

Construction and Use of Surrogate Models for the Dynamic Analysis of Multibody Systems

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ABSTRACT

This study outlines an approach for speeding up the simulation of the dynamic response of vehicle models that include hysteretic nonlinear tire components. The method proposed replaces the hysteretic nonlinear tire model with a surrogate model that emulates the dynamic response of the actual tire.

The approach is demonstrated via a dynamic simulation of a quarter vehicle model. In the proposed methodology, training information generated with a reduced number of harmonic excitations is used to construct the tire hysteretic force emulator using a Neural Network (NN) element. The proposed approach has two stages: a learning stage, followed by an embedding of the learned model into the quarter car model. The learning related main challenge stems from the attempt to capture with the NN element the behavior of a hysteretic element whose response depends on its loading history. The methodology is demonstrated in conjunction with a simple nonlinear quarter vehicle system as well as an ADAMS based model that uses a complex tire element. The results obtained with the surrogate model prove to be accurate and are obtained at a fraction of the CPU time required to handle the original models. The approach proposed is anticipated to be useful for reducing the duration of vehicle simulations, or when a tire model is not available but experimental data can be used to generate a surrogate model.

NOMENCLATURE

t	Time
$x_{sp}(t)$	Sprung mass displacement
$x_{tire}(t)$	Tire displacement
$y(t)$	Base displacement
m_{tire}	Tire mass
m_{sp}	Sprung mass
k_{sus}	Suspension stiffness
c_{sus}	Suspension damping coefficient

k_{tire}	Tire stiffness
c_{tire}	Tire damping coefficient
$q(t)$	Restoring force
$g(t)$	Non-hysteretic component of restoring force
$z(t)$	Hysteretic component of restoring force
κ, β γ, n	Hysteretic loop shape's control parameters
A_i	Instantaneous amplitude
ω_i	Instantaneous frequency
Δt	Integration time step

INTRODUCTION

Preliminary design of a complex system often involves exploring a broad design space. This calls for repeated use of simulation to probe this design space, a process that might be lengthy and thus adversely impact the product release cycle. In vehicle virtual prototyping the tire is a critical component since it conveys the control forces from the ground to the vehicle. These forces are essential in gauging ride comfort, mobility, stability, and durability. Many advanced simulation packages such as ADAMS and LMS' Lab Motion are available for use in the tire-suspension simulation, but they can be extremely expensive for exploring broad regions of the design space as they rely on sophisticated tire models to capture the physics associated with the actual tires ([Gallrein et al. 2005](#); [Gipser 2005](#)). Additionally, complex as they are, these tire models do not always capture accurately the behavior of the actual tires, in which case even more sophisticated tire models are considered. This is usually the case when running off-road vehicle dynamics analysis and a full blown finite element representation of the tire might be

necessary. Such a tire model might be expensive to generate and extremely CPU intensive to run. An alternate approach is to “learn” the behavior of the actual tire, from carrying out experimental measurements or running a limited number of expensive simulations, and then to use a black box representation, or surrogate model, of the actual tire ([Qian et al. 2006](#)). As a rule, surrogate models are built to operate in a larger model in order to expeditiously capture the behavior of a complex subcomponent and therefore provide shorter simulation times of the large model.

Classical methods for creating surrogate models include response surface modeling ([Myers; Montgomery 1995](#)) and kriging ([Cressie 1989](#); [Laslett 1994](#); [Matheron 1963](#)). A wide variety of techniques is available based on methods rooted in statistical learning ([Smola; Schölkopf 2004](#)), Bayesian learning ([Neal 1997](#); [Pacheco et al. 2003](#)), regression based learning ([Atkeson et al. 1997](#); [Schaal](#); [Atkeson 1997](#); [Vijayakumar; Schaal 1998](#); [Vijayakumar et al. 2005](#); [Williams; Rasmussen 1996](#)), neural network ([Guarneri et al. 2008](#); [Hornik et al. 1990](#); [Neal 1996](#)), or machine learning. The Vapnik-Chervonenskis dimension ([Vapnik 2000](#)) quantifies the ease of learning for the above methods, a small value indicating that learning with the corresponding method can be done efficiently. Two general approaches can be identified: a) approaches that deal with the learning problem off-line, which means there are virtually no constraints on the data analysis and complexity of the learning method; and b) incremental learning approaches, which use computationally inexpensive methods to expeditiously establish an on-line learning capable model (see, for instance, ([Atkeson et al. 1997](#); [Schaal](#); [Atkeson 1997](#)) in the framework of nonparametric regression).

From a different perspective, again the learning methods can be divided in two broad classes: those that attempt to train a surrogate model globally by expanding the input space to the total range of inputs; and approaches that train local surrogate models valid in a spatially localized region to approximate the system behavior locally ([Atkeson et al. 1997](#); [Bottou; Vapnik 1992](#); [Vijayakumar; Schaal 1998](#)). For the latter, moving from region to region is an issue that one has to deal with during simulation. For the former, the surrogate models are far from trivial, costly to evaluate, and typically of reduced accuracy. Local surrogate models can highly reduce simulation time and can be used in both off- and on-line learning. Specifically, one can be in one of the following scenarios: (i) on-line learning for a low-dimensional problem, (ii) on-line learning for a high-dimensional problem, (iii) off-line learning for a low-dimensional problem, or (iv) off-line learning for a high-dimensional problem. With the exception of (i), where recurrent or adaptive NNs are good choices, local surrogate modeling is expected to lead to good accuracy and reduced computational costs.

Neural Networks will be used in this work for generating surrogate models. The surrogate model will be used to characterize the tire behavior drawing on a combination of locally defined NNs. The salient feature of the approach proposed is the fact that training each local NN requires only a small amount of data and learning parameters because the learning process factors in a priori engineering insights associated with the problem at hand. The approach adopted draws on a methodology whose theoretical foundation is outlined in (Bottou; Vapnik 1992; Burges; Vapnik 1995). This analysis introduces a new component locality, in the well-known tradeoff between the capacity of learning and the number of training examples. Based on that, a simple local algorithm is proposed. Specifically, for any testing data, 1) select training data (here the harmonic response of the actual system) similar in nature to (“in the vicinity of”) the regime in which the force element (the tire) operates; 2) train the NN network for each selected region, 3) stitch the resulting NNs in a single architecture and use everywhere to yield the response of the force element.

This approach will be demonstrated in conjunction with two examples. The first is a two degree of freedom (DOF) quarter vehicle model for which the simplified tire includes a hysteretic component that draws on the nonlinear Bouc-Wen model. The results reported suggest good accuracy and very encouraging reduction in simulation times compared to the standard model, which was implemented and solved in MATLAB. The same approach (local off-line learning) is subsequently used to train a neural network surrogate model for a complex tire model (Gipser 2005). The analysis relies on commercial modeling and simulation packages (FTire and ADAMS). Early results confirm the good accuracy and computational efficiency of the proposed methodology.

THE BOUC-WEN HYSTERETIC MODEL

Hysteresis captures the hereditary and memory nature of an inelastic system in which the restoring force depends not only on the instantaneous deformation, but also on the past history of the deformation. The Bouc-Wen model (Wong; Ni 1994; Wong et al. 1994), is a differential model that can be explained using a single DOF oscillatory system subjected to an external force $F(t)$, as shown in Figure 1.

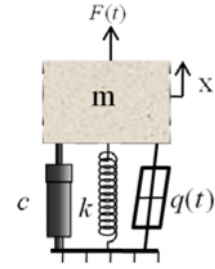


Figure 1. Single DOF Hysteretic System

The force $q(t)$ provided by the hysteretic element is computed as

$$\begin{aligned} q(t) &= g(t) + z(t) \\ g(t) &= k_n x + c_n \dot{x} \end{aligned} \quad (1)$$

Here $g(t)$ is a classical, non-hysteretic component that depends linearly on the relative displacement and velocity, and $z(t)$ is the hysteretic component defined by a differential equation:

$$\dot{z} = \dot{x} \left[\kappa - (\gamma + \beta \times \text{sgn}(\dot{x}) \times \text{sgn}(z)) \times |z|^n \right] \quad (2)$$

The non-hysteretic term $g(t)$ in the expression of $q(t)$ is necessary in order to describe the restoring force of the hysteretic element. If $g(t)$ were not present, this would lead to $\frac{\partial q(t)}{\partial x} = \frac{\partial z(t)}{\partial x}$, which means that $\frac{\partial q(t)}{\partial x}$ (which is equal to $\frac{\partial z(t)}{\partial x}$) only depends on z (also $\text{sign}(\dot{x})$ see Eq. (2)) but not on displacement x . If this was the case, it would prevent the formation of the loop associated with an actual hysteretic element.

The quantities κ , β , γ and n in Eq. (2) are “loop parameters” that control the shape and magnitude of the hysteresis loop. While κ , β and γ are positive real numbers, n may be positive or negative. Introducing the notation

$$\begin{aligned} k_t &= k_n + k \\ c_t &= c_n + c \end{aligned} \quad (3)$$

the time evolution of the mass m is the solution of the following second order differential equation obtained using Newton's second law:

$$m\ddot{x} + c_t \dot{x} + k_t x + z = F \quad (4)$$

QUARTER-CAR MODEL

Figure 2 shows the two DOF quarter-car model used to demonstrate surrogate modeling using NN-based off-line learning of the tire element. The model comprises a simplified vehicle body (the sprung mass) and one axle. These two masses are allowed to oscillate in the vertical direction. The suspension is modeled by a linear spring in parallel with a viscous damper, whereas the tire is modeled using a linear spring, viscous damper and nonlinear hysteretic element.

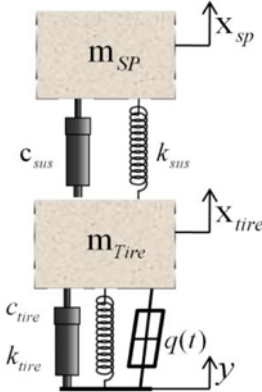


Figure 2. Quarter Car Model

The time evolution of this system is described by the following set of differential equations:

$$\begin{aligned} m_{tire} \ddot{x}_{tire} + (c_t + c_{sus}) \dot{x}_{tire} - c_{sus} \dot{x}_{sp} + (k_t + k_{sus}) x_{tire} - k_{sus} x_{sp} + z &= k_t y + c_t \dot{y} \\ m_{sp} \ddot{x}_{sp} - c_{sus} \dot{x}_{tire} + c_{sus} \dot{x}_{sp} - k_{sus} x_{tire} + k_{sus} x_{sp} &= 0 \\ \dot{z} &= (\dot{x}_{tire} - \dot{y}) \left[\kappa - (\gamma + \beta \times \text{sgn}(\dot{x}_{tire} - \dot{y}) \times \text{sgn}(z)) \times |z|^n \right] \end{aligned} \quad (5)$$

It should be noted that the non-hysteretic force $g(t)$ is combined with the elastic and damping forces of tire.

$$\begin{aligned} g(t) &= k_n (x_{tire} - y) + c_n (\dot{x}_{tire} - \dot{y}) \\ k_t &= k_n + k_{tire} \\ c_t &= c_n + c_{tire} \end{aligned} \quad (6)$$

These equations can be rewritten in matrix form as

$$\dot{X} = \begin{bmatrix} 0_{2 \times 2} & I_{2 \times 2} & 0_{2 \times 1} \\ -M^{-1}K & -M^{-1}C & \begin{bmatrix} -1/m_{tire} \\ 0 \end{bmatrix} \\ 0 & 0 & F & 0 & 0 \end{bmatrix}_{5 \times 5} X + \begin{bmatrix} 0_{2 \times 2} & 0_{2 \times 2} \\ 0_{2 \times 2} & M^{-1}D \\ 0_{1 \times 2} & 0 & -F \end{bmatrix} U \quad (7)$$

with the state and input vectors defined as

$$\begin{aligned} X &= [x_{tire} \ x_{sp} \ \dot{x}_{tire} \ \dot{x}_{sp} \ z]^T \\ U &= [0 \ 0 \ y \ \dot{y}]^T \end{aligned} \quad (8)$$

The quantities M, C, K, D and F are finally defined as

$$\begin{aligned} M &= \begin{bmatrix} m_{tire} & 0 \\ 0 & m_{sp} \end{bmatrix}, \quad C = \begin{bmatrix} c_t + c_{sus} & -c_{sus} \\ -c_{sus} & c_{sus} \end{bmatrix}, \quad K = \begin{bmatrix} k_t + k_{sus} & -k_{sus} \\ -k_{sus} & k_{sus} \end{bmatrix} \\ D &= \begin{bmatrix} k_t & c_t \\ 0 & 0 \end{bmatrix}, \quad F = \kappa - (\gamma + \beta \times \text{sgn}(\dot{x}_{tire} - \dot{y}) \times \text{sgn}(z)) \times |z|^n \end{aligned} \quad (9)$$

HYSTERETIC FORCE ANALYSIS

The most important part of the learning process is to capture the non-linear hysteretic dynamics of the tire (see Eq. (2)). Here the tire is fixed and the base is excited with a harmonic motion. The hysteretic force can be represented by a loop whose inner area represents the total dissipated energy in a cycle ((Bouc 1967; Ni et al. 1998), see figure below).

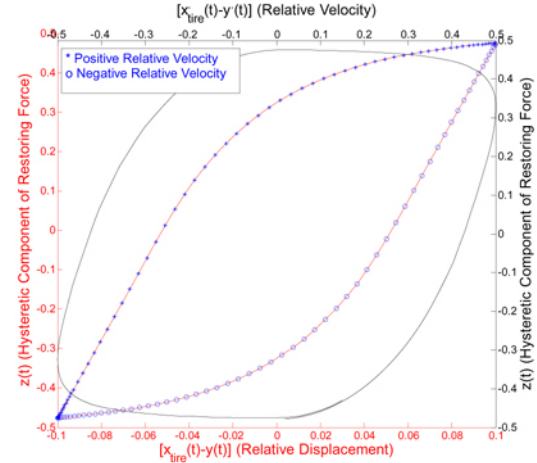


Figure 3. Hysteretic Force Loop

Learning the tire dynamics is equivalent to quantifying the effect of each independent variable (inputs that might depend on time) on the output (which here is the vertical force). A preferably unique or at least small number of representations of the mentioned relation are needed in order to make the approach useful.

The figures below show the effect of each independent variable on the hysteretic force excited by harmonic input. For harmonic excitation, we investigate the impact of (a) the amplitude of the relative displacement and (b) the frequency of excitation on the shape of the hysteretic force. The figures show the loop shapes for amplitudes of the relative