Assessment of Roadway Surface Conditions Using Vehicle-Intrinsic Sensors, Phase II

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16. Abstract

Using onboard vehicle sensors to provide real-time identification of hazardous road surface conditions, such as the presence of ice, will allow drivers to receive warnings to proceed with caution on compromised road sections, thus reducing crash risks. In the near future, Connected and Automated Vehicle technologies may also allow this information to be shared among vehicles so that drivers can plan their trips more efficiently by selecting alternative routes to avoid inclement road weather areas.

The main objective of Phase II of this study was to establish a real-time correlation between certain variables collected by vehicle onboard sensors (e.g., wheel speed and wheel rotational pulse) and roadway surface conditions under several driving scenarios (e.g., different constant speeds and road grades, roadway ice patches, etc.). In Phase I of the study it was hypothesized that the relative difference in tire rotation, between the driven and nondriven (or free-rolling) wheels that results from tire microslip might be used to assess pavement surface condition, and thus, vehicle traction. Traction represents the amount of grip that a tire exhibits while in contact with the pavement surface and influences the vehicle's steering control and direction stability during driving.

To further investigate the microslip phenomenon, front-, rear-, and all-wheel drive vehicles were tested to determine the relative rotational displacements of driven and nondriven wheels under dry, wet, snowy/slushy, and icy road surface conditions. All vehicles were driven under controlled conditions of constant speed, no braking, and minimal steering over straight pavement sections of different grades and lengths to compare results. Additionally, onboard safety systems, such as traction control or electronic stability control, were monitored during testing sessions as they were considered potential confounding variables when active. Collected data were employed to calculate ratios of distances traveled per unit of time by driven and nondriven wheels in order to distinguish between different pavement surface conditions. The obtained ratios, termed "Traction Indexes" (TI), were an indicator of a specific road condition and/or incline for the respective road sections.

The results of experimentation with multiple test configurations and passes conducted on road conditions ranging from dry to snowy to icy showed small but statistically discernable differences in the TI values. Changes in these observed values when transitioning from dry to icy surfaces were clearly associated with pavement conditions known to yield poor traction, such as wet or snow-covered. Lower TI values were always obtained for slick surfaces and uphill direction due to the increased relative rotational displacement for the driven versus nondriven wheels.

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Executive Summary

Background

Modern vehicles are equipped with sensors that support multiple onboard systems. Safety systems such as anti-lock brakes (ABS) and electronic stability control (ESC) rely upon accurate measurement of individual wheel speeds for their function. These speed sensors may also be used to provide relatively accurate and timely information about the location and severity of hazardous road conditions through real-time analysis of tire "microslip". Microslip occurs at the tire-pavement interface resulting in either over- or under-rotation of wheels with respect to the distance traveled. A comparison of microslip rates between driven and nondriven (or free-rolling) wheels during vehicle operation can be used to evaluate road slipperiness affecting tire traction. An increase in microslip is usually associated with a decrease in the friction coefficient between the tire and the pavement. This information may then be shared with the vehicle driver, onboard safety systems, other drivers, or road maintenance agencies to reduce the safety impacts of road hazards, enhance winter road maintenance, and decrease adverse associated environmental impacts.

Objective and Approach

This Phase II report presents test results and analyses of near real-time tire microslip at different speeds and on different road grades and surface conditions ranging from dry to snowy to icy. The purpose of this phase of research was to further improve and refine a road condition assessment technique developed in Phase I of the study, in which vehicle intrinsic sensors (i.e., wheel speed and rotation sensors) were employed to supply real-time wheel speed data under various driving scenarios. The concept relies on utilizing the ratio of relative rotational displacement (i.e., measured wheel rotation pulses supplied by the pulse count sensor) of driven and free-rolling wheels to account for the microslippage between the tire and pavement surface. Under constant speeds a change in the relative rotational rates of driven versus nondriven wheels is indicative of changing road surface conditions, (e.g., transitioning from a dry surface to a wet surface). The work in Phase 1 relied on distance-based evaluation methods to calculate the microslip and traction index (TI) factor indicative of pavement surface condition. However, this approach proved problematic as the sampling rate of the external distance measurement sensor provided insufficient precision.

Specifically, Phase II of the study focused on addressing key issues such as short-term and time-related traction evaluation, real-time detection of road hazards, and speed and road incline influence on TI. To resolve these issues, TIs were calculated on a per unit time basis regardless of distance traveled. In this way, instantaneous or short time quantification of the TI could be acquired as a calculated/reported value every second or every 10 seconds depending on the requirements of the in-vehicle safety application or system. Furthermore, the effect of speed and road incline on the TI values were taken into account to compare values across different surface states such as wet, dry, or snowy/icy. The TI provides not only information about the tire grip while a vehicle is driven on dry or slick pavement surfaces, but may also indicate whether the vehicle is traveling on flat or inclined (uphill or downhill) roadway sections under similar weather and speed conditions.

To collect the necessary data, several vehicle platforms and drive types were selected, instrumented, and driven on the Virginia Smart Road and State Highway 460, a proximate public road. A portable data acquisition system, which can be readily installed in a test vehicle, was developed and deployed for data collection. Experimental driving sessions were conducted on road sections varying in length from 1/3 mile to 1 mile of flat and inclined road segments of pavements where the vehicles were driven at constant selected speeds ranging from 40 mph to 65 mph over the entire segment. Collected data were reduced and analyzed to establish correlations between TI values and road surface conditions resulting from adverse weather.

Key Findings

Data analysis indicated that all vehicles—front wheel drive (FWD), rear wheel drive (RWD), and all-wheel drive (AWD)—exhibited similar traction behavior trends in that the TI values decreased as speed, road incline, and slipperiness increased. Differences among TI values were minimal across the speed spectrum and similar road conditions or incline, with TI numbers being comparable for dry and wet conditions. As detailed in Phase 1 of the study, this behavior was expected due to the fact that clean road surfaces covered by a thin water film typically exhibit adequate traction while contaminated wet surfaces are slipperier. Data analyses also indicated that progressively smaller TI values were acquired for increased surface slipperiness and speed while driving in both uphill and downhill directions, as well as on level pavement, with significantly larger decreases in TI values for the uphill direction (i.e., more driven tire deformation and slippage), especially for snow and ice covered surfaces.

Furthermore, the TI differences increased significantly with an increase in road slipperiness and slope, whether upward or downward. Comparisons among different inclines indicated that TI values obtained using Smart Road data at 6% slope were lower than values acquired when using US 460 data at about 1% incline. By using this approach, road sections of various inclines can be identified from calculated TI ratios as compared to known flat road segments, with TI values for flat sections always being situated between ratios acquired for uphill and downhill directions. Typically, the TI ratios obtained from downhill driving data were slightly larger than those calculated using uphill data for any surface condition or speed indicating that averaging the TI values for the two directions approximates a level surface value. These differences also indicate that, in the uphill direction, there is always more deformation at the driven wheels (i.e., an increase in wheel pulses) than the nondriven wheels. This phenomenon is more pronounced with the increase in the road slipperiness or speed. However, TI values were not significantly different for flat and moderately inclined road sections such as those on US 460.

Also, based on the wheel rotational data and calculated TI ratios for all vehicles, it can be stated that the newly developed time-based TI ratio calculation approach performed better than the distance measurement technique for assessing different road surface conditions. This new approach, although based on the same nondriven/driven wheel pulses ratios, eliminated the requirement of measuring the traveled distances, which involved accurate collection of location and lengthy calculations. An additional advantage is that the traction condition of road sections of different lengths can be characterized using wheel speeds and elapsed time alone, which negates the need for accurate and precise position measurement.

Furthermore, acceleration and deceleration events produced additional deformation and slip at the driven wheels, which translated into a more rapid increase/decrease of the TI values than those acquired at constant speed, irrespective of direction of travel. Similar trends (i.e., lower TIs during acceleration and greater TIs during deceleration) were observed for all vehicles for analogous acceleration/deceleration ranges. Data analysis showed that uphill TI values were lower than flat ratios during acceleration whereas TI values were slightly greater in the downhill direction compared to the flat section during deceleration. This information could be especially useful on very slippery surfaces when an alert based on a rapid change in the TI ratio for a known slope could be sent to the driver prior to safety system activation.

Conclusions

This Phase II study has provided a methodical assessment of how native vehicle sensor data such as that available from wheel speed sensors, can help in providing valuable information about road weather conditions in real-time. Specifically, the mobile data collection by on-board vehicle systems and subsequent analysis provides timely insights on potential near-future "threats" when road conditions might deteriorate toward an unsafe situation. In other words, alerts can be sent to drivers, based on differential wheel rotational displacement data, through various means such as head-up displays or flashing dashboard icons informing them in advance of hazardous road conditions. It was also established that the proposed TI factor can distinguish between a baseline dry road surface condition and various slippery conditions indicative of poor traction. This detection of change in surface state can be achieved for different vehicle platforms, drive types, and speeds and cover a relatively wide array of time intervals ranging from 1 second (i.e., instantaneous) to tens of seconds or minutes depending on the length of the monitored or tested road section.

Furthermore, to address a confounding situation such as driving on road inclines and distinguish from wind drag effect, TI values were computed for various road inclines on the Smart Road and U.S. 460. Results indicated that TI numbers predictably decreased when driving uphill and on a steep slope whereas the same numbers were higher when driving downhill on a similar slope. However, no significant differences were observed between TI values obtained on flat surfaces and moderately inclined slopes. In addition, it was noted that TI numbers followed similar trends during acceleration and/or deceleration events when vehicles were driven on road segments of different inclines and at varying speeds. All this information proves to be beneficial when travelers often encounter roadway sections of rapidly changing surface conditions and need to be warned in real-time of these changes to avoid a potential crash. In addition, with the proliferation of the connected vehicles (CV) technologies roadway weather data sharing among these vehicles will have the utmost impact on traffic safety as it facilitates an increase of the situational awareness of drivers and reduce or eliminate crashes through driver advisories, driver warnings, and vehicle and/or infrastructure controls. CV technologies along with traffic sensing technologies can also help integrate data collected from multiple data sources for use in traveler information, transportation management, and planning applications.

Recommendations

Adverse weather impacts on traffic operations have become a growing concern for roadway management agencies. As this Phase II study was funded by FHWA's Road Weather

Management Program (RWMP) it is expected that more emphasis will be placed on future projects on employing vehicle native sensors to assess road weather conditions in real-time for operational purposes. Therefore, based on data analysis and findings the research team proposes the following recommendations:

FHWA should continue to fund research on using vehicle native sensors as mobile road weather data collected via vehicle probes will help fill existing gaps related to improving the timeliness of updated traveler information and the situational awareness of maintenance staff during field operations. The collected data may offer useful information regarding improved road condition reporting by maintenance staff.

FHWA should consider a small scale (e.g., district level) implementation of the proposed methodology for assessing the road surface conditions on maintenance vehicles. If feasible, additional variables such as fuel consumption or throttle position may be analyzed with the goal of better assessment of potential confounds that may impact accurate detection of pavement surface condition. The acquired data can be integrated into Weather Responsive Traffic Management (WRTM) and to support vehicle based CV safety systems through the basic safety message (BSM) data packet.

FHWA should also consider integrating collected vehicle sensor data into algorithms and applications that may result in more accurate analyses and forecasts of road weather parameters. The overarching goal of this initiative from a weather perspective is to utilize vehicle data to improve weather and road condition products such as characterization of surface conditions for weather models and to provide those products to transportation system decision makers and travelers. Moreover, collected data may be integrated into a data processor such as a Weather Data Translator (WDT) where it is filtered to extract only the data that represent selected parameters over a specific region and time.

Chapter 1 Introduction

Background

The adverse impact of weather on road conditions is a major contributing cause of vehicle crashes in the U.S. 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. Recent data on traffic-related crashes in the U.S. have shown that the fatality rate is still at a high level, with more than 20 percent of all vehicle crashes occurring in adverse weather conditions, resulting in numerous deaths and injuries on average per year (Al-Kaisy et al., 2015; Council et al., 2010; IIHS, 2015). A slick pavement surface is cited as a primary cause of 35 percent and a contributing cause of 63 percent of these adverse weather crashes, with nearly a quarter of these crashes occurring on roads covered by snow or ice (Richard et al., 2015; Tefft, 2016). The total economic costs of weather-related crashes exceed $50 billion annually, with road maintenance agencies spending more than $2.3 billion on snow and ice control operations during the winter (Rall, 2012).

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 through hydroplaning during heavy rain or in wintry conditions such as snow and ice (Erdogan, 2007; Blau, 2009; Murphy et al., 2012). During hard braking, the anti-lock braking system (ABS) prevents the wheels from locking up in an effort to maximize traction so that the vehicle moves without tire sliding. At the same time, the traction control system (TCS) has an essential role in keeping vehicles safe on the road by minimizing wheel spin during acceleration (Gillespie, 1992; Mehler et al., 2014; Levinson et al., 2016). Each of these systems, including electronic stability control (ESC), is designed to monitor wheel events linked to the pavement/tire interface and is coupled with adjustments performed by other onboard systems, such as the throttle and steering system, to offer the greatest amount of traction possible.

Wheel lock, spin, and sideslip are more likely by far to occur during adverse road conditions when surface friction is low due to rain, snow, etc., and the prevention of these occurrences before the activation of safety systems will greatly reduce crash risks. With the increased utilization of vehicle-based safety systems such as ESC or TCS under compromised pavement surface circumstances, the issuance of pre-alerts based on the novel wheel slip detection technique proposed herein can be used to prevent the vehicle from going into an uncontrolled skid. These warnings will be especially useful for very slick road conditions when safety systems are only able to assist to a degree because, ultimately, a vehicle's steering or stopping ability is limited by the frictional force existing between tires and pavement.

Tire-Pavement Interaction

As presented in Phase I of this study, the wheel longitudinal displacement phenomenon, known as "slip," occurs because of the relative motion that develops between the tire and the road surface. Typically, there are two types of slip that occur at the tire–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 tire and pavement decreases. This means that the "static" and “sliding,” or “dynamic” regions, will expand or contract depending on the degree of slipperiness of the road surface, vehicle speed, and level of braking (Noyce et al., 2007; Savaresi, 2011; Pacejka & Besselink, 2012; Rajamani, 2012). Microslip, which may lead to diminished tire grip, was quantified in real-time using data from the wheel-speed sensors available on all tested vehicles. This information is required prior to the macro-slip-exceeding threshold that would activate the vehicle’s onboard safety systems.

Alternatively, *macroslip* takes place when the entire contact patch area “glides” or “skids” relative to the pavement’s surface and generally may invoke activation of one or more of the vehicle’s safety systems. Potential loss of control or crashes may occur when the capabilities of these systems are exceeded due to phenomena such as hydroplaning, where the tire is riding on a relatively thick water layer, aquaplaning, where the tire skids on dirty roads, or in icy conditions (NHTSA, 2009). During these events of slipping or sliding, the force transfer between the tires and pavement is mainly achieved through two types of friction:

1. Adhesive friction, which depends on tire and pavement microscale interaction.
2. Hysteretic friction, which depends on the tire and pavement surface condition.

Hysteresis is a viscoelastic phenomenon that is related to the tire’s ability to recover after being elastically deformed, a process that continues until the tire returns to its original shape after the deformation force vanishes. Hysteretic friction depends highly on the amount of contact between the tire tread and the roughness of the pavement surface. As an example, a tire made of a material with a large damping coefficient will also have a higher friction coefficient (i.e., better grip) due to an increased hysteresis (Druta & Alden, 2014). Hence, adhesion may largely govern the friction of dry, fine-textured surfaces, as it depends on the micro-level roughness of the aggregate particles or fine materials contained in the surface. Hysteresis, however, is the prevailing component on wet and coarse or rough-textured pavement surfaces. Also, whereas the adhesion force is responsible for providing good traction at low speeds, the hysteresis component is more prevalent at high speeds where pavement macrotexture plays a critical role. A summary of the two types of friction is presented in Table 1-1.

Table 1-1 Tire-Pavement Friction Phenomena

Friction Type	Surface Type	Surface Condition	Speed Level	Other
Hysteretic	Pavement surface macrotexture	Prevails on wet pavement surfaces	Speeds over 30 mph	Depends on tire’s damping coefficient
Adhesive	Aggregate surface microtexture	Prevails on dry aggregate surfaces	Speeds below 30 mph	Tire-aggregate intermolecular interaction

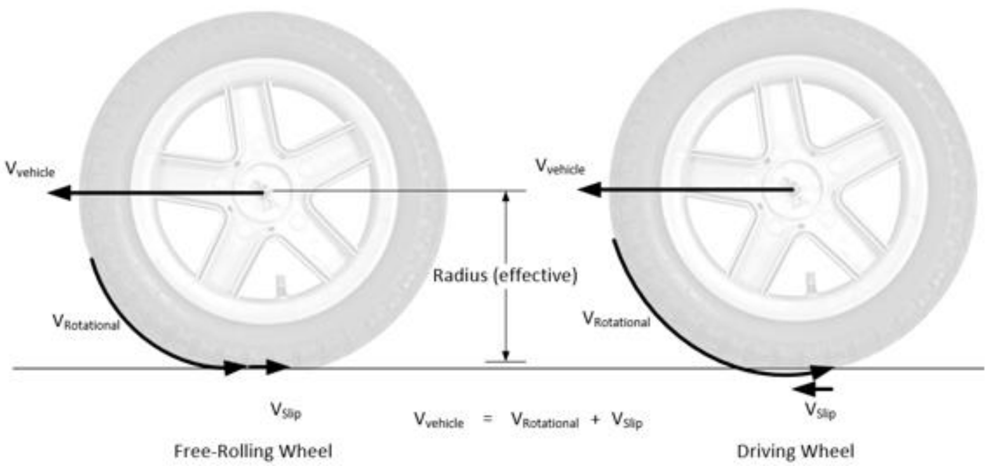
Source: VTTI

Considering the information provided above, a comparison of the rotational displacement of the driven versus free-rolling wheels over a traveled road segment when using probe vehicles may provide an indication of the pavement surface’s friction level. The slip due to road grade (i.e., incline) as well as the speed gradient can also be determined to allow for evaluation of pavement frictional characteristics such as surface slipperiness.

Chapter 2 Proposed Concept

Casual observations by Virginia Tech Transportation Institute (VTTI) researchers when using instrumented vehicles on the Smart Road indicated that the rotational displacement in the driven wheels in relation to the distance traveled by a vehicle may vary with respect to roadway conditions such as incline and tire grip. This finding led to the assumption that the driven wheels in a vehicle may rotate more than the free-rolling (or nondriven) wheels over a similar travel distance or time interval due to a phenomenon known as *tire microslip*. As explained in Chapter 1, tire microslip occurs because of the relative motion that develops between the tire and the road surface under certain driving conditions.

Hence, this assumption was employed as a method for estimating road surface friction (or traction) based on real-time tire microslip data using only the relative rotational displacement of driven and free-rolling wheels. As shown in Figure 2-1, the applied and reaction forces observed at the interface between the pavement's surface and the driven and free-rolling tires are hypothesized to act in opposition at constant speeds.



Source: VTTI

Figure 2-1. Longitudinal slip occurring in opposite directions at the wheel-pavement interface.

As the driven wheel rotates forward, it creates a reaction force at the pavement in the direction of travel, as opposed to the force applied to the free-rolling wheel by the pavement that causes that wheel to rotate. The slip phenomenon that occurs at the driven and free-rolling wheels will result in a decrease in tire grip, leading to a greater differential in rotational displacement (i.e., the driven wheel will turn more than the free-rolling wheel). Therefore, the change in the relative rotational rates of driven versus free-rolling wheels will be predictive of changes in pavement friction.

Project Objective and Scope

VTTI proposed using on-road vehicle testing in fairly controlled conditions to validate whether the relative measured rotational rates of vehicle wheels can be used to assess road surface friction in real-time. These tests were performed at the Virginia Smart Road facility in Blacksburg and U.S. Route 460 (US 460), an adjacent U.S. highway. The Smart Road is a closed test bed built to interstate specifications with the capability to create rain, mist, snow, and ice on a variety of full-width test pavement sections that are tested for friction annually.

In this phase of the project, the braking, acceleration, and road incline were investigated to assess their effect on the tire-pavement frictional interactions. As opposed to Phase I of the project, when a sole speed of 35 mph was employed for verifying the microslip concept, several speed values were selected, ranging from 45 mph to 70 mph, depending on the road section, to account for microslip variation for different pavement surface conditions. Furthermore, an AWD vehicle was added to the vehicle test matrix to verify its performance prior to and during increased road slipperiness for comparison purposes. Proposed testing was conducted seasonally and under different artificially created weather conditions to maximize the range of available road friction values.

Current Road Condition Evaluation Using Vehicle Sensors

In the last decade, various private companies, transportation institutes, and agencies alike have tried to utilize vehicle onboard sensors such as engine torque, angular speed, etc., or have developed automatic slipperiness detection systems relying on information collected from these sensors, to evaluate roadway slipperiness conditions. However, regardless of their outcome, in almost all cases they also relied on external optical sensors, which introduce additional challenges as engineers try to integrate several streams of environmental and onboard information to calculate the traction available for a particular maneuver. When trying to determine vehicle traction, the major challenge to be overcome is that the acquired data have to provide a fairly adequate estimation of the compromised surface condition prior to the point at which either onboard safety controls or the driver have confirmed excessive tire macroslip.

Macroslip occurs when there is no physical contact between the tire and pavement due to an existing water, snow, or ice layer of certain thickness separating the two surfaces (Blundell and Harty, 2004; Druta & Alden, 2014). This section documents several techniques and systems that rely on vehicle inherent components to assess road surface slipperiness in a relatively real-time manner. Other mobile devices or built-in sensors, such as optical friction meters, etc., which can be integrated into vehicles and used to measure road surface conditions, were covered in the Phase I report and are thus not listed here. The results from the literature search covering national and international efforts related to the researched topic, including existing intellectual property, patents, and trademarks, are presented in Table 2-1.

VTTI further refined the concept proposed in Phase I by expanding testing on a broader range of variables to cover potential confounds, such as slope, introduced by road geometry. Battelle and the University of Nevada have used alternating braking and acceleration events to obtain a friction coefficient and a slip factor, respectively (Gustaffson, 1997; Hall et al., 2009; Sheaf et al., 2014; Verbal Communication, Nevada DOT). Although these actions certainly reveal road slipperiness, they are mostly based on the vehicle's safety systems, which activate when macroslippage has already occurred due to tire loss of contact with the pavement.

Table 2-1. Surface Friction Related Studies Using Vehicle-Based Sensor Data

Organization	Technique	Variables	Safety System State	Vehicle Platform	Product	Patent/ IP
VTTI (USA)	Relative wheel rotational displacement ratio (microslip)	Wheel pulses, wheel speed, time, acceleration	Deactivated	FWD, RWD, AWD	- Traction Index (TI) indicative of pavement surface condition - Proposed algorithm to implement with Connected Vehicles/Automated Vehicles	No
Battelle (USA)	Application of brakes and acceleration to obtain a friction coefficient	Engine torque, ABS	Active	FWD	On-board diagnostics (OBD) II Module	Yes
Univ. of Nevada, Reno (USA)	Measurement of the wheel rotation	Angular velocity, acceleration	N/A	FWD	Friction detection algorithm	N/A
VTT (FIN), Technical Research Center	Measurement of axle speed to determine pavement friction	Angular velocity, engine torque	Active	FWD	Friction Detection Module, OBD II Module	Yes
VTI (SWE), Transport Research Institute	Various braking cycles	ABS	Active	FWD	Active Safety System (City Safety)	Yes
NIRA Dynamics	Axle speed measurement	ABS, axle torque ratio	Active	FWD	Algorithm to detect tire-pavement traction	Yes

Source: VTTI

The Technical Research Center in Finland and the Transport Research Institute in Sweden have based their approaches on axle torque distribution and braking cycles at different speeds, respectively (Koskinen & Peussa, 2010; Hjort et al., 2015). However, these and similar proposed approaches for estimating surface friction levels need thorough calibration and tuning, as many other variables such as vehicle weight, tire type and size, etc. come into play during data acquisition (Petty and Mahoney, 2007; Hartikainen et al., 2015).

NIRA Dynamics®'s proposed technique called Tire Grip Indicator continuously monitors all of a vehicle's wheels and sends alerts to the driver when slippery conditions occur. The technique is based on variable wheel rotation (i.e., angular velocity) events as a function of transmission torque inputs (similar to the VTT method) as the tire grip fluctuates for different pavement weather conditions. The method has been tested on a few vehicles, but there is no indication that it has yet been implemented in any mass-produced vehicles. All of these approaches are necessary to develop proper validation methods and procedures for an accurate estimation of surface friction, as roadway data collection is vital for traffic safety and winter maintenance operations.

Other studies aimed at evaluating slippery road conditions (Do & Roe, 2008; Robinson, 2012; Belzowski & Ekstrom, 2015) either relied on optical (Loprencipe & Cantisani, 2013) capacitive (Troiano et al., 2011), or embedded sensors (Erdogan et al., 2012) and were thus prone to data collection errors due to technology-specific factors such as sensing range, calibration, etc. Where researchers have investigated the potential use of Controller Area Network (CAN) bus data to detect slippery road conditions (Robinson, 2012; Bettisworth et al., 2015), they had to request access to certain basic parameters from the auto manufacturer to assess those conditions. Based on the acquired data, a road surface evaluation rating system was developed using only relevant CAN parameters to rate hazardous pavement sections. Efforts are on-going in negotiating non-disclosure agreements with other manufacturers through joint efforts of the national Connected Vehicles Pilot program (Robinson, 2012).

As surface friction evaluation studies have progressed to provide more ways to determine road conditions, several companies have also developed weather sensors to remotely monitor these conditions to accurately and reliably provide the collected information to travelers and maintenance operations staff. Table 2-2 lists three of the most utilized road weather sensors deployed for different applications aimed at improving traffic safety and flow.

Table 2-2. Road Surface Condition Sensors

Company/Model	Sensor Type	Road Surface Condition	Install Mode	Risk Warning
High Sierra Electronics IceSight 5433 (USA)	Electro-optical	Wet, snow, ice	Pole, RWIS tower	Hydroplaning, black ice
Lufft-Marwis (GER)	Optical spectra	Wet, snow, ice	Pole, vehicle	Black ice, low traction
Vaisala (USA) DSC 111	Optical	Wet, snow, ice	Pole, vehicle	Black ice, low traction

Source: VTTI

Note: Other road surface sensors may be available on demand, depending on project requirements, providing supplemental technical features for various applications. The link below offers additional information on a wide range of pavement-weather sensors.[1]

[1] A collection of road condition sensors can be found at: http://observator.com/en/meteo-hydro/products/meteorological-sensors/road-condition-sensors

Chapter 3 Vehicle Instrumentation

Prior to conducting the proposed testing and data evaluation, the research team developed a Data Acquisition Plan to ensure that the project requirements were met and the goals achieved on time. Topics addressed in this plan are as follows:

- Selecting vehicle platforms and drive types that could offer the relevant parameters required for traction calculations.
- Instrumenting vehicles to acquire the selected parameters needed for data sampling.
- Ensuring that the selected parameters are correctly acquired, valid and transmitted to the central server at the designated rates.
- Ensuring that testing occurs under the desired road conditions and specified speeds for the selected testing sections.
- Evaluating the maturity level of the technology needed to ascertain pavement slipperiness demonstrated in Phase I.
- Verifying tradeoffs or changes to the overall strategy that must be introduced due to particularities of each vehicle configuration and/or test environment.

Vehicle Selection

Selection of vehicles was coordinated with the Center for Technology Development researchers at VTTI, as they manage the institute's fleet and possess extensive expertise in setting up test kits and parameter scanning procedures for preliminary data collection and verification. Table 3-1 lists the vehicles employed for testing along with their related features. All vehicles were scanned for available relevant elements supplied by the CAN bus variables based on the requirements identified by the research team. Preliminary scanning to verify the availability of certain variables that would aid in the assessment of the road slipperiness was a prerequisite for each vehicle considered for data acquisition. As noted below, several vehicles did not supply some of the needed parameters, even though other related parameters were readily available, and were thus not considered for further field deployment.

Table 3-1. Vehicles Selected for Road Surface Condition Testing

Make	Model	Year	Drive Type	Platform	Safety Systems
Chevy	Tahoe	2009	Rear-Wheel	Sport Utility	ABS, ESC, TCS
Chevy	Impala	2014	Front-Wheel	Sedan	ABS, TCS
Chevy	Equinox	2012	Front/All wheel	Sport Utility	ABS, ESC, TCS
Chevy	Malibu	2015	Front-Wheel	Sedan	ABS, ESC, TCS
Mercedes	RS 350	2007	Front-Wheel	Sport Utility	ABS, ESC, TCS
Chevy	Cobalt	2009	Front-Wheel	Sedan	ABS, TCS
Toyota	Tacoma	2011	Rear-Wheel	Light pick-up truck	ABS, ESC, TCS
Ford	Focus	2014	Front-Wheel	Sedan	ABS, ESC, TCS

Source: VTTI

Note: Gray cells indicate the vehicles that could not supply the required CAN bus variables.

Vehicle Variable Selection

Key vehicle network bus variables selected for extraction, storage, and data reduction are listed in Table 3-2. Selection was based on prior experience gained from testing in Phase I of the project, 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 and recorded throughout the driving sessions.

Similarly, under certain circumstances arising from the employment of various onboard sensors used to gather roadway data, individual variables or parameters required frequent verification for reliability purposes. This procedure determined whether the sensor output was within predefined “acceptable limits” per the manufacturer’s specifications so that it did not start supplying intermittent erroneous data.

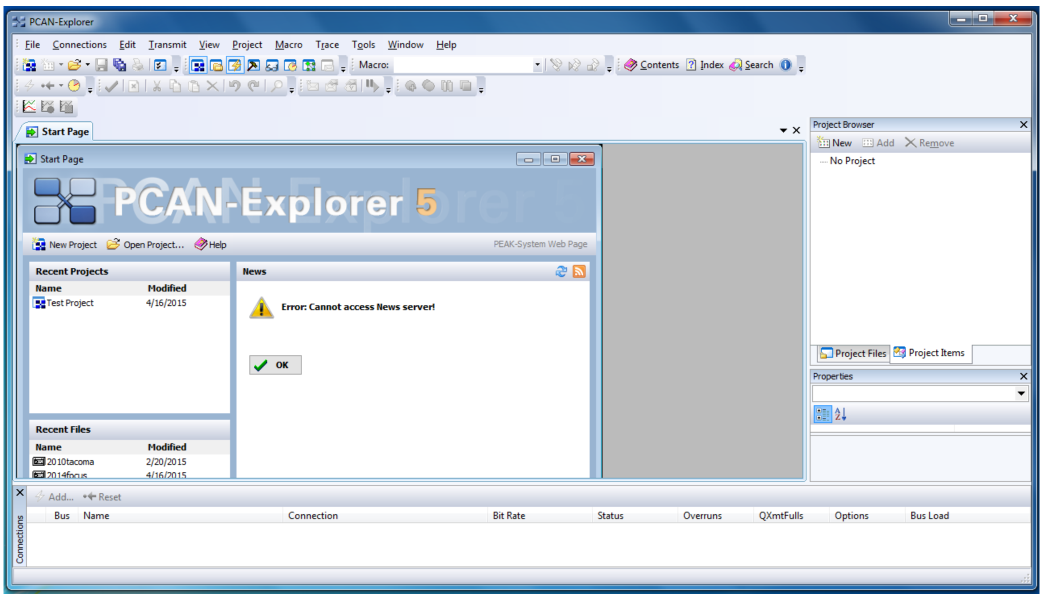
Table 3-2. Selected Vehicle Primary Experimental Variables

Variable	Type	Measurement Method/Sensor	Notes
Time	Control (via DAS)	NextGen data acquisition system (DAS)	Time stamp recorded by the portable test kit @ 100 Hz
Wheel driven/nondriven pulse counter (Left/Right axle)	Dependent (upon vehicle sensor)	Vehicle network (ABS sensors)	Wheel rotational displacement measured for all 4 wheels independently
Wheel pulses per revolution driven and nondriven axle	Dependent (upon vehicle sensor)	Vehicle network (CAN)	Per axle (numbers vary for different vehicles) Tahoe: 32/55 pls; Impala: NA Equinox: 47/48 pls; Malibu: 48/48 pls
Vehicle speed average per driven/nondriven axle (horizontal, vertical)	Control (driver input)	Vehicle network (via DAS), GPS	Speed to be kept constant throughout each test trip
Vehicle acceleration (x, y, z)	Control (driver input)	Inertial measurement unit (IMU), CAN bus (longitudinal), actual throttle	Zero to light acceleration over test course
Vehicle change of direction (steering)	Control (driver input)	Yaw angle (CAN)	Zero vehicle direction change over test course
Distance traveled	Dependent (vehicle sensor)	Odometer (CAN)	GPS Start/stop locations (latitude, longitude, altitude)
Tire condition	Independent	Hand-held device or vehicle network (pressure sensor)	Monitored, recorded
Road grade	Independent	Inclinometer (N/A in the selected vehicles)	Known or calculated
Weather condition	Independent	Hand-held 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 SR weather system)
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

Source: VTTI

Vehicle CAN Bus Scanning

Preliminary network parameter scanning was conducted on each vehicle to ensure that all required variables were available and could be recorded and reduced for further manipulations. To accomplish this, specialized hardware and software was employed to acquire vehicle network raw data files at various speeds depending on the type of CAN bus. A special adapter in the testing kit was used to automatically detect CAN bus data transmission speed. Data were retrieved and transmitted using a device plugged into the on-board diagnostics (OBD) II port and then transferred to a laptop for real-time analysis. Subsequently, acquired raw data files were saved with a unique title, including vehicle model and year, then analyzed for variable reliability, ID, source, sampling rate, and other relevant indicators using specialized vehicle network scan data software (Figure 3-1).



Source: VTTI

Figure 3-1. Vehicle PCAN Explorer software for variable scanning.

Once it was established that all the desired variables were available in the network and could be acquired and evaluated to comply with the technical requirements, such as sampling rate, record format, variable module, etc., the vehicle was instrumented and deployed for pilot road testing. This activity involved driving the vehicle on public roads for a short period of time, typically 30 minutes, following certain scenarios such as varying speed or incline, then analyzing the recorded data to verify and validate the developed procedure. If the data collected on the mandatory variables complied with all the technical requirements, then the selected vehicle was deployed for further testing. Additional information on vehicle instrumentation and deployment is provided in the following sections.

Installation of Vehicle Instrumentation

As Table 3-1 shows, all selected vehicles (General Motors, Chevy make) were instrumented prior to being deployed for road friction assessment testing after being scanned via the vehicle data bus P-SCAN for parameter identification and availability. In this study, VTTI built a portable testing kit suitcase for data acquisition that can be easily transported and installed on any testing vehicle. The kit includes in-house developed firmware and hardware necessary for conducting on-road experimental studies. The suitcase install is pictured in Figure 3-2 and shows the NextGen hardware in the foot well, along with other communication components, such as the signal modulator.

Source: VTTI

Figure 3-2. Data acquisition testing kit installed in the vehicle's back seat.

Other devices that are interconnected within the vehicle and to the NextGen data acquisition system (DAS) are listed below.

- Vehicle CAN bus interface module (for communication inside the vehicle).
- Windshield-mounted head unit incorporating inertial measurement sensors for linear and angular acceleration and three cameras.
- Network interface box.

Brief descriptions of these units are provided below along with pictures; more details are available in the Phase I final report (Druta & Alden, 2014).

NextGen DAS

The NextGen DAS was developed at VTTI and can be mounted on any commercial vehicle to capture a wide variety of performance parameters (i.e., CAN bus variables) that can be used to evaluate its safety and operational performance. This modular data collection system (Figure 3-3) that can be configured for almost any research application includes a wired communications network and protocols, as well as data handling/storage capabilities, such as a solid-state drive (SSD).

Source: VTTI

Figure 3-3. NextGen DAS showing SSD on the side.

The front of the unit displays various ports for in-vehicle connectivity and a standard 12-V DC power connection. Vehicle or CAN bus protocols allow various microcontrollers or devices to easily and efficiently communicate with each other inside a vehicle without being connected to a computer or network host. Moreover, the software applications include all of the necessary functions to support efficient transfer of collected data, using the SSD, from vehicles to a data storage center for accurate data analysis and access.

Software for use in the DAS units is regulated by researchers' needs and complemented by supplying and integrating data triggers for use in data collection. This feature helps to ensure that the relevant vehicle parameters are extracted and communicated correctly, and the vehicles report valid values for these variables at the selected sampling rates.

Head Unit

The head unit, also developed at VTTI, is typically mounted on the windshield behind the rearview mirror and is set up to capture forward roadway, cabin, and face camera views (Figure 3-4). The unit can collect standard Global Positioning System (GPS) data readings and comprises the following:

- three-axis accelerometers,
- three-axis gyroscopes,
- three cameras covering forward, cabin, and rear directions.

Source: VTTI

Figure 3-4. Head unit installed on windshield.

Network Box

The network box is a VTTI-developed, in-vehicle communication unit (Figure 3-5) designed to interface with a variety of vehicle network types, including the CAN bus and external sensors such as laser, load detection, etc. The box was located beneath the driver-side dashboard and communicated with the DAS and onboard computer. Standard variables collected with the network box included acceleration, braking, wheel rotation pulses, weather variables, and the status of onboard safety systems. During testing all collected data were stored on the DAS hard drive shown above.

Source: VTTI

Figure 3-5. VTTI DAS network interface box.

Tire and Weather Data Collection

Site weather data, such as pavement and air temperature, humidity, wind, etc., and tire temperature and pressure parameters were collected using versatile handheld meters (Figure 3-6). Additionally, an external temperature sensor and waterproof casing allowed for gauging the temperature of water and snow.

Source: VTTI

Figure 3-6. Handheld weather meter (Kestrel 3000).

Chapter 4 Testing and Data Acquisition Methodology

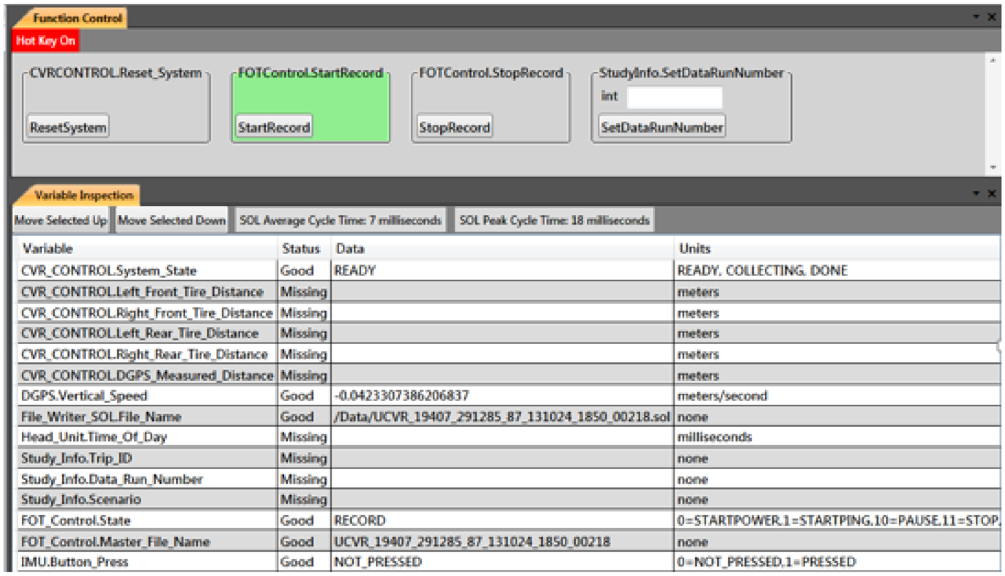
Preliminary Testing

Several driving sessions were conducted to validate test methods and data collection protocols before actual testing was conducted on the Smart Road and adjacent public roads US 460 under various weather and road conditions. This allowed shakedown testing of the instrumented vehicles without the related expenses and scheduling constraints associated with Smart Road use. Each instrumented vehicle was driven at different speeds to verify that the DAS testing kit was operational and data were recorded within required parameters. Data retrieval, upload to servers, and subsequent access for verification were performed to validate testing and data management methods.

Experimental Data Acquisition

Recorded data, including the sensing parameters described in the previous chapter, were retrieved from different data modules in the Hawkeye database (Hawkeye is a proprietary VTTI-developed data viewer software, described in more detail later in this section.) (Druta & Alden, 2014). It was necessary to closely monitor the acquisition statuses of parameters of interest to ensure that all statuses would show correctly in the real-time Variable Inspection window and that no communication losses that might lead to data corruption or invalidation would occur (Figure 4-1). Proprietary software installed on a laptop was employed for variable verification and control prior to each data acquisition session. Additionally, a constant speed was maintained for vehicles throughout each run on US 460 or the Smart Road, steering input was minimal, and there was no brake application.

Recorded data of interest were transferred to a storage network server via SSD after each driving session for subsequent retrieval, reduction, and analysis. These data were collected at a time resolution dependent upon their availability from CAN bus sensors. Table 4-1 lists some of the key variables specifications collected by all vehicles that were used to compute a TI indicative of road surface condition.



Source: VTTI

Figure 4-1. Real-time variable data collection and verification.

Other variables, such as acceleration or ESC status, were employed for comparison purposes such as observing speed variations under various road surface conditions or ensuring that safety systems did not engage on certain slick pavements.

Table 4-1. Vehicle Variable Specifications

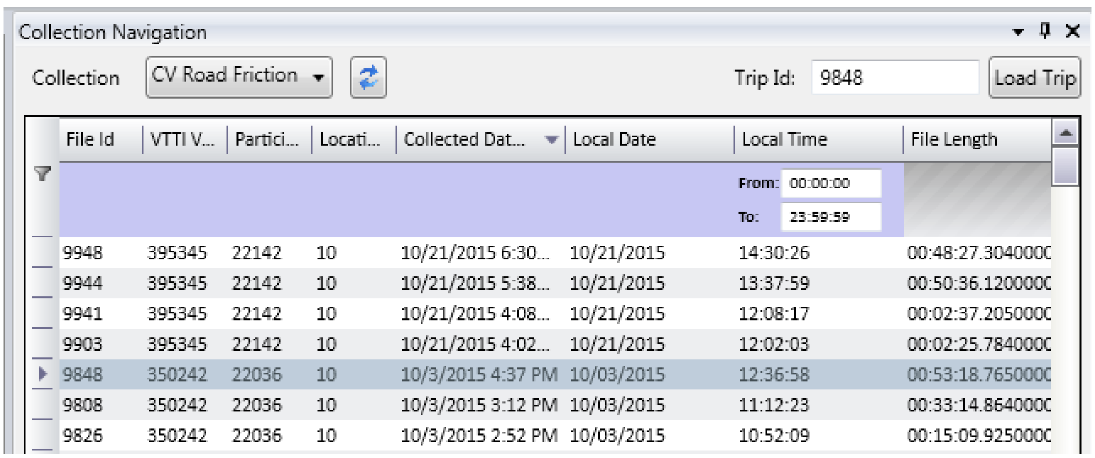
Variable	Source	Type	Unit	Sampling Rate
Time	All modules	Integer	ms	10 Hz to 100 Hz
Wheel Driven Pulse Counter (Left and right)	Vehicle CAN module	Integer	Counts	100 Hz
Wheel Nondriven Pulse Counter (Left and right)	Vehicle CAN module	Integer	Counts	100 Hz
Wheel Pulses per Revolution Driven	Vehicle CAN module	Integer	None	10 Hz
Wheel Pulses per Revolution Nondriven	Vehicle CAN module	Integer	None	10 Hz
Vehicle Speed Average Driven	Vehicle CAN module	Floating point	km/h	20 Hz
Vehicle Speed Average Nondriven	Vehicle CAN module	Floating point	km/h	20 Hz
Vehicle Horizontal Acceleration	Vehicle CAN module	Floating point	m/s^2	10 Hz
ABS Active	Vehicle CAN module	Enumerated	0=False 1=True	1 Hz
ESC	Vehicle CAN module	Enumerated	0=Inactive 1=Active	1 Hz

Source: VTTI

Note: Wheel Pulses per Revolution Driven/Nondriven variables were not available for the Chevy Impala. The ratio value (pulses per nondriven axle/pulses per driven axle) was derived by interpolating traction TI values obtained from data acquisition.

Hawkeye was used to extract and reduce relevant data for subsequent analysis from the databases. This program retrieves a single data collection, which contains all the recorded data sets, at a time, then displays a list of certain variables and variable properties depending on the hard drive used for data collection (Figure 4-2).

Additional information specifying the recorded data file name (a separate file name can be selected prior to start a testing session), vehicle used to collect data, date and time, and other parameters is supplied by the Collection Navigation pane.



Source: VTTI

Figure 4-2. Hawkeye data collection viewer software: Collection Navigation pane.

A variable control feature enabled the start and stop of the data acquisition routine during a driving trip once the optimal driving speed was reached and all safety systems such as ESC, TCS, etc., were turned off. Typically, a pre-driving session of 5 minutes was conducted each time before the actual data acquisition commenced, so that the tires would attain optimal temperature and pressure levels. These two parameters were continually monitored throughout the driving sessions to ensure consistent values for all trips. A time stamp, usually in milliseconds (ms), was recorded for each variable value under all the OBD modules and was used as reference value to calculate the number of wheel pulses and average wheel speed per length of road or time interval.

Video data files capturing aspects of road features and weather conditions are also available for retrieval within Hawkeye to aid in identifying the correct location of the vehicle while analyzing the data for a specific event. Other data collection fields are available from the database menu. Tabulated variable data can be transferred to a spreadsheet file for further manipulation.

Smart Road Testing

Vehicles instrumented using the procedure described above were deployed for testing on the Smart Road facility as scheduled. For this purpose, only the inclined (6% slope) and relatively straight portion of the road, which was about 600 m long, was selected for conducting the proposed measurements, as testing on flat pavement was conducted on the primary road (i.e., US 460). The selected road segment is paved with hot-mix asphalt and lies within the precipitation-making area (Figure 4-3). All measurements were conducted on pavement surfaces ranging from dry to wet to icy and in the uphill and downhill directions to properly assess the microslip effect.

Source: VTTI

Figure 4-3. Smart Road testing section.

Driving sessions consisted of 10 passes driven by the same driver under similar conditions of constant speed, minimal steering, and no braking, and at speeds varying from 40 mph to 60 mph, up and down the testing section. For safety reasons, lower speeds of up to 45 mph were employed for very slippery conditions such as snow or ice. Additionally, two 20 m long and 40 m apart ice patches were created on the testing section to assess tire slippage at different speeds.

Prior to starting the data collection, tire-related parameters such as temperature, pressure, and circumference were recorded. These parameters were also monitored with hand held meters throughout each testing session. Example values for these parameters are presented in Table 4-2**.** Tire pressure was checked and adjusted, if required, every five trips, while onboard safety systems were monitored to ensure they were not activated during tests. The pressure was kept constant throughout the entire testing period. Detailed information on tires, pavement surface, and weather conditions is provided in Appendices D and E.

Table 4-2. Tire-Related Parameters Recorded During Testing (RWD Vehicle)

Wheel	Tire pressure (psi)	Tire temperature (°C)		Circumference (cm)
		Tread	Sidewall	
Left Front	37	23	24	249.7
Right Front	37	23	24	249.8
Left Rear	37	23	24	249.8
Right Rear	37	23	24	249.9

Source: VTTI

US 460 Testing

Following a similar procedure, the instrumented vehicles were deployed for data acquisition and validation on US 460. They also were driven 10 trips each on dry, wet, and snowy pavement sections at speeds varying from 40–50 mph (snow) to 70 mph (dry and wet). Selected test sections were 2 miles long, providing a flat and inclined segment (1% slope) of 1 mile each. No tests were conducted on icy surfaces due to safety concerns. Preliminary data analyses indicated that most of the designated parameters were appropriately acquired in terms of sampling rates and accuracy. A data acquisition matrix is presented in Table 4-3 comprising the instrumented vehicles, surface testing conditions, and relative speeds.

Table 4-3. Road Friction Assessment Testing Matrix

Surface Condition	Vehicle	Speed (mph)	Road Section	Test Period
Dry	All vehicles	40 to 70	Smart Road & US 460	Mar – Sep, 2015
Wet	All vehicles	40 to 70	Smart Road & US 460	May – Oct, 2015
Snowy/Slushy	Tahoe, Impala	40 to 55	Smart Road & US 460	Feb – Mar, 2015
Icy	Tahoe, Impala	40 to 55	Smart Road	Feb – Mar, 2015

Source: VTTI

Note: The 2015 Chevy Malibu was not driven on the Smart road, only on US 460.

The 2011 Chevy Equinox (FWD/AWD) and 2015 Malibu (FWD) were driven only on dry and wet surfaces to assess their capabilities (i.e., wheel pulse granularity) and to determine if acquired data and results were comparable to the other two vehicles. These vehicles were also driven on a steeper slope of road similar to the one on the Smart Road (i.e., 6%) at higher speeds for traction results comparisons.

Chapter 5 Data Analysis Methodology and Test Results

Data analysis relied on utilizing the raw data supplied by the vehicle's network via the variable modules recorded and downloaded in a database after each driving session. As shown in Figure 4-2, a user-defined database was created and tailored based on input from the research team and variable characteristics obtained from scanning each vehicle's CAN bus. The methodology used to calculate a TI parameter needed for assessing the degree of surface slipperiness or friction level was similar to that developed in Phase I (Druta & Alden, 2014). The former approach employed GPS coordinates to calculate the total distance traveled by a vehicle and compared the result to a distance calculated using the total number of wheel pulses accumulated for the same distance. Then, ratios of these distances corresponding to driven and nondriven axles were calculated for various surface conditions to try to differentiate between two or more surface states (e.g., dry vs. wet, wet vs. snow, etc.)

Traction Index Calculation

To determine the TI, Phase II employed an approach similar to that used in Phase I. But instead of calculating traveled distances from GPS and wheel rotation data, which might not be very accurate, the wheel pulses data were used to compute similar ratios over a certain time interval, typically larger than 1 second. Figure 5-1 presents acquired speeds (left columns) and rotational data (i.e., counted sensor pulses) for each wheel, tabulated and arranged by a time stamp column recorded at 100 Hz.

1	Time (ms)	WS Lfront (km/h)	WS RightF (km/h)	WSLeftR (km/h)	WS RightR (km/h)	Time (ms)	Pulses_Left Front (ND)	Pulses_Right Front (ND)	Pulses_Left Rear (D)	Pulses_Right Rear (D)
2	138835	40.03	40.13	40.53	40.66	138832	296	500	583	690
3	138883	40.19	40.53	40.69	40.94	138841	299	502	585	692
4	138935	40.53	40.81	40.81	41.09	138851	301	505	586	693
5	138983	40.75	40.94	40.88	41.22	138861	304	507	588	695
6	139035	40.88	41.03	41.22	41.38	138871	306	510	589	696
7	139083	40.94	41.31	41.44	41.72	138881	309	512	591	698
8	139135	41.22	41.66	41.66	42.00	138891	311	515	592	699
9	139183	41.66	41.88	41.66	42.00	138901	314	517	594	701
10	139235	41.78	41.88	41.88	42.22	138912	316	520	595	702
11	139283	41.72	41.88	42.28	42.44	138921	319	523	597	704
12	139335	42.00	42.38	42.38	42.72	138932	321	525	598	705
13	139383	42.28	42.50	42.34	42.50	138941	324	528	600	707
14	139435	42.38	42.50	42.56	42.84	138951	326	530	601	708
15	139483	42.34	42.72	42.91	43.00	138961	329	533	603	710
16	139535	42.56	43.06	42.84	43.16	138971	331	535	604	711
17	139583	42.84	43.16	42.94	43.28	138981	334	538	606	713
18	139635	43.00	43.16	43.06	43.41	138991	337	540	607	714
19	139684	42.91	43.34	43.34	43.50	139001	339	543	609	716
20	139735	43.00	43.50	43.28	43.69	139012	342	546	610	717
21	139783	43.28	43.72	43.34	43.63	139021	344	548	612	719

Source: VTTI

Figure 5-1. Wheel pulses and speeds retrieved from the vehicle CAN bus.

This approach provides better control over the reduced data (i.e., determining the number of pulses for a selected time interval) as instantaneous or short time (e.g., 2 sec, 5 sec, etc.) ratios of wheel pulses, driven (D) vs nondriven (ND), can be calculated in order to infer the road surface condition. It also eliminates the need for accurate distance measurements, which may not be an available built-in vehicle feature. Additionally, TI can be obtained over longer time segments, or longer distances, by computing a ratio of cumulated number of pulses for the nondriven axle to the number pulses for the driven axle (Eq. 1).

Traction Index (unitless): $TI = NWP_{ND}/NWP_D$ (1)

where: NWP is the total number of wheel pulses per specific time interval or selected distance averaged over D and nondriven wheels.

The example in Figure 5-2 shows columns of pulse increments per wheel every 10 ms at a sampling rate of 100 Hz, average speed, and computed TI values (green column) per 1 sec segments at a constant speed of 40 mph.

Pulse Increment (LF)	Pulse Increment (RF)	Pulse Increment (LR)	Pulse Increment (RR)	Pulses/Sec (LF)	Pulses/Sec (RF)	Pulses/Sec (LR)	Pulses/Sec (RR)	Average Speed (km/h)	Average Speed (mph)	Front/Rear Ratio (TI)
3	3	2	1	400	400	234	234	63.62	39.51	1.70940
3	4	2	2	400	400	234	233	63.69	39.56	1.71306
3	3	2	2	401	400	235	234	63.87	39.67	1.70789
3	3	1	2	402	401	235	235	64.00	39.75	1.70851
4	3	2	2	403	402	236	235	64.12	39.82	1.70913
3	3	2	2	404	404	236	236	64.10	39.81	1.71186
3	3	2	2	403	403	236	236	64.10	39.81	1.70763
3	4	2	1	404	403	235	235	64.08	39.80	1.71702
3	3	2	2	404	403	237	236	64.32	39.95	1.70613
3	3	1	2	404	404	236	236	64.39	39.99	1.71186
3	3	2	2	406	405	237	237	64.43	40.02	1.71097
4	3	2	2	406	406	237	237	64.31	39.95	1.71308
3	3	2	2	406	405	237	236	64.28	39.92	1.71459
3	3	2	1	405	404	237	237	64.19	39.87	1.70675
3	4	2	2	405	405	237	236	64.30	39.94	1.71247
3	3	2	2	404	404	236	236	64.30	39.94	1.71186
3	3	1	2	405	404	237	237	64.36	39.98	1.70675
4	3	2	2	404	405	236	236	64.20	39.88	1.71398

Source: VTTI

Figure 5-2. Example of calculated TI ratios for a constant speed.

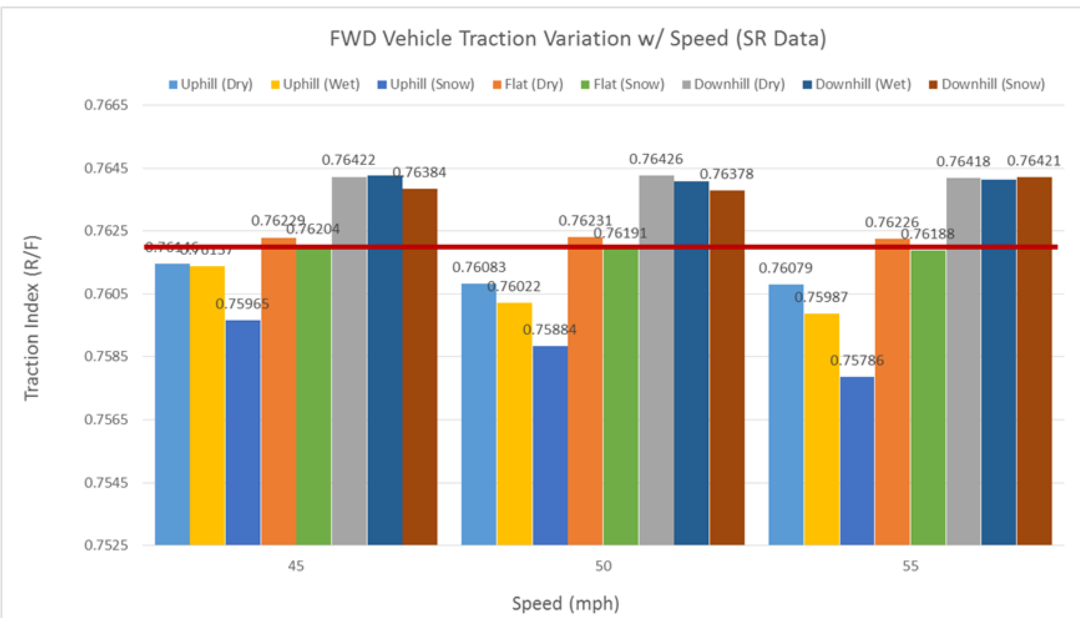
The computed TI ratio for a specific constant speed would be indicative of changes in the surface state, as it tends to decrease as the road slipperiness increases and friction decreases. To calculate a TI over a selected distance, start and stop time stamps are selected, then corresponding pulses are summed up and averaged for driven and nondriven wheels over that time segment. Furthermore, similar calculations are required for the vehicle speeds so that they correlate with the TI values of the same tested road section. Additional information on testing results from different vehicles and road conditions (e.g., wet, snow, etc.) are presented in the next sections.

Traction Index Testing Results

Calculated TI Ratios for the 2014 FWD Vehicle (Chevy Impala)

Charts of calculated TI values for all of the road surface conditions and speeds are presented in Figure 5-3 for Smart Road testing and in Figure 5-5 for US 460 testing, respectively. Data were collected at constant speeds ranging from 45 mph to 55 mph while driving on the Smart Road and at 60 mph and 70 mph while driving on US 460. All the runs were conducted on flat and uphill/downhill directions to investigate the slope effect. The slope on the Smart Road was more pronounced than the slope on US 460).

As illustrated in Figure 5-3, all TI values below the red line corresponded to the uphill direction, indicating a noticeable effect of the slope on traction when compared to the flat surface or downhill direction. This drop in the TI when driving up an inclined road section is attributed to increased tire deformation (more wheel pulses over time) at the driven wheels compared to the nondriven wheels at any given speed. Typically, the deformation occurs as the vehicle's weight is redistributed around its center of gravity (i.e., more torque is applied at the driven wheels to keep the speed constant), due to an additional rolling resistance force created by the incline angle and acting opposite to the direction of travel (Heising, 2011). Conversely, a propulsive force results as the vehicle is driven downhill, reducing the wheel load, and therefore decreasing the torque applied to the driven axle.

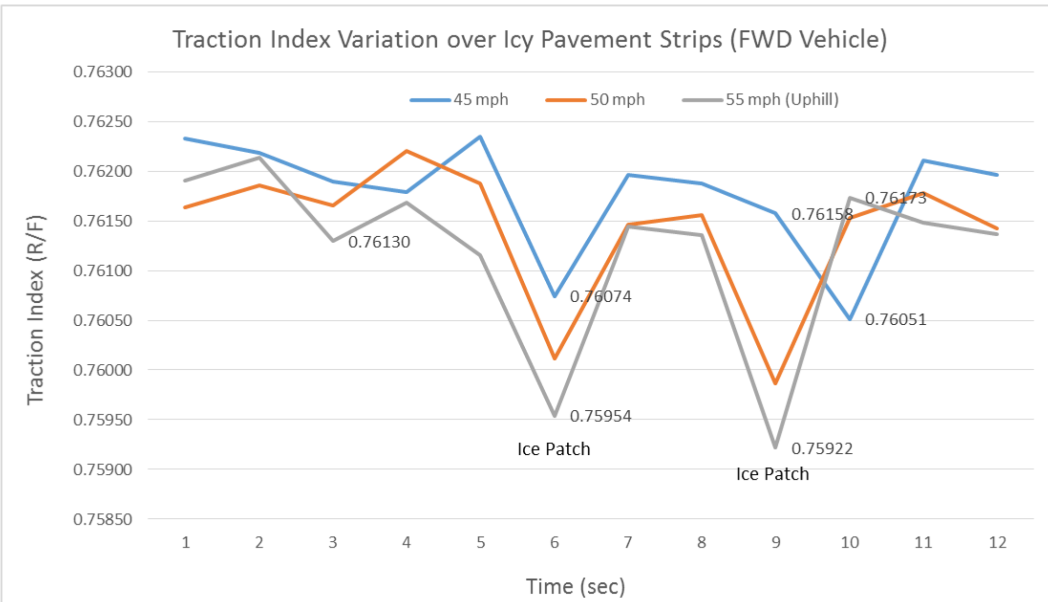


Source: VTTI

Figure 5-3. Traction Index ratios (grouped by speed) using Smart Road data.

Figure 5-3 also indicates that there were minor differences between the dry, wet and snowy surface conditions for the flat and downhill road sections; however, the uphill TI ratios started to decline as the speed and slipperiness levels increased from dry to snow. This decline was more pronounced in the uphill direction due to the phenomena explained above. The red line shows that the effect of speed was minimal when driving on the flat surface and that corresponding TI values always fell between the uphill and downhill interval, indicating that more tire deformation (i.e., more pulses are recorded) occurs while driving uphill than driving downhill. The fresh snow depth was in the range of 2–4 inches and gradually decreased to about 1 inch–1 ½ inch after several passes.

The vehicle speeds were computed concurrently over the same traveled distance, using analogous time stamps, to ensure that they corresponded to the appropriate averaged wheel pulses (i.e., pulses recorded for the respective road section at the designated speed with matching time variables). In this way, TI variations could be monitored over small time segments of 1 or 2 seconds or over the span of an entire road section of interest. Figure 5-4 provides an example of such evaluation as the FWD vehicle was driven over two ice patches, approximately ¼ inch (4 mm) thick, at different speeds to validate the instantaneous response of driven and nondriven wheels. For this particular case, the vehicle was driven only in uphill/downhill directions.



Source: VTTI

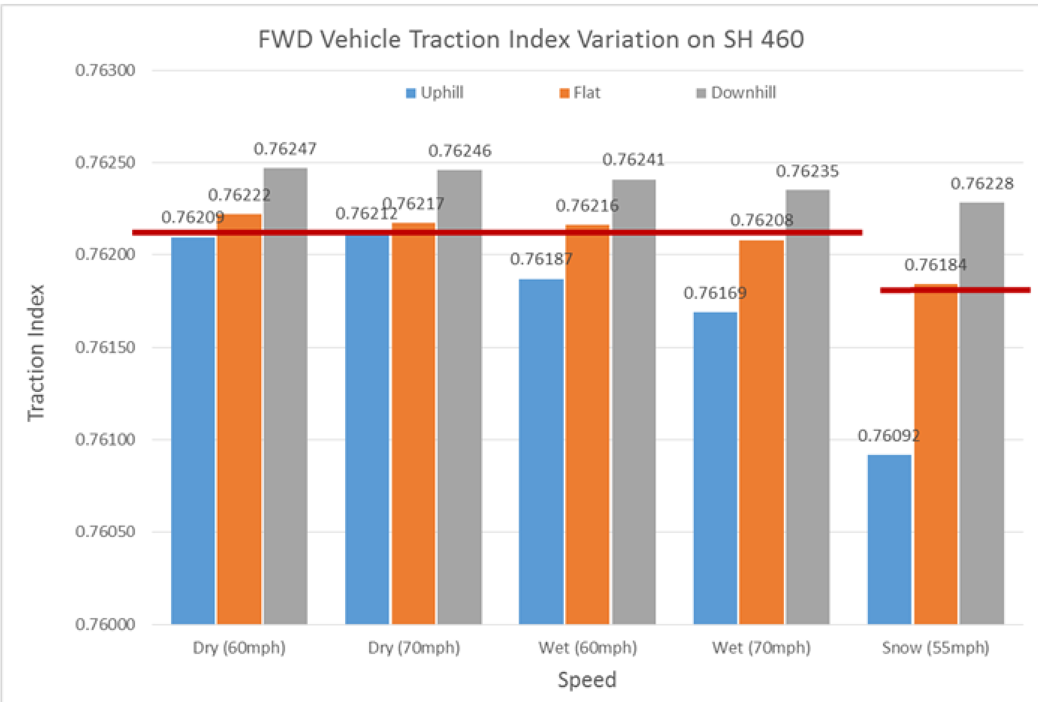
Figure 5-4. Traction Index variation on Smart Road ice patches (uphill direction).

As the figure shows, a progressive drop in TI values takes place as the speed increases. As expected, the lowest calculated TI values correspond to the highest speed of 55 mph, with some values being similar (0.760) to the values obtained when driving in snow (0.758).

The data collected on US 460 are presented in Figure 5-5. A simplified chart indicates comparable trends to the TI ratios calculated using Smart Road raw data. The results were grouped by speed and surface conditions for driving sessions conducted on flat surface and uphill/downhill directions at speeds of 60 mph and 70 mph.

As noted above, the red line, drawn on top of the orange TI bars corresponding to flat surface data, acts as a divider by separating the uphill/downhill TI ratios. Again, a minimal speed effect can be observed in the figure for the flat road surface driving conditions, whether dry or wet. However, transitioning from wet to snowy conditions resulted in a substantial drop in the TI values even though it was also associated with a drop in speed to around 55 mph. All of these TI values were comparable to those obtained from the Smart Road data.

Moreover, it appears that the road slope, which is around 1%, did play a key role in the calculations of the TI ratios, as fairly higher values were acquired from data collected in the uphill direction compared to those obtained in the same direction on the Smart Road section. An opposite effect was observed for TI values calculated for the downhill direction: they slightly decreased compared to those determined using Smart Road data.



Source: VTTI

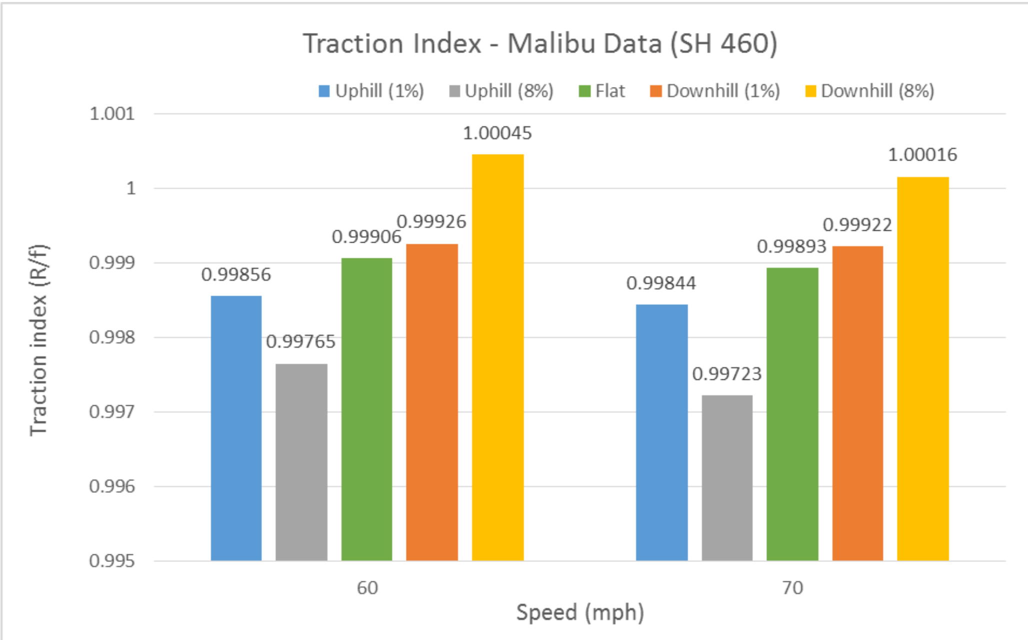
Figure 5-5. TI ratios (grouped by speed and road condition) using US 460 road data.

These findings indicate that a steeper road section, like the Smart Road test bed, will affect the number of pulses differently at both driven and nondriven wheels compared to a less inclined section. Therefore, it can be noted that TI values obtained from the Smart Road data were lower than their counterparts from US 460 data for the uphill direction whereas the downhill direction TIs were greater, irrespective of the road condition. Moreover, TI values acquired for the Smart Road dry condition were significantly lower than TI values for the U.S. 460 wet condition and comparable to snow conditions for the uphill direction.

Typically, the microslip phenomenon will be more pronounced at the driven wheels compared to the nondriven wheels while driving up a more inclined road section (i.e., more pulse counts recorded) whereas driving down the same section will generate less slip (i.e., less tire deformation) at the driven wheels. Therefore, lower TI values will always be obtained for larger incline angles going uphill, whereas larger TI ratios will be acquired going downhill. Additionally, greater TI ratios will be obtained going uphill, as the slope angle decreases, whereas smaller TI values will be acquired going downhill for a declining angle. To avoid confusion, these assertions hold true for constant speeds only, with minimal steering input and no braking. Details on how the TI values are affected by these factors are presented in the Acceleration/Deceleration Effects section.

Calculated TI Ratios for the 2015 FWD Vehicle (Chevy Malibu)

For comparison purposes, TI ratios pertaining to a different vehicle model with a ratio of driven over nondriven wheel pulses per revolution equal to 1 (i.e., 48 pulses per driven and 48 pulses per nondriven wheels) are presented in Figure 5-6. To avoid poor readability issues, only the data analysis for the dry pavement surface was plotted for two speeds and road inclines, respectively.



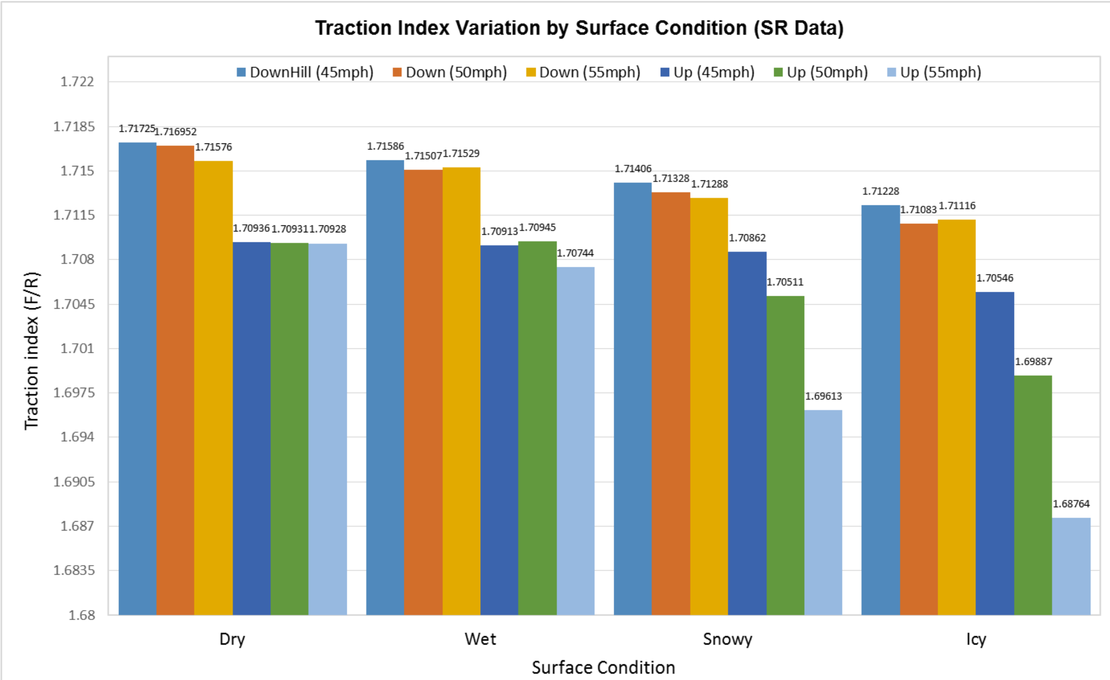
Source: VTTI

Figure 5-6. Traction Index ratios calculated using US 460 dry surface data for different slopes.

As the figure shows, comparable results were acquired for both speeds with slightly lower values for the TI ratios calculated using data at 70 mph. This vehicle was not tested on the Smart Road but was driven on a section of US 460 with a similar incline. The figure shows that TI values followed an identical pattern of peaks and valleys as pertaining to uphill/downhill directions of different grades, with the ratios for the flat section falling between values derived for the two directions. For this particular case, however, values larger than one were obtained for the TI calculated for the steeper downhill direction, indicating that slightly more rotation occurred at the nondriven wheels due to the propulsive force. Relatively similar values were determined for the flat (0.9991) and less inclined road sections (0.9992), respectively. Following the same trend as for the FWD Impala, larger ratios were calculated for the downhill direction compared to the uphill directions. TI values for the wet road surface are presented in Appendix B.

Calculated TI Ratios for the RWD Vehicle (Chevy Tahoe)

A similar approach was employed for determining the TI ratios using the data acquired by the RWD vehicle on the Smart Road as illustrated in Figure 5-7.



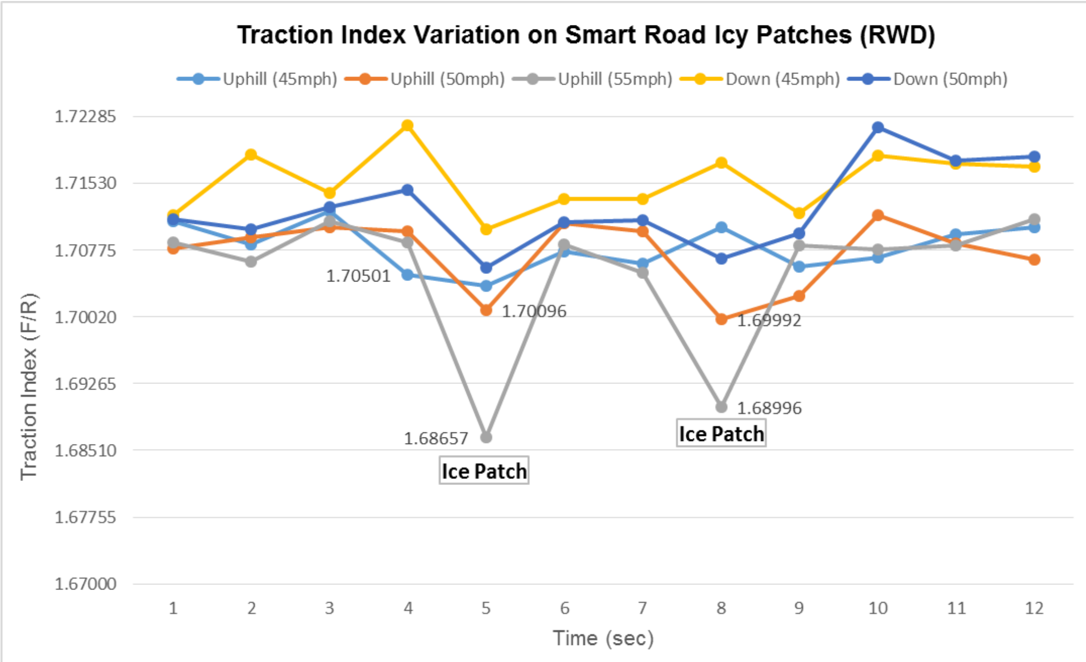
Source: VTTI

Figure 5-7. Traction Index ratios calculated using Smart Road data (grouped by surface condition).

For readability, the data pertaining to the flat surface was omitted from the chart. As depicted in the figure, TI ratios showed relatively similar values corresponding to dry and wet surfaces, but started to decrease as speed and surface slipperiness conditions increased. Moreover, following the same trend as the FWD vehicle, higher TI ratios were acquired in the downhill direction than the uphill direction, indicating a similar tire deformation effect due to the force shifting (i.e., propulsive and resistance forces) acting in both directions. TI values calculated from the data collected on flat surface sections at various speeds were also situated between uphill and downhill values, respectively. Appendix B presents all the TI values calculated for different road surfaces, vehicles, speeds and inclines.

TI values greater than one are due to the fact that more pulses are supplied by the front wheel sensor (55 pulses) than the rear, driven wheel sensor (32 pulses), respectively. Again, a more pronounced slope effect can be observed from the figure, especially for snow and ice covered surfaces, as reduced TI values were obtained for the uphill direction compared to downhill path.

TI ratios acquired for Smart Road icy patches are shown in Figure 5-8. As anticipated, similar results to those obtained using the FWD data can be observed in the figure, as the lowest calculated TI values for the uphill direction were found at the highest speed of 50 mph. By comparison, higher values were calculated for two different speeds in the downhill direction.

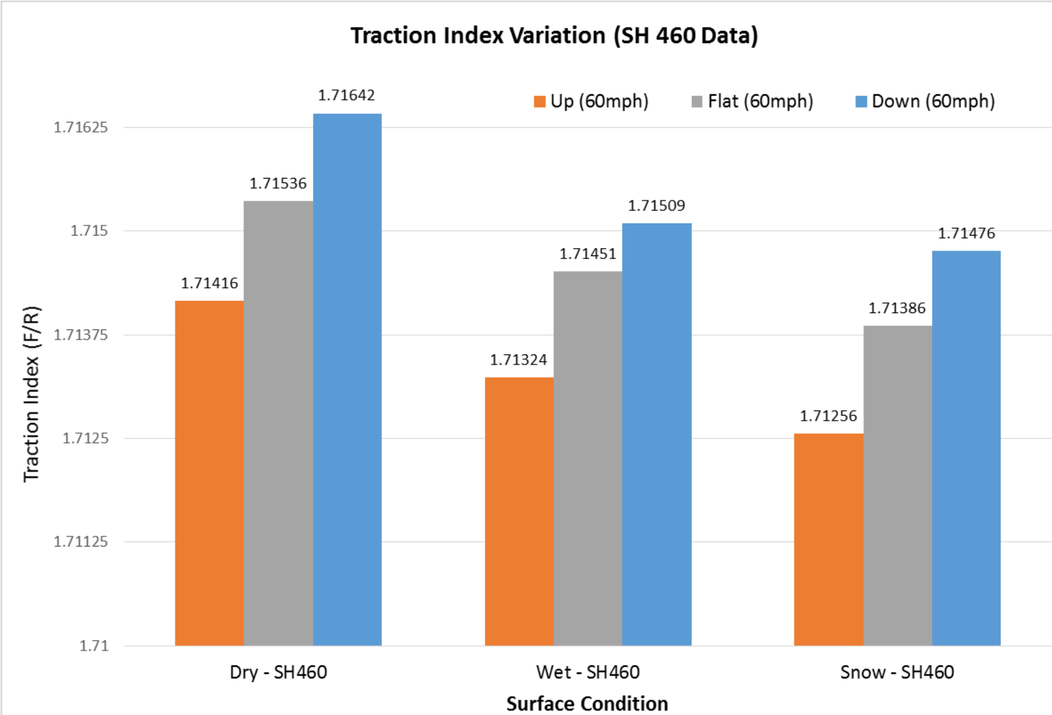


Source: VTTI

Figure 5-8. Traction Index ratios acquired from Smart Road ice patches data.

From the data analysis standpoint, a relative rotational differential of the driven and nondriven wheels can be provided over a short period of time, thus offering valuable information about the immediate road conditions in real-time. During winter maintenance operations, this real-time information could prove critical in assessing road slipperiness after snow removal operations, thereby enabling traffic operations centers to provide more efficient localized deicing activities and improve traffic safety.

TI ratios calculated using the data collected on US 460 are presented in Figure 5-9. For clarity and readability purposes, only the data collected at 60 mph are presented (see Appendix B for all results).



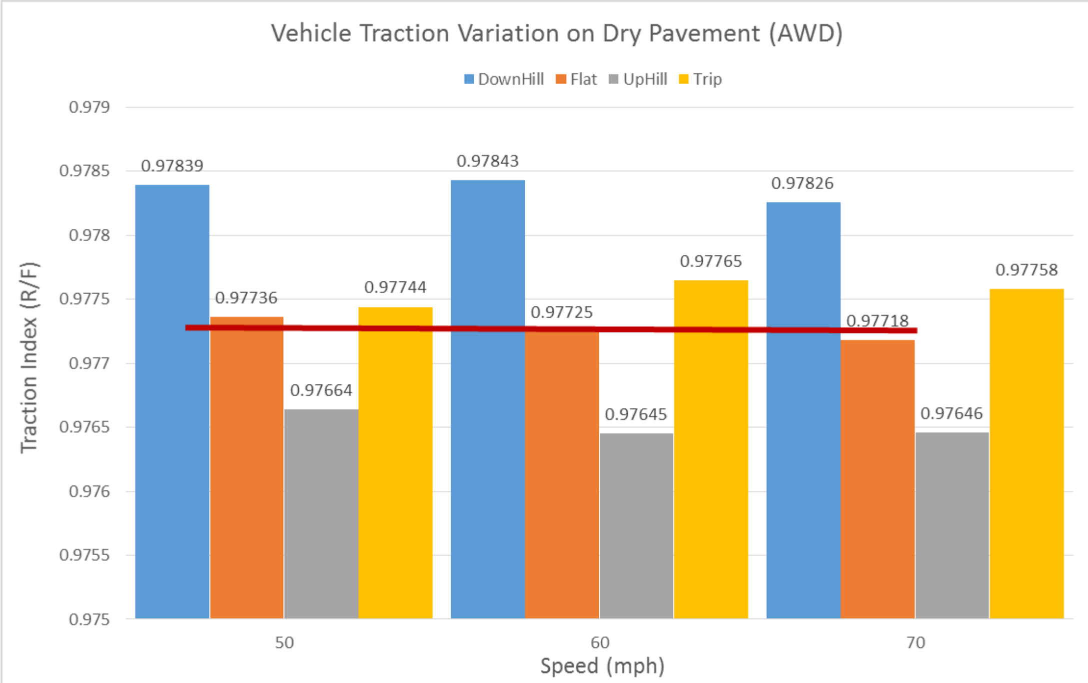
Source: VTTI

Figure 5-9. Traction Index ratios calculated using US 460 data.

As illustrated in the chart, the lowest TI values were obtained for the most slippery road conditions (i.e., snow), with the ratios for the flat surface again falling between the uphill and downhill values. Slightly larger values were also acquired for all surface conditions compared to the Smart Road data results, verifying with a different vehicle that the microslip effect is more pronounced on steeper road inclines (i.e., smaller TI values are obtained due to an increased tire deformation at the driven wheels). Additionally, smaller ratios were obtained at 70 mph (see Appendix B). Note that the maximum speed during snow testing was actually 56 mph.

Calculated Variables for the AWD/FWD Vehicle (Chevy Equinox)

TI ratios exhibiting similar variation patterns were obtained with the Chevy Equinox at different speeds and uphill/downhill directions as shown in Figure 5-10. For readability, only the data collected on US 460 is presented in the figure. Similar trends were acquired from data analysis collected on the Smart Road. Although this vehicle was an AWD vehicle, it was driven as a FWD vehicle while monitoring the rear-axle activation feature throughout the driving sessions. The chart shows that, as for the previous vehicles, smaller TI ratios were obtained for uphill driving compared to downhill, with values calculated for the flat section falling between uphill and downhill values. The red line in the figure indicates the similar TI values for the different speeds. Due to vehicle availability issues and the fact that the data was collected for comparison purposes, this vehicle was driven only on dry and wet pavement surfaces.



Source: VTTI

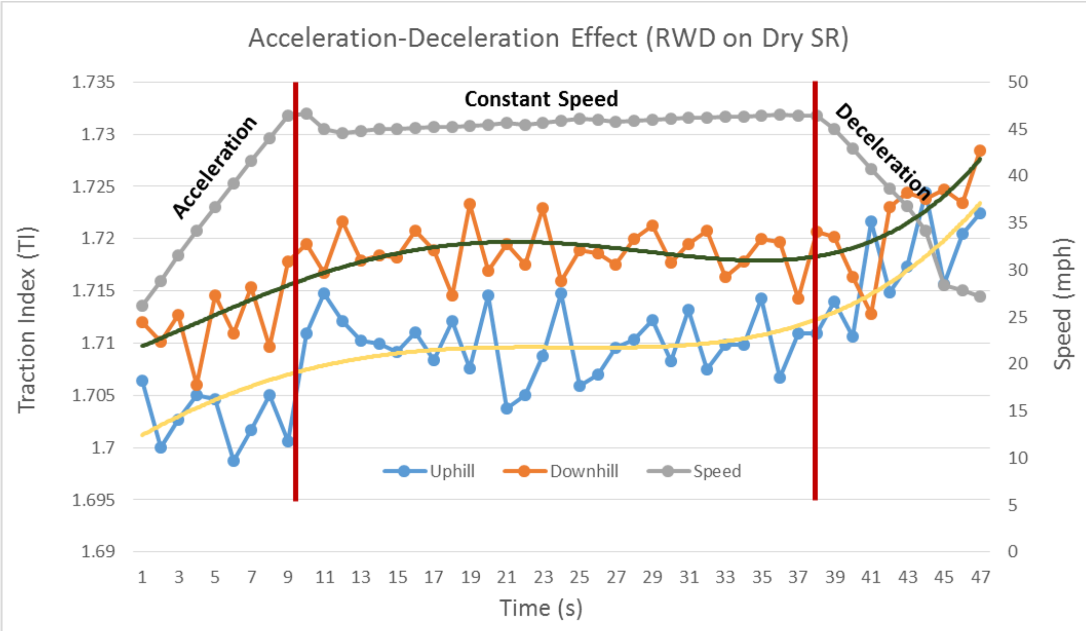
Figure 5-10. Traction Index ratios calculated for the AWD vehicle using US 460 data.

Calculated TI ratios for wet road conditions at the same speeds were slightly smaller than those for dry pavement and are presented in Appendix B along with the ratios calculated from Smart Road data. The previous vehicles exhibited similar TI ratio trends to those calculated using the Smart Road data: lower TI values were found when driving uphill or on wet pavement; larger values were found when driving downhill, etc. Time intervals of about 40 seconds were required when driving on the Smart Road sections, whereas approximately 60 seconds were needed to cover a road segment, whether flat or inclined, on US 460.

The "Trip" ratios in the chart represent a full trip on the uphill and downhill section as well as accelerating and decelerating (braking) events during that trip. This comparison was done because an inference can be made about the TI ratio based on road features, such as slope, or vehicle events, such as braking. As shown in the figure, the trip TI ratios, which typically depend on several road surface and tire related (e.g., tire diameter, pressure, etc.) parameters, had similar values compared to the flat surface TI ratios. This statistic indicates that for relatively similar speeds, the start and end portions of the TI time-dependent curve tend to cancel out, thus leaving the section of fairly constant speed to define the actual TI ratio. Details on this approach are described in the next section.

Acceleration/Deceleration Effect on TI Ratios

As previously mentioned, the Acceleration/Deceleration effect on the wheel pulses and the implications that has for the TI was also investigated. Results presented in Figure 5-11 indicate that at the beginning and end of a trip the TI ratios have different trajectories, as they tend to decrease while the vehicle accelerates then follow an ascending path as the vehicle slows down. These patterns occur because during an acceleration event, the number of pulses at the driven wheels increases, therefore lowering the TI ratio, since the number of pulses at the free-rolling wheels do not change at the same rate. A reversed process follows when the vehicle decelerates, as the number of pulses at the driven wheels start to decrease at a higher rate compared to the non-driven wheels.



Source: VTTI

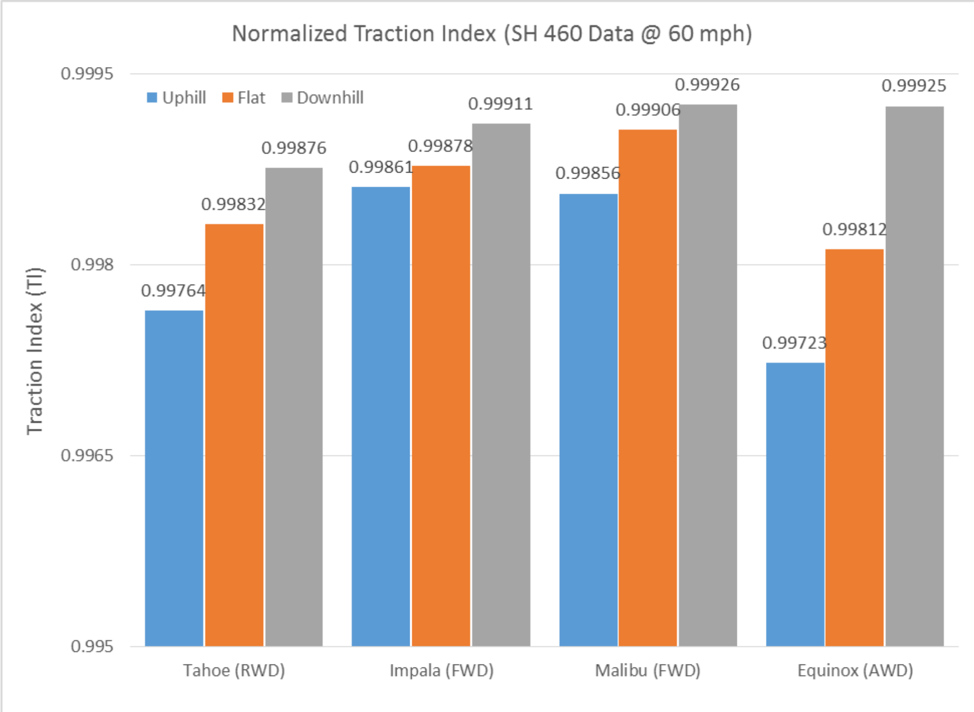
Figure 5-11. Example of acceleration-deceleration effect on the TI ratios.

The figure also shows that uphill TI values were smaller than downhill ratios as the middle values followed a level curve for the constant speed. This information could be especially useful on very slippery surfaces when an alert based on a changed TI ratio could be sent to the driver prior to safety system activation.

As discussed in the next section, in order to better understand how the vehicles performed during certain driving sessions, a normalization procedure was applied to the TI ratios to enable a comparison across all vehicles.

Traction Index Normalization

A normalization of the TI ratios for each vehicle was conducted for the dry surface condition to enable a traction comparison across all vehicles. This procedure was performed by dividing each calculated TI ratio for a certain vehicle by the vehicle's known ratio of nondriven over driven wheel pulses per wheel revolution (these ratios are available in Table 3-2). The ratio for the Chevy Impala was obtained by extrapolation, as the front/rear wheel pulses per revolution were not available. Figure 5-12 shows an example of normalized TI ratios calculated using data collected on a dry surface at 60 mph on US 460.

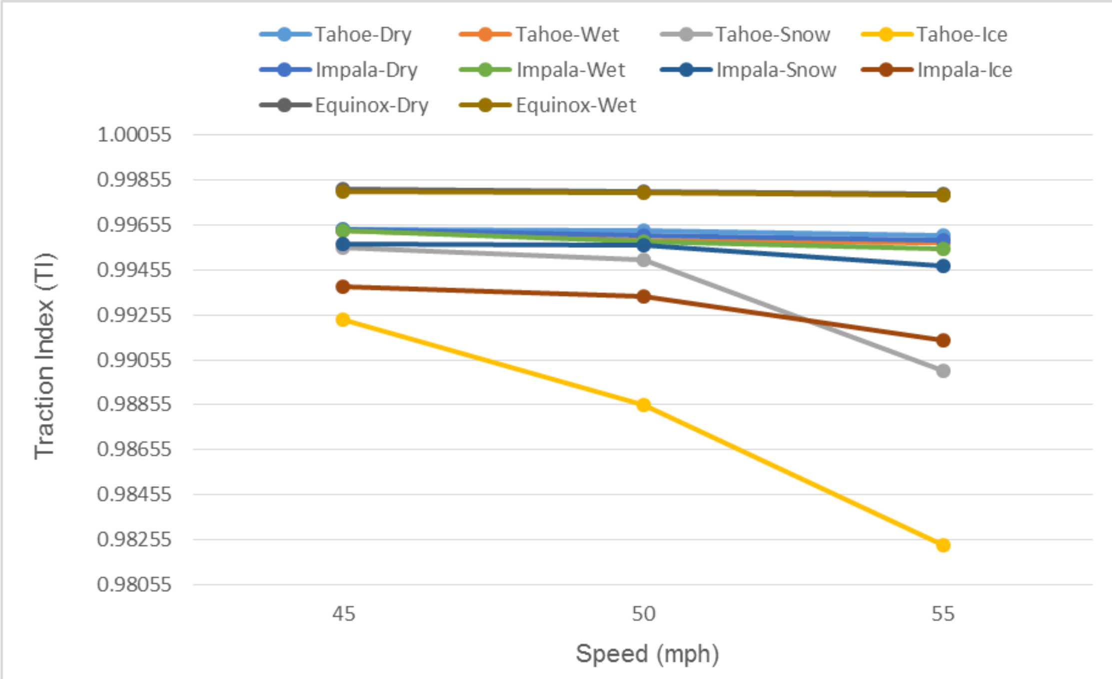


Source: VTTI

Figure 5-12. Vehicle normalized Traction Index ratios for dry surface.

The figure shows that similar values were obtained for all vehicles, especially for the downhill direction, indicating that the method could be effectively applied to any tested vehicles providing a valid number of pulses per revolution. In this way, TI ratios can be evaluated across multiple vehicle platforms and drive types under various driving scenarios (e.g., varying speeds, slick roads, etc.) such that comparable TI ranges can be established for each vehicle.

A similar normalized plot based on Smart Road data for the flat surface only and at different speeds is presented in Figure 5-13. The data used in this plot was supplied by three vehicles, as the Chevy Malibu was not driven on the Smart Road. Also, the Chevy Equinox was driven on dry and wet surfaces only. TI data for the icy road sections used in the plot pertain to the uphill direction.



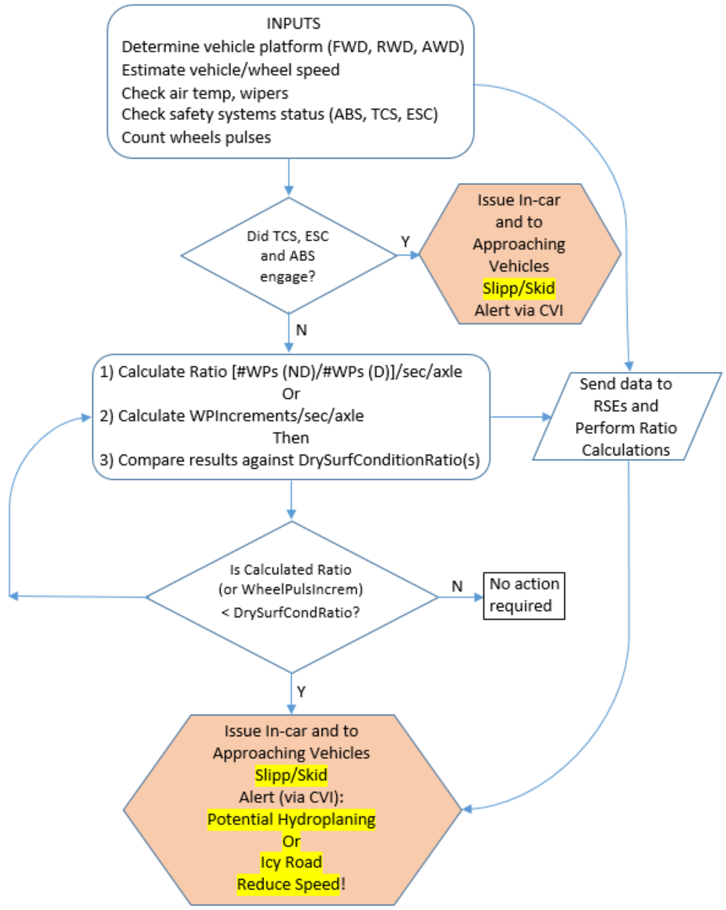
Source: VTTI

Figure 5-13. Vehicle normalized Traction Index ratios using Smart Road data.

The figure shows that similar descending trends were obtained from the Smart Road data for all three vehicles as the speed and slipperiness conditions increased. The RWD Chevy Tahoe exhibited an increased number of rotations at the driven wheels while traveling over the icy surface patches, potentially due to the shift of center mass toward the rear, inducing more slip at these wheels. Similar behavior was observed for the snowy condition at same speed, showing a consistent trend on these slipperier road surfaces. The Chevy Impala showed a comparable performance on the icy surface, indicating that increased tire slip can be detected by the vehicle's intrinsic (speed) sensors at certain speed levels.

Development of a Flowchart Diagram for Real-Time Road Surface Assessment

Based on data collection and analysis, a flowchart diagram (Figure 5-14) was developed so that unsafe pavement surface conditions or tire traction could be assessed in real-time from supplied specific input parameters such as wheel rotational pulses or acceleration. This algorithm could be either incorporated into the vehicle's infotainment system or provided as a separate hardware module to be plugged into an OBD port for data collection and transmission. It is assumed that the road incline is known for the road section being monitored.



Source: VTTI

Figure 5-14. Algorithm flowchart for determining the road surface condition.

In this way, through in-vehicle and connected vehicle technology, alerts can be sent to motorists when hazardous conditions occur. Moreover, the vehicle dynamic control and advanced driver assistance systems may benefit from this road surface friction estimation system, which supplies additional real-time information on tire-road contact. Currently, the lack of certainty about precipitation type impacts most transportation operations, particularly winter maintenance, as traffic personnel typically assume the worst-case scenarios and mobilize snow and ice control assets to address critical situations.

Although research has been conducted and is ongoing to assess the applicability of using friction data from probe and winter maintenance vehicles to monitor roadway conditions, pavement friction varies significantly over small sections of road and over time, making it difficult to determine what constitutes a representative level of friction. These vehicle-based road observations or TI values could be treated as relatively high quality surface data and be utilized by algorithms designed to analyze precipitation type over a broad area. An updated TI value supplied by probe vehicles may also provide a good understanding of the current surface state relative to the normal condition (i.e., dry surface).

Absence or shortage of surface observations also impacts the ability of traffic operations centers to monitor and respond to rapidly changing road conditions efficiently. This could, in turn, lead to potentially wasted or miscalculated snow and ice control efforts involving unnecessary costs and unforeseen delays. If probe vehicles could provide the needed information in the form of TI ratio data, it would dramatically improve the ability of winter maintenance officials, for example, to effectively determine the atmospheric conditions and pavement freezing levels and develop accurate winter maintenance strategies.

Chapter 6 Statistical Analysis

Statistical Comparisons of TI Ratios using Smart Road Data

As determined in Phase I of the project, 10 trips conducted with each vehicle provided sufficient data to perform statistical analyses needed for various testing conditions. Therefore, a similar number of trips was employed in this phase to provide the necessary data for statistical inferences covering the four road surface conditions. To make these inferences, t-test analyses were conducted using Microsoft Excel 2013 to determine significant differences or correlations between various groups of data (e.g., dry vs. wet, uphill vs downhill, etc.) for a particular test condition (e.g., wet and uphill road segment at 60 mph, etc.)

Figure 6-1 presents an example of t-test statistics, assuming equal variances, for two road surface conditions at different speeds using data collected by the RWD Chevy Tahoe. In this test, paired sets of data were compared for different surface conditions and similar numbers of runs (i.e., observations) assuming similar means and variances. For all inferences or comparisons across the vehicles, the null hypothesis stated that all means are equal (i.e., no significant difference between TI ratios), whereas the alternative hypothesis (i.e., TI ratios are different) states otherwise.

t-Test: Two-Sample Assuming Equal Variances			t-Test: Two-Sample Assuming Equal Variances		
	45 mph UpWet	*45 mph DnWet*		*60 mph UpDry*	*60 mph FlDry*
Mean	1.709564051	1.717791672	Mean	1.709148898	1.712286811
Variance	1.67328E-05	5.69621E-06	Variance	2.06994E-05	9.62055E-06
Observations	10	10	Observations	10	10
Pooled Variance	1.12145E-05		Pooled Variance	1.516E-05	
Hypothesized Mea	0		Hypothesized Mean [	0	
df	18		df	18	
t Stat	-5.493755932		t Stat	-1.802091065	
P(T<=t) one-tail	1.61502E-05		P(T<=t) one-tail	0.044151697	
t Critical one-tail	1.734063607		t Critical one-tail	1.734063607	
P(T<=t) two-tail	3.23003E-05		P(T<=t) two-tail	0.088303394	
t Critical two-tail	2.10092204		t Critical two-tail	2.10092204	

Source: VTTI

Figure 6-1. t-test statistical analysis of Smart Road data collected with RWD vehicle.

The pre-specified level of significance for which the null hypothesis would be rejected was set at α = 0.05, meaning that there is a 95% certainty that the null hypothesis is correct. In the above example, the analyses showed that there were statistical differences between TI ratios at the respective speeds and surface conditions, as both *p* values were smaller than α. Therefore the null hypothesis will be rejected.

Figure 6-1 also shows that the *p* values for the paired uphill/downhill set of data (p=1.615E-05) were much smaller than the uphill vs flat values (*p*=0.0441) indicating a more pronounced slope effect difference for the former comparison.

Table 6-1 presents statistical comparisons for the Chevy Impala across different speeds and road surface conditions using Smart Road data. As expected, the inferences showed that there were significant differences across different surface conditions but not substantial variances among speeds, especially for similar slope directions or the flat surface (*p* values are larger than α). This indicates that although an increase in speed may affect the TI ratio, the differences may not be significant. Similar statistical differences were determined for the uphill and downhill directions at different speeds and surface conditions, respectively.

Table 6-1. t-test Data Analysis for the Chevy Impala (SR Data)

Speed (mph)	Road condition	Variance	P variable (T≤t)	t Critical (one-tail)
45	Uphill vs Downhill (Dry)	1.21765E-06	6.18415E-07	1.734063607
	Uphill vs Flat (Dry)	1.21863E-06	0.009112711	1.735063506
	Downhill vs Flat (Dry)	2.31675E-07	3.30868E-07	1.844066508
	Dry vs Wet	2.43661E-07	2.55237E-07	1.445627513
	Dry vs Snow	1.42125E-07	2.48863E-07	1.832761816
	Dry vs Ice	1.71645E-05	3.31180E-06	1.644066508
	Wet vs Snow	1.21876E-06	0.008300827	1.732063604
	Wet vs Ice	6.38004E-07	0.003611546	1.735063605
50	Uphill vs Downhill (Dry)	6.17671E-07	3.12806E-09	1.734063606
	Uphill vs Flat (Dry)	1.72136E-05	0.009300833	1.736063604
	Downhill vs Flat (Dry)	1.62325E-05	0.000485363	1.756761934
	Dry vs Wet	1.72628E-05	1.28326E-06	1.632765496
	Dry vs Snow	1.44629E-05	3.12683E-07	1.785761332
	Dry vs Ice	1.21765E-06	0.008300834	1.736063614
	Wet vs Snow	2.06414E-07	0.330141543	1.735062137
	Wet vs Ice	1.64725E-05	0.000485363	1.756761934
55	Uphill vs Downhill	1.23876E-07	0.007420823	1.745063358
	Uphill vs Flat	1.33869E-05	0.004142628	1.751063806
	Downhill vs Flat	1.72136E-05	2.28866E-07	1.865761814
	Dry vs Wet	1.62439E-05	3.36382E-06	1.844066742
	Dry vs Snow	1.52576E-05	2.86384E-07	1.724036922
	Dry vs Ice	6.25612E-06	2.1092E-204	1.717650506
	Wet vs Snow	2.26917E-06	0.129971299	1.761215163
	Wet vs Ice	5.82662E-06	9.98755E-08	1.734063607

Source: VTTI

For brevity, only comparisons of the dry surface condition vs wet, snow and ice were presented in the table.

Other conditions, such as dry vs. wet or dry vs. snow were only calculated for the flat road surface, as similar differences were obtained for uphill/downhill road sections (see Appendix C). The table also shows that some of the *p*-values were considerably smaller (e.g., xxxE-05) than the selected threshold, α = 0.05, which strongly infers that there were significant differences between the respective data sets. Shaded cells are indicative of no statistical difference for the particular road condition being evaluated.

Statistical Comparisons of TI Ratios using US 460 Data

Figure 6-2 shows an example of statistical inference using data collected on US 460 via the Chevy Malibu at a constant speed of 60 mph and assuming equal means for the selected data blocks. In this case, the figure shows that there was no significant difference between the uphill and flat surface (the slope is around 1%, and so is considered small) as *p* (=0.155) > α (0.005), whereas a significant difference existed between the uphill and downhill directions (*p* = 3.471E-05 << 0.05). Similar results were obtained for other road conditions at constant speeds. No statistical dissimilarities were acquired for different speeds with the same road geometry. In other words, the hypothesis that the means and variances of TI ratios for the same road sections (e.g., dry uphill at 60 mph vs dry uphill at 70 mph) at different speeds was accepted as being true for *p* values > α.

Also, as illustrated in Figure 6-2, some comparisons between uphill/downhill and the flat road surface rendered *p* values > α for the US 460 sections only, implying that similar TI ratios could be obtained on moderate road inclines.

t-Test: Two-Sample Assuming Equal Variances			t-Test: Two-Sample Assuming Equal Variances		
	60 mph UpDry	*60 mph FlDry*		*60 mph UpDry*	*60 mph DnDry*
Mean	0.998563299	0.998876539	Mean	0.998563299	0.999123683
Variance	2.02842E-08	3.97914E-07	Variance	2.02842E-08	7.64704E-09
Observations	5	5	Observations	5	5
Pooled Variance	2.09099E-07		Pooled Variance	1.39656E-08	
Hypothesized Mea	0		Hypothesized Mea	0	
df	8		df	8	
t Stat	-1.083106323		t Stat	-7.497654835	
P(T<=t) one-tail	0.15516146		P(T<=t) one-tail	3.47157E-05	
t Critical one-tail	1.859548038		t Critical one-tail	1.859548038	
P(T<=t) two-tail	0.31032292		P(T<=t) two-tail	6.94315E-05	
t Critical two-tail	2.306004135		t Critical two-tail	2.306004135	

Source: VTTI

Figure 6-2. t-test statistical analysis of US 460 data collected with Chevy Malibu.

Another example of statistical inference of two different inclines on US 460 (1% and 8%), also using data collected via the Chevy Malibu, is presented in Figure 6-3. For this comparison, the *t*-test analysis indicated that the *p* values (highlighted) were both << α, meaning there was a significant difference between the two inclines.

t-Test: Two-Sample Assuming Equal Variances			t-Test: Two-Sample Assuming Equal Variances		
	70 mph UpWet (1%)	*70 mph UpWet (8%)*		*70 mph DnWet (1%)*	*70 mph DnWet (8%)*
Mean	0.998322782	0.996761019	Mean	0.999096543	1.000253563
Variance	1.78598E-07	2.76891E-07	Variance	2.01528E-07	5.10639E-09
Observations	5	5	Observations	5	5
Pooled Variance	2.27745E-07		Pooled Variance	1.03317E-07	
Hypothesized Mea	0		Hypothesized Mea	0	
df	8		df	8	
t Stat	5.174412291		t Stat	-5.691464619	
P(T<=t) one-tail	0.000424269		P(T<=t) one-tail	0.000229438	
t Critical one-tail	1.859548038		t Critical one-tail	1.859548038	
P(T<=t) two-tail	0.000848539		P(T<=t) two-tail	0.000458876	
t Critical two-tail	2.306004135		t Critical two-tail	2.306004135	

Source: VTTI

Figure 6-3. Statistical comparison between 1% and 8% road inclines on US 460.

Comparison between TI Ratios Acquired on the Smart Road vs US 460 Ratios

A comparison between TI ratios calculated from data collected on the Smart Road and US 460 is provided in Figure 6-4. In this example, data collected by the Chevy Impala on a dry surface at 55 mph on the Smart Road and 60 mph on US 460, in both the uphill and downhill direction, were employed to conduct the statistical analysis.

t-Test: Two-Sample Assuming Equal Variances			t-Test: Two-Sample Assuming Equal Variances		
	55 mph UpDry	*60 mph UpDry*		*55 mph DnDry*	*60 mph DnDry*
Mean	0.760689074	0.762019585	Mean	0.763973954	0.762800879
Variance	2.02178E-07	1.31982E-07	Variance	4.25423E-07	1.34834E-07
Observations	10	10	Observations	10	10
Pooled Variance	1.6708E-07		Pooled Varian	2.80129E-07	
Hypothesized Mea	0		Hypothesized	0	
df	18		df	18	
t Stat	-7.278487059		t Stat	4.956005414	
P(T<=t) one-tail	4.58219E-07		P(T<=t) one-ta	5.10627E-05	
t Critical one-tail	1.734063607		t Critical one-t	1.734063607	
P(T<=t) two-tail	9.16437E-07		P(T<=t) two-ta	0.000102125	
t Critical two-tail	2.10092204		t Critical two-t	2.10092204	

Source: VTTI

Figure 6-4. Statistical comparison between Smart Road and US 460 road inclines.

This comparison was carried out to assess the difference between two road inclines at different speeds and verify the results against the values obtained from the US 460 data described in the previous section.

The figure shows that for both Smart Road and US 460 road sections, significant differences existed, as the *p* values were considerably smaller than the threshold value α (= 0.05) selected for Student's t-test analysis. These statistical results indicate that TI ratios can accurately reveal variations in road geometry, if known data for a certain road segment are available, as well as sudden changes in road surface conditions for various speeds.

Additional statistical analyses data on all of the vehicles and road tests are presented in Appendix C.

As previously noted, this type of information would enable improved identification of slippery pavements and help provide superior input data for surface transportation decision support systems such as the Maintenance Decision Support System. Consequently, the real-time data supplied by the probe vehicles could enhance future decision support systems to serve traffic, incident and emergency management, and general roadway maintenance operations.

Chapter 7 Lessons Learned

Following, we present a number of lessons learned during the course of this study.

- Several vehicles scanned prior to being deployed for road testing did not have readily available parameters needed for TI ratio calculation even though the variable data identification name existed in the database created upon scanning. Their respective fields in the variable data block were either blank or displayed a zero value. It is believed that those parameters could be extracted only if the manufacturer were to provide access via proprietary software programs.

- For the 2015 Chevy Malibu, the network scanning process had to be conducted while the vehicle was driven at a speed above 20 mph to acquire the necessary parameters, as multiple static attempts rendered no valid information.

- A special OBD-II adapter was required to connect to the CAN bus to match the appropriate vehicle bus speed (i.e., medium or high speed CAN bus). To successfully record the raw wheel parameter data, the correct network and the bus speed of that network need to be identified.

Chapter 8 Summary and Conclusions

This report describes a novel approach aimed at evaluating real-time road surface conditions using data supplied by a vehicle's wheel-speed sensors. Using this approach, wheel pulse data acquired through the vehicle CAN, along with other parameters, could be used as a new tool to effectively detect slippery, and therefore hazardous, road conditions. This data can be shared among vehicles traveling in certain locations using connected vehicle technology to provide warnings or alerts about the imminent dangers.

The developed approach could also help to more effectively mitigate speed-related crashes or crash severity as well as further improve winter maintenance operations and reduce costs associated with materials and equipment, particularly when combined with other weather-responsive, traffic-management strategies. Additionally, this phase of the project investigated new aspects of the approach, such as varying speeds and road inclines, as well as employing a time-based traction measurement rather than distance measurement.

General findings based on the overall results from Phase II of the study include the following:

- Based on the wheel rotational data and calculated TI ratios for all vehicles, it can be inferred that the newly developed time-based TI ratio calculation approach performed better than the distance measurement technique for assessing different road surface conditions. This new approach, although based on the same nondriven over driven wheel pulses ratios, eliminated the requirement of measuring the traveled distances, which involved accurate collection of coordinates and lengthy calculations. An additional advantage is that certain road sections of interest of different lengths can be appraised based on start and end time stamps, which practically delineate that road segment without requiring precise measurement.

- Road sections of various inclines can be identified from calculated TI ratios as compared to known flat road segments, with TI values for flat sections always being situated between ratios acquired for uphill and downhill directions. In this scenario, the TI ratios obtained from downhill driving data were slightly larger than those calculated using uphill data for any surface condition or speed. These small differences indicate that, in the uphill direction, there is always more deformation at the driven wheels (i.e., an increase in wheel pulses) than the nondriven wheels. This phenomenon is more pronounced when the road surface becomes more slippery or the speed increases.

- Less inclined (i.e., below 2% grade) road sections such as US 460 produced moderately larger TI ratios than steeper sections (i.e., 6% grade or more) for uphill driving trips, whereas smaller ratios were obtained for driving downhill on a gradually decreasing gradient. It should be noted that although TI ratios decrease during uphill driving, the actual vehicle traction (or skid resistance) is not affected in any way, as the index is a parameter quantifying the degree of microslip rather than a coefficient of friction. In other words, a smaller TI ratio for the uphill direction does not indicate poorer friction compared to the downhill or flat surface ratios, *assuming similar driving speed and surface conditions*, but increased tire deformation at the driven wheels due to a shift in vehicle's center of mass. The ratio also supplies information about the change in surface condition during constant driving speed.

- Data analyses also indicated that progressively smaller TI values were acquired for increased surface slipperiness and speed while driving in both uphill and downhill directions, as well as on flat pavement, with significantly larger drops in TI values for the uphill direction (i.e., more driven tire deformation and slippage), especially for snow and ice covered surfaces.

- The newly time-based approach allows for almost instantaneous TI ratios to be calculated (i.e., for a 1 second period of time), a feature which can be a key indicator of localized road hazards such as water puddling during rain, or black ice in freezing temperatures. This information can be made available to drivers via alert messages provided in-vehicle, by phone, or by an alternative method, so that they can adjust their current driving to the new road conditions before the activation of the safety systems. For example, a certain speed value could be recommended via the head-up display to suggest safe driving conditions.

- TI ratios calculated for the snowy and icy surfaces showed, as expected, the lowest TI ratio values, indicating that considerably more rotation and microslip occurred at the driven wheel than the nondriven wheel compared to the wet surfaces.

- Acceleration and deceleration events produced additional deformation and slip at the driven wheels, which translated into a more rapid increase/decrease of the TI values than those acquired at constant speed, irrespective of direction of travel.

- Statistical analyses of TI ratios showed that there were significant differences among the diverse road surface conditions and speeds for all vehicles. Less significant differences were found for ratios acquired on similar surface conditions for various speeds (e.g., 50 mph vs 55 mph on a dry surface, etc.) or between flat and less-inclined road sections (1–2% slope), such as those driven on US 460.

Chapter 9 Recommendations

As this study aimed at evaluating the tire traction in various road weather conditions using vehicle native speed sensors it is expected that the information acquired in the process to be utilized by various departments of transportation to improve the timeliness of surface condition reporting updates. Therefore, based on the data analysis and findings of this study, the research team proposes the following recommendations:

FHWA should continue to fund research on using vehicle native sensors as mobile road weather data collected via vehicle probes will help fill existing gaps related to improving the timeliness of updated traveler information and the situational awareness of maintenance staff during field operations. The collected data may offer useful information regarding improved road condition reporting by maintenance staff.

FHWA should consider a small scale (e.g., district level) implementation of the proposed methodology for assessing the road surface conditions on maintenance vehicles. If feasible, additional variables such as fuel consumption or throttle position may be analyzed with the goal of better assessment of potential confounds that may impact accurate detection of pavement surface condition. The acquired data can be integrated into Weather Responsive Traffic Management (WRTM) and to support vehicle based CV safety systems through the basic safety message (BSM) data packet.

FHWA should also consider integrating collected vehicle sensor data into algorithms and applications that may result in more accurate analyses and forecasts of road weather parameters. The overarching goal of this initiative from a weather perspective is to utilize vehicle data to improve weather and road condition products such as characterization of surface conditions for weather models and to provide those products to transportation system decision makers and travelers. Moreover, collected data may be integrated into a data processor such as a Weather Data Translator (WDT) where it is filtered to extract only the data that represent selected parameters over a specific region and time.

Chapter 10 References

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APPENDIX A. List of Acronyms

ABS	Anti-lock Braking System
AWD	All-wheel drive
CAN	Controller Area Network
D	Driven (wheels)
DAS	Data Acquisition System
ESC	Electronic Stability Control
FHWA	Federal Highway Administration
FWD	Front-wheel drive
GPS	Global Positioning System
IMU	Inertial Measurement Unit
ND	Nondriven (wheels)
RWD	Rear-wheel drive
SSD	Solid-state drive
TCS	Traction Control System
TI	Traction Index
US 460	U.S. Route 460
VTTI	Virginia Tech Transportation Institute

APPENDIX B. Vehicle Traction Index Ratios

Table B-10-1. Traction Index Ratios for Chevy Tahoe (Smart Road)

Speed (mph)	Surface Condition	Road Geometry	Traction Index
45	Dry	Uphill	1.70936
		Flat	1.71323
		Downhill	1.71725
	Wet	Uphill	1.70826
		Flat	1.71255
		Downhill	1.71779
	Snow	Uphill	1.70826
		Flat	1.71113
		Downhill	1.71804
	Ice	Uphill	1.70561
		Flat	-
		Downhill	1.71192
50	Dry	Uphill	1.71075
		Flat	1.71287
		Downhill	1.71881
	Wet	Uphill	1.70784
		Flat	1.71302
		Downhill	1.71808
	Snow	Uphill	1.70681
		Flat	1.71104
		Downhill	1.71307
	Ice	Uphill	1.68836
		Flat	-
		Downhill	1.70994
55	Dry	Uphill	1.71037
		Flat	1.71202
		Downhill	1.71811
	Wet	Uphill	1.70845
		Flat	1.71285
		Downhill	1.71821
	Snow	Uphill	1.70048
		Flat	1.71008
		Downhill	1.71218
	Ice	Uphill	1.68836
		Flat	-
		Downhill	1.70994

Table B-10-2. Traction Index Ratios for Chevy Tahoe (US 460)

Speed (mph)	Surface Condition	Road Geometry	Traction Index
60	Dry	Uphill	1.71432
		Flat	1.71534
		Downhill	1.71641
	Wet	Uphill	1.71381
		Flat	1.71528
		Downhill	1.71637
	Snow @ 50 mph	Uphill	1.71170
		Flat	1.71381
		Downhill	1.71474
70	Dry	Uphill	1.71424
		Flat	1.71529
		Downhill	1.71623
	Wet	Uphill	1.71365
		Flat	1.71518
		Downhill	1.71603
	Snow @ 55 mph	Uphill	1.71151
		Flat	1.71338
		Downhill	1.71467

Table B-10-3. Traction Index Ratios for Chevy Impala (Smart Road)

Speed (mph)	Surface Condition	Road Geometry	Traction Index
45	Dry	Uphill	0.76149
		Flat	0.76249
		Downhill	0.76425
	Wet	Uphill	0.76136
		Flat	0.76243
		Downhill	0.76415
	Snow	Uphill	0.75968
		Flat	0.76198
		Downhill	0.76386
	Ice	Uphill	0.76052
		Flat	-
		Downhill	0.76402
50	Dry	Uphill	0.76084
		Flat	0.76226
		Downhill	0.76419
	Wet	Uphill	0.76021
		Flat	0.76216
		Downhill	0.76399
	Snow	Uphill	0.75886
		Flat	0.76192
		Downhill	0.76362
	Ice	Uphill	0.75748
		Flat	-
		Downhill	0.76294
	Dry	Uphill	0.76076
		Flat	0.76231

Speed (mph)	Surface Condition	Road Geometry	Traction Index
55		Downhill	0.76414
	Wet	Uphill	0.75988
		Flat	0.76225
		Downhill	0.76406
	Snow	Uphill	0.75836
		Flat	0.76244
		Downhill	0.76358
	Ice	Uphill	0.75703
		Flat	-
		Downhill	0.76304

Table B-10-4. Traction Index Ratios for Chevy Impala (US 460)

Speed (mph)	Surface Condition	Road Geometry	Traction Index
60	Dry	Uphill	0.76202
		Flat	0.76231
		Downhill	0.76280
	Wet	Uphill	0.76195
		Flat	0.76226
		Downhill	0.76278
	Snow @ 50 mph	Uphill	0.75953
		Flat	0.76166
		Downhill	0.76261
70	Dry	Uphill	0.76195
		Flat	0.76226
		Downhill	0.76278
	Wet	Uphill	0.76182
		Flat	0.76216
		Downhill	0.76275
	Snow @ 56 mph	Uphill	0.75953
		Flat	0.76166
		Downhill	0.76261

* Maximum speed was 56 mph

Table B-10-5. Traction Index Ratios for Chevy Equinox (Smart Road)

Speed (mph)	Surface Condition	Road Geometry	Traction Index
50	Dry	Uphill	0.97573
		Flat	0.97728
		Downhill	0.97815
	Wet	Uphill	0.97566
		Flat	0.97719
		Downhill	0.97677
60	Dry	Uphill	0.97586
		Flat	0.97714
		Downhill	0.97809
	Wet	Uphill	0.97536
		Flat	0.97707
		Downhill	0.97788

Table B-10-6. Traction Index Ratios for Chevy Equinox (US 460)

Speed (mph)	Surface Condition	Road Geometry	Traction Index
60	Dry	Uphill	0.97645
		Flat	0.97724
		Downhill	0.97843
	Wet	Uphill	0.97625
		Flat	0.97698
		Downhill	0.97836
70	Dry	Uphill	0.97638
		Flat	0.97718
		Downhill	0.97837
	Wet	Uphill	0.97617
		Flat	0.97692
		Downhill	0.97831

Table B-10-7. Traction Index Ratios for Chevy Malibu (US 460)

Speed (mph)	Surface Condition	Road Geometry	Traction Index
60	Dry	Uphill	0.99856
		Flat	0.99888
		Downhill	0.99912
	Wet	Uphill	0.99847
		Flat	0.99876
		Downhill	0.99909
70	Dry	Uphill	0.99852
		Flat	0.99884
		Downhill	0.99911
	Wet	Uphill	0.99832
		Flat	0.99882
		Downhill	0.99910

APPENDIX C. Statistical Data

Table C-10-1. t-Test Data Analysis for the Chevy Impala (US 460 Dry Surface Data)

Speed (mph)	Road condition	Variance	P variable (T<=t)
60	Uphill vs Downhill (Dry)	1.31982E-07	7.4395E-05
	Uphill vs Flat (Dry)	1.32178E-07	0.079344925
	Downhill vs Flat (Dry)	2.64273E-07	0.01248466
	Dry vs Wet (Flat Section)	2.54675E-07	0.389601802
70	Uphill vs Downhill (Dry)	4.48864E-08	3.13427E-06
	Uphill vs Flat (Dry)	1.32162E-07	1.98127E-07
	Downhill vs Flat (Dry)	8.34585E-08	0.001147825
	Dry vs Wet (Flat)	2.54543E-07	3.14421E-06

Note: Uphill vs Downhill, Uphill vs Flat, and Downhill vs. Flat values represent the dry surface condition.

Table C-10-2. t-Test Data Analysis for the Chevy Impala (US 460 Dry vs Wet Surface Data)

Speed (mph)	**Road condition**	**Variance**	**P variable (T<=t)**
60	Uphill (Dry-Wet)	1.31644E-07	7.46541E-05
	Flat (Dry-Wet)	1.26145E-07	0.03932631
	Downhill (Dry-Wet)	2.58253E-07	0.01368386
70	Uphill (Dry-Wet)	3.46425E-08	3.43422E-06
	Flat (Dry-Wet)	1.32162E-07	1.87134E-07
	Downhill (Dry-Wet)	8.33642E-08	0.001827753

Table C-10-8. t-Test Data Analysis for the Chevy Impala (US 460 Dry vs Snow Surface Data)

Speed (mph)	**Road condition**	**Variance**	**P variable (T<=t)**
50	Uphill (Dry-Snow)	1.34463E-07	7.39552E-05
	Flat (Dry-Snow)	1.32178E-07	0.079344925
	Downhill (Dry-Snow)	2.64273E-07	0.05248466
55	Uphill (Dry-Snow)	4.48594E-08	3.44625E-06
	Flat (Dry-Snow)	1.32468E-07	1.91237E-07
	Downhill (Dry-Snow)	8.34585E-08	0.001247328

***** Highlighted cells indicate marginal difference.

Table C-10-9. t-Test Data Analysis for the Chevy Tahoe (Smart Road Data)

Speed (mph)	Road condition	Variance	P variable (T<=t)
45	Uphill vs Downhill (Dry)	1.67328E-05	1.61502E-05
	Uphill vs Flat	2.06994E-05	0.044151697
	Downhill vs Flat (Dry)	1.36042E-05	0.000133458
	Dry vs Wet	1.34673E-05	0.004739604
	Dry vs Snow (Flat Section)	1.42027E-05	0.000718609
	Dry vs Ice	1.26853E-05	4.60082E-05
	Wet vs Snow	2.63776E-06	0.273867445
	Wet vs Ice	2.87462E-06	1.57364E-07
50	Uphill vs Downhill	1.62619E-05	1.49703E-05
	Uphill vs Flat	1.63823E-05	0.126879632
	Downhill vs Flat	1.46358E-05	2.78481E-05
	Dry vs Wet	1.63123E-05	0.176460851
	Dry vs Snow	1.70636E-07	0.002921702
	Dry vs Ice	1.49236E-05	0.047661841
	Wet vs Snow	1.064129-06	0.004734891
	Wet vs Ice	2.31953E-06	0.002737445
55	Uphill vs Downhill	3.50324E-06	0.003805387
	Uphill vs Flat	1.16503E-06	2.69125E-07
	Downhill vs Flat	2.33457E-06	1.06912E-05
	Dry vs Wet	1.12145E-05	2.19224E-07
	Dry vs Snow	1.51643E-06	3.23003E-06
	Dry vs Ice	2.04865E-05	2.76184E-06
	Wet vs Snow	1.55048E-05	1.08949E-07
	Wet vs Ice	2.06612E-06	1.11571E-06

Table C-10-10. t-Test Data Analysis for the Chevy Tahoe (U.S. 460)

Speed (mph)	Road condition	Variance	P variable (T<=t)
45	Dry vs Snow (Flat Section)	1.42027E-05	0.000586429
	Dry vs Ice	1.26853E-05	4.61588E-05
	Wet vs Snow	2.63456E-06	0.283167352
	Wet vs Ice	2.63428E-05	1.57364E-07
50	Uphill vs Downhill	1.62619E-05	1.49703E-05
	Uphill vs Flat	1.68426E-05	0.126879632
	Downhill vs Flat	1.56358E-05	2.78481E-05
	Dry vs Wet	1.63123E-05	0.176460851
	Dry vs Snow	1.71636E-07	0.002921702
	Dry vs Ice	1.49236E-05	0.054661841
	Wet vs Snow	1.064129-06	0.004734891
	Wet vs Ice	2.31953E-06	0.002737445
55	Uphill vs Downhill	3.50324E-06	0.003825387
	Uphill vs Flat	1.16384E-06	2.58126E-07
	Downhill vs Flat	2.63457E-06	1.22912E-05
	Dry vs Wet	1.12548E-05	2.48225E-07
	Dry vs Snow	1.52743E-06	2.43523E-06
	Dry vs Ice	2.14863E-05	2.56164E-06

	Wet vs Snow	1.46042E-05	1.33846E-07
	Wet vs Ice	2.06712E-06	1.41568E-06
60	Uphill vs Downhill	4.54327E-06	0.003805387
	Uphill vs Flat	1.17531E-06	2.69125E-07
	Downhill vs Flat	2.61455E-06	1.06912E-05
	Dry vs Wet	1.16148E-05	2.19224E-07

Table C-10-6. t-Test Data Analysis for the Chevy Equinox (US 460)

Speed (mph)	Road condition	Variance	P variable (T<=t)
60	Uphill vs Downhill (Dry)	1.44326E-05	1.56524E-05
	Uphill vs Flat	2.14948E-05	1.43128E-06
	Downhill vs Flat (Dry)	1.62241E-06	0.000156493
	Dry vs Wet	1.54543E-05	0.000873654
70	Uphill vs Downhill	1.32619E-05	1.79724E-06
	Uphill vs Flat	1.73524E-05	0.000426771
	Downhill vs Flat	1.41955E-05	2.65475E-05
	Dry vs Wet	2.13187E-05	0.000073464

APPENDIX D. Weather Parameters

Table D-10-11. Site Weather Parameters for Chevy Tahoe (Smart Road)

Pavement Surface Condition	Air Temperature (°C)	Road Temperature (°C)	Wind (mph)	Dew Point	Humidity (%)
Dry	16.7	23.6	1.2	12.4	81.8
Wet	13.9	10.8	2.2	13.2	88.7
Ice	-7.8	-13.8	0.4	-16	39.4
Snow	-3.2	-3.7	0.8	1.3	96.3

Table D-10-12. Site Weather Parameters for Chevy Impala (Smart Road)

Pavement Surface Condition	Air Temperature (°C)	Road Temperature (°C)	Wind (mph)	Dew Point	Humidity (%)
Dry	2.6	3.7	0.91	-11.6	36.6
Wet	7.6	9.5	6.41	1.7	71.3
Ice	-14.6	-15.8	0.32	-17.2	34.6
Snow	-11.5	-12.2	1.27	-6.8	42.6

Table D-10-13. Site Weather Parameters for Chevy Equinox (Smart Road)

Pavement Surface Condition	Air Temperature (°C)	Road Temperature (°C)	Wind (mph)	Dew Point	Humidity (%)
Dry	22.6	36.4	1.79	14.4	32.8
Wet	17.3	11.5	2.46	1.7	74.8

Table D-10-14. Site Weather Parameters for Chevy Malibu (Smart Road)

Pavement Surface Condition	Air Temperature (°C)	Road Temperature (°C)	Wind (mph)	Dew Point	Humidity (%)
Dry	22.6	36.4	1.79	14.4	32.8
Wet	17.3	11.5	2.46	1.7	74.8

APPENDIX E. Tire Parameters

Table E-10-15. Tire Parameters for Smart Road Testing (Chevy Tahoe)

Tire	Left Front		Right Front		Left Rear		Right Rear	
	Side	**Tread**	**Side**	**Tread**	**Side**	**Tread**	**Side**	**Tread**
	DRY PAVEMENT SURFACE (Apr 2015)							
Temperature (°C)	21.8	20.1	21.1	18.4	21.5	21.1	20.7	19.9
Pressure (psi)*	37		37		37		37	
	WET PAVEMENT SURFACE (Apr 2015)							
Temperature	21.6	20.1	23.4	21.6	21.8	21.9	20.8	19.7
	ICY PAVEMENT SURFACE (Feb 2015)							
Temperature	9.3	2.4	10.1	2.6	2.3	0.8	2.6	1.9
	SNOWY PAVEMENT SURFACE (Mar 2015)							
Temperature	8.4	6.2	7.1	6.4	7.4	6.4	6.6	5.8

* Tire pressure was kept constant for all vehicles during the testing sessions.

Table E-10-16. Tire Parameters for US 460 Testing (Chevy Tahoe)

Tire	Left Front		Right Front		Left Rear		Right Rear	
	Side	**Tread**	**Side**	**Tread**	**Side**	**Tread**	**Side**	**Tread**
	DRY PAVEMENT SURFACE (Apr 2015)							
Temperature (°C)	23.6	22.5	22.1	19.7	22.5	21.4	20.3	21.4
Pressure (psi)*	37		37		37		37	
	WET PAVEMENT SURFACE (Apr 2015)							
Temperature	22.6	22.3	23.1	22.8	21.9	22.6	21.6	21.8
	ICY PAVEMENT SURFACE (Feb 2015)							
Temperature	9.3	2.4	10.1	3.3	2.9	2.1	2.6	2.5
	SNOWY PAVEMENT SURFACE (Mar 2015)							
Temperature	7.8	6.6	6.3	5.7	7.7	6.8	7.4	8.3

Table E-10-17. Tire Parameters for Smart Road Testing (Chevy Impala)

Tire	Left Front		Right Front		Left Rear		Right Rear	
	Side	**Tread**	**Side**	**Tread**	**Side**	**Tread**	**Side**	**Tread**
	DRY PAVEMENT SURFACE (Feb 2015)							
Temperature (°C)	13.6	12.4	13.8	12.4	8.7	7.8	8.6	7.7
Pressure (psi)	34		34		34		34	
	WET PAVEMENT SURFACE (Apr 2015)							
Temperature	14.6	13.8	14.8	13.5	12.7	10.9	13.2	12.6
	ICY PAVEMENT SURFACE (Feb 2015)							
Temperature	7.2	1.8	6.8	1.4	6.5	1.2	6.4	1.1
	SNOWY PAVEMENT SURFACE (Mar 2015)							
Temperature	6.9	5.8	6.3	5.9	7.1	6.6	6.4	5.9

Table E-10-18. Tire Parameters for US 460 Testing (Chevy Impala)

Tire	Left Front		Right Front		Left Rear		Right Rear	
	Side	Tread	Side	Tread	Side	Tread	Side	Tread
	DRY PAVEMENT SURFACE (Feb 2015)							
Temperature (°C)	13.6	12.4	13.8	12.4	8.7	7.8	8.6	7.7
Pressure (psi)	34		34		34		34	
	WET PAVEMENT SURFACE (Apr 2015)							
Temperature	14.6	13.8	14.8	13.5	12.7	10.9	13.2	12.6
	ICY PAVEMENT SURFACE (Feb 2015)							
Temperature	7.2	1.8	6.8	1.4	6.5	1.2	6.4	1.1
	SNOWY PAVEMENT SURFACE (Mar 2015)							
Temperature	6.9	5.8	6.3	5.9	7.1	6.6	6.4	5.9

Table E-10-19. Tire parameters for Smart Road testing (Chevy Equinox)

Tire	Left Front		Right Front		Left Rear		Right Rear	
	Side	Tread	Side	Tread	Side	Tread	Side	Tread
	DRY PAVEMENT SURFACE (Mar 2015)							
Temperature (°C)	14.4	12.4	13.8	12.4	8.7	7.8	8.6	7.7
Pressure (psi)*	38		38		38		38	
	WET PAVEMENT SURFACE (Mar 2015)							
Temperature	15.7	13.8	14.8	13.5	12.7	10.9	13.2	12.6
	ICY PAVEMENT SURFACE (Feb 2015)							
Temperature	6.5	1.4	6.8	1.4	6.5	1.2	6.9	2.1
	SNOWY PAVEMENT SURFACE (Mar 2015)							
Temperature	6.2	5.8	6.3	5.9	6.3	6.6	6.7	6.2

Table E-10-20. Tire parameters for US 460 testing (Chevy Equinox)

Tire	Left Front		Right Front		Left Rear		Right Rear	
	Side	Tread	Side	Tread	Side	Tread	Side	Tread
	DRY PAVEMENT SURFACE (Apr 2015)							
Temperature (°C)	21.8	20.1	21.1	18.4	21.5	21.1	20.7	19.9
Pressure (psi)*	37		37		37		37	
	WET PAVEMENT SURFACE (Apr 2015)							
Temperature	21.6	20.1	23.4	21.6	21.8	21.9	20.8	19.7
	ICY PAVEMENT SURFACE (Feb 2015)							
Temperature	9.3	2.4	10.1	2.6	2.3	0.8	2.6	0.9
	SNOWY PAVEMENT SURFACE (Mar 2015)							
Temperature	7.8	6.9	7.1	6.4	7.4	6.4	6.6	5.8

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