PSO tuned Adaptive Neuro-fuzzy Controller for Vehicle Suspension Systems

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***Abstract*— In this paper, Particle Swarm Optimization (PSO) technique is applied to tune the Adaptive Neuro Fuzzy Controller (ANFIS) for vehicle suspension system. LQR controller is used to obtain the training data set for the vehicle suspension system. Subtractive clustering technique is used to formulate ANFIS which approximates the actuator output force as a function of system states. PSO algorithm search for optimal radii for subtractive clustering based ANFIS. Training is done off line and the cost function is based on the minimization of the error between actual and approximated output. Simulation results show that the PSO-ANFIS based vehicle suspension system exhibits an improved ride comfort and good road holding ability.**

***Index Terms*— Vehicle suspension, Quarter car model, ANFIS, FLC, ride comfort.**

I. INTRODUCTION

Active suspension systems have been currently of great interest both academically and in the automobile industry. The basic idea in active suspension is to use an active element (the actuator) to apply a desired force between the vehicle body and wheel axle. This desired force is computed by the vehicle control unit to achieve certain performance objectives under external disturbances, such as passenger's comfort under road imperfections [1]. The main advantage of an active suspension is its adaptation potential where the suspension characteristics can be adjusted according to the profile of the road being traversed.

Various control strategies such as optimal state-feedback [2-4], back stepping method [5], fuzzy control [6], sliding mode control [7, 8] and Fuzzy sliding mode control [9] have been proposed in the past to control the active suspension system. Vehicle suspension systems are very complicated and highly non-linear. Suspension parameters will change when a vehicle rides on various road conditions. Conventional control strategies depend on accurate system model and cannot adapt to environmental conditions. Fuzzy control is suitable to system that has nonlinearity, complex and no precise math model and hence Fuzzy Logic Control (FLC) is used for disturbance rejection control in active suspension system. Neural networks possess a variety of alternative features such as massive parallelism, distributed representation and computation, generalization ability, adaptability and inherent contextual information processing. They are well suited to modeling different forms of uncertainties and ambiguities, often encountered in real life. The objective of the hybridization (using neural networks and fuzzy logic) through Adaptive Neuro Fuzzy Inference System (ANFIS) has been used to overcome the weaknesses in one technology during its application, with the strengths of the other by appropriately integrating them.

Emergence of soft computing or computational intelligence inspired by biological, social behavior of bird flocking and human intelligence play a significant role in the development of intelligent robotic system, machine system and mechatronics system. Adaptive particle swarm optimization has been used for adapting the weights of fuzzy neural networks on line for D.C.Motor speed control [10]. Particle swarm optimization tuned subtractive clustering based adaptive neuro fuzzy control has been developed to provide critical information about the presence or absence of a fault in a two tank process [11].

In this paper, Particle Swarm Optimization (PSO) is used to train Subtractive clustering based Adaptive Neuro-Fuzzy Inference System (ANFIS) and applied for vehicle suspension system to give better vibration isolation of vehicle body. PSO algorithm is adopted for several reasons like stable convergence [12], the fact that it can generate a high quality solution in a shorter calculation time than other stochastic methods [13] and its successful applications in many nonlinear and highly complex problems [14].

The LQR control method has been used to obtain the training data for the ANFIS controller. Performance of the suspension system is evaluated in terms of power spectral density of sprung mass acceleration and tyre deflection which in turn influence the vehicle riding comfort performance and road holding ability. Organization of the paper is as follows. Quarter-car model is briefly explained in section 2. PSO tuned

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ANFIS is discussed in section 3. The detailed PSO algorithm is explained in section 4. Simulation results are discussed and presented in section 5. Finally, the last section concludes the paper.

II. Active Suspension – Dynamics

A. Quarter car model

A two degree of freedom "Quarter-car" automotive suspension system is shown in Fig. 1. It represents the automotive system at each wheel i.e. the motion of the axle and of the vehicle body at any one of the four wheels

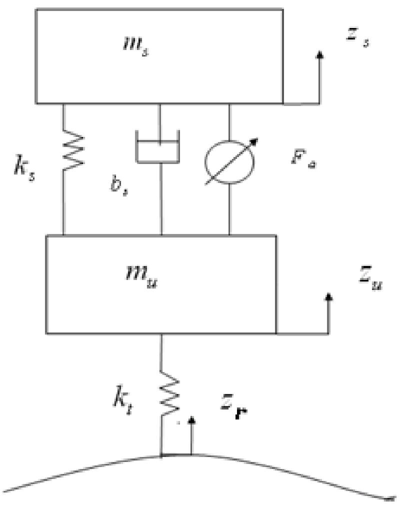

Figure 1. Quarter car model

of the vehicle. Quarter car model is considered because it is simple and one can observe the basic features of the active suspension system such as a sprung and unsprung mass, suspension deflection and tyre deflection [15]. The suspension is shown to consist of a spring k_s, a damper b_s and an active force actuator F_a. The active force can be set to zero in a passive suspension. The sprung mass m_s represents the quarter car equivalent of the vehicle body mass. An unsprung mass m_u represents the equivalent mass due to axle and tyre. The vertical stiffness of 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 the sprung mass, unsprung mass and the road respectively. Equations of motion of the two degree of freedom quarter car suspension is given by

$$m_s \ddot{Z}_s = F_a - k_s(Z_s - Z_u) - b_s(\dot{Z}_s - \dot{Z}_u)$$
$$m_u \ddot{Z}_u = k_s(Z_s - Z_u) + b_s(\dot{Z}_s - \dot{Z}_u) + k_t(Z_r - Z_u) - F_a \qquad (1)$$

It is assumed that the suspension spring stiffness and tyre stiffness are linear in their operating ranges and that tyre does not leave the ground.

B. Data collection

The Optimal control method is used to obtain the training data for the ANFIS controller. Data collection is obtained by subjecting the quarter car model of active suspension system to a random road profile excitation.

III. PSO tuned ANFIS

The adaptive capability of ANFIS makes it possible for immediate adaptive and learning control. This adaptive network has good ability and performance in system identification, prediction and control and has been applied in many different systems. ANFIS has the advantage of good applicability as it can be interpreted as local linearization modelling and conventional linear techniques for state estimation and control are directly applicable [16]. The ANFIS based model is used to implement the controller for vehicle suspension system. First, it uses the training data set to build the fuzzy system in which, membership functions are adjusted using the back propagation algorithm, allowing that the system learns with the data that it is modelling. The ANFIS model which computes the actuator force has two input variables suspension deflection, sprung mass velocity (Z_s-Z_u, $\dot{Z}_u$) and one output variable actuator force F_a. First order Sugeno type fuzzy inference is used for ANFIS and the typical fuzzy rule is of the form

If *sus deflection* is *Ai* and sprung mass velocity *is Bi*
then $u = f(Z_s\text{-}Z_u, \dot{Z}_u)$.

where *A* and *B* are fuzzy sets in the antecedent and $u = f(Z_s\text{-}Z_u, \dot{Z}_u)$ is a crisp function in consequent.

A. Adaptive neuro-fuzzy architecture

An ANFIS is proposed as a core neuro-fuzzy model that can incorporate human expertise as well as adapt itself through repeated learning. An adaptive network is a multi-layer feed forward network in which each node (neuron) performs a particular function on incoming signals. The form of the node functions may vary from node to node. In an adaptive network, there are two types of nodes: adaptive and fixed. The function and the grouping of the neurons are dependent on the overall function of the network. Based on the ability of an ANFIS to learn from training data, it is possible to create an ANFIS structure from extremely limited or no mathematical representation of the system. In sequel, the ANFIS architecture can identify near-optimal membership functions of fuzzy logic for achieving desired input-output mappings. The network applies a combination of the least square method and the back propagation gradient descent method for training fuzzy inference system (FIS) membership function parameters to emulate a given training data set. The system

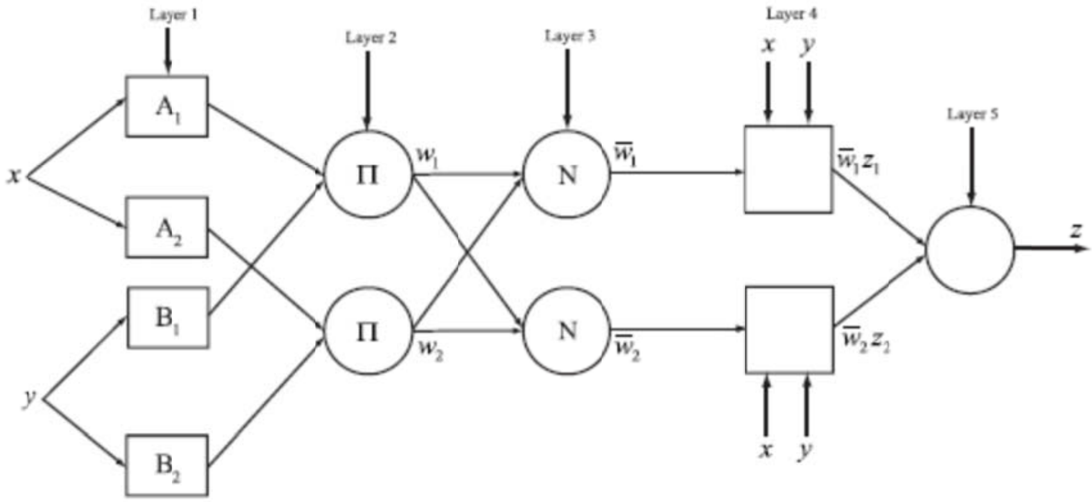

Figure 2. ANFIS architecture

converges when the training and checking errors are within the acceptable bound. This architecture has demonstrated high performance in many applications. The ANFIS system generated in the MATLAB allows for generation of a standard Sugeno style fuzzy inference system or a fuzzy inference system based on sub-clustering of the data (MathWorks, 1995).

A typical ANFIS architecture is shown in Fig. 2, where nodes of the same layer have similar functions. For simplicity, consider two inputs x, y and one output z. Among many FIS models, the Sugeno model is the most widely applied one for its high interpretability and computational efficiency and built in optimal and adaptive techniques [17]. For a first order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is the following:

Rule1: If x is A_1 and y is B_1, then $\boldsymbol{f_1 = p_1x + q_1y + r_1}$

Rule2: If x is A_2 and y is B_2, then $\boldsymbol{f_2 = p_2x + q_2y + r_2}$

Where $\boldsymbol{A_i}$ and *B*i are the fuzzy sets in the antecedent, and p_i, q_i and r_i are the design parameters that are determined during the training process. As in Fig. 2, the ANFIS consists of five layers:

Layer 1: Every node i in this layer is an adaptive node with a node function

$O_{1,i} = \mu_{Ai}(x)$, for i=1,2 or

$O_{1,i} = \mu_{Bi-2}(y)$, for i = 3,4. (2)

Where μ_{A_i} and μ_{B_i} can adopt any fuzzy membership function.

Layer 2: Every node in this layer calculates the firing strength of a rule via multiplication of all incoming signals.

$O_{2,i}=\omega_i = \mu_{A_i}(x)\mu_{B_i}(y),\ i = 1,2.$ (3)

Layer 3: The ith node calculates the ratio of the ith rule's firing strength to the sum of all rules firing strengths:

$O_{3,i}=\overline{w_i} = \frac{w_i}{w_1+w_2},\ i = 1,2.$ (4)

Where $\overline{w_i}$ is referred to as the normalized firing strengths.

Layer 4: Every node i in this layer is an adaptive node with a node function

$$O_{4,i}=\overline{w_i}f_i = \overline{w_i}(p_ix + q_iy + r_i), \quad (5)$$

where $\overline{w_i}$ is a normalized firing strength from layer 3 and $\{p_i,\ q_i,\ r_i\}$ is the parameter set of this node. Parameters in this layer are referred to as consequent parameters.

Layer 5: The single node in this layer is a fixed node labelled Σ, which computes the overall output as the summation of all incoming signals:

$$\text{Overall output} = O_{5,i}= \sum_i \overline{w_i}\, f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (6)$$

B.Subtractive Clustering

Subtractive Clustering (SC) technique is used to formulate an ANFIS. Subtractive Clustering looks for an optimal data point by dividing the data into clusters and defining a cluster center based on the density of surrounding data points [18]. The subtractive clustering method assumes each data point as a potential cluster center and calculates a measure of the likelihood that each data point would define a cluster center, based on the density of surrounding data points. The algorithm does the following:

1. Selects the data point with the highest potential to be the first cluster center.
2. Removes all data points in the vicinity of the first cluster center (as determined by radii), in order to determine the next data cluster and its center location
3. Iterates on this process until all of the data is within radii of a cluster center.

With proper cluster radii SC algorithm finds the optimal point defining a cluster center.

IV. Tuning of SC-ANFIS Simultion Results

Subtractive clustering is performed with random radius size for all three inputs and outputs. Two radii sizes of 0.7 and 0.4 are chosen at random to develop two SC based ANFIS. Training errors for both the developed SC-ANFIS systems with radii 0.7 and 0.4, shown in table 1 stress the importance of tuning the cluster radii in order to reduce these high errors. For this purpose, an objective function based on squared error is minimized using PSO, and optimal cluster radii are searched.

$$J = \sum_{n=1}^{N} \frac{(\hat{Y}-Y)^2}{N} \qquad (7)$$

where $\hat{Y}$ is the predicted control output and Y is the actual control output. In order to reduce the Mean Square Error (M.S.E) value of the actual and approximated control outputs it is necessary to tune the cluster radii. Hence PSO technique is used to tune the cluster radii with the cost function J as MSE.

$r_i^{min} \leq r_i \leq r_i^{max}$, $i= 1, 2, 3$

The minimum value of $r_{1,2,3}^{min}$ is set to 0.1 while the maximum values are set to half the range of respective inputs and outputs. PSO is applied to obtain the optimal values of r_1, r_2 and r_3 for the two inputs and one output.

A. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by the social behavior of bird flocking or fish schooling [19]. In PSO algorithm, the individual is called particle and the trajectory of each individual in the search space is adjusted dynamically by altering the velocity of each particle, according to its own flying experience and the flying experience of the other particles in the search space.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating iterations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far and is represented as Pbest. Another "best" value is the best solution obtained so far by any particle in the population. This is represented as Gbest. Each particle knows the best value so far (Pbest) and best value in the group (Gbest). The particle tries to modify its position using the current velocity and the distance from Pbest and Gbest. The modified velocity and position of each particle can be calculated using the following formulas [10]

$$v_i^{k+1} = w * v_i^k + c_1 * rand_1 * (pbest_i - x_i) + c_2 * rand_2 * (gbest_i - x_i) \qquad (8)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \qquad (9)$$

w = inertia weight parameter
c_1, c_2 = weight factors
v_i^k = velocity of particle i in k^{th} iteration
x_i^k = position of particle i in k^{th} iteration
$rand_1$, $rand_2$ = random number between 0 and 1

Suitable selection of inertia weight w provides a balance between global and local explorations. In general, the inertia weight w is set according to the following equation:

$$w = w_{max} - ((w_{max} - w_{min}) * t / T) \qquad (10)$$

where w is an adjustable parameter between w_{max} *and* w_{min}

t = current iteration number
T = maximum number of iterations

V. Simultion Results

The parameters of the quarter car model are obtained from [20] and listed as follows

Sprung Mass (m_s)	240 kg
Unsprung Mass (m_u)	36 kg
Damper coefficient (b_s)	980 Ns/m
Suspension Stiffness (k_s)	16,000 N/m
Tyre Stiffness (k_t)	160,000 N/m

Simulations are performed using MATLAB and Simulink. The road profile is a 3-Hz sinusoidal function of 10cm amplitude. Simulations are conducted for open loop passive, active suspension with ANFIS and active suspension with PSO tuned ANFIS to evaluate their performances.

ANFIS controller is a function of suspension deflection (Z_s-Z_u)and sprung velocity ($\dot{Z}_u$). The dimension of search space is 27. The PSO algorithm parameters chosen for the tuning purpose are: population size = 30, c_1 *and* c_2 = 2, No. of iterations = 100. w_{max} = 0.9, w_{min}=0.4.

PSO algorithm is applied off line to tune the ANFIS through clustering radius. Sinusoidal road profile of 3 Hz is applied as disturbance to the quarter car model. Simulations are conducted for open loop passive, active suspension with ANFIS, SCANFIS and active suspension with PSO tuned SCANFIS. From Table 1 it is obvious that with PSO tuned ANFIS controller with proper radii, the training error got reduced. The convergence of cost function is also shown in fig.3. Since the road conditions are uncertain, controller should be robust to any type of road disturbance. PSO technique is incorporated in tuning the perfect radii so that optimal membership function of the ANFIS is obtained. The PSO algorithm determines the optimal radii point such that ANFIS control reduces the vertical sprung mass deflection and enhances the ride comfort.

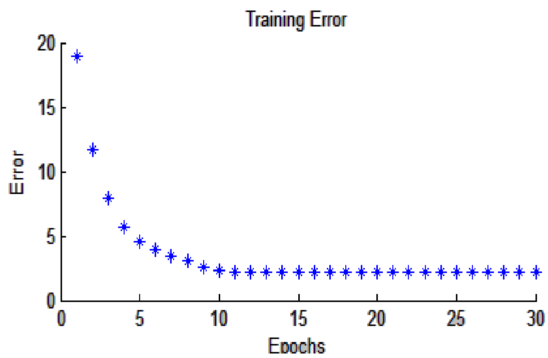

Figure 3. Training error of the PSO-ANFIS

TABLE I.

TRAINING ERROR FOR DIFFERENT CLUSTER RADII

Controller	Training MSE
SCANFIS r_1, r_2, r_3 = 0.4	4.4301
SCANFIS r_1, r_2, r_3 = 0.7	6.0043
PSO-SCANFIS r_1=0.2762, r_2= 0.7506 and r_3 = 0.1257	2.0968

From fig 4 and 5, it is observed that the amplitude of the sprung mass displacement and sprung mass acceleration for an active suspension based on PSO-SCANFIS shows considerable improvement compared to ANFIS scheme without PSO tuning. Fig. 6 indicates that the suspension deflection controlled by ANFIS , SCANFIS and PSO-SCANFIS are of same magnitude but smaller than that of passive. Fig. 7 illustrates how effectively the active suspension (both ANFIS and PSO - ANFIS) absorbs the vehicle vibration compared to the passive system. Except for the transients tyre deflection is much smaller for PSO-SCANFIS and thus the road holding ability is maintained by the same.

In the evaluation of vehicle ride quality, the Power Spectral Density (PSD) of the sprung mass acceleration as a function of frequency is of prime interest and shown in fig.8. It shows that the sprung mass acceleration has been brought down within the frequency between 0.4 Hz to 3.5 Hz by the PSO-SCANFIS scheme. Thus the active suspension with PSO-SCANFIS scheme could greatly contribute to the improvement of the vehicle ride comfort and marginally contribute to the road holding ability.

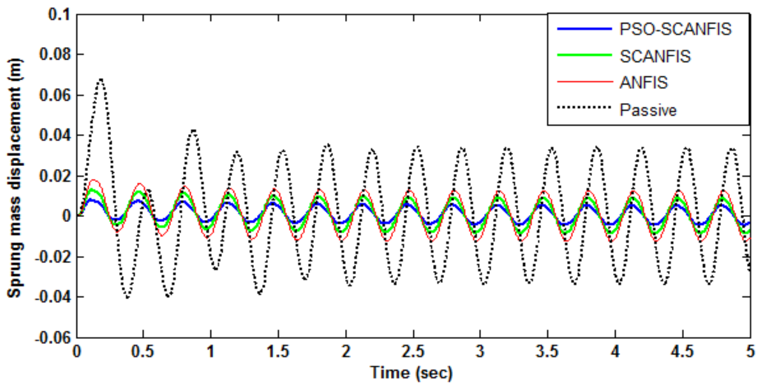

Figure 4. Sprung mass displacement

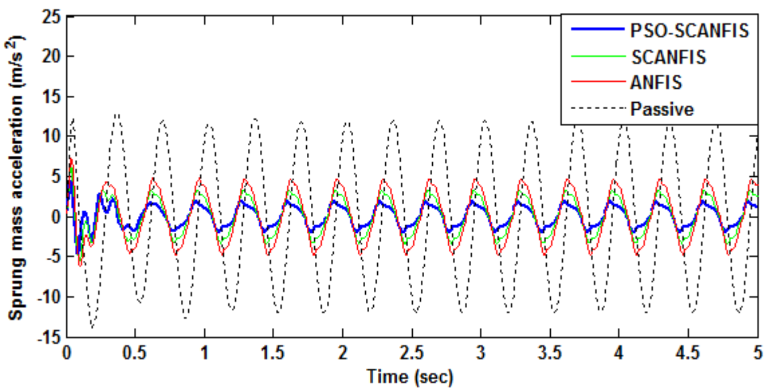

Figure 5.Sprung mass acceleration

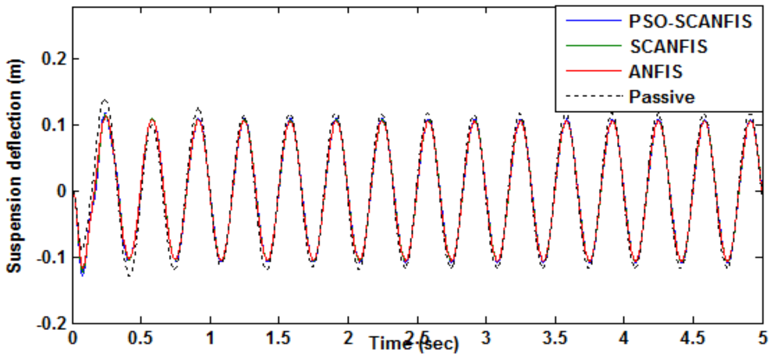

Figure 6. Suspension deflection

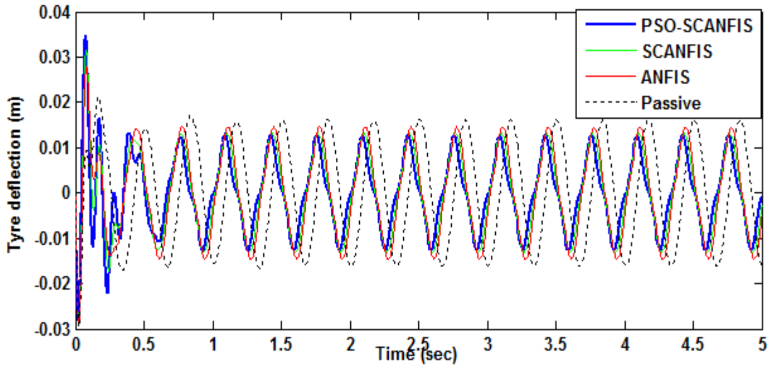

Figure 7. Tyre deflection

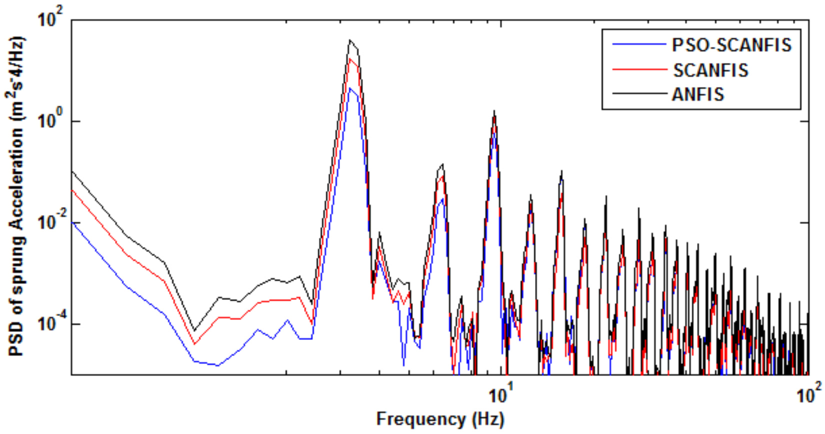

Figure 8.PSD of Sprung mass acceleration

VI. Conclusion

In this paper, particle swarm optimization technique has been used to tune the ANFIS controller through subtractive clustering for the quarter car model based active suspension system. The cost function associated with PSO algorithm is formulated as square of error between actual and approximated control signals. Trained ANFIS simplified the control of active suspension system. ANFIS requires low computational complexity and it was found to be more convenient to obtain the desired relationship between inputs and output. Simulation results demonstrate the effectiveness of the proposed controller. ANFIS based active suspension provides higher ride comfort and road handling qualities when compared to existing passive and ANFIS without PSO.

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