Optimal Seat Suspension Design Using Genetic Algorithms

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Abstract: The linear seat suspension is considered due to the low cost consideration therefore, the optimal linear seat suspension design method can be used for this purpose. In this paper, the design of a passive vehicle seat suspension system was handled in the framework of linear optimization. The variance of the dynamic load resulting from the vibrating vehicle operating at a constant speed was used as the performance measure of a suspension system. Using 4-DOF human body model developed by Abbas et al., with linear seat suspension and coupled with half car model. A genetic algorithm is applied to solve the linear optimization problem. The optimal design parameters of the seat suspension systems obtained are $k_{se} = 3012.5 \text{ N/m}$ and $c_{se} = 1210.4 \text{ N.s/m}$, respectively.

Key words: Biodynamic response, seated human models, simulation, genetic algorithms.

1. Introduction

In the last fifty years, many people become more concerned about the ride quality of vehicle which is directly related to driver fatigue, discomfort, and safety. As traveling increases, the driver is more exposed to vibration mostly originating from the interaction between the road and vehicle. Vibration will make them feel discomfort and fatigue sometimes along with injury. It is important to know how the vibration is transmitted through the human body before we try to manage it.

Many researchers discussed a various biodynamic models that have been developed to depict human motion from a single-DOF to multi-DOF models. These models can be divided as distributed (finite element) models, lumped parameter models and multibody models. The distributed model treats the spine as a layered structure of rigid elements, representing the vertebral bodies, and deformable elements representing the intervertebral discs by the finite element method [1-2]. Multibody human models are made of several rigid bodies interconnected by pin (two-dimensional) or ball and socket (three-dimensional) joints, and can be further separated into kinetic and kinematic models. The kinetics is interested in the study of forces associated with motion, while kinematics is a study of the description of motion, including considerations of space and time, and are often used in the study of human exercise and injury assessment in a vehicle crash.
The lumped parameter models consider the human body as several rigid bodies and spring-dampers. This type of model is simple to analyze and easy to validate with experiments. However, the disadvantage is the limitation to one-directional analysis. These models can be summarized as: 1-DOF model [3], 2-DOF human body [4], 3-DOF analytical model [5], 4-DOF human model [6-8], 6-DOF nonlinear model [9], and 7-DOF model [10]. A complete study on lumped-parameter models for seated human under vertical vibration excitation has been carried out by Liang and Chiang [11], based on an analytical study and experimental validation. So, it is known that the lumped parameter model is probably one of the most popular analytical methods in the study of biodynamic responses of seated human subjects, though it is limited to one-directional analysis. However, vertical vibration exposure of the driver is our main concern.

Some lumped-parameter models were further modified to represent seated human vehicle’s driver with seat and integrated with a vehicle model to assess the biodynamic responses of seated human body expose to vertical vibrations in driving conditions [12-14]. On the other hand, a genetic algorithms (GA) method increases the probability of finding the global optimal solution and avoids convergence to a local minimum which is a drawback of gradient-based methods [15-17]. Therefore, genetic algorithms optimization is used to determine both the active control and passive mechanical parameters of a vehicle suspension system and to minimize the extreme acceleration of the passenger’s seat, subjected to constraints representing the required road-holding ability and suspension working space. In this paper presents 4-DOF human body with linear seat suspension and coupled with half car model. With this model, the genetic algorithm is applied to search for the optimal parameters of the seat in order to minimize seat suspension deflection and driver’s body acceleration to achieve the best comfort of the driver. The paper is organized as follows: section 2 discusses the mathematical model formulations; section 3 introduces the optimal linear seat suspension design; section 4 presents results and discussions; section 5 gives conclusions and recommendations.

2. Mathematical Model Formulations

2.1 Proposal Model

This section is devoted to the mathematical modeling of proposed model, including the biodynamic lumped human linear seat model coupled with half model of ground vehicles as illustrated in Fig. 1.

The human-body, has a 4-DOF that proposed by Abbas et al. [18]. In this model, the seated human body was constructed with four separate mass segments interconnected by five sets of springs and dampers, with a total human mass of 60.67 kg. The four masses represent the following body segments: head and neck ($m_1$), upper torso ($m_2$), lower torso ($m_3$), and thighs and pelvis ($m_4$). The arms and legs are combined with the upper torso and thigh, respectively. The stiffness and damping properties of thighs and pelvis are ($k_5$) and ($c_5$), the lower torso are ($k_4$) and ($c_4$), upper torso are ($k_2$, $k_3$) and ($c_2$, $c_3$), and head are ($k_1$) and ($c_1$). The schematic of the model is shown in Fig. 2a, and biomechanical parameters of the model are listed in Table 1.

![Fig. 1 Schematic diagram of biodynamic lumped human linear seat models coupled with half car model.](image-url)
Table 1 The biomechanical parameters of the Abbas model.

<table>
<thead>
<tr>
<th>Mass ( (\text{kg}) )</th>
<th>Damping coefficient ( (\text{N.s/m}) )</th>
<th>Spring constant ( (\text{N/m}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( m_1 ) = 4.17</td>
<td>( C_i = 310 )</td>
<td>( k_i = 166,990 )</td>
</tr>
<tr>
<td>( m_2 ) = 15</td>
<td>( C_2 = 200 )</td>
<td>( k_2 = 10,000 )</td>
</tr>
<tr>
<td>( m_3 ) = 5.5</td>
<td>( C_3 = 909.1 )</td>
<td>( k_3 = 144,000 )</td>
</tr>
<tr>
<td>( m_4 ) = 36</td>
<td>( C_4 = 330 )</td>
<td>( k_4 = 20,000 )</td>
</tr>
<tr>
<td>-</td>
<td>( C_5 = 2,475 )</td>
<td>( k_5 = 49,340 )</td>
</tr>
</tbody>
</table>

A half car model with four degrees of freedom is shown in Fig. 1, taking into consideration the pitch motion of the vehicle’s body. The degrees of freedom are: vertical body displacement \( x_b \), vehicle body pitch angle \( \theta \), front wheel displacement \( x_{wf} \) and rear wheel displacement \( x_{wr} \). The front wheel of the vehicle is represented by the mass \( m_{wf} \), the damping coefficient \( C_f \) and the spring coefficient \( K_f \). Similarly the rear wheel is represented by the mass \( m_{sr} \), the damping coefficient \( C_r \) and the spring coefficient \( K_r \). The suspensions of the front and rear wheels are described by the damper’s coefficients \( C_d \) and \( C_c \) and the spring’s coefficients \( K_f \) and \( K_s \), respectively. The mass \( m_b \) and the inertia \( I \) represent the vehicle body sprung mass. The location of the centre of gravity is given by \( L_i \) and \( L_2 \). Typical design parameters for the half car and seat suspension are listed in Table 2.

The equations of motion of the resulting coupled model can be put in the classical form:

\[
m_1 \ddot{x}_1 = -c_1(x_1 - \dot{x}_2) - k_1(x_1 - x_2) \tag{1}
\]

\[
m_2 \ddot{x}_2 = c_1(x_1 - \dot{x}_2) + k_1(x_1 - x_2) - c_2(x_2 - \dot{x}_3) - k_2(x_2 - x_3) - c_3(x_2 - \dot{x}_4) - k_3(x_2 - x_4) \tag{2}
\]

\[
m_3 \ddot{x}_3 = c_2(x_2 - \dot{x}_3) + k_2(x_2 - x_3) - c_4(x_3 - \dot{x}_4) - k_4(x_3 - x_4) \tag{3}
\]

\[
m_4 \ddot{x}_4 = c_4(x_3 - \dot{x}_4) + k_4(x_3 - x_4) + c_5(x_4 - \dot{x}_5) + k_5(x_4 - x_5) \tag{4}
\]

\[
m_{se} \ddot{x}_{se} = c_5(x_4 - \dot{x}_{se}) - k_5(x_4 - x_{se}) + a\dot{\theta} - \dot{x}_b \tag{5}
\]

\[
m_{se}\ddot{x}_{se} = -c_{se}a \dot{x}_{se} - k_{se}x_{se} + c_{se}\dot{x}_{se} + a\dot{\theta} - \dot{x}_b \tag{6}
\]

In this work, the sinusoidal road profiles excitation is adopted to evaluate the proposed system. In simple analytical ride studies the sinusoidal road is considered to have only one spatial frequency of bumps at a time. The sinusoidal road equations are listed below:

\[
x_{of} = H_0 \sin(\omega(t)) \tag{7}
\]

\[
x_{or} = H_0 \sin(\omega(t + \tau)) \tag{8}
\]

where \( \omega \) the radian frequency of the road, is \( \omega = \frac{\pi V}{L_B} \)

Mathematical model of road profile can be derived as the follows: vehicle with wheelbase \( L_2 \) passing over each hump with speed \( V \) will have front ground displacement \( x_{of} \). The rear ground \( x_{or} \) follows the same track as the front with a given time delay \( \tau \) (wheelbase correlation) and that is equal to the wheelbase divided by vehicle speed \( \tau = \frac{L_B}{V} \). In this study, assuming that the vehicle model travels with the constant velocity of \( 20 \text{ km/h} \) \( (5.55 \text{ m/s}) \), \( H_0 = 0.035 \text{ m} \) is the hump height, and \( L_B = 1 \text{ m} \) is the width of the hump.

3. Optimal Linear Seat Suspension Design

3.1 Numerical Simulations

The displacement, velocity, and acceleration for the model in terms time domain are obtained by solving equations of motion represented by (1-9). Using MATLAB software ver. 7.10 (R2010a), dynamic system simulation software, Simulink. The initial conditions are assumed at equilibrium position. In this assumption, the driver is seated but the input excitation
has not been provided to the seat. Therefore, the initial velocity and displacement for each mass is equal to zero.

When the spring is free, no force is generated. At equilibrium position, the spring is compressed by the weight of the human and seat. In this work the maximum static displacement is selected to be 0.157m (this value depend on the cab space restriction for the vehicle). Therefore, the initial stiffness of the spring can be determined:

\[
k_{se(0)}\delta_{st} = \frac{(m_1 + m_2 + m_3 + m_3 + m_{se}) \cdot g}{\delta_{st}}
\]

\[
k_{se(0)} = \frac{(m_1 + m_2 + m_3 + m_3 + m_{se}) \cdot g}{\delta_{st}}
\]

### 3.2 Optimization Via Genetic Algorithms

In this section, optimization software based on stochastic techniques search methods, Genetic algorithms (GAs), is employed to search for the optimal linear parameters of the seat to achieve the best comfort of the driver. The upper boundaries of seat suspension parameters are selected based on previous studies. Table 3 shows the genetic algorithms parameters and its selected values.

<table>
<thead>
<tr>
<th>GA parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>50</td>
</tr>
<tr>
<td>No of generations</td>
<td>200</td>
</tr>
<tr>
<td>Fitness scaling</td>
<td>Rank</td>
</tr>
<tr>
<td>Crossover technique</td>
<td>Heuristic</td>
</tr>
<tr>
<td>Probability of crossover</td>
<td>0.8</td>
</tr>
<tr>
<td>Mutation technique</td>
<td>Uniform</td>
</tr>
<tr>
<td>Generation gap</td>
<td>0.9</td>
</tr>
<tr>
<td>Lower boundary</td>
<td>130-3,000</td>
</tr>
<tr>
<td>Upper boundary</td>
<td>1,600-200,000</td>
</tr>
<tr>
<td>Objective function accuracy</td>
<td>(10^{-15})</td>
</tr>
</tbody>
</table>

(1) Objective function

Since the health of the driver is as important as the stability of the car, the desired objective is proposed as the minimization of a multi-objective function formed by the combination of not only seat suspension working space (seat suspension deflection ‘ssws’) but also the head acceleration \((\ddot{x}_1)\), and seat mass acceleration \((\ddot{x}_{se})\).

This study used the classical weighted sum approaches to solve a multi-objective optimization problem as equation

\[
OBJ = w_1 \cdot (\ddot{x}_1) + w_2 \cdot (ssws) + w_3 \cdot (\ddot{x}_{se})
\]

where, \(w_1, w_2\) and \(w_3\) are weighting factors to emphasize the relative importance of the terms. Table 4 shows weighting factors used in excitation inputs.

(2) Optimization procedure

First, the bounds of the design variables and initialize suspension design variables \(k_s\) and \(c_s\). Then \(k_s\) and \(c_s\) are passed into the proposal model to solve for the dynamic response (displacement, velocity, and accelerations values) of the system. The population is then coded into chromosomes, a binary representation of a solution (consisting of the components of the

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Front and rear tire stiffness (N/m).</td>
<td>(K_{tf},K_{tr})</td>
<td>155,900</td>
</tr>
<tr>
<td>Front and rear axle masses (Kg).</td>
<td>(m_{wf},m_{wr})</td>
<td>28.58, 54.3</td>
</tr>
<tr>
<td>Linear front and rear suspension damping Coefficients (N.s/m).</td>
<td>(C_{sf},C_{sr})</td>
<td>1,828</td>
</tr>
<tr>
<td>Front and rear tire damping Coefficients (N.s/m).</td>
<td>(C_{tf},C_{tr})</td>
<td>0</td>
</tr>
<tr>
<td>Front and rear suspension stiffness (N/m).</td>
<td>(K_{sf},K_{sr})</td>
<td>15,000</td>
</tr>
<tr>
<td>Distance between the C.G and front axle (m).</td>
<td>(L_1)</td>
<td>1.098</td>
</tr>
<tr>
<td>Distance between the C.G and rear axle (m).</td>
<td>(L_2)</td>
<td>1.468</td>
</tr>
<tr>
<td>Distance between the C.G and seat (m).</td>
<td>(a)</td>
<td>0.7</td>
</tr>
<tr>
<td>Body mass &quot;sprung mass&quot; (Kg).</td>
<td>(m_b)</td>
<td>505.1</td>
</tr>
<tr>
<td>Body mass moment of inertia (Kg.m²).</td>
<td>(I)</td>
<td>651</td>
</tr>
<tr>
<td>Seat mass (Kg).</td>
<td>(m_{se})</td>
<td>35</td>
</tr>
<tr>
<td>Seat damping Coefficients (N.s/m).</td>
<td>(C_{se})</td>
<td>150</td>
</tr>
<tr>
<td>Seat suspension stiffness (N/m).</td>
<td>(K_{se})</td>
<td>15,000</td>
</tr>
</tbody>
</table>
decision variables known as genes in the genetic algorithm). The whole population of chromosomes represents a generation. An evaluation function rates solutions in terms of their fitness. Here, fitness is a numerical value describing the probability for a solution (genome) to survive and reproduce. Only a portion of the population (survivors or solutions with higher fitness values) is selected for creating a new population (offspring production). This new population is created by using a crossover operator.

Crossover is a procedure for exchanging pieces of chromosome data with one another. Crossover allows genes that generate good fitness to be preserved and enlarged in a new generation of the population. Mutation is a genetic operator and it randomly flips the bits of an offspring’s genotype. This is equivalent to perturbing the mated population stochastically. Mutation prevents the population from homogenizing in a particular set of genes such that any gene in a generation has a certain probability (determined by the mutation rate) of being mutated in future generations. The new population is being mixed up to bring some new information into this set of genes, and this needs to happen in a well-balanced way.

Once the new generation is created, the aforementioned steps are repeated until some convergence criteria are satisfied, such as running time or fitness. The overall technique is summarized in the flowchart given in Fig. 2.

4. Results and Discussion

The optimal linear seat parameters for the present model were determined by genetic algorithms method, and compared with current passive parameters are tabulated in Table 5.

Fig. 3 shows the displacement histories obtained for head, upper torso, lower torso, pelvis, and seat respectively. Fig. 4 present the acceleration histories obtained at the coupled human seat with half car model.

The figure presents four human components, head, upper torso, lower torso, and pelvis, and seat acceleration respectively. The obtained results by genetic algorithms method were compared with passive model.

The results obtained by GA were compared to those passive results in terms of RMS values is given in Table 6. From the table, the percentage improvement for head acceleration is 37.09%, for upper torso acceleration is 37.22%, for lower torso acceleration is 37.29%, and for pelvic acceleration is 37.09. On the other hand the percentage improvement for seat acceleration is 36.33%.

Table 7 indicates that the reduction of the human’s vertical acceleration and displacement peak. It can be

<table>
<thead>
<tr>
<th>Weight</th>
<th>$w_1$</th>
<th>$w_2$</th>
<th>$w_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excitation input</td>
<td>0.5</td>
<td>0.3</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Table 4  Weighting factors used in excitation inputs.

<table>
<thead>
<tr>
<th>Seat suspension setting</th>
<th>$K_{se}$ (N/m)</th>
<th>$C_{se}$ (N.s/m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Passive</td>
<td>15 000</td>
<td>150</td>
</tr>
<tr>
<td>GA optimization</td>
<td>3 012.5</td>
<td>1 210.4</td>
</tr>
</tbody>
</table>

Table 5  The design results from the GA program.

Fig. 2  Design process using GA.
observed that the reduction of the human’s vertical peak acceleration is approximately 54.76-60.46% in case of GA suspension as compared with passive suspension.

The reduction of the human’s vertical displacement peak is approximately 31.21-31.236% in case of GA suspension as compared with passive suspension. Also, the reduction of the seat vertical peak acceleration is 57.02% and the reduction of the seat vertical displacement peak is 31.29% of GA suspension as compared with passive suspension.

Fig. 3  Displacement histories obtained (a) road input, (b) head, (c) upper torso, (d) lower torso, (e) pelvic and (f) seat.
Optimal Seat Suspension Design Using Genetic Algorithms

Fig. 4 Acceleration histories obtained: (a) head, (b) upper torso, (c) lower torso, (d) pelvic, and (e) seat.

Table 6 RMS percentage improvement results for half car model.

<table>
<thead>
<tr>
<th></th>
<th>RMS for head acc.</th>
<th>RMS for upper torso acc.</th>
<th>RMS for lower torso acc.</th>
<th>RMS for pelvic acc.</th>
<th>RMS for seat acc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Passive</td>
<td>8.0766</td>
<td>8.0671</td>
<td>8.1102</td>
<td>7.9901</td>
<td>7.4788</td>
</tr>
<tr>
<td>GA</td>
<td>5.08</td>
<td>5.0643</td>
<td>5.0857</td>
<td>5.0258</td>
<td>4.7613</td>
</tr>
<tr>
<td>% Improvement</td>
<td>37.09</td>
<td>37.22</td>
<td>37.29</td>
<td>37.09</td>
<td>36.33</td>
</tr>
</tbody>
</table>
Table 7  Reduction in peak values for half car model.

<table>
<thead>
<tr>
<th>Acceleration (m/s²)</th>
<th>Head overshoot</th>
<th>Maximum overshoot</th>
<th>%Reduction peak overshoot</th>
</tr>
</thead>
<tbody>
<tr>
<td>Head</td>
<td>19.7899</td>
<td>8.9513</td>
<td>54.76</td>
</tr>
<tr>
<td>Upper torso</td>
<td>20.3072</td>
<td>8.0281</td>
<td>60.46</td>
</tr>
<tr>
<td>Lower torso</td>
<td>19.6788</td>
<td>7.9230</td>
<td>59.73</td>
</tr>
<tr>
<td>Pelvic</td>
<td>19.2235</td>
<td>7.8414</td>
<td>59.20</td>
</tr>
<tr>
<td>Seat</td>
<td>17.3471</td>
<td>7.4546</td>
<td>57.02</td>
</tr>
<tr>
<td>Head displacement (m)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head</td>
<td>0.2672</td>
<td>0.1838</td>
<td>31.21</td>
</tr>
<tr>
<td>Upper torso</td>
<td>0.2670</td>
<td>0.1836</td>
<td>31.23</td>
</tr>
<tr>
<td>Lower torso</td>
<td>0.2680</td>
<td>0.1843</td>
<td>31.23</td>
</tr>
<tr>
<td>Pelvic</td>
<td>0.2654</td>
<td>0.1825</td>
<td>31.24</td>
</tr>
<tr>
<td>Seat</td>
<td>0.2528</td>
<td>0.1737</td>
<td>31.29</td>
</tr>
</tbody>
</table>

5. Conclusions and Recommendations

This paper the genetic algorithm is applied for obtaining the optimal linear and nonlinear parameters of the seat in order to minimize seat suspension deflection and driver's body acceleration to achieve the best comfort of the driver. It can be concluded that:

1. Optimal linear seat suspension by using genetic algorithms has successfully managed improving for all the dynamic performance parameters. Genetic algorithms explore the entire space to search for the optimal solutions from a population of solutions to another population of solutions, rather than from one solution to another, this characteristic makes GAs uniquely suited to multi-objective optimization;

2. The results of optimal linear seat suspension characteristics show that, to obtain the best vibration isolation, the stiffness of the spring near to the lower boundary;

3. The results and the plots indicate that optimal linear seat suspension system is less oscillatory, and have lower values of maximum over shoots than passive suspension system. This is directly related to driver fatigue, discomfort, and safety;

4. The optimal linear seat suspension has limitation on improving the vibration isolation.

References


