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Adaptive control of a time-varying rotary servo system using a fuzzy model reference learning controller with variable adaptation gain

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Abstract: The constant parameters in a conventional fuzzy controller lead to a poor performance for time-varying systems. In this study, a fuzzy model reference learning controller (FMRLC) with a newly defined variable adaptation gain is designed and implemented in the adaptive fuzzy control of a time-varying rotary servo (TVRS) system. In the design of the FMRLC, a knowledge-base modification algorithm with variable adaptation gain is used instead of a fuzzy relation table. Hence, it is provided that the learning and adaptation mechanism continuously updates the knowledge base of the adaptive fuzzy controller against any parameter variations, such as changing loads. By means of the learning and adaptation mechanism, the TVRS system behaves as a defined reference model in the desired performance in time. The initial parameters of the FMRLC are easily determined by trial and error because of the variable adaptation gain. Using the designed controller, the adaptive fuzzy control of the TVRS system performs successfully in the simulation and practical implementation. The simulation of the system is executed in a MATLAB-Simulink environment and the practical application is implemented in a Quanser Q3 experimental servo module based on MATLAB-Simulink. The simulation and experimental results are given to demonstrate the effectiveness of the proposed control structure.

Key words: Adaptive fuzzy control, fuzzy model reference learning control, variable adaptation gain, time varying servo system

1. Introduction

Most of the dynamic control systems have steady or slowly changing imprecise parameters in time. For example, the power systems are exposed to large deviations in loading conditions, and the mass and center of gravity of a plane depends on the fullness of its fuel tank and the number of passengers. As another example, a sailing ship's rudder control parameters [1] are affected by external influences, such as wind effects, density, and by its mass. Similarly, the control parameters of the conveyor modules change with a variable load, which finds a wide use in industry [2]. In the literature, adaptive control methods have been extensively used to remove the changing parameters' effect for these systems. The main objective of an adaptive control system is calculating the unknown parameters in the system, to be controlled simultaneously, over the scaled system signals, and employing the calculated parameters to determine the control inputs. Therefore, an adaptive control system behaves in a similar way as a control system with real-time parameter calculation [3].

In recent years, linguistic rule-based fuzzy control has emerged as a practical alternative to the traditional

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control methods for controlling systems in which a mathematical model is not well defined [4]. Fuzzy control has a large number of applications in industry, such as transportation, home appliances, automotive, and security [5]. However, fuzzy control also has some major drawbacks, especially in the design process, such as needing a specialist. The reason is that the precise and complete determination of the fuzzy controller parameters is not very clear. In addition, the fuzzy controller may become unable to operate in the event of unanticipated and wide parameter changes, structural changes, or the destructive effects from outside influences. Moreover, it is difficult to decide about the performance of the controller [6].

Adaptive fuzzy control systems have been used to improve system performance by removing the drawbacks of conventional fuzzy control systems [7]. Similar to the conventional adaptive control systems, the main objective of adaptive fuzzy control is calculating unknown system parameters to be controlled simultaneously over the scaled system signals and employing the calculated parameters to determine control inputs [8].

The fuzzy model reference learning controller (FMRLC) is an adaptive control algorithm intended for eliminating some of the difficulties in the fuzzy control design. The adaptive fuzzy control algorithm uses a reference model with the desired performance to get feedback related to the closed loop control performance to design and adjust a rule-based fuzzy controller [9]. A reference model with the desired performance demonstrates the ideal or desired behavior of the controlled system. In the FMRLC, the ideal or desired system performance can be achieved accurately using a 1st- or 2nd-order reference model.

In conventional fuzzy control systems, several parameters of the membership functions, such as the base width and places, are determined based on the trial and error method. For this purpose, the learning mechanism is used in the design of the FMRLC method. It should be noted that Procky and Mamdani's knowledge-based update algorithm used in the literature is based on a fuzzy relationship rule base, which establishes a fuzzy relationship between the inputs and outputs of a fuzzy controller [10].

In this study, a variable adaptation gain (Np), depending on the error, was defined for the conventional adaptive fuzzy control structure and applied to the control of the time-varying rotary servo (TVRS) system. With this proposed approach, the adaptive control system intended to provide a more effective adaptation.

2. Design of the FMRLC with variable adaptation gain (N_p)

In the FMRLC, the learning mechanism observes the plant outputs and adjusts the membership functions and rule base array, so that the overall system acts like the desired reference model. By means of the designed learning control system, the performance of the closed-loop system is improved by generating command inputs to the plant and utilizing the feedback information from the plant. Figure 1 shows the learning control technique, which uses a learning mechanism that observes the outputs from a fuzzy control system, characterizes its current performance, and automatically synthesizes and modifies the fuzzy controller parameters so that some prespecified performance objectives are met [11].

Figure 1 indicates a nonlinear map that was found to be useful in many applications. The fuzzy control structure shown in Figure 1 is assumed to have reference input $r(kT)$, reference model output or desired process output $y_m(kT)$, and plant output $y(kT)$. The inputs to the adaptive fuzzy controller are the error $e(kT)$ and the change in error $c(kT)$, defined as:

$$e(kT) = r(kT) - y(kT), \tag{1}$$

$$c(kT) = \frac{e(kT) - e(kT - T)}{T}, \tag{2}$$

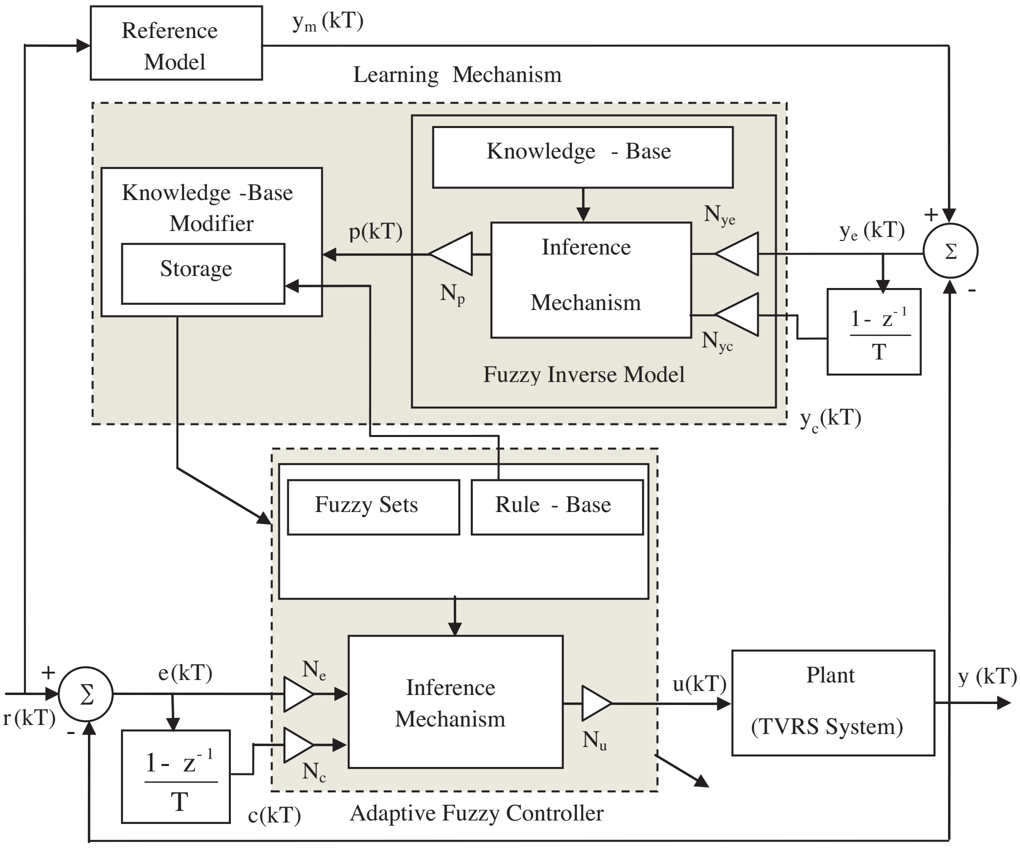


Figure 1. Functional architecture of the FMRLC.

where T is the sampling period and $e(kT-T)$ is the previous error of the system [12]. In the literature, to obtain more flexibility in an adaptive fuzzy control system, by means of the scaling factors, the space of discourse for each process' inputs and output are frequently scaled to the interval $[-1, +1]$. For our adaptive fuzzy controller design, the gains indicated by N_e, N_c, and N_u are used to normalize the space of discourse for the error $e(kT)$, change in error $c(kT)$, and output of the fuzzy controller $u(kT)$, respectively.

The inputs to the fuzzy inverse model in the learning mechanism are the error, $y_e(kT)$, which is the difference between the reference model output $y_m(kT)$ and the plant output $y(kT)$, and the change in the error $y_c(kT)$, defined as:

$$y_e(kT) = y_m(kT) - y(kT), \tag{3}$$

$$y_c(kT) = \frac{y_e(kT) - y_e(kT-T)}{T}. \tag{4}$$

The reference model given in the FMRLC system characterizes the desirable design criteria, such as the stability, rise time, overshoot, and settling time. As shown in Figure 1, the input reference signal $r(kT)$ is applied to the reference model. The reference model output $y_m(kT)$ is the desired value of our system to act. The desired performance of the controlled process is met if the learning mechanism forces $y_e(kT)$ to be kept at a very small value for the entire time. Hence, if the performance is met, i.e. $y_e(kT) \approx 0$, then no significant modifications are performed by the learning mechanism to the adaptive fuzzy controller [13]. The learning mechanism, which is the most important part of the controller, consists of 2 parts: a fuzzy inverse model and a knowledge-base modifier.

2.1. Fuzzy inverse model with variable adaptation gain (N_p)

For adaptive control systems, a fuzzy inverse model was enhanced in the linguistic self-organizing control structure by investigating methods to reduce the problems using the inverse process model. Procyk and Mamdani's [14] use of the inverse process model depended upon the use of an explicit mathematical model of the process, and eventually assumptions about the underlying physical process. In applying this approach, dependence on a mathematical model of the process often causes considerable difficulties.

The aim of employing a fuzzy inverse model is to characterize how to change the plant inputs $u(kT)$ to force the plant output $y(kT)$ to be as close as possible to the reference model output $y_m(kT)$. It should be noted that, similar to the fuzzy controller, as shown in Figure 1, the fuzzy inverse model contains normalizing scaling factors, namely N_{ye}, N_{yc}, and N_p, for each space of discourse of the inputs and output. Selection of the normalizing gains, N_{ye}, N_{yc}, and N_p, can affect the overall performance of the system [13]. In this study, the input scaling factors of the fuzzy inverse model (N_{ye} and N_{yc}) are conventionally defined as constants. Moreover, the output scaling factor of the fuzzy inverse model (N_p) is defined as a new variable adaptation gain depending on the error, $y_e(kT)$, as given by Eq. (5):

$$N_p(kT) = a + b \times |y_e(kT)|\,, \tag{5}$$

where a and b are roughly set constants. The system changes the amount of adaptation according to the error, i.e. a big error means a bigger adaptation, and a small error means a smaller adaptation. The variation curve of the variable adaptation gain (N_p) is shown in Figure 2. The adaptive fuzzy control system with variable adaptation gain has become more dynamic.

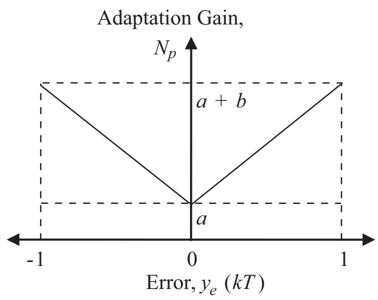


Figure 2. Variation curve of the variable adaptation gain (N_p).

In the adaptive fuzzy controller and fuzzy inverse model, the same types of triangular membership functions (m_1–m_{11}) are used for the 2 inputs and an output as shown in Figure 3.

The rule base array for the fuzzy inverse model and the fuzzy controller is shown in Table 1 [12]. Y_e and Y_c denote the fuzzy sets associated with $y_e(kT)$ and $y_c(kT)$, respectively, and P denotes the fuzzy sets quantifying the desired process input change $p(kT)$ that it is multiplied by the variable adaptation gain.

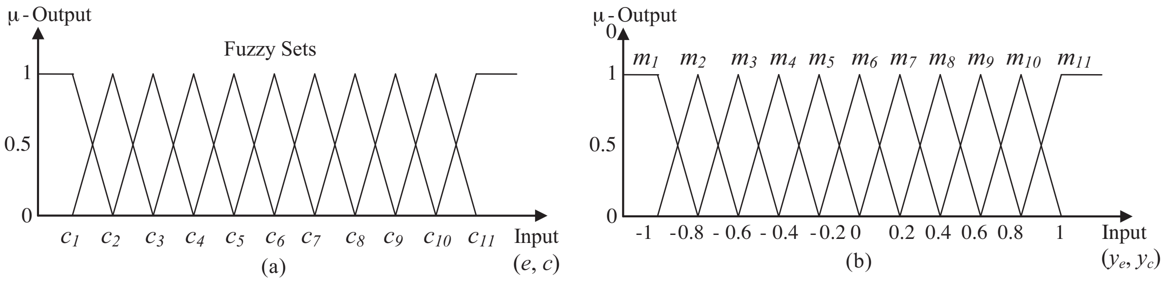


Figure 3. Membership functions of a) the adaptive fuzzy controller (e, c) and b) fuzzy inverse model (y_e, y_c).

Table 1. Rule base for the fuzzy controller and fuzzy inverse model.

P, U		Y_c, C										
		m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	m_{10}	m_{11}
	m_1	–1.0	–1.0	–1.0	–1.0	–1.0	–1.0	–0.8	–0.6	–0.4	–0.2	0.0
	m_2	–1.0	–1.0	–1.0	–1.0	–1.0	–0.8	–0.6	–0.4	–0.2	0.0	+0.2
	m_3	–1.0	–1.0	–1.0	–1.0	–0.8	–0.6	–0.4	–0.2	0.0	+0.2	+0.4
	m_4	–1.0	–1.0	–1.0	–0.8	–0.6	–0.4	–0.2	0.0	+0.2	+0.4	+0.6
	m_5	–1.0	–1.0	–0.8	–0.6	–0.4	–0.2	0.0	+0.2	+0.4	+0.6	+0.8
Y_e, E	m_6	–1.0	–0.8	–0.6	–0.4	–0.2	0.0	+0.2	+0.4	+0.6	+0.8	+1.0
	m_7	–0.8	–0.6	–0.4	–0.2	0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0
	m_8	–0.6	–0.4	–0.2	0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0
	m_9	–0.4	–0.2	0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0	+1.0
	m_{10}	–0.2	0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0	+1.0	+1.0
	m_{11}	0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0	+1.0	+1.0	+1.0

2.2. Knowledge-base modifier

In this study, for the modification of the fuzzy controller, we use the knowledge-base modification algorithm, given by Passino and Yurkovich [11], which increases the computational efficiency by modifying the membership functions of the consequent fuzzy sets (U). The knowledge-base modifier changes the knowledge base of the fuzzy controller using an adaptation value, $p(kT)$, that is the output of the fuzzy inverse model, so that the previously applied control operation will be modified by the amount $p(kT)$. Hence, the previously computed control action contributed to the system performance of the present control action in a good or bad way with the knowledge-base modifier [15]. The adaptation value of the system, $p(kT)$, is produced by the fuzzy inverse model, depending on variable adaptation gain, N_p or error, $y_e(kT)$. Accordingly, adaptation value of the system, $p(kT)$, can be expressed by Eq. (6):

$$p(kT) = \bar{p}(kT) \times N_p(kT), \tag{6}$$

where $\bar{p}(kT)$ is the output of the fuzzy inverse model without scaling. The desired adaptive fuzzy controller output, $\bar{u}(kT - T)$, is expressed by:

$$\bar{u}(kT - T) = u(kT - T) + p(kT). \tag{7}$$

It can be seen by examining Eq. (7) that we may force the fuzzy controller to produce this desired output, given similar controller inputs, by modifying the fuzzy controller's knowledge base [16].

Knowledge-base modification is implemented by shifting the centers of the membership functions (c_n) of the fuzzy sets (U), which are associated with the fuzzy implications that contributed to the previous control action $u(kT-T)$. This modification involves shifting these triangular membership functions by an amount specified with $p(kT)=[p_1(kT).....p_n(kT)]^T$, thus:

$$c_n(kT)=c_n(kT-T)+p_n(kT). \tag{8}$$

3. Modeling of a TVRS system

Permanent magnet DC (PMDC) motors are commonly used as an actuator in control systems. They directly provide rotary motion or moment and, coupled with wheels or drums and cables, can provide transitional motion or force [17]. In this study, the TVRS system actuated with a PMDC motor that has the electric circuit of the armature and the loaded body diagram of the rotor are shown in Figure 4. The rotary servo plant and PMDC motor parameters are given in Table 2.

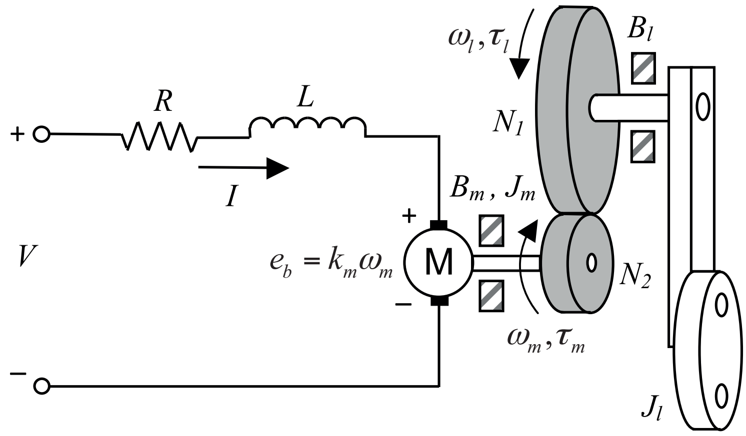


Figure 4. Equivalent circuit of the TVRS system.

Table 2. Rotary servo system and load parameters.

Symbol	Definition	Value
V	Nominal voltage of the DC motor	6 V
R	Motor armature resistance	2.6 Ω
L	Motor armature inductance	0.18 mH
k_t	Motor torque constant	0.00767 N m/A
k_b	Motor back-EMF constant	0.00767 V/(rad/s)
Ng	Total gear ratio (N_2/N_1)	70
η_g	Gearbox efficiency	0.90
J_m	Motor inertia	4.6×10^{-7} kg m^2
B_m	Motor viscous damping coefficient	≅ 0 (negligible)
J_{l_in}	Initial load and gearbox moment of inertia	4.83×10^{-7} kg m^2
J_{l_sub}	Subsequent load and gearbox moment of inertia	4.83×10^{-6}, kg m^2
B_{l_in}	Initial load viscous damping coefficient	3.41×10^{-6} N m/(rad/s)
B_{l_sub}	Subsequent load viscous damping coefficient	3.41×10^{-5} N m/(rad/s)

From Figure 4 we can write the following dynamic equations based on Newton's law combined with Kirchhoff's law [17,18]:

$$V(t)=Ri(t)+L\frac{di(t)}{dt}+e_b(t), \tag{9}$$

$$\tau_m(t) = J_m \frac{d^2\theta_m(t)}{dt^2} + B_m \frac{d\theta_m(t)}{dt} + \tau_l(t), \tag{10}$$

where $i(t)$ is the armature current, $e_b(t)$ is the back emf voltage, $\tau_m(t)$ is the motor torque, $\tau_l(t)$ is the load torque, and $\theta_m(t)$ is the angle of the armature. The motor torque, $\tau_m(t)$, is related to the armature current, $i(t)$, by a constant factor k_t. The back emf, $e_b(t)$, is related to the rotational velocity of armature, $\omega_m(t)$ or $\frac{\theta_m(t)}{dt}$, by the following equations:

$$\tau_m(t) = k_t i(t), \tag{11}$$

$$e_b(t) = k_m \omega_m(t) = k_m \frac{d\theta_m(t)}{dt}. \tag{12}$$

In the TVRS system, the rotational angle of the load, $\theta_l(t)$, transmitted by the gear box from the armature angle, $\theta_m(t)$, and variable load torque , $\tau_l(t)$, may be expressed as:

$$\theta_l(t) = \frac{1}{N_g} \theta_m(t), \tag{13}$$

$$\tau_l(t) = \frac{1}{N_g \eta_g} (J_l \frac{d^2\theta_l(t)}{dt^2} + B_l \frac{d\theta_l(t)}{dt}), \tag{14}$$

where N_g is the total gear ratio and η_g is the gearbox efficiency. Using Eqs. (9)–(14), the Simulink model of the TVRS system with variable load parameters (J_l, B_l) has been obtained, as shown in Figure 5.

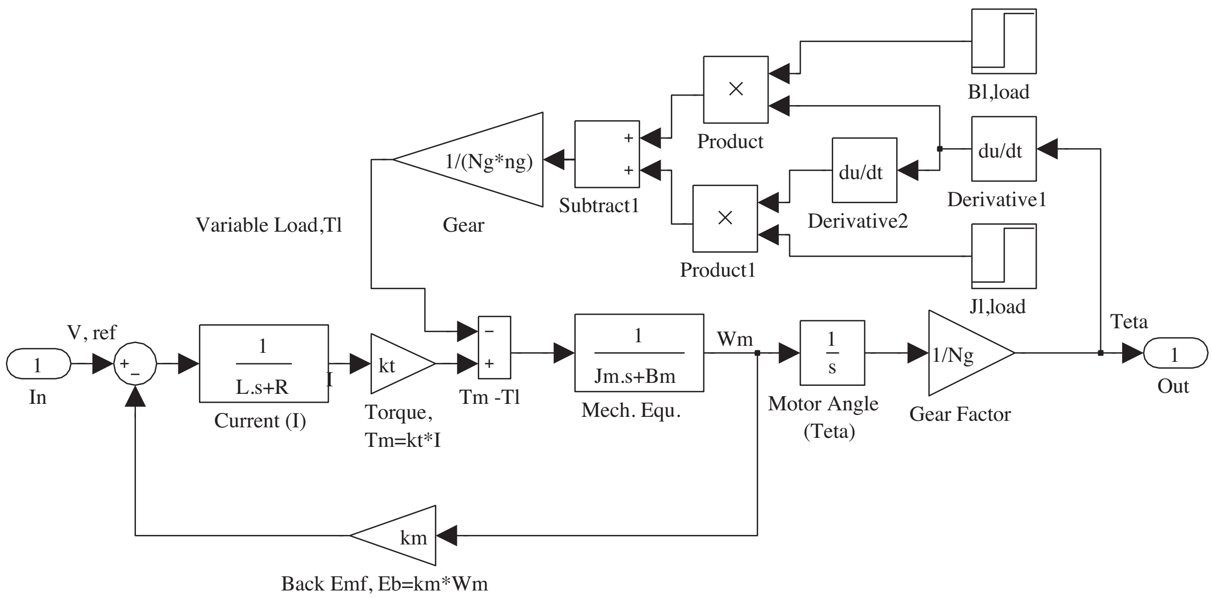


Figure 5. Simulink model of the TVRS system with a variable load (J_l , B_l).

4. Fuzzy model reference learning control of the TVRS system

The MATLAB-Simulink model of the simulation and experimental system used in this study is shown in Figure 6, where the rule base adaptation and modification process are carried out in the MATLAB s-function and the first-order reference model is defined [19,20]. The variable adaptation gain (N_p) is performed according to Eq. (5) and the TVRS system shown in Figure 5 is carried out as a subsystem in Figure 6.

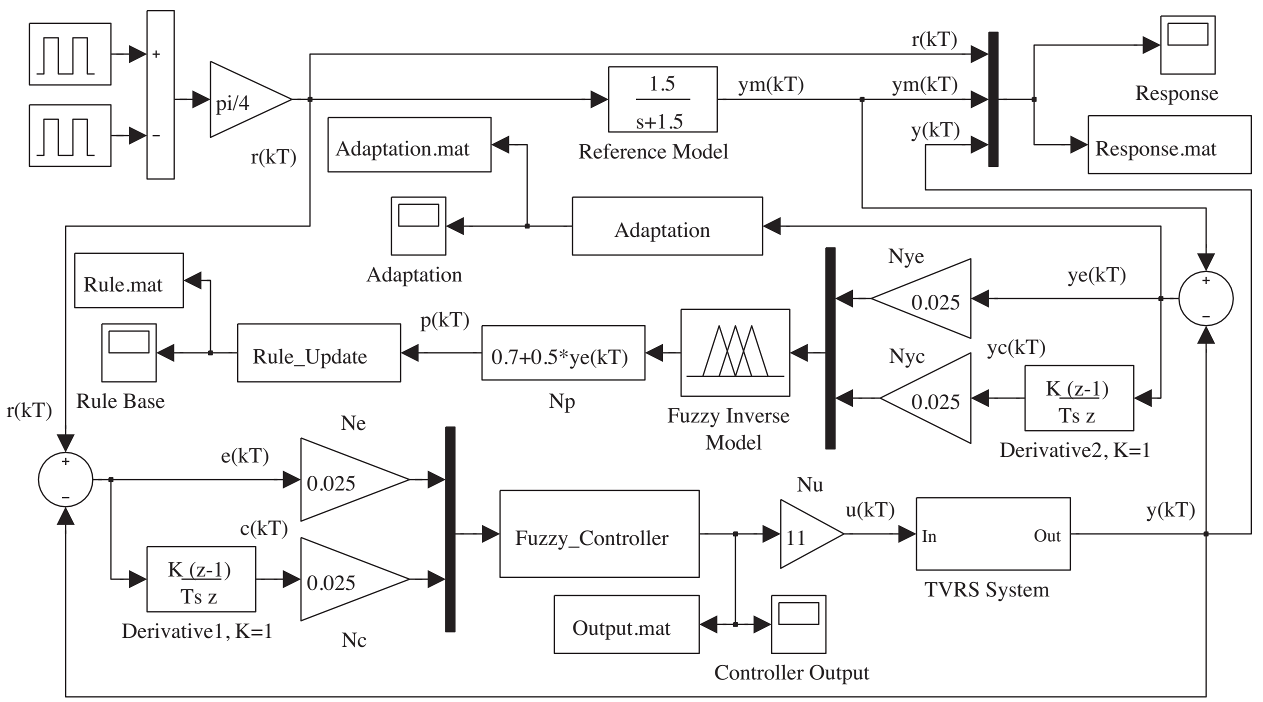
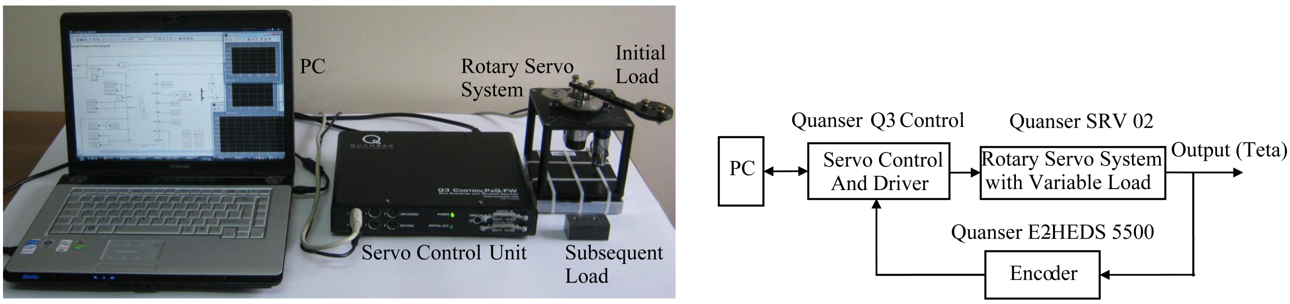


Figure 6. Simulink model of the FMRLC for the simulation and experimental system.

A photograph of the experimental system is given in Figure 7a. In the experimental system, a digital signal processing-based Quanser SRV-02 servo module has been used. As can be seen in Figure 7a, this module can be loaded with variable loads. A Q3 control PaQ-FW data acquisition board, which has its own built-in amplifier, is also utilized. Moreover, the MATLAB-Simulink based QuarC 2.0 software, which executes the FMRLC algorithm, has been used [21]. A block diagram of the experimental system is shown in Figure 7b.



(a) (b)

Figure 7. Photograph (a) and block diagram (b) of the experimental system.

5. Simulation and experimental results

The reference model for the simulation and experimental system was chosen to represent the somewhat realistic performance specifications and is expressed by Eq. (15) in the Laplace (s) domain.

$$T_{ref}(s) = \frac{1.5}{s + 1.5} \tag{15}$$

In both the fuzzy controller and fuzzy inverse models' inputs and outputs, 11 fuzzy sets are defined with a triangular shape, with a base width of 0.4 membership functions, shown in Figure 3. Table 1 is used for the fuzzy inverse model as a rule base.

For both the simulation and experimental tests, a step-wave signal for 3 reference points $(+\frac{\pi}{4}, 0, -\frac{\pi}{4}$ rad.) is used. In the adaptive fuzzy controller, the normalizing controller gains for the error, change in error, and the controller output are obtained as $N_e = 0.025$, $N_c = 0.025$, and $N_u = 11$, respectively. The adaptive fuzzy controller sampling period is defined as $T = 0.1$ s. In the fuzzy inverse model, the normalizing controller gains associated with $y_e(kT)$, $y_c(kT)$, and $p(kT)$ are obtained as $N_{ye} = 0.025$, $N_{yc} = 0.025$, and $N_p(kT) = 0.7 + 0.5 \times |y_e(kT)|$, respectively, by trial and error.

In both the simulation and experimental implementation, the servo system is initially loaded with the parameters $J_l = 4.83 \times 10^{-7}$ kg m^2 and $B_l = 3.41 \times 10^{-6}$ N m/(rad/s). After a while (at $t = 125$ s), the servo system is subsequently loaded with the parameters $J_l = 4.83 \times 10^{-6}$ kg m^2 and $B_l = 3.41 \times 10^{-5}$ N m/(rad/s). The responses of the simulation and experimental system, error signals, and control signals have been observed.

In the control systems, performance indices are used to measure the system performance. In this study, the performance values of the simulation and experimental system have been measured using the integrate absolute error (IAE) index given by Eq. (16).

$$IAE = \int_0^t |e(t)|\, dt \tag{16}$$

The IAE index is widely used in the literature because it is more selective in transient response and can be easily calculated. The IAE values of the simulation and experimental system was calculated for both the constant and variable values of the N_p parameter.

5.1. Simulation results

The simulation process is carried out regarding Figure 6 based on a MATLAB-Simulink environment. The input signal $(r(kT))$, reference model response $(y_m(kT))$, and servo position responses $(y(kT))$ of the simulation are shown in Figure 8 and the zoom area is shown in Figure 9. Over time, the servo position response overlaps with the reference model response, as shown in Figure 8. At $t = 125$ s, the load is increased. At this time the value of the error increases but over time, this error value decreases again, as shown in Figure 10. The error, which is the difference between the reference model and the servo position response, gets smaller with time. Figure 11 shows the output or control signal of the adaptive fuzzy controller. The adaptive fuzzy controller produces a control signal, again at $t = 125$ s, and manages to control the system response on the reference model.

The change in the knowledge base of the adaptive fuzzy controller before and after the simulation is shown in Table 3.

5.2. Experimental results

The experimental implementation of the proposed system is based on a Quanser SRV-02 servo module, as shown in Figure 7. The input signal $(r(kT))$, the experimental response of the reference model $(y_m(kT))$, and the servo position response $(y(kT))$ are shown in Figure 12. The servo position response overlaps the reference model output exactly, as shown in Figure 12. At $t = 125$ s, the load is increased. At this time, the value of the

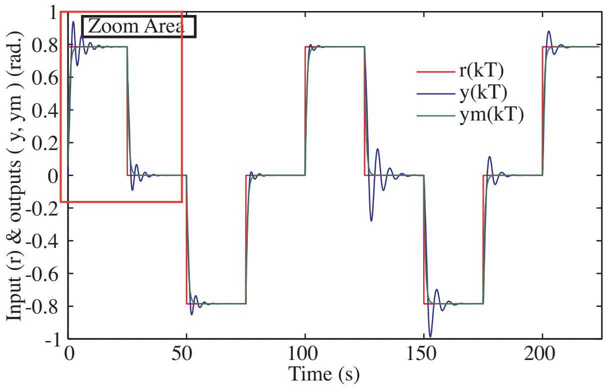


Figure 8. Input signal, reference model, and servo position responses of the simulation system.

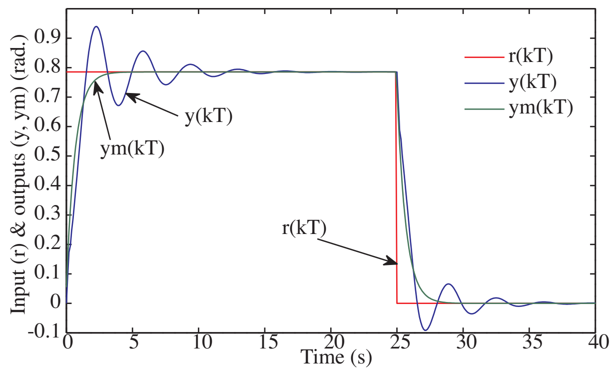


Figure 9. Zoom area in Figure 8.

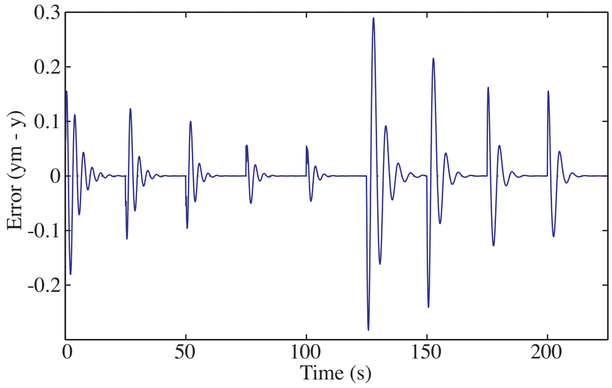


Figure 10. Error that is the difference between the reference model and the TVRS system output of the simulation system.

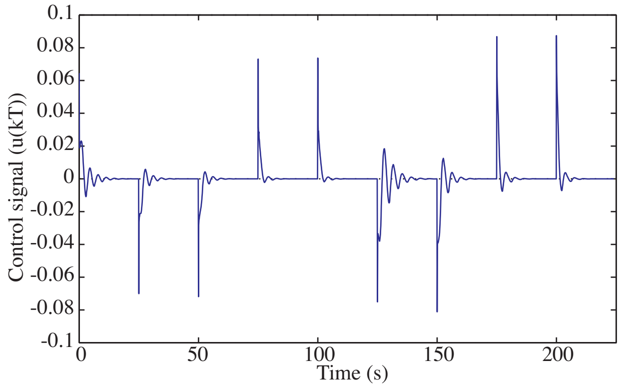


Figure 11. Simulation output of the adaptive fuzzy controller.

Table 3. Knowledge base of the adaptive fuzzy controller before and after the simulation.

Mem. Func.	Initial centers			Adapted (final) centers		
	C_e	C_c	C_u	C_e	C_c	C_u
c_1	–1.0	–1.0	–0.8	–1.000000	–1.000000	–0.800000
c_2	–1.0	–0.8	–0.6	–1.000000	–0.800000	–0.600000
c_3	–0.8	–0.6	–0.4	–0.800000	–0.600000	–0.400000
c_4	–0.6	–0.4	–0.2	–0.742232	–0.542232	–0.342232
c_5	–0.4	–0.2	0.0	–0.558066	–0.358066	–0.158066
c_6	–0.2	0.0	0.2	–0.199997	0.000003	0.200003
c_7	0.0	0.2	0.4	0.380312	0.580312	0.780312
c_8	0.2	0.4	0.6	0.358069	0.558069	0.758069
c_9	0.4	0.6	0.8	0.400000	0.600000	0.800000
c_{10}	0.6	0.8	1.0	0.600000	0.800000	1.000000
c_{11}	0.8	1.0	1.0	0.800000	1.000000	1.000000

error has been increased, but the servo position response overlaps the reference model output exactly in time. Figure 13 shows the error, which is the difference between the reference model and the TVRS system output. The adaptive fuzzy controller output, which is the control signal, is shown in Figure 14. The adaptive fuzzy controller produces a control signal again at $t = 125$ s, and manages to control the system response on the reference model.

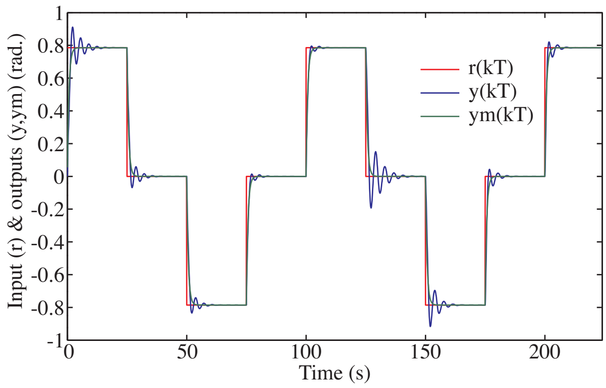


Figure 12. Input signal, reference model, and servo position responses of the experimental system.

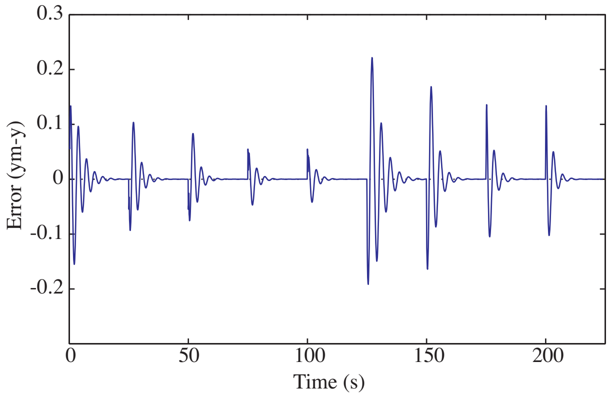


Figure 13. Error that is the difference between the reference model and the TVRS system output of the experimental system.

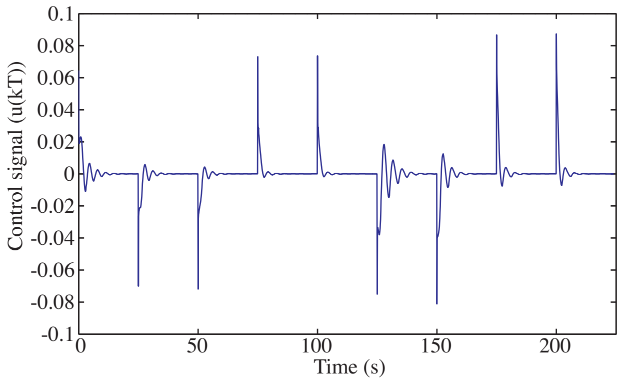


Figure 14. Experimental output of the adaptive fuzzy controller.

The change in the knowledge base of the fuzzy controller before and after the experimental application is shown in Table 4.

The performance measurements obtained by calculating IAE indices for the simulation and experimental system in the case of both constant gain ($N_p = 0.7$) and the newly defined variable gain ($N_p = 0.7{+}0.5\times|y_e|$) are given in Table 5. It is seen from Table 5 that the performance index (IAE) has a lower value for the simulation and experimental system, in which the gain depends on the error ($y_e(kT)$). These results demonstrate that the proposed variable gain method provides a better performance compared to the traditional constant gain approach.

Table 4. Knowledge base of the adaptive fuzzy controller before and after the experimental application.

Mem. func.	Initial centers			Adapted (final) centers		
	C_e	C_c	C_u	C_e	C_c	C_u
c_1	–1.0	–1.0	–0.8	–1.000000	–1.000000	–0.800000
c_2	–1.0	–0.8	–0.6	–1.000000	–0.800000	–0.600000
c_3	–0.8	–0.6	–0.4	–0.800000	–0.600000	–0.400000
c_4	–0.6	–0.4	–0.2	–0.705990	–0.505990	–0.305990
c_5	–0.4	–0.2	0.0	–0.517573	–0.317573	–0.117573
c_6	–0.2	0.0	0.2	–0.200002	–0.000002	0.199998
c_7	0.0	0.2	0.4	0.252435	0.452435	0.652435
c_8	0.2	0.4	0.6	0.317571	0.517571	0.717571
c_9	0.4	0.6	0.8	0.400000	0.600000	0.800000
c_{10}	0.6	0.8	1.0	0.600000	0.800000	1.000000
c_{11}	0.8	1.0	1.0	0.800000	1.000000	1.000000

Table 5. Performance measurements of the simulation and experimental system.

Perf. index	Simulation system		Experimental system	
	$N_p = 0.7$	$N_p = 0.7 + 0.5 \times \lvert y_e \rvert$	$N_p = 0.7$	$N_p = 0.7 + 0.5 \times \lvert y_e \rvert$
IAE	10.4527	8.6697	9.1567	7.0367

6. Conclusions

In this paper, the simulation and experimental implementation of a fuzzy model reference learning control technique with a variable adaptation gain (N_p) is studied for the position control of the TVRS system. The FMRLC structure provides an automatic method to synthesize the knowledge base. The learning and adaptation mechanism in the FMRLC continuously updates the knowledge base in the adaptive fuzzy controller. Hence, when unpredictable changes occur within the plant, the FMRLC can make on-line adjustments in the fuzzy controller to follow the reference model. Thus, the TVRS system response overlaps the reference model output. Moreover, the error, which is the difference between the reference model and system output, gets smaller with time. The reference model is overlapped more quickly by the adaptive fuzzy control system with the new definition of the variable adaptation gain (N_p). As can be seen from the simulation and experimental results and the performance measurements, the proposed system has become more robust against time-varying loads. As a result, the proposed FMRLC of the TVRS system has been successfully realized in the simulation and practical application system.

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