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Regeneration Energy for Nonlinear Active Suspension System Using Electromagnetic Actuator

Ammar A. Aldair*, Eman Badee Alsaedee
Electrical Engineering Department, University of Basrah, Basrah, Iraq

Correspondence
*Ammar A. Aldair
Electrical Engineering Department,
University of Basrah, Basrah, Iraq
Email: ammar.abdulhameed@uobasrah.edu.iq

Abstract
The main purpose of using the suspension system in vehicles is to prevent the road disturbance from being transmitted to the passengers. Therefore, a precise controller should be designed to improve the performances of suspension system. This paper presents a modeling and control of the nonlinear full vehicle active suspension system with passenger seat utilizing Fuzzy Model Reference Learning Control (FMRLC) technique. The components of the suspension system are: damper, spring and actuator, all of those components have nonlinear behavior, so that, nonlinear forces that are generated by those components should be taken into account when designed the control system. The designed controller consumes high power so that when the control system is used, the vehicle will consume high amount of fuel. It notes that, when vehicle is driven on a rough road; there will be a shock between the sprung mass and the unsprung mass. This mechanical power dissipates and converts into heat power by a damper. In this paper, the wasted power has reclaimed in a proper way by using electromagnetic actuator. The electromagnetic actuator converts the mechanical power into electrical power which can be used to drive the control system. Therefore, overall power consumption demand for the vehicle can be reduced. When the electromagnetic actuator is used three main advantages can be obtained: firstly, fuel consumption by the vehicle is decreased, secondly, the harmful emission is decreases, therefore, our environment is protected, and thirdly, the performance of the suspension system is improved as shown in the obtained results.

KEYWORDS: Electromagnetic actuator, intelligent control, nonlinear active suspensions.

I. INTRODUCTION

Recently, the researchers have carried out research to reduce the fuel consumption required for the vehicle and decrease the harmful emission to protect the environment. Therefore, a suitable energy regenerative device should be used to recover the wasted energy dissipated by the dampers into useful energy. There are many types of energy regenerative devices are designed such as: hydraulic storage suspension [1], battery coil induction suspension [2], rack and pinion suspension [3], ball screw suspension [4] and linear motion suspension [5].

In the recent years, worldwide attempts concentrated on vehicle vibration control and energy regeneration, theoretical and experimental progresses [6-9] have been achieved. The repaid developments that occurred in permanent magnet materials, power electronics devices, and microelectronic components enable the implementation of electromagnetic actuators to improve the performances of suspension systems [10]. The idea of an energy recovering of active suspension systems in hybrid vehicles is investigated in reference [11]. An energy storage system which consists of super capacitors and batteries is introduced and implemented. In Reference [12], the authors proposed a new hydraulic electromagnetic energy regenerative suspension design. In order to prove the evaluation of the proposed design, a comparisons based on the structural and working principles are performed with the other energy regenerative suspension designs. A modificated regenerative shock absorber is developed and tested to convert the vibration energy to electrical energy in an efficient way [13].

The nonlinear active suspensions are complex mechanical systems with many uncertainty parameters and various types of damping characteristic. The main function of the suspension system is to isolate passengers and the chassis from the roughness of the road. Therefore, to provide a more comfortable ride for the passengers and to increasing the road handling for the vehicles, an active suspension system should be used [14, 15].

Many researchers proposed different strategies to discuss the problem of vehicle suspension control in order to improve performance of vehicles such as: ride comfort and driving safety. The developing on suspension control system is start from sim-active suspension system to intelligent suspension system. The intelligent suspension system consists of precise control system, sensors and actuators are added in parallel with passive suspension components. By this development of suspension system, the response of the vehicle is significantly improved and carried out, and the suspension systems are called controllable suspension system [16, 17].

To convert the passive suspension to active suspension system, a controlled actuator (such as: hydraulic actuator, magneto-rheological actuator or pneumatic actuator) should be connected in parallel with the passive elements. In this work, the hydraulic actuator is used as controlled actuator. The main function of the connected actuators is generation additional forces to the suspension system, those forces will eliminate the vibrations that come from rough roads. An intelligent control law utilize data from sensors that are attached to vehicle is used these to generate the actuator forces [18].

Many intelligent controllers are proposed and tested to improve comfortable ride for the passengers and to increase the road handling for the vehicles. For example, adaptive controller, LQR controller, LQG controller, H_∞ controller are utilized and developed for active suspensions model to obtain more comfortable riding for passengers and guarantee road handling for the vehicle [14,15].

One of the most important control systems is the fuzzy logic control that has been developed rapidly in the last years as the effective alternatives to some conventional control. It has shown success in many control strategies and engineering applications in particular when the ability to describe the system model mathematically becomes more difficult or even impossible due to highly nonlinear, time variant and ill-defined processes. Mathematical model of a system is required for controlling the conventional controller. While, the fuzzy logic based control theory is a rule based system hence it does not require a mathematical model. Therefore, fuzzy logic controller has an advantage over classical controllers [19, 21]. On the other hand, the fuzzy control systems have significant drawbacks especially in their designing and selecting the parameters. The designing of fuzzy controllers are unlike the designing of traditional controllers because they have several effective parameters that should be adjustable and tuned. While, there is no systematic process or general rules to tune these parameters, so the designing task is not easy and relying on the quality of the human expert. In other word, it needs specialist knowledge and consumes much time to adjust the control parameters. Also, it is often hard to justify the choices for many parameters in the fuzzy controller (e.g., the membership functions, rules, and scaling gains) [22, 24].

Moreover, the dynamics of most of plants is changing with time, for that reason the classical controllers will be unreliable and thus the system performance is affected seriously. In these cases, using of an adaptive controller is needed. To overcome the drawbacks of traditional fuzzy control system, some researchers over the last two decades, proposed adaptive algorithms to design the fuzzy system with optimal parameters. A significant class of adaptive controllers based on fuzzy logic approach is represented by self-organizing, self-structuring or self- learning controllers [25, 26].

In 1979, the first self-organizing fuzzy controller was developed by Mamdani and Procyk, where the work of Mamdani and his colleagues on fuzzy logic control was incited by Zadeh's work. Then the work of Procyk and Mamdani on the linguistic self-organizing controller has been further elaborated by many authors, especially by Yamazaki in 1982 and Shao in 1988. The proposed controllers in those works are designed with difficulty for tracking reference signals, therefore, those controllers did not become successfully to used. This algorithm was later modified and extended by Layne and Passino (1992) and Layne and Passino (1993) to what it is called Fuzzy Model Reference Learning Control (FMRLC). This method developed by synthesizing several basic ideas from fuzzy set and control theory, conventional adaptive control, and self-organizing control. The main idea of this algorithm is based on model reference adaptive control (MRAC) [Astrom and Wittenmark (2008)]. In 2006; Kovai and Bogdan have described other self-learning or adaptive fuzzy control methods [27, 28].

In this paper, the mathematical model for full vehicle nonlinear active suspension systems with 8 degrees of freedom included a passenger seat with hydraulic actuators has been derived to take into account all the motions of the vehicle and the nonlinearity behaviors of active suspension system and hydraulic actuators. To eliminating the drawbacks of fuzzy controller and to improve the performances of the active suspension system, a self-learning control algorithm is proposed. This algorithm uses a reference model structure to provide closed-loop performance feedback controller and to tune the parameters of fuzzy controllers. A reference model with the desired performance demonstrates of how the designer would like the controlled system to behave. Therefore, this proposed algorithm is referred to as a Fuzzy Model Reference Learning Controller (FMRLC). The performance of vehicle with FMRLC is compared with passive system by implement computer simulations through the MATLAB and SIMULINK toolbox. The consumption energy by each suspension has been calculated.

II. Mathematical Model For Full Vehicle Nonlinear Active Suspension System With Passenger Seat

A full vehicle model with 8DOF is introduced for investigating the problem of balancing road handling and riding comfort. In this work, the model of passenger seat is added with the vehicle model to estimate the responses of the passenger due to a roughness road as shown in Figure (1). In order to simplify the designing, the control for suspension models, many researchers dealt with the suspension system as linear model by omitting the nonlinearities behaviors of suspension systems. But with this assumption, the results become inaccurate. Therefore, the effects of nonlinearities behavior of suspension systems should be taken into account to make the obtained result more realistic. So that, in this work, the effects of the nonlinearities behaviors, which are came from damper, spring and actuator models, have been highlighted.

Figure 1 shows the structure of full vehicle nonlinear active suspension system with a passenger seat model that is used in this study. This structure consists of passenger seat, sprung mass(M_s), which is referred to the part of the vehicle that is supported on suspension; and unsprung mass(M_{us}) which is referred the total mass of the components under the suspension system. The tires are modelled as linear springs and linear dampers connected in parallel as shown in Fig. 1, while the suspension systems and passenger seat have the nonlinear hydraulic actuators which are connected in parallel with nonlinear springs and nonlinear dampers. The spring and damper in model of each tire has stiffness coefficient and damping coefficient labeled as k_{ti}, c_{ti} respectively, while the spring and damper in model of each suspension system has stiffness coefficient and damping coefficient labeled as k_{si}, c_{si}.

In order to design the controller system for controlling the motions of vehicle body, the vehicle model sprung mass is considered to have 3DOF. The types of vehicle motions can be classified into three different motions: yaw motion, roll motion and pitch motion. On the other hand, passenger seat and four unsprung mass are considered to have 1DOF for each of them. To obtain the differential equations of the full vehicle nonlinear active suspension system with passenger seat, the Newton's third law of motion can be used explain below.

The heave motion of sprung mass can be obtained as

$$M_s\ddot{z}_c = -\sum_{i=1}^{5} F_{ksi} - \sum_{i=1}^{5} F_{csi} + \sum_{i=1}^{5} F_i \tag{1}$$

Where:

F_{ksi} are the nonlinear forces of i^{th} spring

F_{csi} are the nonlinear forces of i^{th} damper

F_i is the applied nonlinear force between the sprung mass and unsprung masses which is generated from i^{th}hydraulic actuator. Those nonlinear forces can be written as

$$F_{ksi} = K_{si}(z_{si} - z_{usi}) + \zeta K_{si}(z_{si} - z_{usi})^3 \tag{2}$$

$$F_{csi} = C_{si}(\dot{z_{si}} - \dot{z_{usi}}) + \zeta C_{si}(\dot{z_{si}} - \dot{z_{usi}})^2 sgn(\dot{z_{si}} - \dot{z_{usi}}) \tag{3}$$

$$F_i = F_{hi} - F_{fi} \tag{4}$$

Where:

z_{usi} are the vertical displacements of unsprung masses

ζ is the empirical operator

F_{hi} is the i^{th}nonlinear hydraulic real force

F_{fi} is the i^{th} nonlinear frictional force

The force F_{hi}that generated by the i^{th} hydraulic actuators can be written as

$$F_{hi} = A_p P_{Li} \tag{5}$$

Where P_{Li} the pressure across the i^{th}actuator's piston or the load pressure, can be written this pressure equation in term of spool valve displacement x_{vi} as bellow

$$\dot{P_{Li}} = -\beta P_{Li} - \sigma A_p \dot{x_{pi}} + \sigma C_d \omega x_{vi}\sqrt{\frac{1}{\rho}(P_{si} - sgn(x_{vi})P_{Li})} \tag{6}$$

Where x_{pi} is the difference between the vertical displacement of i^{th} corner of sprung mass $z_{si}$and the vertical displacement of corresponding i^{th} unsprung massz_{usi}, i.e. $x_{pi} = z_{si} - z_{usi}$.

The actuator friction represents the friction associated with mechanical surfaces rubbing together, bearing friction, viscous friction, and so on. Those frictional forces have significant magnitude its effect must be taken into account. The net forces provided by the actuators are the different between the hydraulic forces and the frictional forces. Frictional forces can be modeled as Signum function [17]. So that, the mathematical model of friction forces can be obtained as:

$$F_{fi} = \begin{cases} \mu\, sgn(\dot{x_{pi}}) & for\ |\dot{x_{pi}}| \geq 0.01 \\ \mu \sin\left(\frac{\pi \dot{x_{pi}}}{0.02}\right) & for\ |\dot{x_{pi}}| < 0.01 \end{cases} \tag{7}$$

Where µ is the empirical operator

Then the rolling motions of the sprung mass can be given as

$$J_x\ddot{\alpha} = ((F_{ks1} - F_{ks2} - F_{ks3} + F_{ks4})\frac{b}{2} + b_s F_{ks5} + ((F_{cs1} - F_{cs2} - F_{cs3} + F_{cs4})\frac{b}{2} + b_s F_{cs5}) + ((F_3 - F_1 + F_2 - F_4)\frac{b}{2} b_s F_5) + T_x \tag{8}$$

Where:

J_x is the roll moment of inertia about x-axis.

T_x is the cornering torque.

The pitching motion of sprung mass can be written as

$$J_y\ddot{\eta} = (F_{ks3} + F_{ks4})l_2 - (F_{ks1} + F_{ks2})l_1 + l_s F_{ks5} + (F_{cs3} + F_{cs4})l_2 - (F_{cs1} + F_{cs2})l_1 + l_s F_{cs5} + (F_1 + F_2)l_1 - (F_3 + F_4)l_2 - l_s F_5 + T_y \tag{9}$$

Where:

J_y is the pitch moment of inertia about y-axis.

T_y is the braking torque.

While the heave motion of unsprung masses can be governed by the following equation

$$M_{usi}\ddot{z}_{usi} = -k_{ti}(z_{usi} - u_{ri}) - c_{ti}(\dot{z}_{usi} - \dot{u}_{ri}) + F_{ksi} + F_{csi} - F_i \tag{10}$$

Where u_{ri} is the road input.

III Fuzzy Model Reference Learning Control (FMRLC)

The FMRLC is a novel learning control technique was first proposed by Mamdani in 1989. The FMRLC is based on combining two control technologies: the Fuzzy Logic Control (FLC) and the Model Reference Adaptive Control (MRAC) scheme that guarantees stability with satisfactory performance for non-linear systems. It goes one step beyond direct fuzzy control since it has the ability to modifying the performance of the closed loop system [29, 30].

The FMRLC presents the learning mechanisms that obtained by a fuzzy control system and characterize its current performance to adjust the fuzzy controller, therefore, some given performance objectives are met. The performance objectives are highlighted via the reference model shown in Figure (2). The learning mechanism is used to adjust the fuzzy controllers parameters so that the closed loop system (the map from $r(kT)$ to $y(kT)$) acts like a pre-specified reference model. For a much more detailed each

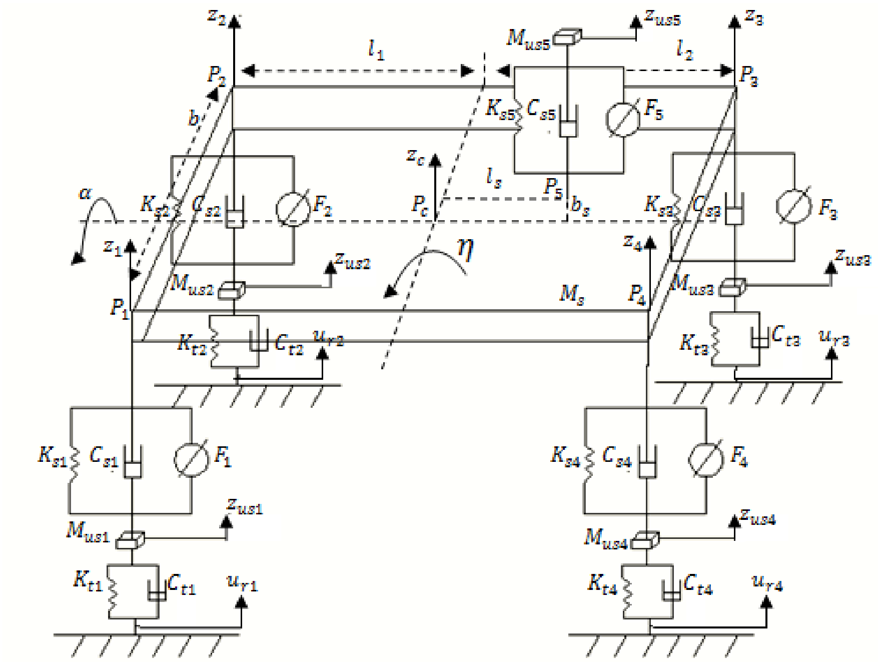

Fig 1: Full vehicle model with 8-DOF

component of the FMRLC will describe in the following subsection [31, 32].

A. *The fuzzy controller*

The major components of the direct fuzzy controller are the fuzzification, inference mechanism and defuzzification. As shown in Figure (2), the fuzzy controller is multi inputs single out put system where it has two inputs and one output. The inputs to the fuzzy controller are generated by finding the difference between the output of the plant $y(kT)$ and reference signal $r(kT)$. So the inputs to the fuzzy controller are represented by the error *e(kT)* and the change of error *c(kT)* as which are given below.

$$e(kT) = r(kT) - y(kT) \tag{11}$$

$$c(kT) = \frac{e(kT)-e(kT-1)}{T} \tag{12}$$

The control signal input into the plant (the output of the fuzzy controller) is$u(kT)$. The signals error, change in error and controller output are scaled using the scaling gainsg_e, g_c and g_u respectively.

The knowledge-base for the fuzzy system which is associated with the input of the plant is obtained from IF-THEN part of fuzzy rules as:

$$R_q{:}\, IF\ \tilde{e}\ is\ \tilde{E}_q^j\ and\ \tilde{c}\ is\ \tilde{C}_q^l\ Then\ \tilde{u}\ is\ \tilde{U}_q^r$$

where $\tilde{e}$ and $\tilde{c}$ denote the linguistic variables associated with controller inputs *e(kT)* and *c(kT)* respectively, $\tilde{u}$denote the linguistic variables associated with controller output $u(kT)$,R_q denote the q^{th} rule of the fuzzy controller and $\tilde{E}_q^j$, $\tilde{C}_q^l$ and $\tilde{U}_q^r$ denote the j^{th}, l^{th} and r^{th}linguistic values of the q^{th}rule associated with $\tilde{e}$, $\tilde{c}$ and $\tilde{u}$respectively[19].

In this work, the triangular shape membership functions have been used for both input and output linguistic values. The fuzzy controller's rule base can be initialized by either setting all centers of the output membership functions to zero or providing an initial guess as to how the controller should act. The Center Average (CA) defuzzification method has been applied to compute the output of the fuzzy controller.

B. *The reference model*

The main function of reference model is providing a ability for quantifying the desired behavior for the close feedback loop. It can take any type of dynamical system such as linear or non-linear, time-invariant or time-variant, discrete or continuous time etc. The reference model characterizes design criteria should be given, such as stability, rise time, overshot, settling time, etc.[20].

As shown in Fig. 2 *r(kT)* is the input to the reference model which is called the reference input. The desired behavior of the controlled plant is obtained if difference between reference model output ($y_m(kT)$) and plant output $y(kT)$ approaches to very small (nearly zero) at any time. If the desired performance is obtained ($y_e(kT)) \approx 0$) then the learning mechanism will not make any modifications to the fuzzy system. On the other hand, if $y_e(kT)$ is big, the desired performance is not met and the learning mechanism must modify the parameters of the fuzzy controller [32].

C. *The learning mechanism system*

As it is mentioned before, the main function of learning mechanism is to update the parameters of the knowledge base of the fuzzy controller in feed forward loop, so that the performance of the closed-loop system becomes like the performance of desired reference model behaves, or by other ward the value of $y_e(kT)$ will be very small value. These modifications are obtained based on collected data from the controlled plant, the reference model; and the fuzzy controller [9].

The as shown in Fig. 2, the learning mechanism has only two main parts. The first part is fuzzy inverse model, while

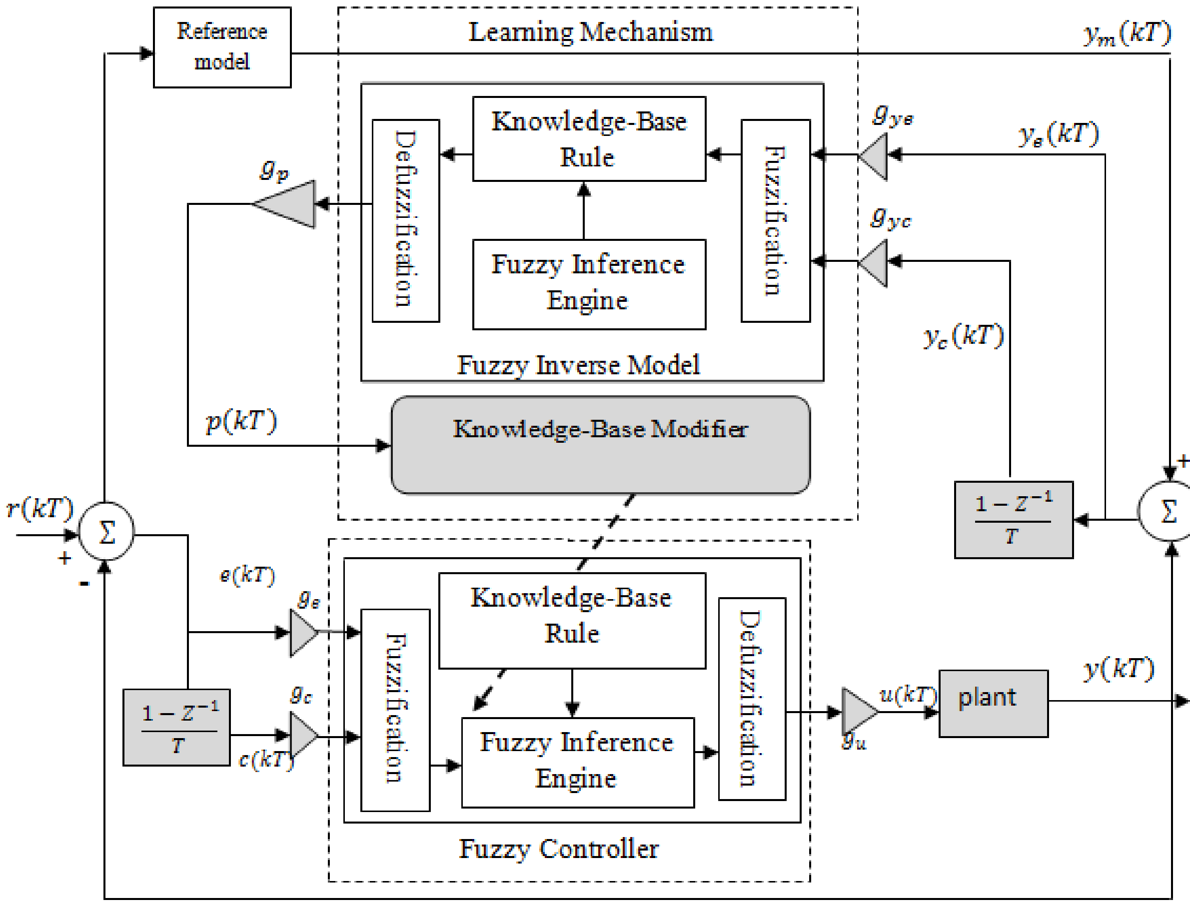

Fig 2: Architecture of the FMRLC

the second one is a knowledge base modifier. The function of fuzzy inverse model is generation the suitable control output *p (kT)* to force the error $y_e(kT)$ to be zero. While the main function of the knowledge base modifier is performance the function of modifying the fuzzy controller's rule-base to apply the needed changes in the process inputs [10]. These parts are explained in details as follows:

- The fuzzy inverse model

The fuzzy inverse model is a direct fuzzy logic system which performs the function mapping of $y_e(kT)$ and possibly functions of $y_e(kT)$ such as the rate of error ($y_c(kT) = \frac{1}{T}(y_e(kT) - y_e(kT-T))$ or the plant operating conditions, to the relative changes in the plant inputs $p(kT)$ that are necessary to force the process output $y(kT)$ to be as close as possible to model reference output $y_m(kT)$ (i.e., to force $y_e(kT)$ to zero) [32, 33].

As shown in Figure (2), the fuzzy inverse model similar to the fuzzy controller where contains normalizing scaling factors, namely g_{ye}, g_{yc} *and* y_p for each universe of discourse. Selection of the normalizing gains is significantly effect on the overall behaviors of the plant [19]. The knowledgebase form for the fuzzy inverse model can be written as

$$R_v: If\ \tilde{y}_e\ is\ \tilde{Y}^j_{e,v}\ and\ \tilde{y}_c\ is\ \tilde{Y}^l_{c,v}\ Then\ \tilde{p}\ is\ \tilde{P}^r_v$$

Where $\tilde{y}_e$ and $\tilde{y}_c$ denote the fuzzy set for the error and change in error $y_e(kT)$ and $y_c(kT)$, respectively associated with plant output. The variable $\tilde{p}$ denotes the linguistic variables describing the necessary change in the process input, associated with fuzzy inverse model output *p(kT).* R_v denoted the v^{th} rule of the fuzzy inverse model; $\tilde{Y}^j_{e,v}$, $\tilde{Y}^l_{c,v}$ and $\tilde{P}^r_v$ denoted the j^{th}, l^{th} and r^{th} linguistic values of the v^{th} rule associated with $\tilde{y}_e$, $\tilde{y}_c$ and $\tilde{p}$, respectively[32].

As with the fuzzy controller, the membership functions utilize for normalized input universes of discourse. Any membership function shapes can be assumed. In this work, a symmetric triangular membership functions have been utilized.

It is important to note that the development of the fuzzy inverse model does not depend on the existence and specification of the mathematical model of the plant or its inverse. The inverse mathematical system of the plant is not like the fuzzy inverse system, where the inverse mathematical system of the plant is used in the fixed control such as in the non-adaptive control [32, 33].

D. The Knowledge-Base Modifier

It is used to give the indication about the changes in the input of the plant, which are denoted by *p(kT)* which is applied to force the error $y_e(kT)$ to very small value. It is some time used to change the rule-base of the fuzzy controller in which the previously control action will be updated by the amount $p\ (kT)$ [32].

Therefore consider that the previously computed control action is $u(kT)$which contribute to the present good or bad system performance. Note that *e (kT-T)* and $c(kT-T)$ would have been the processed error and the change in error respectively at time$(kT-T)$. Likewise, *u (kT-T)* would have been the controller output at that time. In order to force the fuzzy controller to produce small error, the fuzzy controller's knowledgebase should be modifying to produce a desired output $u(kT-T)+p(kT)$ [33].

Assume that a symmetric output membership functions are utilized for the fuzzy controller, where c_m denote the center value of the output membership functions associated with $\tilde{B}_q^r$. Knowledgebase modification is performed by shifting centers of the membership functions (c_m) of the output linguistic value $\tilde{B}_q^r$ which are associated with the fuzzy controller rules that contributed to the previous control action *u (kT −T)* [9].

To modify the centers of the output membership functions, the following two stages should perform:

1. The active set of rules for the fuzzy controller at time $(kT-T)$ is first determined ($\mu_i(e(kT-k), c(kT-T))>0$); those rules set can be characterized by indices of the input membership functions of each rule that is on. Since all possible combinations of rules have been used, so one output membership function for each possible rule will be on [12].
2. the centers of the membership functions at output side of fuzzy controller are updated as shown in the following equation

$$c_m(kT)=c_m(kT-T)+p(kT) \tag{13}$$

Where $c_m(kT)$ represents the center of the m^{th} output membership function at the time kT.The centers of the output membership functions that are not in the active set of rules will not be update. So that just the rules that actually contributed to the current output $y(kT)$ are updated [34].

This kind of learning is very useful since it does not need to entire rule base in order to be adjusted for every time step, just those rules that have been applied to the present statuses will be updated and stored. So, when the process encounter familiar operating conditions it does not required re-adapt again, where the controller will actually know how to cope with the process. This represents a feature for this type of controller due to its rid from the time consuming at re-learning.

III. MATHEMATICAL MODEL OF THE ELECTROMAGNETIC ACTUATOR

The electromagnetic actuator consists of a permanent-magnet DC motor with ball screw and a nut. Figure 3 shows the prototype of the electromagnetic actuator (copy from article [35]).

Fig. 3: Electromagnetic Actuator

The electromagnetic actuator converts the vibration energy (that comes from the rough road) into electrical power by using the DC motor and stores it in the storage unit. Therefore, the generated electrical energy can contribute to run the electrical pumps of the hydraulic actuators.

The DC motor can operate here in the electromotor mode or generator mode. In general, the power of the motor (Pe) can be represented as:

$$P_e=\frac{4\pi\Phi}{P_H}vI \tag{14}$$

where Φ is the flux linkage; P_H is the lead of the ball-screw, v is the relative velocity; and I is the electric current flow through the motor's coils.

If the demand power is positive, the DC motor operates in the electromotor mode and the current flows from the battery into the positive terminal of the motor and the energy of battery will be consumed. On the other hand, if the power is negative, the motor operates inversely and the current flows to the positive electrode of the battery and the motor charges the battery as a generator with reclaimed energy from vibration of the vehicle.

The torque of the DC motor (T_e) can be written as:

$$T_e=C_eI \tag{15}$$

where the value of equivalent torque constant C_e is computed as:

$$C_e=2\Phi \tag{16}$$

There are two types of forces which can be generated by using an electromagnetic actuator. The first force is called damping force (F_m) which comes from the mechanism friction and inertia. The second force is called the vertical force F_a. Therefore, the overall force generated by the electromagnetic mechanism device is computed as:

$$F_c=F_m+F_a=C_m(\dot{z_{si}}-\dot{z_{usi}})+(\frac{2\Phi cos\varphi}{r})I \tag{17}$$

where r is the effective radius for force conversion.

IV. SIMULATION AND RESULTS

In this section, the simulation results for the full vehicle nonlinear active suspension systems including passenger seat with hydraulic actuators are presented. The performance of the fuzzy logic controllers that which designed based on the FMRLC algorithm, in this approach the centers of the output membership functions of the fuzzy logic controller are modify. The MATLAB/SIMULINK program package has been utilized to simulate the FRMLC with the controlled system as illustrate in Figure (4). As shown in this Figure the inputs of the fuzzy inverse model are the error and change of error, the output is an adaptation factor p(kT) that which utilized by the rule base modifier to adapted the center of the

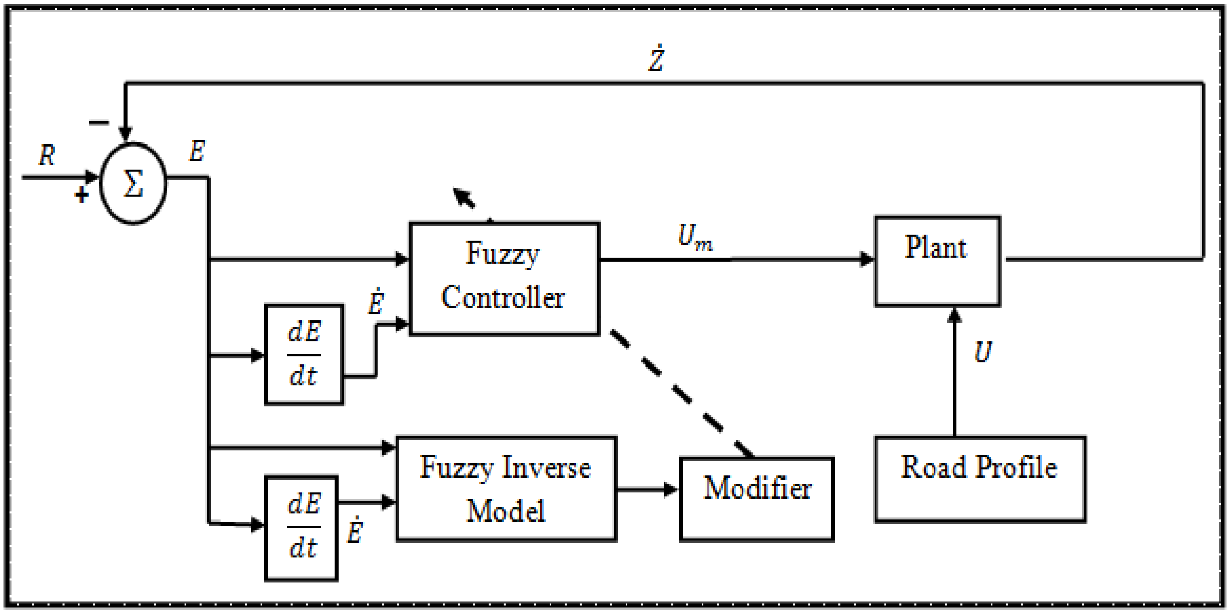

Fig 4: Fuzzy model reference learning control with plant

output MFs of fuzzy controller. For these inputs and output, 7 fuzzy sets are defined with triangular form MFs which are equally distributed on the properly universe of discourse. For simplicity the fuzzy inverse model is selected as the same structure of standard fuzzy controller (the same membership function, rule base, inference engine, fuzzification and defuzzification). The reference model has been chosen to be a unity block.

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Each inputs and output of the fuzzy control have seven membership functions linked with seven linguistic values are defined as: NB negative big, NM negative medium, NS negative small, ZE zero, and PS positive small, PM positive medium and PB positive big. These MFs are selected to be symmetric triangular in shape because they are widely used and convenient. The input membership functions are equally distributed on the normalized input universe of discourse, while the distributed of output MFs on the output universe of discourse are initialized randomly.

Table 1 represents the fuzzy controller rules are represented linguistic values of IF-THEN of rules, the total numbers of rules are $7 \times 7 = 49$ which are designed heuristically based on the knowledge of the controlled system.

TABLE 1
The rule base for the fuzzy control

u_m		$\dot{e}$						
		NB	**NM**	**NS**	**Z**	**PS**	**PM**	**PB**
e	**NB**	NM	NS	NS	NS	Z	PS	PM
	NM	NM	NM	NM	NS	PS	PM	PM
	NS	NB	NM	NM	NS	PM	PB	PB
	Z	NB	NB	NM	Z	PM	PB	PB
	PS	NB	NB	NM	PS	PM	PM	PB
	PM	NM	NM	NS	PS	PM	PM	PM
	PB	NM	NS	Z	PS	PS	PS	PM

Then the COG defuzzification method and the inference mechanism in the FRMLC case are utilized to obtain the crisp output this output represent the controller output or the input of the controlled system. For simplicity the fuzzy inverse model is selected as the same structure of standard fuzzy controller (the same membership function, rule base, inference engine, fuzzification and defuzzification).The reference model has been chosen to be a unity block.

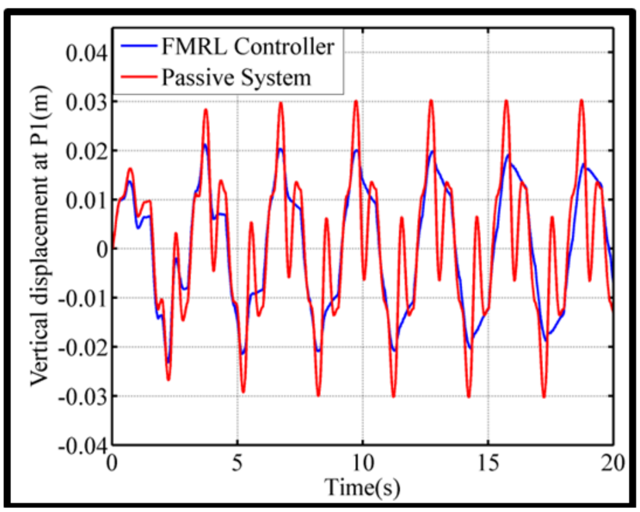
After training phase, the optimal values of the centers (c_m) of output MFs of the five fuzzy controllers that obtained from using the FMRLC are given in Table (2) and, where the initial values are zeros.

TABLE 2
Optimal solutions of each FMRLC

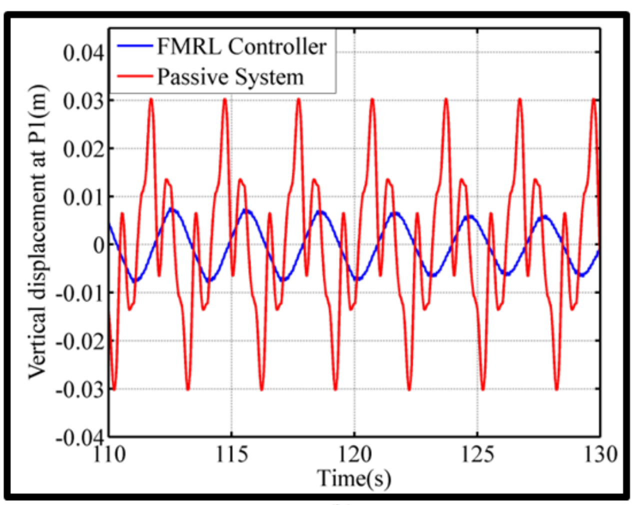
c_1	c_2	c_3	c_4	c_5	c_6	c_7
0	-36.4143	-404.1287	-0.0371	404.0915	36.3772	0

The vertical displacement for each corner of the vehicle body, passenger seat and vehicle center, that obtained during training phase with FMRLC approach are shown in Figures (5-10).

In order to evaluate the efficient of the proposed controller method the optimal values for the center output MFs must be examined. Figures (11-12) illustrate a comparison between the outputs of controlled system with FMRLC and corresponding outputs of the passive system also, in this status, the square input has been provided as a road profile with a range [-0.01 0.01] meters.

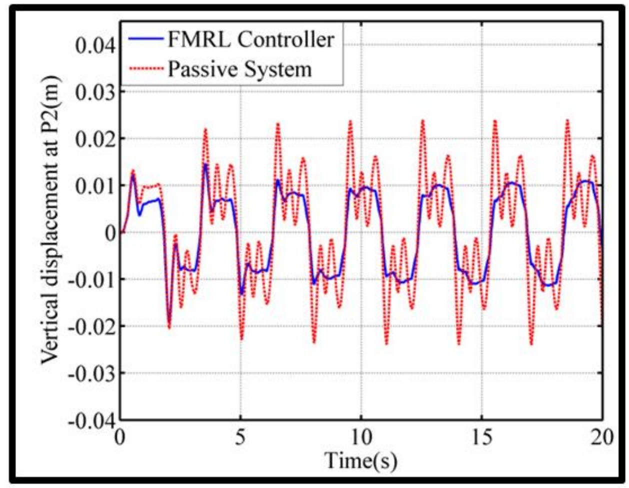


(a)

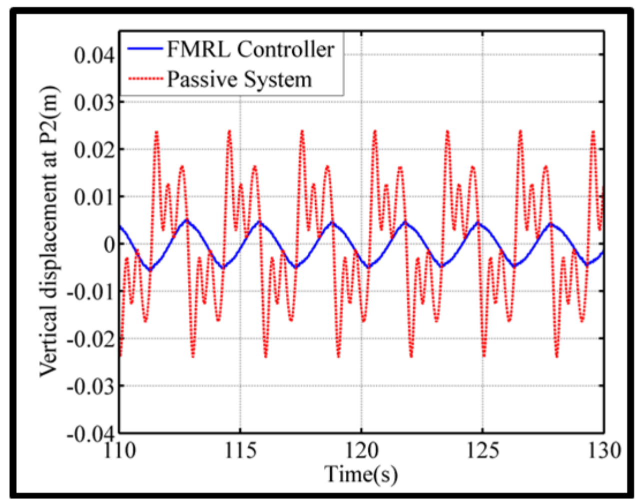


(b)

Fig 5: Vertical displacement at P1 for (a) first 7 training periods, (b) last 7 training periods

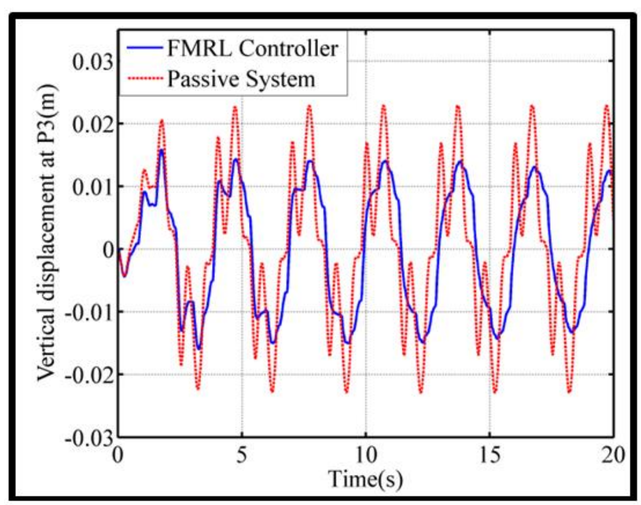


(a)



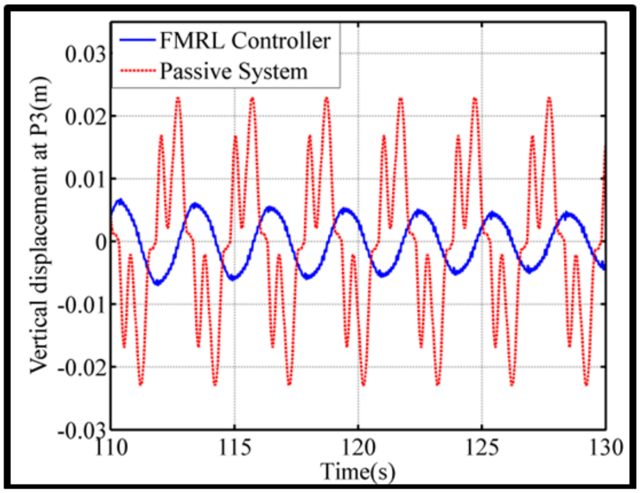
(b)

Fig 6: Vertical displacement at P2 for **(a)** first 7 training periods, **(b)**last 7 training periods



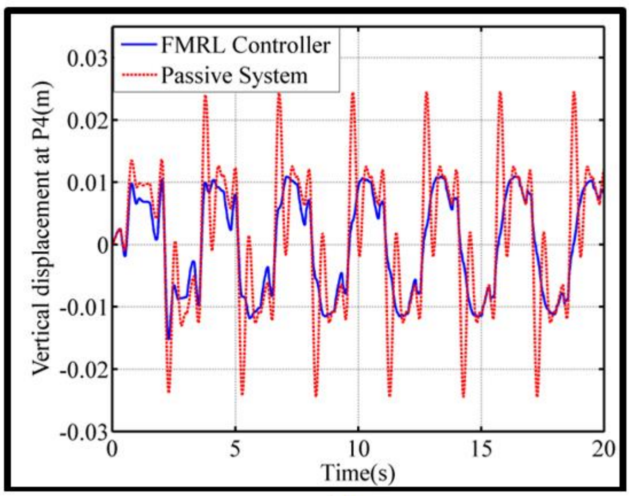
(a)

Fig 7: Vertical displacement at P3 for (a) first 7 training periods, (b) last 7 training periods

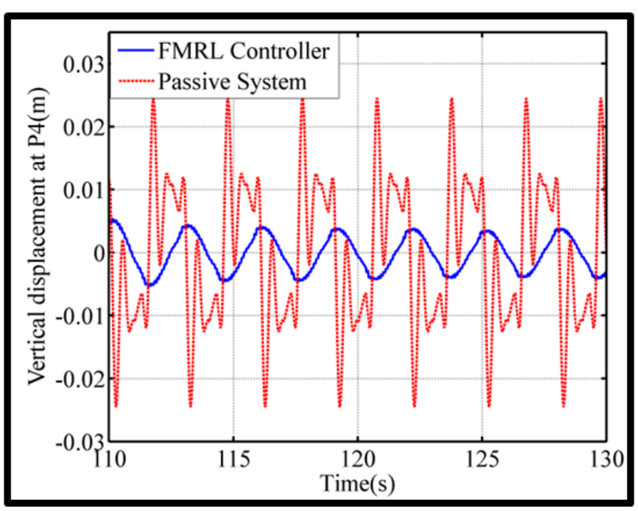


(b)

Fig 7: Continued.

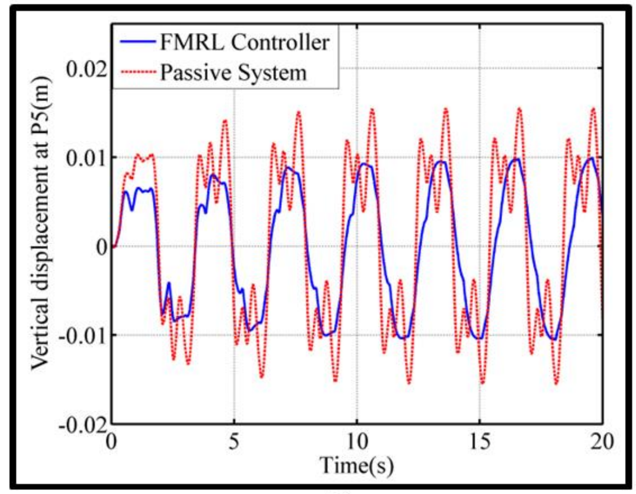


(a)

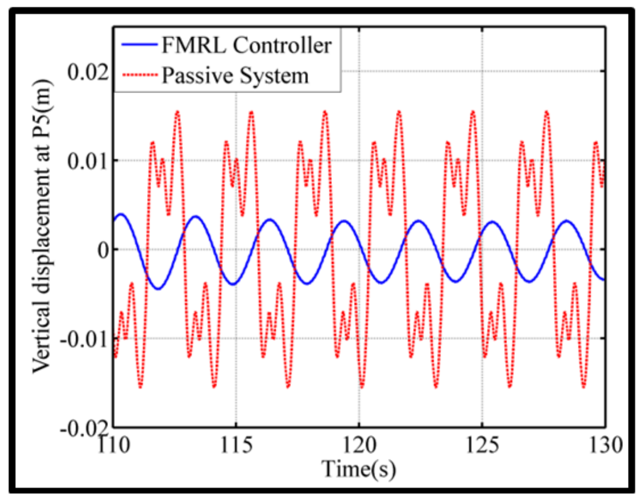


(b)

Fig 8: Vertical displacement at P4 for (a) first 7 training periods, (b)last 7 training periods

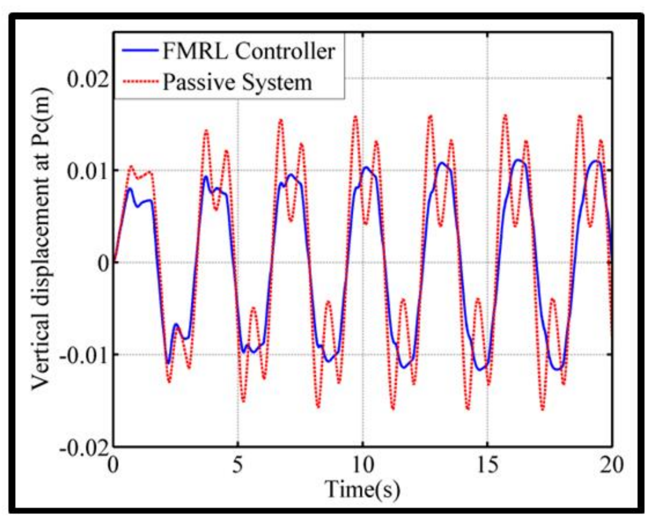


(a)



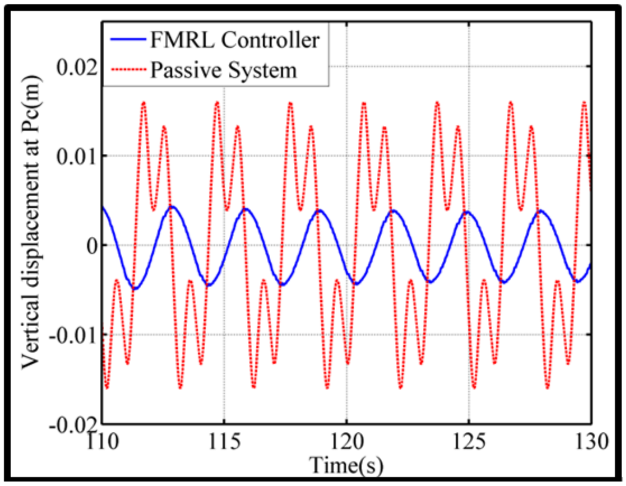
(b)

Figure 9: Vertical displacement at P5 for (a) first 7 training periods, (b) last 7 training periods



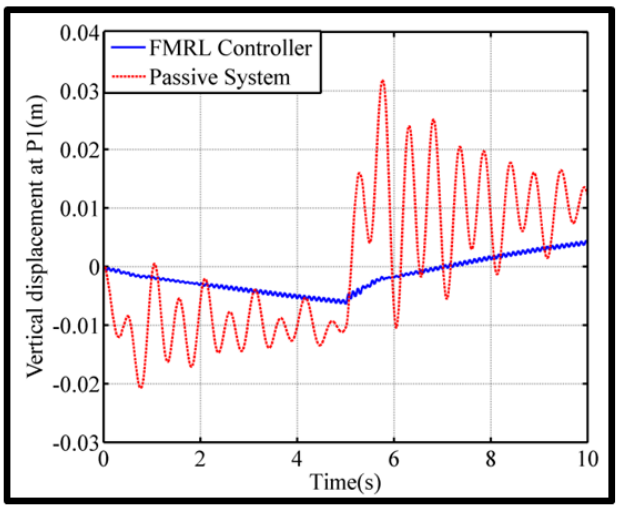
(a)

Fig 10: Vertical displacement at Pc for **(a)** first 7 training periods, **(b)** last 7 training periods

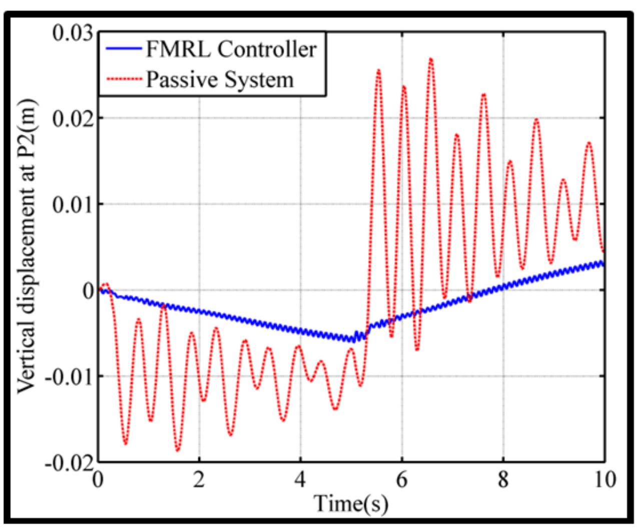


(b)

Fig 10: Continued.

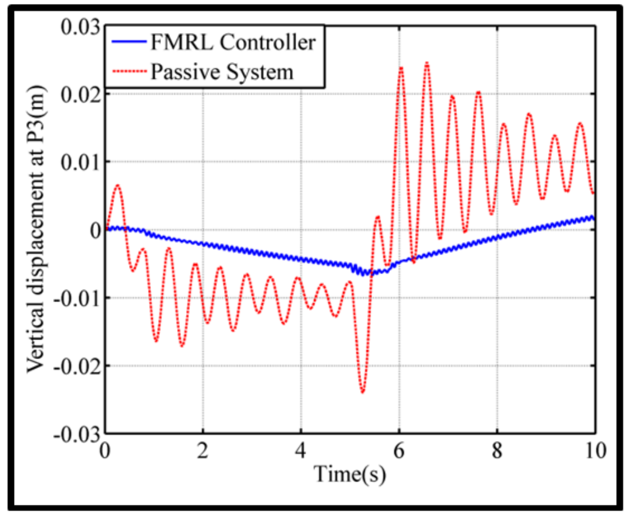


(a)

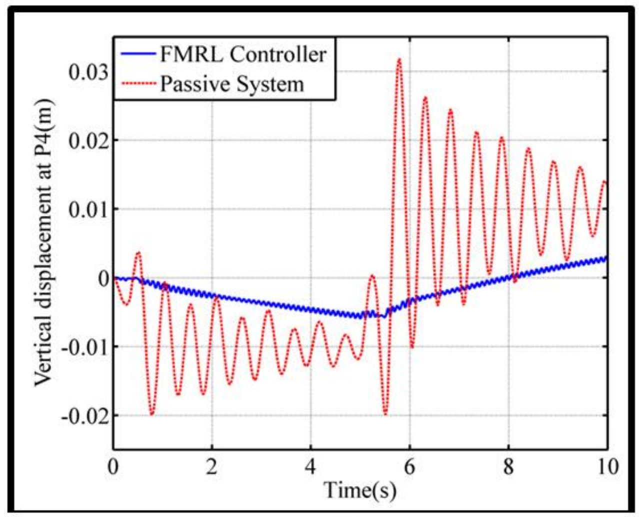


(b)

Fig11: Time response of vertical displacement at (a) P1; (b) P2; (c) P3; (d) P4

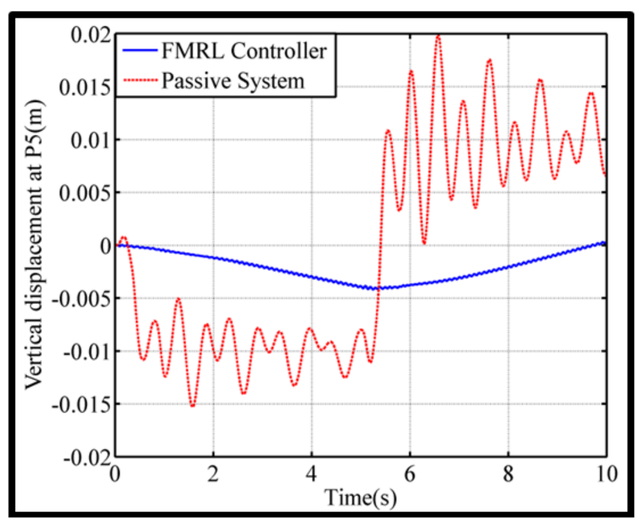


(c)



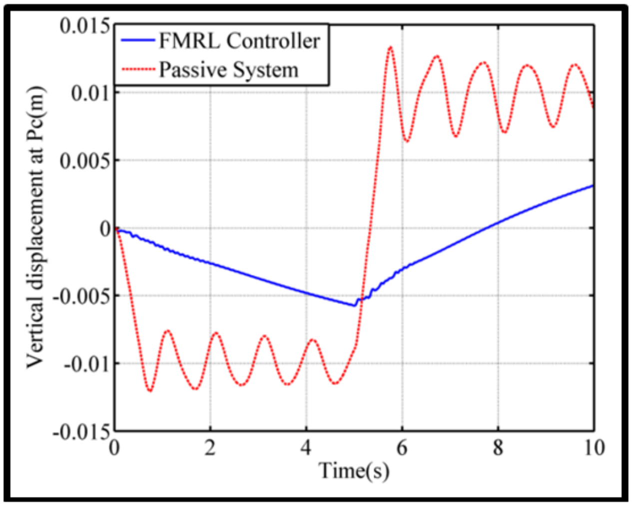
(d)

Fig11: Continued.

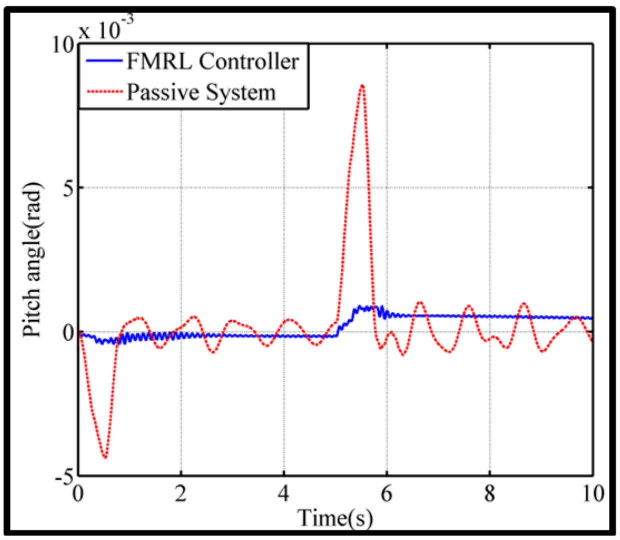


(a)

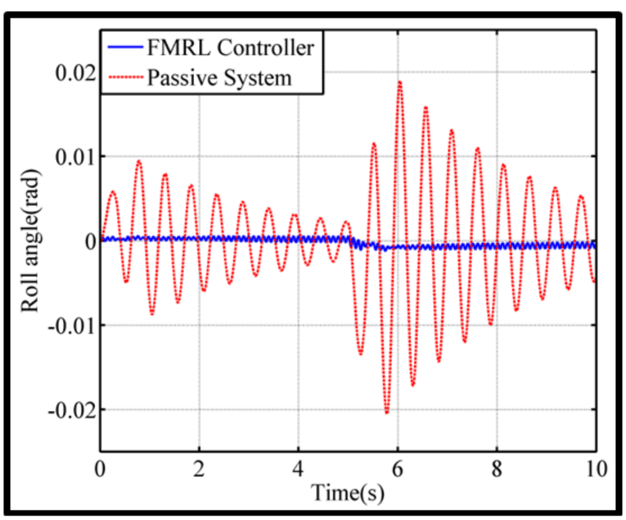
Fig 12: Time response for **(a)** vertical displacement at P5; **(b)** vertical displacement at Pc **(c)** Pitch angle; **(d)** Roll angle



(b)



(c)



(d)

Fig 12: Continued.

V. Calculation of Consumption Power

The j^{th} consumption power by i^{th} hydraulic actuators can be calculated from the following equation:

$$P_{ci}(j) = F_i(j) * \left(\left(\dot{z}_{si}(j) - \dot{z}_{usi}(j)\right) - \left(\dot{z}_{si}(j-1) - \dot{z}_{usi}(j-1)\right)\right) \quad (18)$$

The total consumption power by the i^{th} hydraulic actuator can be calculated from the following equation:

$$P_{ti} = \sum_j \begin{array}{c} F_i(j) *) * \left(\left(\dot{z}_{si}(j) - \dot{z}_{usi}(j)\right)\right. \\ \left. -\left(\dot{z}_{si}(j-1) - \dot{z}_{usi}(j-1)\right)\right) \end{array} \quad (19)$$

The power generated from the i^{th} electromagnetic actuator can be calculated from Eq.(14).

Figures 13-16 show the power generated from the DC motors of the electromagnetic active suspension device. From those Figures, because the power generated is only negative so that the DC motors operate as a generator. The generated energy is used to drive the pumps of the hydraulic actuators to generate damping forces that is applied to improve the vehicle performances. It means that the energy consumption by the active suspension systems has been reduced and the problem of the energy consumption resulting for driving the actuators in the active suspension has been solved.

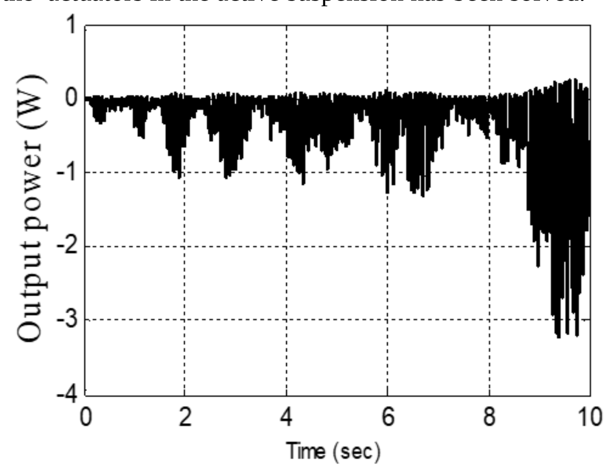


Fig. 13 Output power from front-right suspension

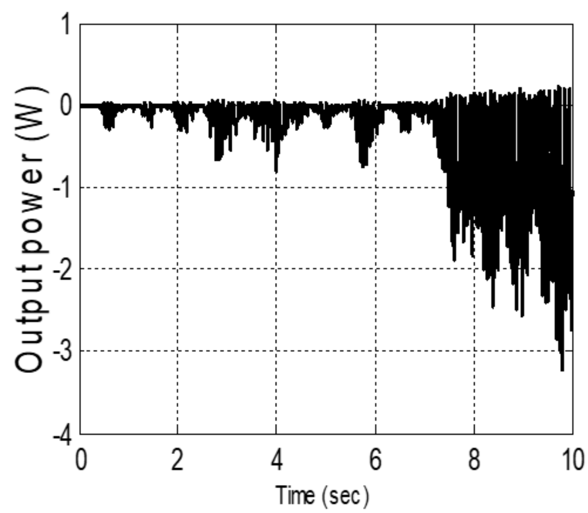


Fig. 14 Output power from front-lift suspension

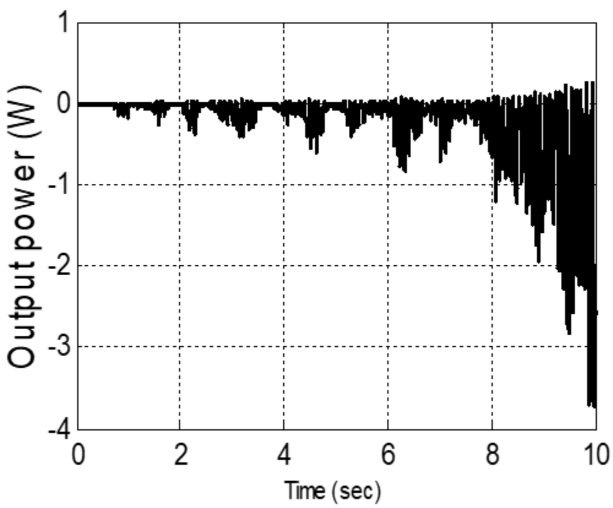


Fig. 15 Output power from rear-right suspension

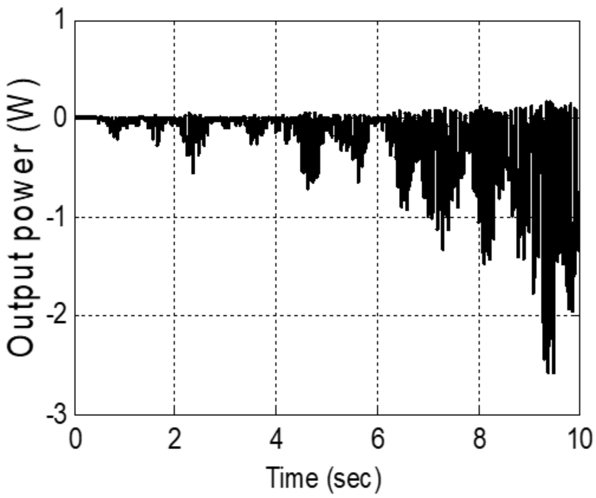


Fig. 16 Output power from rear-lift suspension

VI. Conclusions

In this study, FMRL technique is proposed to improve the performance of full active suspension system and the results have been presented. The motivation of utilizing the proposed FMRL controller is to improve the vehicle suspension system and overcome the drawback of utilized the fuzzy system as a controller, where it is hard to justify the selection of fuzzy controller parameters.

The suggested controller method have the ability of tuning some of its parameters depending on the errors between the system outputs and the desired outputs to generate a suitable control signals to modify the hydraulic actuators forces to reduce the tendency of vehicle to rollover during sharp maneuvers such as cornering and breaking and to minimize the vertical displacements at each suspension when travelling on rough roads achieve the objectives control.

Five FMRL controllers have been designed, one for each suspension system. The centers parameters of the output membership functions, obtained from used the FMRL controller approach during the training phase, are set as parameters of the output membership functions of the fuzzy controller during the working phase. The results of proposed model are compared with the passive system. According to the results of the computer simulation when only the square input has been applied as road profile the suspension system with the FMRLC given the superior performance than the passive system.

The electromagnetic actuator has been used in this paper to reduce the consumption power of the active suspension system by converting the vibration energy which comes from rough road to electrical energy. The results show that, the DC motor will be act as generator to convert the vibration energy to electrical energy.

Conflict of Interest

The authors have no conflict of relevant interest to this article.

References

[1] C. Shian, H. Ren, and L. Senlin, "New Reclaiming Energy Suspension and its Working Principle", Chines Journal of Mechanical Engineering, Vol. 13, No. 11, pp. 177-182, 2007

[2] H. Ren, C. Shian, and L. Senlin, "A Permanent Magnetic Energy Regenerative Suspension.", ZL 200520072480.9, 2005.

[3] C. Shian, H. Ren, and L. Senlin, "Operation Theory and Structure Evaluation of Reclaiming Energy Suspension." Transactions of the Chinese Society for Agricultural Machinery, Vol. 37, No. 5, pp. 5-9, 2006.

[4] Z. Yong-chao, U. Fan, G. Yong-hui, and Z. Xue-chun, "Isolation and Energy regenarative Performance Experimental Verification of Automotive Electrical Suspension." Journal of Shanghai Jiaotong University, Vol. 42, No. 6, pp. 874-877, 2008.

[5] L. Zheng, Y. N. Li, J. Shao, and X. S. Sun, "The Design of a Fuzzy-sliding Mode Controller of Semi-active Suspension Systems with MR Dampers", IEEE International Conference on Fuzzy Systems and knowledge Discovery, Vol. 4, pp. 514-518, 2007.

[6] D. Karnopp, "Power requirements for traversing uneven roadways", Vehicle System Dynamics, Vol. 7, pp. 135-152, 1978.

[7] D. Karnopp, "Permanent Magent Linear Motors used as Variable Mechanical Dampers for Vehicle Suspensions", Vehicle System Dynamics, Vol. 18, pp. 187-200, 1989.

[8] Y. Sada, and T. Shiiba, "A New Hybrid Suspension System with Active Control and Energy Regeneration", Vehicle System Dynamics, Vol. 25, pp. 641-654, 1996.

[9] S. Velinsky, and R. White, "Vehicle Energy Dissipation due to Road roughness", Vehicle System Dynamics, Vol. 9, pp. 359-384, 1980.

[10] I. Martins, J. Esteves, G. Marques, and F. Silva, "Permanent-Magnets Linear Actuators Applicability in Automobile Active Suspensions", IEEE Transaction on Vehicular Technology, Vol. 55, No. 1, pp. 86-94, 2006.

[11] M. Montazeri, and M. Soleymani, "Investigation of the Energy Regeneration of Active Suspension Systemin Hybrid Electric Vehicles", IEEE Transaction on Industral Electronics, Vol. 57, No. 3, pp. 918- 925, 2010.

[12] L. Xu, X. Guo, and J. Liu, "Evaluation of Energy-regenerative Suspension Structure Based on Fuzzy Comprehensive Judgment", Advanced Materiral Research, pp. 139-141, 2010.

[13] L. Zuo, B. Scully, J. Shestani, and Y. Zhou, "Design and Characterization of an Electromagnetic Energy Harvester for Vehicle Suspensions", Smart Mater. Structure., Vol. 19, pp. 1-10, 2010.

[14] R. Guclu, K. Gulez, "Neural network control of seat vibrations of a non-linear full vehicle model using PMSM", Journal of Mathematical and Computer Modeling, Vol. 47, No. 11, pp.1356-1371, (2008).

[15] R. Güçlü, "Active control of seat vibrations of a vehicle model using various suspension alternatives", Turkish Journal of Engineering and Environmental Sciences, Vol. 27, No. 6, pp.361-374, (2003).

[16] S. Lajqi, S. Pehan, "Designs and optimizations of active and semi-active non-linear suspension systems for a terrain vehicle", Strojniški vestnik Journal of Mechanical Engineering, Vol. 58, No. 12, pp.732-743, (2012).

[17] J. Lin, R. J. Lian, "Intelligent control of active suspension systems", IEEE Transactions on Industrial Electronics, Vol. 58, No. 2, pp.618-628, (2011).

[18] F. A. Ansari, R. Taparia, "Modeling, analysis and control of active suspension system using sliding mode control and disturbance observer", International Journal of Scientific and Research Publications, Vol. 3, No. 1, pp.1-6, (2013).

[19] N. G. Jabson, K.G. B. Leong, S. W. Licarte, G. M. S. Oblepias, E. M. J. Palomado, E .P. Dadios, "The Autonomous Golf Playing Micro Robot: With Global Vision And Fuzzy Logic Controller", International Journal On Smart Sensing And Intelligent Systems, Vol. 1, NO. 4, DECEMBER 2008

[20] C. C. Lee, "Fuzzy logic in control systems: Fuzzy logic controller-Part1", IEEE Transactions on Systems, Man and Cybernetics, Vol. 20, No. 2, pp.404-418, (1990).

[21] L. j. Yue, C. y. Tang, H. Li, "Research on vehicle suspension systems based on fuzzy logic control", Proceedings of the IEEE International Conference on Automation and Logistics(ICAL) Qingdao, China, pp. 1817-1821,(2008).

[22] T. R. Rao, P. Anusha, "Active suspension system of a 3 DOF quarter car using fuzzy logic control for ride comfort" , IEEE International Conference on Control, Automation, Robotics and Embedded Systems (CARE), pp. 1-6, (2013).

[23] T. K. Dakhlallah, M. A. Zohdy, "Type-2 Fuzzy Kalman Hybrid Application for Dynamic Security Monitoring Systems based on Multiple Sensor Fusion" International Journal On Smart Sensing And Intelligent Systems Vol. 4, NO. 4, DECEMBER 2011

[24] J. R. Layne, K. M. Passino, "Fuzzy model reference learning control for cargo ship steering", IEEE Control Systems, Vol. 13, No. 6, pp.23-34, (1993).

[25] J. R. Layne, K.M. Passino, "Fuzzy Model Reference Learning Control", Journal of Intelligent and Fuzzy Systems, Vol. 4, No. 1, pp. 33–47, (1996).

[26] B. I. Saeed, B. Mehrdadi, "Zero overshoot and fast transient response using a fuzzy logic controller", IEEE 17th International Conference on Automation and Computing (ICAC) London, ISBN: 9781467300001, pp. 116-120, (2011).

[27] S. Ramesh, S. A. Lincon, "Fuzzy Model Reference Learning Control for Non-Linear Spherical Tank Process", International Journal of Engineering Trends and Technology, Vol.1, No. 4, pp.4459-4465, (2013).

[28] O. Cerman, P. Husek, "Fuzzy model reference learning control with convergent rule base", Proceedings of the International Federation of Automatic Control, Vol. 43, No. 4, pp.282-286, (2010).

[29] A. Kharola, "A Pid Based Anfis & Fuzzy Control Of Inverted Pendulum On Inclined Plane (IPIP)" International Journal On Smart Sensing And Intelligent Systems Vol. 9, NO. 2, JUNE 2016

[30] G. Kopasakis, "Nonlinear performance seeking control using Fuzzy Model Reference Learning Control and the method of Steepest Descent", National Aeronautics and Space Administration Lewis Research Center, (1997).

[31] S. Riaz, L. Khan, "Adaptive soft computing strategy for ride quality improvement with anti-lock braking system", Proceedings of the IEEE International Bhurban Conference on Applied Sciences and Technology (IBCAST), pp. 280-285, (2016).

[33] Zheng, L., Li, Y. N., Shao, J., and Sun, X. S. (2007). "The Design of a Fuzzy-sliding Mode Controller of Semi-active Suspension Systems with MR Dampers " IEEE International Conference on Fuzzy Systems and knowledge Discovery., 4, 514-518.

[34] R. Rajamani, J. k. Hedrick, "Adaptive Observers for active automotive suspension: Theory and experiment", IEEE Transaction on control system technology, Vol.3, No. 1, pp.86-92, (1995).

[35] R. Ghazali,Y. M. Sam, M. F. Rahmat, K. Jusoff, Zulfatman, A. W. I. M. Hashim" Self-Tuning Control of an Electro-Hydraulic Actuator System" International Journal on Smart Sensing And Intelligent Systems Vol. 4, NO. 2, JUNE 2011.