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Accurate Shock Absorber Load Modeling in an All Terrain Vehicle Using Black Box Neural Network Techniques

Christoph Leser, Thomas E. Renner and David C. Salmon
MTS Systems Corp.

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ABSTRACT

This paper presents the results of a study of using a neural network black box model of a shock absorber of an ATV (All Terrain Vehicle, four wheel drive, off road, single person vehicle) for accurate load modeling. This study is part of a larger investigation into the dynamic behavior and associated fatigue of an ATV vehicle, which is conducted under the auspices of the Fatigue Design and Evaluation Committee of SAE of North America (www.fatigue.org).

The general objectives are to develop new correlated methodologies that will allow engineers to predict the durability of components of proposed vehicles by means of a "digital prototype" simulation. Current state of the art multi body dynamics predictions use linear frequency response functions or non-linear polynomial approximations to describe the behavior of non-linear suspension components such as shock absorbers or bushings.

The proposed method yields more accurate predictions due to the fact that both the non-linear and hysteretic behavior of the shock absorber are modeled. This paper demonstrates how neural network black box technologies, particularly in the form of the Empirical Dynamics Models, can be used for accurate prediction of shock absorber loads encountered by a vehicle and the potential improvement in fatigue life predictions under this approach.

INTRODUCTION

A number of technologies exist today to predict analytically the durability of automotive structures (components, systems and full vehicles) prior to building actual physical specimen. To improve the predictive capabilities the Fatigue Design and Evaluation (FD&E) Committee of the Society of Automotive Engineers (SAE) of North America has elected to investigate what technologies are available today and aid the engineering community in developing improved methods for predicting fatigue life of complex structures [1]. To support this project, the authors of this paper present the study of neural network black box modeling for accurate load description of components under complex loading. The technique employed can be used to predict the behavior of a variety of dynamically loaded components with inherent complex behavior. In particular, the response behavior of a shock absorber under random loading is predicted and compared to a measured response and predictions achieved via currently commonly used methods.

FATIGUE DESIGN AND EVALUATION COMMITTEE (FD&E) OF THE SAE – The FD&E committee is dedicated to improve the understanding of fatigue processes in materials and engineering structures. The committee meets twice per year in different locations and also hosts a special session during the annual SAE World Congress in Detroit. The committee consists of members from academia, research institutes and industry and is open to the public. Contributions to projects are made through monetary and labor donations. All results are placed in the public domain.

Past contributions in the field of fatigue prediction have been published by the committee through a series of handbooks and conference proceedings, e.g. [2], [3] and [4]. Under it's latest effort the committee has elected to advance the state of the art in predicting the fatigue life of structural components and systems through an investigation entitled “Digital Prototypes for Durability”. The mission statement for this project states [1]:

Systematically apply, develop, integrate, and validate all the tools and processes necessary to evaluate the structural durability of a vehicle by means of a digital simulation.

The objectives were established as [1]:

- *Pool the resources of the committee to evaluate the current simulation processes as they relate to structural durability.*
- *Foster development of new tools and processes.*
- *Transfer the technology to users.*

To achieve these objectives it was decided to [1]:

Select an inexpensive, simple, existing vehicle that can be easily modeled with respect to vehicle dynamics and component stress-strain behavior. Create a computer model of the vehicle and "drive" it over a digital proving ground route. Test the actual vehicle on the real course and measure the component loads, test the component durability, and then compare the digital predictions with the test results. Assess where models need to be improved and fix the deficient theory. After good correlation has been achieved, try changing some components, through light weight material substitutions or material processing changes, and then re-test and re-analyze for prove-out of the digital prototype procedure.

The vehicle chosen is a Honda ATV (All Terrain Vehicle), Model TRX 300 4x4 (Figure 1). This type of vehicle was chosen as it is relatively inexpensive to purchase, maintain, and transport, yet it’s frame and suspension are complex enough to realistically represent components that are under investigation in commercial projects at manufactures of vehicles, systems and components. This motivates a broad participation from both OEMs, suppliers and academic parties that have the most to gain from the expected results. The Honda Corporation is not actively involved in the project at the current time.

The main venue for information exchange is via the website the committee has established at www.fatigue.org. Results of the studies conducted to date are archived at this website. These consists most notably of road load data from a data acquisition exercise with wheel force transducers under realistic operating conditions, FEA models, modal studies, flexible body dynamic simulations. Finally, a number of physical tests

Figure 1. Photo of Honda ATV

of components, sub systems and a full vehicle test on a spindle coupled road simulator have been documented.

BLACK BOX NEURAL NETWORK MODELING TECHNIQUE

Methods currently in use for modeling the behavior of suspension components such as dampers and bushings do not account for the full complexity that these components exhibit. Most notably, the inherent non-linearity and frequency dependent behavior can often not be described adequately through ‘first principles’ modeling, i.e. the formulation of the geometry, the material properties, and general differential equations relating the dynamic response of a component to any input. The ‘first principles’ approach, also commonly referred to as white box modeling, has shown great success for a number of applications of complex structures and systems. However, due the lack of understanding of the influence of friction, difficulty in defining and measuring adequate material properties for elastomers and the accurate formulation of equations for complex fluid dynamics white box models of the aforementioned suspension components are inadequate to accurately predict their dynamic behavior.

To improve on the predictive ability of the dynamic models, while keeping the computational effort at a minimum when using the model in more complex simulations of sub-systems or full vehicle models, the authors present a method that uses black box neural network models based on physical measurements performed on the part to be modeled. This method has been described in detail in [5] and is from here on referred to as Empirical Dynamics Modeling (EDM) as it is based on measured, ‘empirical’ data and typically applied to the modeling of dynamically loaded components. Empirical Dynamics and EDM are trademarks of MTS Systems Corporation.

A neural network is constructed of a number of units called ‘neurons’, where each neuron (Figure 2) takes a series of various inputs u_k and multiplies them by constant weights w_k, sums these along with a constant bias term, and then applies the result to a nonlinear ‘activation’ function to yield an output value y.

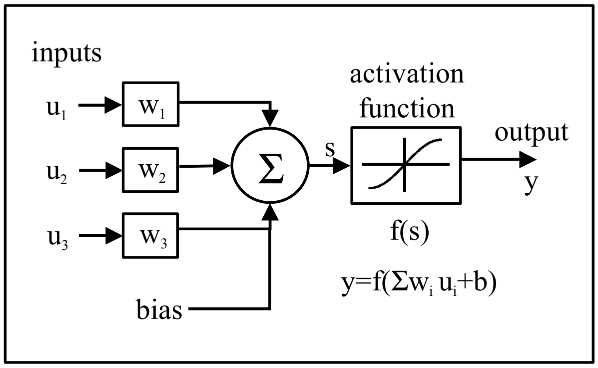

Figure 2. Neuron, Block Diagram

A neural network is constructed by connecting a number of neurons to the same inputs to form a ‘layer’ (Figure 3), and by using the outputs of one layer as inputs to another layer. This structure is called a multilayer perceptron (Figure 4).

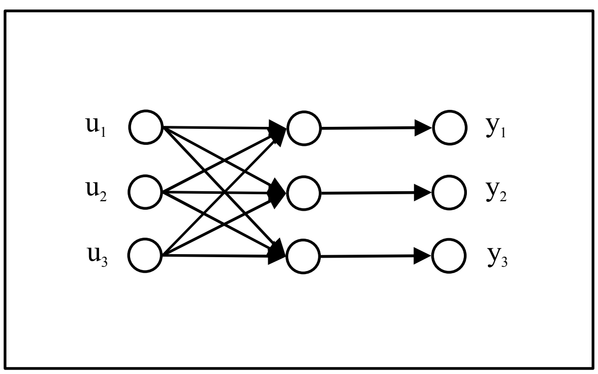

Figure 3. Neurons formed into a layer

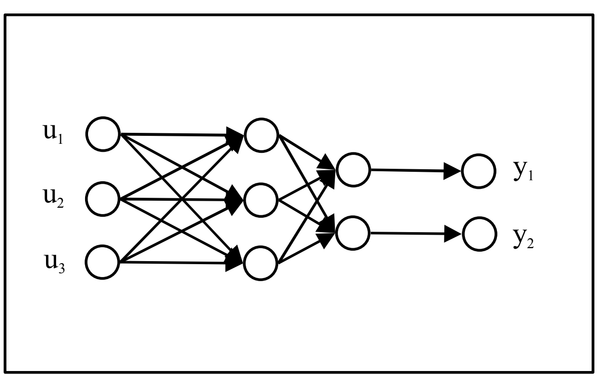

Figure 4. Multilayer perceptron

To represent a dynamic input-output relationship of a component not only current inputs and outputs but also a number of past inputs and outputs will be connected via a neural network. This is referred to as a tapped delay structure and Figure 5 below depicts this using the z^{-1} transform notation.

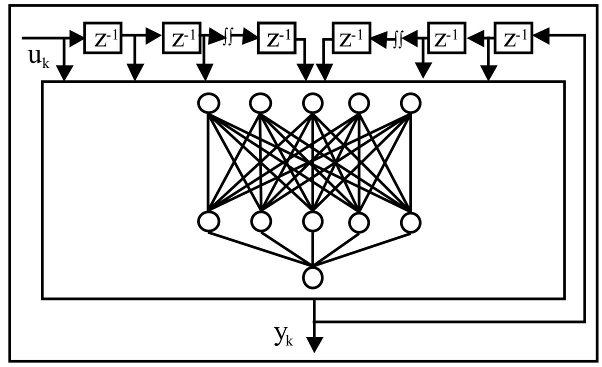

Figure 5. Tapped Delay Structure for Neural Network

The weights of the network are estimated by a ‘training’ process, which is essentially a minimum square error estimation algorithm finding the set of weights that minimizes the error between measured and predicted data. One part of the measured data (training data) is used to estimate the weights of the network, Figure 6.

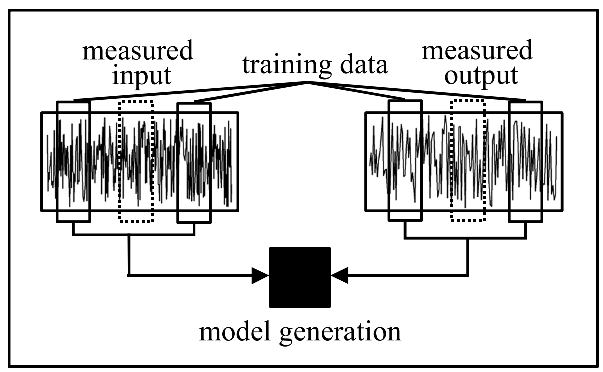

Figure 6. Model generation

While another part of the data (validation data) is used to calculate the error between predicted output and measured output. The learning process is typically terminated, when no significant reduction of the error between measured and predicted output can be achieved, Figure 7.

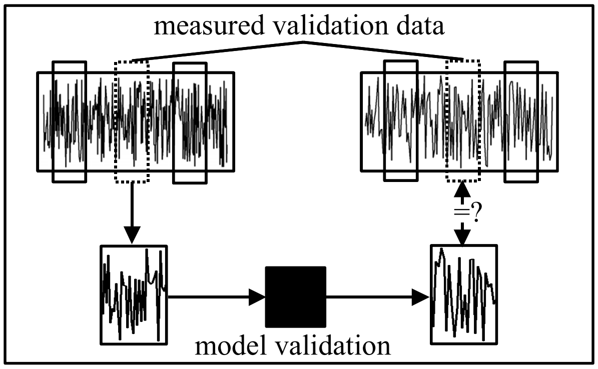

Figure 7. Model validation

The optimal structure of the network depends on the dynamic characteristics such as inherent hysteresis, excitation bandwidth, and sampling frequency of the training data.

Advantages of the black box modeling technique are the high accuracy in predicting output and the numerical efficiency in generating the predicted output. Because the black box models consist of a set of algebraic equations, the predicted output can be generated very fast. White box models, in contrast, typically require the solution of a set of differential equations, which often are solved in an iterative manner, requiring longer execution time.

SHOCK ABSORBER EMPIRICAL DYNAMICS MODEL

To demonstrate the efficacy of the Empirical Dynamics Modeling method a shock absorber of the ATV was studied. The first step was to mount the specimen into a shock absorber characterization machine of type MTS 850. The specimen (see Figure 8) was then subjected to a "training-validation" random displacement input time history.

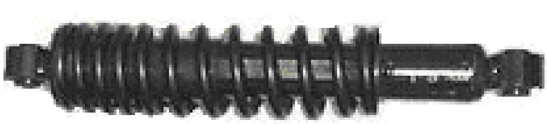

Figure 8. Photo ATV shock absorber

This history was a 55 seconds long white noise record with an auto-spectral density amplitude shaped by $1/f^2$ and an excitation bandwidth of 0-60 Hz. This type of signal was chosen as it "excites" a broad band of frequencies that contribute to fatigue damage when the component is operating under typical road load inputs. The corresponding achieved displacements and reaction forces were recorded (see Figures 9, 10, 11).

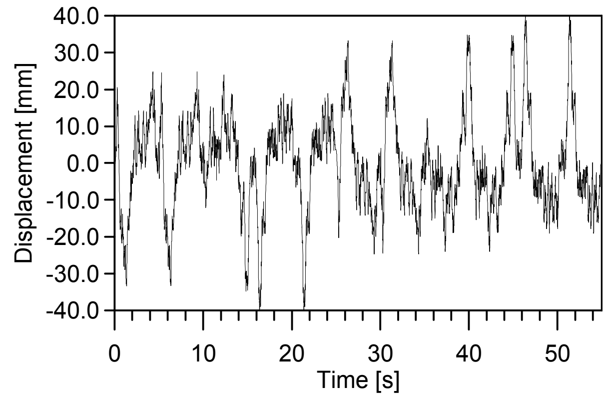

Figure 9. Measured training-validation data, displacement input time signal

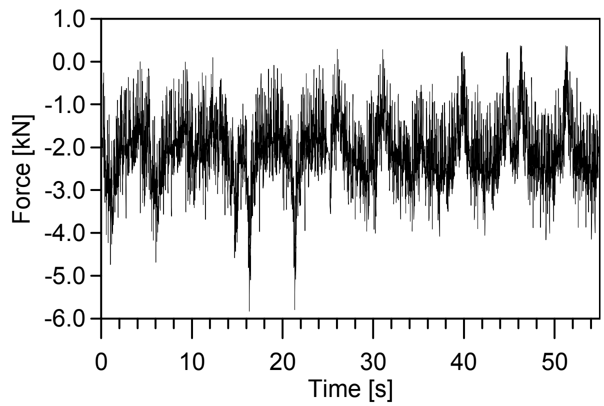

Figure 10. Measured training-validation data, force output time signal

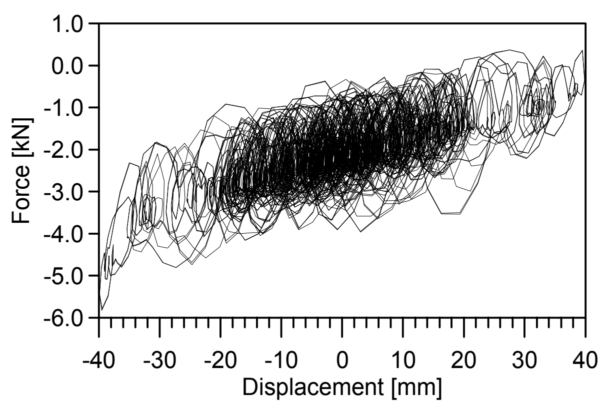

Figure 11. Measured training-validation data, displacement input vs. force output signal

A proprietary neural network structure [6] that was previously optimized for automotive shock absorbers was used to model the dynamic behavior of this specimen. Measured input and output history of the training-validation signal were used to estimate the actual weighting factors of the network.

To demonstrate the accuracy of the model an additional "prediction" random time history was generated (same excitation bandwidth and spectral shape as the training-validation data, length of 5 seconds, and an amplitude range that was 75% of that of the training data) and used as an input to the specimen on the test stand. The range of the prediction data is typically chosen less than the training data because the ED models cannot accurately predict wave forms with amplitudes larger than what was used to develop the model. The actual measured response to this prediction input signal was then compared to:

a) Predicted response by a linear transfer function estimate (frequency response function, FRF)

b) Predicted response by the polynomial fit

c) Predicted response by the ED model

FATIGUE LIFE CALCULATION

To demonstrate the sensitivity with respect to fatigue life when predicting loads, the authors present fatigue life calculations for a generic fictitious component. This could be some part of the suspension or frame structure. This component is considered to be loaded directly proportional to the measured and predicted force output history of the shock absorber. The local strain approach is employed in life calculations, and therefore predicts the initiation of easily detectable engineering size cracks. The history is considered to be observed at a critical location such as the notch root of the component.

Fatigue life was calculated for a steel of type SAE 1045 (see Table 1 according to [7]) and a stress concentration factor equal to 3. The actual measured response for the prediction history was scaled such that a fatigue life of 10^4 repetitions (blocks) to failure was achieved and then considered to be the nominal value for fatigue life. All other fatigue life values are reported as a fraction or multiple of the value for the measured time history.

Modulus of Elasticity, E (MPa)	202000
Fatigue Strength coefficient, σ'_f (MPa)	948
Cyclic strength coefficient, K' (MPa)	1258
Cyclic strain hardening exponent, n'	0.208
Fatigue Strength exponent, b	-0.092
Fatigue ductility coefficient, ε'_f	0.260
Fatigue ductility exponent, c	-0.445

Table 1. Material Properties SAE 1045 Steel

When the local strain approach (a fairly typical procedure, described in [8] and elsewhere) is employed in fatigue analysis, it requires both the stable cyclic stress-strain curve and the strain-life curve for the material. These are given by

$$\varepsilon_a = \sigma_a / E + \left(\sigma_a / K'\right)^{1/n'} \qquad (1)$$

$$\varepsilon_a = \frac{\sigma'_f}{E}\left(2N_0\right)^b + \varepsilon'_f\left(2N_0\right)^c \qquad (2)$$

where ε_a and σ_a are the strain and stress amplitudes, respectively, E is the modulus of elasticity, N_0 is the life in cycles for the case of zero mean stress, and the parameters ε'_f, σ'_f, K', n', b and c are material constants.

The Smith-Watson-Topper model for mean stresses is used, in particular, the strain amplitude is coupled with the maximum stress to incorporate mean stress effects. The equation describing this model is:

$$\sigma_{\max}\frac{\Delta\varepsilon_1}{2} = \sigma'_f\varepsilon'_f\left(2N_f\right)^{b+c} + \frac{\sigma'^2_f}{E}\left(2N_f\right)^{2b} \qquad (3)$$

where the right hand side is based on the strain life curve generated from completely reversed controlled strain testing.

For histories with varying amplitudes, the method of rainflow cycle counting has proven to be successful to identify full load reversals, or hysteresis loops, that are fatigue damage relevant. This method is well documented (e.g. [9]) and not further described herein. According to the Palmgren-Miner rule ([10], [11]), the damage, D_i, that corresponds to a particular rainflow cycle, is calculated from the cycle ratio by

$$D_i = \frac{n_i}{N_i} \qquad (4)$$

where n_i and N_i are the number of cycles counted and the number of cycles to failure for the given rainflow cycle, respectively. The component life, N_B, is then calculated from the induced damage due to all rainflow cycles as

$$N_B = \left(\sum_i D_i \right)^{-1} \qquad (5)$$

where N_B is given in terms of the number of blocks (repetitions) of the load history.

RESULTS

After exciting the specimen with the training-validation input signal and measuring the response this data was used to estimate:

a) Least square fit by a linear transfer function (commonly referred to as a frequency response function, FRF), see Figure 12.

b) Least square polynomial fit, a polynomial of order 10 was found to be efficient in the sense that the residual error did not significantly decline for higher orders, see Figure 13

c) Empirical Dynamics model, where the model was built using a standard Pentium PC with a speed of 500 MHZ. After 10 minutes of calculation time an RMS error of 0.0522 kN was achieved and not further reduced during more training.

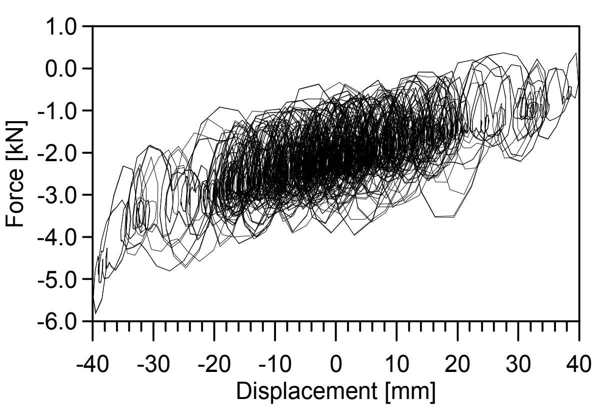

Figure 12. Frequency Response Function (FRF) fit of training-validation data

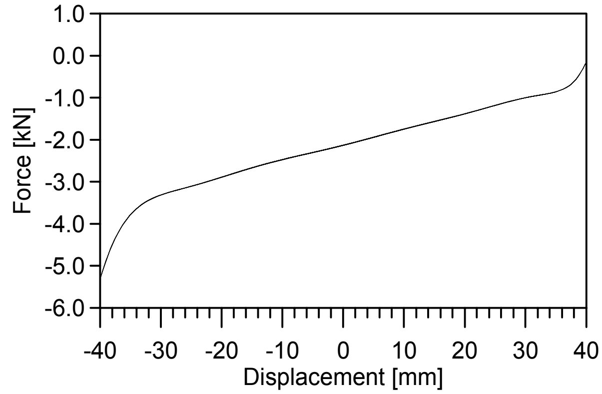

Figure 13. Polynomial fit of training-validation data

After all models have been built, the prediction displacement input time history is applied to the specimen and the corresponding force response is measured, Figures 14, 15, 16.

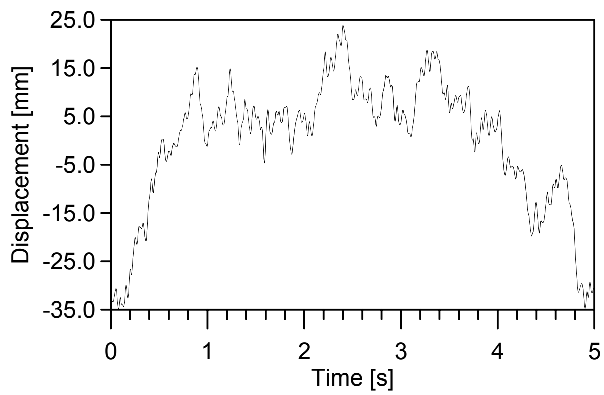

Figure 14. Measured "prediction" displacement input time history

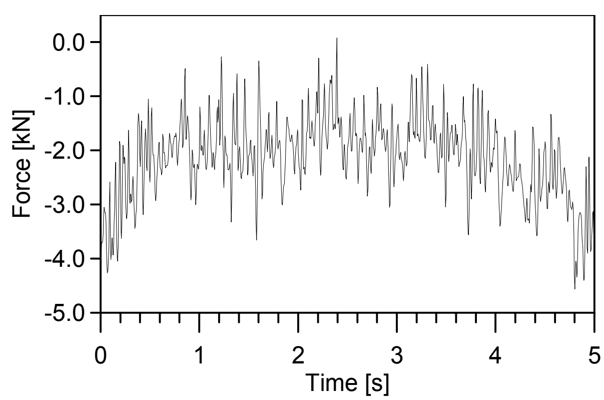

Figure 15. Measured "prediction" force output time history

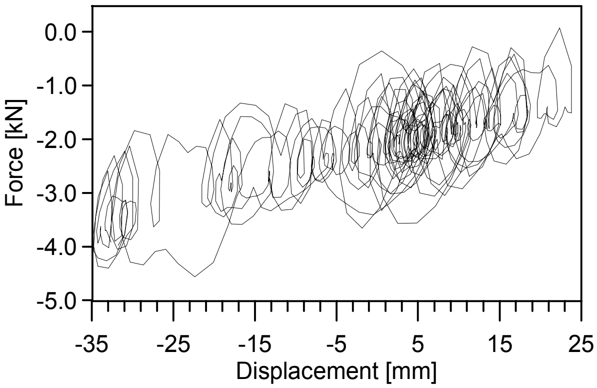

Figure 16. Measured displacement input vs. measured force output history for prediction data set

Subsequently, the prediction input history is applied to the FRF-model, polynomial-model and ED model and the predicted outputs are calculated. The following plots show the predictive capabilities of the three models by comparing the measured and predicted output for the prediction data set.

A: TIME DOMAIN COMPARISONS – The FRF fit traces maxima and minima well with respect to phase but underestimates the amplitudes due to the fact it is only a linear presentation of a component that exhibits non-linear behavior. The polynomial fit can be seen as an approximation of the "running average" of the history, but it misses individual maxima and minima due to the fact that it does not capture the inherent hysteresis in the component behavior. The ED model prediction traces the measured output history so closely that the lines practically overlap and, therefore, cannot easily be distinguished in Figure 17 below.

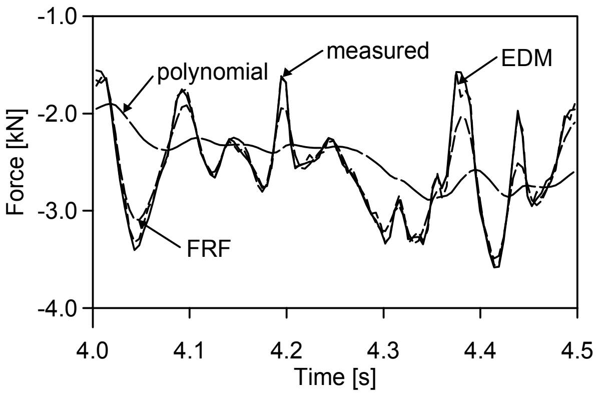

Figure 17. Portion of Measured and predicted time histories for FRF, Polynomial and ED model

B: INPUT VS. OUTPUT COMPARISONS – The following figures should be compared to Figure 16 to demonstrate how well each fit captures the input-output relationship.

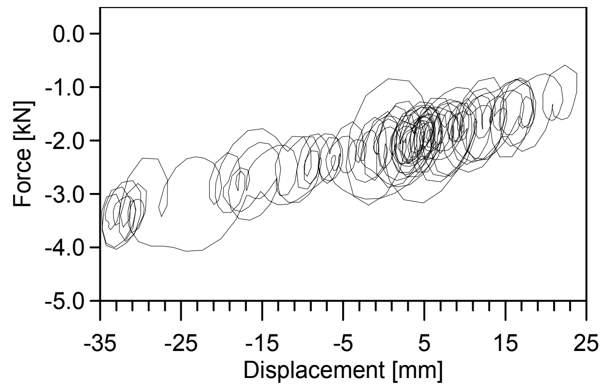

Figure 18. Measured displacement input vs. FRF fit predicted force output history

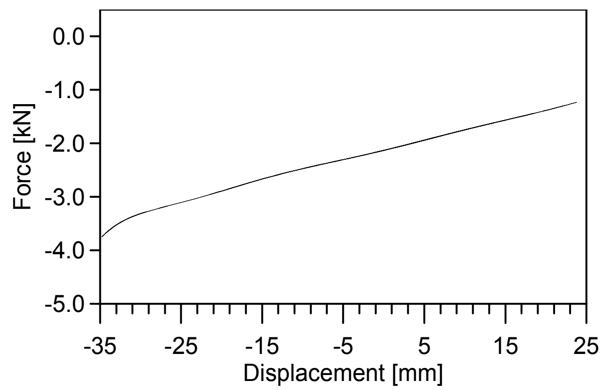

Figure 19. Measured displacement input vs. polynomial fit predicted force output history

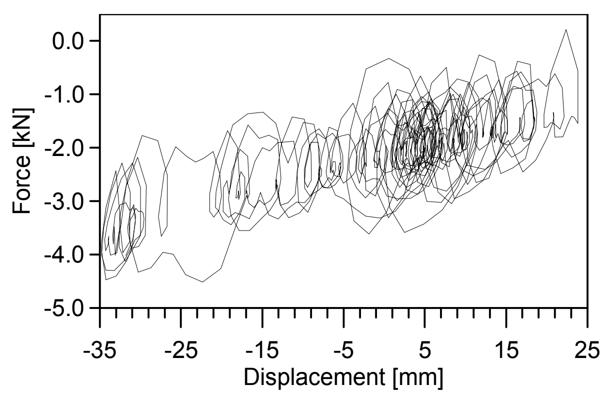

Figure 20. Measured displacement input vs. ED model predicted force output history

C: FATIGUE LIFE COMPARISONS – The following table summarizes the fatigue predictions. Fatigue life for the FRF fit is somewhat longer as the peak amplitudes were slightly underestimated which is due to the fact that the FRF fit is linear in nature and does not represent the nonlinear increase in force amplitude for displacement extremes. The polynomial fit predicts a significantly longer life as it averages between extreme values in the time domain (see Figure 19) and, therefore, predicts significantly fewer cycles than the number that was present in the measured data. The ED model prediction is close to the one for the measured history.

History Type (Force Output)	Fatigue Life
Measured	1
FRF Fit	8.20
Polynomial Fit	308.70
Empirical Dynamics Model	0.98

Table 2. Fatigue life estimate for measured and predicted histories

CONCLUSION

The method of modeling the complex dynamic behavior of a shock absorber via an empirical dynamics black box models shows much improved predictive capability when compared to currently used methods such as linear transfer function models or nonlinear polynomial fitting functions. Use of this method allows for the numerically efficient, high fidelity, description of the dynamic behavior of components such as shock absorbers that have defied accurate modeling in the past. This is particularly valuable for the analytical evaluation of systems in multi-body dynamics models where an accurate load prediction for each component is required to obtain an accurate system model for fatigue life predictions.

ACKNOWLEDGEMENTS

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