Optimal FLC-Sugeno Controller based on PSO for an Active Damping System

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ABSTRACT

In this paper, a method for the design of an optimal Sugeno model (FLC-Sugeno) fuzzy logic controller for the active suspension system of quarter-vehicle models is presented. The parameters of the FLC-Sugeno controller are optimally searched, using the Particle Swarm Optimization (PSO) algorithm. The 16 optimized parameters include 3 parameters for adjusting the domain of the input state variables and control variables at the controller's output, 4 fuzzy set adjustment numbers of the linguistic variables, and 9 parameters as the fuzzy rule weights of the rule system control. To compare and evaluate the effectiveness of the optimal FLC-Sugeno controller, an optimal PID controller using PSO is also implemented. Simulation results of the active damping system with the controllers when affected by the same type and standard road surface excitation show that the FLC-Sugeno controller is optimal for the quick ending of the oscillations of vehicle body displacement. The result shows that the proposed controlling scheme can be extended and applied to more complex active damping system models.

Keywords-FLC-Sugeno; particle swarm optimization; active suspension system; quarter-vehicle models

I. INTRODUCTION

Considering quarter-vehicle models, the active damping controlling model has the best quality but a complex structure because it involves an additional controller for the damper. Different algorithms give highly divergent control efficiency values. Selecting and designing a controller according to the optimal algorithm is the goal of the research on the active damper model. The active damping system, in addition to the spring mechanism and the soft damping element, also involves a component that generates electromagnetic force from the electric motor with the purpose to quickly extinguish the oscillation process in the vertical direction of the system, or in other words, minimize the road surface impact on the vehicle body.

Many scientists have researched the application of fuzzy controllers in damping systems [1-7]. Active suspension of cars, using fuzzy logic controller, optimized by the genetic algorithm (GA), was proposed in [1]. The authors performed membership function adjustment utilizing GA. The limition was that they stoped when the membership function was optimized, and did not optimize the other parameters of the controller. Today there are many studies showing that there are many optimization algorithms superior to GA, such as the PSO employed in the current study. Many studies evaluated the effectiveness of Fuzzy Logic Control (FLC) and compared its results to the ones of PID controller, which provides effective control in a narrow working area [3]. The PID controller can also have its coefficients adjusted by a fuzzy set to form an adaptive fuzzy PID controller [8-10]. However, the controller structure is often complex. The FLC is widely researched, and applied in active damping systems [11-14].

A common feature of previous studies when applying FLC controller to damping systems in general is the design of fuzzy controllers without optimizing the controller parameters or utilizing the outdated optimization algorithm GA to ameliorate the membership function of the fuzzy set [1]. To overcome this limitation, in this study the proposed solution is to design the FLC-Sugeno controller that optimizes at the same time the fuzzy set of the membership functions and the weights of the rule system. The optimal technique considered is PSO [16, 17].

II. DAMPING SYSTEM MODELS

A. The Active Damping System Model

The active suspension system quarter-vehicle model is presented in Figure 1.

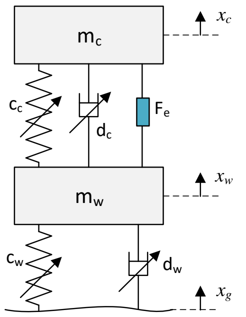

Fig. 1. The active suspension system quarter-vehicle model.

In Figure 1, the lower body block m_w represents the tires, wheels, brakes, and components in the wheel that act on the system, m_c represents a quarter of a vehicle's mass including passengers and payload. The tire is characterized by the stiffness parameter c_w and the damping coefficient d_w. The upper and lower body blocks are linked by spring mechanism c_c, damping mechanism d_c, and electromagnetic force generating mechanism F_e. Let the displacements of road surface, lower body block, upper body block be x_g, x_w x_c. The Linear Brushless Permanent Magnet (LBPM) motor creates force F_e with the purpose of minimizing the vibration of the system or the impact of the road surface x_g on the upper body mass. Thus, the system includes two inputs: the noise from the road surface x_g and the force F_e. The output of the system consists of x_c and x_w, the purpose of the control process is $x_c \to 0$. The following differential equation system describes the system:

$$\begin{aligned} & m_c\ddot{x}_c = -c_c(x_c - x_w) - d_c(t)(\dot{x}_c - \dot{x}_w) + F_e(t) \\ & m_w\ddot{x}_w = c_c(x_c - x_w) + d_c(t)(\dot{x}_c - \dot{x}_w) \\ & -c_w(t)(x_w - x_g) + d_w(t)(\dot{x}_w - \dot{x}_g) - F_e(t) \end{aligned} \tag{1}$$

According to [18], the damper spring c_c is chosen because it behaves linearly within the working range, assuming c_c is a constant. The coefficients $d_c(t)$, $c_w(t)$, and $d_w(t)$ change in a small range around the working point location.

$$\begin{aligned} & d_c(t) = d_{c0} + \Delta d_c;\ c_w(t) = \\ & c_{w0} + \Delta c_w;\ d_w(t) = d_{w0} + \Delta d_w \end{aligned} \tag{2}$$

where d_{c0}, c_{w0}, d_{w0} are the values at the working point and Δd_c, Δc_w, Δd_w are their value changes around the working point.

B. Linear Brushless Permanent Magnet Motor Model

The structure of the LBM is shown in Figure 2 with the following assumptions: The inductance of the motor's stator coils is constant, the rotor l is infinite to ignore terminal effects, the magnetic flux intensity of the magnet is constant, and the the magnetic saturation effect is ignored [20]. The LBM model is written in the form of dq coordinates as:

$$\begin{cases} u_d = R_s i_d + \frac{d\Psi_d}{d_t} - \frac{d_x}{d_t}\frac{\pi}{\tau_p}\Psi_q;\ u_q = R_s i_q + \frac{d\Psi_d}{d_t} - \frac{d_x}{d_t}\frac{\pi}{\tau_p}\Psi_d \\ F_e = \frac{\pi}{\tau_p}\Psi_m i_q;\ F_e - \left(K_1\frac{d_x}{d_t} + K_2 + F_t\right) = I\frac{d^2x}{dt^2} \end{cases} \tag{3}$$

where u_d, u_q, i_d, and u_q are the voltage and current on stator, R_s is the stator resistance, ψ_d and ψ_q represent the magnetic flux on the d and q axes, F_e is the electromagnetic force, I is the inertial force of the motor shaft, x is the distance movement of the motor shaft, K_d and K_e are the dynamic resistance and static resistance coefficients, and F_t is the external resistance force.

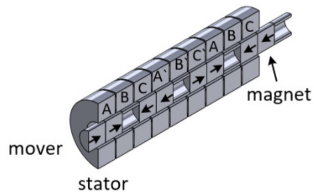

Fig. 2. Structure of the linear brushless permanent magnet motor.

C. The Model of Active Damping System using LBM

Substituting (2) into (1), we get the system of differential equations describing the damping system:

$$\begin{aligned} & m_c\ddot{x}_c = -c_c(x_c - x_w) - \\ & (d_{c0} + \Delta d_c)(\dot{x}_c - \dot{x}_w) + F_e(t) \\ & m_w\ddot{x}_w = c_c(x_c - x_w) + (d_{c0} + \Delta d_c)(\dot{x}_c - \dot{x}_w) \\ & -(c_{w0} + \Delta c_w)(x_w - x_g) + \\ & (d_{w0} + \Delta d_w)(\dot{x}_w - \dot{x}_g) - F_e(t) \end{aligned} \tag{4}$$

The state variables are set as:

$$\underline{x} = [x_1\ x_2\ x_3\ x_4\,]^T = \left[(x_c - x_w)\ \dot{x}_c\ (x_w - x_g)\ \ \dot{x}_w\,\right]^T \tag{5}$$

The output variable y is:

$$y = [\,\ddot{x}_c \quad F \quad (x_c - x_w)\,]^T \tag{6}$$

where F is the dynamic load force created by the wheel:

$$F = (c_{w0} + \Delta c_w)(x_g - x_w) + (d_{w0} + \Delta d_w)(\dot{x}_g - \dot{x}_w) \tag{7}$$

From this way of setting the state variable, we bring (4) to the system of state equations:

$$\begin{cases} \dot{\underline{x}} = A\underline{x} + BF + \Delta\underline{x} + N\dot{x}_g \\ y = C\underline{x} + DF + M\dot{x}_g \end{cases} \tag{8}$$

With the matrices:

$$A = \begin{bmatrix} 0 & 1 & 0 & -1 \\ -\frac{c_c}{m_c} & -\frac{d_{c0}}{m_c} & 0 & \frac{d_{c0}}{m_c} \\ 0 & 0 & 0 & 1 \\ \frac{c_c}{m_w} & \frac{d_{c0}}{m_w} & \frac{c_c}{m_w} & \frac{d_{w0}+d_{w0}}{m_w} \end{bmatrix};\ B = \begin{bmatrix} 0 \\ \frac{1}{m_c} \\ 0 \\ -\frac{1}{m_w} \end{bmatrix};\ N = \begin{bmatrix} 0 \\ 0 \\ -1 \\ \frac{d_{w0}}{m_w} \end{bmatrix}$$

$$\Delta = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & \frac{\Delta d_{c0}}{m_c} & 0 & \frac{\Delta d_{c0}}{m_c} \\ 0 & 0 & 0 & 1 \\ 0 & \frac{\Delta d_{c0}}{m_w} & -\frac{\Delta c_c}{m_w} & -\frac{\Delta d_{w0}}{m_w} \end{bmatrix}; D = \begin{bmatrix} \frac{1}{m_c} \\ 0 \\ 0 \end{bmatrix}$$

$$C = \begin{bmatrix} -\frac{c_c}{m_c} & -\frac{d_c}{m_c} & 0 & \frac{d_c}{m_c} \\ 0 & 0 & -c_w & -d_w \\ 1 & 0 & 0 & 0 \end{bmatrix}; M = \begin{bmatrix} 0 \\ d_{c0} + \Delta d_{w0} \\ 0 \end{bmatrix}$$

III. THE PROPOSED NEW OPTIMAL CONTROLLER FOR ACTIVE DAMPING SYSTEMS

With the purpose of minimizing the impact of road surface noise on the upper body, which means reducing the amplitude x_c to 0 in the shortest time, we propose an output feedback controller as shown in Figure 3. The Electric motor block includes a linear motor, a current controller, and a conversion block to the *dq* system. The suspension system damper block is influenced by road surface noise $x_g(t)$, and receives the impact force F_e from the Electric motor block.

A. Design of the FLC Controller Structure

The fuzzy logic controller is selected accoding to the Sugeno model. It includes two inputs, *e* and *ce* and one output, *u.* The fuzzy sets for input/output linguistic variables are:

- Input variables: *e, ce* include 5 triangular fuzzy sets NB, N, ZE, PS, PB defined in the domain [-1, 1]. The fuzzy sets are designed as strong fuzzy partitions, which means that for any real value *x*, the total membership of *x* in the fuzzy sets is equal to 1.
- The output variable *u* consists of 7 singleton fuzzy sets, NB, N, NS, ZE, PS, P, PB defined in the domain [-1, 1].

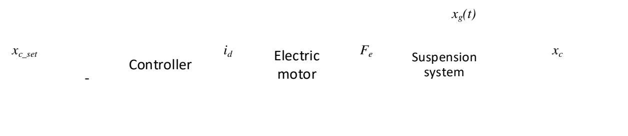

Fig. 3. The proposed active suspension system quarter-vehicle model.

The FLC-Sugeno controller is designed with the value domain of input/output variables normalized on the interval [-1, 1]. When coupled to the system, the coefficient K_e, K_{ce}, and K_u will correct their values to the real domain of the signal. In this way, we can flexibly combine the FLC-Sugeno controller into different control systems. The simulation blocks of the control system are shown in Figures 4 – 8.

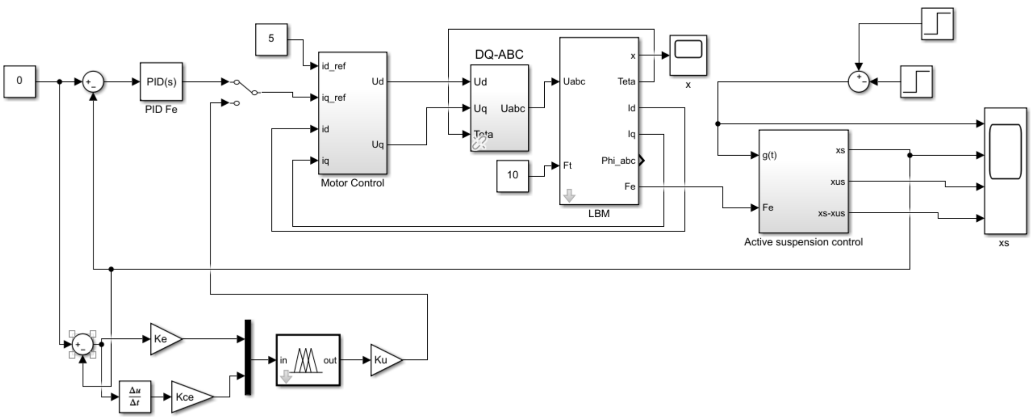

Fig. 4. Simulation diagram of the active damping system using the FLC-Sugeno controller.

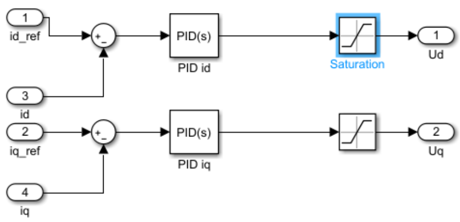

Fig. 5. The structure of the motor control block.

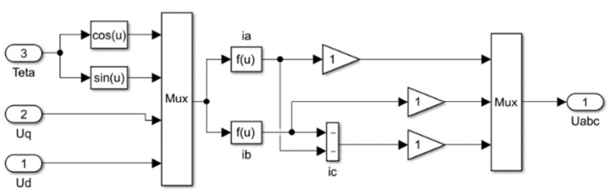

Fig. 6. The structure of the dq to abc block.

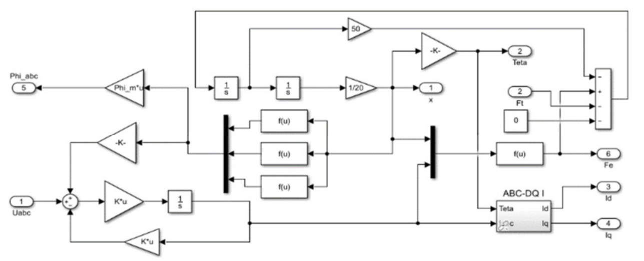

Fig. 7. The linear brushless permanent magnet motor model.

The motor control block includes two current control loops. The i_d current has a fixed set value, while the i_q current receives its set value from the PID F_e controller. The DQ-ABC block receives signals u_d, u_q through the *dq* coordinate conversion to control the linear motor. The motor creates the electromagnetic force F_e that participates in the oscillation process of the damping system built on (8).

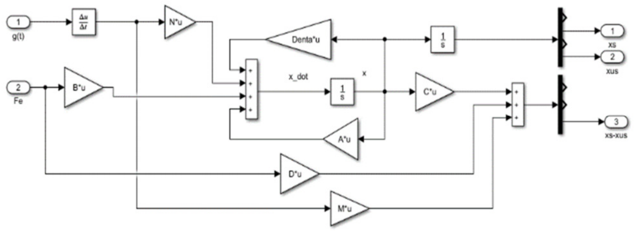

Fig. 8. The damping system model.

B. Optimizing Controller Parameters with PSO

The PSO optimization algorithm [17] is a random search algorithm based on simulating the behavior and interaction of birds when searching for food sources. Each individual (or element) in the swarm is characterized by two components, the displacement velocity vector v_i and the position vector x_i. Each element in the swarm has a *ftiness value*, which is evaluated by the *fitness fuction*. The objective fuction of the optimization process is chosen as the IAE (Integral of the Absolute magnitude of the Error):

$$finess = IAE = \sum_{n=1}^{j} |e(n)| \rightarrow min \quad (9)$$

The optimal diagram of the fuzzy controller is shown in Figure 9.

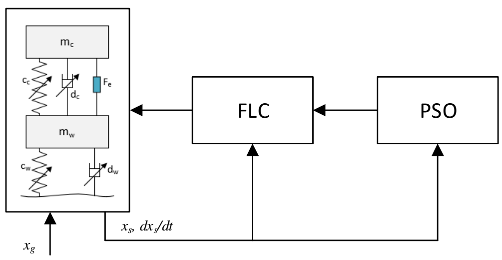

Fig. 9. Optimal diagram of the FLC controller using PSO.

1) Fuzzy Set Optimization

The diagram that optimizes the parameters of the FLC using the PSO algorithm is shown in Figure 10.

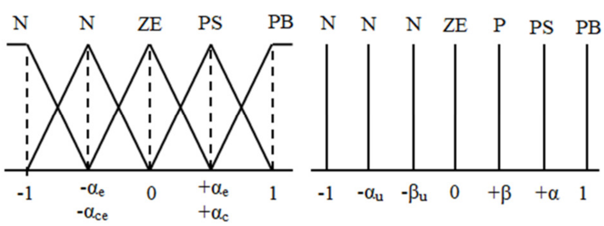

Fig. 10. Optimal fuzzy sets based on PSO.

To find the optimal fuzzy set shape, we limit the following conditions:

- The fuzzy set ZE is an isosceles triangle with a vertex at 0.
- Fuzzy sets PB and NB are symmetric at point 0. Conrrespondingly, we have other symmetric fuzzy sets at point 0 (N, P), (NS, PS).

Regarding the upper limit, by determining the fuzzy sets with symmetry for the optimal controller, our goal is to find the parameters α_e, α_{ce}, α_u, and β_u. The search domain for these parameters is chosen in the range: α_e, $\alpha_{ce} \in [0.2, 0.75]$; $\beta_u \in [0.25, 0.5]$; $\alpha_u \in [0.5, 0.75]$.

2) Optimizing the Weights of Fuzzy Rules

Each control rule carries a weight that determines the level of reliability of that rule. Most scientists only focus on researching the fuzzy set design and determining the rule system without paying attention to the weight of the rules. In this study, we use the PSO algorithm to find the weight of each rule. The control rule system and the weight of each rule is shown in Table I. We have 25 rules with w_i (i=1, 9) being the weight of each rule. We acquired 9 weights for 25 rules because it was discovered that, according to the nature of this control system, the rule system is symmetrical considering the center of the rule table, so rules in symmetrical positions will have equal weight. Specifically, the rule *"if e=NB and ce=NB then u=NB"* and rule *"if e=PB and ce=PB then u=PB"* have the same weight w_1, rules *"if e=NB and ce=NS then u=NB"* and *"if e=PB and ce=PS then u=PB"* have the same weight w_2, etc. With that symmetric property, we can reduce the number of variables that need to be optimized from 25 to 9.

TABLE I. CONTROL SYSTEM WITH WEIGHTS

e \ ce	NB		NS		ZE		PS		PB	
NB	NB	w_1	NB	w_2	N	w_3	NS	w_4	ZE	w_5
NS	NB	w_4	N	w_5	NS	w_6	ZE	w_7	PS	w_8
ZE	N	w_7	NS	w_8	ZE	w_9	PS	w_8	P	w_7
PS	NS	w_8	ZE	w_7	PS	w_6	P	w_5	PB	w_4
PB	ZE	w_5	PS	w_4	P	w_3	PB	w_2	PB	w_1

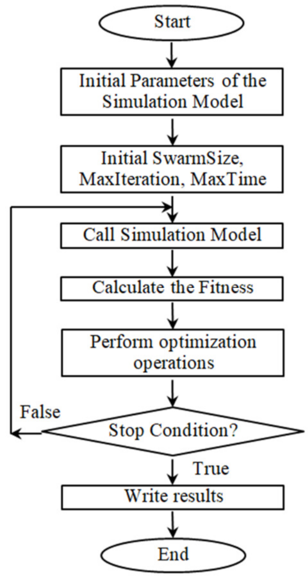

Fig. 11. Optimization flow chart based on PSO.

Thus, to design the proposed optimal FLC-Sugeno controller, the PSO algorithm will search for 16 parameters:

- 3 correction parameters K_e, K_{ce}, and K_u.

- 4 fuzzy set parameters α_e, α_{ce}, α_u, and β_u.
- 9 weights of the control rule system (w_i).

The optimal algorithm flow chart is shown in Figure 11. We used the function `particleswarm()` from the MATLAB/Simulink toolbox. This function supports the optimization algorithm PSO.

IV. SIMULATION RESULTS

The simulated system was built, and the received physical parameters of the model are shown in Table II. The parameters of the linear motor are given tin Table III.

TABLE II. DAMPER MODEL PHYSICAL PARAMETERS

Symbol	Value
m_c	256 kg
m_w	31 kg
c_{c0}	20200 N/m
Δc_c	1010 N/m
d_{c0}	1140 Ns/m
Δd_c	57 Ns/m
c_{w0}	128000 N/m
Δc_w	1280 N/m
d_{w0}	0 Ns/m

TABLE III. LINEAR MOTOR PARAMETERS

Symbol	Value
R_s	0.2 Ω
Ls	8.5 mH
Ms	2 mH
τ_p	10 mm
Ψ_m	10 mH
F_t	10N
R_{abc}	0.2 Ω
L_{abc}	8.5 mH
Ψ_{abc}	2 mH
I	10
K_d	50 N
K_e	5N

After running the optimization, we get the results shown in Table IV. To evaluate the control efficiency of the optimal FLC-Sugeno set, we additionally designed an optimal PID controller with parameters K_P, K_I, and K_D also optimized by PSO.

TABLE IV. OPTIMAL PARAMETER VALUES OF FLC-SUGENO

Fuzzy set parameters	Weight of the rule system
$\alpha_e = 0.398389$	$w_1 = 0.198813$
$\alpha_{ce} = 0.625307$	$w_2 = 0.257075$
$\alpha_u = 0.636611$	$w_3 = 0.0747781$
$\beta_u = 0.406224$	$w_4 = 1$
Parameters for adjusting the domain of variables	$w_5 = 0.337037$
$Ke = 0.3$	$w_6 = 0.723424$
$Kce = 0.289315$	$w_7 = 0.905881$
$Ku = 4101.68$	$w_8 = 0.868694$
	$w_9 = 0.125044$

The simulation scenario is set up with a total simulation time of 5.5 s. On 0.5 s, step excitation with amplitude 0.3 is applied. On 3 s, step stimulation with amplitude -0.3 is added. The simulation results of the active damping system subjected to the ISO standard excitation with optimal controllers are shown in Figure 12. On 0.5 s, when the road surface stimulus is introduced into the system, the blue line is the vehicle body displacement response without control. It takes 3 oscillation cycles to reach stable value. The maximum magnitude of vehicle body displacement without control is 15.5% lager than with optimal PID control. Meanwhile, with the optimal PID controller (yellow line), a stable value is reached after only 2 control cycles, but the switching amplitude is still quite large. The red line is the vehicle body displacement response with the proposed optimal FLC-Sugeno controller. It can be clearly seen that the response still has many oscillation peaks, but the transition amplitude is greatly reduced. At 3 s, a stimulus equal to -0.3 is applied to the system. the responses have the same appearance and trend as those applied at 0.5 s.

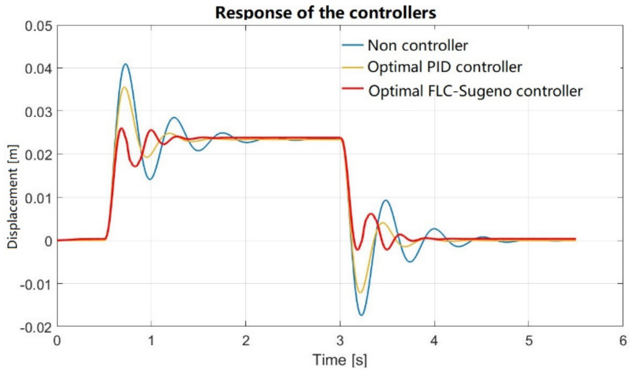

Fig. 12. Response of the active damping system with excitation and optimal controllers.

The results of this study show that the vehcile body motion amplitude is much reduced compared to the results in [2].

V. CONCLUSIONS

In this study, an optimal fuzzy controller according to the Sugeno model was proposed. The parameters of the controller were optimized with the the PSO algorithm in terms of fuzzy set and weighting rules. This optimal fuzzy controller is applied to the active damping system according to the quarter-vehicle model. The simulation results showed the efficiency of the optimal fuzzy controller.

Through the above findings, it can be seen that the optimal FLC-Sugeno controller responds well in highly nonlinear damping systems. When optimized with PSO, the FLC-Sugeno gives much better control response than the PID controller. The research results indicate that when performing overall optimization of both membership functions of fuzzy sets and fuzzy rule weights using PSO, the optimal FLC-Sugeno works very well. From here, the control design can be applied to more complex models such as the ½ model or the overall model of an entire vehicle.

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