# Neural Network based Vibration Control for Vehicle Active Suspension System

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### Abstract

This paper presents a novel Neural Network (NN) based vibration control of a Vehicle Active Suspension System (VASS) when subjected to road disturbance for enhancing the travelling comfort to the passengers. The simulation for the vibration control of VASS with Proportional Integral and Derivative (PID) controller is used for training the NN. The nonlinearities of the system parameters can be effectively handled by the NN and also it can deal with unfocused data by considering the prejudiced phenomena such as logical reasoning and perception beyond its domain. The idea of this work is to design, simulate and compare the performance of NN based VASS with that of the uncontrolled suspension system (passive) and the VASS controlled with PID controller. The Root Mean Square (RMS) value of body acceleration as the performance index for genetic optimization, the simulation is carried out using MATLAB/SIMULINK software. Simulation results such as sprung mass displacement, body acceleration, suspension deflection, tyre deflection and Power Spectral Density (PSD) of body acceleration shows the effectiveness of NN in suppression of the vibration of vehicle body compared to passive system, PID based VASS and optimized PID controller.

Keywords: Genetic Algorithms, Neural Networks, Simulation, Suspensions, Vibration Control

## 1. Introduction

Vibration in an automobile is undesirable since it will lead to unwanted noise in the vehicle, damage to the fittings attached to the vehicle and cause severe health problems to the passengers. Development of automobile industries made the research on vibration control more important. In reality, a vehicle undergoes random vibration as it moves on a rough road. The suspension system of an automobile plays a vital role in vehicle handling and ride comfort.

Vehicle suspension system is currently of great interest, both academically and in the automobile industry worldwide. Vehicle handling depends on the force acting between the road surface and the wheels. Ride comfort is related to vehicle motion sensed by the passenger. In order to improve the handling and ride comfort performance, instead of conventional passive spring and damper system, semi-active and active systems are being developed.

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A semi-active suspension discussed by<sup>14</sup> involves the use of dampers with variable gain. An active suspension involves the passive components augmented by actuators that supply additional forces. Alternatively, an active suspension system has the capability to reduce the acceleration of sprung mass continuously as well as to minimize suspension deflection which results in the improvement of tyre grip with the road surface<sup>6</sup>. In<sup>10</sup> proposed a nonlinear design for the control of active suspension systems which allows the closed loop system to behave differently in different operating regions thereby eliminating the problem of whether to use a soft or stiff suspension setting.

Increased competition in the automotive market has forced industries to research the control strategies for Vehicle Active Suspension System (VASS). Several control approaches have been proposed by<sup>1-5,7,8,11,13,15,16,18-21</sup> in the past for the control of active suspension system. It is possible to derive the mathematical model based on the differential equations governing the system to implement a model based controller. In reality, the complexity of this approach would be huge and the tuning of controller is very difficult which can be overcome with an intelligent controller which is not model dependent.

In this paper a PID, GA optimized PID and NN controllers are designed for an active vehicle suspension system and a comparative study is carried out by simulation. PID controller takes the control action by in view of the past, present and future error which is the deviation of output variable value from the desired value. One kind of stochastic global optimization technique GA is used for the optimization of PID tuning parameters by considering the continuous RMS as the fitness function. The GA optimization speed is too slow to use in real-time applications. On the other hand the NN, like human, learn by example and past experience and provides the control action very fast. Thus it is suitable for many complex real world problems. It highly fits for the nonlinear system that can't establish its accurate mathematical model. The information required for training the NN are obtained from the simulation results of PID based VASS. PID, optimized PID and NN controllers are compared for better ride comfort and good road holding ability.

Organization of the paper is as follows. Quarter Car (QC) model dynamics of an active suspension system is briefly explained in section 2. General control structure in this work is given in section 3. The PID control scheme without optimization and with GA optimization, proposed NN control scheme are discussed in the sub sections of section 3. In section 4, the simulation results are shown and discussed. The final section concludes the paper.

## 2. Quarter Car Model

A two Degree of Freedom (DOF) QC model of VASS is shown in Figure 1. It represents the automotive system at each wheel i.e., the motion of the axle and the vehicle body at any one of the four wheels of the vehicle. QC model is considered because it is simple and one can observe the basic features of the VASS such as sprung mass displacement, body acceleration, suspension deflection and tyre deflection<sup>15</sup>.

The suspension model consists of a spring  $k_s$ , a damper  $b_s$  and an actuator to provide active force  $F_a$ . For a passive suspension,  $F_a$  can be set to zero. The sprung mass  $m_s$  represents the QC equivalent of the vehicle body mass. An unsprung mass  $m_u$  represents the equivalent mass due to axle and tyre. The vertical stiffness of



Figure 1. Two DOF quarter car model.

the tyre is represented by the spring  $k_t$ . The variables  $z_s$ ,  $z_u$  and  $z_r$  represent the vertical displacements from static equilibrium of sprung mass, unsprung mass and the road respectively. Equations of motion of two DOF QC model of VASS are given in Equations (1) and (2).

$$m_{s}\ddot{z}_{s} + b_{s}(\dot{z}_{s} - \dot{z}_{u}) + k_{s}(z_{s} - z_{u}) = F_{a}$$
(1)

 $m_{s}\ddot{z}_{s} - b_{s}(\dot{z}_{s} - \dot{z}_{u}) - k_{s}(z_{s} - z_{u}) - k_{t}(z_{r} - z_{u}) = -F_{a} \quad (2)$ 

It is assumed that the suspension spring stiffness and tyre stiffness are linear in their operating ranges and that the tyre does not leave the ground. The state space representation of above QC model is given by where

$$\begin{bmatrix} \dot{x}_{1} \\ \dot{x}_{2} \\ \dot{x}_{3} \\ \dot{x}_{4} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ \frac{-k_{S}}{m_{S}} & \frac{-b_{S}}{m_{S}} & \frac{k_{S}}{m_{S}} & \frac{b_{S}}{m_{S}} \\ 0 & 0 & 0 & 1 \\ \frac{k_{S}}{m_{u}} & \frac{b_{S}}{m_{u}} & \frac{-k_{S}-k_{t}}{m_{u}} & \frac{-b_{S}}{m_{u}} \end{bmatrix} \begin{bmatrix} x_{1} \\ x_{2} \\ x_{3} \\ x_{4} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{k_{t}}{m_{u}} \end{bmatrix} z_{r} + \begin{bmatrix} 0 \\ \frac{1}{m_{S}} \\ 0 \\ \frac{-1}{m_{u}} \end{bmatrix} F_{a} \quad (3)$$

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The natural frequency of unsprung mass is

$$\omega_0 = \sqrt{\frac{k_s + k_t}{m_u}} \tag{4}$$

## 3. General Control Structure

The block diagram representation of control scheme of VASS used for the simulation is shown in Figure 2. The road disturbance is the input to the QC model. To reduce the effect of this input, one of the system output sprung mass displacement is fedback to the controller. The controller



Figure 2. Block diagram representation of VASS with controller.

uses an error value that is the difference between the sprung mass displacement  $(z_s)$  and desired set point  $(z_{sdesired})$  which is taken as zero in this work<sup>8</sup>. The controller attempts to diminish the error by adjusting the control input to the process. G is the gain of linear actuator. The actuator force F which is the additional input to the system is proportional to the controller output to have better comfort.

#### 3.1 PID Controller

PID controller which is a combination of proportional, integral and derivative controller that can improve the total performance of the system i.e., both the transient response and steady state response is used for controlling the VASS. PID control law that can be used in VASS is as follows.

$$G_{c} = k_{p}e(t) + k_{i}\int e(t)dt + k_{d}\frac{de}{dt}$$
(5)

Where,

G is the controller output.

 $k_{p}$  is the proportional gain.

k is the integral gain.

 $k_{\rm k}$  is the differential gain.

 $e(t) \stackrel{r_d}{=} z_s - z_{sdesired}$  is the error signal. je(t)dt is the time integral of the error signal.

 $\frac{de}{dt}$  is the time derivative of the error signal.

The tuning of gains such as  $k_{p}$ ,  $k_{i}$  and  $k_{d}$  of PID controller is an ad-hoc process that involves trial and error. By the method proposed by<sup>22</sup>, the tuned parameters are  $k_p = 4.998$ ,  $k_i = 2.07$  and  $k_d = 3.0175$  with the ultimate gain  $k_{cu} = 8.33$  and ultimate period  $p_{cr} = 4.83$ .

Further PID parameters are optimized using GA12 to improve the performance of the system.

In this work GA is used to find the PID tuning parameters to give optimum RMS value of body acceleration. To optimize the continuous time body acceleration signal (f(t)) energy, cumulative RMS value which is defined as follows is taken as the fitness function.

$$J = \sqrt{\frac{1}{T} \int_{0}^{T} \left\| \mathbf{f}(t) \right\|^{2} dt}$$
(6)

Parameters for GA optimization used are given below

Number of generations	: 50
Number of chromosomes in each generation	: 30
Crossover Probability	: 0.9
Mutation Probability	: 0.05

The optimized values of PID parameters using GA are tabulated in Table 1.

#### 3.2 Proposed Neural Network Controller

The NN control is generally non-linear and adaptive in nature. The key inspiration behind proposing a NN controller for this problem is the ease, its ability to handle nonlinearity and unspecified data and also it's reasonable performance. Simulation of PID based VASS provides the necessary data required for giving knowledge to the NN controller. A supervised learning method Back Propagation (BP) algorithm is used for training the feed forward NN with an objective to achieve the global minima. The BP network shown in Figure 3 consists of three

 Table 1.
 Tuned PID parameters using GA

Gain	Bump	Sinusoidal	Random
k <sub>p</sub>	0.0075	0.0025	0.0700
k <sub>i</sub>	6.2000	7.6000	3.7500
k <sub>d</sub>	1.1900	0.7950	1.1450



Figure 3. Back propagation neural network with one hidden layer.

layers: An input layer, one intermediate hidden layer, and an output layer with n, p, m number of units in the respective layers. A sigmoid activation function is chosen for the hidden layer and a linear activation function for the output layer. The weights of each layer of the NN controller are adjusted to lessen the error.

The BP algorithm for a three layered network is as follows.

x Input training vector. x =  $(x_1, \dots, x_i, \dots, x_n)$ t Output target vector. t =  $(t_1, \dots, t_k, \dots, t_m)$ z Output of hidden unit. z =  $(z_1, \dots, z_j, \dots, z_p)$ y Output from output unit. y =  $(y_1, \dots, y_k, \dots, y_m)$ 

 $\boldsymbol{v}_{_{ij}}$  is the weight connecting the input node to the hidden node.

 $\boldsymbol{w}_{_{jk}}$  is the weight connecting the hidden node to the output node.

 $v_{_{0j}}$  is the bias on hidden unit j and  $w_{_{0k}}$  the bias on output unit k are taken as 1 and during training, the propagation error is calculated as in  $^9$ .

Weights between the input layer and hidden layer are updated as in<sup>17</sup>.

$$\Delta \mathbf{v}_{ij}(t) = -\eta \frac{\partial \mathbf{E}_{1}(t)}{\partial \mathbf{v}_{ii}(t)} + -\Delta \mathbf{v}_{ij}(t-1)$$
(7)

Weights between the hidden layer and output layer are updated as

$$\Delta w_{jk}(t) = -\eta \frac{\partial E_2(t)}{\partial w_{ik}(t)} + -\Delta w_{jk}(t-1)$$
(8)

Where,

 $\eta$  is learning rate.

 $\boldsymbol{\alpha}$  is the momentum term.

 $E_1(t)$  is the propagation error between hidden layer and input layer.

 $\mathrm{E_2}(\mathrm{t})$  is the propagation error between output layer and hidden layer.

Structural and training parameters of the neural network model used for simulation are as follows: Number of units in the input layer n = 2

Number of units in the hidden layer p = 30

Number of units in the output layer m = 1

Total number of samples for	training	= 10,000
Training		= 70% of data
Validation		= 15% of data
Testing		= 15% of data
Sampling time		= 0.001
Learning rate	η	= 0.25
Momentum term	α	= 0.4

## 4. Simulation and Results

The parameters of the QC model taken from<sup>15</sup> are listed below.

Sprung mass ( m <sub>s</sub> )	= 290 kg
Unsprung mass (m <sub>1</sub> )	= 59 kg
Damper coefficient $(b_s)$	= 1,000 Ns/m
Suspension stiffness $(k_s)$	= 16,812 N/m
Tyre stiffness ( k )	= 190,000 N/m

International Organization for Standardization gives the classification of road roughness using Power Spectral Density (PSD) values. A dual bump shown in Figure 4 represents a speed breaker in the road. Mathematical representation of this input with 6cm and 3cm amplitude can be stated as

$$z_{\rm r}(t) = \frac{a(1 - \cos(8\pi t))}{2} \text{ if } 0 \le t \le 0.25 \& 0.5 \le t \le 0.75$$
(9)  
Otherwise

where 'a' denotes the bump amplitude.

Figure 4 also shows a sinusoidal disturbance with 3cm amplitude and 20Hz frequency. The actual road like random disturbance with peak amplitude of 2 cm is also superimposed in Figure 4.

The static tyre deflection 0.018019 m is obtained from

$$S = (m_s + m_u) \times \frac{9.81}{k_t} \tag{10}$$



Figure 4. Road input profiles.

The mathematical model of vehicle suspension system in Equations (1) and (2) with the controllers as discussed in section 3 are simulated with dual bump, sinusoidal and random kind of road input profiles and the simulation results are shown in Figure 5(a-d), Figure 6(a-d), Figure 7(a-d), Table 2, Table 3, and Table 4.



**Figure 5.** (a) Sprung mass displacement. (b) Body acceleration. (c) Suspension deflection. (d) Tyre deflection with dual bump input.



**Figure 6.** (a) Sprung mass displacement. (b) Body acceleration. (c). Suspension deflection. (d) Tyre deflection with sinusoidal input.

Figure 5(a) shows the sprung mass displacement is very much reduced by NN controller and the maximum displacement is very close to zero. Figure 5(b) shows that NN reduces the body acceleration by 95.73% compared to passive and 33.79% compared to PID based VASS. The body acceleration of NN based VASS is nearly 1/24<sup>th</sup> of as



**Figure 7.** (a) Sprung mass displacement. (b) Body acceleration. (c) Suspension deflection. (d) Tyre deflection with random input.

that of passive system and it improves the ride comfort to a great extend where as that of PID based VASS is nearly half of the value of the passive system. The optimized PID controller output is around  $1/10^{\text{th}}$  of passive system. Also Figure 5(c) shows that the suspension deflection is maintained within the static deflection  $\pm 8$ cm by all the controllers. Figure 5(d) illustrates the road holding ability maintained by the controllers. Tyre displacements for the active systems are higher than that of the passive suspension system. The RMS values of the time responses of the four outputs with the bump input profile are listed in Table 2 which shows the effectiveness of NN based VASS for betterment of ride and travelling comfort with reduced body acceleration.

With reference to Figure 6a, desired point tracking is closely attained with NN based controller. This controller reduces the vehicle body acceleration considerably (Figure 6(b)). The suspension deflection and tyre deflection are increased with this controller compared to PID controller but are within the limits only. Table 3 which shows the RMS values of the time responses of QC model with sinusoidal input indicated the proposed NN based controller improves the overall response without breaking the constraints.

Figure 7(a) shows that the sprung mass displacement with random input disturbance is well controlled by NN based controller. Figure 7(b) shows the body acceleration and it is inferred from the Table 4 that it is evidently reduced where as the suspension deflection and tyre deflection are increased in comparison with passive and PID based systems.

In the evaluation of vehicle ride quality, the PSD for the body acceleration as a function of frequency is of prime interest and is plotted (Figure 8.) for passive, PID, optimized PID and NN based VASS with specified road inputs. Both the controllers suppress the acceleration of sprung mass in the lower frequency band and apparently between 0.2 Hz to 8 Hz. The suppression of vibration is effective with the NN based VASS compared to PID based VASS. It is also clear

Table 2. RMS values of the time responses with dual bump input

System	Sprung Mass Displacement	Body Acceleration	Suspension Deflection	Tyre Deflection
	×10 <sup>-3</sup> (m)	×10 <sup>-3</sup> (m/s <sup>2</sup> )	×10 <sup>-3</sup> (m)	×10 <sup>-3</sup> (m)
Passive	7.97	2347	25.31	3.868
PID	4.821	1747	23.75	4.796
PIDGA	0.5972	355.4	24.51	6.592
NN	7.25×10 <sup>-03</sup>	114.6	25.87	9.424

System	Sprung Mass Displacement ×10 <sup>-3</sup> (m)	Body Acceleration ×10 <sup>-3</sup> (m/s2)	Suspension Deflection ×10 <sup>-3</sup> (m)	Tyre Deflection ×10 <sup>-3</sup> (m)
Passive	20.66	2024	25.13	3.699
PID	7.150	1130	19.65	4.266
PIDGA	1.803	255.2	21.85	4.719
NN	5.8×10–03	86.24	23.01	6.453

Table 3. RMS values of the time responses with sinusoidal input

Table 4. RMS values of the time responses with random input

System	Sprung Mass Displacement ×10 <sup>-3</sup> (m)	Body Acceleration ×10 <sup>-3</sup> (m/s2)	Suspension Deflection ×10 <sup>-3</sup> (m)	Tyre Deflection ×10 <sup>-3</sup> (m)
Passive	1237	1747	15.6	7.279
PID	3.196	1513	15.09	8.514
PIDGA	0.5147	766	20.61	15.41
NN	1.038 ×10-2	449.8	24.16	17.42



**Figure 8.** PSD of body acceleration with. (a) dual bump input. (b) sinusoidal input. (c) random input.

from Table 2 to Table 4 that the intelligent based controller works good for minimizing the performance index.

# 5. Conclusion

In this paper the design procedure has been discussed for a quarter car model without the actuator dynamics. The designing of the NN controller guarantees better performance compared to passive system, conventional PID and GA optimized PID controller based VASS. The designed NN controller significantly reduces the body acceleration and ensures travelling comfort to passengers especially, riding over bump and sinusoidal road profiles. Higher reduction of the sprung mass displacement is achieved with the intelligent based controller and the suspension deflection is much lesser in case of PID based VASS for all the three inputs. The controllers discussed in this paper are easy to implement and with reference to the PSD of body acceleration, it is clear that both the controllers provide better vibration control compared to the passive system. Comparatively, the NN based VASS performs best for the control of vibration.

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