Intelligent Neuro-Fuzzy Application in Semi-Active Suspension System

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1. Introduction

In the field of artificial intelligence, Neuro-Fuzzy (NF) refers to combinations of artificial neural networks and fuzzy logic and first time introduced in 1990s. Neuro-fuzzy results in a intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks. NF is widely termed as Fuzzy Neural Network (FNN) or Neuro-Fuzzy System (NFS) in the literature. NFS (the more popular term is used henceforth) incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main strength of neuro-fuzzy systems is that they are universal approximations with the ability to solicit interpretable IF-THEN rules.

The strength of neuro-fuzzy systems involves two contradictory requirements in fuzzy modeling: interpretability versus accuracy. In practice, one of the two properties prevails. The neuro-fuzzy in fuzzy modeling research field is divided into two areas: linguistic fuzzy modeling that is focused on interpretability, mainly the Mamdani model; and precise fuzzy modeling that is focused on accuracy, mainly the Takagi-Sugeno-Kang (TSK) model.

The previous studies made full use of the advantages of the neural-network and the fuzzy logic controller and solved the different problems in suspension systems. Few researches involved combination of the two techniques to solve the time-delay and the inherent nonlinear nature of the Magneto-Rheological (MR) dampers in semi-active strategy for full car model with high degrees of freedom. In this chapter, four MR dampers are added in a suspension system between body and wheels parallel with passive dampers. For the intelligent system, fuzzy controller which inputs are relative velocities across MR dampers that are excited by road profile for predicting the force of MR damper to receive a desired passenger's displacement is applied. When predicting the displacement and velocity of MR dampers, a four-layer feed forward neural network, trained on-line under the Levenberg–Marquardt (LM) algorithm, is adopted. In order to verify the effectiveness of the proposed neuro-fuzzy control strategy, the uncontrolled system and the clipped optimal controlled suspension system are compared with the neuro-fuzzy controlled system. Through a numerical example under actual road profile excitation, it can be concluded that the control strategy is very important for semi-active control, the neuro-fuzzy control strategy can

determine voltage of the MR damper quickly and accurately, and the control effect of the neuro-fuzzy control strategy is better than that of the other control strategies. First have brief reviewed on modelling of a full car model and third section clearly reveals more detailed information about neuro-fuzzy strategy for the full-car model. Finally in sections 4 and 5 the results will be presented and discussed.

2. Full car model

In the full-car model, 11-DOFs is assumed, all wheels and passengers are dependent on each other and on the car's body. It is assumed that each wheel has an effect on the spring and damper of other wheels, and two axles of vehicle are dependent. MR actuator is utilized to damp the effect of road profile on the passengers. Note that MR shock absorber is added between the axel and car's body. In the full-car model, the effects of the rotations of the body around the roll and pitch axes are simulated. The suspension system using a full-car model has 11-DOFs, four of them for the four wheels, three for body displacement and its rotations and the last four for the passengers. Schematic of the full-car model with 11-DOFs and addition of the MR damper is shown in Fig. 1.
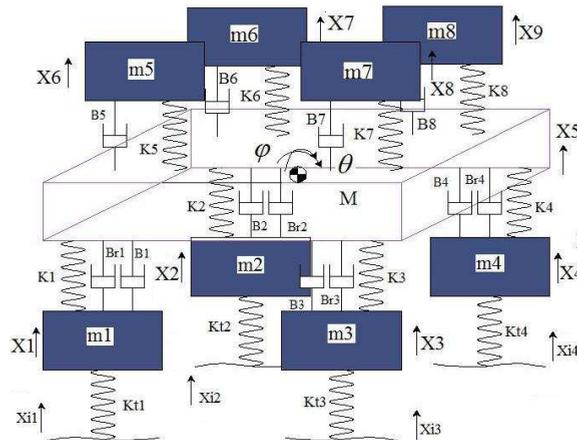

Fig. 1. Full-car model with 11-DOFs

where M_b, m_1, m_2, m_3, m_4, m_5, m_6, m_7 and m_8 stand for the mass of the car's body, mass of four wheels and mass of passengers, respectively. I_1 and I_2 are the moments of inertia of the car's body around two axes. The terms k_1, k_2, k_3, k_4, k_5, k_6, k_7 and k_8 are stiffness of the springs of the suspension system and stiffness of the springs of passengers seat, respectively. The terms k_{t1}, k_{t2}, k_{t3} and k_{t4} are stiffness of the tires. The terms b_1, b_2, b_3, b_4, b_5, b_6, b_7 and b_8 are coefficients of car and passenger's seat dampers. Then, b_{r1}, b_{r2}, b_{r3} and b_{r4} are passive coefficients of the MR dampers, respectively. x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, φ and θ indicate the DOFs of the suspension system model. The terms x_{i1}, x_{i2}, x_{i3} and x_{i4} indicate load profile disturbance, respectively. These parameters are used to clipped optimal strategy which is considered as a desire to train neural network and tuning fuzzy memberships. Here optimal force is depending on all state variables (Zareh et al); therefore model with detail information is necessary.

2.1 Clipped optimal algorithm

The clipped optimal control strategy for an MR damper usually involves two steps. The first step is to assume an ideal actively–controlled device and construct an optimal controller for this active device. In the second step, a secondary controller finally determines the input voltage of the MR damper.

That is, the secondary controller clips the optimal force in a manner consistent with the dissipative nature of the device. The block diagram of the clipped optimal algorithm is shown in Fig. 2.

The clipped optimal control approach is to append a force feedback loop to induce the MR damper to produce approximately a desired control force f_c. The Linear Quadratic Regulator (LQR) algorithm has been employed both for active control and for semi-active control. Using this algorithm, the optimal control force f_c for f, which is force generated by an MR damper. (Zareh et al) utilized clipped optimal algorithm for semi-active full car model.
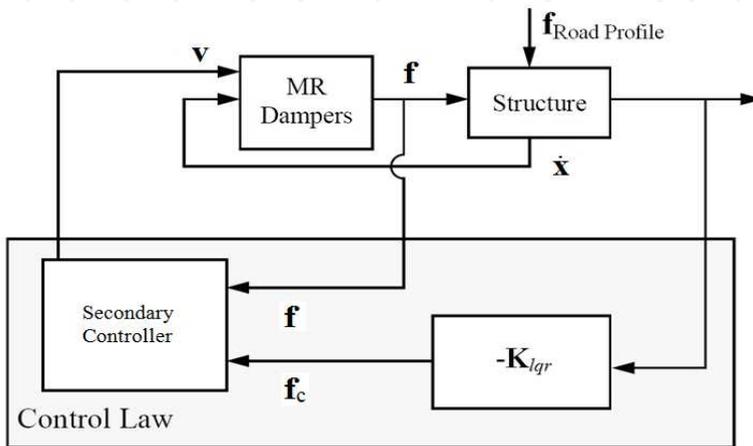

Fig. 2. Clipped optimal algorithm block diagram

3. Neuro-fuzzy strategy using in semi-active vibration control

Unfortunately, due to the inherent nonlinear nature of the MR damper to generate a force, a similar model for its inverse dynamics is difficult to obtain mathematically and also due to the nonlinearity of suspension system, its equations are complicated. Because of these reasons, a neural network with fuzzy logic controller is constructed to copy the inverse dynamics of the MR damper and suspension system.

Neuro-fuzzy controller is an artificial neural network, which is used to aggregate rules and to provide control result for the designed fuzzy logic controller. Application of fuzzy inference systems as a Fuzzy Logic Controller (FLC) has gradually been recognized as the most significant and fruitful application for fuzzy logic and fuzzy set theory. In the past few years, advances in microprocessors and hardware technologies have created an even more diversified application domain for fuzzy logic controllers, which range from consumer electronics to the automobile industry.

Indeed, for complex and/or ill-defined systems that are not easily subjected to conventional automatic control methods, FLCs provide a feasible alternative since they can capture the approximate, qualitative aspects of human reasoning and decision-making processes. However, without adaptive capability, the performance of FLCs relies exclusively on two factors: the availability of human experts, and the knowledge acquisition techniques to convert human expertise into appropriate fuzzy if-then rules and membership functions. These two factors substantially restrict the application domain of FLCs.

Consequently, a neural control design approach can usually be carried over directly to the design of fuzzy controllers, unless the design method depends directly on the specific architecture of the neural networks used. This portability endows us with a number of design methods for fuzzy controllers which can easily take advantage of a priori human information and expertise in the form of fuzzy if-then rules. The result of the above methodology is called Neuro-Fuzzy Control method. Neural and fuzzy logic controllers have been successfully implemented in the control of linear and nonlinear systems.

Unlike conventional controllers, such controllers do not require mathematical model and they can easily deal with the nonlinearities and uncertainties of the controlled systems. Also, a Levenberg-Marquardt (LM) neural controller has been designed for variable geometry suspension systems with MR actuators.

In the present research, an optimal controller Linear Quadratic Regulator (LQR) is designed for control of a semi-active suspension system for a full-model vehicle, using a neuro-fuzzy along with Levenberg-Marquardt learning and the results compared with Linear Quadratic Gaussian (LQG) (Zareh et al). The purpose in a vehicle suspension system is reduction of transmittance of vibrational effects from the road to the vehicle's passengers, hence providing ride comfort. To accomplish this, one can first design a LQR controller for the suspension system, using an optimal control method and use it to train a neuro-fuzzy controller. This controller can be trained using the LQR controller output error on an online manner.

Once trained, the LQR controller is automatically removed from the control loop and the neuro-fuzzy controller takes on. In case of a change in the parameters of the system under control or excitations, the LQR controller enters the control loop again and the neural network gets trained again for the new condition therefore it can ensure the robustness of strategy due to changes in excitations (Sadati et al). An important characteristic of the proposed controller is that no mathematical model is needed for the system components, such as the non-linear actuator, spring, or shock absorbers.

The basic idea of the proposed neuro-fuzzy control strategy is that the forces of the MR dampers are determined by a fuzzy controller, whose inputs are the measured velocity response predicted by a neural network (Zh et al). The architecture of this strategy is shown in Fig. 3, which consists of two parts to perform different tasks. The first part is for the neural network to be trained on-line. The numbers of the sample data pairs are 3500, the training data pairs increase step by step during the entrance disturbance from road profile.

To select the network architecture, it is required to determine the numbers of inputs, outputs, hidden layers, and nodes in the hidden layers; this is usually done by trial and error. Therefore, one hidden layer, with six nodes, was adopted as one of the best suitable topologies for neural network.
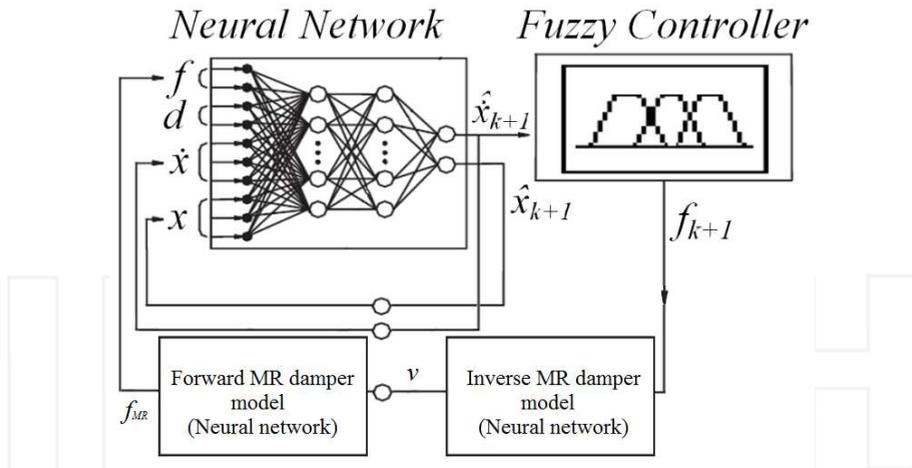
Fig. 3. Architecture of the neuro-fuzzy control strategy

The neural network is trained to generate the one step ahead prediction of the displacement $\hat{x}_{k+1}$ and the velocity $\hat{\dot{x}}_{k+1}$. Inputs to this network are the delayed outputs (x_{k+3}, x_{k+2}, x_{k+1}, x_k, $\dot{x}_{k+3}$, $\dot{x}_{k+2}$, $\dot{x}_{k+1}$, $\dot{x}_k$), the delayed force which is predicted by fuzzy controller (f_{k+1}), and the disturbance input (d_k). At the initial time, the inputs of the network will be assigned the value of zero in accordance with the actual initial circumstance. Before online training, the network is trained off-line so as to obtain the weights that are as near to the desired value as possible (Yildirim et al).

The second part is the fuzzy controller, whose input is the measured relative velocity across MR dampers. The disturbance can be calculated by road profile model. The output of the fuzzy controller is the control force of the MR dampers. The main aim of this part is to determine the control force of the MR dampers quickly in accordance with the input excitation. How to design the fuzzy controller will be explained in the following subsection. In order to reach this aim, it is required to predict the responses of passengers in accordance with the optimal responses.

The third part is the feedforward neural network to be trained on-line to generate the required voltage of MR damper v. In fact, this part is the inverse dynamics model of MR damper.

This block diagram is designed by authors using of combination of advanced works. In this strategy there are three neural networks. First is to mapping of suspension system. Second is inverse model of MR damper and third is forward model of MR damper. The difference between inverse and forward model is their inputs and outputs where the inputs of inverse model is outputs of forward model and vice-versa. All data that are used to training, testing and validating are LQR results because, they are optimal and our desired.

As mentioned, due to the inherent non-linear nature of the MR damper, a model for inverse dynamics of MR damper is difficult to obtain mathematically. Because of this reason, a feedforward back propagation neural network is constructed to copy the inverse dynamics of the MR damper. This neural network model is trained using input-output data generated analytically using the simulated MR model based on clipped algorithm. Using this inverse

dynamics of MR damper, the required voltage signal v is calculated based on the desired control force f_c, the velocity of MR dampers $\hat{\dot{x}}_{k+1}$, and the displacement of MR damper x_{k+1}.

The fourth part is the feedforward back propagation neural network to be trained on-line in order to generate the MR damper forces fMR. The inputs of this neural network are voltage signal v, the velocity of MR damper $\hat{\dot{x}}_{k+1}$, and the displacement of MR damper x_{k+1}. The difference between inverse and forward model is in inputs and outputs. The outputs of inverse model are the inputs of forward model.

The third and fourth part of the proposed neuro-fuzzy control strategy which is a three-layer feedforward neural network consists of an input layer with 3 nodes, a hidden layer with 6 nodes, and output layer with one node. Determining the numbers of inputs, outputs, hidden layers, and nodes in hidden layers of these three neural networks is done by trial and error. For all neural parts some of the corresponded results that are obtained by LQR are used as a desire data and some others are used as a testing data.

At the same time, the actual responses will feed back to the neural network and the weights and bias will be revised in real time. In this research, results from the optimal control history analysis method are used to simulate the actual measured responses. The errors between the predicted responses and the actual responses are used to update the weights of the neural network on-line.

3.1 The neural network based on Levenberg-Marquardt (LM) algorithm

The MR damper model discussed earlier in this research estimates the damper forces based on the inputs of the reactive velocity. In such case, it is essential to develop an inverse dynamic model that predicts the corresponding control force which is to be generated by dampers.

Neural network is a simplified model of the biological structure which is found in human brains. This model consists of elementary processing units (also called neurons). It is the large amount of interconnections between these neurons and their capability to learn from data which makes neural network as a strong predicting and classification tool. In this study, a three-layer feed forward neural network, which consists of an input layer, one hidden layer, and an output layer ,as shown in Fig. 4, is selected to predict the responses with MR dampers.

Here the networks are trained by LQR results (as a sample data). For example displacements, velocity and forces that are obtained by LQR are selected as a sample data for training and testing. Also target of networks are LQR results. For example in the second network (Inverse model of MR damper) the targets are voltages that obtained by LQR part of clipped method.

The net input value net_k of the neuron k in some layer and the output value O_k of the same neuron can be calculated by the following equations:

$$net_k = \sum w_{jk} O_j \tag{1}$$
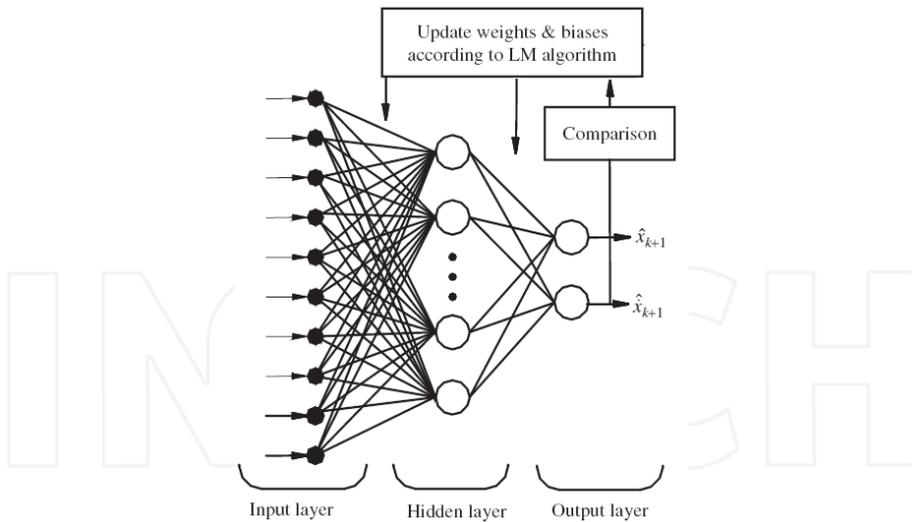
$$O_k = f(net_k + \theta_k) \tag{2}$$

Fig. 4. The neural network architecture

where w_{jk} is the weight between the jth neuron in the previous layer and the kth neuron in the current layer, O_j is the output of the jth neuron in the previous layer, f(.) is the neuron's activation function which can be a linear function, a radial basis function, and a sigmoid function, and y_k is the bias of the kth neuron. Feed forward neural network often has one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. In the neural network architecture as shown in Fig. 4, the logarithmic sigmoid transfer function is chosen as the activation function of the hidden layer.

$$O_k = f(net_k + \theta_k) = 1/(1 + e^{-(net_k + \theta_k)}) \tag{3}$$

The linear transfer function is chosen as the activation function of the output layer.

$$O_k = f(net_k + \theta_k) = net_k + \theta_k \tag{4}$$

We note that neural network needs to be trained before it can predict any responses. As the inputs are applied to the neural network, the network outputs ($\hat{}$) are compared with the targets (.). The difference or error between both is processed back through the network to update the weights and biases of the neural network so that the network outputs match closer with the targets.

The input and output data are usually represented by vectors called training pairs. The process as mentioned above is repeated for all the training pairs in the data set, until the network error converges to a threshold minimum defined by a corresponding performance function. In this research, the Mean Square Error (MSE) function is adopted (desired MSE is 1e-5). LM algorithm is adapted to train the neural network (Zh et al), which can be written as a following equation:

$$w^{i+1} = w^i - [(\delta^2 E/\delta w^{i^2}) + \mu I]^{-1}(\delta E/\delta w^i) \tag{5}$$

where i is the iteration index, $\delta E/\delta w^i$ is the gradient descent of the performance function E with respect to the parameter matrix w^i, $\mu \geq 0$ is the learning factor, and I is the unity matrix. During the vibration process, the neural network updates the weights and bias of neurons in real time in accordance with sampling pairs till the objective error is satisfied, i.e. the property of the system is acquired.

As we know, the main aim of the neural network is to predict the dynamic responses of the system, and to provide inputs to the fuzzy controller and also data for calculating the control force of MR dampers. Thus outputs of the neural network are predictions of displacement $\hat{x}_{k+1}$ and velocity $\dot{\hat{x}}_{k+1}$. In order to predict the dynamic responses of the system accurately, the most direct and important factors which affect the predicted dynamic responses are considered, i.e. the delayed outputs (x_{k+3}, x_{k+2}, x_{k+1}, x_k, $\dot{x}_{k+3}$, $\dot{x}_{k+2}$, $\dot{x}_{k+1}$, $\dot{x}_k$), the predicted force (f_{k+1}), and the disturbance input (d_k). LM algorithm is encoded in Neural Networks Toolbox in MATLAB software.

3.2 Design of fuzzy controller

The first step of designing a fuzzy controller is determining the basic domains of inputs and outputs. The desired displacement and velocity responses are chosen as inputs of the fuzzy controller. The output of fuzzy controller is the control force of the MR damper, whose basic domain is -700N – 300N same as the working force of the MR damper calculated using LQR (Zareh et al).

The membership functions are usually chosen in accordance with their characters and design experience.

For simplifying the calculation, triangular or trapezoidal functions are usually adopted as the membership functions. The triangular membership function is more sensitive to inputs than the trapezoidal form (Zh et al), in expectation that the control forces of the MR dampers are sensitive to excitations and responses, but in this case Gaussian and triangular forms are used because they have demonstrated better responses through trial and error. In this research, gaussian and triangular functions are adopted as the membership functions of velocity. The membership function curves of the velocity are shown in Figs. 5-8. (Relative velocity across dampers)
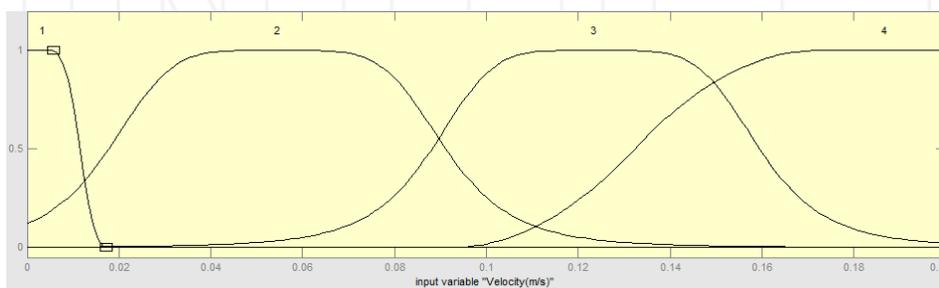

Fig. 5. Membership function of front-left damper velocity
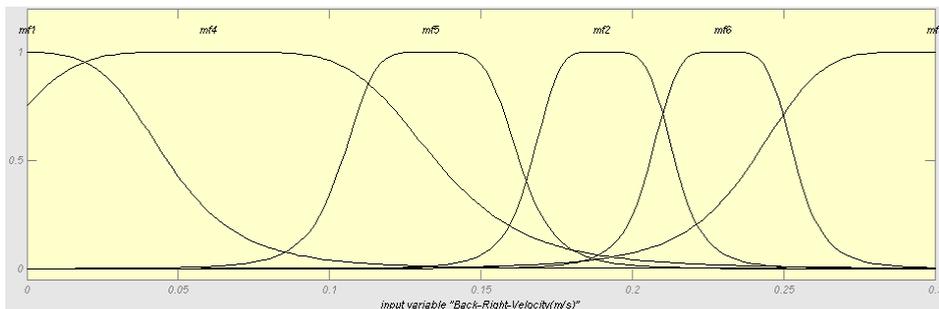
Fig. 6. Membership function of front-right damper velocity
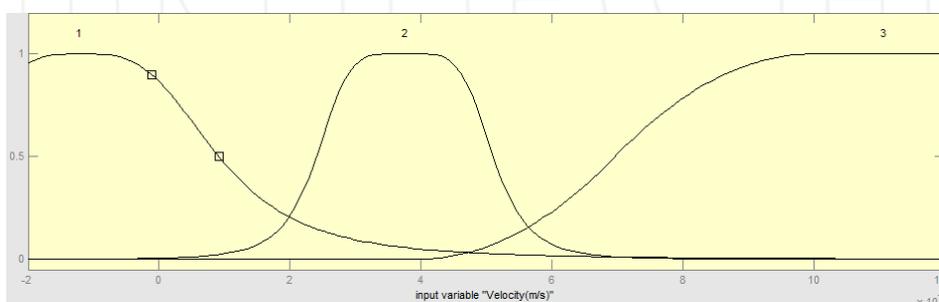

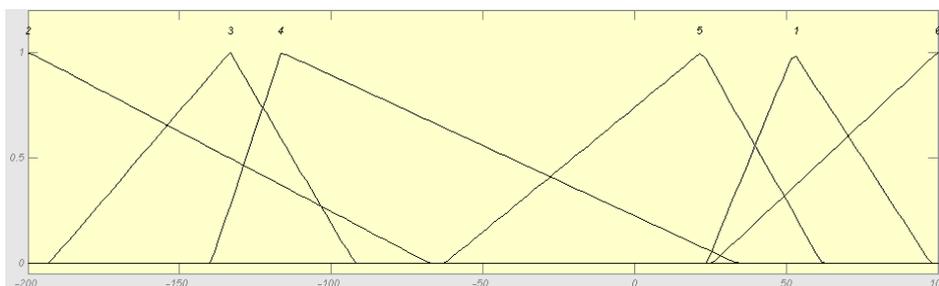Fig. 7. Membership function of back-left damper velocity

Fig. 8. Membership function of back-right damper velocity

Here, Sugeno inference engine with linear output is used, the main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant. It has led to reduction of computational cost because it does not need any defuzzification procedure. A Sugeno fuzzy model is computationally efficient platform that is well suited for implementation of non-linear associations through the construction of many piecewise linear relationships (Yen et al) .A typical rule in a Sugeno fuzzy model has the form:

If X is A1 and Y is B1 then Z = p1*x + q1*y + r1,

If X is A2 and Y is B2 then Z = p2*x + q2*y + r2,

where q1 and q2 are constant. One of the main advantages of Sugeno method is well suited to mathematical analysis and is also computationally efficient, but Mamdani method is well suited to human input and it is intuitive. The basic idea of the fuzzy rules is that the control force increases with the increasing velocity responses. In this research, OR function is MAX, AND function is MIN and the defuzzification method is chosen as the Weighted Average (wtaver) method. The structure of considered fuzzy controller is shown in Fig. 9.
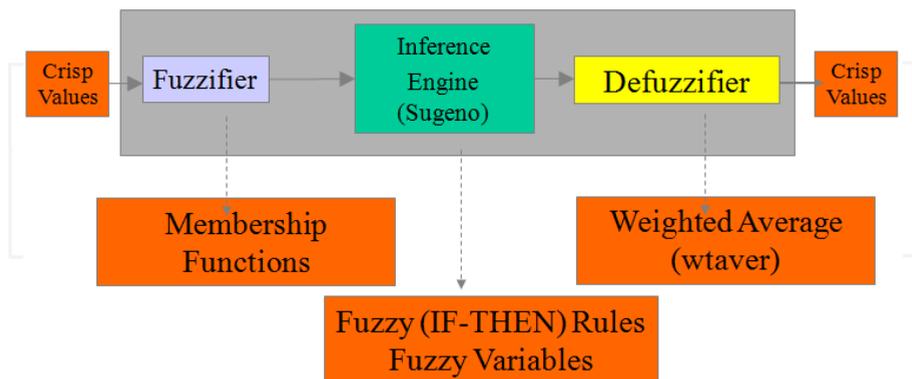
Fig. 9. The structure of fuzzy controller

For defuzzification we apply centre of gravity for singletons (COGS). Since we are implementing a Sugeno type controller, the combined activation, accumulation, and defuzzification operation simplifies to weighted average, with the activation strengths weighting the singleton positions (Jantzen 2007). Weighted Average defuzzifier is illustrated in Fig. 10.
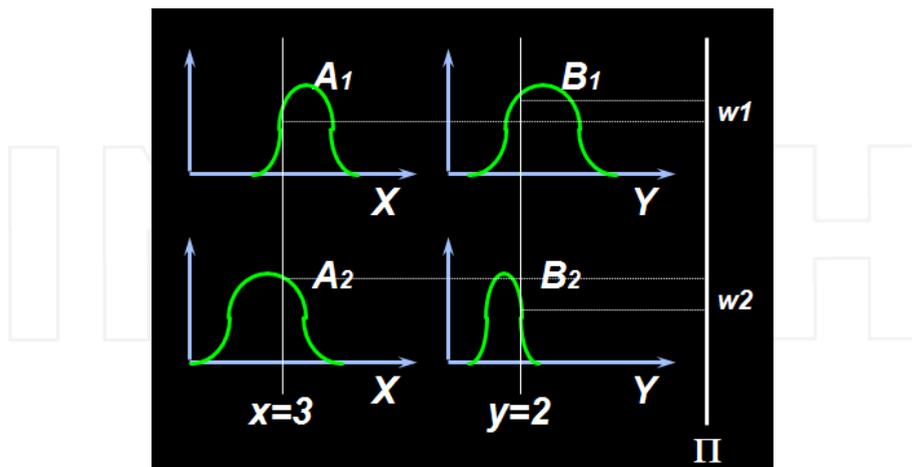

Fig. 10. Sugeno-style rule evaluation

$$z1 = p1*x + q1*y + r1 \qquad (6)$$

$$z2 = p2*x + q2*y + r2 \qquad (7)$$

$$Z = [w1*z1 + w2*z2]/[w1+w2] \qquad (8)$$

The membership function curves of the force for front-left damper as a fuzzy output (force vs. velocity) is shown in Fig. 11.
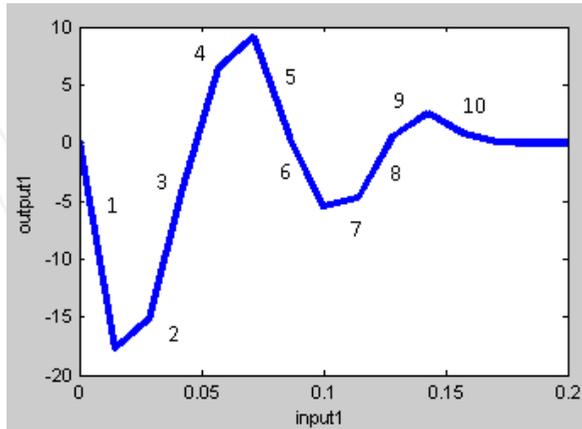

Fig. 11. Membership function of back-right damper velocity (force on vertical axis vs. velocity on horizontal axis)

The rule base used in the semi-active suspension system shown in Table 1 with fuzzy terms derived by the designer's knowledge and experience (because of shortage of space some of them are presented).

Front-left	Front-right	Back-left	Back-right	Force
1	mf_3	1	2	1
1	mf_3	1	3	1
1	mf_4	2	3	6
1	mf_2	2	5	4
2	mf_6	1	5	6
2	mf_5	3	6	6
3	mf_6	2	1	8
3	mf_2	1	1	10
4	mf_5	3	1	1

Table 1. Rule base

4. Results

The full-car model with MR damper and disturbance is modeled by the dynamic equations and state space matrices. One of the desired points of this study is to decrease the amplitude of passenger's displacement, when the suspension system excited from the road profile. Therefore the effect of LQR and LQG controllers and neuro-fuzzy strategy are simulated for road excitation with calculated their amplitude, and then compared with each other. The

displacement trajectories for front-right passenger's seat that is excited by bumper under front left wheel are shown in Fig. 12. Notice that, in all graphs, time duration is selected for the best resolution and critical responses are happened when car strikes with bumper.

The trajectories of neuro-fuzzy strategy show that this strategy reduces the amplitude of vibration lower than the passive system and also to some extent as well as optimal controllers; because displacement is predicted by feed forward neural networks.
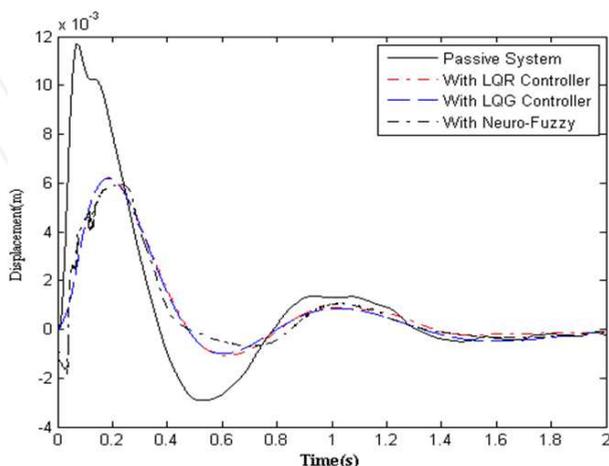
Fig. 12. Displacement of front right seat from front left wheel excite

The primary oscillations are due to the less number of network input to train, on the other hand, there are not strong history in transient, therefore the transient part of response not as well as steady state part. The trajectory for the optimal force which produces the desired displacement is shown in Fig. 13.
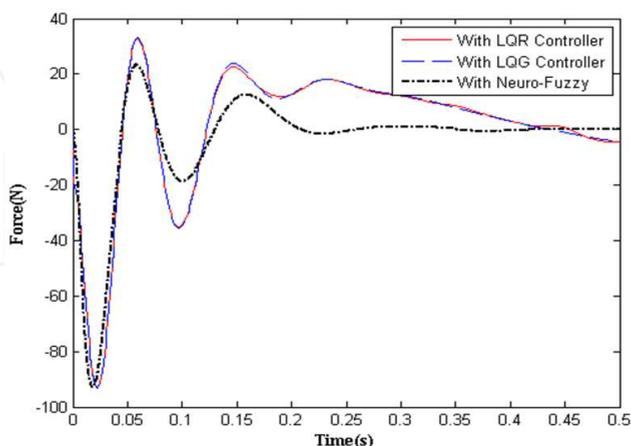

Fig. 13. Generated force by front right MR damper from front left wheel excited

One of the main advantages of using neuro-fuzzy, the control effort of dampers is less than LQR and LQG responses. Forces of neuro-fuzzy cannot follow optimal controller; because, optimal forces depend on twenty two state variables and the forces obtained by fuzzy part of neuro-fuzzy strategy depend on four state variables (relative velocity across MR dampers). The requirement voltage to receive optimal forces is shown in Fig. 14.

The voltages are calculated using of neuro-fuzzy has a less oscillations, therefore it cause of save energy and cost. Performance of the network is shown in Fig. 15.
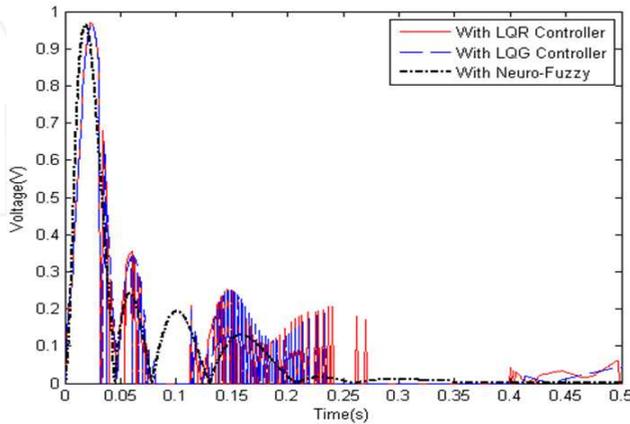
Fig. 14. Requirement voltages to front right MR damper from front left wheel excited
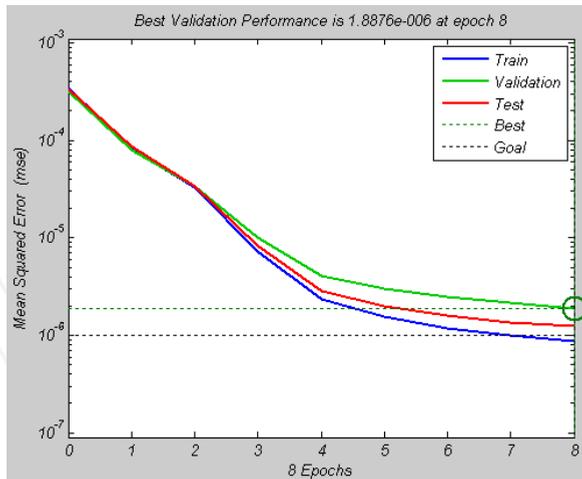

Fig. 15. Performance of the network

5. Conclusion

Usual suspension systems are utilized in the vehicle, and damped the vibration from road profile.Unfortunately, due to the inherent nonlinear nature of the MR damper to generate

force and suspension system, a model like that for its inverse dynamics is difficult to obtain mathematically. Because of this reason, a neural network with fuzzy logic controller is constructed to copy the inverse dynamics of the MR damper.

In the proposed control system, a dynamic-feedback neural network has been employed to model non-linear dynamic system and the fuzzy logic controller has been used to determine the control forces of MR dampers. Required voltages and actual forces of MR dampers have been obtained by use of two feedforward neural networks, in which the first neural network and second one have acted as the inverse and forward dynamics models of the MR dampers, respectively.

The most important characteristic of the proposed intelligent control strategy is its inherent robustness and its ability to handle the non-linear behavior of the system. Besides, no mathematical model is needed for calculating forces produced by MR dampers.

The performance of the proposed neuro-fuzzy control system has been compared with that of a traditional semi-active control strategy, i.e., clipped optimal control system with LQR and LQR, through computer simulations, while the uncontrolled system response has been used as the baseline.

According to the graphs that show above, the trajectories of neuro-fuzzy strategy can reduce the amplitude of vibration to some extent as well as optimal controllers with less control effort and oscillation. In addition, the neuro-fuzzy control system is more robust to process/sensing noises.

6. Acknowledgment

7. References

Atray V. S.; Roschke P. N. (2004). Neuro-Fuzzy Control of Railcar Vibrations Using Semi active Dampers. Computer-Aided Civil and Infrastructure Engineering, Vol.19, pp. 81-92

Biglarbegian M.; Melek W.; Golnaraghi F. (2006). Intelligent control of vehicle semi-active suspension system for improved ride comfort and road handling. IEEE International conference, pp. 19-24

Chang C. C.; Zhou L. (2002). Neural Network Emulation of Inverse Dynamics for a Magnetorheological Damper. Journal of Structural Engineering, vol. 2, pp. 231–239

Jahromi A. F.; Zabihollah A. (2010). Linear Quadratic Regulator and Fuzzy controller Application in Full-car Model of Suspension System with Magnetorheological Shock Absorber. IEEE/ASME International Conference on Mechanical and Embedded Systems and Applications, pp. 522-528

Jang J. R. (1997). Neuro-Fuzzy and Soft Computing: A computational Approach to Learning and Machine Intelligence. Prentice-Hall, ISBN: 0-13-261066-3

Jantzen J. (2007). Foundation of Fuzzy Control. John Wiley & Sons, Ltd. ISBN: 978-0-470-02963-3

Khajekaramodin A.; Hajikazemi H.; Rowhanimanesh A.; Akbarzadeh M. R. (2007).Semi-active Control of Structures Using Neuro-Inverse Model of MR Dampers. First Joint Congress on Fuzzy and Intelligent Systems, Iran, pp. 789-803

Ok S. Y.; Kim D. S.; Park K. S.; Koh H. M. (2007). Semi-active fuzzy control of cable-stayed bridges using magneto-rheological dampers. Engineering Structures, vol. 29, pp. 776–788

Sadati S. H.; Shooredeli M. A.; Panah A. D. (2008) Designing a neuro-fuzzy controller for a vehicle suspension system using feedback error learning. Journal of mechanics and aerospace, Vol.4, No.3, pp. 45-57

Schurter K. C.; Roschke P. N. (2000). Neuro-Fuzzy Modeling of a Magnetorheological Damper Using ANFIS. Proceeding of 9th IEEE International Conference on Fuzzy Systems, San Antonio, TX, pp. 122–127

Shiraishi T.;Nakaya N.; Morishita S. (2001). Vibration Control of Structure Equipped with MR Damper Using Neural Network. Proceeding of Dynamics and Design Conference, vol. 8, pp. 1748–1752

Suhardjo J.; Kareem A. (2001). Feedback-Feedforward Control of Offshore Platforms under Random Waves. Journal of Earthquake Engineering and Structural Dynamics, vol. 30, pp. 213–235

Sun J.; Yang Q. (2008). Modeling and intelligent control of vehicle active suspension system. IEEE International conference on RAM, pp. 239-242

Sung K. G.; Han Y. M., Cho J. W.; Choi S. B. (2007). Vibration control of vehicle ER suspension system using fuzzy moving sliding mode controller. Journal of Sound and Vibration, Vol.311, pp. 1004-1019

Wang H.; Hu H. (2009). The Neuro-Fuzzy Identification of MR Damper. Proceeding of 6th International Conference on Fuzzy Systems and Knowledge Discovery, pp. 464–468

Wang L. X. (1994). Adaptive Fuzzy Systems and Control: Design and Stability Analysis. Prentice-Hall, Englewood Cliffs, New Jersey

Yan G.; Zhou L. L. (2006). Integrated Fuzzy Logic and Genetic Algorithms for Multi-Objective Control of Structures Using MR Dampers. Journal of Sound and Vibration, Vol. 296, pp. 368–392

Yen J.; Langari R. (1999). Fuzzy Logic: Intelligence, Control, and Information. Prentice-Hall, New York, NY

Yildirim S.; Eski I. (2009). Vibration analysis of an experimental suspension system using artificial neural networks. Journal of Scientific & Industrial Research, Vol.68, pp. 522-529

Zareh S. H.; Fellahjahromi A.; Hayeri R.; Khayyat A. A. A.; Zabihollah A. (2011). LQR and Fuzzy Controller Application with Bingham Modified Model in Semi Active

Vibration Control of 11-DOFs Full Car Suspension System. International Journal on Computing, Vol. 1, No. 3, pp. 39-44

Zareh S. H.; Sarrafan A.; Khayyat A. A. A. (2011). Clipped Optimal Control of 11-DOFs of a Passenger Car Using Magnetorheological Damper. IEEE International Conference on Computer Control and Automation , Korea, ISBN: 978-1-4244-9767-6, pp. 162-167

Zareh S. H.; Sarrafan A.; Khayyat A. A. A.; Fellahjahromi A. (2011). Linear Quadratic Gaussian Application and Clipped Optimal Algorithm Using for Semi Active Vibration of Passenger Car. IEEE International Conference on Mechatronics, Turkey, pp. 122-127

Zh. D. X.; Guo Y. Q. (2008). Neuro-Fuzzy control strategy for earthquake-excited nonlinear magnetorheological structures. Soil Dynamics and Earthquake Engineering, Vol.28, pp. 717-727

Zhou L.; Chang C. C.; Wang L. X. (2003). Adaptive Fuzzy Control for Non-Linear Building-Magnetorheological Damper System. Journal of Structural Engineering: Special Issue on Structural Control, Vol. 7, pp. 905–913
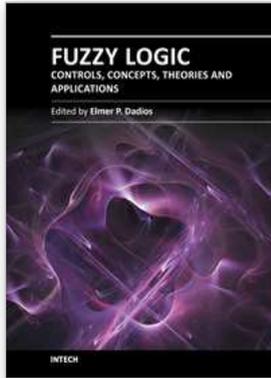
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