Optimization of damping characteristics for improved vehicle ride and handling

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Abstract

This paper presents a method to improve ride and handling of a vehicle by optimizing a shock absorber characteristic. A design problem based on a multibody vehicle model is formulated and solved using a multi-objective genetic algorithm. For a realistic damper representation a shock-absorber model is created. To reduce computation time a proper response surface is applied to approximate the target functions. Results for optimum ride and handling are shown.

Keywords: optimization, evolutionary methods, multibody dynamics

1. Introduction

Improving driving comfort often referred to as ride while at the same time ensuring vehicle stability and good handling properties is the primary objective in suspension design. The shock absorber is one of the key components which determine the ride and handling quality.

In recent years even passive systems with features like frequency or stroke dependent damping became very complex, making on-road tuning a time and cost intensive work. To fulfil the demand of short development time and cost reduction a method is developed to optimize the damping characteristic by the use of simulation tools and optimization algorithms. This approach leads to an optimised damper design before hardware for experimental testing is available. Furthermore it allows an automated process which finds optimum solutions, even if not better, at least quicker than the common trial and error approach.

2. Ride and Handling

In order to optimise ride and handling with an optimization algorithm objective functions have to be defined. In general car body acceleration is identified to assess vehicle comfort. Hence reducing body acceleration is a major optimization target. As human perception is complex not the absolute acceleration is used, instead a frequency-weighted acceleration is calculated, incorporating the human sensation. This performance index is calculated according to Daimler internal specifications and is called BVS (in German: Bewertungsverfahren Schwingungs-empfinden [1]). The applied logic is similar to the one published in VDI 2057 guideline. But instead of the proposed weighting factors internal correction factors and weighting curves, defined after exhaustive research on this topic, are used. The BVS performance index K is calculated as

$$K=W_{Sx}K_{Sx} + W_{Sy}K_{Sy} + W_{Sz}K_{Sz} \tag{1}$$

where K_{Si} are the translational accelerations measured on the seat rail and W_{Si} are weighting factors.

Handling or control is evaluated by computing dynamic tire forces. As the tires' capability to transfer longitudinal and lateral forces - necessary for the cars ability to follow the drivers steering input - depends on vertical load and tire contact patch area, the aim is to reduce dynamic normal tire forces $F_{N,eff}$.

In addition, experience shows that reduction of car body roll gives a better response on steering input to the driver. Investigation of the correlation between the vehicles roll characteristic and the driver's sensation led to the Daimler internal performance index called R_I (roll index [2]). It is calculated as

$$R_I = \left(\frac{\ddot{\varphi}}{a_y} h_k\right)\frac{1}{\omega} + \left(\frac{\dot{\varphi}}{a_y} h_1\right) + \left(\frac{\varphi}{a_y} h_1\right)\omega \tag{2}$$

where φ, $\dot{\varphi}$ and $\ddot{\varphi}$ are maximum roll angle, velocity and acceleration, respectively, a_y is the lateral acceleration, ω is the wheel steering frequency, h_k is the distance from roll axis to passenger head, and h_1 is a characteristic length. The R_I is used as an additional target function. The fourth criterion K_{cleat} is a modification of the BVS performance index, introduced to measure vehicle comfort passing a cleat.

3. Simulation Model

The car is modelled as a multibody system incorporating all chassis components including bushings, anti-roll bars and a sophisticated tyre model. Excitation is performed with digital roads matching measured real road profiles and covering typical conditions as smooth roads with high frequency and small amplitude excitation, rough roads with high amplitudes and low frequencies as well as cleats.

In order to obtain a shock absorber behavior which is close to the real damper regarding its damping characteristic while being simple and easy to parameterize, a new damper model is created in Matlab/Simulink. It is based on a Look-Up-Table including a logic which generates the damping force not only as function of excitation velocity, but also depends on excitation frequency and amplitude. Figure 1 shows the relation between damper force and damper velocity for measured (black stars) and simulated (blue squares) output. The characteristics are typical for a frequency depending shock absorber, where maximum force is delivered for small frequencies while low forces are generated for high frequency excitations. The damping force F is calculated as

$$F=F_l+w\, f_a\,(F_h-F_l) + (1-w)\, f_f\,(F_h-F_l) \qquad (3)$$

where F_l is damping-low-force, F_h is maximum damping force, $f_a \in [0,1]$ is a function of damper displacement, $f_f \in [0,1]$ is a function of excitation frequency and $w \in [0,1]$ is a distribution factor.

This model allows to calculate damping forces with high accuracy compared to real hardware while keeping the amount of parameters low. The model parameters are found with an automated identification procedure, where the difference between measured forces and simulated output is minimized for different excitation signals.

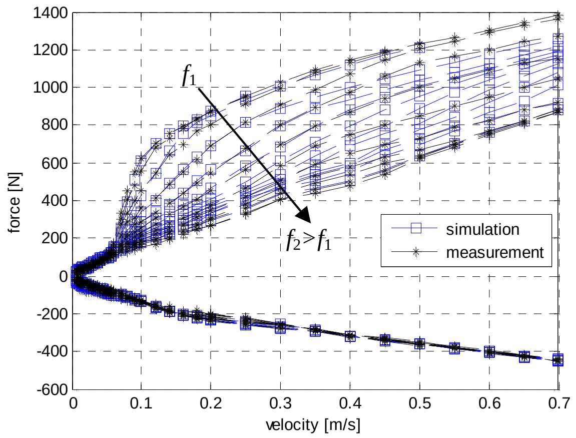

Figure 1: Typical damping characteristic

4. Optimization

The design objective is to determine the optimal shock absorber characteristic that minimizes the target functions. Mathematically such a problem is defined as:

$$\min_{\mathbf{p}\in P} \mathbf{f}(\mathbf{p}) \text{ where } P=\{\mathbf{p}\in \mathbb{R}^h \mid \mathbf{p}^l \le \mathbf{p} \le \mathbf{p}^u\}, \qquad (4)$$

f is a target vector function, **p** is the design vector and $\mathbf{p}^l$ and $\mathbf{p}^u$ summarize lower and upper bounds for the design parameters.

As the computational time for function evaluation is long due to the complexity of the vehicle model, the response surface method (RS [3]) is used to approximate the target functions. To generate a response surface a specified number of different designs in the feasible design space has to be computed using the simulation model. A sensible selection of supporting points for the RS is not trivial and is performed by using Latin Hypercube Sampling (LHS), which is a strategy for generating random sample points spreading over the whole design space. To solve Eqn. (4) a genetic algorithm (GA) is used. Deb et al. have proposed an algorithm based on GA for solving multi-objective optimization problems, called NSGA-II [4]. Unlike most classic optimization methods, genetic algorithms are not gradient-based, i.e. they do not require continuous target functions neither do they need information about the derivates. As the proposed optimization problem is highly non-linear, GA is favoured. Its drawback of large computing effort due to the large number of iterations is compensated for by the response surface, resulting in a very quick optimization loop, once the response surface is generated.

5. Results

Typically there is no unique solution but a set of compromises defining the Pareto front, where the decision maker has to choose one of the alternative solutions. Every Pareto-optimal solution is equally acceptable. As the optimization problem is more then two dimensional the spider graph illustration is preferred to visualise the different optimal results. In this diagram the maximum value for each criterion is shown and concurrently the relative improvement in percentage. Thus a design which lies on the inner side for all criteria would be the best solution. A spider graph gives a quite clear illustration of the different solutions and their pros and cons over other Pareto-optimal designs. Figure 2 shows a sample of the obtained EP points compared to the initial design (black). All solutions shown are best in one criterion, but are dominated in at least one other, so none of the designs is ultimately the best. All solutions found are obviously better than the initial design offering several proposals for a damper characteristic which improves ride and handling behavior of the vehicle.

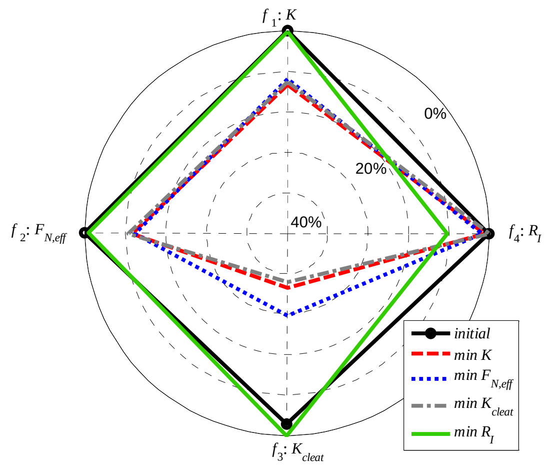

Figure 2: Spider graph showing optimal results

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