

A Multi Objective Optimization Approach to Optimize Vehicle Ride and Handling Characteristics

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Abstract—Vehicle suspension design must fulfill some conflicting criteria. Among those is ride comfort which is attained by minimizing the acceleration transmitted to the sprung mass, via suspension spring and damper. Also good handling of a vehicle is a desirable property which requires stiff suspension and therefore is in contrast with a vehicle with good ride. Among the other desirable features of a suspension is the minimization of the maximum travel of suspension. This travel which is called suspension working space in vehicle dynamics literature is also a design constraint and it favors good ride. In this research a full car 8 degrees of freedom model has been developed and the three above mentioned criteria, namely: ride, handling and working space has been adopted as objective functions. The Multi Objective Programming (MOP) discipline has been used to find the Pareto Front and some reasoning used to chose a design point between these non dominated points of Pareto Front.

Keywords—Vehicle, Ride, Handling, Suspension, Working Space, Multi Objective Programming.

I. INTRODUCTION

EVER since the first steam driven vehicle has been built in Eighteen century, the designers were interested to improve the vehicle safety, comfort and controllability. The suspension system of a vehicle has a vital role in this regards. Suspension system of vehicles categorize in three classes, namely: 1) Passive, 2) Semi Active and 3) Active suspension systems. Vehicle vibration due to road profile irregularities is well developed and comes under broader topic of vibration control. From a historical point of view passive suspension systems which consist of a spring and damper first introduced. Due to its simplicity and low cost most of the passenger vehicles use this kind of suspension. Because of the nature of elements of this kind of suspension which are passive the comfort it can provide for passengers are limited and it cannot succeed the Fatigue or decreased proficiency boundaries of ISO 2631 which is the internationally accepted standard for human tolerance to whole body vibration [1]. To achieve better vibration isolation and reach the reduced comfort boundaries of ISO 2631 the active and semi active suspension should be used. The active suspension system uses a hydraulic jack based on a control scheme to eliminate unwanted vibration of the vehicle. Although the performance of Active suspension systems are slightly better than semi active one, due to the complexity, cost and power consumption of these systems,

their use have been limited and they are being replaced by the simpler, and cheaper semi active suspension systems on luxurious vehicles. The main element of a semi active suspension system is a damper with variable damping coefficient. These are either electrorheological or magnetorheological dampers. The fluid in these dampers are sensitive to magnetic or electric field so the viscosity of the damper fluid and hence the damping coefficient of the damper can be changed by varying these fields almost instantly. The time constant of this phenomenon is about two milliseconds. Having a damper with a varying damping coefficient there are a number of control strategies to control the vibration of sprung mass, unsprung mass or a number of compromises between the two [2]. Since the number of the passenger vehicles with passive suspension systems are far more than vehicles with semi active suspension we focus our attention on passive suspension and multi objective optimization of such systems. In section II of the paper the equations of a full car with 8 degrees of freedom is introduced. Then the criteria for good ride and handling and suspension working space is defined. Section III briefly introduce multi objective programming (MOP) and the NSGAI algorithm which was used here for determining best coefficients for the passive suspension system. These coefficients are damping ratio of the suspension dampers as well as spring stiffness of suspension springs. In this section the results of the response of an optimized passive suspension and some other responses have been shown.

II. SYSTEM MODEL

The full car 8 degrees of freedom model which has been used in this study was taken from [3]. In the following the motion equations and the system model picture is directly quoted from that [3].

$$z_{ps} = z_s - r_x \theta + r_y \varphi, \quad (1)$$

$$z_{s11} = z_s - l_f \theta + a \varphi, \quad (2)$$

$$z_{s12} = z_s - l_r \theta - b \varphi, \quad (3)$$

$$z_{s21} = z_s + l_r \theta + c \varphi, \quad (4)$$

$$z_{s22} = z_s + l_f \theta - d \varphi, \quad (5)$$

$$F_{SS} = K_{SS} (z_c - z_{ps}) + C_{SS} (\dot{z}_c - \dot{z}_{ps}), \quad (6)$$

$$F_{S11} = K_{S11}(z_{S11} - z_{11}) + C_{S11}(\dot{z}_{S11} - \dot{z}_{11}), \quad (7)$$

$$F_{S12} = K_{S12}(z_{S12} - z_{12}) + C_{S12}(\dot{z}_{S12} - \dot{z}_{12}), \quad (8)$$

$$F_{S22} = K_{S22}(z_{S22} - z_{22}) + C_{S22}(\dot{z}_{S22} - \dot{z}_{22}), \quad (9)$$

$$F_{S21} = K_{S21}(z_{S21} - z_{21}) + C_{S21}(\dot{z}_{S21} - \dot{z}_{21}), \quad (10)$$

$$m_c \ddot{z}_c = -F_{SS}, \quad (11)$$

$$m_s \ddot{z}_s = -F_{S11} - F_{S12} - F_{S22} - F_{S21} + F_{SS}, \quad (12)$$

$$I_{Sy} \ddot{\theta} = l_f F_{S11} + l_f F_{S12} - l_r F_{S22} - l_r F_{S21} - r_x F_S, \quad (13)$$

$$I_{Sx} \ddot{\phi} = -a F_{S11} + b F_{S12} - c F_{S22} + d F_{S21} + r_y F_{SS} \quad (14)$$

$$m_{11} \ddot{z}_{11} = F_{S11} + F_{a11} - K_{p11}(z_{11} - z_{p11}) \quad (15)$$

$$m_{12} \ddot{z}_{12} = F_{S12} + F_{a12} - K_{p12}(z_{12} - z_{p12}) \quad (16)$$

$$m_{22} \ddot{z}_{22} = F_{S22} + F_{a22} - K_{p22}(z_{22} - z_{p22}) \quad (17)$$

$$m_{21} \ddot{z}_{21} = F_{S21} + F_{a21} - K_{p21}(z_{21} - z_{p21}) \quad (18)$$

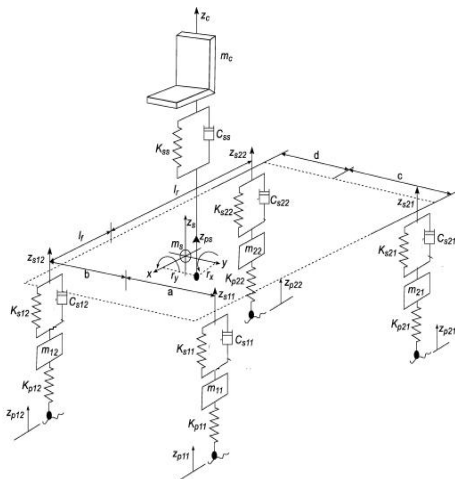


Fig. 1 3D vehicle model

The vertical dynamic equations of motion have been simulated by MATLAB/SIMULINK software, so the response of the vehicle to any input from different road profile can be assessed. The geometric and mass and inertia properties of the vehicle are taken from [3] as given in the following table.

TABLE I
GEOMETRIC, MASS AND INERTIA PROPERTIES OF THE VEHICLE

| mc | ms | m11 | m12 | m21 | m22 |
|------------------------|------------------------|------------------|------------------|------------------|------------------|
| 75 Kg | 730 Kg | 40 Kg | 40 Kg | 35.5 Kg | 35.5 Kg |
| I _{sy} | I _{sx} | K _{s11} | K _{s12} | K _{s21} | K _{s22} |
| 1230 Kg.m ² | 1230 Kg.m ² | 19.96 KN/m | 19.96 KN/m | 17.5 KN/m | 17.5 KN/m |
| l _f | l _r | a | b | c | d |
| 1.011 m | 1.803 m | 0.761 m | 0.761 m | 0.755 m | 0.755 m |
| C _{s11} | C _{s12} | C _{s21} | C _{s22} | | |
| 1290 N.s/m | 1290 N.s/m | 1620 N.s/m | 1620 N.s/m | | |
| K _{p11} | K _{p12} | K _{p21} | K _{p22} | | |
| 17.5 KN/m | 17.5 KN/m | 17.5 KN/m | 17.5 KN/m | | |

III. MULTI OBJECTIVE PROGRAMMING (MOP) AND THE GENETIC ALGORITHM (GA)

In most of the engineering problems, more than one objective function is important for the designer. Usually some conflicting objectives should be optimized by the designer at the same time. For example in a vehicle fuel efficiency and engine power are two opposite objectives which are sought by the designer. In such problems, in opposite to single objective optimization problems, in which there is only one extremum point for the problem, there are a set of optimum design vectors which are called Pareto front. The important characteristic of these solutions is that none of them are dominated by the other ones. The designer based on his or her needs chooses one of these solutions as the optimal one.

Multi-objective optimization has been defined as finding a vector of decision variables satisfying constraints to give acceptable values to all objective functions [4]. Such problems can be mathematically defined as:

$$\text{Find the vector } X^* = [x_1^*, x_2^*, \dots, x_n^*]^T \text{ to optimize:}$$

$$F(X) = [f_1(X), f_2(X), \dots, f_k(X)]^T,$$

subject to m inequality constraints

$$g_i(X) \leq 0, \quad i = 1 \text{ to } m,$$

and p equality constraints

$$h_j(X) = 0, \quad j = 1 \text{ to } p,$$

Where $X^* \in \mathfrak{R}^n$ is the vector of decision or design variables, and $F(X) \in \mathfrak{R}^k$ is the vector of objective functions, which must each be either minimized or maximized. However, without loss of generality, it is assumed that all objective functions are to be minimized.

In recent decade, Genetic Algorithm (GA) have been used extensively in diverse fields, such as science, commerce and engineering. The main use of GA is for optimizations.

In 1975 John Holland a professor of Psychology and Electrical Engineering from university of Michigan introduced Genetic Algorithm concept.

Genetic algorithm works fine on solving MOP. Srinivas et al in recent years have proposed an algorithm based on GA for solving MOPs [5]. This method which is called Non-dominated Sorting Genetic Algorithm NSGA is superior to the previous algorithms. Due to some difficulties of this method, the modified algorithm was developed by Deb et al some years later which was called NSGA II [6].

To compromise between ride comfort, handling and minimum suspension working space some criteria should be defined.

These criteria include seat acceleration \ddot{z}_c , bounce acceleration of the sprung mass \ddot{z}_s , pitch acceleration $\ddot{\theta}$, and roll acceleration $\ddot{\phi}$ of the sprung mass, suspension deflections $d_{ij} = (z_{sij} - z_{ij})$, and the wheel velocities \dot{z}_{ij} , $i=1,2$ and $j=1,2$.

It is now desired to find a trade-off optimum design point out of all non-dominated 12 objective functions. It is now possible to seek an optimum design point which is located almost on all Pareto fronts. This can be achieved by two different methods employed in this paper, namely:

- 1) The nearest to ideal point method
- 2) The mapping method.

In the nearest to ideal point method, first, an ideal point with the best values of each objective functions is considered. Secondly, the distances among all non-dominated points to the ideal point is calculated. In this method, the suggested point represents minimum distance to the ideal point.

In the mapping method, the values of objective functions of all non-dominated point are mapped into interval 0 and 1. Using the sum of these values for each non-dominated point, the suggested point simply represents the minimum of the sum of those values.

Fig. 2 shows the flow diagram of a multi objective genetic algorithm.

Using the NSGA II algorithm with the two methods presented above interesting results obtained. The input to the car suspension system was a sinusoidal displacement input to the vehicle tires.

Consequently, optimum design points A, B are the points which have been obtained from the nearest to ideal point method and mapping method, respectively. The optimal suspension parameters from [3] are tested in model with sinusoidal input and the result of performance criteria in rms for point C and optimum design points A,B are shown in Table III.

Table II shows the design constraints which should be met in finding the optimum values of the design variables.

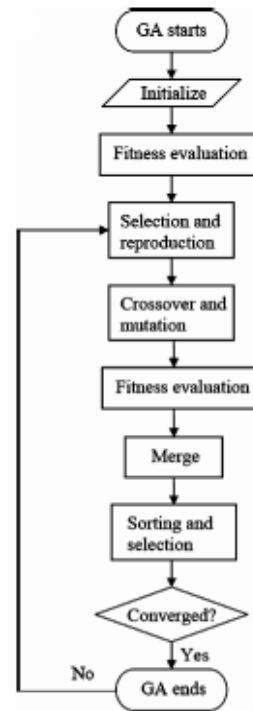


Fig. 2 Flow diagram of a multi objective genetic algorithm

TABLE II
RANGE OF DESIGN CONSTRAINTS

| Unit | Design Constraint |
|----------|------------------------------|
| (KN/m) | $10 < K_{s11}, K_{s12} < 30$ |
| (KN/m) | $10 < K_{s21}, K_{s22} < 30$ |
| (KN/m) | $50 < K_{ss} < 150$ |
| (KN s/m) | $0.5 < C_{s11}, C_{s12} < 2$ |
| (KN s/m) | $0.5 < C_{s21}, C_{s22} < 2$ |
| (KN s/m) | $0.5 < C_{ss} < 4$ |
| (KN s/m) | $0.5 < g_{11}, g_{12} < 2$ |
| (KN s/m) | $0.5 < g_{21}, g_{22} < 2$ |
| (m) | $0 < r_x < 0.7$ |
| (m) | $0.2 < r_y < 0.7$ |

TABLE III
OPTIMAL VALUES FOR THE SINUSOIDAL ROAD PROFILE

| Point Name | B | A | C |
|--|--------|--------|--------|
| Ks11,Ks12 (KN/m) | 12667 | 30000 | 14805 |
| Ks21,Ks22 (KN/m) | 11333 | 16667 | 22537 |
| Kss (KN/m) | 83333 | 50000 | 97985 |
| Cs11,Cs12 (KN s/m) | 500 | 1400 | 1384 |
| Cs21,Cs22 (KN s/m) | 500 | 1900 | 1118 |
| Css (KN s/m) | 1667 | 1433 | 1926 |
| r_x (m) | 0.1867 | 0.6533 | 0.36 |
| r_y (m) | 0.6667 | 0.4333 | 0.234 |
| \ddot{z}_c (m/s ²) | 0.6398 | 0.4017 | 0.8636 |
| $\dot{\theta}$ (rad/ s ²) | 1.2667 | 2.1689 | 1.8897 |
| $\dot{\varphi}$ (rad/ s ²) | 0.0302 | 0.012 | 0.0131 |
| d11(m) | 0.0046 | 0.0017 | 0.0217 |
| d12(m) | 0.0043 | 0.0016 | 0.0024 |
| d21(m) | 0.0184 | 0.0095 | 0.0124 |
| d22(m) | 0.0187 | 0.0096 | 0.0124 |
| \dot{z}_{11} (m/s) | 0.0672 | 0.0706 | 0.0701 |
| \dot{z}_{12} (m/s) | 0.0672 | 0.0706 | 0.0701 |
| \dot{z}_{21} (m/s) | 0.073 | 0.0695 | 0.07 |
| \dot{z}_{22} (m/s) | 0.073 | 0.0695 | 0.07 |
| \ddot{z}_s (m/ s ²) | 1.1277 | 1.9939 | 1.7145 |

Figs. 3 to 6 depicts the non-dominated individuals of 12-objective optimization in the plane of $(\ddot{z}_c - \dot{\theta})$ and $(\ddot{z}_c - \dot{\varphi})$ respectively. As it can be seen in both figure point B dominates points A and C. It is obvious from Fig. 2 that point B laid on pareto front of Plane $(\ddot{z}_c - \dot{\theta})$. However, it can be observed that points A and B have each one have their advantages for designer.

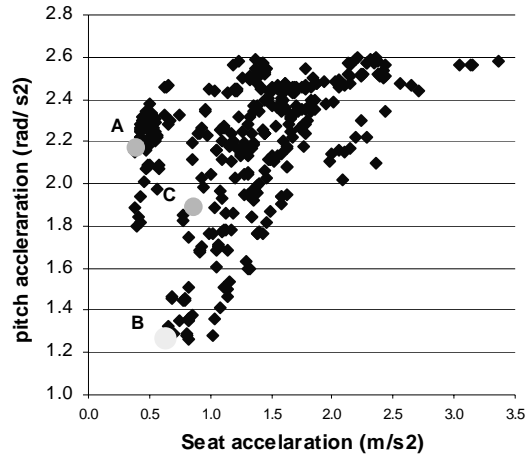


Fig. 3 Seat acceleration versus pitch acceleration

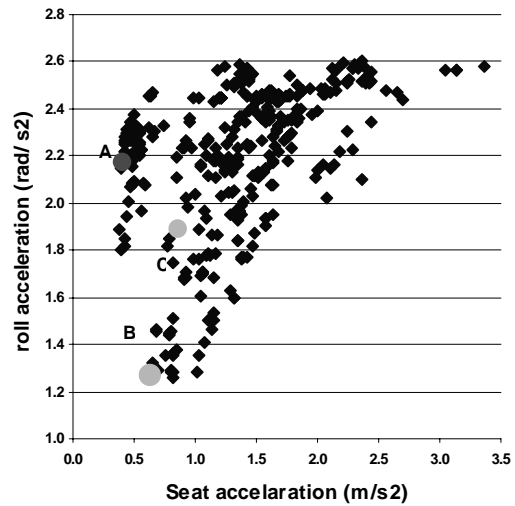


Fig. 4 Seat acceleration versus roll acceleration

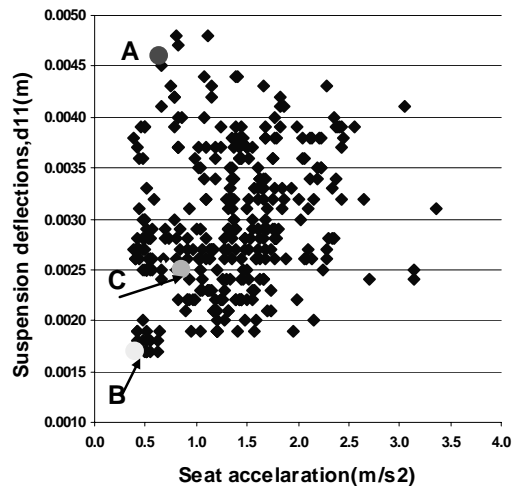


Fig. 5 Seat acceleration versus suspension deflection

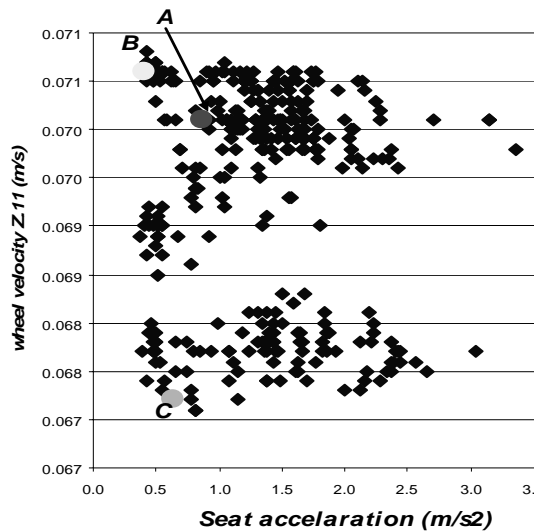


Fig. 6 Seat acceleration versus wheel velocity

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