DESIGN OF ADAPTIVE FUZZY CONTROLLERS USING SCALING FACTORS

Gustavo Luiz C. M. de Abreu
José F. Ribeiro
Universidade Federal de Uberlândia, Centro de Ciências Exatas e Tecnologia, Departamento de Engenharia Mecânica, 38400-089, Uberlândia, MG, Brasil.
E-mails: gmanhaes@mecanica.ufu.br e jribeiro@mecanica.ufu.br

Abstract

This paper deals with a design of adaptive fuzzy controller used in real time for the control of dynamic systems modifying the scaling factors as the adaptation mechanism. The on line adaptation mechanism modifies the scaling factors for the error and change-of-error of the fuzzy controller on the basis of any detected changes. The adaptive controller proposed uses a measure of controller performance as the squared error over the fixed number of sampling times. The efficiency and the potentiality of the theoretical procedure are shown through numerical simulation. The control algorithm is implemented in a computer and the performance of adaptive fuzzy control is evaluated under a set of experimental tests made to the active control of vibrations of a mechanical system of 1 degree of freedom actuated by magnetic bearings.

Keywords: Adaptive Fuzzy Controller, Scaling Factors, Active Control of Vibrations, Mechanical Systems and Magnetic Bearings.

1. INTRODUCTION

In recent years, there has been growing interest in using fuzzy logic for control systems (Ribeiro *et al.*, 1999). Fuzzy logic theory have been considered as effective tools to deal with uncertainties in terms of vagueness, ignorance, and imprecision. This theory is based on a set of rules which sum up people's common sense and experience. The idea of the fuzzy logic is useful for representing linguistic terms numerically and making reliable decisions with ambiguous and imprecise events or facts.

Fuzzy controllers are most suitable for systems that cannot be precisely described by mathematical formulations. In this case, a control designer captures operators knowledge and converts it into a set of fuzzy control rules. The benefit of the simple design procedure of a fuzzy controller leads to the successful applications of a variety of engineering systems (Lee, 1990).

Most of the real-world systems that require automatic control are nonlinear in nature. That is, their parameter values alter as the operating point changes, over time, or both. As conventional control schemes are linear, a controller can only be tuned to give good performance at a particular operating point or for a limited period of time. The controller needs to be retuned if the operating point changes, or retuned periodically if the process changes with time. This necessity to retune has driven the need for adaptive controllers that can automatically retune themselves to match the current process characteristics.

Basically, there are three types of adaptation mechanisms that can be used to modify the parameters of the fuzzy controller and consequently its performance: a) the if-then rules; b) the fuzzy set representing the meaning of linguistic values and c) the scaling factors for each variable.

The first type (a) also called self-organizing controllers can modify an existing set of rules or they can start with no rules at all and "learn" their control strategy as they go. Most reported applications (Shao, 1988) have resorted to heuristic methods for constructing the self-organizing controllers. One idea is to try to identify which rule is responsible for the current poor control performance, and then to replace it with a better rule (Driankov *et al.*, 1996). But it is difficult to develop a control strategy and to calibrate control rules when complex systems are involved. Automatic rule generation and automatic rule calibration are required to overcome the first difficult. Learning capability of neural networks and optimization techniques such as genetic algorithms play the central role (Túpac *et al.*, 1999).

The second type of adaptation mechanism (b) is the tuning mechanism that alters the shapes of the fuzzy sets defining the meaning of linguistic values. There has been some argument (Driankov *et al.*, 1996) that changing the fuzzy set definitions should not be used to tune the controller. The fuzzy set definitions are not arbitrary but are chosen to reflect the meaning of the linguistic values taken by the variables. Recent works have centered on the use of mathematical optimization techniques to alter the shapes of the fuzzy sets so that the output from the fuzzy controller matches a suitable set of reference data as closely as possible (Homaifar *et al.*, 1995). This procedure is carried out off-line and so tunes the controller before it is used. No subsequent on-line adaptation is performed, so the controllers are not strictly adaptive. However, the technique is closely allied to the adaptive methods discussed in Driankov *et al.* (1996), and it has been demonstrated that it can be used on-line (Glorennec, 1991). A truly adaptive fuzzy controller that modifies the shapes of the fuzzy sets on-line has been developed by Bartolini *et al.* (1982) that applied this adaptive controller to the control of a simulation of a continuous casting plant.

The third type (c) is the simplest of the adaptation mechanism schemes and it must be used for the development of fuzzy controllers when the knowledge about the range value of the input variables is not too simple. In this mechanism, the input or output values are mapped onto the universe of discourse of the fuzzy set definitions, and the range value of the input variables is multiplied by a scaling factor. Altering the scaling factor changes the classification of an input value. This reduces the sensitivity of the controller to the input, and so reduces the controller gain (Driankov *et al.*, 1996). Yamashita *et al.* (1988), designed a fuzzy controller with the error and change-of error of the temperature as the inputs, and the change in hydrogen gas flow rate to the reactor as the output. They used the following scheme to automatically increase the controller gain once the operating temperature was reached by altering the scaling factors for the error and change-of-error. Hayashi, (1991) has derived a set of equations for calculating the input and output scaling factors for a PI like a fuzzy controller from the parameters of the first-order model of the process.

This study investigates the use of a adaptation mechanism altering scaling factors to solve the problem concerning the on-line fuzzy logic control. The proposed mechanism can control the vibrations in real-time, for achieving a satisfactory response, of a dynamic system constituted by a vibratory mechanical system of 1 degree of freedom actuated by magnetic bearings.

This paper is divided as follows. In Section 2 we present some basic notions about fuzzy logic controllers. In Section 3 the adaptation mechanism is shown. In Section 4 the control problem is presented. In Section 5 the on-line mechanism is employed to control a vibratory mechanical system and we also present the results of the numerical simulations and a set of experimental tests are made to evaluate the proposed controller action under some operating conditions of the system. The discussion and conclusions are given in Section 6.

2. BASIC CONCEPTS OF FUZZY LOGIC CONTROL

Fuzzy set theory was proposed by Zadeh (1965), and it was employed as an alternative to traditional modeling and control design in order to provide a suitable representation of complex systems.

In order to obtain the control design for a nonlinear or complex dynamic system, there are four basic steps in designing a conventional fuzzy logic controller (FLC) for a physical system: 1) the definition of input/output fuzzy variables; 2) the decision making of fuzzy control rules; 3) fuzzy inference logic, and 4) defuzzification and aggregation (see Fig. 1).

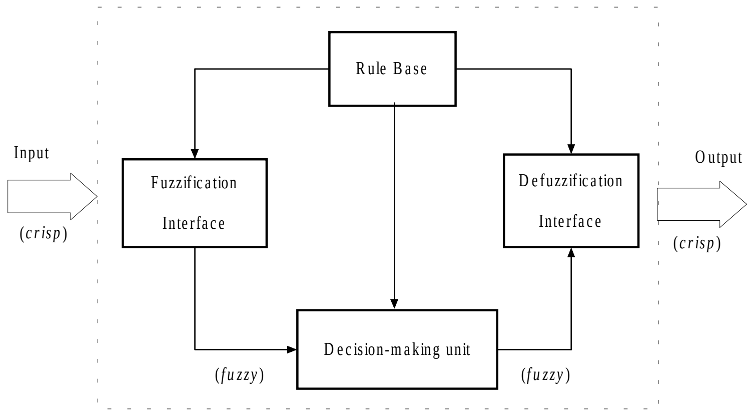

Figure 1. The Fuzzy Inference System.

The inference operations upon fuzzy if-then rules performed by fuzzy inference systems are described as follows.

1. The definition of input/output variables. The input/output variables of a fuzzy controller can be divided into system variables, and linguistic variables. Most fuzzy controllers employ the error and error rate of system variables as the input and the force, voltage or another variable of the control law as the output.

2. The fuzzy control rule is important to the successful operation of the fuzzy control system. The rule base (knowledge base), containing a number of fuzzy if-then rules, is composed as follows:

$$R_i: \quad \textbf{If } x_1 \text{ is } \underbrace{A_{i1}}_{\textit{Antecedent}} \text{ and } x_2 \text{ is } A_{i2} \ldots \text{ and } x_n \text{ is } A_{in} \textbf{ then } \underbrace{y \text{ is } B_i}_{\textit{Consequent}} \quad (1)$$

   where x_1, x_2, ..., x_n and y are system variables and A_{i1}, A_{i2}, ..., A_{in} are linguistic values of the fuzzy variable to express the universe of discourse of the fuzzy sets in the antecedent, and B_i are linguistic values of the fuzzy variable to express the universe of discourse of the fuzzy sets in the consequent, and it describes the output of the system within the fuzzy region specified by the antecedent of the rule.

3. Fuzzy inference logic. The fuzzy inference method based on fuzzy relation composition law (Zadeh, 1965) is employed in this work. This fuzzy inference logic employs the *Max-Min* product composition to operate the fuzzy control rules. The membership values on the premise part to get *weight* of each rule. The specific operator is usually *Min*.

4. Defuzzyfication and aggregation. In order to obtain the correct control input for this control system, it is necessary to defuzzify the fuzzy sets and aggregate the qualified consequent parts to produce a crisp output. In this work, the centroid of area was employed to calculate the final output.

The basic objective, after to construct the controller, is to tune the range of the input variables for achieving a satisfactory response of a dynamic system using the adaptation mechanism described in the next section.

3. ALTERING SCALING FACTORS

The following control scheme can be used to automatically increase or decrease the controller gains once the operating input variables by altering the scaling factors for the error and change-of-error using a performance measure.

The choice of performance measures depends on the type of response the control system designer wishes to achieve. Usually the performance measure is the average of the square error over the previous *k* sampling times. At sample time, *k*, a scaling factor modifier, Ce_k or CCe_k, is calculated as a function of the performance measure, ASE_k or $ASCE_k$, according to the set of linguistic fuzzy rules as for example:

If ASE_k is VERY LARGE ***then*** Ce_k is VERY LARGE

If $ASCE_k$ is SMALL ***then*** CCe_k is VERY SMALL,

for the error and change-of-error, respectively.

The range for the error (*GE*) and change-of-error (*GCE*) are then updated via:

$$\begin{aligned} GE_k &= Ce_k GE_0 \\ GCE_k &= CCe_k GCE_0 \end{aligned} \tag{2}$$

where GE_0 and GCE_0 are fixed initial range values of the fuzzy controller.

These rules for Ce_k and CCe_k can be implemented in a fuzzy scale system (Fig.2). The rules have the effect of increasing the fuzzy controller gain by increasing the scaling factors, as the average squared error decreases as the process is maintained around its set-point.

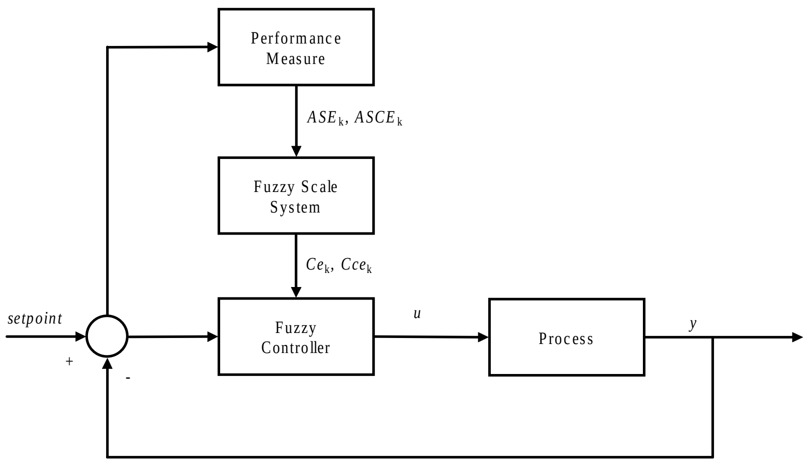

Figure 2. The Adaptive Fuzzy Controller Altering Scaling Factors.

To demonstrate the efficiency of this simple adaptation mechanism, the present scheme is implemented in a computer to control the vibrations, in real-time, of a dynamic system constituted by a vibratory mechanical system of 1 degree of freedom actuated by magnetic bearings described in the next section.

4. THE CONTROL PROBLEM

In this section, the characteristics of a simple dynamic system are shown to illustrate the validity of the adaptation mechanism.

The system is composed of a vibratory mechanical system of 1 degree of freedom, a fuzzy controller, one sensor of proximity that detects its lateral movements, and it is actuated by magnetic bearings that produces the control forces. The physical structure of the mechanical system and all the constituent elements are shown in Fig. 3.

The block diagram of the control system is shown in Fig. 3. The fuzzy controller is implemented on the personal computer. The output of the sensor (X_s) is read by the A/D converter and the sampling period is chosen as 5 [ms]. The computed control signal (v_c) is sent to the current driver (I_1) via a D/A converter and it feeds the solenoids of the magnetic bearing that produces the control force (F).

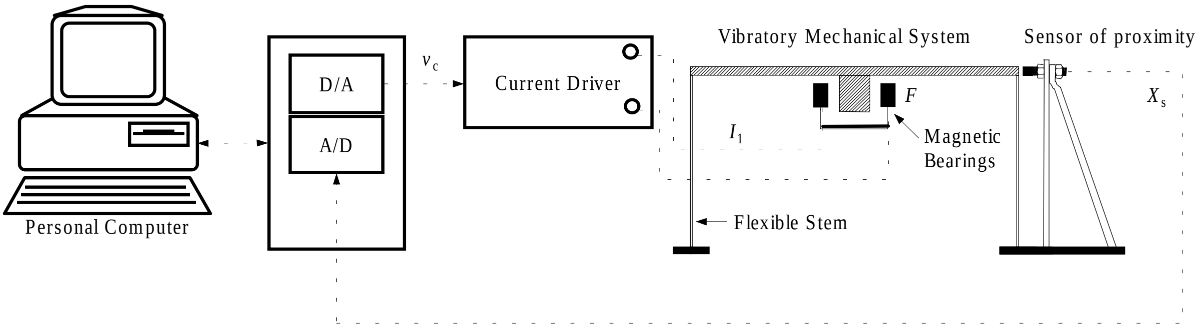

Figure 3. Experimental Setup for implementing the Control Design.

The objective is to use the actuator, which can provide a force F which will bring the system to reduce the amplitudes from an arbitrary initial conditions in minimum time.

The system is modeled by the transfer function of second order described as follows:

$$G(s) = \frac{X(s)}{F(s)} = \frac{\omega_n^2}{s^2 + 2\xi\omega_n + \omega_n^2} \tag{3}$$

where X(s) is the Laplace transformed of the displacement and F(s) is the Laplace transformed of the forces, w_n is the natural frequency, and ξ is the damping.

In Ribeiro *et al*. (1997) are shown the characteristics of the magnetic bearings utilized in this work. The equations of the current driver and sensor of proximity, and the parameters of each component of the physical system were obtained experimentally and are described in detail in Ribeiro *et al.* (1999).

Vibratory system:

(a) Natural Frequency: w_n = 77,5 [rad/s]
(b) Damping: ξ = 7,07E-3
(c) k = 11377,882 N.m^{-1}

Magnetic Actuator:

(a) Pole area: A = 225 mm^2
(b) Number of coils: N = 100 coils
(c) Constant current: i_2 = 0,5 Ampère
(d) Nominal gap: s = 1,5 mm

The sensor of proximity and current driver gains are: k_{sensor} = 2,0 [Volts/mm] and K_{driver} = 0.435 [Ampère/Volts], respectively.

5. NUMERICAL AND EXPERIMENTAL EVALUATION OF THE CONTROLLER

The efficiency of the adaptive fuzzy controller was verified through numerical and experimental simulations to the controlled and not controlled system.

The vibratory system used in the experimental tests is shown in Fig.4.

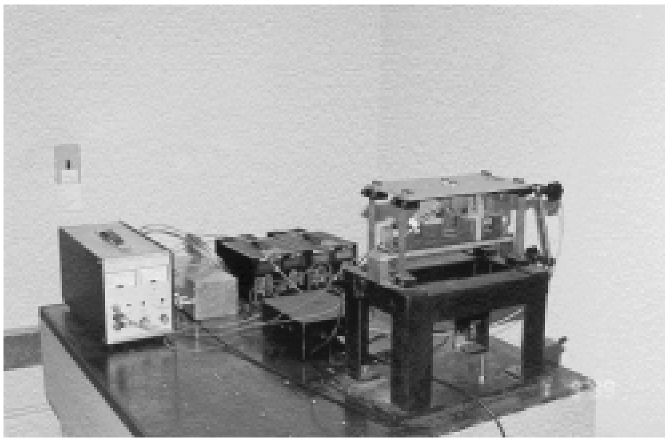

Figure 4. The Experimental Apparatus of the Vibratory Mechanical System.

The numerical simulations of the system were implemented using the simulation software Matlab®. The Fig. 5 shows the block diagram of the close loop system with the adaptive fuzzy controller. The two-input, e(t) and ce(t), and single-output v_c(t) (MISO) control problem is considered in Fig.5. The aim is to maintain a single process-state variable e(t) at set-point r(t).

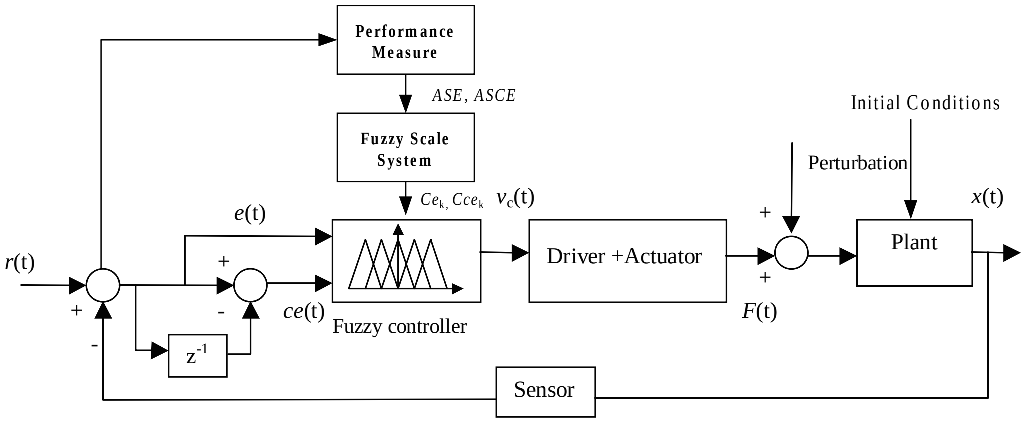

Figure 5. Close Loop System using the Adaptive Fuzzy Controller.

The performance measure uses the average square error (*ASE*) and change-of-error (*ASCE*) as the performance indices calculated over a fixed observation period k = 20 (Eq. 2), and the results are the inputs of the fuzzy scale system (*ASE* and *ASCE*). These inputs are constituted by 4 triangular membership functions (ZERO, LOW, MEDIUM and HIGH) for each one, and the cross-point ratio of all is 0.5.

The universe of discourse of the inputs are: 0 to 1.4 [mm^2] for the *ASE* input and 0 to 6.10^5 [mm^2/s^2] for the *ASCE* input. The universe of discourse of the outputs of the fuzzy scale system are: 0.1 to 1.5 for both outputs (Ce_k and Cce_k) and it was utilized 8 fuzzy inference rules described as follows.

The fuzzy scale system changes the scaling factor of the error Ce_k and the scaling factors of the change-of-error Cce_k depending on the values of the performance indices (*ASE* and *ASCE*).

If *ASE* is ZERO **then** Ce_k is ZERO
If *ASE* is LOW **then** Ce_k is LOW
If *ASE* is MEDIUM **then** Ce_k is MEDIUM
If *ASE* is HIGH **then** Ce_k is HIGH
If *ASCE* is ZERO **then** Cce_k is ZERO
If *ASCE* is LOW **then** Cce_k is LOW
If *ASCE* is MEDIUM **then** Cce_k is MEDIUM
If *ASCE* is HIGH **then** Cce_k is HIGH

The fuzzy controller presents two inputs, $e(t)$ and $ce(t)$ and one output $v_c(t)$. The inputs and output are composed by 7 gauss-shaped membership functions (NH, NM, NS, Z, PS, PM and PH) and the cross-point ratio of all is 0.5. More detail about this parameters see Ribeiro *et al.* (1999). The fuzzy rules base is constituted by 27 rules and are described in Table 1.

Table 1. Fuzzy Rules Base used by Fuzzy Controller.

Error (*e*)

Change-of-error (*Ce*)

	NH	NM	NS	Z	PS	PM	PH
NH	NH			NH			Z
NM		NM		NM		Z	
NS			NS	NS	Z	PM	
Z	NH	NM	NS	Z	PS	PM	PH
PS		PS	Z	PS	PS		
PM		Z		PM		PM	
PH	Z			PH			PH

The not controlled system is shown in Fig. 6 and to evaluate the efficiency of the fuzzy controller, the plant was simulated numerically and experimentally. The results are shown in Fig. 6, where solid and dashed curves correspond to the experimentally and numerically controlled system respectively. The numerical initial conditions to [*e*, *ce*] were [0 mm, 5E-2 mm/s] and it was applied a impulsive force, as a perturbation, to excite the experimental system. The initial ranges utilized to $e(t)$ and $ce(t)$ were [-50 Volts, 50 Volts] and [-100 Volts/s, 100 Volts/s] respectively. The final ranges to these input variables were [-12.5 Volts, 12.5 Volts] and [-25 Volts/s, 25 Volts/s], respectively to both numerical and experimental results. It is remarkable to note how the controller can reduce the amplitudes from the initial conditions in minimum time.

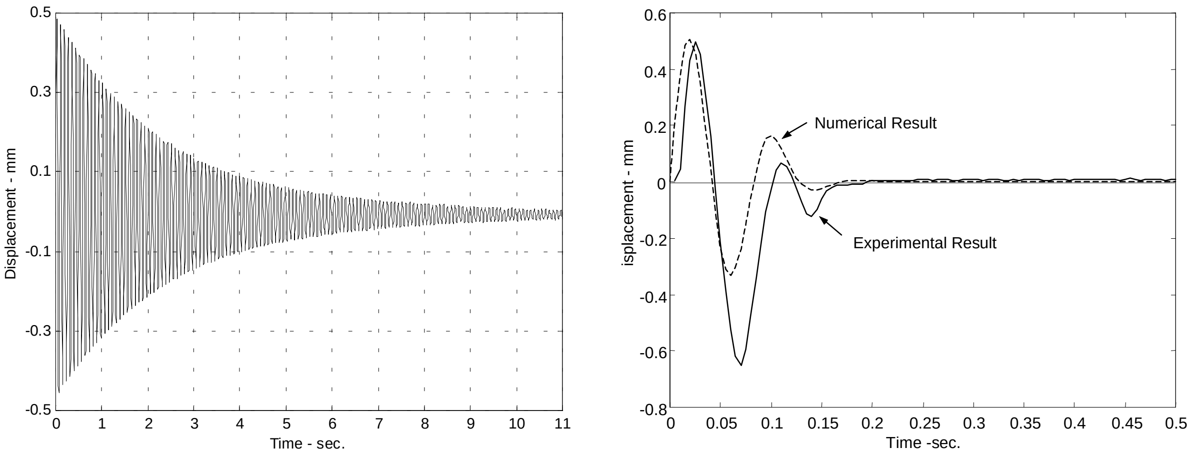

Figure 6. Not controlled System and the Experimentally and Numerically Controlled System.

6. CONCLUSIONS

The adaptive fuzzy controller altering scaling factors as the adaptation mechanism presented in the paper is suitable for real-time control and posses a quite strong ability to self-tuning the range of the input variables using the average square error and change-of-error as the performance indices. All the trial experiments showed that the controller has satisfying performance of the initial range of the fuzzy input variables. The present control scheme represents an interesting tool for the development of fuzzy controllers when the knowledge about the range value of the input variables is not too simple. The fuzzy control proposed in this paper is certainly the simplest approach to adaptive fuzzy control which has proved itself through present application study. The on-line fuzzy self-organizing controller and its control algorithm constitutes the next implementation for this work.

7. ACKNOWLEDGEMENTS

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