Chassis Control based on Fuzzy Logic

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***Abstract*—Based on a Global Chassis Control system with three-layers architecture (decision, control, and physical layers) a Fuzzy Logic (*FL*) approach is exploited. The *FL* based decision layer identifies the current driving condition of the vehicle and decides the control strategy to take care of this driving condition. A *confusion matrix* validates the classification results. The control strategy is implemented through the subsystems (suspension, steering, and braking) at the *FL* based control layer. The strategy was evaluated under two different tests: slalom and double line change by comparing the performance with an UnControlled system. Early results show the proposed strategy has less roll, yaw movement and side slip angle than an UnControlled system during a double line change maneuver; also, for the slalom test the proposal improves the dynamic vehicle performance allowing the driver to maintain the vehicle under control.**

I. Introduction

The internal combustion engine has powered cars, trucks and other vehicles for over a century. Hybrid electric vehicles, plug-in hybrid electric vehicles, pure electric vehicles, and other technologies can all be properly classified as *Next-Generation Vehicles* (*NGV*). Certainly, reduce oil consumption is one of the main features of *NGV*; but, reducing oil consumption reduces pollution too, [1]. The technology areas supporting *NVG* are *(a) Electric vehicle system*: electric, hybrid and fuel cell vehicles; *(b) Advanced vehicle motion performance*: active control, drive assistance, preventive safety; *(c) Smart structure*: light-weight/highly, efficient structure, collision safe; and, *(d) Intelligence*: car electronics/control/information/communication. The cost of electronics and software content in automobiles was less than 20 % of the total cost a decade ago, today is $\sim$ 35 %. Electronics systems continue to contribute more than 90 % of innovations and new features, [2].

Intelligence for vehicles is the technology that should be related to almost all automotive technologies; however, especially in the active control area aiming at prevention and safety. Significant advances have been made in recent years in chassis control systems. Various control systems have been developed with the aim of enhancing vehicle dynamic performance; such as, *Vehicle Control Systems* (*VCS*) include *Anti-lock Brake Systems* (*ABS*), *Electronic Stability Control* (*ESC*), *Electric Power Steering* (*EPS*), Active Suspension, and variable torque distribution four-Wheel Drive (*4WD*). Coordinated and integrated controls play an indispensable role among these systems, [3]. An *Integrated Vehicle Dynamics Control* considers the coordinated integration of those different *VCS* to pursuit a common goal. Many approaches for *Global Chassis Control* (*GChC*) have already been developed, [4].

It is seen that a main issue is the number of possibilities to affect the motion of the vehicle, based on the actuators configuration. In [4], [5] a *GChC* system is implemented with a supervisory decentralized control architecture (for flexibility and modularity). First, the system classifies the current driving condition using a clustering-based classifier [6]. Second, each subsystem is coordinated to ensure the best possible global performance. The subsystems are: *Semi Active Suspension* (*SAS*), *Active Front Steering* (*AFS*) and *4-Wheel Independent Braking* (*4WIB*). These subsystems work simultaneously looking for three main goals: stability, handling and comfort. Based on this *GChC* system a new *Fuzzy Logic* (*FL*) based classifier is proposed.

This paper is organized as follows. Section II briefly introduces the *GChC* system. Section III describes in detail the *FL* based classifier. Section IV presents *FL* based controllers. A study case validates the results in section V. Finally, section VI concludes the research paper.

II. Global Chassis Control System

The architecture of the *Global Chassis Control* (*GChC*) system, Fig. 1, considers three main layers: Decision, Control and Physical [4].

A. Decision layer

This *GChC* system coordinates the mode of operation of the control subsystems based on the actual driving condition of the vehicle. For this purpose, two main functions are carried on: classify the driving condition and coordinate the control strategy for the current driving condition.

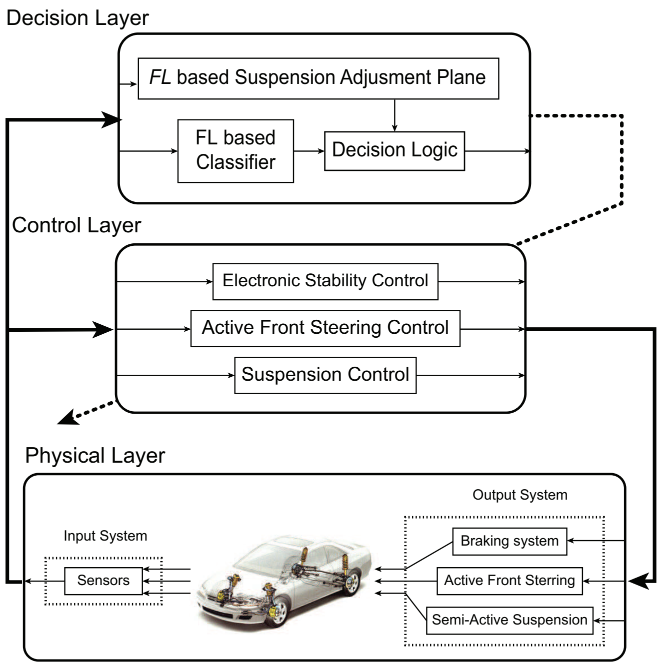

Fig. 1. *GChC* system

The classification procedure is carried out using a *Fuzzy Inference System* (*FIS*), it classifies the current situation based on measurements only. To assist the classifier a *Fuzzy logic Suspension Adjustment Plane* (*FSAP*) is included. It adjusts the suspension system based on the vertical load transfer of the vehicle.

B. Control layer

In this layer there are *FL* based controllers for the actuation subsystems located in the physical layer. This layer has two main functions: control allocation and local controllers. The control allocation step computes the desired manipulation using the adaptable set point defined in the decision layer, such allocation is calculated using *FL* algorithms. The local controllers execute the needed controller output.

C. Physical layer

The physical layer is integrated by the sensors and actuators of the *SA* suspension system, *AFS* system and the 4-Wheel Independent Braking system.

III. Decision Layer

The main task of the *Decision Layer* (*DL*) is to adapt the control actions of the vehicle subsystems using the vehicle driving condition as the coordination parameter. Seven Driving Conditions (D_C) were considered: 1) Riding, 2) Road irregularity, 3) Acceleration/Braking, 4) Hard braking, 5) Cornering, 6) Rapid Steering, and 7) Loss of control.

For each D_C there is a set of actuation gains (a_u) that coordinates the operation of the actuation subsystems: $a_{u_{susp}}$ for the suspension system, $a_{u_{steer}}$ for the steering system, and

TABLE I
D_C vectors for different driving conditions.

Driving situation	D_C			
	s_i	$a_{u_{susp}}$	$a_{u_{steer}}$	$a_{u_{braking}}$
Ride	1	[0,0,0,0]	0	0
Road irregularity	2	*FSAP*	0	0
Acceleration/Braking	3	*FSAP*	0	0
Hard Braking	4	*FSAP*	0	0
Cornering	5	*FSAP*	1	0
Rapid Steering	6	*FSAP*	1	1
Loss of control	7	[1,1,1,1]	1	1

$a_{u_{braking}}$ for the braking. The coordination for each D_C is described in Table I.

The system needs the current driving condition of the vehicle. A *FIS* is proposed to classify the driving condition based on 4 operating variables: pitch angle ($\phi \in [-2, 2]$), absolute value of yaw rate ($|\dot{\psi}| \in [0, 100]$), and the absolute values of the steering wheel angle and steering wheel angle rate ($|\delta| \in [0, 20]$, and $|\dot{\delta}| \in [0, 100]$).

As inputs of the system consider three of the operating variables were fuzzified using two trapezoidal *Membership Functions* (*MF*s): $\{|\dot{\psi}|, |\delta|, |\dot{\delta}|\} = \{Z, P\}$ and for the last operating variable 4 triangular and 2 trapezoidal *MF*s where used as: $\phi = \{NB, NS, Z, PS, PM, PB\}$.

As output, seven *MF* were used. Figure 2 shows the used *MF* as I/O of the classifier. Table II describes the meanings of the linguistic terms.

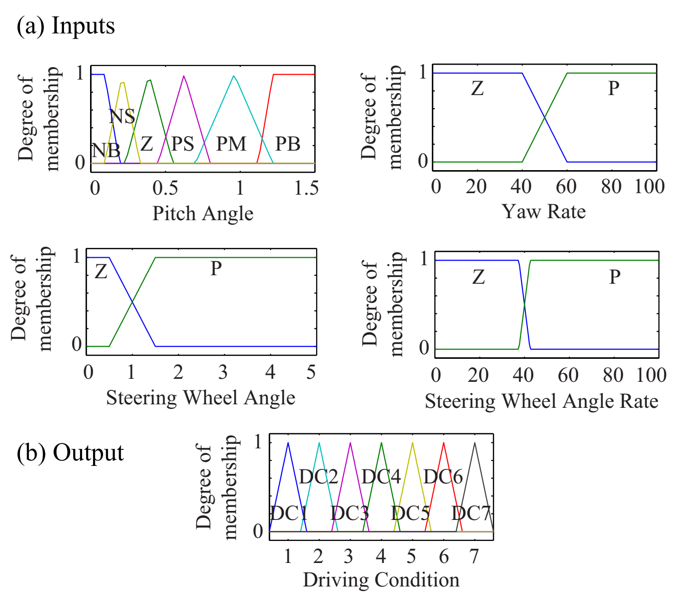

Fig. 2. Classifier Membership Functions.

Table III shows the proposed linguistic rules for the classifier. The X, element is used as a wild card for simplicity and with the intention of save space to avoid repeating rules.

The performance of the proposed classifier was qualitatively evaluated through a series of tests. Figure 3 shows the results of the evaluation. The first test, Fig. 3a, is a rough road with a bump that appears around 1 s, the classifier identifies the bump

TABLE II
LINGUISTIC TERMS.

N	Negative	PS	Positive Small
NB	Negative Big	PMS	Positive Medium Small
NMH	Negative Medium High	PM	Positive Medium
NM	Negative Medium	PMH	Positive Medium High
NMS	Negative Medium Small	PB	Positive Big
NS	Negative Small	P	Positive
Z	Zero		

TABLE III
FUZZY INFERENCE RULES FOR THE CLASSIFIER

Inputs				**Output**
ϕ	$\dot{\psi}$	δ	$\dot{\delta}$	
Z	Z	Z	Z	DC1
NS	Z	Z	Z	DC2
PS	Z	Z	Z	DC2
NB	Z	Z	Z	DC3
PM	Z	Z	Z	DC3
PB	Z	Z	Z	DC4
X	Z	P	Z	DC5
X	Z	X	P	DC6
X	P	X	X	DC7

but the generated oscillations by the transient response of the vehicle causes some misclassification. For the second test Fig. 3b shows a braking distance test, representing a hard braking action at the beginning followed by a normal braking until stop, the classifier also performs well, but the misclassification were caused by the oscillatory movement. For the third test Fig. 3c presents a rapid steering maneuver; whereas the fourth test Fig. 3d consists in a sustained turning action. Finally, for the fifth test, Fig. 3e shows a raking maneuver in a slippery road, which causes the vehicle to spin without control.

To visualize of the performance and summarize the evaluation of the *FL* based classifier, the *Confusion Matrix* (*Error Matrix*) was computed in Fig. 4, [7]. It can be seen that, the classifier has a good performance. For most of the driving conditions present more than 80 % of classification probability, with less than 15 % of false alarms probability. These results give an 85 % of average performance for the classifier.

Finally, a *Fuzzy logic Suspension Adjustment Plane* (*FSAP*) is proposed into the *Decision Layer*. This plane is based in the load transfer of the vehicle caused by the vehicle vertical forward and lateral movements. It allocates the control actions of the *SA* dampers in the suspension system. Figure 5 shows the regions of the *FSAP* with the proposed output vector for $a_{u_{susp}}$ in each region. The vector is formed as: $a_{u_{susp}}$ =[Front Left (FL), Front Right (FR), Rear Left (RL), Rear Right (RR)].

The proposed *FIS* for the *FSAP* uses 2 inputs: roll angle ($\theta \in [-5, 5]$) and pitch angle ($\phi \in [-1, 3]$). The output is formed by 4 elements:($a_{u_{susp_{i,j}}} \in [0, 1]$), where $a_{u_{susp_{i,j}}}$ is the weighting parameter for each corner of the vehicle. For the two inputs, 3 triangular *Membership Functions* (*MF*) where used for each variables: $\{\theta, \phi\} = \{N, Z, P\}$. For the output variables 2 triangular *MF*s were used: $a_{u_{susp_{i,j}}} = \{Z, P\}$. Table IV shows the linguistic rules that govern the *FSAP*.

This *FL* system is intended to adjust the control objective

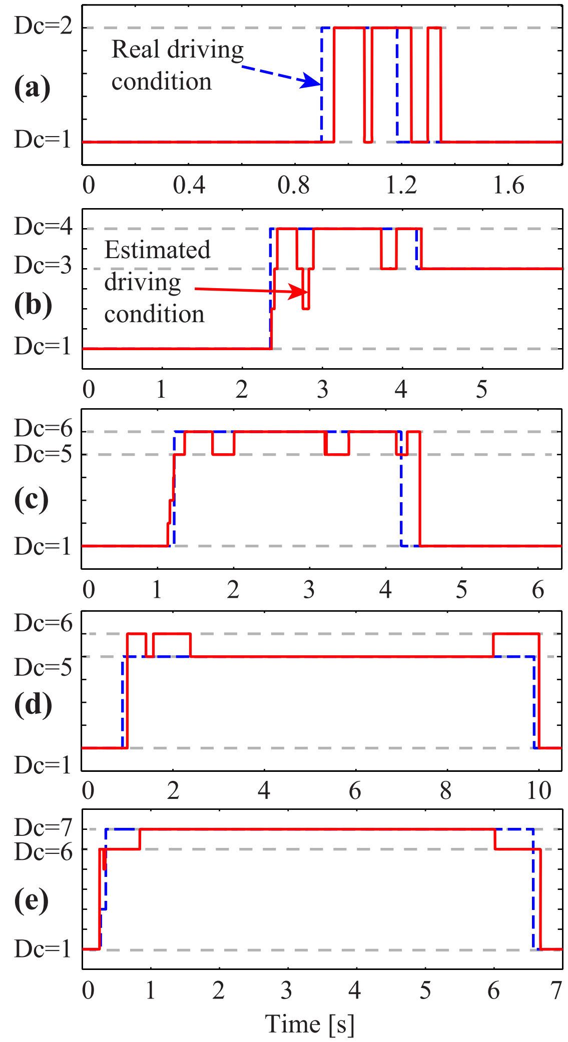

Fig. 3. Evaluation of the *FL* based classifier. Comparison of real (dashed blue) and estimated (solid red) driving condition.

TABLE IV
FUZZY INFERENCE RULES FOR THE *FSAP*.

			Roll angle (θ)					
			N		Z		P	
		$a_{u_{susp}}$	L	R	L	R	L	R
Pitch angle (ϕ)	P	F	P	P	P	P	P	P
		R	P	Z	Z	Z	Z	P
	Z	F	P	Z	Z	Z	Z	P
		R	P	Z	Z	Z	Z	P
	N	F	P	Z	Z	Z	Z	P
		R	P	Z	P	P	Z	P

of each damper of the *SAS*, i.e. if the vehicle has a sufficient roll movement to the right, then the two dampers of that side must be oriented to road holding mode to compensate the increased vertical force generated by the roll movement. The implementation of a *FIS* guarantees a smooth and continuous transition between the heuristic controllers of the *SAS* system avoiding abrupt switching behavior.

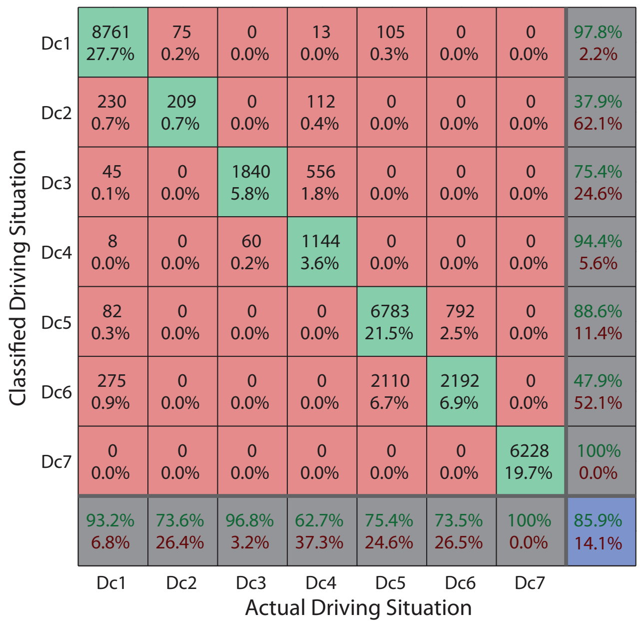

Fig. 4. *Confusion matrix* for the classifier.

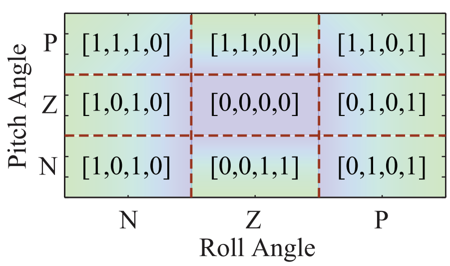

Fig. 5. *FSAP* diagram showing the proposed output vector for $a_{u_{susp}}$.

IV. Control Layer

This layer comprehends the control actions (allocation, manipulation) to be implemented through the physical layer.

A. Control Allocation

Based on the driving situation, the desired control action for each subsystem is defined. The control mode acts as a gain:

$$u_c^* = a_u \cdot u_c \tag{1}$$

where u_c^* is the controller output which depends directly from the gain a_u, where $a_u = 1$ means that the *GChC* demands the actuation of the subsystem, and vice versa. Thus, u_c is the local controller output of the subsystem, but before the full dynamics integration. The allocation controllers for each subsystems are defined as follows.

1) Semi-Active Suspension System: The *SA* dampers must always receive a manipulation, the decision is whether to select a manipulation oriented to comfort ($U|_{comf}$) or to road-holding ($U|_{rh}$) for each corner of the vehicle:

$$U_{susp}^* = (1 - a_{u_{susp}}) \cdot U|_{comf} + a_{u_{susp}} \cdot U|_{rh} \tag{2}$$

where $U_{susp}^* = u_{susp_{F,L}}, u_{susp_{F,R}}, u_{susp_{R,L}}, u_{susp_{R,R}}$. Note that, according to the driving situation, the *GChC* can orient the suspension to comfort or to road-holding using the weighting parameter $a_{u_{susp}}$.

At each corner, the Semi-Active Suspension controller output can be oriented to comfort ($u_{i,j}|_{comf}$) or to road-holding ($u_{i,j}|_{rh}$) inspired in the classical *Sky-Hook* and *Ground-Hook* control strategies, such that:

$$u_{i,j}|_{rh} = \begin{cases} c_{min} & \text{if} \quad -\dot{z}_{us} \cdot \dot{z}_{def} \leq 0 \\ c_{max} & \text{if} \quad -\dot{z}_{us} \cdot \dot{z}_{def} > 0 \end{cases} \tag{3}$$

$$u_{i,j}|_{comf} = \begin{cases} c_{min} & \text{if} \quad \dot{z}_{s} \cdot \dot{z}_{def} \leq 0 \\ c_{max} & \text{if} \quad \dot{z}_{s} \cdot \dot{z}_{def} > 0 \end{cases} \tag{4}$$

where $c_{min} = 0$ and $c_{max} = 1$ represent the softest and hardest damping coefficient, respectively.

2) Braking System: The braking action is determined based on a *FL* based controller, [8]. It uses two inputs: the side slip angle error ($e(\beta) = \beta - \beta_d$) and the yaw rate error ($e(\dot{\psi}) = \dot{\psi} - \dot{\psi}_d$) and one output: the corrective yaw moment (M_z). The control goal is to reduce the errors to zero; for this purpose the reference signals are defined as $\beta_d = 0$, since the goal is to have β as close to zero as possible and $\dot{\psi}_d = \frac{V_x}{l}\delta_{driver}$ where V_x is the longitudinal velocity of the vehicle, l is the wheel base and δ_{driver} is the drivers steering angle command. Table V shows the rules for the proposed *FL* controller. This fuzzy controller uses a *Mandani Fuzzy Inference System* (*FIS*).

TABLE V
Fuzzy inference rules for the braking system

$e(\beta)$	$e(\dot{\psi})$ NB	NS	Z	PS	PB
NB	PB	PB	NS	NB	NB
NS	PB	PM	NS	NM	NB
Z	PM	PS	Z	NS	NM
PS	PB	PM	PS	NM	NB
PB	PB	PS	PS	NS	NB

To allocate the desired output for the braking local controllers, M_z is transformed in terms of *ESCs* as

$$\begin{aligned} M_z > 0 \quad & \rightarrow \text{Brake rear left wheel}: \\ & T_{ESC_r} = 0, T_{ESC_l} = T_G \cdot M_z \\ M_z = 0 \quad & \rightarrow \text{No added braking} \\ & T_{ESC_r} = 0, T_{ESC_l} = 0 \\ M_z < 0 \quad & \rightarrow \text{Brake rear right wheel} \\ & T_{ESC_r} = -T_G \cdot M_z, T_{ESC_l} = 0 \end{aligned} \tag{5}$$

where T_G is a parameter that relates the corrective yaw moment (M_z) and the brake pressure. The coordinated allocation affects the action of the *FL* based controller, by using $a_{u_{braking}}$ as a gain:

$$T_{ESC}^* = a_{u_{braking}} \cdot T_{ESC} \tag{6}$$

3) Active Front Steering System: The allocation introduces the *AFS* control action:

$$\delta^* = \delta_{driver} + a_{u_{steer}} \cdot \delta_{AFS} \tag{7}$$

where δ^* is the desired steering wheel angle, δ_{driver} is the driver's command, and δ_{AFS} is the compensation angle

calculated by the *AFS* system. The steering action is computed using a *FL* based controller, [9] with three input variables: side slip angle ($\beta \in [-10, 10]$), the yaw rate error ($e(\dot{\psi}) = \dot{\psi} - \dot{\psi}_d \in [-10, 10]$) and the steering angle input ($\delta_{driver} \in [-10, 10]$).

The output is the steering wheel correction angle ($\delta_{AFS} \in [-5, 5]$). The *FL* based controller is oriented to create a steering wheel angle correction that minimizes the yaw rate error. Table VI shows the rules for the proposed *FL* controller, whose linguistic definitions are given in Table II.

TABLE VI
FUZZY INFERENCE RULES FOR THE STEERING SYSTEM

β	δ_{driver}	$e(\dot{\psi})$ NB	NS	Z	PS	PB
Low	NB	NS	NS	Z	PB	PB
	NS	NMS	NMS	Z	PMH	PMH
	Z	NM	NM	Z	PM	PM
	PS	NMH	NMH	Z	PMS	PMS
	PB	NH	NH	Z	PS	PS
High	NB	NH	NH	Z	PS	PS
	NS	NMH	NMH	Z	PMS	PMS
	Z	NM	NM	NS	PMS	PMS
	PS	NMS	NMS	NS	NS	NS
	PB	NS	NS	NS	NS	NS

B. Local Controllers

These controllers receive the desired set-point u_c^* from the control allocation sublayer, the subsystem controllers are:

- *SA Suspension*: because the control command is binary, the force control system is:

$$\begin{bmatrix} c_{min} \\ c_{max} \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \mapsto \upsilon = \begin{bmatrix} 10\% \\ 90\% \end{bmatrix} \quad (8)$$

  where υ is the manipulation delivered to the *SA* damper, (i.e. electric current, voltage, duty cycle, etc.)
- *Steering*: the command is in terms of tire angles, to transform it to a single gain controller:

$$\delta^*_{steering\,wheel} = \frac{28.74}{1.18}\delta^*_{tires} \quad (9)$$

- *Braking*: the local controller is an *ABS*, it modifies the desired command as:

$$T_b^* = G_{ABS} \cdot max(T_{driver}, T^*_{ESC}) \quad (10)$$

  where T_{driver} is the driver braking command, T_{ESC} is the braking command from the allocation system and G_{ABS} is the gain of the *ABS* that releases the tire when it is locked. This control law considers the maximum between the command coming from the allocation system and the command from the driver.

V. CASE STUDY

For the case study the proposed *GChC* system was evaluated using the standard *CarSim*™, along with *MatLab*™ in a *Software-in-the-Loop* (*SiL*) configuration; the vehicle model and tests were hosted in *CarSim*, while the *GChC* system was developed in *Matlab*.

A. Vehicle Model

The selected vehicle is a D-segment sedan. According to the *European Commission*, this segment includes vehicles in the medium to high range (large cars). Table VII shows some general parameters of the model.

TABLE VII
CarSim GENERIC D-SEGMENT MODEL PARAMETERS [10]

Parameter	Value	Units	Parameter	Value	Units
m_s	1370	kg	I_{xx}	671.3	km-m^2
$m_{us_{i,j}}$	40	kg	I_{yy}	1972.8	km-m^2
L	2.78	m	I_{zz}	2315.3	km-m^2
b	1.11	m	ks_f	153	N/mm
h	0.52	m	ks_r	82	N/mm
t_f, t_r	1.55	m	k_t	268	N/mm

B. Evaluation Tests

Two tests were implemented to evaluate the proposed *GChC* system, Fig. 6 illustrates these tests:

- *Double Line Change (DLC) maneuver*. It consists in a change of driving line to simulate an obstacle avoidance maneuver or an overtaking action at high speed (120 km/h). A rapid steering maneuver is taken by the driver to change from the original line, and then another rapid steering action to turn back to the original line.
- *Slalom test*. This test evaluates how fast the vehicle can drive through the obstacles in a zigzag movement without touching them and not loosing control. It consists in a series of cones that the vehicle has to evade as fast as possible, this test forces the vehicle to its limits of adhesion and maneuverability.

C. Performance Indexes

The proposed *GChC* system is evaluated and compared with an *UnControlled* (*UC*) system, i.e. it is a vehicle which lacks of any control system and that it is equipped with standard actuators and a passive suspension system. To quantitatively evaluate the performance at each driving test, the *Root Mean Square* (*RMS*) value of the signals is used. To have a point of comparison, the *RMS* values of the *GChC* system will be normalized with respect to the *UC* system:

$$\%\,\text{of Imp} = \frac{RMS(X_{i_{UC}}) - RMS(X_{i_{GChC}})}{RMS(X_{i_{UC}})} \quad (11)$$

where *% of Imp* is the percentage of improvement, $X_{i_{UC}}$ and $X_{i_{GChC}}$ are the variables of interest i of the *UC* and the *GChC* systems respectively. The objective of this index is to show how much the control system improves the behavior of the vehicle in terms of the variables of interest, giving the same driver model, a topic which is not addressed in this work.

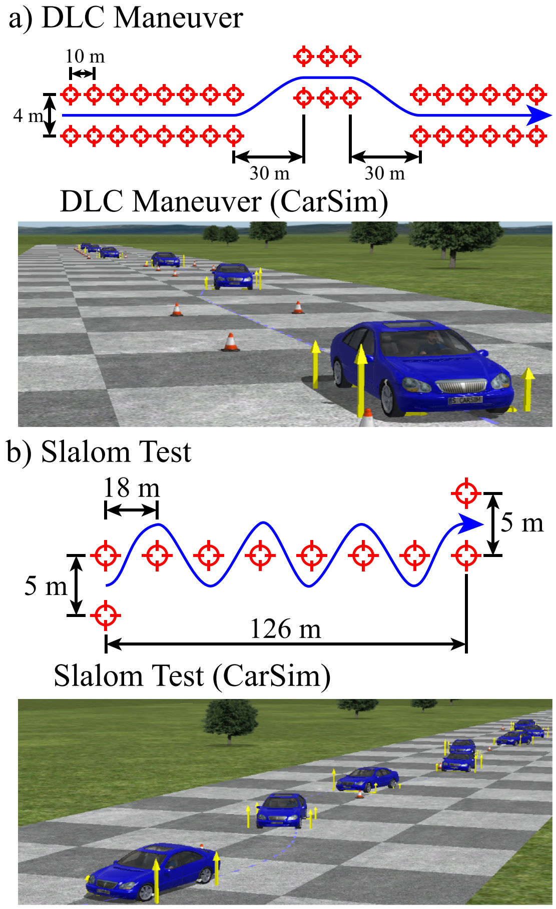

Fig. 6. Implemented tests in *CarSim*™.

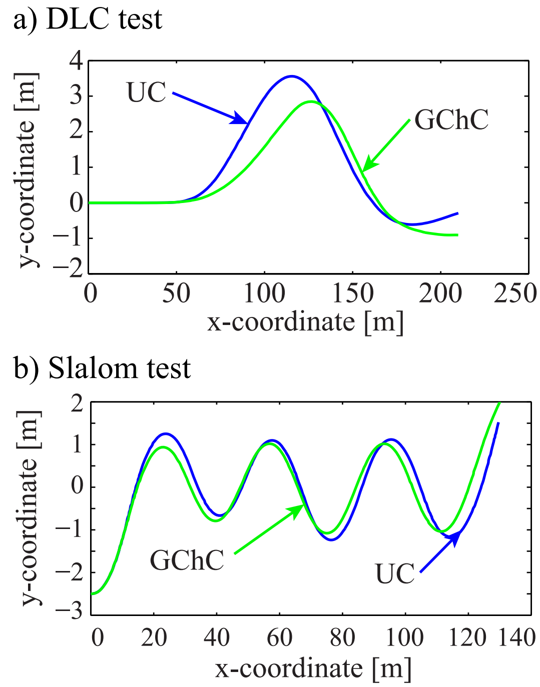

Fig. 7. Vehicle trajectory for both *DLC* and *Slalom* tests.

D. Results

The results are presented in terms of the variables of importance for each test. Here the important variables to analyze are: 1) vehicle trajectory, 2) θ 3) $\dot{\psi}$, and 4) β. Figure 7 shows the trajectory of both cases: *UC* (blue) and *GChC* (green). Figures 8 and 9 show the behavior of the other variables of importance for the *DLC* maneuverer and slalom test, respectively.

For a quantitative analysis Table VIII present the *RMS* value of the important variables in terms of its % of improvement, calculated using (11).

TABLE VIII
PERFORMANCE INDICES FOR BOTH TESTS.

Test	*DLC*			Slalom		
Variable	θ	$\dot{\psi}$	β	θ	$\dot{\psi}$	β
% of Imp.	10 %	12.5 %	14.4 %	11.1 %	20.5 %	76 %

E. Discussion

1) DLC test: From Fig. 7a, it can be observed that the *GChC* system has smaller y-coordinate deviation, also its end is straight. For the *UC* system the y-coordinate deviation is bigger and at the end its path is diverging.

Figure 8a illustrates the *GChC* has 10 % less roll movement than the *UC* system, Table VIII, and also, the roll movement has a rapid stabilization. In Fig. 8b the *GChC* system has 12.5 % less yaw motion than the *UC*. In terms of the side slip angle, Fig. 8c shows the *GChC* system maintains the β angle closest to zero as much as possible reducing it about 14.4 % compared to the *UC* system.

2) Slalom test: In Fig. 7b the *UC* system presents a slightly wider path than the *GChC* system, this causes the vehicle to be less controllable. This can be seen at the end the trajectory, where the *UC* case seems to finish the track perpendicular to the horizontal axis, contrary to the *GChC* system that recovers the horizontal path.

Even when in the trajectory evaluation the advantage of the *GChC* system was not clear enough, analyzing the variables of interest, it becomes evident. First the *GChC* reduces the roll movements, Fig. 9a, in 11.1 % by maintaining the vehicle in an horizontal position, Table VIII. In terms of the yaw rate, Fig. 9b, the proposed control system has an improvement of 20.5 % when compared with the *UC* system avoiding the vehicle to skid. Finally, the side slip angle, Fig. 9c, was improved in 76 % maintaining it as close to zero as possible, whereas in the *UC* system, at the end of the test, the vehicle losses control and start to spin.

VI. CONCLUSIONS

A *Fuzzy Logic* (*FL*) based *Global Chassis Control* system was proposed. The system considers a three layer architecture: Decision, Control and Physical. The *FL* framework was exploited in the Decision Layer to classify the current driving condition. Also, it was implemented in the Control

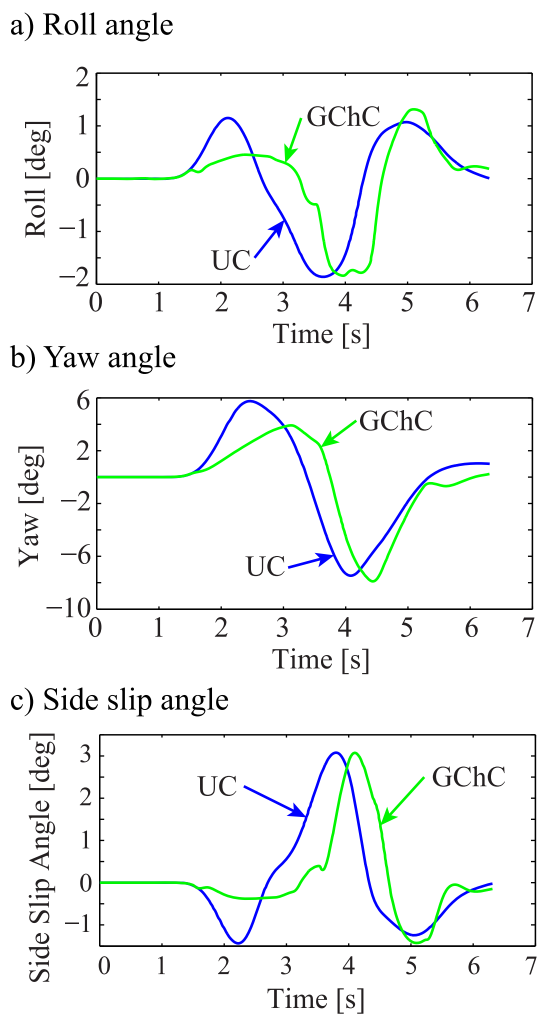

Fig. 8. *DLC* test results

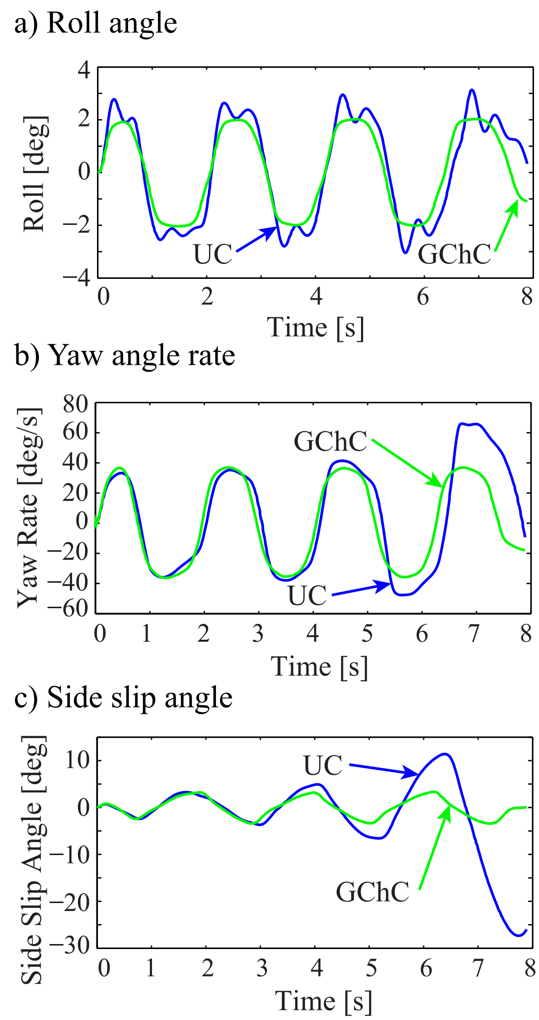

Fig. 9. *Slalom* test results

Layer for the suspension, steering and braking control systems. In the Decision layer the *FL* systems gave the possibility to use the a priory knowledge of the vehicle behavior to classify the current driving situation without a model of the system, having an average performance of 85 % based on a *Confussion Matrix* analysis. In terms of the performance of the control system, two tests: double line change and slalom, were used for evaluation. The results demonstrated that the proposal improves the vertical dynamics in at least 10 %, and the longitudinal ones, about 12.5 % as minimum,proving the ability of the system to act in the three dynamic planes.

Acknowledgment

Authors thank *Tecnológico de Monterrey* and *CONACyT* for their partial support through the *Automotive Consortium* research chair and PCP 06/13 bilateral (México-France) project.

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