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Impact of Terrain Variability on Chassis Parameter Identifiability for a Heavy-Duty Vehicle

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Abstract— **This paper analyzes the impact of road grade variability on the identifiability of vehicle chassis parameters. The paper is motivated by the need for accurate parameter estimation in both active safety and chassis model validation applications. The literature addresses this need through several algorithms capable of both estimating vehicle chassis parameters from experimental data and assessing the accuracy of these estimates. However, the dependence of these algorithms' estimation accuracy on road grade variability remains relatively unexplored. We address this research problem in the specific context of utilizing nonlinear least squares methods for estimating the parameters of a longitudinal vehicle dynamics model. Specifically, we use Fisher information analysis to obtain Cramér-Rao bounds on the accuracy of the least squares parameter estimates. We then examine the impact of mean square road grade variability on these error bounds, both in simulation and experimentally. This examination is performed for a heavy-duty commercial truck, which is instrumented and driven on a variety of rural and interstate roads for the purpose of gathering experimental data. The impact of terrain variability on parameter identifiability is shown to be quite significant, both in simulation studies and experiments.**

I. INTRODUCTION

This paper examines the problem of evaluating the accuracy with which the parameters of a longitudinal vehicle dynamics model can be estimated from experimental data. The paper focuses specifically on the impact of road grade variability on this estimation accuracy. Estimating vehicle chassis parameters serves several important purposes. Accurate estimation of chassis parameters allows precise simulation of vehicle longitudinal dynamics, which can help researchers model and predict vehicle performance. Comparing chassis parameter estimates to known parameter values also enables a degree of chassis model validation. Finally, vehicle parameter estimation is becoming increasingly important as the transportation infrastructure trends towards intelligent vehicle systems, where real-time parameter estimates can be important for evaluating performance under varying road and vehicle conditions [1].

Different methods exist in the literature for estimating vehicle chassis parameters from experimental data. One can classify these algorithms based on the dynamic models used for estimation. For instance, there is a significant body of literature on estimating parameters such as the mass, rolling resistance, and aerodynamic drag coefficient of a vehicle using a model of its longitudinal dynamics. One example is Bae *et al.*'s utilization of road data from a passenger automobile, together with a model of its longitudinal dynamics, to estimate the above parameters [2]. More recent research by Altmannshofer *et al.* develops a longitudinal dynamics-based parameter estimation algorithm that accommodates non-Gaussian measurement errors and insufficient excitation [1]. Furthermore, in the absence of road grade data, Vahidi *et al.* develop an estimation algorithm that estimates a vehicle's mass, drag coefficient, and the underlying road's grade [3-4]. Other work applies Bayesian methods to this estimation problem with similar success [5].

Beyond longitudinal dynamics, one can also estimate a vehicle's chassis parameters, including its mass, from vertical and lateral dynamics. For example, work by Rajamani *et al.* demonstrates the effective estimation of vehicle states and mass through measurement of suspension dynamics [6]. More recent work by Pence *et al.* estimates vehicle parameters using suspension dynamics, with significant emphasis on the use of low-cost sensors [7]. Lateral and powertrain dynamics have also been applied to estimate vehicle states and chassis parameters successfully [8-9].

The accuracy with which the above algorithms can estimate vehicle parameters depends on the choice of vehicle, choice of algorithm, and most importantly the choice of *experiment* used for estimation. Estimating the parameters of a vehicle's suspension dynamics model, for instance, requires rich vertical road excitations. Müller *et al.* demonstrate this by showing how the addition of speed bumps in a road test increases the accuracy of the resulting parameter estimates [10]. Given this interplay between the design of vehicle experiments and the accuracy of the resulting parameter estimates, the automotive industry has developed guidelines and standards for chassis testing. One common testing standard is SAE J2263, which details a coast-down experiment that generally yields a dataset rich enough to provide accurate estimates of several chassis parameters [11].

In summary, there is a rich existing literature on estimating vehicle chassis parameters from experimental data. Moreover, this literature recognizes the impact of the design of a vehicle experiment on the accuracy of the resulting chassis parameter estimates. One question that remains relatively unexplored by this literature is the relative impact of different vehicle test characteristics on chassis parameter estimation accuracy. For example, if one's goal is to estimate a vehicle's mass from its longitudinal dynamics, it is reasonable to anticipate better estimation accuracy from either larger accelerations or hillier terrains. However, the relative importance of these two factors is not very clear from the literature. For example, the literature lacks detailed answers to questions such as: *what is the best-achievable*

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estimation accuracy for constant-speed driving on a hilly road?

The overarching goal of this paper is to address the above open research challenge by examining the impact of terrain variability on the Fisher identifiability of longitudinal chassis model parameters. We perform this analysis for a commercial heavy-duty diesel truck, namely, the Volvo VNL 300. However, the underlying foundation of the work is broadly applicable to other vehicle types and sizes. *Identifiability analysis* is an attractive tool for assessing the accuracy with which one can estimate a dynamic system's parameters from input-output experimental data. The parameters are *structurally identifiable* if the problem of estimating them from experimental data is solvable. Moreover, assuming structural identifiability, the Cramér-Rao theorem states that the best parameter estimation covariance achievable by an unbiased estimator equals the inverse of the corresponding Fisher information matrix.

To perform Fisher identifiability analysis, we first develop a simple longitudinal dynamics model for the Volvo VNL 300. We then operate this truck on the road along rural and interstate routes offering a rich mix of aggressive accelerations, constant speeds, and terrain variability. The truck used in this work is equipped with sensors for measuring driveline torque, vehicle velocity, and road grade (using GPS). We use specific segments of the collected experimental data to obtain initial estimates of the vehicle's mass, rolling resistance, and drag coefficient. We then formulate a nonlinear least squares problem for estimating these three parameters simultaneously. Fisher analysis provides an estimate of the best estimation covariance achievable by the above least squares algorithm. Moreover, the mean square grade of a given road provides an estimate of road grade variability for the corresponding experiment. We perform a simulation-based study where we vary this road grade variability metric by scaling a given road profile, and examine the resulting variations in Fisher identifiability. This study shows a strong monotonic dependence of chassis parameter estimation error bounds on road grade variability. Next, we repeat the above Fisher analysis for multiple vehicle road tests, and see a similar overall trend, with hillier terrains providing better Fisher parameter identifiability. The end result is a study that shows, both in simulation and experimentally, the degree to which terrain variability can enhance chassis parameter estimation accuracy.

The remainder of this paper is organized as follows. Sections II and III describe the vehicle model and least squares parameter estimation algorithm. Section IV details the numerical Fisher error analysis utilized to calculate estimation error values. Section V illustrates the terrain analysis, including how this paper quantifies terrain variability. Section VI then details the simulation study examining the relationship between terrain variability and parameter identifiability. Finally, section VII shows the results from on-road experiments, and how they support the simulation study, and Section VIII concludes the paper.

II. LONGITUDINAL VEHICLE MODEL AND VEHICLE EXPERIMENTAL SETUP

This paper uses a longitudinal dynamics model to estimate the mass, drag coefficient, and rolling resistance coefficient of the VNL 300 truck. Table 1 provides a nomenclature for this model.

TABLE 1. Vehicle Parameters

Parameter	Description
M	vehicle mass with no trailer [8845 kg]
g	gravitational acceleration constant [9.81 m/s2]
τ_{FD}	torque at final drive [(kg.m2)/s2]
R_{FD}	final drive gear ratio [2.47]
r_{wheel}	wheel radius [0.5004 m]
ρ_{air}	ambient air density [1.2 kg/m3]
C_d	drag coefficient [0.49]
A_{ref}	frontal area of the truck [10.67 m2]
C_r	rolling resistance coefficient [0.0056528]
θ_{road}	road grade [rad]
V_{veh}	vehicle velocity [m/s]
X	vehicle position [m]

A common state-space representation of longitudinal vehicle dynamics is given below, assuming negligible wheel slip, no braking, and longitudinal motion:

State variables: $x_1 = X,\ x_2 = V_{veh}$
Input variables: $u = \tau_{FD}$
Disturbances: $w_1 = \theta_{road}$
Model: $\dot{x}_1 = x_2,$

$$\dot{x}_2 = \frac{1}{M}[F_{prop} - F_{drag} - F_{roll} - F_{grade}] \quad (1)$$

where each term is represented by:

$$F_{prop} = \frac{\tau_{FD} R_{FD}}{r_{wheel}} \quad (2)$$

$$F_{drag} = \frac{1}{2}\rho_{air} C_d A_{ref} {V_{veh}}^2 \quad (3)$$

$$F_{roll} = C_r M g cos(\theta_{road}) \quad (4)$$

$$F_{grade} = M g sin(\theta_{road}). \quad (5)$$

The truck utilized in the on-road experiments is a Volvo VNL 300, with no trailer attached during driving. Fig. 1 shows a diagram detailing the flow of data on the experimental setup.

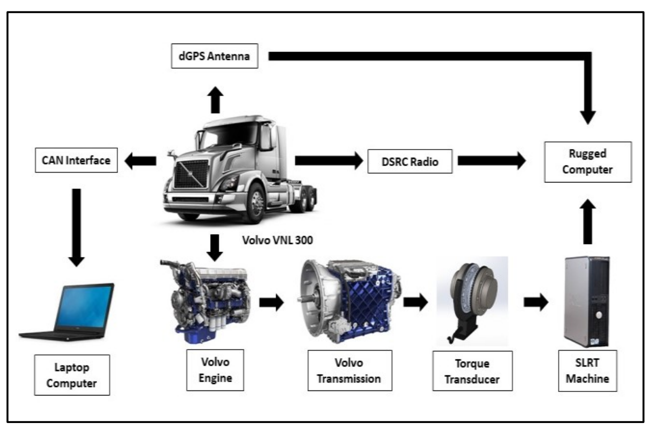

Figure 1. Data Flow Diagram for Experimental Setup

The torque measurements are obtained with a torque sensor installed between the final drive and cardan shaft of the truck. The road grade approximation is generated with a finite difference method, utilizing GPS data for altitude and distance traversed. GPS instrumentation is also used for calculating vehicle velocity. The CAN signals of the vehicle are also recorded for reference.

III. PARAMETER ESTIMATION ALGORITHM AND EXPERIMENTATION

This paper incorporates a common formulation of a nonlinear least-squares estimation algorithm to obtain initial chassis parameter estimates. The formulation of the corresponding optimization problem is as follows:

$$\text{Minimize} \quad \sum_{i=1}^{N}(\hat{V}_{i;veh} - V_{i;veh})^2 \tag{6}$$

Sub. to:

$$\hat{\theta} = [\hat{M} \quad \hat{C}_d \quad \hat{C}_r]^T$$
$$\hat{\theta}_{lb} \leq \hat{\theta} \leq \theta_{ub}$$
$$\hat{\theta} \in \mathbb{R}$$
$$\dot{\hat{V}}_{veh} = \frac{1}{M}\left[F_{prop} - F_{drag} - F_{roll} - F_{grade}\right]$$
$$\hat{V}_{veh}(0) = V_0$$

where $\hat{\theta}$ is a guess of the chassis parameters, and θ_{lb} and θ_{ub} are the bounds on the possible parameter values. These constraints are set liberally, and none of the estimates are boundary solutions to the optimization problem.

Fig. 2 shows the velocity trajectory of the overall data sample which this paper utilizes to estimate chassis parameters. A braking indicator is obtained from the vehicle's CAN signals. Since our measurements do not include brake torque, we use this signal to cut the data used for solving the above optimization problem. Specifically, the above estimation problem is only solved for those time periods where there is no braking.

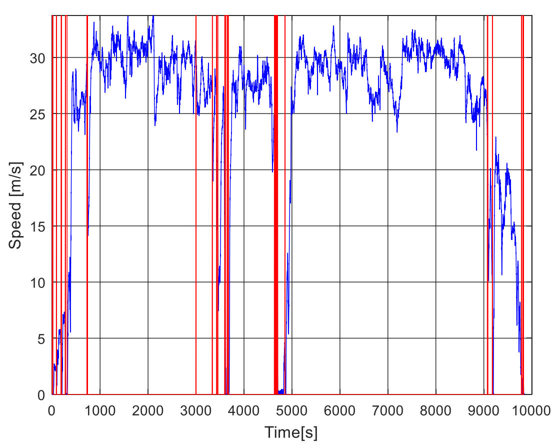

Figure 2. Velocity Trajectory with Braking Regions Highlighted

To highlight the importance of "cutting" the data corresponding to braking prior to parameter estimation, we performed the following simple sanity check. We first applied a low-pass filter with a cutoff frequency of ω_c = 5 rad/s to the vehicle speed signal. Then we ran the vehicle dynamics model in (1-5) "backwards" to estimate the final drive torque. Fig. 3 compares the resulting torque estimates to the measured final drive torque. Very significant differences exist between these two signals, but only when the brake indicator signal is active.

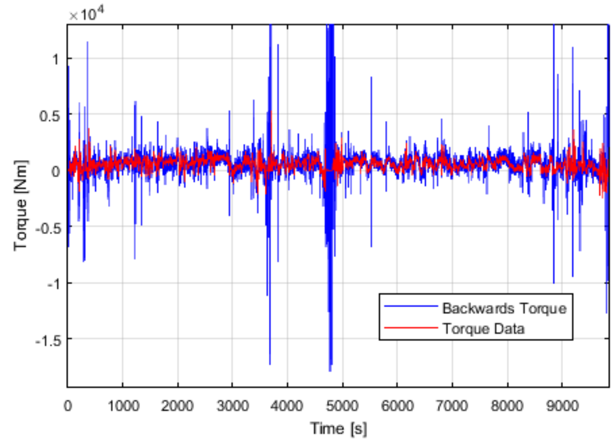

Figure 3. Comparison of Torque Estimates and Final Drive Torque Data

Table 2 provides a list of all of the data segments used throughout this paper. Each sample is 400 seconds long, and for each sample all three chassis parameters in question are estimated simultaneously by solving the nonlinear regression problem in (6). From this point forward, the specific experiments will be referred to by their numbering listed in this table.

TABLE 2. List of Experiments and Corresponding Parameter Estimates

#	M [kg]	C_d [-]	C_r [-]
1	8845.18	0.5893	0.005978
2	9028.18	0.3975	0.011883
3	8843.26	0.5030	0.004529
4	9141.27	0.5478	0.005861
5	8817.55	0.5328	0.005773
6	8946.25	0.4507	0.008659
7	6793.52	0.4670	0.010134
8	7850.81	0.4106	0.007248
9	8890.31	0.3419	0.011280
10	8241.73	0.4950	0.004611
11	7785.70	0.3526	0.012317
12	8830.87	0.4488	0.005572
13	8994.22	0.4077	0.006771
14	7745.36	0.4259	0.006328
15	8254.37	0.5162	0.006051
16	7953.42	0.5610	0.005827

IV. APPROXIMATION OF FISHER INFORMATION

The analysis presented in this paper requires accurate calculations for the estimation error values. To satisfy this requirement, the Fisher information metric is chosen for the identifiability analysis of this paper. Historically, Fisher analysis has proven to be an effective and relatively simple technique to quantify parameter identifiability in a system. In performing Fisher analysis, we assume measurement noise to be independent, identically distributed, zero mean, and Gaussian.

Given the usage of actual experimental data, a numerical approximation of Fisher information is incorporated into this paper. The formulation of this approximation follows that illustrated in [13], beginning with the computation of the Fisher information matrix.

$$F = \frac{1}{\sigma^2}\begin{bmatrix} \sum_{i=1}^{N} S_{i1}{}^2 & \cdots & \sum_{i=1}^{N} S_{i1}S_{ik} \\ \vdots & \ddots & \vdots \\ \sum_{i=1}^{N} S_{ik}S_{i1} & \cdots & \sum_{i=1}^{N} S_{ik}{}^2 \end{bmatrix} \tag{7}$$

The value for measurement error σ is assumed to correspond to a reasonable vehicle speed measurement error of 1.0 m/s. The sensitivity of the output with respect to each parameter θ_j, denoted S_{ij}, is approximated numerically as follows:

$$S_{ij} = \frac{\partial y(t_i)}{\partial \theta_j} = \frac{y(t_i,\theta_j+\delta\theta_j)-y(t_i,\theta_j)}{\delta\theta_j} \quad (8)$$

where $\delta\theta_j$ is a sufficiently small perturbation applied to the optimal parameter value θ_j. With regards to this paper's specific problem formulation, the format of the Fisher matrix is shown in (9).

$$\mathrm{F} = \frac{1}{\sigma^2}\begin{bmatrix} \sum_{i=1}^{N} S_{iM}^2 & \sum_{i=1}^{N} S_{iM}S_{iC_d} & \sum_{i=1}^{N} S_{iM}S_{iC_r} \\ \sum_{i=1}^{N} S_{iC_d}S_{iM} & \sum_{i=1}^{N} S_{iC_d}^2 & \sum_{i=1}^{N} S_{iC_d}S_{iC_r} \\ \sum_{i=1}^{N} S_{iC_r}S_{iM} & \sum_{i=1}^{N} S_{iC_r}S_{iC_d} & \sum_{i=1}^{N} S_{iC_r}^2 \end{bmatrix} \quad (9)$$

The Cramér–Rao lower bound for the variance of each θ is found along the diagonal of the covariance matrix, being the inverse of the Fisher metric. Under the conditions of white and Gaussian measurement noise, this bound represents the theoretical value for the estimation variance. Estimation error is calculated by taking the square root of this quantity for each θ.

V. TERRAIN VARIABILITY QUANTIFICATION

As a means to ensure the efficacy of this analysis, the relevant experimental data exhibits both terrain variability and mixed driving through interstate and rural roads throughout the sample. These features create a dataset which yields accurate parameter estimates, and enables the comparison of segments of on-road data which follow varying terrain profiles.

The analysis of terrain variability requires a metric for road terrain. This paper implements the following metric ς, the mean of the road grade squared for a given vehicle duty cycle (i.e., trip).

$$\varsigma = \frac{\sum_{i=1}^{N} \theta_{i;road}^2}{N} \quad (10)$$

In this case, the nature of the terrain variability (e.g. whether it exhibits periodic or constant **grade**) is not important for this analysis. Insights from the Fisher information matrix demonstrate that in fact, the mean square of road grade itself can be approximated to have a direct correlation to the size of the Fisher matrix, and therefore to the accuracy of parameter estimates. For example, this can be seen by showing that, with the small angle approximation, terms like:

$$\sum_{i=1}^{N} {S_{iC_r}}^2, \quad (11)$$

where

$$S_{C_r} \sim \frac{\partial}{\partial C_r}\int\left[F_{prop} - F_{drag} - F_{roll} - F_{grade}\right] dt \propto \theta_{road} \quad (12)$$

are proportional to the road grade metric ς. Given that a 'larger' Fisher matrix produces smaller estimation errors, it follows that the magnitude of the road grade, as opposed to its overall variability, is in this case the primary contributor to the estimation accuracy.

VI. SIMULATION STUDY

This paper demonstrates the relationship between the metric defined by (10) and the estimation error value obtained from a given trip through simulation. A Volvo powertrain model and simulated terrain profile are utilized to obtain parameter estimates and their corresponding estimation error values. For this simulation study, all three chassis parameters in question are estimated simultaneously using the same procedure outlined in section III. After parameter estimates are acquired from the sample terrain profile, the simulation begins to scale the terrain profile, and uses the Fisher information metric to calculate the new estimation errors given the exaggerated terrain profile. From intuition, this relationship should be decreasing for the estimation error, since the road excitation is increasing.

Fig. 4, 5, and 6 show the output from these simulations for each chassis parameter M, C_d, and C_r, where terrain is scaled up to a factor of 2.5. The estimation error is obtained from the calculation of the Cramér–Rao bound for the variance of each parameter, and is plotted as a single standard deviation of the parameter estimates. Given different simulated road profiles, the shapes and placements of these plots vary, although the decreasing relationship is consistent.

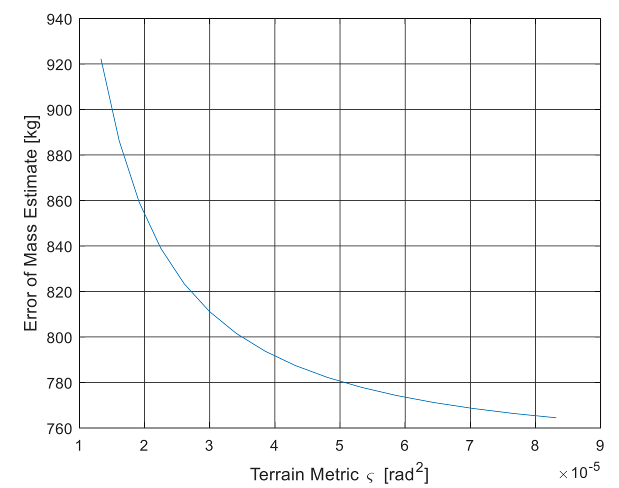

Figure 4. Theoretical Relationship between ς and M Estimate Error

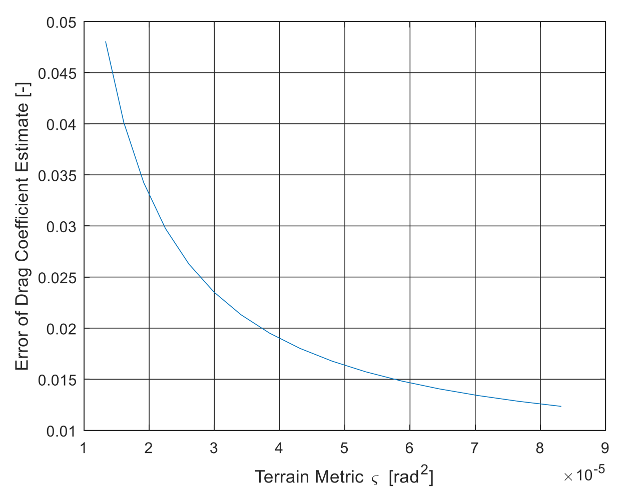

Figure 5. Theoretical Relationship between ς and C_d Estimate Error

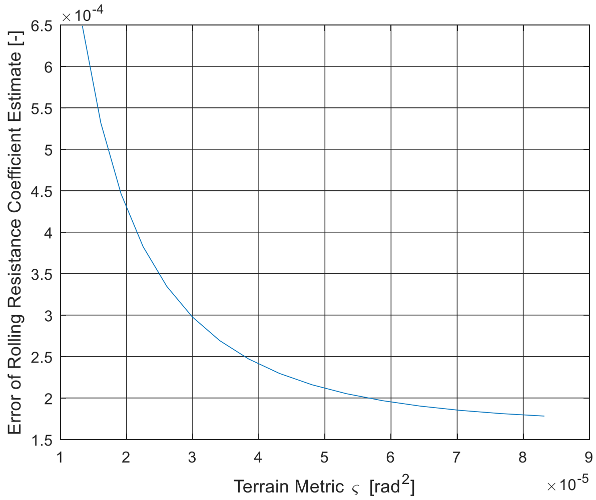

Figure 6. Theoretical Relationship between ς and C_r Estimate Error

Overall, the curves shown in Fig. 4-6 confirm the intuition by illustrating a monotonic and decreasing relationship between estimation error and the terrain variability metric ς defined in section V.

VII. EXPERIMENTAL VALIDATION OF SIMULATION STUDY

Fig. 7-9 show plots of estimation error of a single standard deviation and terrain metric for M, C_d, and C_r, where the points are taken directly from the experiments and parameter estimates listed in Table 2. These plots are not expected to coincide exactly with Fig. 4-6, as there are differences between the datasets used in this experimental comparison which subtly affect the estimation error results. Despite these differences, in the case of the vehicle mass estimation errors shown in Fig. 7, a decreasing relationship between estimation error value and terrain variability is clearly evident.

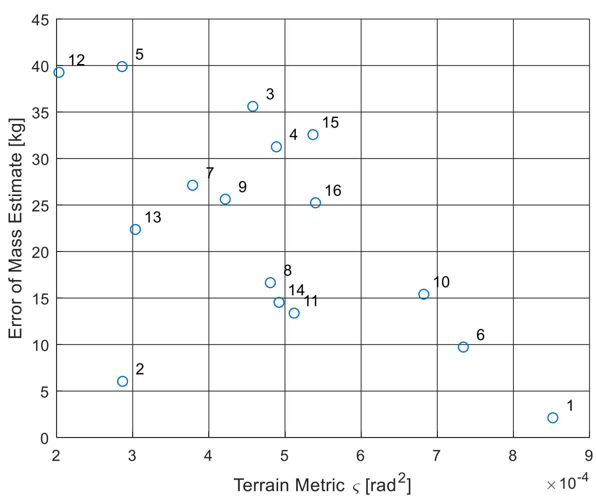

Figure 7. Empirical Relationship between ς and M Estimate Error

Fig. 8 shows this same relationship for the drag coefficient estimates of the Volvo truck. In this case, the same differences between test cases can be expected to slightly influence the placement of the points. However, a downwards trend is still visible, indicating that test cases with higher terrain variability on average yield better drag coefficient estimates.

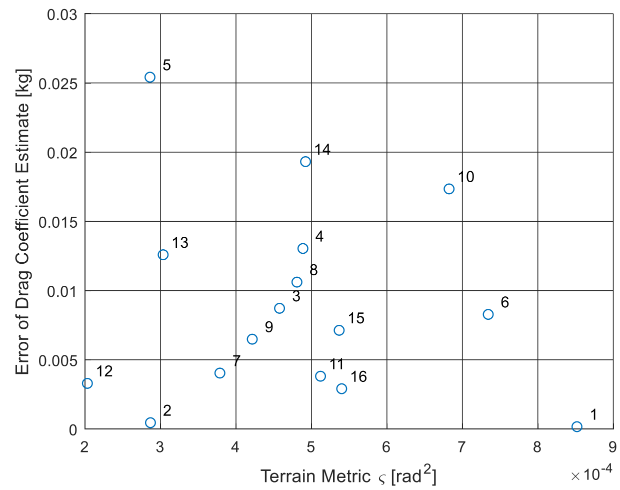

Figure 8. Empirical Relationship between ς and C_d Estimate Error

The same can be said for the truck's rolling resistance coefficient, as Fig. 9 shows a generally decreasing relationship between C_r estimate error and terrain variability.

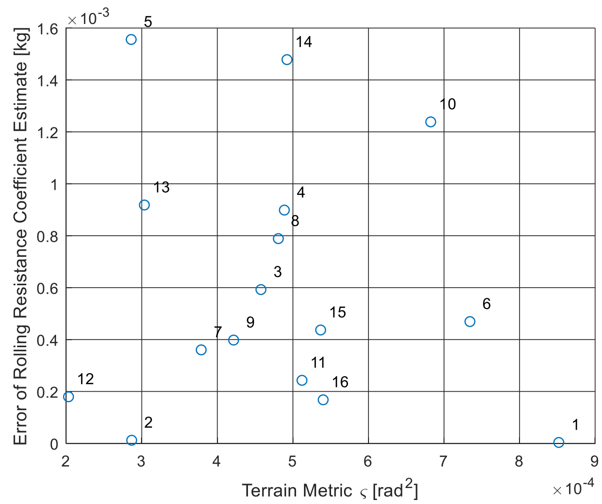

Figure 9. Empirical Relationship between ς and C_r Estimate Error

VIII. DISCUSSION AND CONCLUSIONS

This paper analyzes the impact of terrain variability on the identifiability of vehicle chassis parameter estimates. While the literature presents several analyses where terrain is shown to increase the fidelity and speed of convergence of chassis parameter estimates, the quantified effect from terrain variability has not been examined. This paper presents an analysis which demonstrates the theoretical relationship between quantified terrain variability, and estimation error values through simulation. This theoretical relationship is verified with on-road vehicle experiments performed with an instrumented Volvo truck. We show that terrain variability has significant impact on estimation error, such that higher degrees of variability substantially decrease the estimation error. These results make intuitive sense, in that increasing the richness of a dataset should and does increase parameter identifiability.

The results shown in this paper carry several interesting and meaningful insights, the most recognizable of which is that testing across a rich terrain profile is shown to reduce estimation error dramatically. This finding is directly relevant to experimental design for vehicle chassis parameter estimation, insofar as it illustrates just how important terrain can be to obtain accurate estimates. An important conclusion from this analysis is that effects from terrain can in some cases be more important for accurate parameter estimation than effects from sensor error with regards to speed, torque, and road grade measurement. With regards to experimental design, this observation carries significant importance concerning instrumentation required for effective chassis parameter estimation.

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