

IMPROVEMENTS TO VEHICLE TRACTION CONTROL SYSTEM USING ROAD DATA

Robert Binns
Mechanical Engineering Department
Virginia Tech
Danville, VA

Saied Taheri, PhD
Associate Professor
Mechanical Engineering
Virginia Tech
Danville, VA

John B. Ferris, PhD
Associate Professor
Mechanical Engineering
Virginia Tech
Danville, VA

ABSTRACT

Consumer demand and regulatory pressure have forced automakers to develop features designed to increase passenger car safety regardless of road surface or weather condition. In response, the intelligent tire, proposed in the APOLLO report, is introduced and the parameters useful for traction control system development are identified. Traction control system models are introduced and discussed. A simple vehicle model based on the quarter-car is presented, incorporating a traction control system and tire friction model. This model utilizes the LuGre friction model to relate tractive force to slip ratio and road surface friction level. A sliding-mode control strategy is chosen to model traction control behavior. Three case studies are conducted on two simulated road surfaces to show the interaction between estimated friction level in the sliding-mode control strategy and the tire friction model. To simulate the intelligent tire, where the road surface friction level is directly measured, the estimated friction level and actual road surface friction are set equal. Simulation results demonstrate that an accurate estimation of road surface friction level, which can be directly measured using the intelligent tire, enable the traction control model to control slip ratio to the desired level while not intervening unnecessarily across the two surfaces studied.

INTRODUCTION

Increased regulatory pressure on automakers to improve vehicle safety combined with customer demand for new feature content has led to the development of numerous systems designed to help the driver maintain control of the vehicle when encountering hazardous conditions. While these systems attempt to control the road-tire interaction through assumptions and estimations, the performance of these systems is limited to the accuracy of these estimations. The intelligent tire, proposed in the APOLLO report, is capable of measuring lateral, longitudinal, and normal forces on the tire in addition to estimated road surface friction level. This system, by allowing direct measurement of the tire-road contact forces, offers significant opportunity to

simplify and improve vehicle control system performance across a wide variety of conditions.

The traction control system is reviewed, discussing current attempts to adapt to changing road surface characteristics. Meanwhile, the intelligent tire is presented and its benefits to longitudinal vehicle dynamics are described. A simple traction control system is modeled as a proof of concept to demonstrate the positive impact of the intelligent tire on vehicle control systems. The benefits available from the intelligent tire for the TCS system is discussed. Finally, a traction control system model is developed to demonstrate the quantitative benefits of the intelligent tire.

BACKGROUND

Traction Control Systems

Traction control systems (TCS) are primarily responsible for maximizing adhesion between the tire and road when slip occurs due to an excessive amount of driving torque [1]. Slip ratio, shown in represents the difference between actual vehicle speed, v_x , and the product of the driven wheel rotational speed, ω_w , and rolling radius, R_w :

$$\lambda = 1 - \frac{v_x}{R_w \omega_w} \quad [1]$$

For a slip ratio of 1, the driven wheels spin while the vehicle is stationary. Likewise, a slip ratio of 0 indicates no driven wheel slip. Typical critical slip values, where the tire can generate the highest longitudinal force, vary between 0.08 and 0.3 [1]. Therefore, in order to maximize tractive effort in a stable manner, TCS algorithms strive to maintain a slip ratio level coincident with the "stable region".

In a typical driving scenario, spinning wheels reduce traction to the point where the driver loses control. It also contributes to high rates of wear of the chassis and tire. In a front-wheel drive vehicle, loss of traction by the driving wheels reduces the drivers ability to steer the vehicle. While in a rear-wheel drive vehicle, the control of the vehicle is compromised, and the driver could suffer an accident.

The TCS controller regulates wheel slip by managing drive torque applied to the wheels. This is accomplished by either reducing engine torque or applying the brakes [1]. For vehicles equipped with drive-by-wire control, the engine control unit (ECU) must command a reduction in torque. The ECU can either command a reduction in throttle opening or increase the spark retard.

Significant research has occurred in the area of TCS algorithms. Kabgarian proposed a TCS model based on the sliding mode control method [2]. The sliding mode controller is designed based on dynamic surface control, with the first sliding surface, S_1 , described as the difference between measured slip ratio, λ , and desired slip ratio, λ_{des} :

$$S_1 = \lambda - \lambda_{des} \quad [2]$$

Combining the sliding mode formulation with the equation of motion for the wheel and tire, the desired wheel torque is determined:

$$T_{wf} = \frac{R_w \omega_w^2 I_w}{v_x} \left[\frac{v_x}{R_w \omega_w} + \lambda_{des} - \eta \text{sgn}(S_1) \right] + T_{roll} + R_w F_x \quad [3]$$

The model was evaluated by Kabgarian in simulation with satisfactory performance.

Kang proposed to improve this method using a boundary layer in the sliding mode observer [3]. In addition, the sgn function was replaced with the saturation function, reducing non-linearity in the system.

The TCS algorithm proposed by Kabgarian has been shown to sufficiently control wheel slip to a desired level. However, the desired and optimal slip ratios can differ as the vehicle traverses different types of terrain. If a conservative *a priori* desired slip is chosen, it can control wheel slip to a desired level. However, if a desired slip in excess of the critical slip is chosen, the TCS will allow enough wheel slip such that control can become compromised. Therefore, simple TCS control strategies can be significantly improved through the use of method to estimate road-surface friction with sufficient confidence to predict the critical slip value for a wide variety of road conditions.

Understanding the road-tire surface friction properties is a critical aspect of a successful TCS implementation. Since most vehicles have very few sensors from which to estimate the state of the road surface, significant development has occurred in the area of both modeling and estimating friction properties and other road surface characteristics in real time. The nonlinear behavior of road-surface friction is primarily due to the fact that the friction coefficient, relating normal force to maximum sliding force, is a function of, among many factors, slip ratio [4]. Maximum friction force, F_f , can therefore be simplified in terms of the vertical force, F_z , applied on the tire [5]:

$$F_f = \mu(s) F_z \quad [4]$$

The Pacejka Magic Formula can be used to estimate the relationship between normal force, longitudinal slip, road surface friction, and longitudinal force [6]. While this semi-empirical model has been widely used in estimating the behavior of the pneumatic tire over the road, the coefficients for this model depend directly on the road surface and tire properties [5]. In addition, while the MF model has been shown to accurately predict quasi-static behavior, it is not a dynamic friction model, such as the LuGre model. de Wit proposes a derivation of this model:

$$\dot{z} = v_r - \frac{\sigma |v_r|}{g(v_r)} z \quad [5]$$

$$F = (\sigma_0 z + \sigma_1 \dot{z} + \sigma_2 v_r) F_n \quad [6]$$

$$g(v_r) = \mu_c + (\mu_s - \mu_c) e^{-|v_r/v_s|^{1/2}} \quad [7]$$

Where z is the internal friction state, F is the longitudinal force, F_N is the normal force, v_r is the relative velocity between the point of contact and the wheel center, v_s is the Stribeck relative velocity, μ_c is the coulomb friction coefficient, and μ_s is the coefficient of sliding friction. Tire properties are captured in the σ coefficients. It was shown that the lumped model shown above suitably approximates distributed models accounting for contact patch area [5].

For vehicles with an electric drivetrain, the output torque of the motor can be estimated with sufficient accuracy. Sado exploits this in developing a road-load observer comparing known motor torque and wheel dynamics [4]. The friction coefficient is then obtained by dividing by the normal force. Time rates of change of both friction coefficient and slip ratio are compared, with an adaptive parameter "A" updated using both the recursive least squares or fixed trace algorithm. Assuming a stable calculation of the "A" parameter, the optimal slip ratio for a given road surface friction characteristic can be determined. Since this method is dependent on knowledge of powertrain torque, it is limited to use in electric or hybrid electric drivetrains. Vehicles with conventional powertrains, where torque estimation is a significant issue [7], would not benefit from this development.

Intelligent Tire

All forces and moments acting on the vehicle are transmitted through the tires, and these forces form the foundation of ride, handling, and driveability of the vehicle [8]. The conventional tire is passive systems, with no way of measuring or communicating the loads it is currently undergoing. Methods have been developed to correlate information about the tire-road interface such as friction level with measurements from other components of the vehicle [9]. However, these methods fall short in predicting the actual loads experienced by the tire. The APOLLO project, combining the efforts of both industry and academia, was charged with developing an "intelligent tire" with sensors capable of measuring lateral, longitudinal, and normal forces [10]. In addition, the intelligent tire can also estimate peak friction levels in real-time. The intended use of the intelligent tire is to improve safety and performance of passenger vehicles. For current vehicle dynamics control systems, force and friction data enables automakers to significantly improve performance over a wide variety of conditions. It also helps automakers further improve their vehicles with advanced driver assistance systems such as collision avoidance and automated emergency braking.

MODEL DESCRIPTION

Vehicle Model

A simple 2 degree of freedom longitudinal quarter-car model is proposed to study the interaction between road surface friction and TCS performance. The mass is free to translate and rotate along a flat surface. Factors such as grade and longitudinal dynamics of the vehicle, while important in physical vehicle behavior, are neglected. The free body diagram for this model is shown in Figure 3.

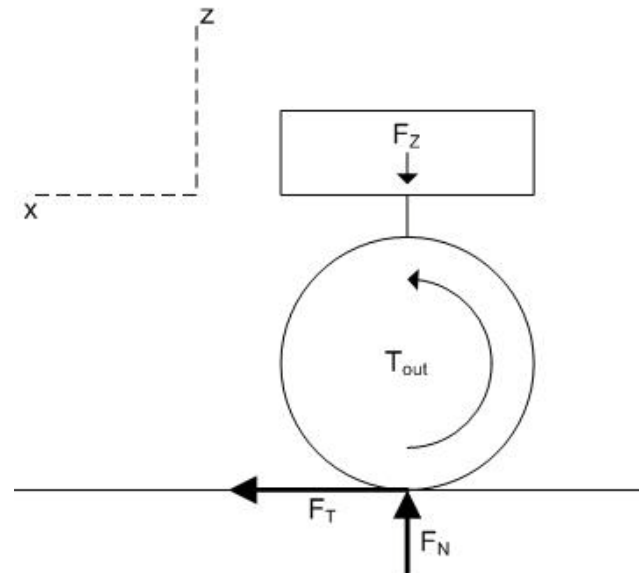


Figure 1. Free body diagram for quarter-car model

The vehicle is considered in static equilibrium in the vertical (z) direction, but the normal force due to the mass of the vehicle is accounted for in the friction model. Unlike some basic dynamic models, the no-slip condition is not enforced between the rotating mass and the ground. Slip is allowed since the friction force, F_T , depends on slip ratio. Finally, output torque, T_{out} , represents the combination of powertrain and braking torque, where TCS intervenes as necessary.

Powertrain Model

The vehicle powertrain is modeled as a lookup table relating throttle position and engine speed to engine output torque. It is based on a quasi-steady state approximation of engine torque. At a given engine speed, the output torque is a percentage of the maximum torque corresponding to the

throttle input. Pedal or throttle level represents the driver's demand.

Engine output torque is arbitrated against external requests. When an external system, such as the transmission or TCS controller, requests a reduction in engine torque, the ECU overrides the driver's demand. On the contrary, when no systems intervene, the driver's demand torque level "wins" arbitration and engine torque remains at that level.

Powertrain output torque is determined by multiplying engine torque by the torque converter ratio (in the case of an automatic transmission), transmission ratio, and final drive ratio. In an effort to replicate the behavior of a production vehicle, the model utilizes the second gear (1.56:1) and final drive (3.06:1) ratios used in the GM HydraMatic 4T65E-HD transmission [11]. The first gear ratio, 2.92:1, is too short for this simulation. When operating at high throttle conditions, the engine quickly approaches the engine's maximum speed (6,000 rpm) and the engine's maximum possible output torque drops significantly, causing wheel slip reduction in addition to that caused by torque reduction requests from the TCS controller.

Tire Friction Model

For simple dynamic models, the sliding friction force between two objects is proportional to the normal force between them. However, the friction force between the tire and road surface is a complex interaction, and therefore a model is required to accurately predict the friction force. The LuGre model proposed by de Wit [5] is chosen for this study. This model is selected as a computationally efficient lumped model capable of reasonably capturing the tire's dynamic friction properties. Baseline model parameters concerning the tire and road surface remain unchanged from de Wit:

Table 1. LuGre Model Parameters

Parameter	Value	Units
σ_0	40	1/m
σ_1	4.9487	s/m
σ_2	0.0018	s/m
μ_s	0.5	-
μ_c	0.9	-
v_s	12.5	m/s

As an initial study, the friction model is evaluated for variation in vehicle speed and friction. Each curve is normalized to the normal force of the vehicle. The non-linear relationship between slip ratio and estimated simple friction coefficient demonstrates the need for a dynamic friction model as opposed to a simple friction model. The curves in Figure 4 suggest significant sensitivity to vehicle

speed in terms of both optimal slip ratio and maximum possible longitudinal force (coincident with highest coefficient of friction). In addition, the maximum possible longitudinal force and optimal slip ratio varies with estimated surface friction as shown in Figure 5.

Both figures suggest an approximate optimal slip ratio of 0.1 - 0.2 for this model. For all simulation studies in this report, the optimal slip ratio is held constant and 0.12.

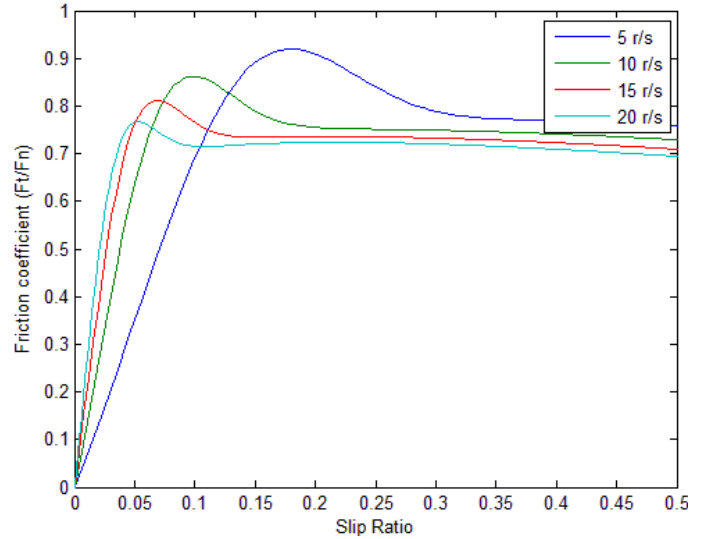


Figure 2. Tire-road friction coefficient dependence on speed

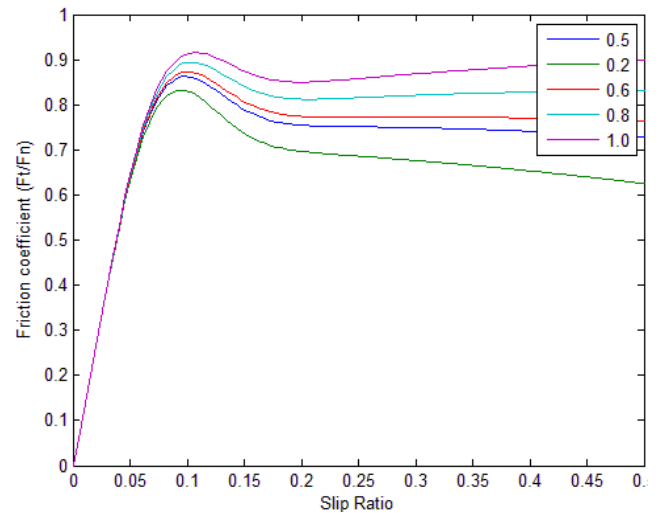


Figure 3. Tire-road friction level dependence on road surface friction coefficient

TCS Control Model

The simulation employs a slip-based TCS algorithm using sliding-mode control [12]. Sliding mode control is a non-linear control strategy that utilizes high-frequency switching action to force a sliding surface to converge to equilibrium in a finite time [13]. For this application, the sliding surface is considered the difference between the slip ratio and a desired slip ratio [5]. For a one-wheel friction model similar to what is used in this simulation, de Wit proposes the control law [5]:

$$u = \left[\frac{J}{rm(1 - s_d)} + r \right] F - k * \text{sgn}(S) \quad [8]$$

Where u is the estimated torque to maintain control, J is the polar moment of inertia of the vehicle, r is the tire radius, m is the mass of the vehicle, s_d is the desired slip ratio, F is the maximum estimated tractive effort (force), and k is a gain. The sliding surface, S , is a function of the slip ratio and the desired slip ratio:

$$S = (s - s_d) r \omega \quad [9]$$

The gain k helps improve rate of convergence of the sliding surface to equilibrium. For this model, the gain is modeled in terms of vehicle properties and an adjustable gain η :

$$k = \frac{J}{(1 - s_d) r \eta} \quad [10]$$

The sliding mode control algorithm presented in equation 8 has been shown to be a robust control strategy, however it is susceptible to chattering. To alleviate this phenomenon, De Wit proposes a modification to the control law in equation [8], where the sign function is replaced with the saturation function [5]. This helps stabilize system behavior near equilibrium, which can be seen in reduced chatter in the TCS desired output torque. For this study, the saturation function is utilized, and is represented in equation 11:

$$u = \left[\frac{J}{rm(1 - s_d)} + r \right] F - k * \text{sat}(S/\varphi) \quad [11]$$

In Figure 4 and Figure 5, the slip ratio corresponding to the maximum possible longitudinal force varies with both road surface friction and vehicle speed. Efforts have been

made to dynamically estimate the optimal slip ratio by fitting the vehicle's behavior to the LuGre model using an adaptive fuzzy-neural controller [14]. For simplicity, this model will consider the optimal slip ratio to be 12%, and constant for all conditions. The maximum tractive force, F , is approximated as the product of the normal force due to the weight of the vehicle and a friction coefficient.

Preliminary test results plotted in Figure 6 show that the TCS algorithm controls wheel slip with sufficient accuracy. In this plot, the same test case is presented with both TCS enabled and disabled. When disabled, the TCS controller does not request a torque reduction from the powertrain controller. The slip ratio in this case exceeds 0.7, and only reduces because the engine speed is allowed to approach its maximum speed. For most conventional SI engines, the maximum possible torque falls precipitously after reaching the operating point yielding maximum horsepower. However, with TCS on, wheel slip is well restricted to the calibrated 0.12 level. If a driver were operating a vehicle with TCS on, the reduced wheel slip would allow him or her to maintain adequate control of the vehicle.

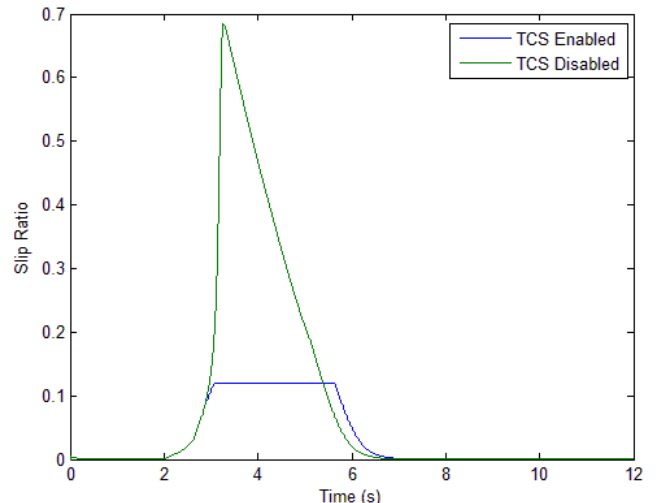


Figure 4. Modeled wheel slip with TCS enabled or disabled

While the test in Figure 6 shows the ability of the TCS to limit wheel slip in high-slip maneuvers, an alternative case is studied where the driver only steps on the throttle 20%. This represents a normal driving scenario, such as entering a highway, where some non-trivial wheel slip would occur, but not enough to require intervention by the TCS. Clearly, the slip ratio resulting from the drivers application of the throttle in Figure 7 is not severe enough to warrant a TCS intervention.

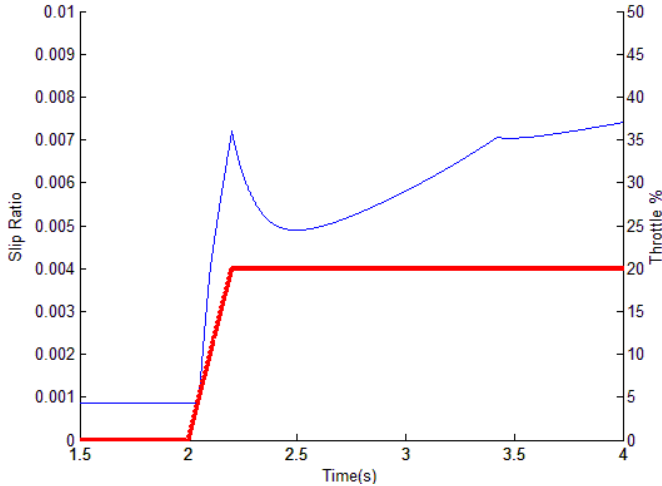


Figure 5. Wheel slip behavior for events where TCS intervention not required

Simulation Results

Case Description

A series of case studies represent a typical driving scenario on different surfaces and TCS controller configurations. In this study, the driver simply steps on the gas pedal resulting in an output torque and hence tractive force sufficient to cause significant wheel spin. Since the LuGre model does not accurately model tire dynamics at low speed, the simulation begins with the vehicle rolling at a 5 m/s steady state velocity with a slip ratio of 0 (pure rolling). Approximately 2 seconds after the simulation begins, the "driver" increases the throttle position to a constant level, resulting in an increased output torque to the powertrain. For the three test cases with varying friction levels, the driver will step to 65% throttle position at a rate of 100 % / sec. This level is maintained for the remainder of the test.

Road surface friction properties are lumped into two friction coefficients used in the LuGre model - the normalized Coulomb and static friction coefficients. The TCS model has a single friction parameter to estimate road surface friction properties. For the three test cases, the TCS model will overestimate, underestimate, and correctly estimate the road surface static friction value. The Coulomb and static friction coefficients for both test cases are 0.5 and 0.9, respectively, to simulate a normal road and 0.2 and 0.6, respectively, for a slick road. The system adjustable gain η remains constant at 600.

TCS Overestimates Road Surface Friction

In the first test case, the TCS estimates a static coefficient of friction of 1. This represents an overestimate of the road surface friction level. The consequence of this configuration is a calculated torque limit to maintain optimal slip ratio that is higher than necessary. If the difference between the controller's estimate and the actual friction coefficient is substantial, the controller may not be able to control the slip ratio to the desired level. In Figure 8, this behavior is confirmed in the lack of control seen over the slick road. For the normal road, however, the controller was able to maintain the optimal slip ratio. Equally important to slip ratio is the output torque during these maneuvers. In Figure 9, it is clear that for the slick road, the torque reduction requested by the TCS was greater than what was requested for the normal road, yet it was insufficient for reducing wheel slip to the desired level.

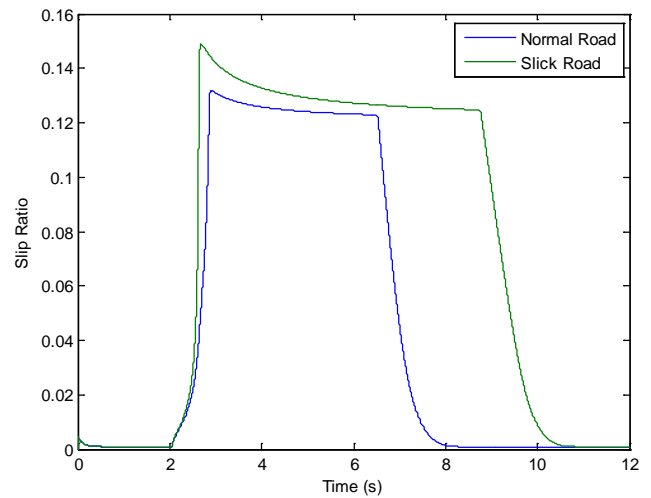


Figure 6. Wheel slip behavior when TCS overestimates friction level

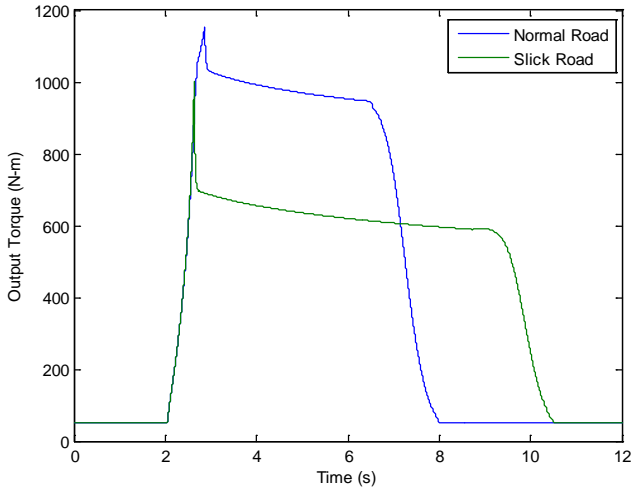


Figure 7. Output torque controlled by TCS when friction level overestimated

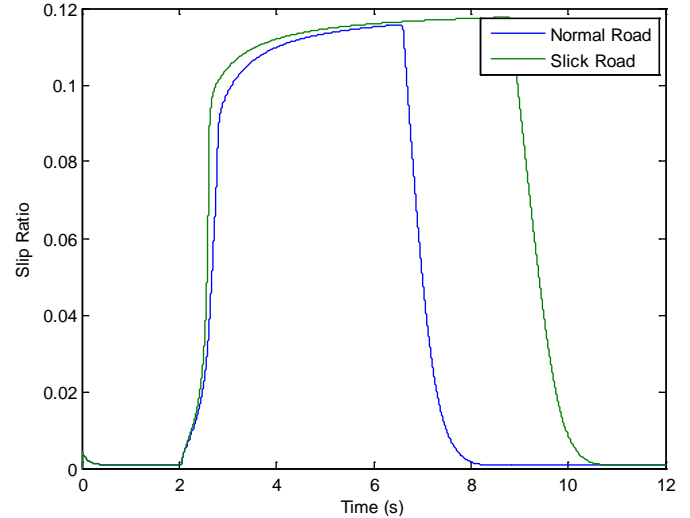


Figure 8. Wheel slip behavior when TCS underestimates friction level

TCS Underestimates Road Surface Friction

For the second test case, the same maneuver is performed, but now the TCS is configured to underestimate the road surface friction level. This primarily affects the first term of the control law equation, specifically in the estimate of maximum longitudinal force. In Figure 10, the TCS is able to maintain the optimal slip ratio for the slick surface. However, for the normal road, slip ratio does not exceed 0.05. The torque behavior in Figure 11 shows that for both cases, the output torque is limited to a lower level than allowed in the previous test case. While the TCS intervention on the slick road appears reasonable, the TCS improperly intervened while driving on the normal road. In this case, the vehicle's performance is compromised by excessive TCS intervention. In Figure 12, the distance traveled by the vehicle on a normal road where the TCS overestimated road surface friction level clearly exceeds the distance traveled by the same vehicle where the TCS underestimated the road surface friction level. This behavior is undesirable because while the system intervenes adequately on slick roads, the system produces unnecessary torque reduction interventions, compromising vehicle performance over normal roads.

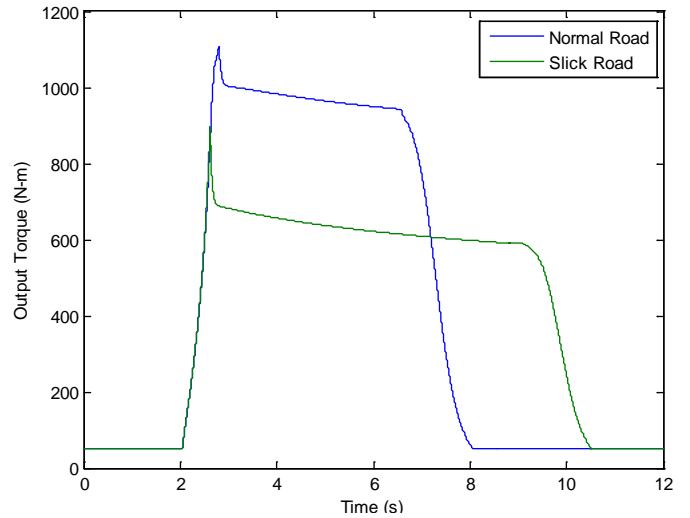


Figure 9. Output torque behavior when TCS overestimates friction level

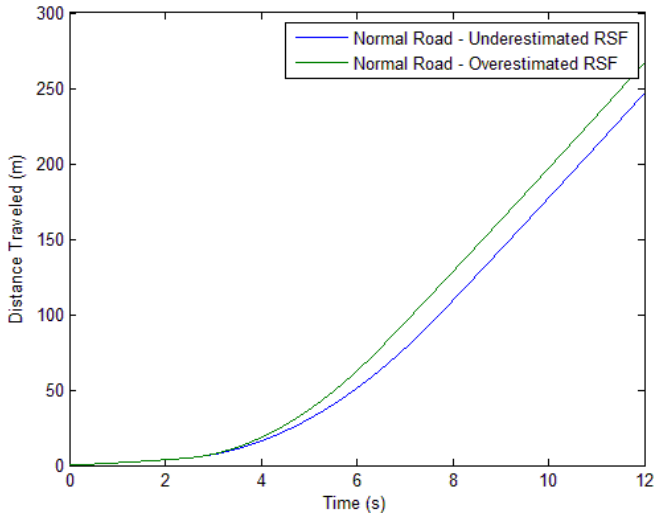


Figure 10. Distance traveled on normal road by vehicle with over and under estimate of road surface friction

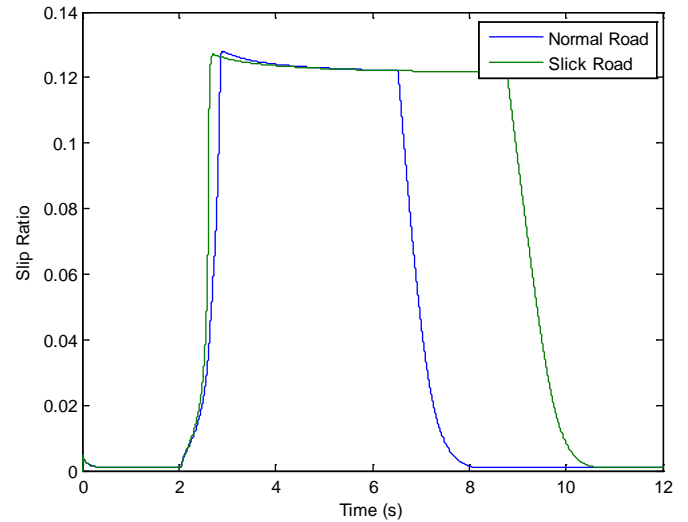


Figure 11. Wheel slip behavior when TCS correctly estimates friction level

TCS Correctly Estimates Road Surface Friction

To simulate the effects of the intelligent tire, the TCS estimated friction level is set equal to the actual static friction level for both the normal and slick road. In practice, the intelligent tire would continuously estimate and communicate the estimated coefficient of friction to other control systems on the vehicle. As mentioned previously, with proper characterization of the tire, the optimal slip ratio can be estimated as well. However, this model assumes an optimal slip ratio of 0.12. In Figure 13, the slip ratio behavior indicates the TCS controller effectively controls slip to the desired level for both the normal and slick roads. In addition, the requested torque reduction shown in Figure 14 is proportional to road surface friction level. This represents a significant performance improvement over the previous case studies in that the TCS intervenes when necessary and adequately controls slip ratio on both normal and slick roads.

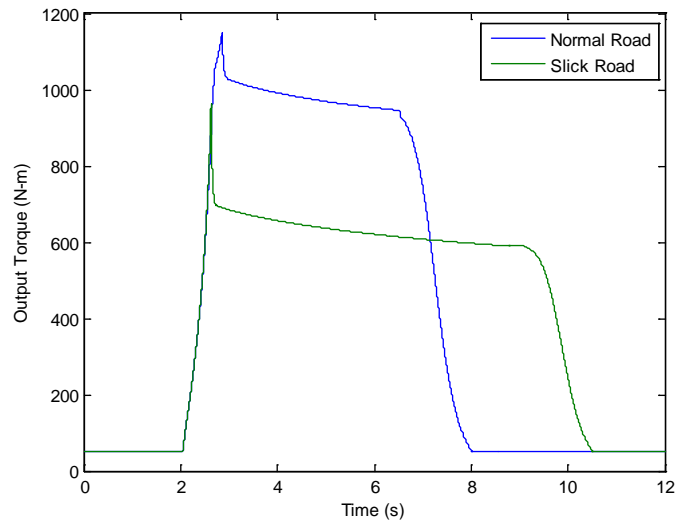


Figure 12. Output torque behavior when TCS correctly estimates friction level

DISCUSSION

The optimal TCS behavior described in the third test case is possible when the control algorithm can deduce or observe and accurate estimation of road friction. While many approaches to estimating road surface friction occur by observing parameters such as wheel slip [4, 15, 16], an improper estimate or slow learning rate could compromise performance of the TCS over roads where the friction level can change significantly - such as over patches of black ice. Friction information provided by an intelligent tire is therefore advantageous because the information is provided in real time. It also simplifies control algorithm

development, where complex calculations can be replaced with a single value received over in-vehicle communication networks. This releases valuable controller memory space that can be reallocated toward feature development.

Future work in this area includes the use of measured terrain in simulation. By utilizing an accurate representation of the actual road, the simulation can be more directly compared to real-world testing. Furthermore, this control algorithm could be applied to a more complex vehicle model, such as a 7-degree of freedom model, to simulate a specific vehicle and drivetrain combination. Finally, this study can be expanded to incorporate other traction control models, which can be useful for assessing relative sensitivity to road surface characteristics.

CONCLUSION

An accurate friction estimate, such as what is possible using the intelligent tire, provides significant benefit to TCS control system development. It reduces the need to develop computationally expensive methods of estimating tire-road friction behavior. For a simple TCS model, friction information from the intelligent tire improved system performance over both normal and slick road conditions. While methods to estimate the road surface friction could be utilized in place of the intelligent tire, direct measurement of friction information represents the most computationally efficient means of estimating road surface friction levels, leading to improved performance and safety regardless of road condition.

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