On Using Fuzzy Logic to Integrate Learning Mechanisms in an Electro-Hydraulic System—Part II: Actuator's Position Control

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Abstract—**In Part I of this paper, fuzzy modeling showed its potential to describe the behavior of the electro-hydraulic system. To verify the possibilities of its application for the system's learning control, two inverse-model compensation schemes were implemented. This paper describes and discusses the experimental results obtained, showing the feasibility and effectiveness of the learning controllers in: generalizing their previously acquired knowledge to possible new trajectories, their ability to learn new rules and update their fuzzy models while functioning, and how they compensate changes in the system's dynamics caused by the variation of the parameters and/or environment perturbations on it.**

I. Introduction

PART I of this paper dealt with the fuzzy modeling of the electro-hydraulic actuator. This second part of the paper describes the application of its fuzzy model and associated learning mechanism to control of the actuator position. Two different control topologies were implemented. The first one was a "direct compensation control" or "feedforward control" [1]. In this control scheme, the inverse model of the process operates in series with the system to achieve, in an ideal situation, a complete compensation. This type of controller has had impact mainly in the development of control systems for robotic manipulators, and more recently in the development of feedforward control schemes using neural networks [2], [3].

The second implemented control topology was based on the "feedback-error-learning" structure proposed in [4]. This controller derives from the result of the association of a conventional closed-loop regulator with a feedforward control scheme. This control topology have been used mainly in neural-network systems, for instance: the control of an automatic braking system to an automobile [5] and the control of robotic manipulators [6]–[9].

A. Learning Control Configurations: Overview

Learning control systems are characterized by the ability of improve their future performance based on past experiences by closed-loop interactions between the system and the environment in which it is placed. Such systems begin to exhibit "intelligent" characteristics in their behavior, which, as shown in the first part of the paper, implies that the control system retains characteristics as memory, adaptation, and generalization abilities.

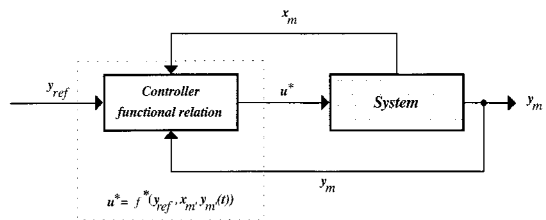

Fig. 1. Functional relation with a controller function.

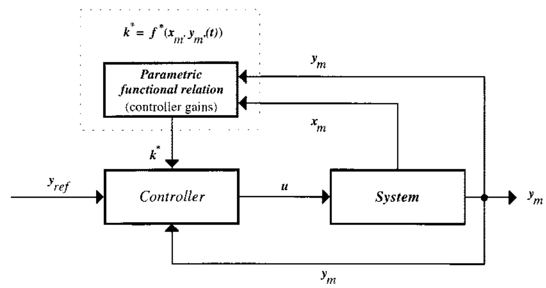

Fig. 2. Parametric functional relation establishing the controller gain values.

The goal of a learning controller is to look for a functional relation between the system states and those desired as response with the objective of acquire a high performance in its designed function. The main configurations found for the learning controllers are as follows.

1) *Configuration 1:* ***Controller*** (see Fig. 1). A controller that relates the system states $(\mathbf{x}_m, \mathbf{y}_m)$ and the reference signal $\mathbf{y}_{\mathrm{ref}}$ to an appropriate set of command actions $\mathbf{u}^*$ [10]–[13]. This functional relation can contain, or not, the time variable t. As we will see later, this will be the configuration implemented in this work.
2) *Configuration 2:* ***Parametric functional relation (controller gains)*** (see Fig. 2). This configuration is composed of a parametric functional relation that establishes the gain set $\mathbf{k}^*$ [14], [15]. These gains are employed by the system controller that now actuates in separate. As in the previous configuration, the parametric functional relation can contain, or not, the time variable t.
3) *Configuration 3:* ***Parametric functional relation (state variables)*** (see Fig. 3). A parametric functional relation estimates the system state variables $\mathbf{x}_m^*$ [16] that are used to design the controller, which sends the command signal $\mathbf{u}$ to the system.

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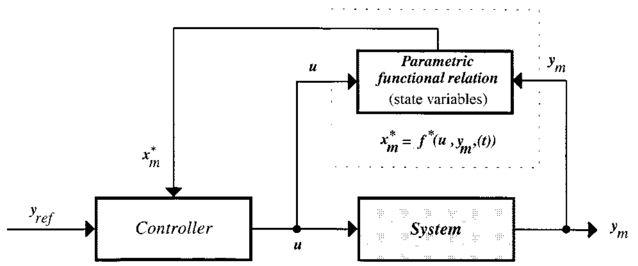

Fig. 3. Parametric functional relation estimating the internal system state variables to the controller design.

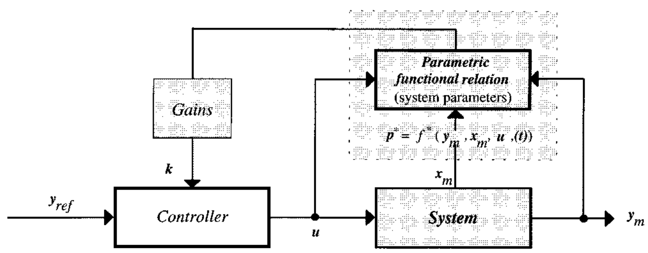

Fig. 4. Parametric functional relation estimating the system parameter values.

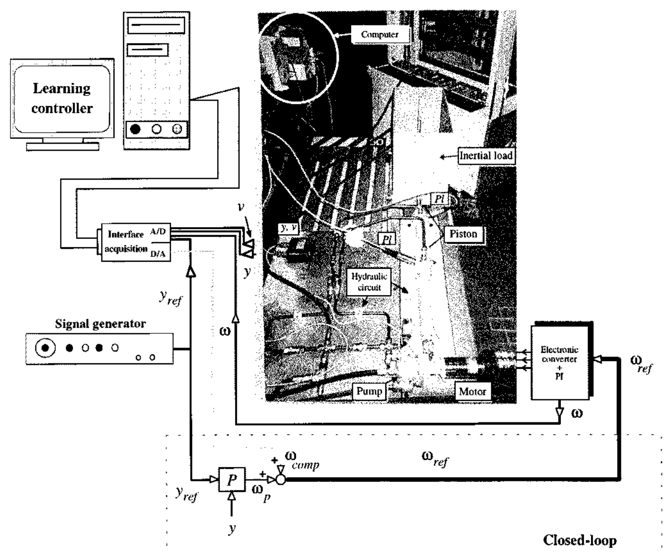

Fig. 5. Electro-hydraulic system with the position control diagram.

4) *Configuration 4:* ***Parametric functional relation (system parameters)*** (see Fig. 4). A parametric functional relation that relates the system operating conditions $(\mathbf{x}_m, \mathbf{y}_m, \mathbf{u}_m)$ with its parameters $\mathbf{p}^*$ to compute the system controller gains [17].

B. Controllers' Implementation Considerations

1) Laboratorial Prototype: A microcomputer with a data acquisition interface has been used in the implementation of the learning controllers, as shown in Fig. 5. All computations were made in real-time, in C language, using the sensor signals acquired from the electro-hydraulic system by the data acquisition interface. At each sampling time, the controller performs the following tasks.

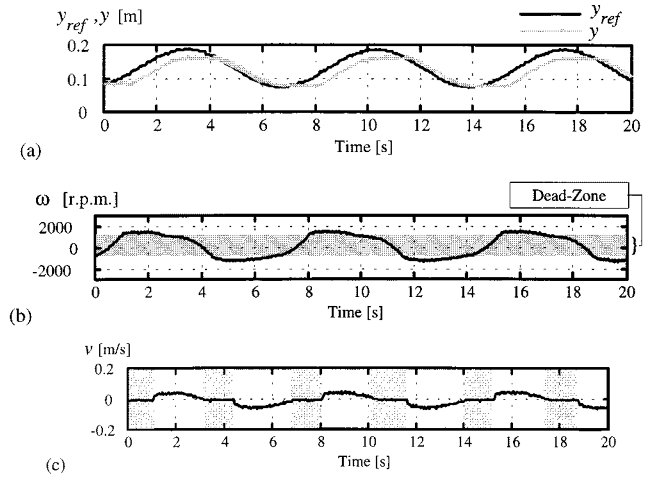

Fig. 6. Electro-hydraulic system commanded only by the proportional regulator. (a) Piston position (y) and reference (y_{ref}), (b) pump speed (ω), and (c) piston speed (v).

- *Acquisition of the system signals:* Piston position y and piston speed v, motor speed ω (considered equal to the speed of hydraulic pump). The reference piston position y_{ref} is obtained from a signal generator by the A/D interface as indicated in Fig. 5.
- *Control algorithm:* Signals sampled from the actuator are codified in a rule set by the learning algorithm using the fuzzy simplified algorithm that was described in the first part of the paper, developed by Wang [19]. The extracted rules are used to update the fuzzy model thus optimizing the already accumulated knowledge.
- *Inference mechanism:* After modifying the rules or including new rules in the model, the control system uses the inference mechanism on the rule-base to generate the compensation signal.

Fig. 6 shows the performance of the electro-hydraulic actuator when using the proportional regulator with a sinusoidal reference position signal (y_{ref}). Fig. 6(a) shows the piston position and its reference signal. Fig. 6(b) shows the speed of the hydraulic pump, and Fig. 6(c) shows the piston speed. The results show that, when operating in closed-loop, the piston follows its reference signal with an asymmetric delay and with an accentuated position error caused by the use of a proportional regulator. The presence of the asymmetric response is caused by the nonlinear characteristic of the pump in the hydraulic system. When the pump operates in the dead-zone, marked in Fig. 6(b), the electromechanical subsystem remains decoupled from the hydraulic one. This makes almost null the stream debited by the pump without inducing enough pressure in the piston to move it. The time intervals where the piston remains immobile are indicated in Fig. 6(c), which correspond to the intervals where the pump operates into the dead-zone.

In the Part I of this paper, we verified the effects on the actuator's fuzzy modeling if the training data were sparsely distributed in the domain. A simple solution was considered to replace the null rules that appear in this situation with interpolative rules. However, solutions like that one require high com-

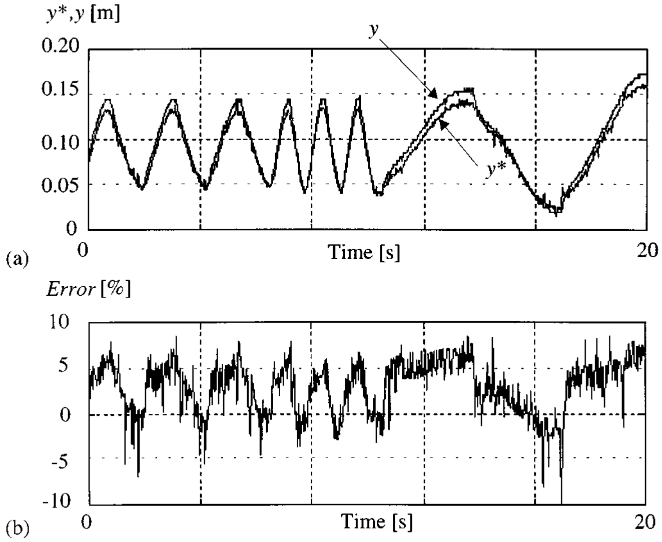

Fig. 7. Fuzzy model performance without learning the new actuator dynamics acquired after coupling a significant load in the piston. (a) Position inferred (y^*) and measured (y) and (b) error signal.

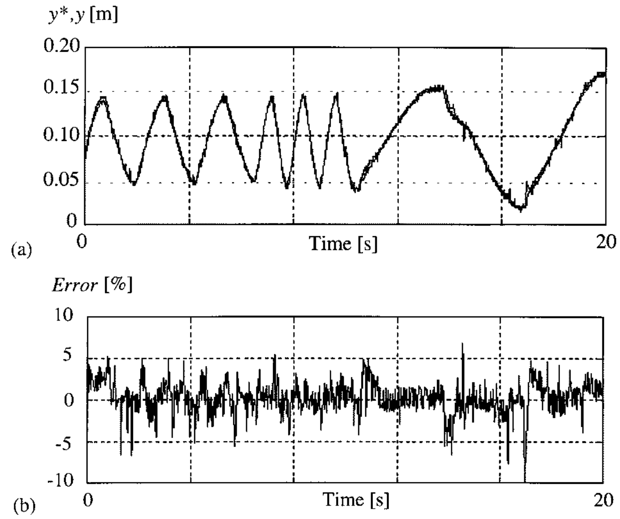

Fig. 8. Fuzzy model performance after present to the learning process new examples characterizing the actuator dynamics for a significant applied load. (a) Position inferred (y^*) and measured (y) and (b) error signal.

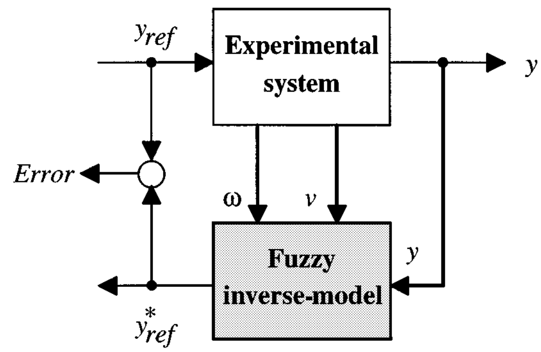

Fig. 9. Acquisition scheme of the inverse relation $y^*_{\rm ref} = g^*(y, \omega, v)$.

putational times when they have to operate in real-time. Such solutions would be practical if used in a process with slow dynamics that would not need to update repeatedly the model, or if interpolation is used off-line to previously optimize the fuzzy model.

2) Fuzzy Model Updating: Learning systems using fuzzy logic methodologies must be able to acquire new rules and to modify those already extracted to improve their performance, and thus learn about the changes occurred in the system and/or its environment. In the next results, we verify the updating ability of the learning system in modify the fuzzy rules to express some new behavior acquired by the electro-hydraulic actuator. The results of Fig. 7(a) show the fuzzy model response y^* when data obtained from the unloaded actuator was presented to the learning system during the training stage, and during the test stage it was used a data set acquired with a significant load applied. Since the extracted rules did not contain the representation of the new actuator dynamics obtained after coupling a significant load, large modeling errors appeared, as can be seen in the error signal shown in Fig. 7(b).

Suppose now that some examples, containing information about the new actuator dynamics, are supplied to the learning algorithm. The learning algorithm has to be able to interpret this new information and incorporate it in the rule-base to achieve more precise position values inferred from the fuzzy model. As proved by the new results in Fig. 8(a) and (b), also comparing with the previous results in Fig. 7(a) and (b), the learning algorithm modified the rules updating the model to the new actuator dynamics, which reduced the error signal.

Apart from presenting a consecutive learning operation, the controller requires the inverse model of the electro-hydraulic system to be used in the compensation loop. This aspect is now dealt with.

3) Inverse Model Acquisition: To obtain the inverse model of the electro-hydraulic system described by the functional relation $y^*_{\rm ref} = g^*(y, \omega, v)$, we considered the scheme shown in Fig. 9. Using the fuzzy algorithm and the training set, Fig. 10(a) shows the position reference $(y_{\rm ref})$ and the signal inferred from the inverse model $(y^*_{\rm ref})$, verifying that large oscillations have occurred in the error, as shown in Fig. 10(b). The error remained high during the time intervals where the piston changed its direction. In this case, the hydraulic pump inverted its rotation. Therefore, if the actuator operates during some time into the dead-zone, an inverse model could not be defined and so the model performance becomes deteriorated, resulting in the high modeling errors.

After presenting in this section the main aspects related with the implementation of the learning controllers (laboratorial prototype, fuzzy model updating, and inverse model acquisition), we describe next the experimental results obtained with the first controller topology, the direct compensation scheme or feedforward controller.

II. Direct Compensation

In a direct compensation scheme, the inverse model of the electro-hydraulic system is used in a command in series with the experimental system, as shown in Fig. 11. Before its experimental implementation, this scheme was tested using the fuzzy direct and the fuzzy inverse models already extracted. As both

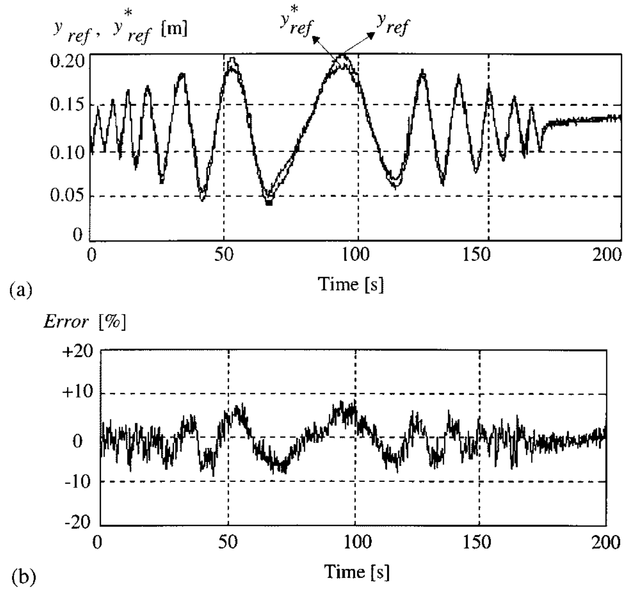

Fig. 10. (a) Position reference $(y_{\rm ref})$ demanded to the system and the one inferred by the inverse relation $y^*_{\rm ref} = g^*(y, \omega, v)$ and (b) error signal characterized by large oscillations since an inverse relation cannot be defined in the dead-zone.

models were obtained from the same experimental data, this test will show the influence of some aspects of the fuzzy inverse model to the compensation performance.

A. Simulated Direct Compensation

Fig. 6(a) showed that the electro-hydraulic system presents an asymmetric behavior caused by the dead-zone in the hydraulic pump. Similar to these results, the fuzzy direct model also shows the same asymmetric behavior, as indicated by its error signal displayed in Fig. 12.

Fig. 13 shows the simulated direct compensation scheme, which uses the fuzzy direct model in series with the fuzzy inverse model. In the figure, the inverse model is given by

$$y^*_{\rm ref} = g^*(y_{\rm ref}, \omega, v) \tag{1}$$

which sends the compensation signal $y^*_{\rm ref}$ as the command signal to the direct model given by

$$y^* = f^*(y^*_{\rm ref}, \omega, v) \tag{2}$$

that generates the position signal y^* to follow its reference $y^*_{\rm ref}$. If the relation (1) is the exact inverse relation of (2), a complete compensation between the two models can be effectuated, making the position signal y^* follow its reference $y_{\rm ref}$ with a null error.

The results of the simulated direct compensation are shown in Fig. 14 by the error signal between $y_{\rm ref}$ and the position inferred from the direct model y^*. It can be verified by comparing these results with those obtained in Fig. 12 that the compensation resulted in a significant decreasing of the error, although with an obtained partial compensation. If only a memorization process had been used for the representation of each model, the direct compensation would be perfect zeroing the error. Nevertheless, the inverse model employs a generalization process which performance depends on the extracted rules, apart from the appearance of errors when the fuzzy model has deficiencies in certain rules, which are obtained from domain regions where the examples were not sufficient to establish an expressive local representation of the system's behavior. The compensation performed still shows large errors caused by the lack of an inverse model when functioning into the dead-zone of the pump. This case results in a performance deterioration of the model, which affects the compensation process.

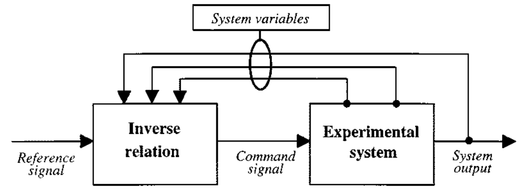

Fig. 11. Direct compensation diagram (feedforward controller).

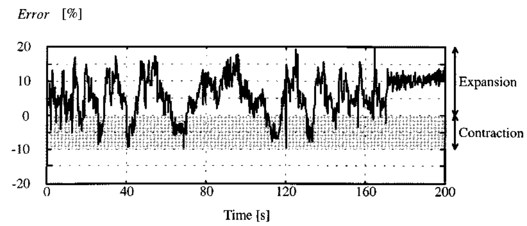

Fig. 12. Error characterizing the asymmetric behavior of the direct fuzzy model.

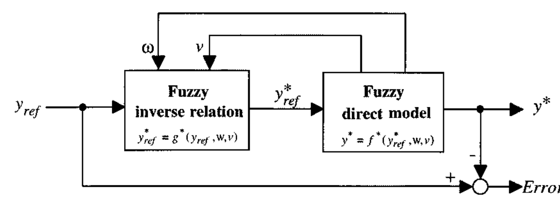

Fig. 13. Diagram of the simulated direct compensation controller.

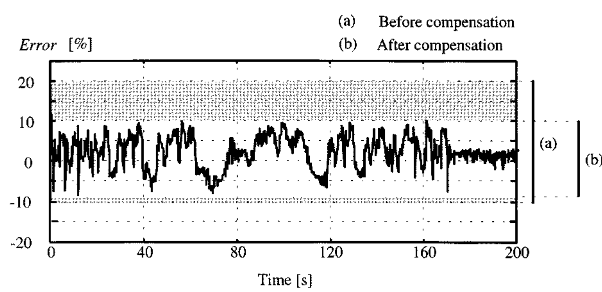

Fig. 14. Error before and after the compensation.

B. Experimental Direct Compensation

Despite the large errors obtained in the previous simulations, this section verifies the direct compensation scheme in the command of the electro-hydraulic system.

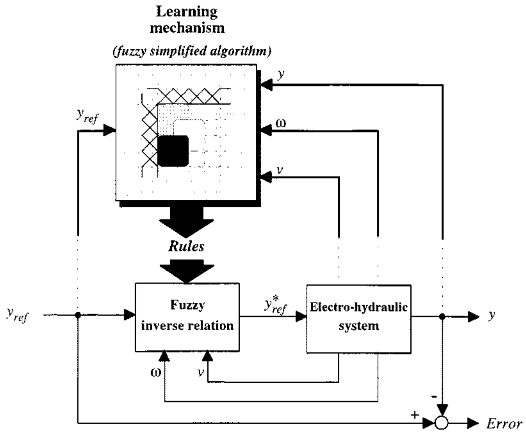

Fig. 15. Diagram of implemented direct compensation learning controller.

The inverse model is initially composed by the fuzzy rules obtained during the training stage with the fuzzy simplified algorithm. Each rule has a form like

$$R^{(l)}\text{: }\textbf{If }\left(y \text{ is } A_1^{(l)} \textbf{ and } \omega \text{ is } A_2^{(l)} \textbf{ and } v \text{ is } A_3^{(l)}\right) \\ \textbf{Then } y_{\text{ref}}^* \text{ is } \omega^{(l)} \tag{3}$$

which represents a local relation between the functioning condition observed from the actuator by the signals y, ω, and v, and respective command signal y_{ref}^*. Hence, for a certain position value requested to the piston, together with the information of its speed and the pump speed signal, the inverse model represented by

$$y_{\text{ref}}^* = g^*(y, \omega, v) \tag{4}$$

gives the command signal that is imposed to the actuator in order to conduct the piston to its reference.

To implement the direct compensation controller, as illustrated in Fig. 15, together with the learning mechanism, the position signal y in (4) has to be replaced by the reference position, y_{ref}, with the compensation signal y_{ref}^* given by

$$y_{\text{ref}}^* = g^*(y_{\text{ref}}, \omega, v). \tag{5}$$

Two experiments were performed with the actuator. The first one did not include the learning mechanism of the fuzzy simplified algorithm in the compensation. In the second experiment, the learning mechanism operating in real-time was included. The controller can thus consider the signals measured from the actuator during its operation and modify some rules, or even incorporate new ones.

1) First Experiment: Direct Compensation Without Learning: To evaluate the implemented direct compensation, Fig. 16 shows the piston position when the control loop includes only the proportional regulator. In Fig. 17, we show the results obtained with the direct compensation using a reference signal with the same amplitude and frequency values of the sinusoidal signal used before in Fig. 16. Since this experiment did not consider the learning mode, the control system could not use any experimental information acquired during the system's operation to update the inverse model. The results obtained in Fig. 17(a) show that the achieved compensation remained incomplete in certain functioning regions. These results indicate the need to improve, complete, or even correct the set of rules that are related with those operating regions showing large errors. More experimental data must be acquired about the system's functioning in these regions, and thus incorporate them in the inverse model through the learning mechanism reducing the error position.

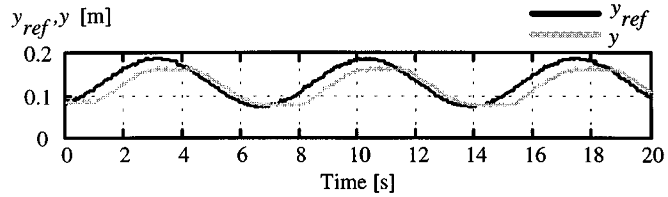

Fig. 16. Piston position (y) and its reference (y_{ref}) when the system is commanded only by the proportional regulator.

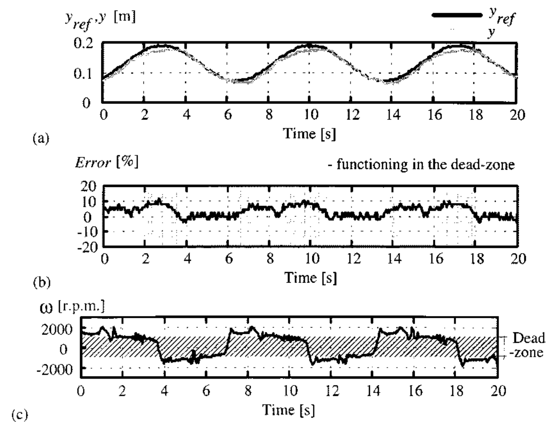

Fig. 17. Experimental direct compensation without the learning mode. (a) Piston position (y) and reference (y_{ref}), (b) error signal, and (c) pump speed (ω).

In Fig. 17(b), the regions marked in gray indicate the time intervals where the electro-hydraulic system operates into the dead-zone, which is indicated in Fig. 17(c). The impossibility of defining an inverse model when operating in the dead-zone generates large control errors. The compensation signals generated in these situations remain thus incorrect, deviating the piston position of its reference, as also shown in the simulation essays.

2) Second Experiment: Direct Compensation with Learning: The results given in Fig. 18 were obtained considering the presence of the learning mode in the control system. As can be observed by the system's performance in Fig. 18(a) and by the respective error in Fig. 18(b), the acquisition of more experimental data allowed the adjustment of some of the deficient rules, which improved the global performance of the system, approaching the piston position to its reference. Comparing the error signal obtained in this experiment [Fig. 18(b)] with that one obtained without the learning mode [Fig. 17(b)], it is important to observe that the system continues to show, in a periodic way, a set of large errors, even before the action of the learning algorithm. In both experiments, as the dead-zone of the nonlinear pump characteristic is asymmetric, it is verified that when the piston is expanding, the pump speed, in order to

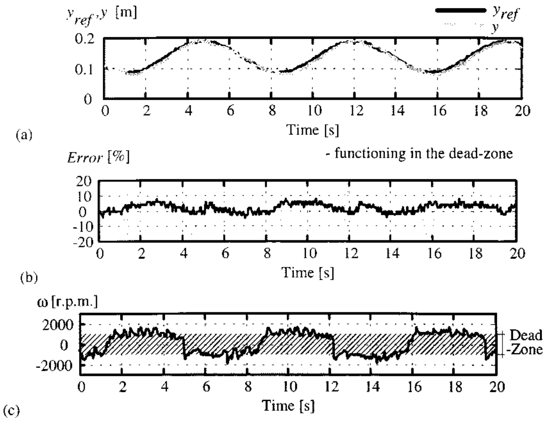

Fig. 18. Experimental direct compensation with the learning mode. (a) Piston position (y) and reference $(y_{\rm ref})$, (b) error signal, and (c) pump speed (ω).

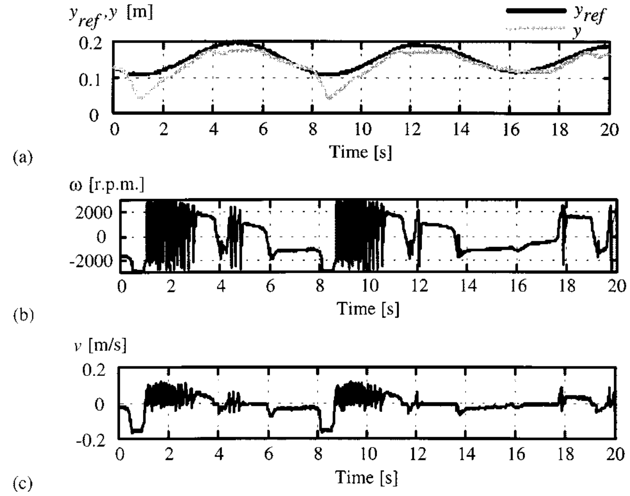

Fig. 19. Actuator instabilities appearing during the experimental compensation test. (a) Piston position (y) and reference $(y_{\rm ref})$, (b) pump speed (ω), and (c) piston displacement speed (v).

surpass the dead-zone, has to reach higher values than those needed when the piston moves in the opposite direction since the dimension of the dead-zone is smaller [see Figs. 17(c) and 18(c)]. As part of the compensation signal action is eliminated by the dead-zone, these effects become more accentuated when the piston is expanding, increasing the error signal, and less accentuated when the piston is contracting, reducing the position error, as shown in Figs. 17(b) and 18(b).

We also see in Fig. 18(c) that the presence of the learning mechanism in this experiment produced a compensation signal which magnitude was enough to bring the speed of the hydraulic pump out of the dead-zone during a large number of periods. This almost did not happen in the experiment without the learning mode shown in Fig. 17, resulting now in a better position control that approaches the piston further to its reference signal.

In the direction of piston expansion, the dead-zone is larger and so the pump operates most of the time in its border, as shown in Fig. 18(c). During some periods, the compensator lets the piston closer to its reference, and sometimes lets the piston to enter in the dead-zone, which makes ineffective the compensation signal action. In the direction of piston contraction, the pump operates most of the time out of the dead-zone since it has a smaller width. This eliminates the nonlinear effects of the dead-zone, conducting the error position to zero values, as shown in Fig. 18(b).

C. Unstable Behavior in the Actuator

Each compensation cycle together with the learning algorithm presents a computation time of about 200 ms. To counteract this delay time in the compensator action, it was implemented a simple solution consisting in adding to each compensation signal a certain quantity linearly extrapolated, based on the difference between the compensation signal computed in the actual control cycle and the value computed in the previous one. Balancing the computation time leads, however, to large oscillations in some system variables, as shown in Fig. 19. The results were obtained during one of the experimental tests and exhibit the appearing of large oscillations in the pump speed [Fig. 19(b)]. The piston speed in Fig. 19(c) also shows significant oscillations, although in a smaller magnitude because of the attenuation effects introduced by the pump's dead-zone. Depending of the oscillations magnitude, they cause large deviations of the piston position from its reference, as we can verify in Fig. 19(a) during some periods.

The verified unstable behavior during the direct compensation tests is characteristic of this type of control systems [1]. The resulting global dynamics of the system remains dominated by poles of the system that were not compensated by the inverse model, since it not represents the exact inverse relation, and they pass to determine the new system's behavior. The oscillatory behavior shows that is necessary to use a more stable control topology.

III. Indirect Compensation

The implementation of the direct compensation scheme revealed large oscillations leading the electro-hydraulic system to unstable behaviors. These effects appear in these control schemes independently of the type of models used, for instance, the models obtained with the bi-orthogonal decomposition described in [8] and in models using neural networks [3]. Because of this behavior, we opted to use a more stable control structure [4] that results from the association of a conventional closed-loop controller with a direct compensator (feedforward controller). As illustrated in Fig. 20, the command signal sent to the experimental system is formed by the addition of the compensation signal generated by the inverse model plus the signal generated from the conventional controller in the closed-loop. In this unsupervised configuration, the feedforward controller has the purpose of compensating the system nonlinearities, while the conventional controller works to attenuate possible instabilities and reduce the error since the direct compensation mechanism is not perfect.

A. Experimental Verification of the Unsupervised Indirect Compensation

The implemented indirect compensation scheme with the presence of the learning mechanism is shown in Fig. 21. The

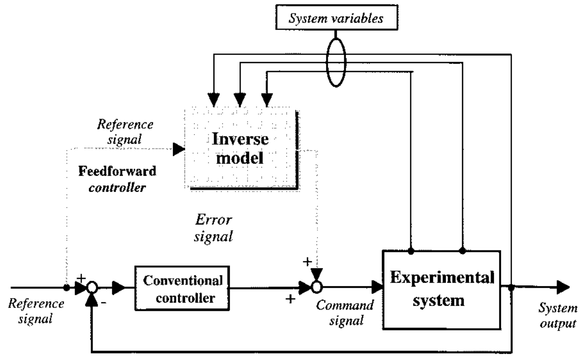

Fig. 20. Indirect compensation scheme.

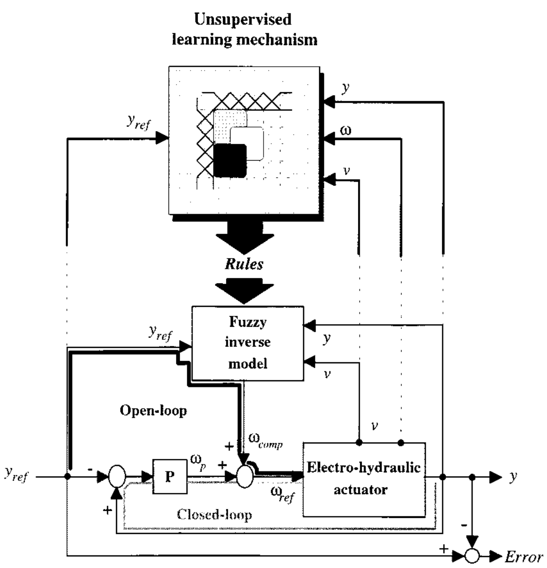

Fig. 21. Indirect compensation scheme implemented using the unsupervised learning mechanism of the fuzzy simplified algorithm.

learning algorithm, which operates in an unsupervised way, uses the signals of the reference position $(y_{\rm ref})$, piston speed (v), pump speed (ω), and piston position (y) to extract the inverse model given by

$$\omega_{\rm comp} = h^*(y_{\rm ref}, v, y). \tag{6}$$

Fig. 21 shows the two control loops forming the indirect compensation scheme: the closed-loop made by the proportional regulator (P) and the direct compensation loop formed by the fuzzy inverse model (6). The command signal $\omega_{\rm ref}$ sent to the electro-hydraulic actuator is obtained by the addition of the closed-loop signal generated by the proportional regulator, ω_p, plus the compensation signal, $\omega_{\rm comp}$, produced by the inverse relation resulting in

$$\omega_{\rm ref} = \omega_p + \omega_{\rm comp}. \tag{7}$$

During each experiment, the inverse relation (6) is again characterized by a set of rules extracted through the fuzzy algorithm during the training stage. Each rule expresses a local relation between the reference signal applied to the system, $y_{\rm ref}$, the piston speed v and position y, and the pump speed value ω, which is

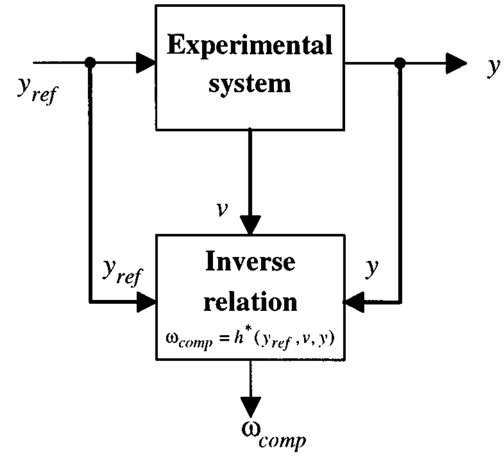

Fig. 22. Acquisition of the inverse relation $\omega_{\rm comp} = h^*(y_{\rm ref}, v, y)$.

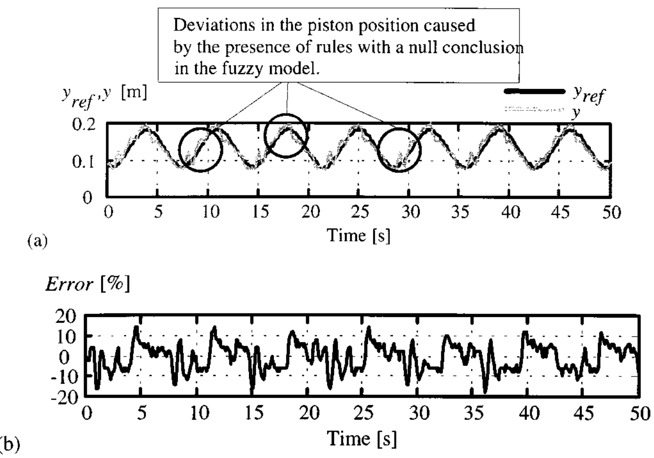

Fig. 23. Actuator performance when some rules of the fuzzy model were randomly perturbed setting their conclusion to a zero value. Results without learning. (a) Piston position (y) and reference $(y_{\rm ref})$ and (b) error signal.

employed as the compensation signal $\omega_{\rm comp}$ after the inference process, as shown in Fig. 22.

In the beginning of each control cycle, the computer acquires experimental information about the actuator's working condition by reading the sensor signals $y_{\rm ref}, v, y$, and ω. The learning mechanism uses these signals to modify the fuzzy rules and/or to complete those rules that could not be extracted during the training stage. After learning, the controller, using the inference mechanism together with the signals $y_{\rm ref}, y$, and v acquired from the system, generates the compensation signal $\omega_{\rm comp}$ that is added to the signal of the proportional controller to form the command signal $\omega_{\rm ref}$ to the drive system.

After describing the functioning stages of the indirect compensation, several experiments were carried out to analyze the potential of this compensator.

1) Experiment 1: Incomplete Model: This experiment verifies the ability of the learning mechanism to complete the fuzzy model when some rules could not be extracted during the training stage. The sinusoidal reference signal has a frequency and amplitude values that are intermediate to those ones used in the training. In the first results shown in Fig. 23, the learning mechanism was not activated, and so the model had to be

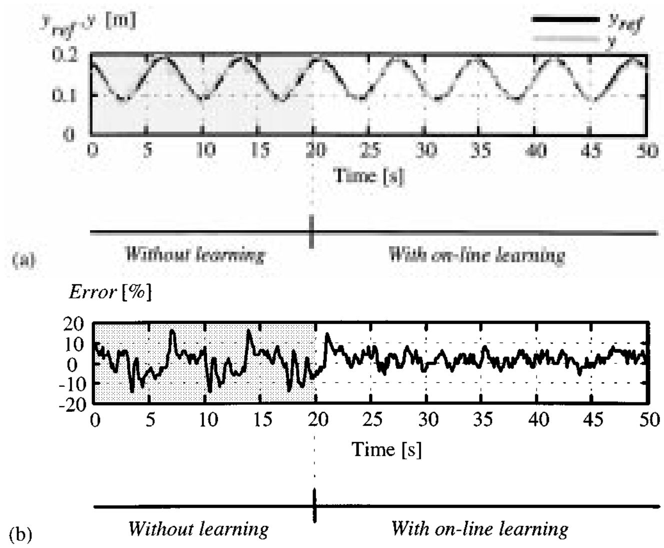

Fig. 24. Actuator performance using the incomplete fuzzy model. Transition between this condition and the action of the learning mechanism in updating the rules. (a) Piston position (y) and reference $(y_{\rm ref})$ and (b) error signal.

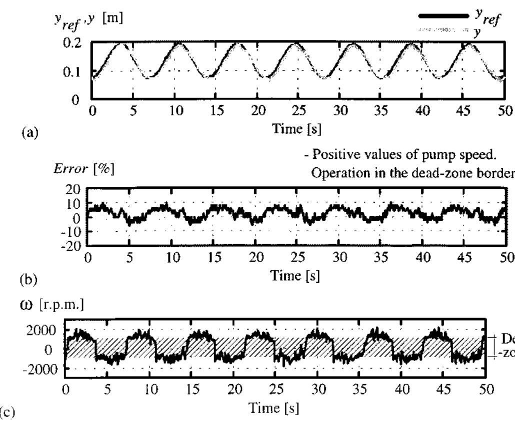

Fig. 25. Actuator performance in stationary regime after inserting the learning mechanism in the control system. (a) Piston position (y) and reference $(y_{\rm ref})$, (b) error signal, and (c) pump speed (ω).

able to generalize its response based only on the previously extracted rules. The electro-hydraulic actuator initially operates with some rules of the fuzzy model randomly perturbed. This consisted in replacing the conclusion of some rules with a null value, simulating the case where the lack of data in some domain regions generated rules without conclusion in the fuzzy model, making it incomplete. When the system operates in the regions where the rules had their conclusion set to zero, the compensation signal is deviated from its correct value, which deviated the piston position from its reference, as verified in Fig. 23(a) and in the obtained error in Fig. 23(b).

Next, the system performance is verified when it initially operates with the incomplete model and its performance after introducing the learning mode to update the model and thus to correct possible disturbances in the system. Fig. 24 shows the compensation system functioning without the learning mode until about 20 s. At this instant, the computer begins to use the experimental information acquired from the system as its go forward, and starts completing and/or correcting the rules using the learning algorithm. Disturbances that appeared before in the piston position decreased as indicated by its error in Fig. 24(b). The rules that were perturbed with a null conclusion were being completed as new system's data was being acquired in their domain regions.

For the case where the reference signal had a shape different from a sinusoidal one, the disturbances in the piston position could be more attenuated or stronger depending on whether the location of the system's operating point was in the domain regions covered by the rules with null conclusions, or not. The same effect could occur respecting the time that the learning mechanism takes to complete the empty rules. If the system operates for long in the areas that were empty before, new data will be acquired faster for the learning mechanism correct the rules and thus eliminate the oscillations in the piston position.

The results in Fig. 25 show the actuator in a stationary regime after the learning transitory period of Fig. 24. The obtained error signal is shown in Fig. 25(b). It is characterized by accentuated values that are periodically established through the beginning of the piston movement in its expanding direction. The regions marked in gray indicate the intervals where the pump operated with a positive speed in the dead-zone border. As for positive speed values, the dead-zone has a larger amplitude than for the negative ones [see Fig. 25(c)], the pump operates in its interior during a large number of time intervals. For this case, almost no fluid was delivered to the hydraulic circuit. Therefore, the piston did not move, which increased the position error, as shown in Fig. 25(b). On the other hand, the hydraulic pump has negative speed values in the time intervals out of the gray areas. Thus, as dead-zone is narrower in these regions, the pump delivered fluid for longer to the hydraulic circuit, which moved the piston. Consequently, the error position decreased during these periods, as shown in Fig. 25(b).

2) Test 2: Incomplete Model (Triangular Reference Signal): This experiment used a triangular reference signal to verify the compensator performance with a signal presenting a larger frequency spectrum. The inverse model was initially perturbed, as before. As shown in Fig. 26(a) and (b), the control system operates with the perturbed model and without the learning mode in the initial 20 s. After that, the controller started to acquire experimental data and used the learning algorithm to complete the empty rules, also updating the set of undisturbed rules reducing the trajectory error.

The learning mode activation caused a transitory period in the control system that is indicated in the results of Fig. 26(b) and (c). During this period, the fuzzy model induced oscillations in the piston position through the compensation signal. This happened because of its discreteness and also caused by the modifications introduced in its rules by the learning algorithm. After this period, the error signal showed again a periodic behavior similar to that of Fig. 25, which was caused by the effect of the asymmetric dead-zone.

3) Experiment 3: Indirect Compensation Without Learning: After verifying the learning performance in updating the incomplete fuzzy model, this experiment used the complete model. The control system operated initially with only the proportional regulator presenting an accentuated

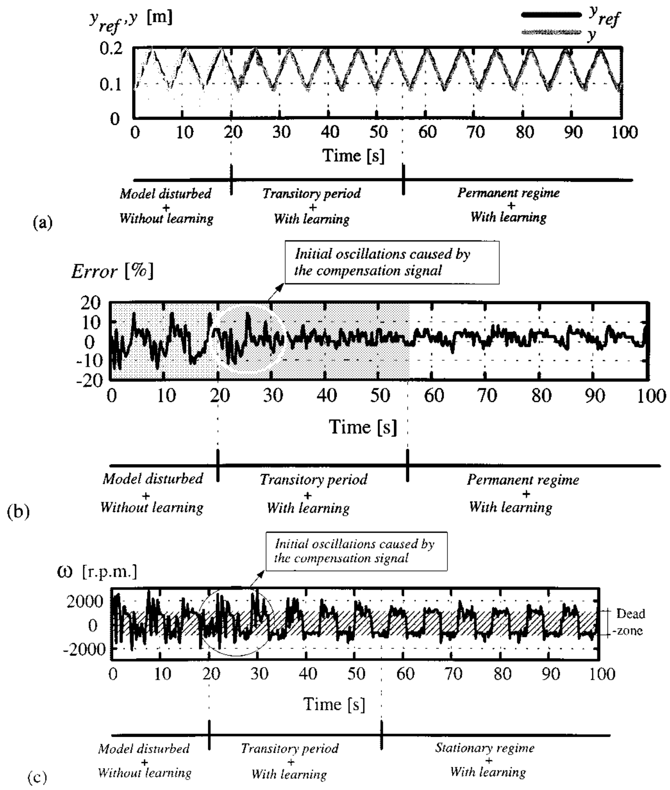

Fig. 26. Actuator performance for a triangular reference signal and an incomplete model. Transition period after inserting the learning mechanism and its evolution in permanent regime. (a) Piston position (y) and reference $(y_{\rm ref})$, (b) error signal, and (c) pump speed (ω).

trajectory error. After, the compensator is activated and its signal added to the proportional regulator signal but without the learning mode. Fig. 27(a) shows the piston position after the addition of the compensation signal. Note that during an initial period, indicated in the figure by the gray area, the system went on to adapt itself, mainly compensating the effect of the nonlinear pump characteristic on its global performance. The obtained gradual error reduction is shown in Fig. 27(b) until the stationary regime is reached. Because during this experiment the fuzzy rules were not updated by the learning mechanism, the error remained around 5%.

4) Experiment 4: Indirect Compensation Scheme with Learning: This experiment shows the electro-hydraulic system when initially the compensator is not present in the control system, and after when it is included and the learning mechanism started to update the inverse model. The use of such a simple controller, as the proportional regulator, makes the electro-hydraulic system very dependent on the precision that the fuzzy model approaches to the "exact" system's model. In the results shown in Fig. 28, the filled region marks the time interval where only the proportional regulator controls the piston position. The regulator did not achieve a compensation of the dominant nonlinearity, which resulted in large position errors, as shown in Fig. 28(a) and (b).

The compensation signal and the learning mechanism were included together with the proportional regulator. As the learning mechanism started to use the actuator's data to correct the fuzzy model, the compensation signal conducted the piston

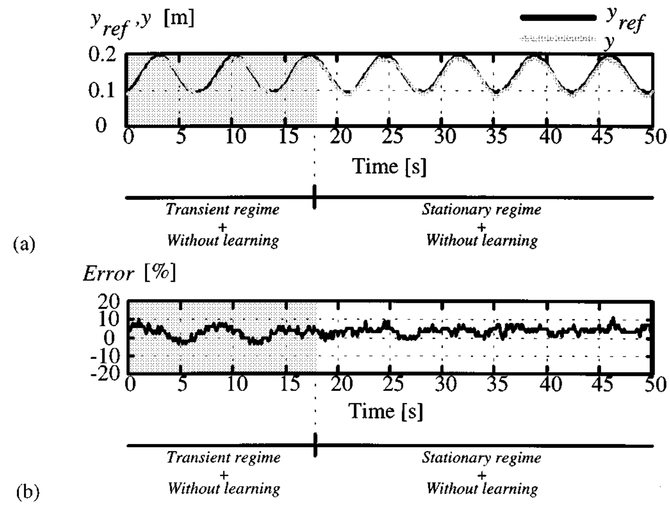

Fig. 27. Performance of the electro-hydraulic system when the compensation signal is added to the proportional regulator signal. In this experiment, the model was not perturbed and the learning mode is not present. (a) Piston position (y) and reference $(y_{\rm ref})$ and (b) error signal.

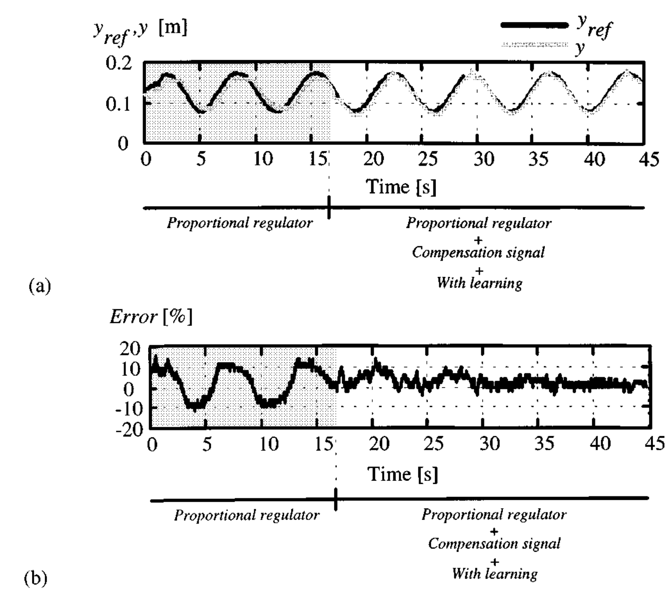

Fig. 28. Actuator performance after inserting the compensator and the learning mechanism. (a) Piston position (y) and reference $(y_{\rm ref})$ and (b) error signal.

position to its reference reducing the error to values near 2.5%, as Fig. 28(b) shows.

5) Experiment 5: Changes in Actuator Dynamics: Every control system with learning properties must adapt itself to changes occurring in the process dynamics caused by variations in its parameters, or by changes imposed by the environment where the system is inserted. To verify this potential, a set of experiments was effectuated to show the adaptable character of the control system to new operating conditions of the electro-hydraulic system.

During the experimental essays, we observed that the actuator dynamics changed significatively with the load magnitude coupled to the piston, with the pressure value of the hydraulic accumulator, and with the system's operating temperature. To

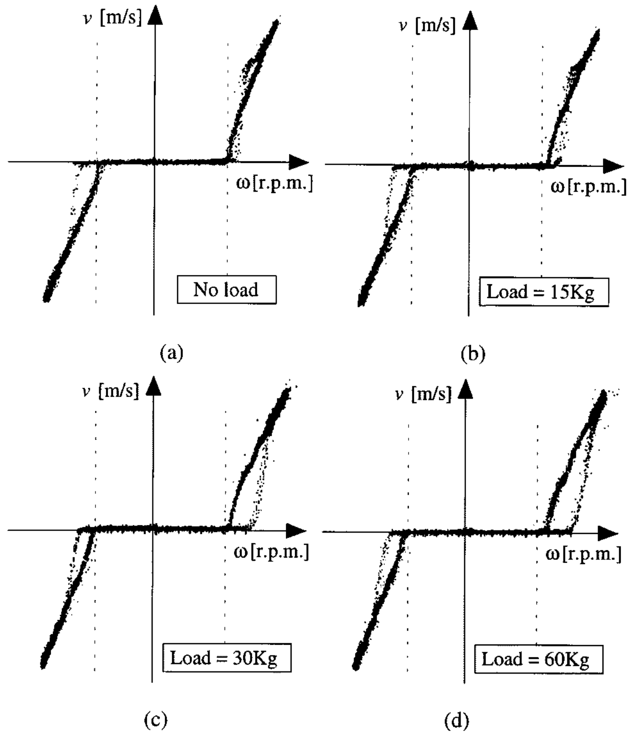

Fig. 29. Relations $v \times \omega$ showing the changes in actuator dynamics after increasing the load. (a) Characteristic without a significant load, (b) load value of 15 Kg, (c) 30 Kg, and (d) 60 Kg.

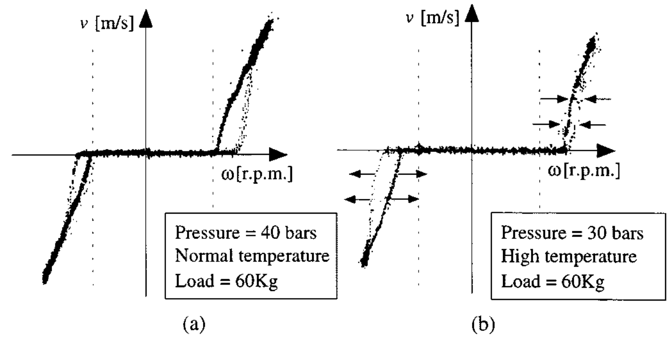

Fig. 30. Relations $v \times \omega$ after a continuous operation of 4 h. (a) Characteristic obtained in the initial stage of the essay and (b) after a operation of 4 h.

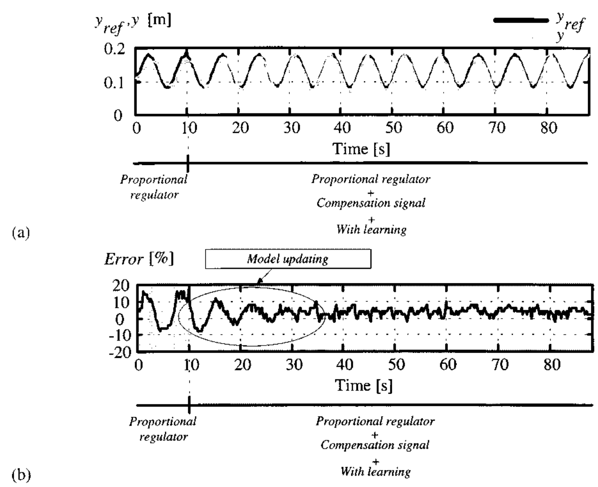

Fig. 31. Actuator performance after learning the new dynamic imposed by a higher piston load. The compensator action reduces the error signal. (a) Piston position (y) and reference $(y_{\rm ref})$ and (b) error signal.

illustrate these facts, Fig. 29 shows a set of experimental characteristics $v \times \omega$ relating the piston speed with the pump speed. They show the changes in actuator dynamics when the load applied to the piston was increased from an initial unload case until a load with 60 Kg. During those essays, the pressure at the hydraulic accumulator remained constant at 40 bars, and with the system keeping a temperature approximate to the environment one (≈25 °C). These facts show the need of the controller to have some ability to self-adjust, updating itself to new operating conditions and acquiring some functioning autonomy.

The characteristic shown in Fig. 29(a) was obtained without load coupled to the piston, while the other curves were obtained increasing it. All figures show two dotted lines that set the limits of the dead-zone. The sequence of figures show that, as the load increases and therefore the total system inertia, the pump operates with high-speed values that remain out of the dead-zone for longer. Because of the increasing system's inertia and the decoupling effect caused by the dead-zone, the hysteresis regions in the characteristic were also expanded.

When the actuator functioned during large time periods, it achieved high temperatures with the hydraulic accumulator pressure decreasing from 40 bars to 30 bars. The modifications provoked in the system dynamics are shown in Fig. 30. The initial $v \times \omega$ characteristic, repeated in Fig. 30(a), was obtained with a normal working pressure of 40 bars, a temperature close to the environment, and with a load value of 60 Kg. After an essay where the actuator worked continuously for four hours, the accumulator pressure decreased to values about 30 bars, and the system temperature increased very much. Using data acquired during this experiment, Fig. 30(b) shows the new characteristic $v \times \omega$, which characterizes the new dynamics. The pump gets higher speeds when it remains longer out of the dead-zone. The system behavior is also affected by the pressure decreasing, as well as by the hydraulic fluid working at high temperatures, which changes its compressibility factor. These effects also decreased the hysteresis region to positive speed values, and caused a widening of the hysteresis to negative speed values, as shown in Fig. 30(b).

6) Load Changes: We describe in the following essays the system performance when changes occur in the actuator dynamics caused by a load increase, and the learning mechanism starts to update the fuzzy model to incorporate the new behavior, adjusting the compensation signal.

In Fig. 31, the electro-hydraulic system had an applied load with a value two times higher than the one used during the training stage. As the load applied to the piston has higher values, the learning mechanism needs to acquire new data values from the actuator to "relearn" the new system's behavior. The control system operates during the initial 10 s using only the proportional regulator. Next, the compensation loop is incorporated in the control system. The learning mechanism takes some time to update the rules and then incorporate the new dynamics derived from load increasing into the model. As shown in Fig. 31(b), the compensation signal was corrected

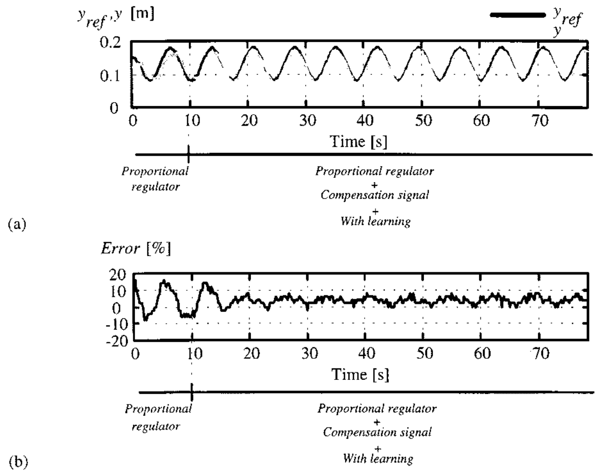

Fig. 32. Increasing the load caused the pump to get higher speed values. Therefore, as the actuator operates much of the time out of the dead-zone, the compensation signal had a small attenuation, resulting in a fast speed compensation. (a) Piston position (y) and reference $(y_{\rm ref})$ and (b) error signal.

approaching the piston to its reference position and thus reducing the error signal.

The results in Fig. 32 correspond to a second experiment that used a higher load than the previous one. Results show that the error signal decreases faster. However, this was not caused by acceleration of the learning mechanism. Presenting a higher load, the system achieves higher pump speed values, operating usually out of the dead-zone. The compensation signal now being not so attenuated by the presence of the dead-zone, had a higher influence in the approximation of piston position to its reference.

The actuator continued to present an error offset in the permanent regime as can be seen in Fig. 32(b). This continued to be caused by the periods where the system operates into the dead-zone and the compensator has its performance deteriorated by the nonexistence of an inverse relation in this zone. Moreover, as referred in the first part of the paper, the pressure signal P_l, when there is a substantial load at the piston, becomes a relevant variable for the electro-hydraulic system's description. As in these tests, we did not consider the pressure signal in the definition of the fuzzy inverse relation; this aspect also contributed to the large error values in the stationary regime.

IV. Conclusion

After the analysis about fuzzy modeling the electro-hydraulic system mode in the first part of the paper, we presented the application of acquired fuzzy model in its learning position control. With this objective, two control topologies were implemented. The first one consisted in the direct compensation control scheme or feedforward control. In spite of the stability problems known about these controllers, these first tests allowed us to enhance the potentialities that the introduction of learning mechanisms represent to the actuator's control.

A second control scheme studied, and usually used as a standard topology in the test of these learning control methodologies, consisted in the scheme named as indirect compensation. This scheme combines the direct compensator with a closed-loop formed by a conventional regulator that stabilizes the system. The experimental results obtained with this topology showed the abilities that these control systems provide to the actuator. It adapts itself to changes in its dynamics, acquiring therefore some autonomy in its functioning.

The difficulties found in the experimental tests, namely in the real-time implementation of these controllers, can be surpassed using faster computational means. Moreover, in electro-hydraulic drive systems, their dynamics can be separated in a fast and slow dynamic in which one can easily perform.

The possibilities that the incorporation of learning mechanisms based on fuzzy logic can represent to drive systems, in general, are an expansion of the conventional controllers already implemented, as well their adaptation to new system conditions without the need to completely replace the conventional controller, or even design a new one. This will bring economy and trust to already implemented systems.

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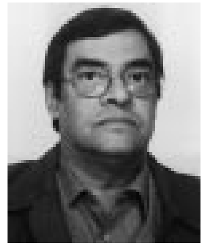
Dr. Costa Branco is included in *Who's Who in the World*.



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