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Comparison of computing efficiency of different hydraulic vehicle damper models

Porównanie efektywności obliczeniowych różnych modeli amortyzatorów samochodowych hydraulicznych

Abstract

This paper deals with comparisons of computing efficiency of 20 damper models with functional and hybrid approaches, which can be used to solve typical problems in vehicle dynamics. Efficiency is evaluated based on model accuracy and computing time. The computed results of different damper models are compared to measurements of an actual car damper. Its damping characteristics were measured on a hydraulic damper test rig with three different excitations.

Keywords: vehicle dynamics, modelling, hydraulic damper, shock absorber

Streszczenie

W artykule porównano efektywność dwudziestu modeli amortyzatorów, funkcjonalnych i hybrydowych, które można stosować przy rozwiązywaniu podstawowych problemów dynamiki pojazdów. Efektywność jest oceniana przez dokładność odwzorowania i czas obliczeń. Odpowiedzi kolejnych modeli amortyzatora porównywano z wynikami badań rzeczywistego amortyzatora samochodowego na stanowisku ze wzbudnikiem.

Słowa kluczowe: dynamika pojazdu, modelowanie, amortyzator hydrauliczny

1. Introduction

Dampers used in vehicle suspensions can be regarded as mechanical-hydraulic systems, which generate resistance forces (F) in dependency on kinematic excitation (x), outside/ambience temperature (T_z) and inside temperature (T_w). This resistance force (F) can consist of several ingredients [1]. The damping force is a force generated by a damper as a function of damper velocity ($v = dx/dt$).

Formulating a damper model can be regarded with the same difficulty as setting up a tire model. The response of a damper is dynamic and extremely non-linear with regard to the amplitude and frequency of excitation [2]. High impact of the damping medium temperature leads to a diversification of damping characteristics within each next damping cycle [10]. The valves inside a damper can be described as three dimensional, serial and parallelly arranged hydraulic obstacles with constant as well as variable areas. Physical and chemical properties of the damping medium (e.g. viscosity, density, compressibility, vapor pressure, heat extension) depend on the proportions of the liquid phase (oil), gaseous phase (nitrogen) and intermediate phase (emulsion, foam) [4].

The aim of this paper is to compare the efficiency of several vehicle damper models, which can be used to solve basic problems of vehicle dynamics. The efficiency is evaluated by calculation of accuracy and computing time. This article describes numerical examples which show comparisons of computed responses of 20 different models and the measured damping behavior obtained at a test rig [3]. The damping characteristics of real vehicle dampers were measured on a hydraulic damper test rig with three different excitations, here with a sine signal of low frequency (W1), high frequency signal (W2) and a sine on sine signal (W3).

The results of this paper can be useful for all those who are working on measuring and modeling dampers and vehicle dynamics.

2. Numerical examples

The numerical examples are based on characteristics of an actual vehicle damper [8]. By making use of a test bench with an electro-hydraulic excitation ram, damping force characteristics were gathered. Three different excitations profiles (W1, W2, W3) were considered in this paper.

Within the MATLAB environment, 20 different damper models were formulated. The simulation results (damping forces as function of damper velocity) are compared to appropriate measurement data for the same excitation.

Because of the work constraints, only three different model outputs (Fig. 1–3) are presented as graphical examples.

All the 20 models are described briefly below, including their advantages and drawbacks. Model deviations are calculated as RMS errors of the computed and measured damping forces and summed up in Fig. 4.

M1) Model M1 (functional approach) is described by one dimensional linear interpolation (algebraic relation) between damping force and damper velocity ($F=f(v)$) with 12 nodes on the measurement data. **Model advantages.** M1 model is simple in implementation. Its prediction deviations (Fig. 4) are at average level (ca 100 N) for all the excitations and its simulation time is quite short (ca 0.2 s). **Model drawbacks**. M1 model is not continuous and does not consider a dynamic response, because of limited use in vehicle dynamics.

M2) Model M2 is based on model M1. Instead of a linear interpolation, a "spline" interpolation with 12 nodes is used. **Model advantages.** Deviations are at a similar level (100 N), compared to M1. **Model drawbacks**. In addition to the disadvantages of M1, the simulation time of M2 is very high (up to 1 s).

M3) Model M3 describes a damping force similar to model M1. Instead of using 12 nodes, this model is set up with two linear sections (Fig. 1), which should describe the damping force. **Model advantages.** This model is very fast (simulation time < 0.1 s) **Model drawbacks**. Model M3 insufficiently describes the damping force. The mean deviation at all excitations is about 370 N.

M4) Model M4 is based on model M3. Instead of using only two linear sections, here four linear sections are used (Fig. 1). **Model advantages.** This model is very fast (simulation time < 0.1 s) and easy to implement. Deviations of the damping force are at an average level (110 N). **Model drawbacks.** As the models described before, M4 does not consider any dynamic response.

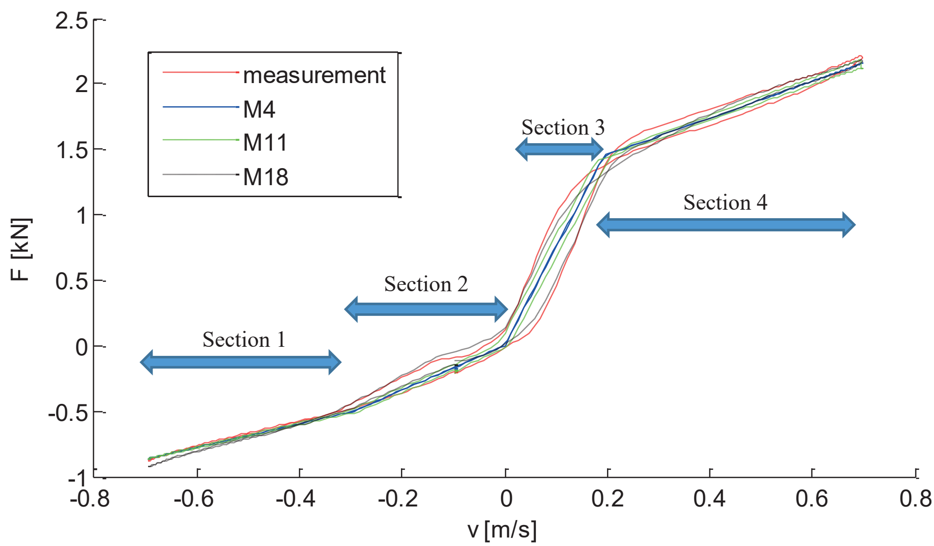

Fig. 1. Damping force vs velocity for W1 excitation. Comparison of M4, M11, M18 models with measured data

M5) Model M5 is an adaption of model M4. In addition, the valve opening behaviour in the rebound phase is considered. **Model advantages.** This model is still very fast (simulation time < 0.1 s) and easy to implement. Compared to model M4 it is slower. Damping force deviations are at an average level (100 N). **Model drawbacks.** Although some dynamic effect is considered, deviation does not enhance significantly.

M6) Model M6 consists of 4 sections (Fig. 1), where section 1 and section 4 are described with a linear function and the remaining sections are described with a 3rd order function. **Model advantages.** The simulation time remains low (< 0.1 s) and deviations of the damping force are similar to model M4 (110 N). **Model drawbacks.** A description of the damping force with functions of higher order does not enhance the model accuracy.

M7) Model M7 is a derivate of model M4. It is described by two dimensions ($F=f(v,x)$), by damper velocity and damper deflection. In this model, the so-called gas forces are taken into account. **Model advantages.** This model has a short simulation time (< 0.1 s). **Model drawbacks.** Damping force deviations remain at an average level (100 N)

M8) Model M8 has again a two dimensional approach (based on M4). Compared to M7, this model is based on damper velocity and damper acceleration ($F=f(v,a)$). **Model advantages.** This model is still fast (simulation time < 0.1 s) and its deviation is at an average level (100 N). **Model drawbacks.** The complexity of additional dimensions does not lead to better correlations between measurement and model results.

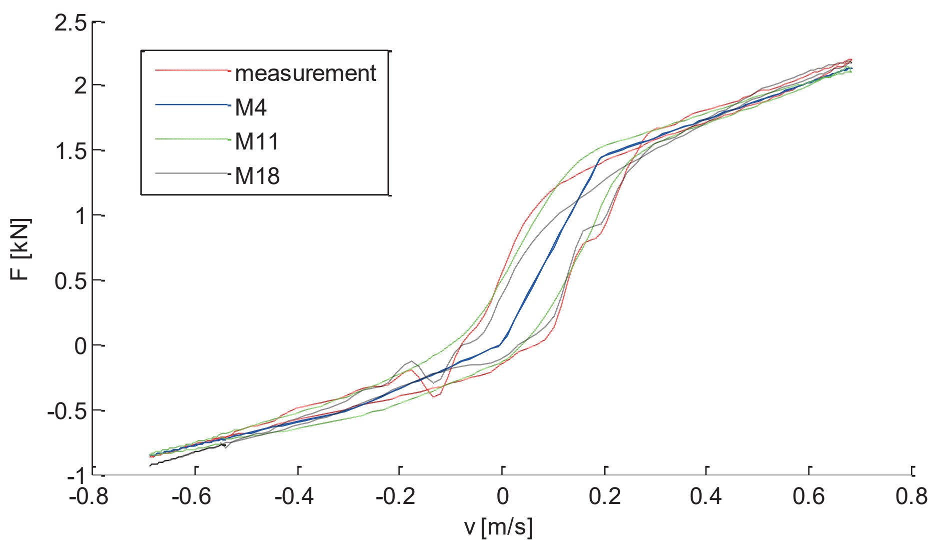

Fig. 2. Damping force vs velocity for W2 excitation. Comparison of M4, M11, M18 models with measured data

M9) Model M9 is built up as a rheological, 1st order inertial system [13]. Its parameters are constant. It is combined with model M4. **Model advantages.** Due to a physical description, the damper's dynamic behaviour is considered, which lowers the average value of deviations (90 N). **Model drawbacks.** Simulation times rises up even to more than one second.

M10) Model M10 is built up analogically to model M9, but with parameters which are dependent on the damping force. **Model advantages.** The damping force deviation is at an average level (90 N). **Model drawbacks.** Simulation times are unacceptably high with more than one second.

M11) Model M11 is a rheological, 1st order system with parameters which are dependent on the damping force, but combined with model M5, which takes into account the valve opening behaviour. **Model advantages.** The damping force deviation is at an average level (90 N). **Model drawbacks.** Simulation times (up to one second) are not feasible for vehicle dynamics simulations.

M12) Model M12 makes use of a neural network of FFB type (2 layers, 10 neurons). It is trained (alg. L-M) on excitations W1 with the damping force as a function of damping velocity ($F=f(v)$). **Model advantages.** Simulation time is very short (< 0.5 s) and the damping force deviation is in the average range of (110 N). **Model drawbacks.** To obtain suitable accordance between measurement data and simulation results, optimal parameters for training have to be determined. Also, the training procedure takes a while.

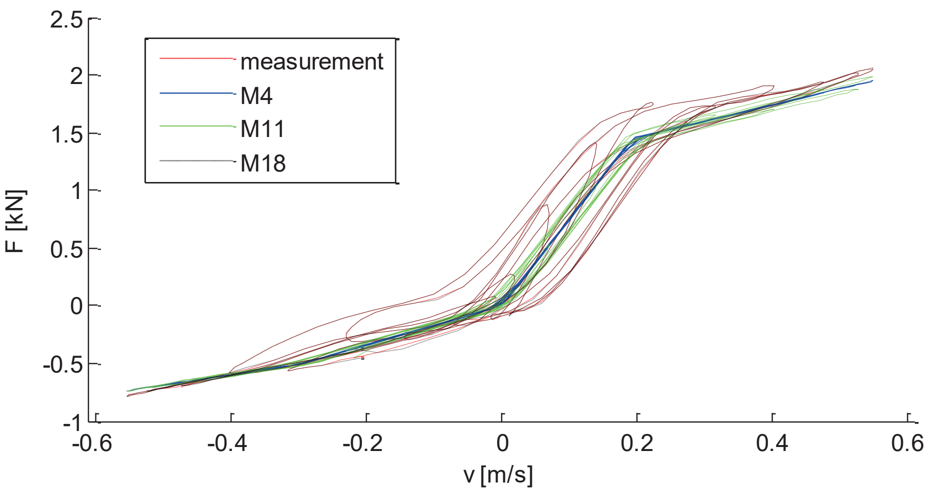

Fig. 3. Damping force vs velocity for W3 excitation. Comparison of M4, M11, M18 models with measured data

M13) Model M13 has the same parameters for the neural network as M12. M13 is trained on excitation W3 with the damping force learn input as a function of velocity and movement ($F=f(v,x)$). **Model advantages.** The results of this model have the best accordance to the damping force at excitation W3 compared to all the aforementioned models. Simulation time is still short (< 0.5 s). **Model drawbacks.** See M12.

M14) Model M14 has the same parameters for the neural network as M12. M14 is trained on excitation W2 with the damping force learn input as a function of velocity and movement ($F=f(v,x)$). **Model advantages.** The results of this model have the best accordance to the damping force at excitation W2 compared to all the aforementioned models. Simulation time is still short (< 0.5 s). **Model drawbacks.** Simulation results at excitation W1 and W3 unfit completely.

M15) Model M15 has the same parameters for the neural network as M12. M15 is trained on excitation W1 with the damping force learn input as a function of velocity and movement ($F=f(v,x)$). **Model advantages.** The results of this model have the best accordance to the damping force at excitation W1 compared to all the aforementioned models. Simulation time is still short (< 0.5 s). **Model drawbacks.** Simulation results at excitation W2 and W3 have a high deviation (200 N).

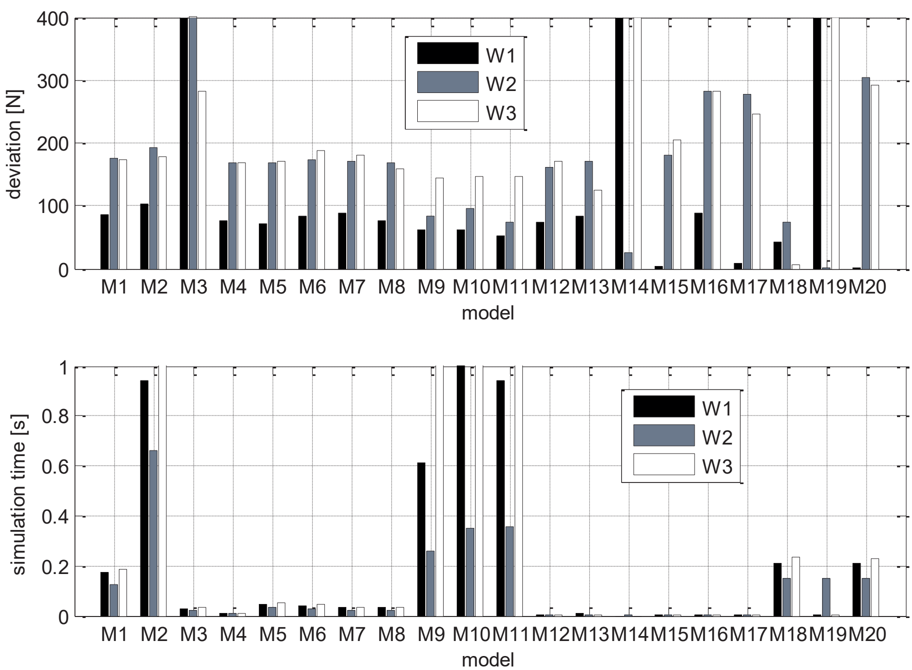

Fig. 4. Overview of deviations and calculation times of the considered damper models for W1, W2 and W3 excitations

M16) Model M16 has the same parameters for the neural network as M12. M15 is trained on excitation W1 with the damping force learn input as a function of velocity, movement and acceleration (F=f(v,x,a)). **Model advantages.** Simulation time is still short (< 0.5 s). **Model drawbacks.** An additional dimension for NN training does not lead to an improvement. Compared to M12, M16 has lower accuracy. For excitation W2 and W3, high deviation (280 N).

M17) Model M17 is a hybrid, by combining model M4 and M13. **Model advantages.** Simulation time is still short (< 0.5 s). **Model drawbacks.** The effort of joining the two models does not lead to the expected enhancement of simulation accuracy. Deviation of simulation results at W2 and W3 are high (250 N).

M18) Model M18 makes use of neural networks of the NARX structure [9]. The model was learned with 17 layers at excitation W3 with the damping force learn input as a function of velocity and damper movement ($F=f(v,x)$). **Model advantages.** The accuracy of the simulated damping force at excitation W3 is the best overall (5 N deviation). At the remaining excitations, deviation is less than 80 N, which is a very good accordance. **Model drawbacks.** Simulation time rises up to 0.2 s.

M19) Model M19 has the same parameters for the neural network as M18. M19 is trained on excitation W2. **Model advantages.** The accuracy of the simulated damping force at excitation W2 is the best overall (1 N deviation). **Model drawbacks.** At the remaining excitations, deviation is too high (> 400 N). Simulation time is high (0.2 s).

M20) Model M20 has the same parameters for the neural network as M18. M20 is trained on excitation W1. **Model advantages.** The accuracy of the simulated damping force at excitation W1 is the best overall (2 N deviation). At the remaining excitations, deviation is too high (300 N). **Model drawbacks.** Simulation time is high (0.2 s).

3. Conclusions

Dampers, as parts of the suspension, have a huge impact on active safety, travelling comfort and the durability of vehicles. Numerical modelling of dampers is still an up-to-date and complex problem. Real damping characteristics highly depend on the time-based excitation, given by e.g. hysteresis loops or other phenomena which are usually omitted in simpler models, but have a major impact on vehicles drivability [12].

The choice of the adequate damper model type should depend on the following aspects: aim of analysis, simulation time, effort for the modelling process and simplicity of model parameter estimation. Applying the appropriate damper model will lead to reducing the time of choosing optimal damping forces for particular use [6], prediction of the influence of damper defects on safety [7] or ride comfort.

In this paper, three different damper model simulation outputs are visualized. M4 is the quickest functional model with average deviation. M11, a rheological model, with best fit but long simulation time. M18 with best fit to all excitations, due to the use of a neutral network. Bar plots with simulation times and model deviations are compiled to the present summary of all 20 models.

As further work, an implantation of the aforementioned damper models in a quarter vehicle model is considered. This enables a dynamic study of damper settings influence on driver vibrations.

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