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OPTIMIZATION OF FULL-CAR MODEL PASSIVE SUSPENSION DYNAMICS USING GENETIC ALGORITHMS

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Abstract

The design of a vehicle's passive suspension system is inherently a multi-objective optimization problem, characterized by the conflicting criteria of passenger comfort and driving (road-holding) stability. Increasing suspension stiffness and damping enhances handling but amplifies vertical vibrations transmitted to passengers, whereas softer suspensions (lower stiffness and damping) improve comfort at the expense of stability. This paper presents a method for the optimal design of a passive suspension for a full-car model using a multi-objective genetic algorithm. A 7-degree-of-freedom full car model is developed, incorporating vertical, pitch, and roll motions of the sprung mass, along with the vertical motions of the four unsprung masses. The passive suspension spring stiffness and damper coefficients are selected as design variables. A genetic algorithm is employed to find their optimal values by simultaneously optimizing conflicting performance criteria: passenger comfort (quantified by chassis acceleration), driving stability (quantified by tire deflection), and vehicle attitude stability (quantified by pitch and roll angles).

***Keywords**: vehicle dynamics, full car model, passive suspension design, multi-objective optimization, genetic algorithm.*

1 INTRODUCTION

The automotive suspension system provides ride comfort and vehicle stability as well as improved handling and control by absorbing shocks from road irregularities and maintaining tire contact with the ground [1]. A typical suspension system consists of several essential parts (Fig. 1) but the most important are the springs (they support the vehicle's weight and absorb and distribute energy from bumps and potholes) and shock absorbers – dampers (they control the rebound and compression of springs to prevent excessive bouncing) [2].

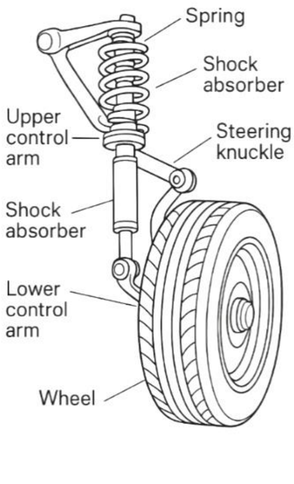

Fig. 1 *Suspension system*

Suspension systems can be broadly classified as passive, semi-active, or active. Passive suspensions, consisting of fixed springs and dampers (shock absorbers), are the most common due to their simplicity, low cost, and reliability. While they offer no adaptability to changing road conditions, their performance can be significantly enhanced through careful parameter tuning. On the other hand, semi-active and active suspensions are capable of matching changing road or dynamic conditions, so they offer superior performance but at a much higher cost, complexity and energy requirements [3]. Semi-active suspension is based on variable-damping shock absorber while active suspension use actuators to change the chassis height when needed [4].

A well-designed suspension system acts as a mediator between the vehicle chassis and the road, serving two primary functions: to isolate the vehicle body and its occupants from road-induced vibrations and shocks (ride comfort), and to maintain continuous contact between the tires and the road surface to provide steering control and stability, especially during cornering and braking (driving stability). These two objectives are fundamentally conflicting and create a well-known and inherent vehicle design conflict - "comfort-controllability trade-off" [5]. A soft suspension (decreased stiffness and damping), optimized for comfort, allows for large wheel movements which detrimentally affect stability. Conversely, a stiff suspension (increased stiffness and damping), optimized for stability, transmits more road vibrations, degrading comfort.

Passive suspensions behave as mechanical low-pass filters, offering a balance determined by fixed spring and damper characteristics. When designers select these characteristics, they implicitly choose a point on the comfort–stability performance curve. These kind of graphs are called Pareto-optimal curves and they show the best possible trade-offs between two or more conflicting objectives. Graph illustrates that you cannot simultaneously maximize both comfort and road holding with a single damping setting, instead, a compromise must be reached. The traditional design of passive suspensions often relies on iterative trial-and-error methods or frequency-response-based optimization which both may not converge to a globally optimal compromise. This paper proposes a systematic, computational approach using multi-objective genetic algorithm [6] to optimize the values for passive suspension components, i.e., spring stiffness and damping coefficients, using a full-car passive suspension model.

The goal of the optimization is to find solutions that best balances the competing criteria of maximizing passenger comfort and road holding, while also keeping vehicle body attitude control (minimizing pitch and roll angles). Approaching the design as a multi-objective optimization problem allows for the simultaneous consideration of multiple, in this case, competing, and performance indices by searching a Pareto frontier of solutions. Obtained solutions represent one-time compromise, since passive suspension characteristics cannot adapt to changing road conditions after they are once set. Finally, in the last section of this paper, the performance of the optimized suspension is compared against a baseline model to quantify the achieved improvements.

2 PASSIVE FULL VEHICLE MODEL

A full-vehicle model with seven degrees of freedom (DOF), illustrated in Fig. 2, is used for multi-objective optimization of passive suspension parameters in this paper as it captures essential vertical, pitch and roll dynamics of the car [7].

The model consists of a single sprung mass (car body) connected to four unsprung masses (wheel subsystems) via spring and damper elements.

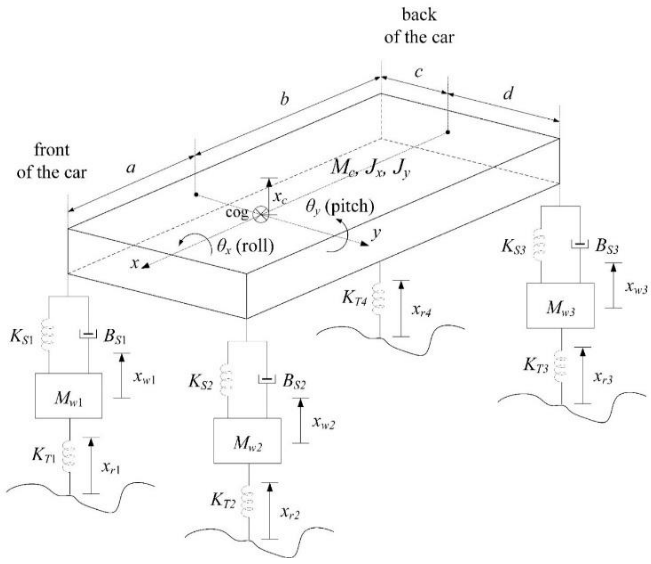

Fig. 2 *Full-vehicle model*

The following labels are used in Fig. 2 for vehicle model variables and parameters and the later simulations (chosen parameter values are typical for a mid-sized passenger vehicle):

x_{ri} - road profile change (system inputs)
x_{wi} - displacement of the wheel
x_c - displacement of the vehicle body
M_{wi} - unsprung mass - the mass of the wheel and suspension=40kg
M_c - sprung mass - the mass of the vehicle body (chassis)=1500kg
θ_x - roll angle
θ_y - pitch angle
cog - center of gravity
a - front displacement from the cog, a =1.6m
b - rear displacement from the cog, b =2.2m
c - left side wheels displacement from the cog, c =1m
d - right side wheels displacement from the cog, d =1m
K_{Ti} - spring coefficient (stiffness) of the tire, K_{Ti}=200000N/m
K_{Si} - spring coefficient (stiffness) of the suspension system, K_{Si} =35000N/m
B_{Si} - damping coefficient of the suspension system, B_{Si} =1500Ns/m
J_x - moment of inertia of the vehicle body around *x* axis, J_x =500kgm^2
J_y - moment of inertia of the vehicle body around *y* axis, J_y =2000kgm^2
v - vehicle speed=15m/s, v =54km/h

Notes: System has 7 degrees of freedom (DOF): x_{w1}, x_{w2}, x_{w3}, x_{w4}, x_c, θ_x and θ_y.

x_{r4} is the same as x_{r1} just delayed, where delay depends on vehicle speed *v*: $x_{r4}(t) = x_{r1}\left(t - \frac{a+b}{v}\right)$

x_{r3} is the same as x_{r2} just delayed, where delay depends on vehicle speed *v*: $x_{r3}(t) = x_{r2}\left(t - \frac{a+b}{v}\right)$

θ_x and θ_y are considered to be small angles $\Rightarrow \sin(\theta_i) \approx \theta_i$

Passive suspension components - spring (K_{Si}) and damping coefficients (B_{Si}) have the same values for all four wheels in the initial model.

They will the subject of optimization in the continuation of the paper and that optimization will be performed in couples, i.e. we will consider separately two front and two rear wheels.

Full-car model given in the Fig. 2 can be translated into the following set of differential equations that will be used in simulations:

$$M_{w1}\ddot{x}_{w1} + B_{S1}\left(\dot{x}_{w1} - \dot{x}_c + c\dot{\theta}_x + a\dot{\theta}_y\right) + K_{S1}\left(x_{w1} - x_c + c\theta_x + a\theta_y\right) = K_{T1}\left(x_{r1} - x_{w1}\right)$$

$$M_{w2}\ddot{x}_{w2} + B_{S2}\left(\dot{x}_{w2} - \dot{x}_c - d\dot{\theta}_x + a\dot{\theta}_y\right) + K_{S2}\left(x_{w2} - x_c - d\theta_x + a\theta_y\right) = K_{T2}\left(x_{r2} - x_{w2}\right)$$

$$M_{w3}\ddot{x}_{w3} + B_{S3}\left(\dot{x}_{w3} - \dot{x}_c - d\dot{\theta}_x - b\dot{\theta}_y\right) + K_{S3}\left(x_{w3} - x_c - d\theta_x - b\theta_y\right) = K_{T3}\left(x_{r3} - x_{w3}\right)$$

$$M_{w4}\ddot{x}_{w4} + B_{S4}\left(\dot{x}_{w4} - \dot{x}_c + c\dot{\theta}_x - b\dot{\theta}_y\right) + K_{S4}\left(x_{w4} - x_c + c\theta_x - b\theta_y\right) = K_{T4}\left(x_{r4} - x_{w4}\right)$$

$$\begin{aligned} M_c\ddot{x}_c = {} & K_{S1}\left(x_{w1} - x_c + c\theta_x + a\theta_y\right) + B_{S1}\left(\dot{x}_{w1} - \dot{x}_c + c\dot{\theta}_x + a\dot{\theta}_y\right) + K_{S2}\left(x_{w2} - x_c - d\theta_x + a\theta_y\right) + \\ & + B_{S2}\left(\dot{x}_{w2} - \dot{x}_c - d\dot{\theta}_x + a\dot{\theta}_y\right) + K_{S3}\left(x_{w3} - x_c - d\theta_x - b\theta_y\right) + B_{S3}\left(\dot{x}_{w3} - \dot{x}_c - d\dot{\theta}_x - b\dot{\theta}_y\right) + \\ & + K_{S4}\left(x_{w4} - x_c + c\theta_x - b\theta_y\right) + B_{S4}\left(\dot{x}_{w4} - \dot{x}_c + c\dot{\theta}_x - b\dot{\theta}_y\right) \end{aligned}$$

$$\begin{aligned} J_x\ddot{\theta}_x & + cK_{S1}\left(x_{w1} - x_c + c\theta_x + a\theta_y\right) + cB_{S1}\left(\dot{x}_{w1} - \dot{x}_c + c\dot{\theta}_x + a\dot{\theta}_y\right) + cK_{S4}\left(x_{w4} - x_c + c\theta_x - b\theta_y\right) + \\ & + cB_{S4}\left(\dot{x}_{w4} - \dot{x}_c + c\dot{\theta}_x - b\dot{\theta}_y\right) = dK_{S2}\left(x_{w2} - x_c - d\theta_x + a\theta_y\right) + dB_{S2}\left(\dot{x}_{w2} - \dot{x}_c - d\dot{\theta}_x + a\dot{\theta}_y\right) + \\ & + dK_{S3}\left(x_{w3} - x_c - d\theta_x - b\theta_y\right) + dB_{S3}\left(\dot{x}_{w3} - \dot{x}_c - d\dot{\theta}_x - b\dot{\theta}_y\right) \end{aligned}$$

$$\begin{aligned} J_y\ddot{\theta}_y & + aK_{S1}\left(x_{w1} - x_c + c\theta_x + a\theta_y\right) + aB_{S1}\left(\dot{x}_{w1} - \dot{x}_c + c\dot{\theta}_x + a\dot{\theta}_y\right) + aK_{S2}\left(x_{w2} - x_c - d\theta_x + a\theta_y\right) + \\ & + aB_{S2}\left(\dot{x}_{w2} - \dot{x}_c - d\dot{\theta}_x + a\dot{\theta}_y\right) = bK_{S3}\left(x_{w3} - x_c - d\theta_x - b\theta_y\right) + bB_{S3}\left(\dot{x}_{w3} - \dot{x}_c - d\dot{\theta}_x - b\dot{\theta}_y\right) + \\ & + bK_{S4}\left(x_{w4} - x_c + c\theta_x - b\theta_y\right) + bB_{S4}\left(\dot{x}_{w4} - \dot{x}_c + c\dot{\theta}_x - b\dot{\theta}_y\right) \end{aligned}$$

3 MULTI-OBJECTIVE OPTIMIZATION OF SUSPENSION PARAMETERS USING GENETIC ALGORITHM

Genetic algorithms are a class of evolutionary optimization techniques inspired by evolutionary processes observed in nature, translated into a computational framework for solving optimization problems. They operate by applying principles of natural selection to a population of candidate solutions, progressively yielding individuals that are better adapted to the problem environment. In this context, the population consists of a set of points within the search space, where each individual encodes a potential solution of optimization problem through its chromosome representation. The fitness of each individual is evaluated using the objective function. The algorithm iteratively improves the population through the application of genetic operators: selection (choosing the fittest individuals), crossover (combining parts of two parents to create offspring), and mutation (introducing random small changes to maintain diversity). In such a way, the algorithm emulates evolutionary mechanisms, leveraging the "survival of the fittest" principle to accelerate convergence toward high-quality solutions. Genetic algorithms have been widely applied across numerous domains - including function optimization, image processing, system identification and control - and have consistently shown strong performance as global optimization methods in a variety of applications, especially when non-linear dynamics and non-convex solution spaces are present [8].

For multi-objective problems, several effective variants of genetic algorithms can be found inside Global Optimization Tollbox of newer versions of MATLAB software [9], [10]. They ranks individuals based on Pareto dominance, ensuring a diverse spread of solutions along the Pareto-optimal front, which represents the set of solutions where no objective can be improved anymore without degrading another. Constructing Pareto front of equally optimal solutions rather than collapsing objectives into a weighted sum [11] allows the designer to visualize the trade-offs and select a final design based on their preferences.

For our case study, set of parameters to be optimized encompass four suspension parameters: [K_{Sf}, K_{Sr}, B_{Sf}, B_{Sr}], where K_{Sf} is stiffness coefficient of two front springs, K_{Sr} of two rear springs, while B_{Sf} and B_{Sr} are damping coefficients of front and rear dampers, respectively. Their bounds during optimization are: 20000 < K_{Sf}, K_{Sr} < 60000N/m and 1000 < B_{Sf}, B_{Sr} < 5000Ns/m.

The multi-objective optimization aims the following three performance indices:

1. Passenger comfort – by minimizing vertical acceleration of the chassis:

$$J_1 = \sqrt{\frac{1}{T}\int_0^T \ddot{x}_c^2(t)dt}$$

2. Road holding – by minimizing vertical tire deflection for all four wheels:

$$J_2 = \sqrt{\frac{1}{T}\int_0^T \sum_{i=1}^{4}\left(x_{wi}(t) - x_{ri}(t)\right)^2 dt}$$

3. Vehicle stability – by minimizing pitch and roll angles variations:

$$J_3 = \sqrt{\frac{1}{T}\int_0^T \left(\theta_x^2(t) + \theta_y^2(t)\right)dt}$$

Also, the following nonlinear constraints were introduced into the optimization algorithm:

Maximum suspension deflection: $\left|x_c - x_{wi}\right| < 0.15m$

Maximum pitch angle: $\left|\theta_x\right| < 0.1rad$

Maximum roll angle: $\left|\theta_y\right| < 0.1rad$

As alreday stated, simulation and optimization was performed in a MATLAB/Simulink environment, in the scope of Global Optimization Toolbox. The road inputs x_{ri} were combined random broad-band excitation followed by a single road bump with total simulation time of 15 seconds. Genetic algorithm was used with a population size of 150 for 200 generations to find the Pareto-optimal set for a balanced weighting of three stated objectives.

4 RESULTS AND ANALYSIS

First set of simulations was performed with pre-set baseline parameters:

$$K_{S1}=K_{S2}=K_{S3}=K_{S4}=35000\text{N/m}$$

$$B_{S1}=B_{S2}=B_{S3}=B_{S4}=1500\text{Ns/m}$$

After the optimization process, where front and rear suspension parameters (spring stiffness and shock absorber damping coefficients) were optimized in pairs, one solution was selected from the Pareto front that offered a balanced improvement across all objectives:

$$K_{Sf}=K_{S1}=K_{S2}=27800\text{N/m}$$

$$K_{Sr}=K_{S3}=K_{S4}=32150\text{N/m}$$

$$B_{Sf}=B_{S1}=B_{S2}=3650\text{Ns/m}$$

$$B_{Sr}=B_{S3}=B_{S4}=4050\text{Ns/m}$$

Then, the new set of simulations were performed, this time with optimized parameters, and the performance of this optimized suspension was compared against the baseline and the performance results are given in the following Table.

Table 1: Performance comparison for baseline and optimized systems

Performance metric	Baseline	Optimized	Improvement [%]
J_1 [m/s^2]	1.83	1.47	19.7
J_2 [m]	0.019	0.016	15.8
J_3 [rad]	0.034	0.031	8.82

The results in Table 1 demonstrate a clear performance gain in all performance indices. The optimized suspension, with its softer springs and firmer dampers, effectively reduces the vertical body acceleration, thereby improving ride comfort by 19.7%. The firmer damping provides better control over body movements, which is evident in the reduced tire deflection (improved stability) for 15.8%, pitch, and roll angles. This confirms the GA's ability to find a superior compromise, allowing designers to move from a subjective baseline values to a quantitatively better Pareto-optimal point, i.e., to select suspension parameters based on specific performance preferences, effectively making a classic engineering compromise with comfort-handling trade-off.

Performance improvements can be also seen in the following Figs. 3, 4 and 5 with simulations performed for a simple road profile (*xr* in Fig. 3) with a road bump and two different suspension set-ups – baseline and optimized.

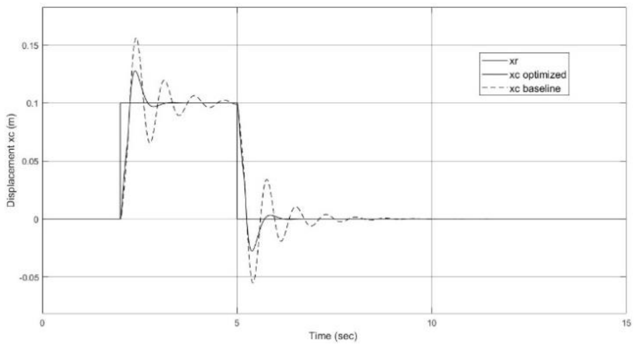

Fig. 3 *Road profile and chassis displacement for baseline and optimized set-ups*

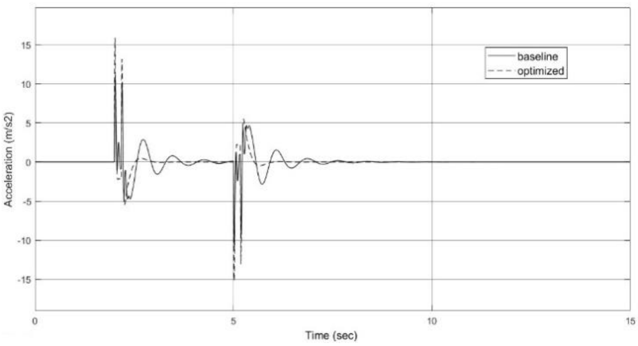

Fig. 4 *Chassis vertical acceleration as a measure of ride comfort for baseline and optimized set-ups*

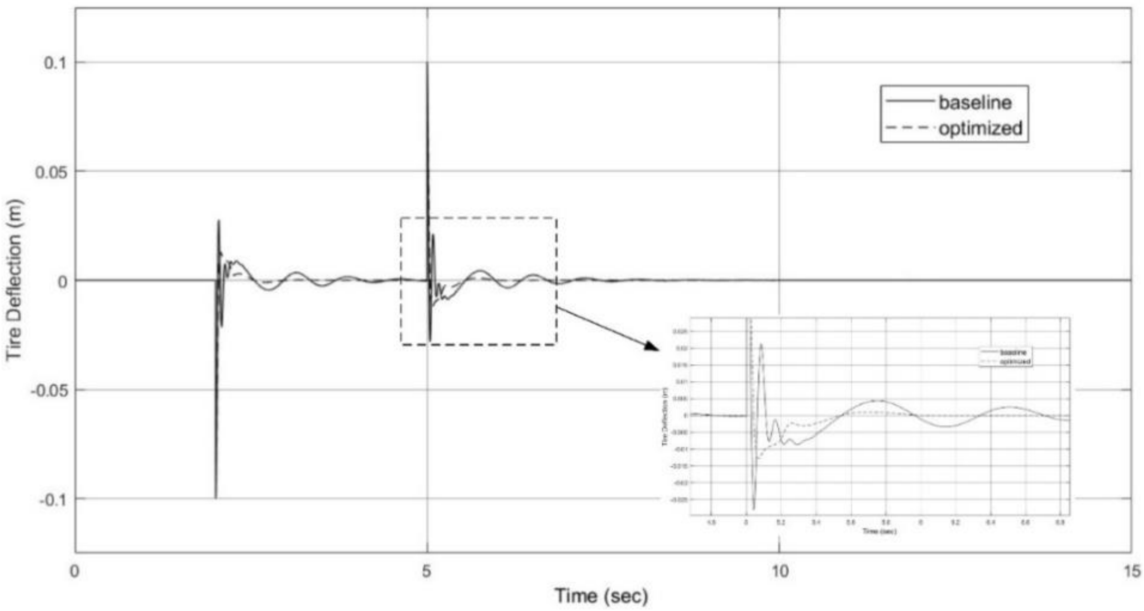

Fig. 5 *Tire deflection as a measure of driving stability for baseline and optimized set-ups with enlarged detail*

5 CONCLUSION

This paper has successfully demonstrated the application of a multi-objective genetic algorithm, for the optimal design of a passive suspension system for a designed seven-degree-of-freedom full-car model. The inherent conflict between passenger comfort and road-holding stability, key but mutually competing performance objectives in suspension design, was formally addressed as a multi-objective optimization problem. By defining three key performance indices - vertical chassis acceleration, tire deflection, and pitch/roll angle variations (both comfort and stability indice) - and treating the front and rear spring stiffness and damping coefficients as design variables, the algorithm was able to efficiently explore the complex design space.

The optimization process yielded a Pareto-optimal set of solutions, from which a balanced compromise was selected. The results confirmed the effectiveness of the proposed methodology, rather than relying on traditional trial-and-error or single-objective approaches. Compared to the baseline suspension parameters, the optimized configuration achieved a significant and simultaneous improvement across all evaluated metrics compared to the baseline configuration. Specifically, vertical chassis acceleration was reduced by nearly 20%, tire deflection by approximately 16%, and pitch–roll variations by almost 9%. These improvements were obtained while respecting nonlinear constraints on suspension deflection and chassis angles, confirming that the optimized parameters remain physically feasible for real-world implementation.

While the passive suspension remains a fixed compromise, this method ensures that the chosen parameters represent a globally superior balance for the defined operating conditions. Beyond the specific solution presented here, the methodology provides a flexible framework that can be extended to incorporate additional objectives, different road excitation models, or more complex suspension architectures such as semi-active systems.

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