

Application of System Identification for Efficient Suspension Tuning in High-Performance Vehicles: Quarter-Car Study

Chris Boggs, Mehdi Ahmadian and Steve Southward
Virginia Institute for Performance Engineering and Research (VIPER)

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ABSTRACT

One popular complement to track testing that successful race teams use to better understand their vehicle's behavior is dynamic shaker rig testing. Compared to track testing, rig testing is more repeatable, costs less, and can be conducted around the clock. While rig testing certainly is an attractive option, an extensive number of tests may be required to find the best setup. To make better use of rig test time, more efficient testing methods are needed. One method to expedite rig testing is to use rig test data to generate a model of the experiment and then applying the model to identify potential gains for further rig study.

This study develops the method at the quarter-car scale, using data from a quarter-car rig with a Penske 7300 shock absorber. The method is first validated using data generated from a known quarter-car model to assure the method can reproduce the original model behavior. Next, the method is applied to experimental data collected from an existing quarter-car rig. The results show that this method can be used to accurately predict sensor measurements during quarter-car rig tests for various actuator inputs and shock selections. Future work will apply the lessons learned from this study to develop a full car model using 8-post rig data.

INTRODUCTION

During a shaker rig test, a vehicle is tested by running a particular drivefile for different suspension setups. The performance of the different setups is compared by calculating a series of performance metrics. These metrics are typically used during rig tests to help summarize how the shock selection affects various aspects of vehicle behavior including mechanical grip, aerodynamics, suspension travel, and suspension loading.

This sensitivity information is one of the main products of the rig test. The team will use this information to help select or eliminate potential shock packages to try on the race track, and will use the sensitivity information to help

make adjustments based on how the vehicle performs on the track.

The main goal of this research is to accurately predict this sensitivity information using simulations, which can augment knowledge gained from rig testing. To create an accurate model for these simulations, we will use rig test data to perform system identification, which will produce a vehicle model.

This paper develops the model generation methods at a quarter-car scale using system identification (ID) techniques. The first section develops the equations of motion for a linear quarter-car model. This model treats the nonlinear shock model force as an input to a linear dynamic system, allowing us to apply linear ID techniques. This linear vehicle model may then be coupled with nonlinear dynamic shock models to create simulated quarter-car rig data sets generated using a known system model.

The methods required to perform the ID are then discussed and applied to the simulated test data. The results of the ID are compared with the theoretical response to verify that the ID process is working properly.

To verify that the method will work on real-world data, the ID process is then applied to real quarter-car rig data and the ID model is used to predict the response for different shock configurations.

BACKGROUND

Due to the highly competitive nature of racing, very little of the work done in 7-post and 8-post testing has been published. Kelly et al. discusses the use of linear frequency response function (FRF) estimates to develop track drivefiles [1]. Kowalczyk uses a linear 7 degree of freedom vehicle model to help identify tradeoffs and determine realistic limitations of tuning [2]. Kasprzak used a half-car model to help find potential gains for further exploration on a 4-post rig with coil springs attached to the chassis to simulate downforce [3]. Each

of these papers successfully used linear models to aid in rig testing.

To evaluate a given model's accuracy in predicting experimental results, it is common practice to use experimental data to validate the model accuracy. If desired, the model can also be updated to better match the experimental data. This process of model validation and updating can be performed on the component level, the system level, or both depending on the application. Some relevant examples showing trends applying experimental data to model validation and updating are shown below.

In the automotive industry, vehicle models are quite commonly used early in the development cycle when vehicle data is not available. This makes model updating using vehicle system data impractical, so the focus is often on integrating validated component models. Vilela correlated proving ground data collected for a selection of different proving ground tests with a detailed ADAMS model assembled using validated component models [4]. The correlation was determined to be acceptable, indicating that the model could have been used before the vehicle was manufactured.

Often, vehicle-level test data for an existing vehicle is used to refine a vehicle model, which will be used in future studies. The experimental data is often assumed to be the ideal response for the model to try to achieve, although experimental errors can make this a poor assumption. One basic method to use test data to update models is to first perform a parametric study to determine the sensitivity of modeling error to model parameters. The model parameters can then be adjusted using the sensitivity information to reduce modeling error [5].

A more systematic method for model updating is to apply optimization methods to find parameter values that minimize some measure of the model error. Hu performed model validation and updating on a half-car ride model using proving ground data [6]. The initial guess at the parameters was defined using component tests, which were then updated to better match the proving ground data using optimization of modeling error.

While many studies use proving ground data for model development, there has been an increasing trend to use laboratory test data since the experiments are run in a more controlled environment with higher repeatability [7]. For example, Cheli and Sabbioni performed 4-post testing on a van to identify the unknown stiffness, damping, and inertial parameters [8]. The parameters were optimized to best fit the experimental data using nonlinear optimization. Further experiments were performed to show that there was acceptable correlation between the model and data. The ability of the model to predict the effect of changing parameters was not discussed.

Most model updating studies attempt to match the displacements and/or accelerations of the sprung and unsprung masses. One additional sensor measurement that is important for a rig testing model to predict is the tire normal force. Ziegenmeyer optimized the parameters of a linear quarter-car model to minimize the prediction error for quarter-car rig test [9]. The model was then used to predict the acceleration of the sprung mass, the unsprung mass and tire normal force with reasonable accuracy.

The above studies all use structural dynamic models to model vehicle behavior, where the models have been constructed using components that have a specific physical meaning, such as masses, springs, dampers, and their geometrical configuration. Many applications do not require accurate estimation of the structural parameters, only a model of the input-output behavior. If this is the case, a more generic dynamic model structure can be used, such as a state-space or transfer function model. These modeling structures have more modeling freedom, allowing them to account for more complex behavior, such as chassis flexible body modes. These models can be identified using generic system identification tools. By using a generic input-output model structure, there is no need for prior knowledge of the geometry of how components in the physical system are arranged or the boundary conditions for their connections. This makes them useful for quickly generating models from test data with minimal model development effort.

This paper will focus on developing a generic linear dynamic model from quarter-car rig data that will allow us to predict the sensor response for different drivefiles and shock selections.

QUARTER-CAR MODEL

The section develops the equations of motion for a quarter-car vehicle model, where the nonlinear shock model force is treated as an input to a linear dynamic vehicle model. This allows us to decouple the nonlinear shock model from the linear vehicle model and apply linear analysis to better understand the effect of shock selection on vehicle performance.

This section develops the decoupled quarter-car model with a shock force input. Once the model is developed, the behavior of the linear model is analyzed using the frequency response.

STATE-SPACE MODEL - A diagram of the quarter-car model is shown in Figure 1. It includes two masses, which represent the inertia of the chassis and the wheel assembly. The two masses are connected through the suspension, which is represented as a linear spring and damper. These linear suspension parameters represent wheel rates, which take into account the motion ratio between the wheel and the physical spring or damper. The linear damping rate can be used to represent a linear shock absorber or other losses in the suspension.

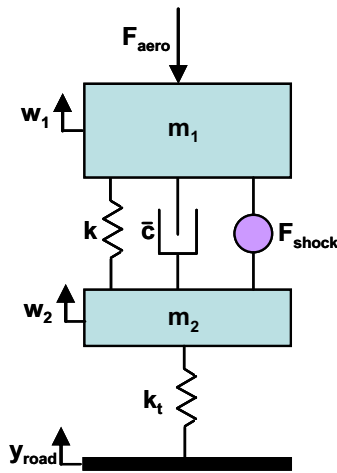


Figure 1. The quarter-car model

The suspension model also includes a generic force input, which will be used to integrate nonlinear shock absorber models into the simulation. This generic force input could also be used to incorporate additional suspension component behavior models, such as variable installation ratio, progressive springs, coil-binding, and suspension friction. These suspension component models would need to be determined using component-level testing and are not a part of the ID process described in this study.

The tire is represented as a linear spring. In addition to the shock force input, there are also inputs that represent the road input and aerodynamic force. During a rig test, the road inputs and aerodynamic inputs are simulated using actuators, which are commonly referred to as wheelloaders and aeroloaders respectively.

The equations of motion for the quarter-car model in Figure 1 are

$$\begin{bmatrix} m_1 & 0 \\ 0 & m_2 \end{bmatrix} \begin{bmatrix} \ddot{w}_1 \\ \ddot{w}_2 \end{bmatrix} + \begin{bmatrix} \bar{c} & -\bar{c} \\ -\bar{c} & \bar{c} \end{bmatrix} \begin{bmatrix} \dot{w}_1 \\ \dot{w}_2 \end{bmatrix} + \begin{bmatrix} k & -k \\ -k & k + k_t \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} 0 & -1 & 1 \\ k_t & 0 & -1 \end{bmatrix} \begin{bmatrix} y_{road} \\ F_{aero} \\ F_{shock} \end{bmatrix} \quad (1)$$

where the shock force is positive during compression. The equations of motion can be represented in state-space form as

$$\begin{bmatrix} \dot{w} \\ \dot{\dot{w}} \end{bmatrix} = \begin{bmatrix} 0_{2 \times 2} & I_2 \\ -M^{-1}K & -M^{-1}\bar{C} \end{bmatrix} \begin{bmatrix} w \\ \dot{w} \end{bmatrix} + \begin{bmatrix} 0_{2 \times 3} \\ M^{-1}L \end{bmatrix} u \quad (2)$$

$$\dot{x} = Ax + Bu$$

Output equations can then be constructed in the form

$$y = Cx + Du \quad (3)$$

to represent the sensors, such as tire force, ride height, shock velocity, and hub acceleration.

The baseline parameter values are shown in Table 1. The sprung and unsprung masses correspond to a 3000 lb car with 90% sprung mass, and 25% of the mass on one corner. While these parameters may not closely match typical Cup car parameters, this model will be sufficient to develop the ID method.

Table 1. Baseline Parameter Values.

m_1 g	Sprung Weight	675 lbf
m_2 g	Unsprung Weight	75 lbf
k	Suspension Stiffness	1280 lbf/in
k_t	Tire Stiffness	1300 lbf/in
c	Suspension Damping	16.67 lbf / (in/s)

An important consideration when treating shock force as an input is ensuring that the shock force signal energy is large enough. If the shock force is too small to excite significant sensor response, the coherence for the frequency response functions (FRF) estimates will be poor. Since we do not directly control the shock force when using a passive shock, the shock force is indirectly excited through the wheelloaders and aeroloaders. Figure 2 shows the frequency response for the shock velocity output and the wheelloader and aeroloaders inputs. As this figure shows, the wheelloader input can excite shock velocity efficiently at higher frequency, but not at lower frequency. Conversely, the aerolader input can provide shock velocity efficiently at lower frequency, but not at higher frequency. This suggests the need to have both high-frequency wheelloader excitation and low-frequency aerolader excitation during a shaker rig test to fully characterize the shock's influence on vehicle behavior.

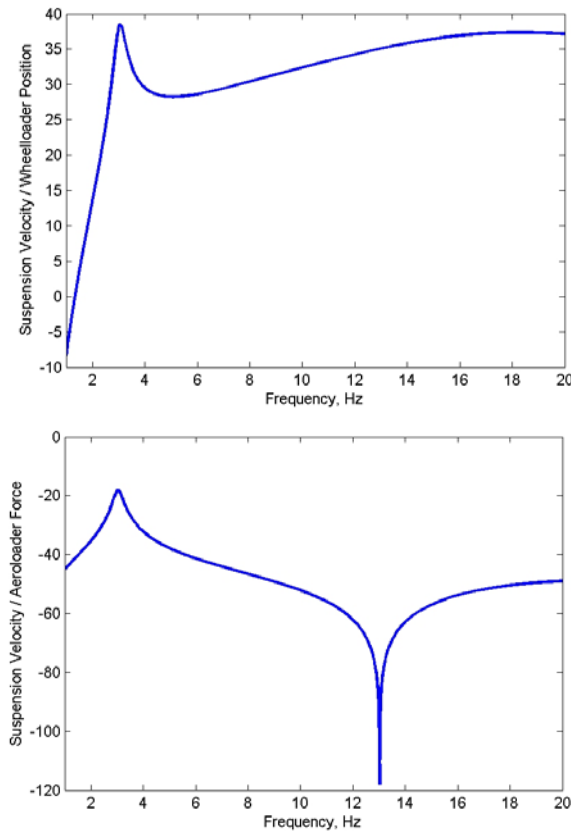


Figure 2. Shock Velocity FRFs

SIMULATED QUARTER-CAR DATA - Now that we have defined a vehicle model, we can combine it with a shock model, as shown in Figure 3. This model can then be used to create simulated data sets, which we will use in our identification process to determine if our ID was successful in reproducing the known model.

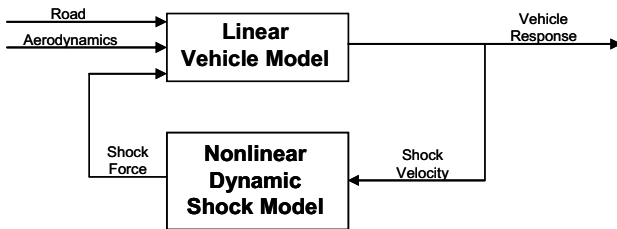


Figure 3. Coupling of vehicle and shock absorber models

To couple the shock model with the quarter-car model, the shock velocity from the quarter-car model is treated as an input to the shock model, and the shock force is treated as an input to the quarter-car model.

The nonlinear dynamic shock model presented in [10] includes a curve fit of the force-velocity curve, a first-order lowpass filter of the curve fit, and a weighting function to combine the two. The equations for these three parts are

$$F_{poly} = f(v) \quad (4)$$

$$F_{lag} = \frac{1}{\tau s + 1} F_{poly} \quad (5)$$

$$F_{shock} = \alpha(F_{poly})F_{lag} + (1 - \alpha(F_{poly}))F_{poly} \quad (6)$$

To improve simulation speed for the linear portions of the simulation, the fourth-order continuous-time state-space model in Equation 2 and the first-order continuous-time lowpass filter in Equation 5 are transformed into linear difference equations with the bilinear transformation using the MATLAB function `c2d`, with a sample rate of 500 Hz. After transforming Equations 2 and 5 into discrete time, they may be written as

$$\begin{aligned} x[i+1] &= A_d x[i] + B_d u[i] \\ y[i] &= C_d x[i] + D_d u[i] \end{aligned} \quad (7)$$

$$F_{LPNL2}(z) = \left[\frac{1 + z^{-1}}{\left(1 + \frac{2\tau}{T}\right) + \left(1 - \frac{2\tau}{T}\right)z^{-1}} \right] F_{polylinear}(z) \quad (8)$$

The final quarter-car model can be implemented in Simulink. The quarter-car model can now be used to create simulated data sets to test our system identification methods. A random drivefile was created for the road and aerodynamic inputs. For both inputs, a flat spectrum was chosen with a bandwidth of 50 Hz and duration 100 seconds. This drivefile was used along with the shock models to create simulated data sets.

SYSTEM IDENTIFICATION METHODS

Now that we have a simulated quarter-car data set from a known system, we can apply our system identification methods and see if the identified model accurately reproduces the system response. This section describes the system identification methods.

We wish to identify a model to describe the relationship between the inputs from the road (u_1), aerodynamics (u_2), and shock force (u_3) and the measured sensor outputs (y). This will allow us to create a model of the complete vehicle and simulate the response for different shock selections. We have measurements of the inputs and outputs from a test conducted where the first two inputs were defined independently, but the shock force was defined by the shock velocity. We will show that the dependence of the shock force on the other two input causes an identifiability issue that should be addressed during the identification process. The subsystem we seek to identify is shown in the dashed box with respect to the complete system in Figure 4.