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# Development of ANFIS Control System for Seismic Response Reduction using Multi-Objective Genetic Algorithm

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***Abstract—*** *Adaptive neuro fuzzy inference system (ANFIS) and Genetic algorithm (GA) was proposed in this study to reduce dynamic responses of a seismically excited building. A multi-objective genetic algorithm (MOGA) was used to optimize the ANFIS+GA controller. Two MR dampers were used as multiple control devices and a scaled five-story building model was selected as an example structure. A fuzzy control algorithm was compared with the proposed ANFIS and ANFIS+GA controller.*
*Adaptive neuro-fuzzy inference system (ANFIS) and Ganetic algorithm with several outputs was proposed. In case study, after numerical simulation, it has been verified that the ANFIS control algorithm can present better control performance compared to the fuzzy control algorithm in reducing both displacement and acceleration responses.*
***Keywords—Adaptive Neuro Fuzzy Inference System (ANFIS), Earthquake loads, Vibration control, Multi-objective optimization using MOGA, Ganetic algorithm (GA).***

## I. INTRODUCTION

Although significant studies have been conducted in recent years toward development and application of semi-active control schemes for vibration control of building structures in seismic zones, the application of intelligent controllers, including ANFIS controllers, has not been addressed extensively. As an alternative to classical control theory, ANFIS controller allows the resolution of imprecise or uncertain information. Because of the inherent robustness and ability to handle nonlinearities and uncertainties, Although ANFIS controller has been used to control a number of structural systems, selection of acceptable fuzzy membership functions has been subjective and time-consuming. To overcome this difficulty, a multi-objective genetic algorithm (MOGA) was used to optimize fuzzy rules and membership functions of ANFIS controller. In order to compare the control efficiency of the proposed MOGA-optimized ANFIS controller, a fuzzy control algorithm was considered as the baseline in this study

A neuro-fuzzy system is based on an inference system formed by a training algorithm derived from the neural theory. There exists several approaches to integrate artificial neuron systems and the fuzzy logic, and very often the choice depends on the application. Jang and Sun introduced the adaptive network-based fuzzy inference system ANFIS. ANFIS was later extended to generalize ANFIS for the modeling of a multivariable system. The proposed ANFIS is used to obtain peak or maximum responce of three functions i.e. displacement, drift and acceleration but our study is concentrated to only two parameters i.e displacement and acceleration.

## II. ANFIS CONTROLLER

### 2.1 Adaptive Neuro-fuzzy Inference System

ANFIS is a neuro-fuzzy system whose structure is a multi-layer ANN see fig.4. It consists of three major parts i.e. IF-part, Rules + Norm-part and THEN-part for rule processing. It embeds fuzzy rules with the ANN and use a back-propagation-like algorithm to fine-tune the parameters of single-output, Sugeno-type fuzzy inference system. The learning algorithm combines least-squares and back-propagation (BP) gradient descent methods. This section introduces the basics of ANFIS network architecture and its hybrid learning rule.

Adaptive Neuro-Fuzzy Inference System is a feed forward adaptive neural network which implies a fuzzy inference system through its structure and neurons. Jang was one of the first to introduce ANFIS[Jang et all (1993)]. He reported that the ANFIS architecture can be employed to model nonlinear functions, identify nonlinear components on-line

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in a control system, and predict a chaotic time series. It is a hybrid neuro-fuzzy technique that brings learning capabilities of neural networks to fuzzy inference systems. The learning algorithm tunes the membership functions of a Sugeno-type Fuzzy Inference System using the training input-output data. For a first order Sugeno type of rule base with two inputs x, y and one output, the structure of ANFIS is shown in Fig.1

As we have already seen, fuzzy systems present particular problems to a developer:

- Rules:-The if-then rules have to be determined somehow. This is usually done by 'knowledge acquisition' from an expert. It is a time consuming process that is fraught with problems.
- Membership functions:-A fuzzy set is fully determined by its membership function. This has to be determined. If it's Gaussian then what are the parameters?

The ANFIS approach learns the rules and membership functions from data.

ANFIS is an *adaptive network*. An adaptive network is network of nodes and directional links. Associated with the network is a learning rule - for example back propagation. It's called adaptive because some, or all, of the nodes have parameters which affect the output of the node. These networks are learning a relationship between inputs and outputs.

An adaptive network covers a number of different approaches but for our purposes we will investigate in some detail the method proposed by Jang known as ANFIS.

The ANFIS architecture is shown below. The circular nodes represent nodes that are fixed whereas the square nodes are nodes that have parameters to be learnt.

A Two Rule Sugeno ANFIS has rules of the form:

$$If\ x\ is\ A_1\ and\ y\ is\ B_1\quad THEN\ f_1 = p_1x + q_1y + r_1$$
$$If\ x\ is\ A_2\ and\ y\ is\ B_2\quad THEN\ f_2 = p_2x + q_2y + r_2$$

For the training of the network, there is a forward pass and a backward pass. We now look at each layer in turn for the forward pass. The forward pass propagates the input vector through the network layer by layer. In the backward pass, the error is sent back through the network in a similar manner to back-propagation.

**Layer 1:** The output of each node is:

$$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$
$$O_{1,i} = \mu_{B_i}(y) \qquad for\ i = 3,4 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

So, the $O_{1,i}(x)$ is essentially the membership grade for $x$ and $y$.

The membership functions could be anything but for illustration purposes we will use the bell shaped function given by:

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where $a_i, b_i, c_i$ are parameters to be learnt. These are the premise parameters.

**Layer 2:** Every node in this layer is fixed. This is where the t-norm is used to 'AND' the\ membership grades - for example the product:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \qquad i = 1,2 \ \ldots\ldots\ldots\ldots (4)$$

**Layer 3:** Layer 3 contains fixed nodes which calculate the ratio of the firing strengths of the rules:

$$O_{3,i} = w_i = \frac{w_i}{w_1 + w_2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

**Layer 4:** The nodes in this layer are adaptive and perform the consequent of the rules:

$$O_{4,i} = \overline{w_i}f_i = \overline{w_i}(p_ix + q_iy + r_i) \ldots\ldots\ldots\ldots\ldots\ldots (6)$$

The parameters in this layer ($p_i, q_i, r_i$) are to be determined and are referred to as the consequent parameters.

**Layer 5:** There is a single node here that computes the overall output:

$$O_{5,i} = \sum_i \overline{w_i}f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

This then is how, typically, the input vector is fed through the network layer by layer. We now consider how the ANFIS learns the premise and consequent parameters for the membership functions and the rules.

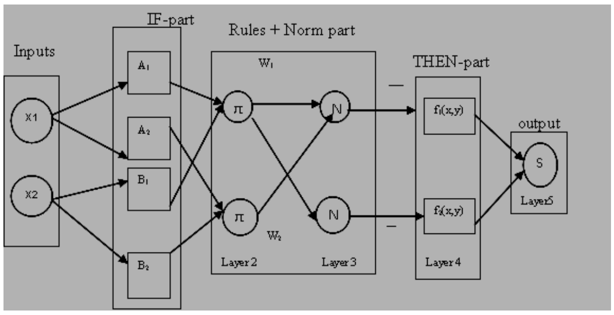


*Fig.1: Structure of ANFIS*

### 2.1.1 Operation of training

The MISO-ANFIS training paradigm uses a gradient descent algorithm to optimize the antecedent parameters, and a least squares algorithm to solve for the consequent parameters. The consequent parameters are updated first using a least squares algorithm, and the antecedent parameters are then updated by back-propagating the errors that still exist.

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**2.1.2 The back-propagation of the gradient**

In the stage of back-propagation, the signal of error is back propagated and local parameters are updated by the method of gradient descent. For the neuro-fuzzy system to an alone output *y*, we have:

$$a_{ij}(t+1) = a_{ij}(t) - \frac{h}{p}\cdot\frac{\partial E}{\partial a_{ij}} \qquad (13)$$

h: the training rate for *i a* ,

p : number of data of x (or *yd* ),

The following rule is used to calculate partial derivatives, employed to update of the parameters of membership function *g*. (Zhenming et al. 2001).

$$\frac{\partial E}{\partial a_i} = \frac{\partial E}{\partial y}\cdot\frac{\partial y}{\partial y_i}\cdot\frac{\partial y_i}{\partial w_i}\cdot\frac{\partial w_i}{\partial g}\cdot\frac{\partial g}{\partial a_i} \qquad (14)$$

$$E = \frac{1}{2}(y - y_d)$$

E: the quadratic cost function,

ANFIS system for three outputs as shown by Fig.1, possesses similar entry weights to these of ANFIS system for an alone output (therefore similar local parameters ($a_i$, $b_i$, $c_i$, $d_i$). The difference resides in consequent parameters. For MISO-ANFIS of single outputs, each output possesses these clean consequent parameters ($p_i$ , $q_i$, $r_i$ for $y_a$ , $p_i$' , $q_i$' , $r'_i$ for $y_b$ and $p_i$" , $q_i$" , $r"_i$ for $y_c$). To make the local parameter correction, MISO-ANFIS of single outputs uses the sum of the gradient of the two errors of the two outputs:

$e_1 = y_a - y_{d1}$ , $e_2 = y_b - y_{d2}$, $e_3 = y_c - y_{d3}$.

Such that

$$a_{ij}(t+1) = a_{ij}(t+1) - \frac{h}{p}\left(\frac{\partial E_1}{\partial a_{ij}} + \frac{\partial E_2}{\partial a_{ij}} + \frac{\partial E_3}{\partial a_{ij}}\right) \qquad (15)$$

Where:

$$\frac{\partial E_1}{\partial a_{ij}} = f(e_1)\cdot \quad \frac{\partial E_2}{\partial a_{ij}} = f(e_2)\cdot \quad \frac{\partial E_3}{\partial a_{ij}} = f(e_3)$$

**2.2 Application of ANFIS systems**

To show the efficiency of the proposed ANFIS, we consider the approximation of the three following functions:

$$y_{d1} = .2*\sin(.3*x) \qquad (16)$$

$$y_{d2} = .2*\sin(-.3*x); \qquad (17)$$

$$y_{d3} = .2*\cos(.3*x); \qquad (18)$$

The precision of ANFIS increases with the number of weight of inputs. For ANFIS of three outputs, it concerns three errors of estimation (for $y_{d1}$ , $y_{d2}$ and $y_{d3}$ ). To make the approximation of these three functions, we have used a ANFIS of three weights in the input (in first layer). Then, and so as to have best results of approximation, we have used a ANFIS with six weights in the input. Then we have made the comparison of the results of the approximation for the two ANFIS systems. Local parameters are initialed to small values that we have chosen to accelerate the convergence. The type of membership function of ANFIS that we have used is the trapezoidal function.

**2.2.1 Scaled Building Model**

In order to develop an MISO semi-active ANFIS for effective control of multiple MR dampers, a 5-story example building structure shown in Fig. 2 is employed. This example structure is developed based on a scaled 3-story shear building model used in the literature. As shown in this figure2, two MR dampers are rigidly connected to the first floor and the second floor of the structure, respectively.

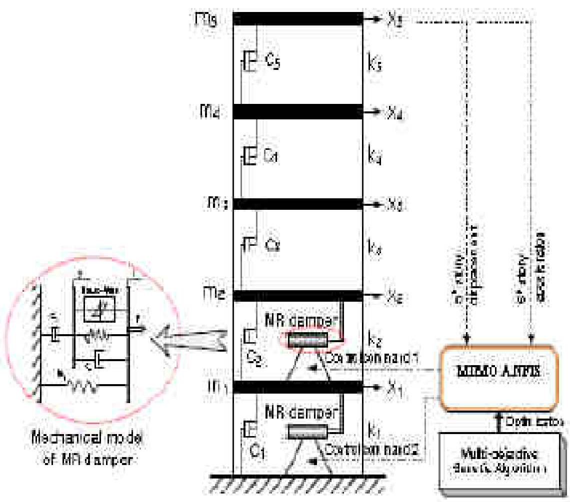


*Fig.2: 5-story example building model*

The first five natural frequencies of the example structure model are 4.12, 11.27, 17.14, 23.02 and 26.31 Hz, respectively. In this study, the modified Bouc-Wen model [ ] is used to describe how the damping force is related to the velocity and applied command voltage. The mechanical model for the MR damper based on the Bouc-Wen hysteresis model is shown in Fig. 2. The detailed description and the parameter values of the MR damper model are presented in Dyke *et al.*'s work [ ]. This MR damper model has a maximum generated force of about 1600 N depending on the relative velocity across the MR damper with a saturation voltage of 2.52 V. In numerical analysis, the model of the example structure is subjected to the SE component of the 1997 Gadha Jabalpur earthquake. Because the system under consideration is a scaled model, the earthquake has been reproduced at five times the recoded rate

**Genetic Algorithm (GA)**

The algorithm begins with a set of solutions (chromosomes) that are called the population. Solutions from one

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population are reproduced to create a new generation in the population. Mutations occur randomly in each population. ANFIS is applied for optimization of the premise parameters (input membership functions) and the consequent parameters (output membership function), GA algorithm will search for the best ANFIS configuration based on minimizing the least mean square error between the expected and real output of the network. The set of possible input membership function is {trimf, trapmf, gbellmf, gaussmf}, output membership function is {constant ($z=c_i$), linear ($z=p_iX+q_iY+r_i$)}, the number of membership functions for each input is in range from 2 to 6.
Two groups of randomly selected chromosomes are generated and the chromosome with the best fitness function is picked up from each group. Then these two chromosomes with the offspring produced by crossover operator are sent to next generation. This process continues to fill the next generation completely.
Since the aim of GA is to optimize the membership functions of a predetermined ANFIS structure to reach the lower error; the fitness function is defined as the inversion of the model's MSE (mean square error) between the data and the model output. Thus trying to upraise the fitness value of the model, GA searches for better parameters to reduce the model error.

## III. THE OPTIMIZATION OF ANFIS BASED ON GA

Traditional genetic algorithm has some inevitable defects, for example, the local optimum solution that produced too early can be concentrated and miss the global optimum solution. This paper introduced immune operator which is obtained from immune choice. Immune choice computes the individual density of some group. Through population Refreshing based on density and sufficiency test, the individual better than the parent generation is chosen into the next group. Traditional algorithm chromosome is monolayer and is easily subjected to following defect; the probability of actual intercrossing and variation of short gene in chromosome is too low if the code of chromosome is long.

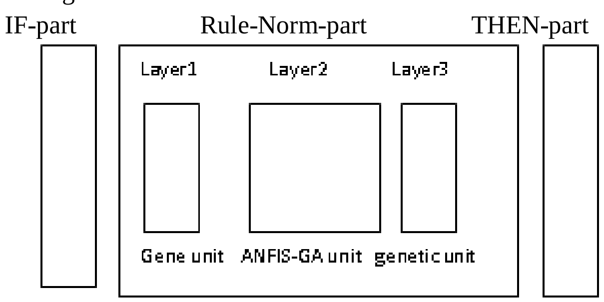



*Fig.3: Chromosome structure*

This paper proposed a chromosome structure with three layers as shown in Fig.3. The first layer is gene unit with Rules-Norm-part of Structure to represent the number of layer Rules-Norm-part in pre-feed backed genetic network. The second layer is ANFIS+GA unit to represent the number of neure under a Rules-Norm-part. The genetic unit of third layer used decimal code to represent all threshold of upper neuron.

## IV. CASE STUDY

A numerical model of the 5-story example building structure with two MR dampers is implemented in SIMULINK and MATLAB. Using this numerical model, time history analyses of 15 seconds with a time step of 0.005 sec are performed in order to investigate the control performance of MR dampers controlled by the MOGA optimized MISO ANFIS. The MOGA based optimization is performed with the population size of 100 individuals. An upper limit on the number of generations is specified to be 1000. As the number of generations increases, the control performance of the elite (i.e. non-dominated) individuals is improved. After optimization run, a set of optimal solutions is obtained. Optimization results show that two objective function values of every solution in optimal record are less than 1. It means that the MOGA optimized MISO-ANFISs can provide better control performance in reducing both displacement and acceleration responses compared to the MIMO fuzzy controller.
Consequently, one controller, that can appropriately control both displacement and acceleration responses, has been selected among the optimal ANFISs. The values of two objectives of the selected ANFIS are both 0.75 and it means that the selected MIMO ANFIS can reduce both the peak 5th floor displacement and acceleration responses by 25%, compared to the MIMO fuzzy controller. The peak responses of the MIMO ANFIS, MIMO FLC controller, and uncontrolled case for the five floors of the seismic-excited example building structure are compared in Table 1.

*Table.1: Comparison of peak story responses.*

| Story | Displacement (cm) | | | | Acceleration ($cm/sec^2$) | | | |
|---|---|---|---|---|---|---|---|---|
| | Uncontrolled | fuzzy | ANFIS | ANFIS+GA | Uncontrolled | fuzzy | ANFIS | ANFIS+GA |
| 1 | 0.340 | 0.101 | 0.115 | 0.1 | 620.6 | 570.3 | 294.8 | 270.5 |
| 2 | 0.601 | 0.198 | 0.181 | 0.17 | 712.1 | 387.5 | 338.9 | 300.3 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **3** | **0.754** | **0.273** | **0.250** | **0.23** | **512..3** | **401.2** | **251.6** | **161.5** |
| **4** | **0.901** | **0.345** | **0.272** | **0.25** | **588.8** | **342.6** | **271.8** | **205.1** |
| **5** | **0.970** | **0.376** | **0.288** | **0.26** | **904.7** | **398.7** | **298.5** | **197.6** |

The peak displacement of the 5th floor of the uncontrolled case is 0.970 cm. On the other hand, the peak displacement of the 5th floor of the MIMO ANFIS is 0.288 cm, which is only 29 % of the uncontrolled case. The peak acceleration of the 5th floor of the MIMO ANFIS is reduced by 71 % compared to the uncontrolled case.

In the elastoplastic analysis of the structure with MR dampers, the frame structure is simulated by the trilinear stiffness degeneration model. The stiffness of each floor changes in the fold line path during the earthquake. The model structure parameters are the mass vector

***m*** = [3.25 3.04 2.88 2.78 2.66] × 104 kg, the initial stiffness vector

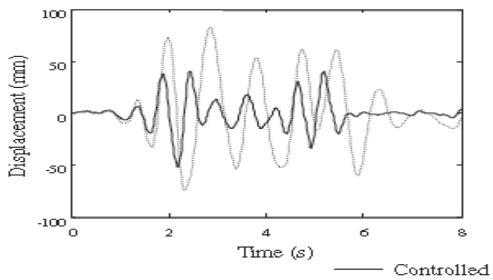
***k*** = [1.82 2.50 2.50 2.50 2.50] × 107 N m−1, the story height

***h*** = [4 3.5 3.5 3.5 3.5] m, the inter-story cracking drifts

**Δ***c* = [6.3 4.9 4.2 3.87 3.75] mm, the inter-story yielding drifts

**Δ***y* = [21.8 18.9 17.2 14.5 11.8] mm.

In this example, the model of the structure is subjected to the south east component of the 1997 Gadha Jabalpur earthquake with 355 gal acceleration amplitude, and the sampling time is 0.025 s, i.e. the delay time. We developed a MATLAB program for the MOGA optimized MIMO-ANFIS control and elastoplastic analysis of the structure with MR dampers.



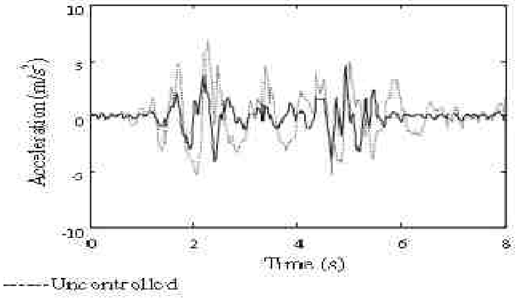




*Fig.4: Response comparison of controlled and uncontrolled structure using MOGA optimized ANFIS+GA.*

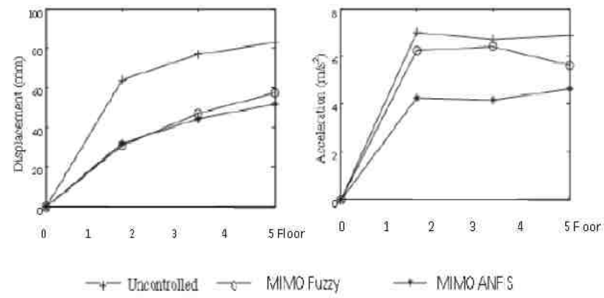



*Fig.5: The maximum responses comparison of each floor.*

The top-floor displacement and acceleration responses of the structure with the MR damper are compared with those of the structure without the MR damper, as shown in figure 4. Both the displacement and the acceleration responses of the controlled structure with the MR damper are reduced effectively. The maximum displacement of the uncontrolled structure is 0.970 cm, while the maximum displacement of the MIMO fuzzy controlled structure is 0.376 cm and of proposed MIMO-ANFIS controlled structure is 0.288 cm for fifth storey. The displacement response is reduced by 29%. The maximum acceleration of the uncontrolled structure is 6.86 m $s^{-2}$, while the maximum acceleration of the controlled structure is 904.7 cm $s^{-2}$ for fifth storey. The peak acceleration of the 5th floor of the MIMO ANFIS is reduced by 71 % compared to the uncontrolled case. It can also be shown that the displacement responses are reduced more effectively than the acceleration responses. This is due to the fact that control forces produced by MR dampers are equivalent to increasing stiffness and damping of structures: both are beneficial to decreasing displacement responses, while increasing of stiffness will possibly increase acceleration responses. Figure 5 compares maximum displacement and maximum acceleration for the uncontrolled structure, the MIMO fuzzy controlled structure and the MIMO-ANFIS controlled structure. Both the displacement and the acceleration responses are reduced effectively when MR dampers are used. At the same time, it can be clearly seen that the MIMO-ANFIS method can reduce the dynamic responses of the structure more effectively than the uncontrolled structure, especially for the acceleration responses. Increasing the control forces blindly is equal to increasing the stiffness and the damping of the structure blindly, which will lead to increase of the dynamic responses, especially for acceleration responses.

## V. CONCLUSIONS

This study investigates the control performance of the MIMO ANFIS optimized by an MOGA for control of a 5-story building subjected to earthquake. For comparison purpose, a MIMO fuzzy control algorithm is considered as the baseline. Based on numerical simulations, it can be seen that the MOGA-optimized MIMO ANFIS+GA can effectively reduce both displacement and acceleration responses of the building structure by 30% compared to the MIMO fuzzy control algorithm. After single optimization run using MATLAB Software, an engineer can simply select another ANFIS that satisfies the desired performance requirements from among a number of optimal solutions. It would be important characteristics of the MOGA based optimization compared to other optimization methods.

In a numerical example, a five-storey smart structure with a MR damper in the first floor is analyzed. Some conclusions can be drawn from the analysis.

(1) The MR damper is a kind of smart damper, and it can reduce the responses of structures effectively.

(2) The MOGA-optimized MIMO ANFIS real-time control method solves the problem of time delay. The responses of the structure with MR dampers by proposed method are smaller than those by the MIMO fuzzy method, especially for the acceleration responses.

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