Optimal Fuzzy Supervisor Controller for an Active Suspension System

N. Ebrahimi, A.Gharaveisi

Abstract— In this paper, an optimal fuzzy supervisor controller is developed to improve the performance of active suspension system. Fuzzy logic is used to tune each parameter of PID Controller and input membership function of fuzzy controller optimized by Discrete Action Reinforcement Learning Automata (DARLA) technique. Through simulation in MATLAB, it is shown that the performance of active suspension system has improved significantly compare to conventional PID controller which is tuned by Zigler- Nichols method.

Index Terms— Active suspension system, Discrete Action Reinforcement Learning Automata (DARLA), Fuzzy supervisor, PID controller

I. INTRODUCTION

Comfort of passenger is an important demand and every one expects from industries to improve it day by day. One of the most important parts of the vehicle affecting the ride comfort of passengers and road holding is suspension system. A good and efficient suspension system must rapidly absorb road shocks and then return to its normal position [1].

So designing a good suspension with minimum vibration is an important task. The use of active suspension on road vehicles has been considered for many years [2-5] and in the last decades, many control methods (Classical and modern methods) have been designed in the mechanical active suspension systems [6-9].

Classical methods, such as PID linear technique has advantages of few parameters tune. However, the use of this technique in the control of a nonlinear process makes the tuning configuration strongly dependent on particular steady state working condition. Thus a fixed tuning of the PID algorithm cannot guarantee good performance of systems. A methodology overcoming this limitation is a hierarchical control strategy, consisting of a fuzzy supervisor and of the PID controller itself [10].

The main objective of this paper is to propose an optimal fuzzy supervisor for an active suspension system.

The membership function values of considered fuzzy model have been optimized by Discrete Action Reinforcement Learning Automata (DARLA).

II. THE MODEL FORMULATION

In this paper, a quarter car model with two degrees of freedom is considered. This model uses an actuator to produce the control force between the vehicle body mass and the wheel mass. The model and parameters are shown in Fig.1.

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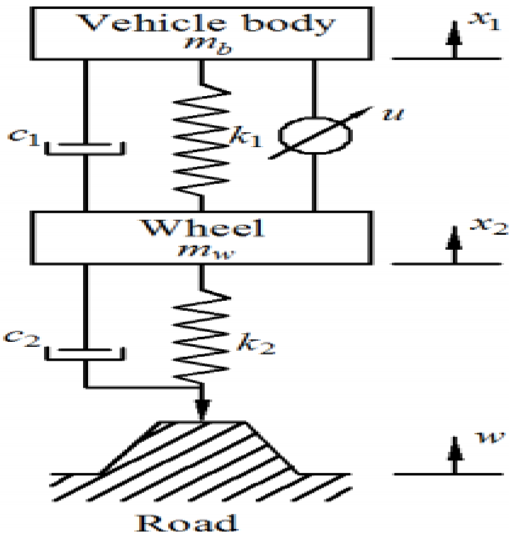

Fig.1: Quarter suspension model

The motion equation of the car body and wheel are as follows.

$$m_b\ddot{x}_1 = -c_1(\dot{x}_1-\dot{x}_2) - k_1(x_1-x_2) + u \quad (1)$$

$$m_w\ddot{x}_2 = c_1(\dot{x}_1-\dot{x}_2) + k_1(x_1-x_2) + c_2(\dot{w}-\dot{x}_2) + k_2(w-x_2) - u \quad (2)$$

With the following constants and variables that are shown in TABLE I.

TABLE I: Parameters of the vehicle

Symbol	Description	Value
m_b	Mass of total car	2500 kg
m_w	Spring constant of the suspension spring	104kg
K_1	Spring constant of the suspension spring	3200N/m
K_2	Spring constant of tire	100600N/m
C_1	Damping coefficient of the suspension system	3200Ns/m
C_2	Damping coefficient of tire	15020Ns/m

Where u is desired force by the cylinder, x_1 is body displacement, x_2 is the wheel displacement and w is road input.

The system output, the suspension deflection $x_1 - x_2$ is chosen instead of whole system deflection $x_1 - w$ because of difficulties in determining of the wheel deflection [11], [12].

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In this paper, we considered road surface input w as a unit step with 10 cm amplitude.

III. PROPOSED CONTROLLER DESIGNING

Due to their simple structure and robust performance, PID controllers are the most commonly used controllers in industrial process control. The transfer function of a PID controller has the following form:

$$y(t) = K_p e(t) + K_d \frac{de}{dt} + K_i \int_0^T e(t)dt \tag{3}$$

Where K_p, K_i and K_d are called the proportional, Integral and derivative gains, respectively. The success of the PID controller depends on appropriate choice of the PID gains. A PID controller can easily tune applying the well-known Ziegler-Nichols technique, but it is reliable only when the system works at the designed operating condition [13], [14]. To solve this problem, we designed a fuzzy supervisor PID controller for an active suspension system.

For the suspension model is given in Fig.1, the controller block diagram is shown in Fig.2. In which u and w are system inputs. Error e is system deflection and de is deviation of error.

A. Designing of fuzzy supervisor controller

Regarding to Fig.2, there are two inputs to fuzzy inference: e and de, and three outputs for each PID controller parameters, respectively K'_p, K'_i and K'_d.

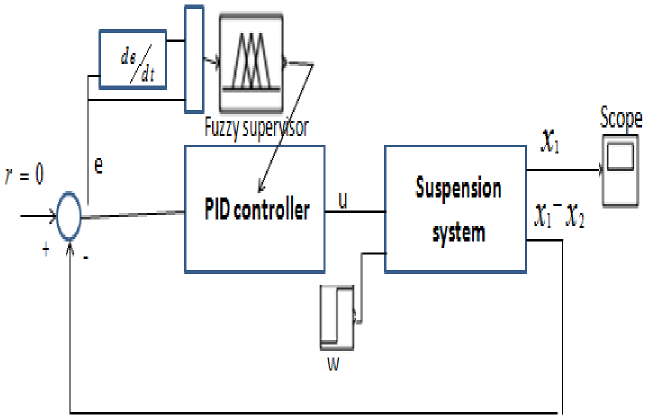

Fig.2: Controller block diagram

We suppose the variable ranges of PID controller parameters are $[K_{p\min}, K_{p\max}]$, $[K_{i\min}, K_{i\max}]$ and $[K_{d\min}, K_{d\max}]$

For convenience these parameters are normalized to the ranges between zero and one by the following linear transfer function [13],[14].

$$K'_p = \frac{K_p - K_{p\min}}{K_{p\max} - K_{p\min}} = \frac{K_p - K_{p\min}}{\Delta K_p} \tag{4}$$

$$K'_i = \frac{K_i - K_{i\min}}{K_{i\max} - K_{i\min}} = \frac{K_i - K_{i\min}}{\Delta K_i} \tag{5}$$

$$K'_d = \frac{K_d - K_{d\min}}{K_{d\max} - K_{d\min}} = \frac{K_d - K_{d\min}}{\Delta K_d} \tag{6}$$

Hence, we obtain:

$$K_p = K'_p \times \Delta K_p + K_{p\min} \tag{7}$$

$$K_i = K'_i \times \Delta K_i + K_{i\min} \tag{8}$$

$$K_d = K'_d \times \Delta K_d + K_{d\min} \tag{9}$$

B. Optimizing fuzzy supervisor controller by Discrete Action Reinforcement Learning Automata (DARLA)

One important note in designing every fuzzy controller is determining best membership function and rules. In most cases these structure should be determined by practical experiences. But they can be optimized for better performance.

To optimized fuzzy controller stated in the previous section, we use the Discrete Action Reinforcement Learning method for optimizing input membership function. Each membership function in the fuzzy controller, except first and last one, specified with three parameters: First point, Midpoint and Final point.

First and final membership function have a cutting part, so they are specified by two parameters only.

On the other hand, each of the above membership function could be specified by distance between midpoints of two neighbor membership functions and the distance between first and final points from the midpoint.

In this fuzzy controller, both inputs are characterized with five fuzzy sets, so there are 26 fuzzy controller coefficients for tuning.

In DARLA, the variations of controller coefficient are divided into the same length limits. A Discrete Probability Distribution Function (DPDF) is assigned for each of them. These DPDFs initially set as a uniform one. Probability of selection of each limit is performed by DPDF and after each selection of decision variables.

The shape of DPDFs is changed proportional to fitness of that selection. Fig.3 shows diagram of DARLA method.

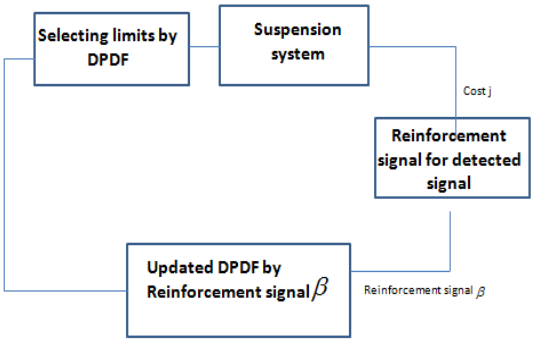

Fig.3: block diagram of DARLA method

As stated, there are 26 fuzzy controller coefficients, where each varies between 0 and 1. Any interval is divided into 10 equal sub- intervals. This limit was divided into 10 equal limits. Number of division does not effect on design performance severely, but it must be selected large enough as Equation (10).

$$f_i^{(0)}(x) = \begin{cases} \frac{1}{X_{i\max} - X_{i\min}} & x \in [X_{i\min}, X_{i\max}] \\ 0 & \text{other} \end{cases} \tag{10}$$

Where $f_i^{(k)}(p)$ is probability of selecting p-th interval for each controller at k-th iteration. After selecting intervals by cumulative probability of DPDF, center of each limit is chosen at the corresponding coefficient of the TSFL and cost J is calculated as Equation (11).

$$J^k = G_1 \int_0^T |e|\,dt + G_2 \int_0^T |u|\,dt \qquad (11)$$

Where J^k is the cost at k-th iteration, T is simulation time and must be large enough, e is error signal and u is control signal. G_1 and G_2 are cost element weights and considered as:

$$G_1 = 15.8 \quad G_2 = 0.07 \qquad (12)$$

After calculating cost, reinforcement signal β will be calculated as Equation (13).

$$\beta(J) = \min\{1, \max\{0, \frac{J_{mean} - J}{J_{mean} - J_{\min}}\}\} \qquad (13)$$

Where $J^{(k)}$ is k-th reinforcement signal and J_{mean} and J_{min} are average and minimum of previous costs, respectively. Defining reinforcement signal as Equation (13) gives average of costs has non- increasing behaviour and guarantees convergence of method.

After obtaining reinforcement signal, DPDFs are updated by (14).

$$f_i^{(k+1)}(n) = \alpha_i^{(k)} \left(f_i^{(k)}(n) + \beta^{(k)} Q_i^{(k)} \right) \quad i = 1, 2, \ldots, n \quad (14)$$

Where $Q_i^{(k)}$ is an exponential function centred at the selected limit and defined as:

$$Q_i^{(k)} = r_q 2^{-\left(n - \tilde{n}_i\right)^2} \qquad (15)$$

Where $\tilde{n}_i$ is the selected limit and r_q is a positive constant. $\alpha_i^{(k)}$ in Equation (14) is a normalization factor calculated as Equation (16).

$$\alpha_i^{(k)} = \frac{1}{\sum_{n=1}^{10} f_i^{(k)}(n) + \beta^{(k)} Q_i^{(k)}} \qquad (16)$$

After sufficient iterations, the selection probability of optimal limit for each DPDF is maximized. The limits with highest probability of selection at the end of iterations for each of controller coefficient are the optimum limit for that coefficient [15], [16].

IV. SIMULATION RESULTS

Simulation for controller of active car suspension model is done by using MATLAB simulink. The input signal type is a step signal by 10 cm amplitude. Two types of controller are applied, they are PID controller which is tuned by Zigler-Nichols technique and optimal PID controller which is tuned by fuzzy supervisor.

Fig.4 is the response of the quarter car active suspension with Zigler- Nichols PID controller.

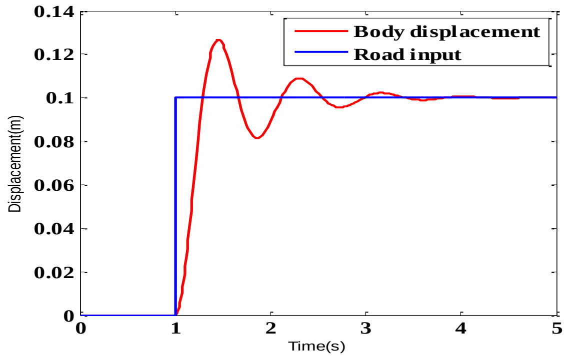

Fig..4: Response of active suspension with Zigler-Nichols PID controller

The red line curve is the step signal and the blue line curve is the quarter car response.

Fig.5 is the control signal of Zigler- Nichols PID controller.

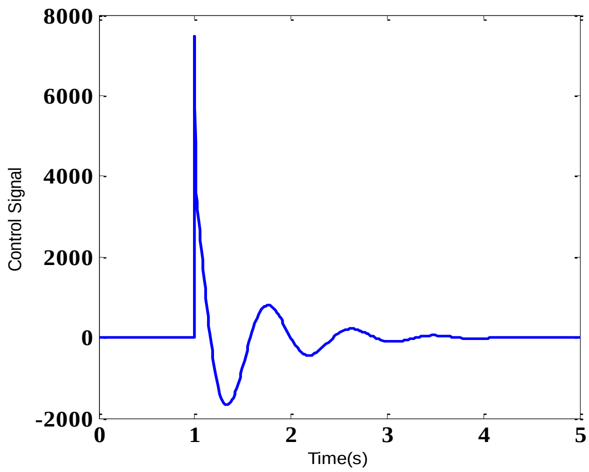

Fig.5: Control signal of Zigler-Nichols PID controller

These figures show that the car suspension with this controller cannot reduce the vibration, as the response has many oscillations.

Fig.6 and Fig.7 are the response of the active suspension system and control signal with proposed controller.

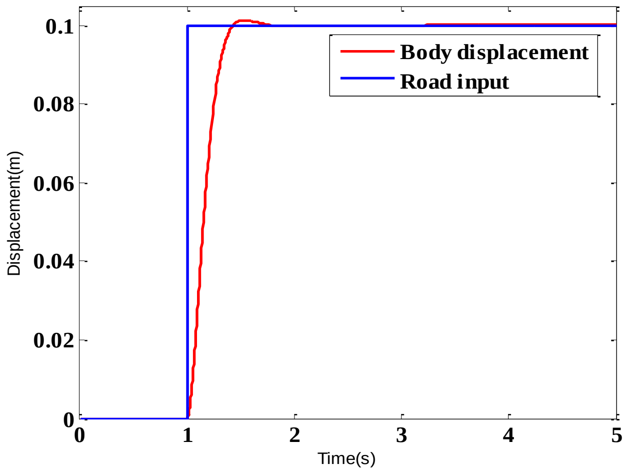

Fig.6: Response of active suspension with proposed controller

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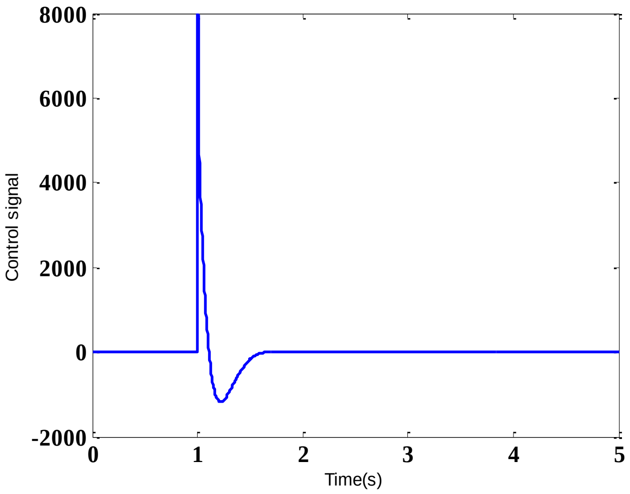

Fig.7: Control signal of Zigler-Nichols PID controller with proposed controller

As it is seen, by nearly same actuator force, the proposed controller damped oscillations.

V. CONCLUSION

In this paper, the active car suspension system has been successfully controlled by using optimal fuzzy supervisor PID controller.

The results of proposed controller are compared with those of PID controller which is tuned by Zigler- Nichols algorithm. It has been seen that proposed controller has better performance than Ziegler- Nichols PID controller.

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