ABCM Symposium Series in Mechatronics - Vol. 1 - pp.418-427

ADAPTIVE FUZZY CONTROL FOR UNDERWATER HYDRAULIC MANIPULATORS

Leonardo Bittencourt Testi
Robotic and Automation Laboratory – COPPE/UFRJ
Federal University of Rio de Janeiro - UFRJ
P.O. Box 68.503– CEP 21.945-970 – Rio de Janeiro, RJ, Brazil
testi@labrob.coppe.ufrj.br

Bruno Cardozo dos Santos
Robotic and Automation Laboratory – COPPE/UFRJ
bcsantos@labrob.coppe.ufrj.br

Max Suell Dutra
Robotic and Automation Laboratory – COPPE/UFRJ
maxdutra@ufrj.br

Abstract. *Underwater hydraulic manipulators are usually systems hard to be modeled and present strong non-linearities in its dynamics behavior. These types of manipulators are operated, nowadays, in a master-slave configuration with simple control algorithms performing tasks in hazardous and unstructured environments. In such conditions only low accuracy simple tasks can be performed. This paper presents the application of a special fuzzy controller in a hydraulic manipulator commonly used in offshore missions. This controller is able to cope with changes in the system parameters adapting itself to a desired system performance. A non-linear analysis of the manipulator's dynamics is developed. Results of simulations comparing the adaptive fuzzy control and a conventional control are also provided.*
Keywords. *fuzzy control, adaptive control, hydraulic manipulators, underwater.*

1. Introduction

Underwater manipulators mounted on remotely operated vehicles (ROVs) have an important role to play in deepwater activities for the oil and gas industry, in military and exploration missions. Nowadays, the use of these manipulators is based mainly in the concept of teleoperation using a master-slave configuration. The operator controls the manipulator (slave) moving a smaller master arm installed in a safe location distant to the worksite. A video cam mounted near the slave manipulator provides images of the work environment allowing the operator to realize the tasks. However, teleoperation present drawbacks that reduce its efficiency. The operator's work is made difficult by the poor quality of the video image and lack of sensibility of what's really happening in the remote location, permitting him to perform only relatively simple tasks.

One step forward in teleoperation would be the accomplishment of tasks in a teleassisted way. This would allow the manipulator to perform tasks like positioning or trajectory following automatically, only supervised by the operator. However in the way to do that it's necessary to introduce a more sophisticated control than the one currently used since the manipulator operates in hazardous and unstructured environments and it's submitted to unknown and continuously changing conditions, that simple controllers are incapable of deal. Teleoperation avoids this problem permitting the operator to adjust the errors induced by the poor controller observing the slave arm with the cam and adjusting its position moving the master arm. Another difficult arises from the actuation system used by underwater manipulators; most of them are hydraulic actuated because of the robustness and good relation force/weight. This also means a further trouble to the control because its dynamics has non-linearities and factors that difficult an accurate positioning of the actuator, like compressibility of the fluid and leakage in the piston's seals. Recently there is an effort to adapt industrial electrical manipulators to operate underwater, but we are still far away to see them working.

The purpose of this paper is to simulate the application, in an underwater hydraulic manipulator, of a control capable to deal with the non-linearities of a hydraulic actuated system and also able to coping with changes in the system's parameters, always maintaining a suitable performance. The control here utilized is a fuzzy control referenced by Layne (1996) as Fuzzy Model Reference Learning Control (FMRLC). In the last years fuzzy controllers has demonstrated to be an effective alternative to conventional controllers, especially when one is interested in controlling systems with non-linearities and/or hard to be modeled. In fact there are many successful cases of fuzzy applications, like air conditioning systems, anti-lock brakes, chemical mixer, elevator control, camera autofocus, and even on robotics systems. Sepehri (1999) already showed a fuzzy control applied in a hydraulic actuated industrial robot. This papers goes further, showing as a simple but powerful algorithm can control in an effective way a hydraulic manipulator with variations on its parameters.

The control here presented is to be used in an independent joint control scheme, where the manipulator is regarded as formed by independent joints and each joint being controlled as a single-input-single-output system. Coupling effect between the joints would be treated as disturbances in the system. In this paper only one joint was modeled but for a full control of the manipulator the same scheme can be applied to the remaining joints.

The paper consists in a kinematics and dynamic analysis of a manipulator's specific joint, a non-linear modeling of the hydraulic actuators, an explanation about fuzzy control and the FMRLC, and finally the simulation results followed by a conclusion chapter.

2. Underwater hydraulic manipulator model

The model here presented was based on the Kraft Grips manipulator, widespread used on underwater operations. It's a six-degree of freedom manipulator with an anthropomorphic configuration, which allows the operator to work in a more instinctive way. This manipulator has to be installed on a remote operated vehicle to utilize its facilities like pressure line, video cam and electronic bottle. Rack-and-pinion rotating actuators, except for the wrist rotation, make all the manipulator's movements. Each actuator is controlled by servo-valves, and position sensing is done by potentiometers installed in the joints. An electronic circuit installed in the ROV's electronic bottle executes a simple control algorithm that sends signals to the servo-valves based on the error between the slave and master position of each joint.

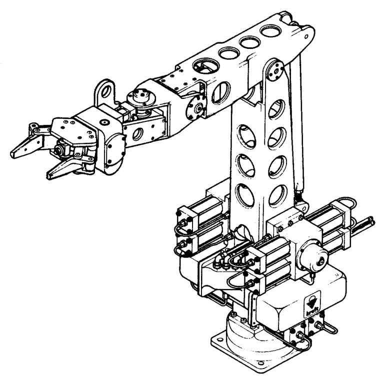

Figure 1. Kraft Grips Manipulator.

2.1. Mechanical system model

The system to be modeled represents the elbow pivot of the Kraft Grips manipulator. This joint presents a great difficult to model as the shoulder elevation joint movement induces motion on it. It's formed by a closed chain that increases its stiffness, reducing the manipulator inertia, but also difficults its kinematics analysis. This joint is actuated through a four bar linkage where q, θ_2, θ_3 and θ_4 are the bars angles and l_1, l_2, l_3, l_4 its lengths, as shown in Fig. (2).

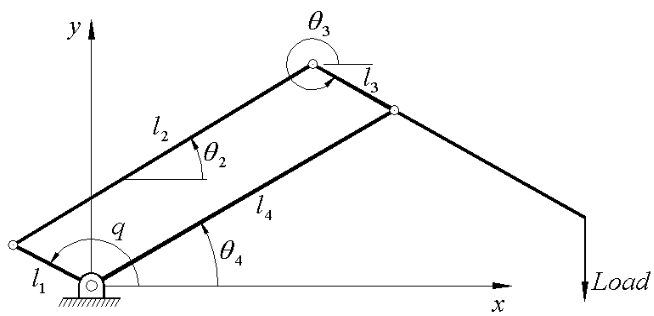

Figure 2. Schematic view of Kraft elbow joint mechanism.

The angle θ_4 is maintained constant because just the elbow's joint mechanism was simulated. It's appropriate to define the angle q as the input variable, because the bar l_1 is the one that is actuated by the hydraulic piston. The four-bar linkage is a single degree of freedom mechanism, so it is fully determined when the input q is specified.

The values of the secondary variables θ_2 and θ_3 were determined from the following position loop equations:

$$\begin{cases} l_1 \cos(q) + l_2 \cos(\theta_2) + l_3 \cos(\theta_3) - l_4 \cos(\theta_4) = 0 \\ l_1 sin(q) + l_2 sin(\theta_2) + l_3 sin(\theta_3) - l_4 sin(\theta_4) = 0 \end{cases} \tag{1}$$

The velocity loop equations are determined by differentiating the position loop equations:

$$\begin{Bmatrix}\dot{\theta}_2\\ \dot{\theta}_3\end{Bmatrix}=\begin{bmatrix}-l_2 sin(\theta_2) & -l_3 sin(\theta_3)\\ l_2\cos(\theta_2) & l_2\cos(\theta_3)\end{bmatrix}^{-1}\dot{q}\begin{Bmatrix}l_1 sin(q)\\ -l_1\cos(q)\end{Bmatrix} \tag{2}$$

The velocity coefficients may be determined by dividing the velocity by $\dot{q}$:

$$\begin{Bmatrix}K_{\theta 2}\\ K_{\theta 3}\end{Bmatrix}=\frac{1}{\dot{q}}\begin{Bmatrix}\dot{\theta}_2\\ \dot{\theta}_3\end{Bmatrix} \tag{3}$$

Time differentiation of the velocity loop equations provides the acceleration loop equation:

$$\begin{Bmatrix}\ddot{\theta}_2\\ \ddot{\theta}_3\end{Bmatrix}=\ddot{q}\begin{Bmatrix}K_{\theta 2}\\ K_{\theta 3}\end{Bmatrix}+\dot{q}^2\begin{Bmatrix}L_{\theta 2}\\ L_{\theta 3}\end{Bmatrix} \tag{4}$$

where:

$$\begin{Bmatrix}L_{\theta 2}\\ L_{\theta 3}\end{Bmatrix}=\frac{d}{dq}\begin{Bmatrix}K_{\theta 2}\\ K_{\theta 3}\end{Bmatrix} \tag{5}$$

is known as velocity coefficient derivatives. Similar procedure allows calculating, for any point of the mechanism, the x and y speed and acceleration's components. Then is possible to determinate its coefficients.

According to Conservation of Energy's Principle the work done on a mechanical system is equal to the change on its kinetic energy. The differential form of this principle can be written as:

$$Power=\frac{d(KineticEnergy)}{dt} \tag{6}$$

The kinetic energy is:

$$T=0.5I(q)\dot{q}^2 \tag{7}$$

where the generalized inertia *I(q)* isn't constant. Differentiating the kinetic energy with respect to time and equating this result to the power expression, it's obtained the equation of motion in Eksergian's form:

$$I(q)\ddot{q}+0.5\frac{d(I(q))}{dq}\dot{q}^2=Q \tag{8}$$

where Q is the generalized force composed by two parts, one conservative $dV(q)/dq$ and the other non-conservative (Q_{nc}). This is an appropriate form to account the potential energy

$$I(q)\ddot{q}+0.5\frac{d(I(q))}{dq}\dot{q}^2+\frac{dV(q)}{dq}=Q_{nc} \tag{9}$$

$V(q)$ is the potential energy due the bar's masses and the payload, its differentiation with respect to q is:

$$\frac{d(V)}{dq}=\left(M_1.K_{y1}+M_2.K_{y2}+M_3.K_{y3a}+Load.K_{y3b}\right).g \tag{10}$$

where g is the acceleration due to gravity, M_1, M_2, M_3 and *Load* are the masses, K_{y1}, K_{y2}, K_{y3a} e K_{y3b} are the velocity coefficients with respect to y, because the forces due to the weights only realize work in this direction.

The forces supplied to the system are originated from the hydraulic actuator, composed by two pistons actuating in the same gear and the forces of viscous friction, considered only in the last pivot, so:

$$Q_{nc}=2.r.F-\upsilon.K_{\theta 3} \tag{11}$$

where r is the radius of the pinion coupled to the actuator's rack, F is the piston's force, and v is the coefficient of viscous friction. The generalized inertia and its differentiation is given by:

$$I(q)=J_{10}+J_{30}K_{\theta 3}{}^2+J_{2cm}K_{\theta 2}{}^2+M2.\left(K_{x2}{}^2+K_{y2}{}^2\right)+J_{Load}K_{\theta 3}{}^2+Load.\left(K_{x3b}{}^2+K_{y3b}{}^2\right) \tag{12}$$

$$\frac{d(I(q))}{dq} = 2.\left(J_{30}K_{\theta 3}L_{\theta 3} + J_{2cm}K_{\theta 2}L_{\theta 2} + M2.\left(K_{x2}L_{x2} + K_{y2}L_{y2}\right) + J_{Load}K_{\theta 3}L_{\theta 3} + Load.\left(K_{x3b}L_{x3b} + K_{y3b}L_{y3}\right)\right) \tag{13}$$

where the *J*s represents the mass moment of inertia for the bars.

2.2. Hydraulic actuation system model

The manipulator joint is actuated by an electrohydraulic system composed by a two-stage four-way electrohydraulic servovalve and a hydraulic actuator coupled with the joint by means of a rack-and-pinion type mechanism.

The servo valve controls the flow to the piston converting a low power electrical signal in a movement of the spool inside the valve, which in turns controls the flow and/or pressure to the hydraulic actuator. The spool movement opens an annular orifice, which allows the passage of the fluid to the actuators as illustrated in Fig. (3).

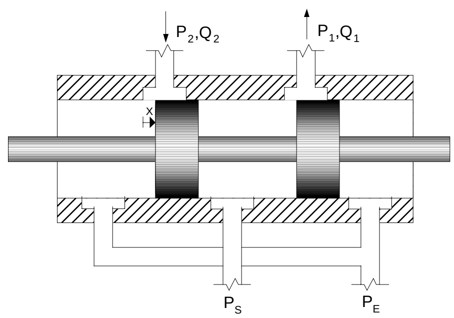

Figure 3. Servovalve schematic diagram.

Four-way servovalve is termed this way since it has four hydraulic connections: one for the supply pressure, one for the exhaust and two control ports connecting the valve to the hydraulic system. Motion of the spool is provided by means of an electric actuator that moves a deflector causing a differential pressure between its extremities. The dynamic analysis of this mechanism is particularly complex, however for low frequencies can be approximated to a 1st order equation:

$$\frac{u(s)}{i(s)} = \frac{K_i}{\tau_i s + 1} \tag{14}$$

where u is the valve aperture, i the input signal, K_i the input gain and τ_i is the spool actuation system time constant. The equation above is valid for a critical-center spool valve.

The flow Q through the servovalve is modeled as a flow through orifices and is given by:

$$Q = \frac{C_D A_0}{\sqrt{\rho}}\sqrt{\Delta P} \tag{15}$$

where C_D is the vena-contracta coefficient, A_0 the orifice area, ρ the density of the fluid and ΔP the difference between the inlet and outlet pressure. The above equation can be rewrite for each control port considering the orifice percent aperture and the flow direction according to the pressure difference:

$$\begin{cases} Q_1 = \mathrm{sgn}(\Delta P_1) K_V x \sqrt{|\Delta P_1|} \\ Q_2 = \mathrm{sgn}(\Delta P_2) K_V x \sqrt{|\Delta P_2|} \end{cases} \tag{16}$$

where:

$$\Delta P_1 = \begin{cases} P_S - P_1 & , \quad x \geq 0 \\ P_1 - P_E & , \quad x < 0 \end{cases}$$

$$\Delta P_2 = \begin{cases} P_2 - P_E & , \quad x \geq 0 \\ P_S - P_2 & , \quad x < 0 \end{cases}$$

P_S is the supply pressure, P_E the exhaust pressure assumed to be negligible and K_V the valve flow coefficient.

Figure (4) illustrates the pinion-rack rotary actuator that moves the joint. The fluid enters in one side of the actuator increasing the pressure in the piston and creating a force F that moves the joint. This movement causes the fluid to leave the other cylinder until reach an equilibrium pressure.

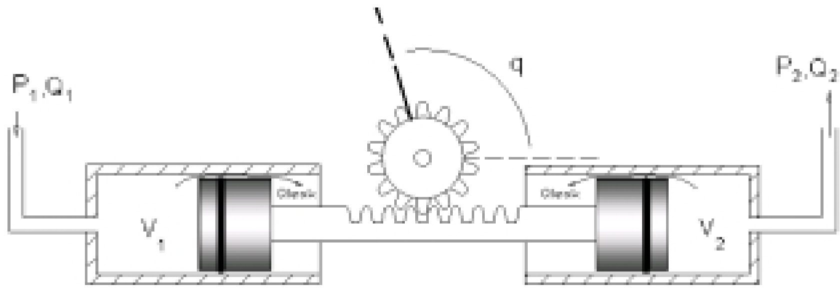

Figure 4. Rack-and-Pinion Hydraulic Rotary Actuator

The force in the piston can be written as:

$$F = A_P(P_1 - P_2) \tag{17}$$

where A_P is the piston area. The dynamic of this mechanism can be found applying the Continuity Equation as presented by Merrit (1967) in the control volumes V_1 and V_2:

$$\sum Q_{IN} - \sum Q_{OUT} = \frac{dV_0}{dt} + \frac{V_0}{\beta}\frac{dP}{dt} \tag{18}$$

The first term on the left side represents the flow caused by a variation in the volume control, hence, by the movement of the piston:

$$\frac{dV_0}{dt} = A_P \dot{y} \tag{19}$$

where $\dot{y}$ is the actuator position (y) time derivative. The second term of the equation represents the compressibility of the fluid produced by the volume control pressure variation, where the volume V_0 of each chamber can be written as:

$$\begin{cases} V_1 = \dfrac{V_T}{2} + A_P y \\ V_2 = \dfrac{V_T}{2} - A_P y \end{cases} \tag{20}$$

where V_T is the total volume in the pistons and connecting tubings. Usually there will be a leakage through the piston's seals, causing a flow outside the control volume. This flow is proportional to the difference between the chamber pressure and the manipulator's fluid compensation oil pressure. This pressure is equal to the return pressure, and, as it, considered negligible. The flow can be written due to leakage in each piston (q_{L1} and q_{L2}) as:

$$\begin{cases} q_{L1} = K_{L1} P_1 \\ q_{L2} = K_{L2} P_2 \end{cases} \tag{21}$$

where K_{L1} and K_{L2} are the piston leakage coefficient. In this model both seals have the same coefficient's value represented by K_L. So the following equations describe the hydraulic actuator's dynamics:

$$\begin{cases} \dot{P}_1 = (Q_1 - K_L P_1 - A_P \dot{y})\dfrac{2\beta}{V_T + A_P y} \\ \dot{P}_2 = (-Q_2 - K_L P_2 + A_P \dot{y})\dfrac{2\beta}{V_T - A_P y} \end{cases} \tag{22}$$

3. Fuzzy control

The fuzzy controller utilized on the hydraulic manipulator has the ability to adapt itself to changes in system parameters trough a learning process that: (i) observes data form a conventional fuzzy control system, (ii) evaluate its performance and (iii) automatically modifies the conventional fuzzy control system so to maintain a pre-specified performance.

3.1 Conventional fuzzy control

The purpose of the conventional fuzzy controller is to compute values of action variables from observation of state variables from the process under control. The action and the state variable here in are, respectively, the servovalve input signal and the error signal defined as:

$$E(kT)=qd(kT)-q(kT) \tag{23}$$

where $qd(kT)$ is the desired angle joint in a time kT (T is the sample period). The Fuzzy controller is based in the concept of fuzzy logic introduced by Zadeh (1973) and consists in covert they states variables in linguistic variables and apply linguistic rules to find the proper action for the plant.

The fuzzy controller is formed by three main components. The first component is the fuzzyfication interface, which converts input data into linguistic values. This is done assigning to the input variable a membership value for each fuzzy set. Fuzzy sets represent linguistics values as "positive-low" or "negative-high". Each fuzzy set has a membership function used to do this conversion. Figure (5) shows an example of membership functions. In this example, for an input of 0.45, the membership value are 0, 0.3 and 0.7 for the fuzzy sets E^{-4}, E^{-3} and E^{-2}, respectively.

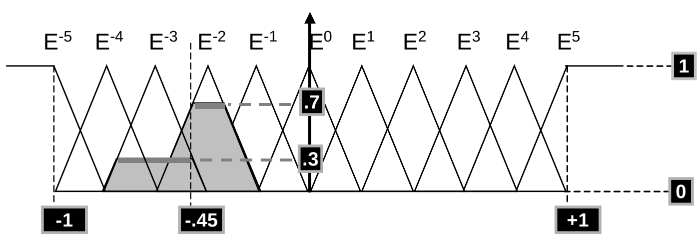

Figure 5. Example of triangular membership functions.

In the second component an inference mechanism maps fuzzy input into fuzzy output based in rules stored in the knowledge base. Example of a rule:

If the (error signal) is [positive-low] then the (servovalve aperture) is [negative-high]

or *If* $E(kT)$ *is* E^j *THEN* $i(kT)$ *is* I^j

Where E^j are input fuzzy sets and I^j are the outputs. The conventional fuzzy control used in this work is a single-input-single-output control system and its rule base array is resumed in Tab. (1).

Table 1. Rules for the SISO conventional controller

E^j	-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
I^j	-1.0	-0.8	-0.6	-0.4	-0.2	-0.0	+0.2	+0.4	+0.6	+0.8	+1.0

The last component is the defuzzyfication interface, which converts all the outputs from the inference mechanism into a non-fuzzy action to be applied in the plant. In this work the output of each rule is a constant numerical value. The final output for the system is the weighted average of all rule outputs, computed as:

$$i = \frac{\sum I^J \delta^J}{\sum \delta^J} \tag{24}$$

where δ^J is the firing strength of each rule, in this case the membership value of the input.

3.2 Learning Mechanism

The conventional fuzzy control evaluation is done comparing the real plant output to a reference model output. The reference model may be any type of dynamical system that characterizes the desired performance for the process. In this work the following equation was used:

$$\dot{q}_m = -2.22q_m + 2.22q_d \qquad (25)$$

The performance of the system is compute with respect to the reference model by generating an error signal *Em(kT)*:

$$Em(kT)=qm(kT)-q(kT) \qquad (26)$$

where *qm(kT)* is the ouput from the reference model in the time *kT*. The learning system observers also the error signal variation:

$$dEm(kT)=(Em(kT)-Em(kT-T))/T \qquad (27)$$

If the performance is met (both errors are zero) then the learning mechanism will not make significant modifications to the fuzzy controller. If the performance is not achieved, the learning mechanism will adjust the fuzzy controller. Two parts compose the learning process. First a component called fuzzy inverse model shows how to change plant inputs to force the plant output to get closer to the desired output. This is done mapping the deviations from the desired performance, represented by *Em(kT)* and d*Em(kT)*, to changes in the process input *p(kT)* that are necessary to force *Em(kT)* to zero.

Table 2. Fuzzy inverse model rule base array table.

$P^{j,k}$		Em^j										
		-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
	-5	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-0.8	-0.6	-0.4	-0.2	0.0
	-4	-1.0	-1.0	-1.0	-1.0	-1.0	-0.8	-0.6	-0.4	-0.2	-0.0	+0.2
	-3	-1.0	-1.0	-1.0	-1.0	-0.8	-0.6	-0.4	-0.2	-0.0	+0.2	+0.4
	-2	-1.0	-1.0	-1.0	-0.8	-0.6	-0.4	-0.2	-0.0	+0.2	+0.4	+0.6
	-1	-1.0	-1.0	-0.8	-0.6	-0.4	-0.2	-0.0	+0.2	+0.4	+0.6	+0.8
dEm^k	0	-1.0	-0.8	-0.6	-0.4	-0.2	-0.0	+0.2	+0.4	+0.6	+0.8	+1.0
	+1	-0.8	-0.6	-0.4	-0.2	-0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0
	+2	-0.6	-0.4	-0.2	-0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0
	+3	-0.4	-0.2	-0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0	+1.0
	+4	-0.2	-0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0	+1.0	+1.0
	+5	-0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0	+1.0	+1.0	+1.0

The FIM is a MISO (multi-input-single-output) system with two inputs and one output. Em^j and dEm^k are the fuzzy sets for the inputs related to *Em(kT)* and d*Em(kT)* respectively. Table (2) shows the rule base employed in this process. The use of the error variation provides some “damping“ to the learning mechanism. Without this overshoot is likely to occur. The FIM rule base array is designed to take advantage of this feature. The defuzzyfication in this case is slightly different form the previous fuzzy control. Using these two inputs the firing strength is calculated as:

$$\delta^{j,k}(kT) = \min\{\mu_{Em^j}(Em(kT)), \mu_{dEm^k}(dEm(kT))\} \qquad (28)$$

where μ_{Em^j} and μ_{dEm^k} denotes the membership function of fuzzy sets Em^j and dEm^k respectively.

The second part consists in changing the knowledge base of the conventional fuzzy controller so that the previous applied control action will be modified by the amount *p(kT)*. The desired controller output, or process input, is expressed by:

$$id(kT-T)=I(kT-T)+p(kT) \qquad (29)$$

Knowledge base modification is done adding *p(kT)* to the output values which are associated to the fuzzy implications that contributed to the previous control action *u(kT-T)*. Only the rules that have a firing strength greater than zero will be modified. The other rules remain unchanged allowing a kind of local learning.

Figure (6) shows the schematic of the FMRLC control.

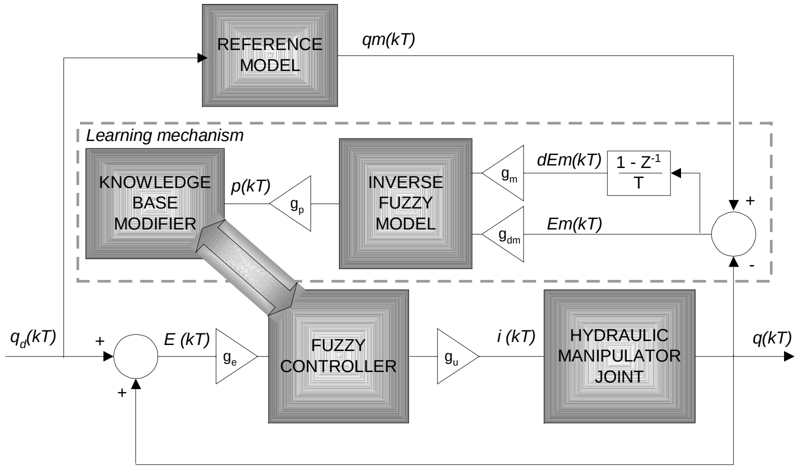

Figure 6. FMRLC Fuzzy Controller

3.3 Implementation issues

For a greater flexibility of the controller, and to make easier to tune it, both conventional fuzzy controller and fuzzy inverse model inputs are “normalized” by means of constant scaling factors. The gains g_e, g_m and g_{dm} were employed to normalize the variables *E(kT)*, *Em(kT)* and *dEm(kT)* respectively. Both fuzzy controllers provides normalized outputs which are converted to useful range by the gains g_i and g_p, respectively for the variables i*(kT)* and *p(kT)*. For sake of simplicity this work uses triangular membership functions in both fuzzy controllers (conventional and FIM), and the membership value for an input *x* in a fuzzy set *A* is calculated with the following equation:

$$\mu_A(x;a,b,c) = \max\left(\min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right),0\right) \qquad (30)$$

here, *a*, *b* and *c* are the triangles vertices in ascending order.

4. Results

The simulation was performed using MATLAB software package. Two controllers were used for comparison. The first is a fuzzy controller with membership functions and outputs were adjusted so to make the fuzzy control correspond to a tradition proportional controller usually applied in this type of systems. Then the learning mechanism was applied on the conventional controller above, modifying its parameters as needed. A sample time of 0.1 s was used in both controllers. The reference model was tuned so to represent the performance of a conventional P-controller applied in the plant in optimal conditions. The desired position is represented by a ramp function until it reaches the final desired angle. As shown in Fig. (7), in optimum conditions both controllers follow the reference model. If the manipulator extremities are loading, the P-controller response deviates from the desired path. The FRMLC control, instead, adjust the outputs of the fuzzy controller maintaining a good performance, see Fig. (8)

In the next simulation the pressure supply was reduced to 75% of its nominal value. Even in this case the system with the FMRLC control was able to follow the reference model. The simple P-control can’t deal with this parameter change and shows a degraded performance, as showed in Fig. (9). Figures (10) and (11) show the system behavior with a different θ_4. As was explained before, the dynamics characteristics of the system change with the variation of θ_4. As can be seen, the results are similar to the obtained before.

The simulation’s parameters used were: g=9.81m.s^{-2}; r=0.022m; υ=20s^{-1}; P_s=1.0345E7N.m^{-2}; Pe=0N.m^{-2}; V_t=7.22E-5m^3; β=7E8N.m^{-2}; Ap=11.37E-4m^2; K_{leak}=8.476E-14m^{5}N^{-1}s^{-1}; J_{10}=0.07kg.m^2; J_{30}=0.80kg.m^2; J_{2cm}=0.11kg.m^2; M_1=3Kg; M_2=4Kg; M_3=10Kg; M_4=13Kg; l_1=0.14m; l_2=0.56m; l_3=0.15m, l_4=0.56m; K_v=3.6045E-8; K_i=1; T_i=0.002; g_e=0.5464; g_u=0.915; g_{dm}=0.5464; g_{yc}=0.2; g_p=0.2, T= 0.05s.

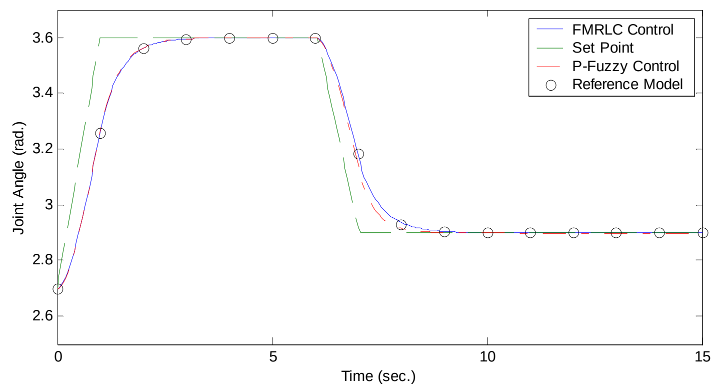

Figure 7. Simulation results - Manipulator without load in optimal conditions and θ_4=2.19 rads

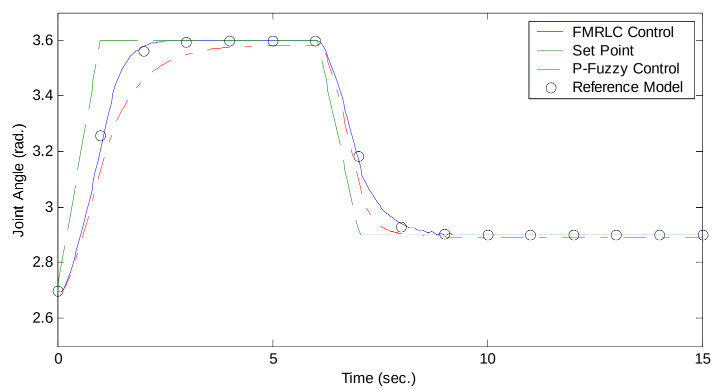

Figure 8. Simulation results - Manipulator loaded with 40 Kg. and θ_4=2.19 rads

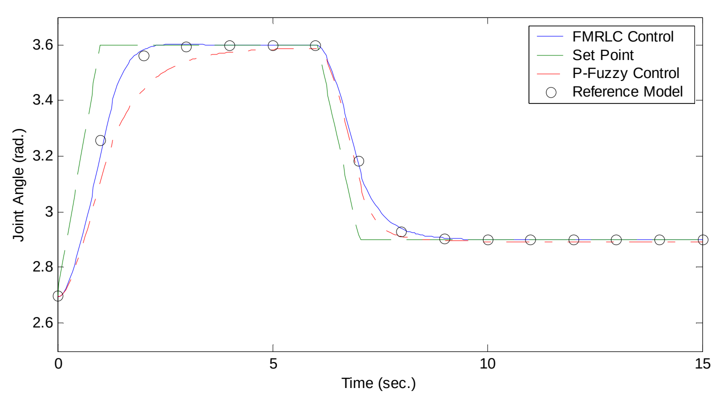

Figure 9.Simulation results - Manipulator with 75% of its nominal pressure supply, loaded with 25 Kg and θ4=2.19 rads

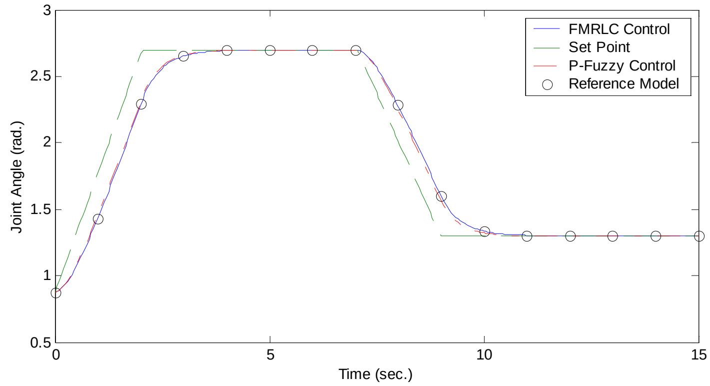

Figure 10. Simulation results - Manipulator without load in optimal conditions and θ_4=.14 rads

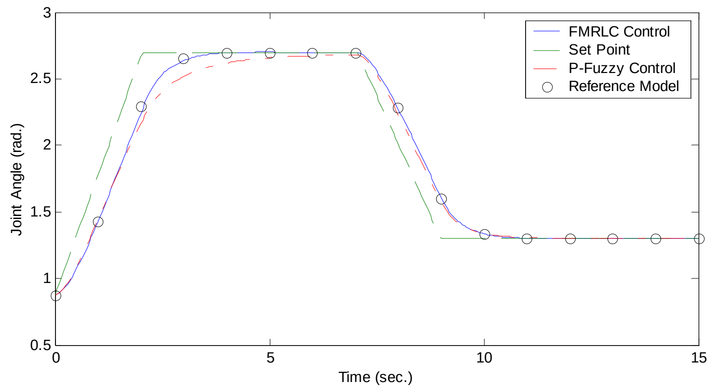

Figure 11. Simulation results - Manipulator loaded with 40 Kg. and θ_4=.14 rads

5. Conclusions

In this work was presented: (a) the development of a non-linear model for the actuation system of a industrial underwater hydraulic manipulator; (b) the modeling of a closed-chain manipulator joint dynamics; (c) the simulation of the application in the elbow pivot Kraft Grips joint of a control algorithm with a learning mechanism able to deal with changing in the system's parameters.

The results demonstrates that this fuzzy control could possibly be applied with success in the control of this type of manipulator, allowing to make tasks in a teleassisted way. In this paper was addressed the problem of positioning control with changing parameters. Future works could address the problem of path following or a hybrid position/force control. Other problems, not addressed here, could emerge when the application of the algorithm in a real manipulator. Noisy sensors, stiction or coloumb friction in the actuator's pistons or manipulator's joints could degrade the control performance and practical solutions should be investigated as needed. In future experimental tests with the manipulator could be used to validate the kinematic and dynamic models presented here.

6. References

Clegg, C.A., 2000, "Self-tuning Position and Force Control of a Hydraulic Manipulator", Ph.D Thesis, Herriot-Watt University.

Doughty, S, 1988, "Mechanics of Machines", John Wiley & Sons, New York.

Layne, R.J., Passino, K.M., 1996, "Fuzzy Model Reference Learning Control", Journal of Intelligent and Fuzzy Systems, Vol. 4, No. 1,pp. 33-47,1996.

Jang, J.–S.R., Sun C.–T., Mizutani,E., 1997, "Neuro-Fuzzy and Soft Computing – A Computational Approach to Learning and Machine Intelligence", Prentice Hall.

Merritt, H. E., 1967, "Hydraulic Control Systems - Part 1", John Wiley & Sons, New York.

Stringer, J., 1976, "Hydraulic Systems Analysis: An Introduction", The Macmillan Press Ltd, London.

Zadeh, L.A., 1973, "Outline of a New Approach to the Analysis of Complex Systems and Decision Process", IEEE Transactions of Systems, Man, and Cybernetic, Vol. SMC-3 No. 1, pp. 28-44.

Sepehri, N., Corbet, T., 1999, "Fuzzy Control System Techniques and their Application in Hydraulic Actuated Industrial Robots", Fuzzy Theory Systems: Techniques and Applications, Vol 2, pp. 577-608.

Grips Underwater Manipulator System Manual, Publication No. G-284-1, Kraft Ocean System, Kansas City