

| Direction | IFCR (L/h) | | | | Throttle Position (%) | | | |
|---|---|---|---|---|---|---|---|---|
| | Dry | Rain | Snow | Ice | Dry | Rain | Snow | Ice |
| **Uphill** | 8.258 | 8.919 | 10.168 | 9.358 | 32.847 | 33.339 | 34.051 | 33.583 |
| **Level** | 6.882 | 7.026 | 7.743 | 6.858 | 26.741 | 24.452 | 25.881 | 24.743 |
| **Downhill** | 1.579 | 1.724 | 2.018 | 1.835 | 9.364 | 9.768 | 10.932 | 9.796 |
| Average | 5.573 | 5.891 | 6.709 | 6.022 | 22.984 | 22.521 | 23.621 | 22.714 |

**Table 4. Averaged IFCR and throttle values for RWD vehicle at 8% slope.**

| Direction | IFCR (L/h) | | | | Throttle Position (%) | | | |
|---|---|---|---|---|---|---|---|---|
| | Dry | Rain | Snow | Ice | Dry | Rain | Snow | Ice |
| **Uphill** | 13.658 | 15.068 | 15.213 | 14.752 | 32.025 | 33.477 | 34.337 | 33.672 |
| **Level** | 9.688 | 9.864 | 10.246 | 10.345 | 23.846 | 24.126 | 24.572 | 24.684 |
| **Downhill** | 1.878 | 1.934 | 2.044 | 1.977 | 8.228 | 8.536 | 8.848 | 8.596 |
| Average | 8.412 | 8.955 | 9.172 | 9.025 | 21.368 | 22.051 | 22.587 | 22.318 |

**Table 5. Averaged IFCR and throttle values for FWD vehicle at 8% slope.**

| Direction | IFCR (L/h) | | Throttle Position (%) | |
|---|---|---|---|---|
| | Dry | Rain | Dry | Rain |
| **Uphill** | 12.958 | 14.258 | 44.345 | 47.881 |
| **Level** | 7.388 | 8.676 | 25.515 | 26.815 |
| **Downhill** | 1.642 | 1.784 | 11.127 | 12.154 |
| Average | 7.332 | 8.241 | 26.996 | 28.966 |

Considering the vehicle dynamics and rotation of driven wheels, the IFCR and throttle increases as the surface condition changes from dry to wet to snow and ice can be attributed to the additional engine power required to overcome the wheel resistance resulting from the water film or snow depth. These increases are also in accordance with results from the literature indicating that a lift force (acting upward) due to contaminants such as water or slush is required to counterbalance a horizontal lift reaction force.[11] The reaction force acts at the contact surface between the tire and the ground and is proportional to the thickness of fluid cover (i.e., water, loose snow, or slush) under the leading edge of the rolling tire. In this process, water or a contaminant accumulates under the tire because there is insufficient time for the fluid to be removed from the tire contact area with the road. Also, the space between the road surface and tire tread may not allow the accumulated fluid to completely fill the existing voids, and thus be able escape readily from under the tire.

IFCR and throttle variable value increases are larger in the case of snow-covered roads as a result of the snow layer that has to be pushed and compacted by the driving wheel, as opposed to water film, which can be broken much more easily. These effects may slightly affect the number of rotational pulses provided by each wheel sensor, depending also on the type of vehicle platform (FWD vs. RWD).

Obtaining the wheel-pulse data required dedicated equipment, OEM cooperation, and development of specialized software, aspects that may prove costly and time-consuming. Statistical *t*-tests indicated that the values between dry and slippery (i.e., dry vs. snow and dry vs. ice) were different ($p$ values $\leq 0.05$ threshold), but were only marginally different between dry and wet for a specific road segment. Negligible differences, mostly below 2%, were obtained for previously calculated TIs irrespective of direction of travel or road condition.

The data shown in Figure 6 illustrate observations of IFCR and calculated TI from mined and newly acquired study vehicle data. While IFCR values trend as expected depending upon road grade, TI values varied widely and erratically, and trends were difficult to identify and quantify. While the research team is unable to explain this, past experience has shown that the complex nature of the factors that affect the speed sensor pulse data makes it difficult to compute a TI coefficient accurately and reliably. One of the sources inducing large variation in TI is that the number of wheel pulse readings also varies with time and is quite different for each wheel. Potential reasons for such fluctuations may reside within the DAS, lateral wandering, minor acceleration or deceleration, engine torque transmission to axles, and road roughness.[12] Unfortunately, the data obtained for this work were of insufficient quality to allow meaningful

analysis with respect to whether TI corrections using IFCR and throttle position to address confounds due to road grade and wind are practicable.

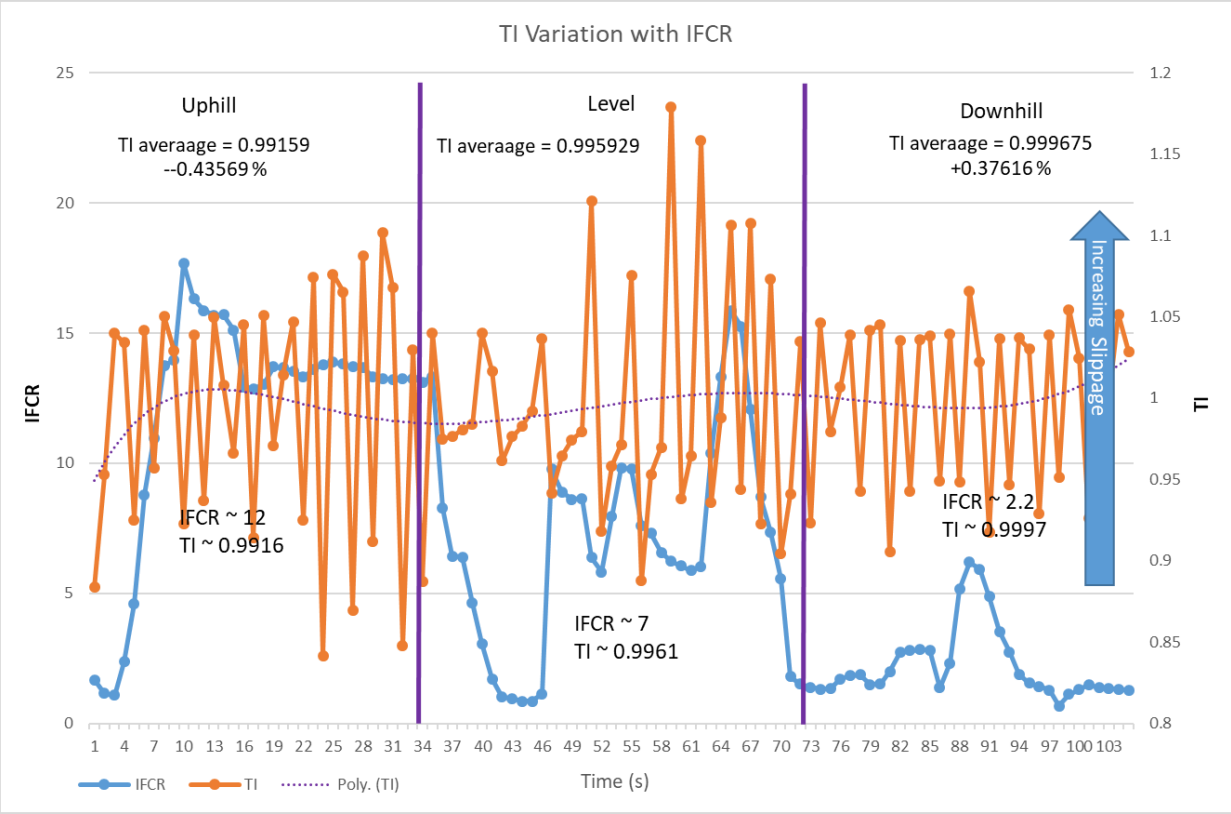



**Figure 6. Graph. Observed IFCR and TI with respect to road slope (8% slope and dry surface).**

# CHAPTER 5. CONCLUSIONS

This research investigated whether targeted vehicle sensor data can be used to adjust previously validated tire microslip measurement estimates, or TIs, of road slipperiness to compensate for confounding influences, such as road incline. Previous research showed that the TI values were very similar, differing only at the level of several decimal places, creating ambiguity in clearly distinguishing among various scenarios where vehicles traveled in different directions on slippery surfaces. Under the new approach, correction of TI values using vehicle intrinsic sensors such as IFCR and throttle position holds promise as a potentially reliable way to provide real-time measurement of vehicle traction even on varying road grades and in the presence of longitudinal winds. Such information can also be acquired in the future using simpler methods and resources than those previously employed. It is envisioned that real-time data from these sensors, along with wheel rotation input, will be aggregated within the vehicle hardware and software to provide slippery road alerts to drivers and others. These alerts will warn drivers of a potential loss of vehicle control based on existing road surface conditions, vehicle speed, and incline before the activation of onboard safety systems such as ABS or TCS.

Data analysis showed that IFCR and throttle position variables can be used interchangeably to determine road grade. This trend indicates that an increased engine effort translated into greater IFCR and throttle position values, respectively. However, these variables may fluctuate as a function of the degree of road covering, type of contaminant (snow vs. ice, mud, or sand), speed, and road grade. With respect to the type of contaminant, driving in snow produced the highest drivetrain effort variable results, followed by wet and icy conditions, which had relatively comparable values.

It should be noted that concepts similar to the TI determination developed by VTTI, including parameter adjustment and calculation methodology using “virtual” sensors, have been researched in the past 10 years by various OEMs, some of whom have adopted the concept for additional improvements and refinements. This concept was one of several subjects studied by the Collision Avoidance Metrics Partnership (CAMP) and VTTI as part of a cooperative agreement with FHWA’s Road Weather program.[13]

Among companies that have developed in-vehicle warning systems aimed at alerting drivers of a slick road surface is NIRA Dynamics, a Swedish enterprise that specializes in providing signal processing software and safety control systems for the automotive industry. The company also develops and supplies OEMs globally and provides support and services in transportation safety to several vehicle manufacturers such as Volvo, Renault, Audi, and Volkswagen. NIRA uses vehicle tire microslip phenomena and other onboard sensors to determine road friction in real time.[14] Several automakers such as VW-Audi have since implemented the technology in different vehicles in order to provide low friction alerts to motorists and transportation system operators.

VTTI and NIRA are currently in discussions related to the use of NIRA’s road friction data in a study focused on the relationship between slippery roads and reported crash data along Interstate 81 in Virginia. There is also an opportunity to incorporate vehicle-based data from sources such as Wejo (https://www.wejo.com/), one of several companies now providing this type of information commercially. As with the FHWA/CAMP/VTTI work mentioned earlier, vehicle-

based data such as wiper and headlight usage, air temperature, and safety system activation might be used to support applications for road weather assessment. The Virginia Department of Transportation recently purchased a large amount of data from Wejo under a use license that allows sharing with Virginia public universities.

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