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A Cascade Predictive Control Strategy for Active Suspension Systems

Shrey Jain, Saksham Jain, and Abhay Prithvi Komanduri

***Abstract*—In this paper, a non-linear Active Suspension System (ASS) for a quarter car model is being controlled using a Neural Network Predictive Controller (NNPC). The non-linearities are being introduced in the system through the actuator, which is being controlled using a simple PI controller. The design of the system consists of two loops. The inner loop is the force control of the actuator, while the outer loop controls the displacement of the system when subjected to road disturbances. The gains of PI controller are optimized using Simulated Annealing (SA). Simulations are carried out in Matlab/Simulink, with desired output showing effectiveness of the proposed control system.**

***Keywords*—Active Suspension System, Predictive Controller, Simulated Annealing, Neural Network, Electro-Servo Hydraulic Actuator.**

I. Introduction

THE main task of the suspension system of an automobile is to reduce the vibrations and disturbances due to a road, leading to increased passenger comfort which is of great interest to researchers and the industry. A Passive Suspension System (PSS) is the most primitive, consisting generally of a spring and damper systems. These do the task of reducing the vibrations but aren't very good at minimizing sudden disturbances. The limitations of a PSS can be overcome using a Semi-Active Suspension System (SASS), which control the gains of the damper which improves the ride quality and handling better than PSS. But these also aren't perfect and their performance can be improved by modeling an actuator which provides an external force which controls the displacement of the sprung mass. Such suspension systems are known as Active Suspension System (ASS), which are the main focus of this paper.

Suspension systems have been the subject of research for many years now due to their importance in daily life. ASS have been considered in literature with a number of proposed control laws ranging from simple On-Off control techniques to highly advanced linear and non-linear control techniques, including Fuzzy Logic Controllers as discussed in [8], Adaptive Sliding Control [16], Neural Network control [9], Lyapunov functions [5] and [6] and Neuro-Fuzzy [11].

This paper proposes a new robust control law for a non linear active suspension system consisting of a Neural Network Predictive Controller to control the displacement with force tracking of the actuator done using a PI controller, and gains of the PI controller optimized using Simulated Annealing. The NNPC is trained using a dataset of about 2000 inputs with their corresponding outputs. This trained NNPC is used for controlling the ASS. Simulated Annealing has been considered because of its lower computational requirements over other optimization techniques like the Firefly Algorithm.

The rest of the paper is organized in the following sections: Section II gives the quarter car model along with actuator dynamics, Section III proposes the control law, Section IV shows the simulations and their results, and finally Section V concludes the paper.

S. Jain, S. Jain, and A. Komanduri are students at Department of Manufacturing Processes and Automation Engineering at Netaji Subhas Institute of Technology, New Delhi-110078, India e-mails: (shreyj.mp, sakshamj.mp, kabhay.mp)@nsit.net.in

II. Quarter Car Model

A. Active Suspension System

A quarter car suspension model with actuator is shown in Figures 1 and 2. In this, m_b is the sprung mass i.e the mass of the car body, and m_w is the unsprung mass. k_t is the stiffness of spring and b_s is the damping coefficient. The displacement of body and wheel are given by x_b and x_w. Road disturbances are represented by r. The force exerted by the actuator is given by f_s.

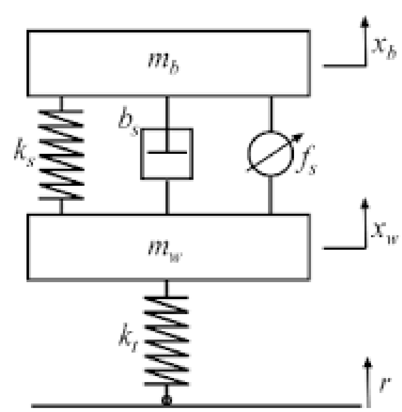

Fig. 1. A quarter car active suspension model

B. Mathematical Modeling

The mathematical model of the above defined system, as given by [2] and [3] is:

$$m_b\ddot{x_b} + b_s(\dot{x_b} - \dot{x_w}) + k_s(x_b - x_w) = f_s \quad (1)$$

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$$m_b\ddot{x_b} - b_s(\dot{x_b} - \dot{x_w}) - k_s(x_b - x_w) - k_t(r - x_w) = -f_s \quad (2)$$

When representing in state space model, the following equations are developed :

$$\begin{bmatrix} \dot{x_1} \\ \ddot{x_2} \\ \dot{x_3} \\ \ddot{x_4} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ \frac{-k_s}{m_s} & \frac{-b_s}{m_s} & \frac{k_s}{m_s} & \frac{b_s}{m_s} \\ 0 & 0 & 0 & 1 \\ \frac{k_s}{m_w} & \frac{b_s}{m_w} & \frac{-k_s-k_t}{m_w} & \frac{-b_s}{m_w} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

$$+ \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{-k_t}{m_w} \end{bmatrix} r + \begin{bmatrix} 0 \\ \frac{1}{m_b} \\ 0 \\ \frac{1}{m_w} \end{bmatrix} f_s$$

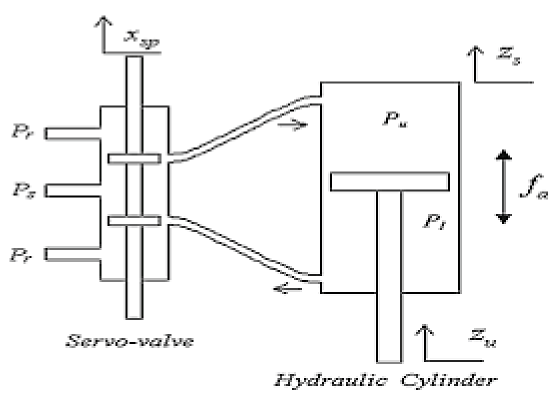

Fig. 2. Actuator Model

The servo valve dynamics are discussed by [4] and [10] and are given as:

$$\dot{x_{sp}} = \frac{1}{\tau}(i_{sv} - x_{sp})$$

Here, i_{sv} is the valve current and τ is the time constant of the mechanical system. The dynamics of the actuator is given by :

$$\dot{f_a} = -\alpha A_p^2(\dot{z_s} - \dot{z_u}) - \beta f_a + \gamma A_p x_{sp}\sqrt{P_s - \frac{sgn(x_{sp})f_a}{A_p}}$$

Here, f_a and A_p are the hydraulic pressure and piston area, resp. And, α, β and γ are the actuator parameters.

III. Proposed Control Law

There are 2 main divisions in the proposed control law, namely :

1) Force Tracking in the inner loop
2) Controlling displacement through the outer loop

Figure 3 shows the basic block diagram of the proposed control law.

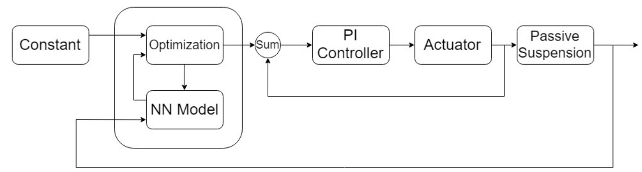

Fig. 3. Block Diagram of the ASS

A. Force Tracking

The inner loop consists of the passive suspension system along with the actuator, as shown in Figure 4. The manipulated variable is the force applied by the actuator. The force output of the actuator is controlled using a simple PI controller. The PI controller has been chosen for the numerous advantages it gives along with decreasing the response time of the over damped systems and their precise set point tracking. This force controls the overall displacement of the suspension system, hence ensuring comfort and ride stability.

$$A(t) = K_i\int_0^t e(t)dt + K_p e(t)$$

where, K_i and K_p are integral and proportional constants respectively.

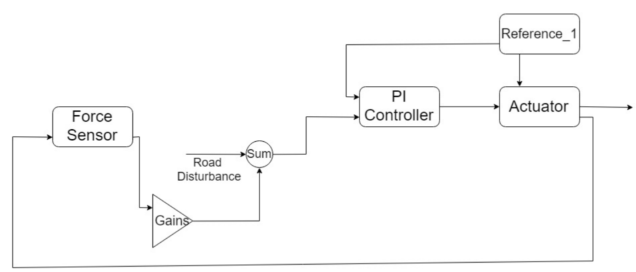

Fig. 4. Inner Loop of proposed model

These constants are optimized using the Simulated Annealing algorithm (SA). SA is an effective and general form of optimization, useful for finding global optima in the presence of a large number of local optima. This works on a simple hill climbing algorithm but on a global level, i.e the next point picked would be a random one. If the new point improves the optima, the point would be accepted. But if the point deteriorates the solution, the algorithm will move to that point with a probability less than 1. This acceptance probability is explained in [12] and is given as,

$$a = e^{\frac{\Delta}{T}}$$

where, a is the acceptance probability, Δ is the change in cost function, T is the temperature. The search for the optima depends on the temperature parameter. Generally, initial values of temperature are kept high, and are slowly lowered in every iteration. At higher temperatures, the probability of random moves is high, which keeps on reducing as temperature decreases.

SA has been chosen as the optimization algorithm as unlike Gradient Descent, it finds the global optima rather than getting stuck at a local optima due to a poor choice of starting point. Apart from this, the computational requirements of SA are much less than other optimization techniques like Grey Wolf Optimization (GWO) or Firefly Algorithm (FA). Other optimization techniques such as Particle Swarm Optimization and heuristic Kalman algorithm were considered, as discussed in [1] and [15] respectively, but due to poorer results and higher computational requirements, were not used.

B. Displacement Control

The NNPC is used to control the overall displacement of the suspension system. This model predicts the future plant performance using a neural network model of a non linear plant. The controller then controls the input to optimize the plant performance. The two main steps for controlling a plant output are : (1) System Identification, (2) Prediction of future performance.

1) System Identification: A neural network is a kind of a feed forward controller, discussed in [13], and hence one of the first tasks is to train a neural network to model the forwards dynamics of the plant [7]. The error between the output of the plant and output from the neural network is used to train the neural network. A predictive controller uses the previous plant inputs and their respective plant outputs to predict the future performance of any plant. Therefore, it is always advised that the data set used for training should be as large as possible for easy prediction of the future performance. The structure of a common neural network model is shown in Figure 5.

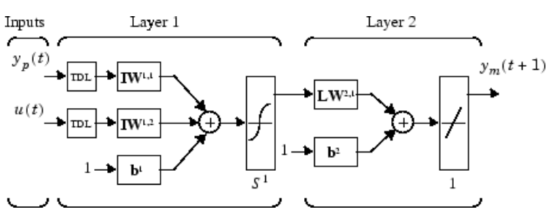

Fig. 5. Neural Network Model

2) Predictive Control: The model predictive control uses the receding horizon technique, given by Soloway and Haley in 1996, as it's base and used in [7]. The NN predicts the plant response over a specified time horizon. The following performance criterion is minimized over the specified control horizon :

$$J = \sum_{i=X_1}^{X_2} (y_d(t+i) - y_{nm}(t+j))^2 + \alpha \sum_{i=1}^{X_u} (c'(t+i-1) - c'(t+i-2))^2$$

Here, X_1,X_2 and X_u are the control horizons over which error and control signals are evaluated. The c' variable is the generated control signal, y_d is the desired output and y_{nm} is the network model response. The α parameter determines the contribution of sum of squares of the control increments on performance index. Figure 6 shows the NNPC block diagram.

IV. Simulations

This section shows the simulation results of the above mentioned control law. The NNPC component is designed using the Neural Network Toolbox in Matlab with simulations being run in Simulink. The SA is also programmed in Matlab and run on the inner loop to determine the gains of the PI controller. The optimized gains of PI controller are found to be a = 30.7242 and b = 30.4103.

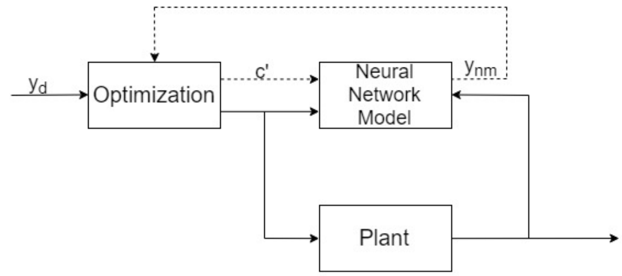

Fig. 6. Neural Network Predictive Controller

TABLE I
System Parameters

Description	Symbol	Value	Unit
Sprung Mass	m_b	600	kg
Unsprung Mass	m_s	60	kg
Damping Coefficients	b_s	2500	$\frac{N}{m/s}$
Stiffness Coefficients	k_s	18000	N/m
Piston Area	A	20	cm^2
Contact Stiffness	k_c	10^6	N/m
Contact Damping	b_c	210	N/(m/s)

TABLE II
Control Parameters

Parameter	Value
Cost Horizon	20
Control Horizon	4
Control Weighting Factor	.02
Search Parameter	.001

The various parameters taken for the actuator model, passive suspension model are shown in Table I. The control parameters are described in Table II.

The road profile which has been used for the simulation is made up of a sinusoidal wave with a delay in the beginning to model flat road conditions. The sinusoidal wave begins at about 1 second with an amplitude of 100 units. The output of the plant when subjected to the above road profile or disturbance generates the output as shown in Figure 7.

The training of the neural network is done by generating the dataset under various inputs and their respective output. The dataset used for training is shown in Figure 8.

The displacement of the suspension system when subjected to a sinusoidal disturbance generates the graph shown in Figure 9.

An active suspension system controlled using only PID controller generates the output as shown in Figure 10. This PID was tuned using Ziegler-Nichols method [18]. These values

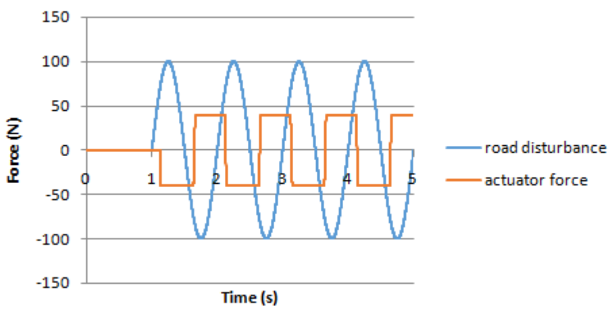

Fig. 7. Force tracking when subjected to external disturbance

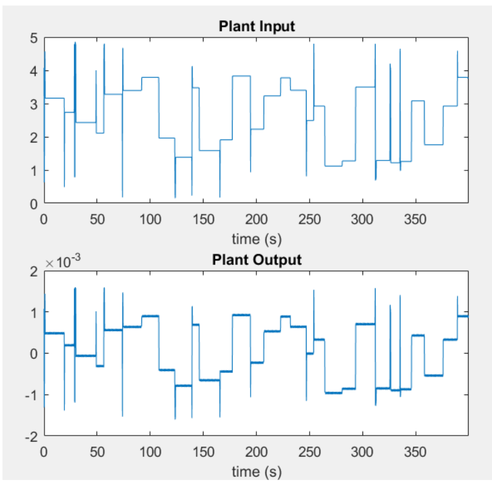

Fig. 8. Dataset used for training

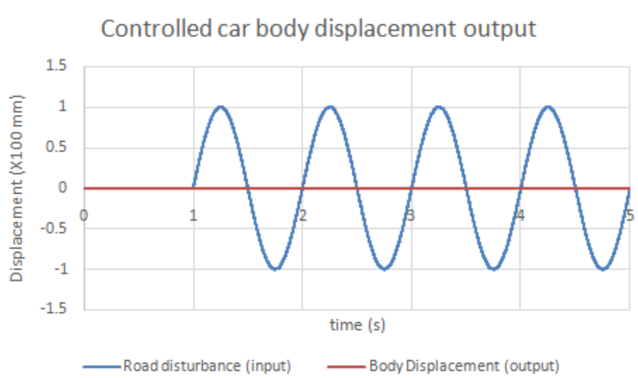

Fig. 9. Displacement when subjected to disturbances

were found to be k_p = 5.062, k_i = 3.4 and k_d = 4.15.

V. Conclusion

This paper proposed a new robust control law for an active suspension system using an NNPC for displacement control and PI controller for force tracking of the actuator. Gains have been optimized using SA, and simulations performed considering the actuator saturation. As seen from the simulations, and comparing the results with an ASS controlled using a PID controller, the proposed control law performs better. When compared to the performance of an ASS controlled

Fig. 10. ASS controlled using PID

using a simple Neural Network Model Predictive Controller as seen in [10], the proposed control law is better. Therefore, the effectiveness of the control law has been verified.

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