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Experimental evaluation of generalized predictive control applied to a hydraulic actuator

N. Sepehri and G. Wu

Experimental Robotics and Teleoperation Laboratory, Department of Mechanical and Industrial Engineering, The University of Manitoba, Winnipeg, Manitoba (Canada) R3T-5V6

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SUMMARY

This paper reports the results of an experimental study, which was conducted to evaluate the performance and implementation aspects of a generalized predictive control (GPC) technique to an electro-hydraulic positioning actuator. Poor dynamics and high nonlinearities form part of the difficulty in the control of hydraulic functions which make the application of adaptive controls an attractive solution. The applicability of GPC to the position control of hydraulic manipulator has been investigated through computer simulations in the literature. However, there is no experimental record of applying this technique to an actual hydraulic system. A suitable plant model is established and recursive U-D factorization technique is adopted for on-line estimation of time-varying plant parameters. Experimental results are obtained from a laboratory electrohydraulic actuator test stand. Various benchmark tests, comprising step and tracking inputs, demonstrate good performance and the promise of the technique. In spite of significant actuator dynamics (control voltage saturation, flow nonlinearity and dry frictional nonlinearity in the hydraulic actuator), successful control tests could be performed repetitively.

KEYWORDS: Hydraulic actuators; Generalized predictive control algorithm; Adaptive controls; CARIMA estimation; Nonlinearities.

1. INTRODUCTION

Amongst the three types of actuators, i.e. electric, peumatic and hydraulic, the utilization of hydraulic ones is becoming inevitable in certain scenarios, due to their standard, safe and easy-to-maintain components as well as their reliable performance and ability to generate high forces for a sustained period of time. For example, in large resource based industries, where electric or pneumatic devices are either incapable to produce forces large enough or would not survive at all, the utilization of hydraulic acutators is obviously the best choice.

Hydraulic systems, on the other hand, are complex, nonlinear and difficult to control. A close investigation has suggested that the problems are mostly related to the nature of hydraulic functions.[1] First of all, in a hydraulic acutator, flexible connecting hoses, large volume of fluid under compression and trapped air in the hydraulic fluid lead to high compliance. High inertia along with high compliance, reduce the natural frequency and the damping effect of the mechanism. Further, hydraulic compliance can not remain constant; during operations, as fluid temperature rises, air starts to dissolve in the system, resulting in a substantial change in compliance. Secondly, the performance of hydraulic valves is highly sensitive to payload. Finally, external and internal leakage, coulomb friction and size of orifices all result in parameter changes of the system. Simple constant gain control schemes, thus, are not sufficient to realize the full potential of the hydraulic systems in terms of accuracy and satisfactory performance.[2] As a result, several researchers have considered the use of adaptive control techniques with their application to manipulators (for example see references 3 to 5). An adaptive control system measures a performance index which is a function of inputs, states, and outputs of the plant. Using this index, an adaptation mechanism modifies the parameters of the controller. Two philosophically different approaches exist for the solution of adaptive control. In the first approach, referred to as “indirect adaptive scheme”, the control signal is updated based on the on-line estimation of system parameters. Conversely, the method that bypasses system parameters estimation and directly adjusts the controller parameters is termed “direct adaptive scheme”.

Several published works have examined various indirect adaptive control algorithms applied to positioning of hydraulic manipulators; for example, minimum variance control,[6] one-step ahead self-tuning control,[7] pole placement method[2] and generalized predictive control (GPC).[8,9] Among them, GPC technique has recently gained much attention. The algorithm which was introduced by Clarke et al.[10,11] in late 1980s, predicts the plant’s future outputs for a sequence of future desired set-points. A cost function, defined based on future output errors and control inputs, is then minimized to produce a set of optimized future control signals. The algorithm has an inherent integral control action, and is capable of stable control of processes with varying parameters, of variable dead-time, with non-minimum-phase plants and with badly damped poles.[11,12] Recently, Kotzev et al.[8] applied this algorithm to the control of a two-link hydraulically actuated manipulator in a computer simulation; the effect of the order changes for the predictor and estimator model on step input commands was also examined.[9] In spite of proven potential of GPC technique, to the best of our knowledge, there is no experimental record of applying it to hydraulic functions.

The goal of the research presented in this paper was to

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document an experimental performance qualification of GPC technique towards position control of hydraulic actuators. The present work, which complements the previous simulation studies,[8,9] makes the following contributions:

(i) Generalized predictive control is implemented and assessed on an industrial hydraulic actuator.
(ii) The results of a wide range of step and trajectory tracking inputs are presented.
(iii) The effect of design parameters is studied and the adaptability of the algorithm under various conditions is investigated.

The article is organized as follows. First, GPC technique is briefly described followed by the description of the general dynamic model of a dypical hydraulic actuator. Next, the test rig, on which all the experiments were performed, is presented along with specific implementation details of the controller. Finally, experimental results showing the controlled actuator's behaviour in various tasks, are documented and discussed.

2. RELEVANT BACKGROUND

2.1 Adaptive generalized predictive control

GPC strategy exploits a particular kind of linear plant model called "controlled autoregressive integrated moving average" (CARIMA) model:

$$A(q^{-1})y(t)=B(q^{-1})u(t-1))+\frac{\xi(t)}{\Delta} \tag{1}$$

where $A(q^{-1})$ and $B(q^{-1})$ are polynomials, of degrees n_a and n_b, in the backward shift operator q^{-1} and $\Delta=(1-q^{-1})$. $\xi(t)$ is an uncorrelated random sequence. $u(t)$ and $y(t)$ represent the input and the output, respectively. The objective of predictive control law is to determine future control signals, based on future predicted plant outputs and a given sequence of future set points. The j-step ahead prediction of $y(t)$ i.e., $\hat{y}(t+j)$, is obtained by solving the Diophantine identity. The final equation is given below;

$$\hat{y}(t+j)=F_j(q^{-1})y(t)+E_j(q^{-1})B(q^{-1})\Delta u(t+t-1) +E_j(q^{-1})\xi(t+j) \tag{2}$$

where $E_j(q^{-1})$ and $F_j(q^{-1})$ are uniquely defined polynomials of orders $(j-1)$ and n_a, respectively. The coefficients in E_j and F_j are computed recursively as shown below;

$$E_{j+1}(q^{-1})=E_j(q^{-1})+q^{-j}f_0 \tag{3a}$$

$$F_{j+1}=q[F_j(q^{-1})-f_0A(q^{-1})\Delta] \tag{3b}$$

with initial condition

$$E_1(q^{-1})=1 \tag{3c}$$

$$F_1(q^{-1})=f_0+f_1q^{-1}+\cdots+f_{n_a}q^{-n_a}=q[1-A(q^{-1})\Delta] \tag{3d}$$

Since the disturbance consists of only the unknown future values, the optimal predictor is

$$\hat{y}(t+j)=F_j(q^{-1})y(t)+G_j(q^{-1})\Delta u(t+j-1) \tag{4}$$

where

$$G_j(q^{-1})=E_j(q^{-1})B(q^{-1})=g_{i0}+g_{i1}1^{-1}+\cdots+g_{ij}q^{-j}$$

Considering predictions at each of N steps into the future, the optimal predictor can then be written in the following key vector form;

$$\hat{\mathbf{y}}=\mathbf{Gu}+\mathbf{f} \tag{5}$$

where

$$\hat{\mathbf{y}}=[\hat{y}(t+1),\hat{y}(t+2),\cdots,\hat{y}(t+N)]^T$$

$$\mathbf{u}=[\Delta u(t),\Delta u(t+1),\cdots,\Delta u(t+N-1)]^T$$

$$\mathbf{f}=[f(t+1),F(t+2),\cdots,f(t+N)]^T$$

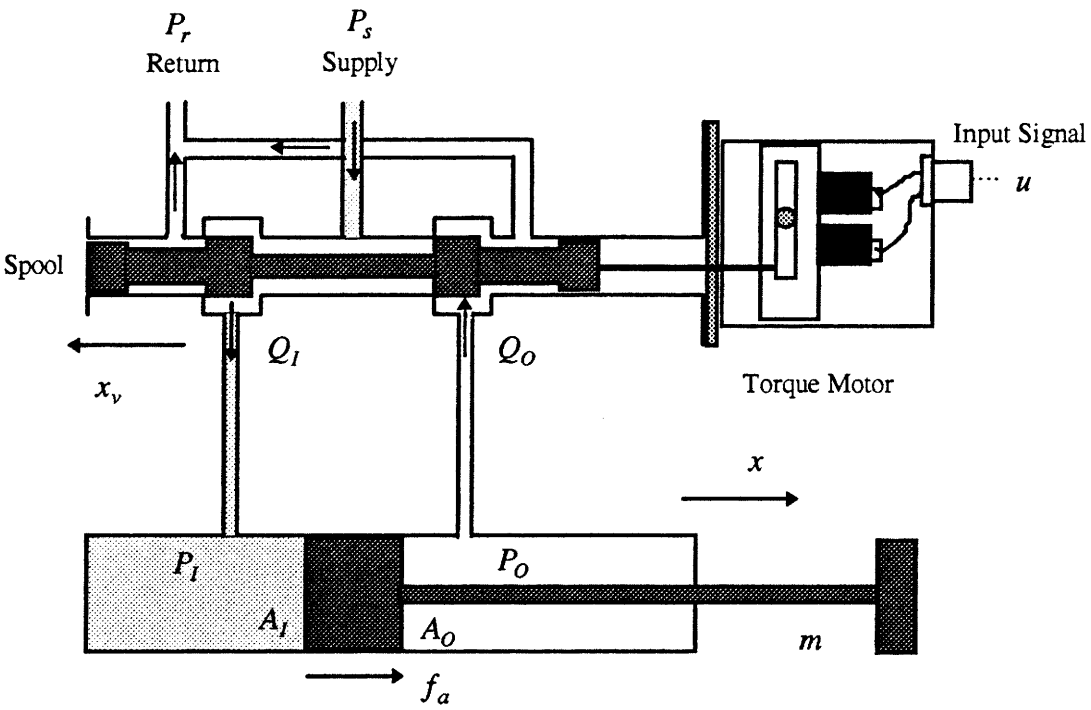
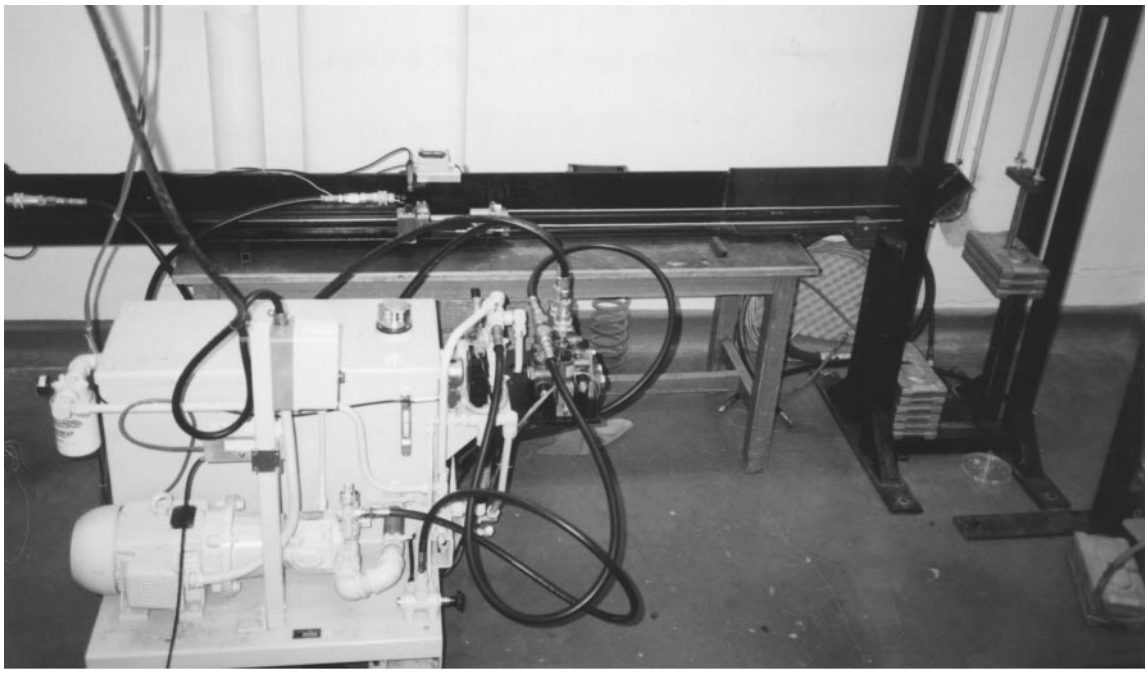
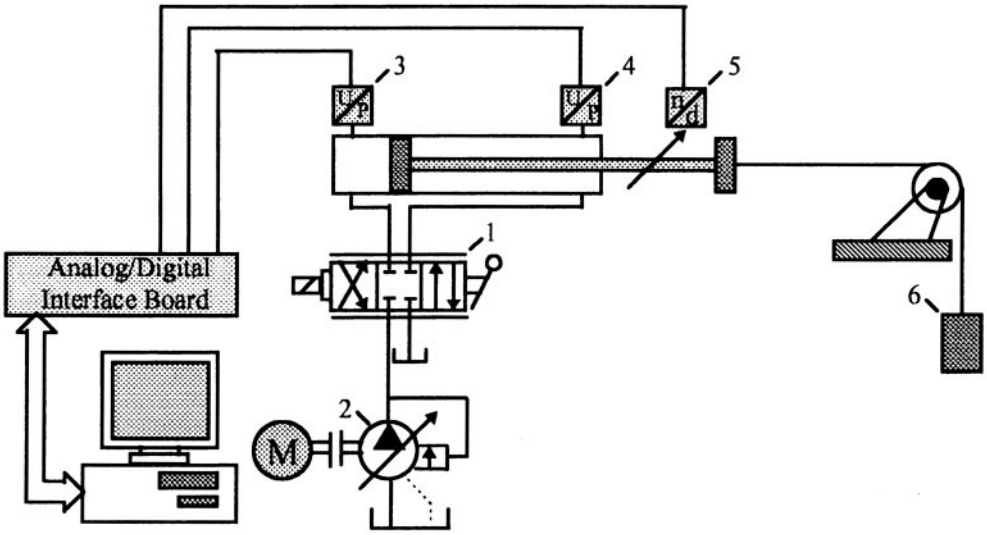


Fig. 1. Schematic of electro-hydraulic positioning drive unit.

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1- Servovalve
2- Pump
3- Supply Line Pressure Transducer
4- Return Line Pressure Transducer
5- Incremental Encoder
6- Load

Fig. 2. Experimental test station.

Vector **f** is composed of signals which are known at time t, i.e.,

$$f(t+1)=[G_1(q^{-1})-g_{10}]\Delta u(t)+F_1(q^{-1})y(t)$$

$$f(t+2)=q[G_2(q^{-1})-q^{-1}g_{21}-g_{20}]\Delta u(t)+F_2(q^{-1})y(t)$$

$$\vdots$$

Note $g_{i0}=g_{i1}=\cdots=g_{i(i-1)}$, or for short, $g_{ij}=g_j$, for $j=0, 1, 2, \cdots, <i$, which is independent of the particular G polynomial. Therefore, **G** is a lower-triangular matrix of dimension $(N\times N)$:

$$\mathbf{G}=\begin{bmatrix} g_0 & 0 & \cdots & 0 \\ g_1 & g_0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ g_{N-1} & g_{N-2} & \cdots & g_0 \end{bmatrix}$$

Based on the prediction of future outputs, GPC algorithm aims at good performance a few steps ahead, and produces a sequence of future control signals by minimizing the following cost function:

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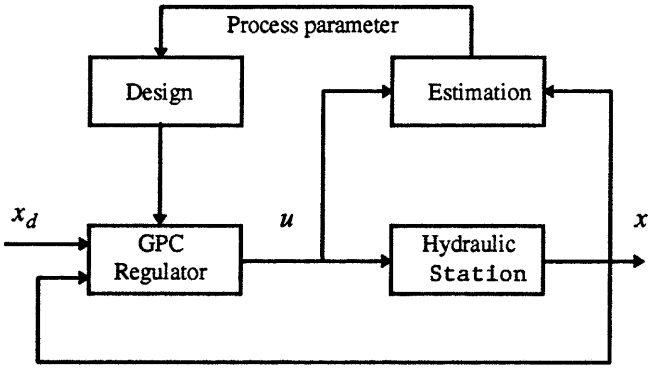


Fig. 3. Adaptive generalized predictive control block diagram.

$$J(N_1, N_2, N_u)=E\left\{\sum_{j=N_1}^{N_2}[\hat{y}(t+j)-w(t+j)]^2 + \sum_{j=1}^{N_u}\lambda(j)[\Delta u(t+j-1)]^2\right\} \quad (6)$$

where N_1 is the minimum output horizon, N_2 is the maximum output horizon, N_u is the control horizon and $\lambda(j)$ is a control weighting sequence which is usually set to a constant λ. $w(t+j)$ is the future set point j-step ahead. Minimizing equation (6) yields the following control increment vector,

$$\Delta\mathbf{u}=(\mathbf{G}^{\mathrm{T}}\mathbf{G}+\lambda\mathbf{I})^{-1}\mathbf{G}^{\mathrm{T}}(\mathbf{w}-\mathbf{f}) \quad (7)$$

where $\mathbf{w}$ is the vector representing future desired set points and $\mathbf{I}$ is the identity matrix. The first element of vector $\Delta\mathbf{u}$ is the current control input increment.

Referring to equation (6), the controller can be tuned by adjusting the value of parameters N_1, N_2, N_u and λ. If the system has a time delay of k sampling periods, then N_1 is normally set to k. If k is not known or is variable, then N_1 can be set to 1 with no loss of stability. N_2 should approximate the rise time of the system. (N_2-N_1) is the number of the future response errors that are to be minimized in the cost function represented by equation (6). Generally, the system response is more stable if more future control increments are taken into minimization. N_u is usually set to 1 for stable plants with delays or with non-minimum phase plants.[10] Note that GPC algorithm assumes that after $N_u<N_2$ number of time steps, the control signal is held constant. Finally, λ, the control weighting sequence, acts as a damping agent for the system. A more detailed explanation of the above parameters can be found in reference[8].

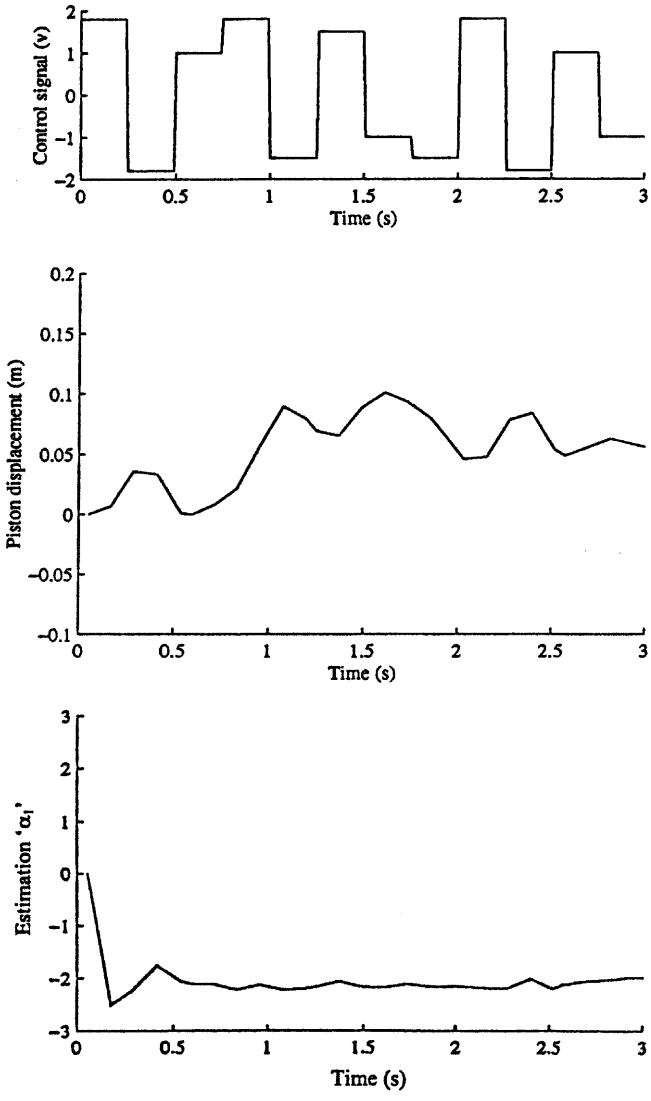


Fig. 4. Off-line estimation experiment.

2.2 Hydraulic functions

Figure 1 depicts the schematic of a typical hydraulic driving unit using a closed-centre four-way valve, operating from a constant pressure pump system. The main components of the unit are the valve, connecting hose, and a cylinder. The linearized dynamics equations of the valve system, in s-domain, are:[13]

$$Q_I=K_u u-K_p P_I \quad (8a)$$

$$Q_O=K_u u+K_p P_O \quad (8b)$$

where

$$K_u=Kw\sqrt{\frac{P_s-P_l}{2}},\quad K_p=\frac{Kwx_v}{\sqrt{2(P_s-P_l)}} \quad \text{and} \quad P_l=P_I-P_O$$

u represents the control input voltage which is proportionally related to the valve spool displacement, x_v. P_s is the supply pump pressure P_r is the return pressure. Q_I and Q_O are the valve flow rates and, P_I and P_O are the line pressures. K is the metering coefficient, and w is the spool area gradient. Alternatively, line pressures and flow rates are related to each other by the following pipe dynamics equations in s-domain,

$$Q_I=CP_I s+A_I Xs \quad (9a)$$

$$Q_O=-CP_O s+A_O Xs \quad (9b)$$

where A_I and A_O are the piston's effective areas and, X represents the piston linear displacement. C is the hydraulic compliance. Equating (8) and (9) to remove Q_I and Q_O arrives at the following relations,

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$$P_I = \frac{K_u u - A_I X s}{K_p + Cs} \tag{10a}$$

$$P_O = \frac{-K_u u + A_O X s}{K_p + Cs} \tag{10b}$$

The actuating force, F_a, is expressed as

$$F_a = P_I A_I - P_O A_O = mXs^2 + dXs \tag{11}$$

where m denotes the payload and d stands for the viscous damping coefficient. Substituting (10) into (11) gives the following third order system:

$$\frac{X(s)}{u(s)} = \frac{K_u(A_I + A_O)}{s[(ms+d)(Cs+K_p) + (A_I^2 + A_O^2)]}$$

Note that the dynamics of the valve, in most robotics applications, is much faster than the dynamics of the load and therefore can be simply represented as a pure gain term in the above equation.

By taking the z-transformation of the above transfer function, including a zero order hold, a discrete form of the system outputs is found:

$$x(t) = -a_1 x(t-1) - a_2 x(t-2) - a_3 x(t-3) + b_1 u(t-1) + b_2 u(t-2) + b_3 u(t-3) + h \tag{12}$$

Term h has been included in the above equation as a forcing term to represent unmeasured disturbances including payload, frictional effect and uncorrelated random noise sequence if it exists. The model parameters a_1, a_2, a_3, b_1, b_2, b_3 and h are time varying – their values are to be identified at each time interval. The method of recursive least squares (RLS)[14] which is based on updating the covariance matrix, **P**, along with Bierman and Thornton's **U-D** factorization method[15] has been used for on-line identification of such parameters. **U-D** factorization method involves factorizing covariance matrix **P** as $\mathbf{P} = \mathbf{U}(t)\mathbf{D}(t)\mathbf{U}^T(t)$ (where **U** is a lower triangular matrix and **D** is a diagonal matrix) to ensure the positivity of covariance matrix during the identification.[6] The method has been identified to have a good convergence behaviour among estimation algorithms.[6] The major difference between this method and the conventional recursive square root algorithm is that it does not require any square root calculation.

3. EXPERIMENTAL EVALUATION

3.1 Experimental setup

Figure 2 shows the test station on which all experiments have been carried out. The main feature of the test station is its open hardware structure, with high computational

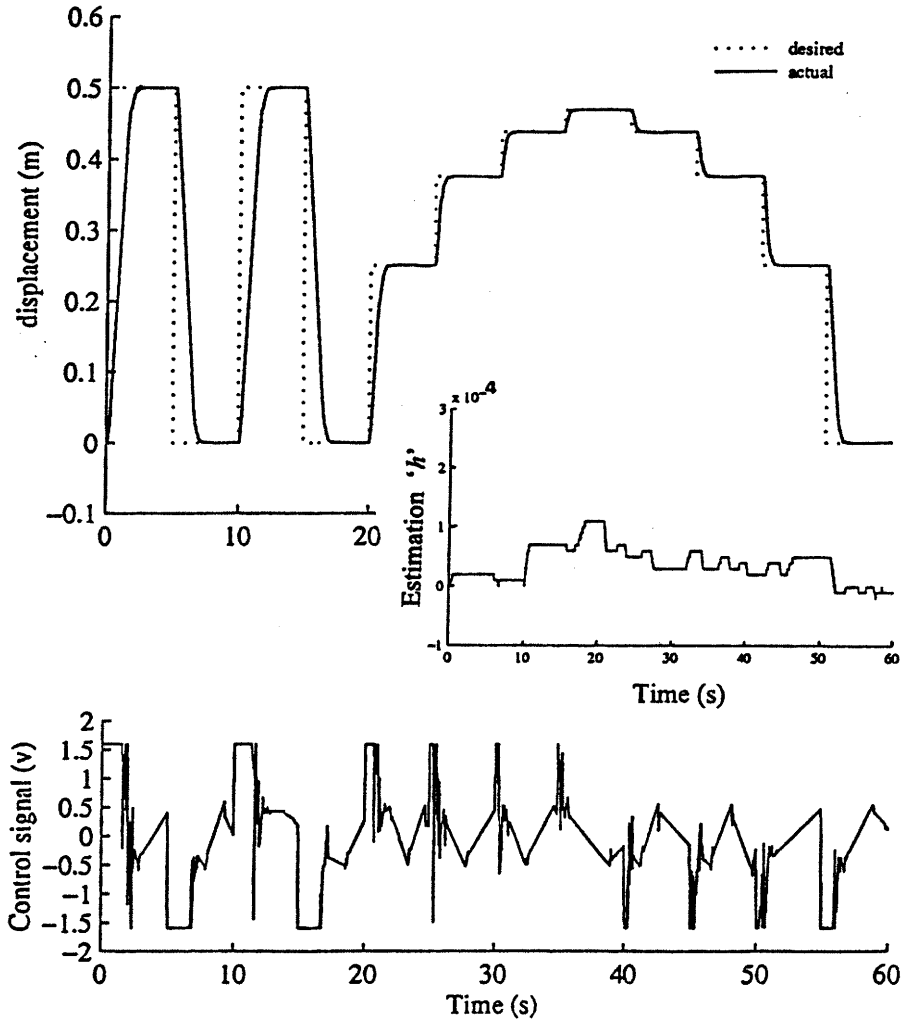


Fig. 5. Control response in multiple step input; $N_1 = 1$, $N_2 = 22$, $N_u = 1$, $\lambda = 0.005$; (*inset*) on-line estimation of parameter h.

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capacity and good software programmability so as to easily take on different control strategies. It is also designed to resemble the basic hydraulic circuit of various manipulator applications. With reference to the schematic diagram in Figure 2, the test station consists of a servovalve-controlled cylinder, a 486/66-based PC with a Mertrabyte M5312 quadrature incremental encoder card, a DAS-16 analog/digital (A/D) conversion card and a payload facility. The hydralic unit consists of a pump, a valve and a cylinder. The pump which runs by a 3700 W electric drive, is set to provide a constant operational supply pressure at ≈7000 kPa. The hydraulic valve is a low-cost closed-centre four-way propotional valve. The positioning of the valve spool is based on the pulse width modulation principle. The reaction time of the valve from the neutral position to maximum spool travel is 120 ms. The cylinder is fixed on a frame, and the load is attached to the actuator piston through steel cables.

Three pressure transmitters read pump, supply line pressures with 1% accuracy. The displacement of the cylinder piston is read by an incremental encoder with sensing resolution of 0.006 mm. The computer compares each digitized position signal with a set-point, and generates a control signal. The control signal is converted to an analog signal by the A/D card, and is transmitted to the hydraulic valve amplifier. The valve operates within the range ±1.8 volt and has a deadband of ±0.4 volt within which the actuator does not move thus, impairing the control result. The sampling time was measured at 10 ms for the experiments.

3.2 Implementation

One crucial aspect in adaptive control is the determination of the model. Thus, first the open-loop Bode plot of the test station was experimentally determined from the output-input ratio (i.e. displacement-control voltage) generated in frequency domain. Square wave signals were used instead of sinusoidal input signals, to circumvent the effect of actuator's flow deadband nonlinearity. It was confirmed that the test station could be modelled as a third order, type one system. For the sampling period of 10 ms, the poles of the system (including the zero-order-hold), in discrete domain, were found to be

$$z_1 = 1, \quad z_2 = 0.825 - 0.0085j \quad \text{and} \quad z_3 = 0.8526 + 0.0085j \tag{13}$$

With reference to Figure 3, at each sampling time, the parameters of the plant model described by equation (12), are to be estimated based on the latest data pair $u - x$. The design block then updates polynomials $E(q^{-1})$, $F(q^{-1})$ and

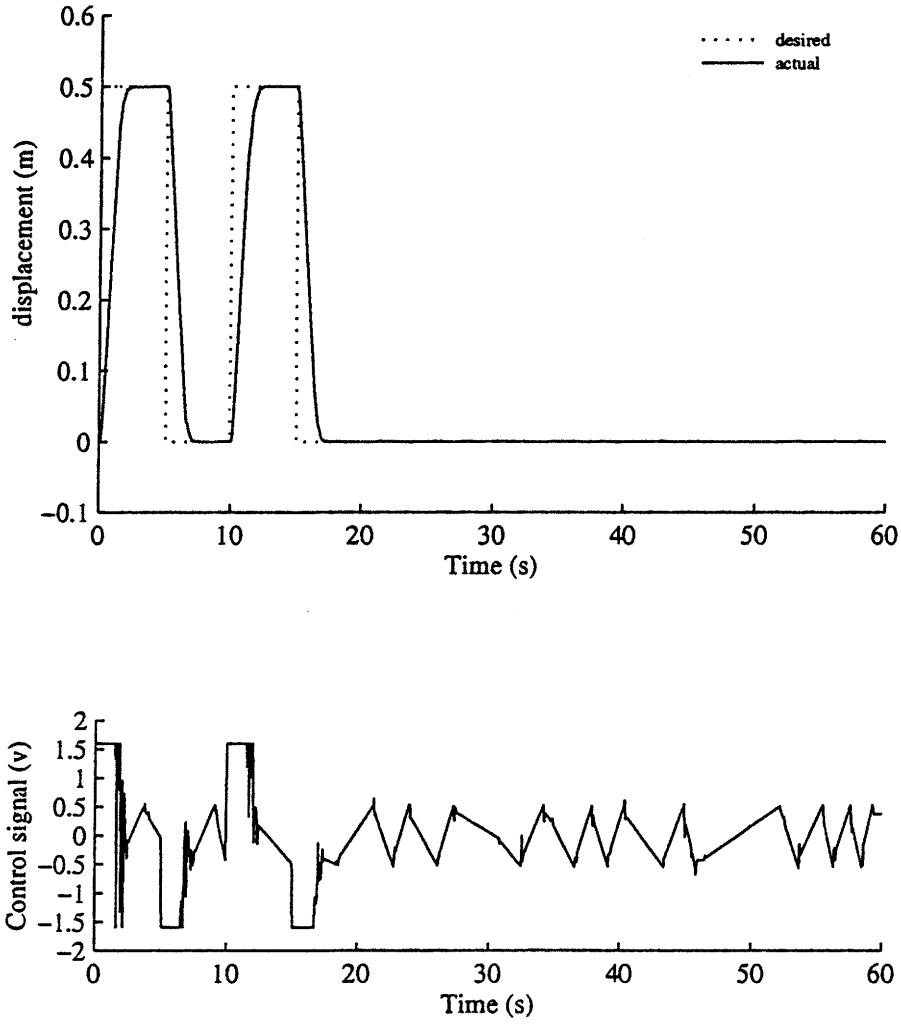


Fig. 6. Prolonged position control test.

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$G(q^{-1})$ using equations (3) and (4). The control increment to be applied to the actuator at time t is finally calculated according to equation (7).

A preliminary experiment was performed to estimate the parameters of the model polynomials, i.e., polynomials A and B in equation (1). This was done by removing the

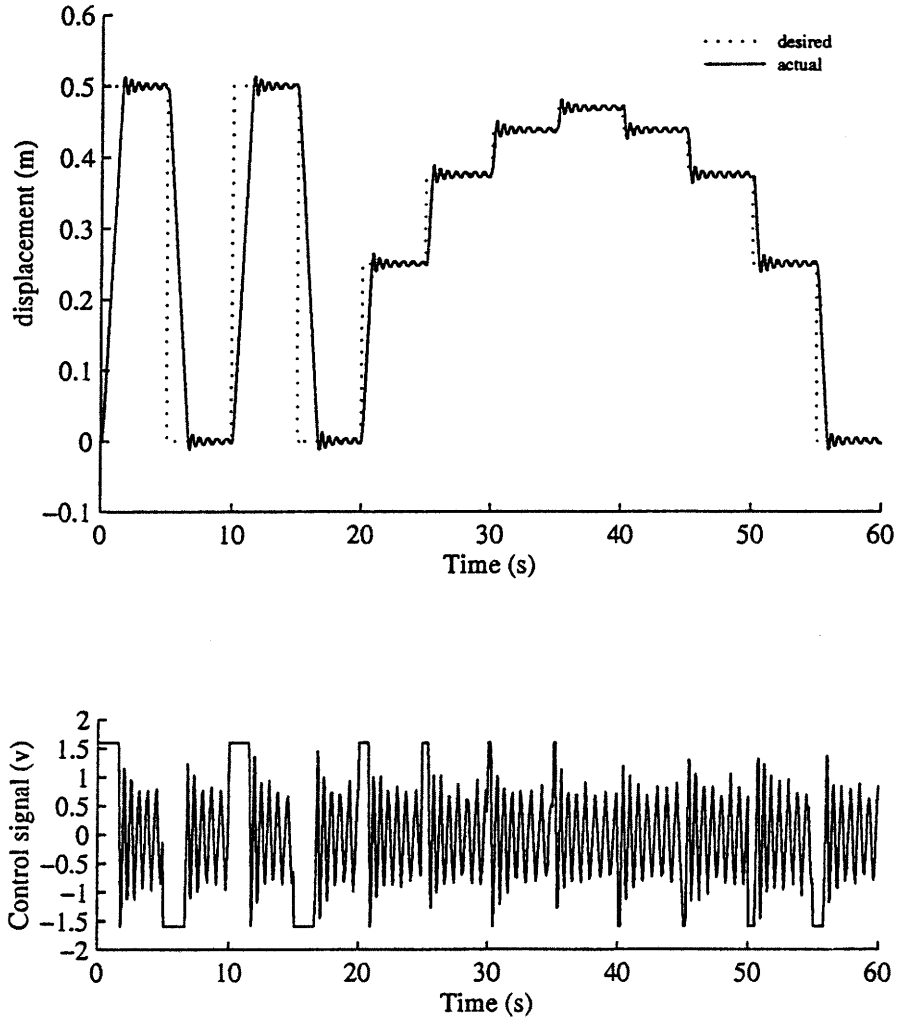


Fig. 7. Control response in multiple step input without on-line estimation.

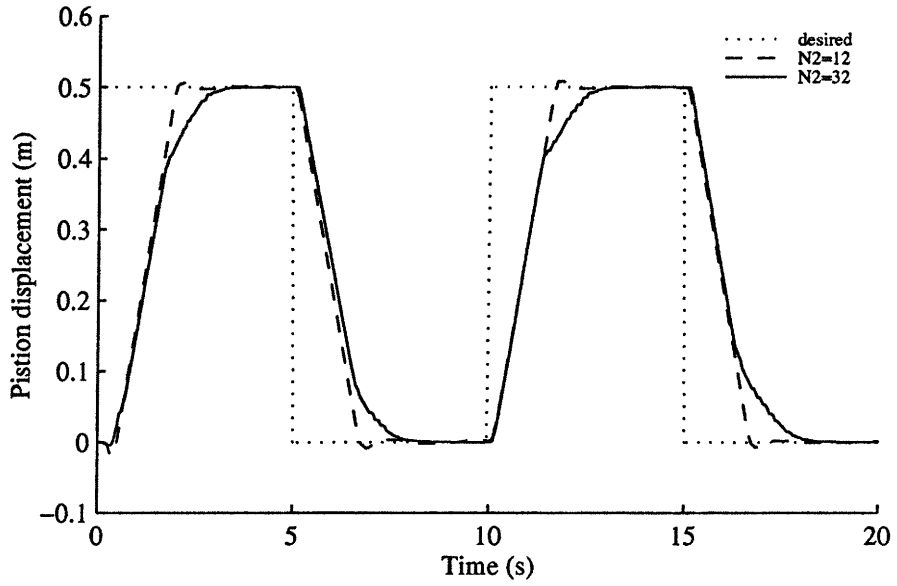


Fig. 8. Effect of maximum output horizon, N_2, on response.

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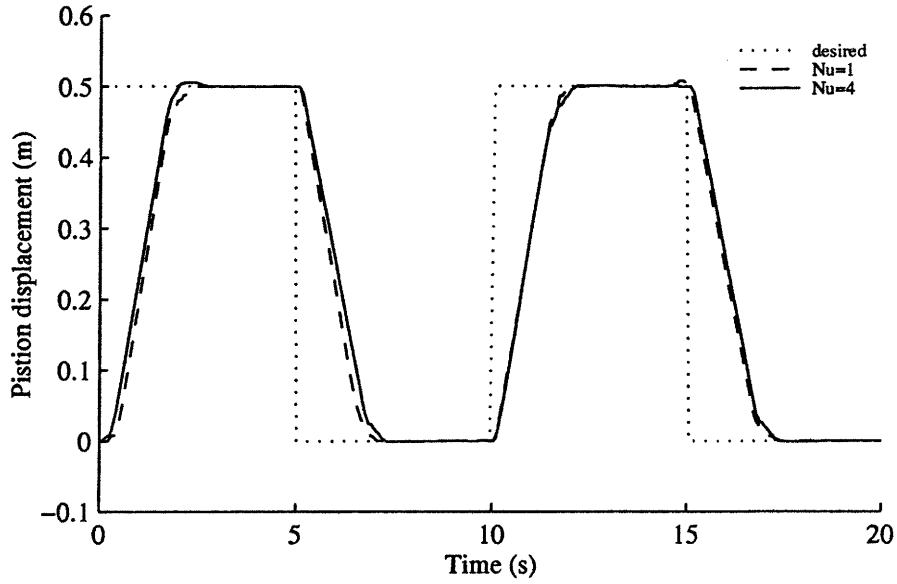


Fig. 9. Effect of control horizon, N_u, on response.

feedback path in Figure 3 and, replacing the controller with a signal generator. The control signal used for the off-line estimation together with the resulting piston displacement response are shown in Figure 4. Initially the values of the parameters were arbitrarily selected as either one or zero; the diagonal elements related to the covariance matrix were set high, indicating little confidence in these estimations. The forgetting factor was set to 0.99 – when the input and output signals are not filered, this choice has been found to be most appropriate (see reference 2 for a discussion on this). The plot of the estimated parameter, a_1, is included in Figure 4. The off-line estimation resulted in the following values for the coefficients of A and B polynomials:

$$a_1 = -2.3, \quad a_2 = 1.82, \quad a_3 = -0.48,$$
$$b_0 = 0.00011, \quad b_1 = 0.00025, \quad b_2 = 0.00018 \qquad (14)$$

These values represent a system with poles close to those obtained through a frequency response analysis (see (13)). They were then used as initial values during the on-line estimation.

Further, it is well known that sufficient excitation is vitally important for correct on-line estimation, specially when a forgetting factor less than unity is used. If the control signal ceases to have sufficient excitation, the elements of the covariance matrix, **P**, start to increase exponentially leading to incorrect parameter values. A technique called "regularization"[14] has been recommended to prevent the parameters from drifting. The method can be incorportated within **U-D** factorization algorithm[15] to limit the values of the elements in matrices **D** and **U**. The above method has been adapted in this work according to the following procedures: (i) when the control signal drops within the deadband (range ± 0.4 volt), the estimation is simply switched off; (ii) the sum of the diagonal elements in **D** matrix is bounded to be within [10,100] and, the sum of the elements in the upper triangular matrix **U** is bounded to

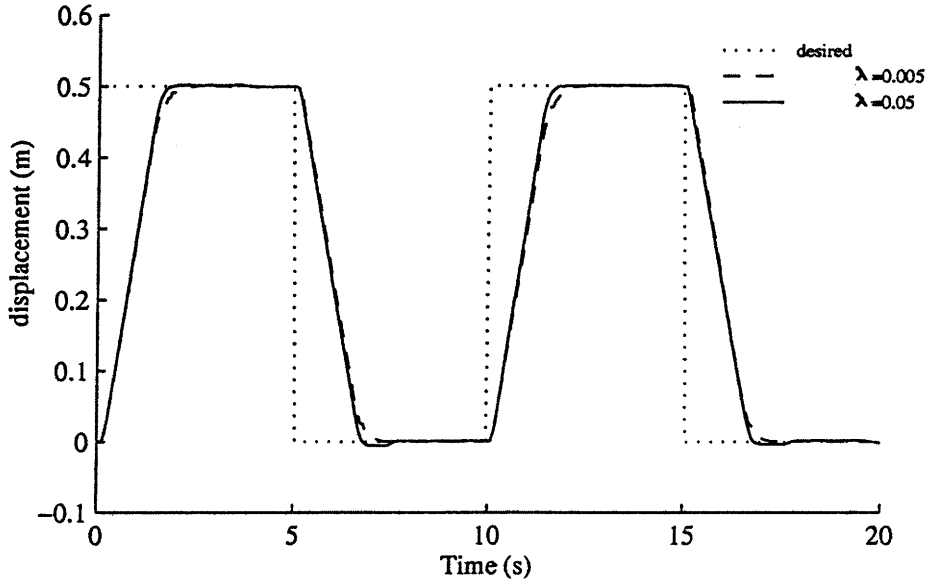


Fig. 10. Effect of control weighting sequence, λ, on response.

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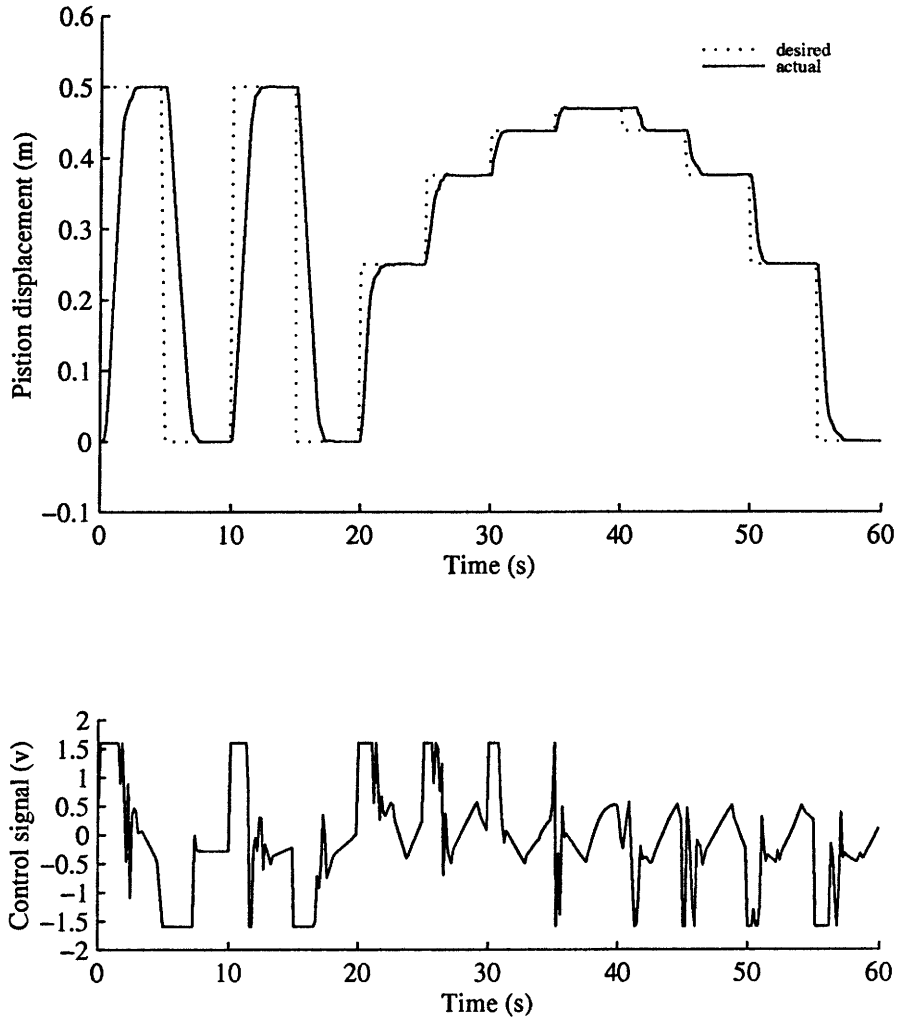


Fig. 11. Controller response to variable payload condition.

be within [0,1.2]. These boundary values were initially chosen according to the off-line identification and were then fine-tuned experimentally, i.e., they were adjusted by observing the parmater drifing during the experiments.

Note that, in this work, the sums of the elements were bounded instead of limiting each element of matrices **U** and **D**. This was because there were 7 elements in **D** matrix and 28 elements in **U** matrix. It was therefore difficult to set boundaries for each individual element correctly. Nevertheless, fairly good results were obtained by bounding the sums. Also, according to Ljung and Soderstrom,[14] it would be sufficient to set only lower boundaries. However, during the experiments, it was found that the upper boundaries also influenced the success of the estimation.

3.3 Benchmark tests

The experimental benchmark consists of a number of desired paths for the purpose of comparing different characteristics of the featured control system. Two types of tests have been chosen, The first test consists of a variable step input pattern to evaluate the controller's ability to regulate and to display the transient responses. The second set of tests consists of ramp and cosine input trajectories to test the ability of the controller in following reference changes.

3.4 Results and discussion

Figure 5 shows the response of the controller, with well tuned parameters, to a variable step input test. The controller exhibits good performance. The response is fast, with no overshoot and with no visible steady-state errors. During the stead-state, the control signal does not chatter around the zero value suggesting that there does not exit significant mis-match between the nonlinear plant model and that represented by the linear model used by the adaptive algorithm. Typical on-line estimation of parameter h [refer to equation (12)] is included in the inset of Figure 5.

The prolonged position control ability of GPC was also tested. The result of a typical trial is shown in Figure 6. No sustained oscillation is seen. The integrating action of the controller, within the valve deadband portion, is clearly seen from the control signal pattern. Figure 7 shows the response of the controller with no on-line estimation, i.e,. the initial values of the model parameters, obtained during the off-line estimation (equations 14), were used and were kept constant during the test. As is seen, the steady-state response is oscillatory. During this period, the valve operated around its null position, which is known to have the least damping.[13] Since the estimator was off, it could not realize the change in the system's operating point. Consequently, the control

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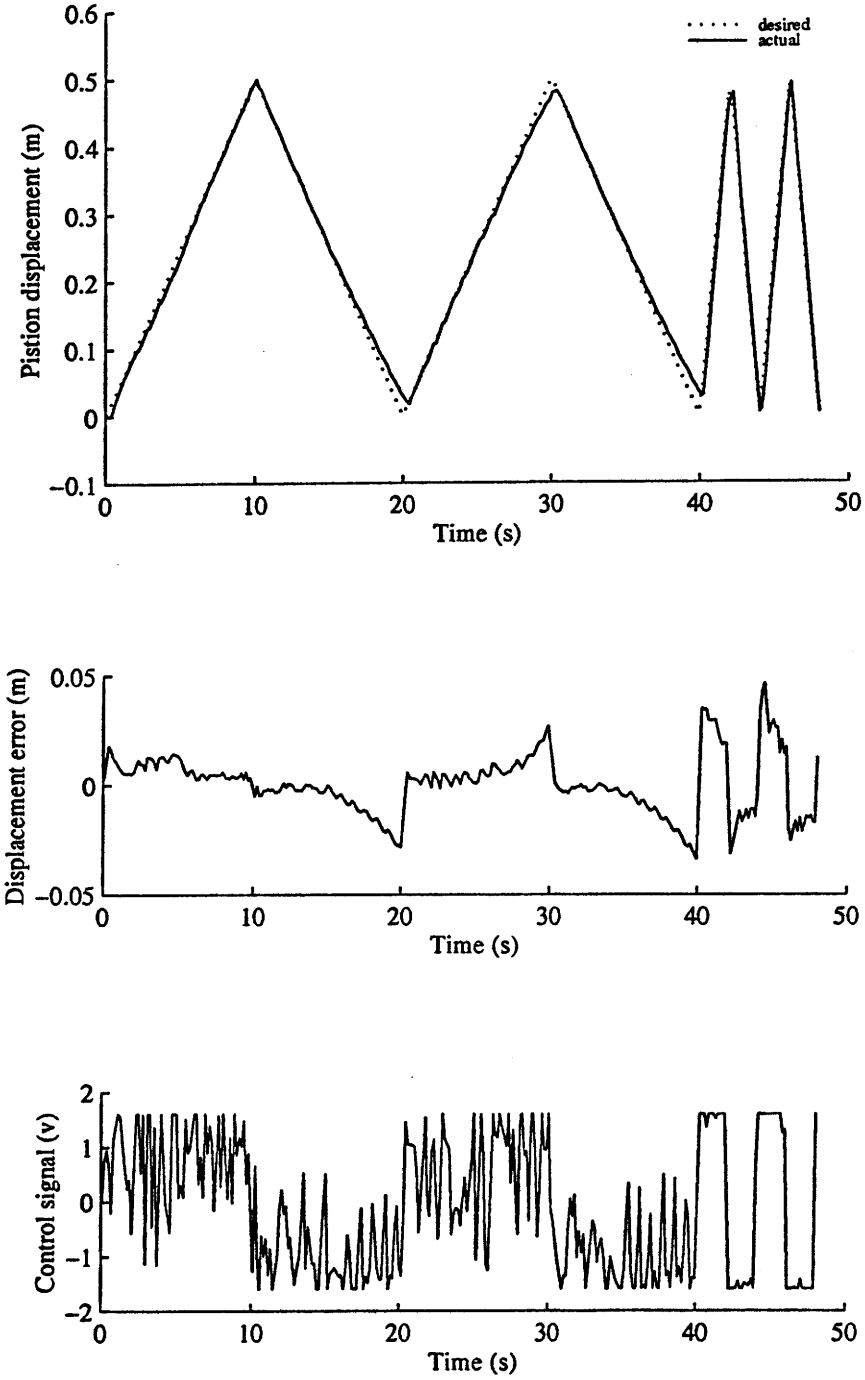


Fig. 12. Controller response to ramp input trajectory tracking.

signal was not adjusted accordingly.

In order to bring further insight into GPC algorithnm, more tests were performed with variations on the values of its parameters. Figure 8 shows the effect of varying the maximum output horizon, N_2, on the response. When N_2 increased to 32, the response became rather sluggish. Larger values have the tendency to stabilize the system since they use predicted errors over a larger period of time. Decreasing N_2 to 12, resulted in fewer predicton steps and more rapid control action; therefore the response exhibited a slight overshoot.

Figure 9 shows the response when the contol horizon, N_u, increased to 4. The response is almost identical to the result with $N_u=1$, suggesting that the experimental system under investigation contains stable and well damped poles. Increasing N_u can result in a more active control action; however, $N_u=1$ is preferred since, a larger N_u demands more comutations.

Figure 10 illustrates the performance of the controller as a result of increasing the control weight sequence, λ, ten times. Increasing this parameter means more punishment on the control signal, which leads to a less active control. Referring to Figure 10, increasing λ resulted in a response with a similar rise time but, with a slight overshoot. This is due to lack of enough control action to brake the movement of the piston as its passes the set-point. These observations are in agreement with the previously reported ones [8] obtained from the simulations.

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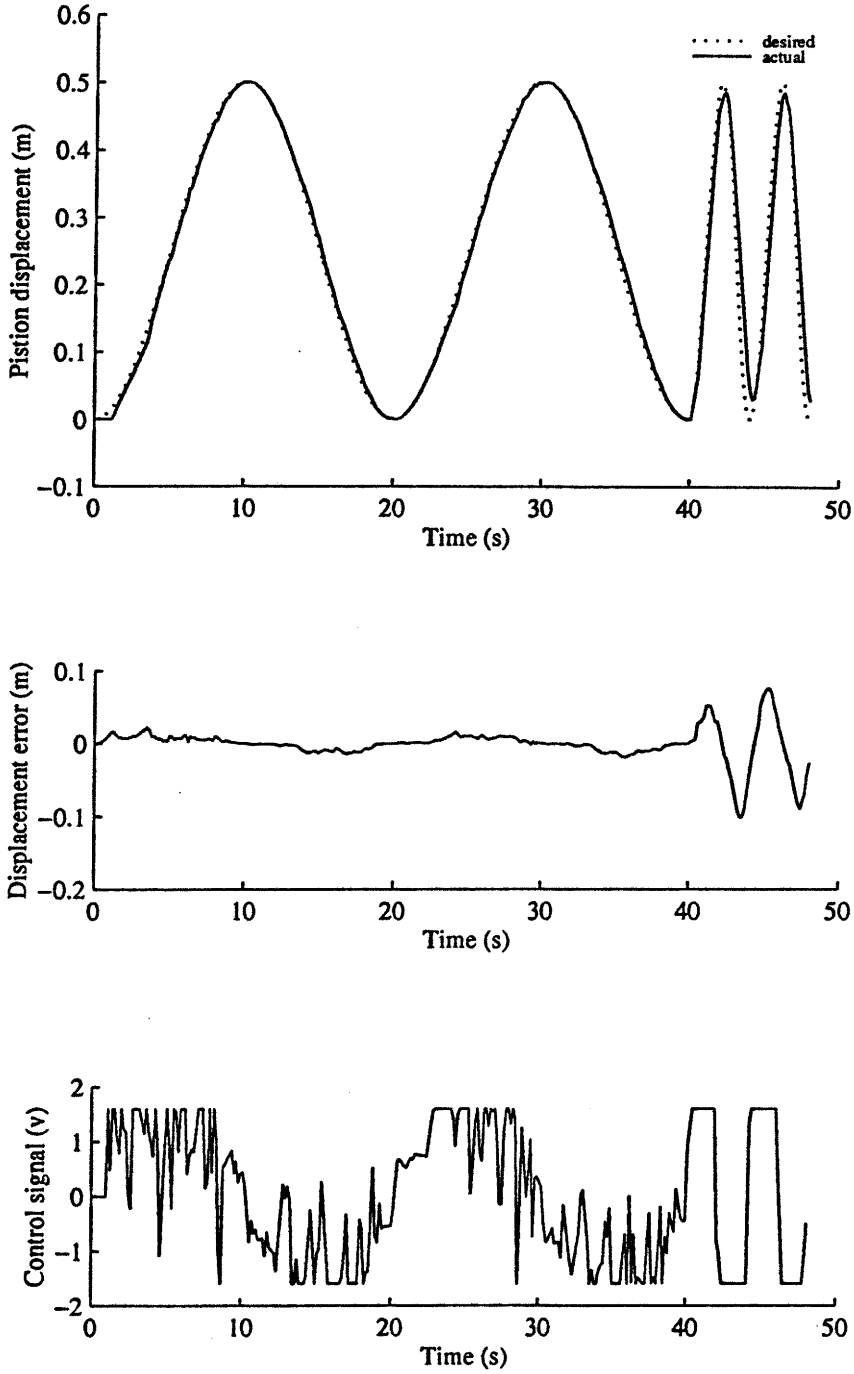


Fig. 13. Controller response to cosine input trajectory tracking.

With the parameter setting as in Figure 5, a load of 180 lb was placed on the hydraulic acutator. During the extension, the load helped the motion; whereas, it opposed the motion when the piston was retracting. Figure 11 shows the response. The controller adapted well to changes in actuator's dynamics due to changes in the direction of movement and payload effect. The introduction of payload resulted in a slightly slow response during small step retractions. This appears to have much to do with the reduced available force, due to the load opposing the motion, needed to accelerate the piston. Further experiments were carried out for ramp and cosine tracking. The slopes for the ramp input were ± 0.05 m/s during the first 40 seconds and ± 0.25 m/s during the next 8 seconds. The frequency of the cosine wave was initally set to 0.05 Hz, and then was changed to 0.25 Hz. Figures 12 and 13 demonstrate the responses together with their respective tracking errors. The tracking response exhibit acceptable tracking errors.

4. Conclusions

This paper presented the digital implementation and experimental evaluation of adaptive generalized predictive position control of highly nonlinear hydraulic actuators. This practical experience brought valuable insight into the applicability and the potential of GPC technique. It was shown that the controller which only utilized position measurements, (i) achieved good tracking and regulating

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abilities for both large and small changes in set-point and under variable loading conditions, (ii) responded quickly to changes in set-point and, (iii) reversed directions without overshoots. The experiments also demonstrated consistently good adaptability of the technique despite the presence of many nonidealities such as variable compliance due to volume change of the fluid in different part of the stroke, nonlinear valve flow-pressure characteristics, valve saturation, directional nonlinearity due to the single-ended cylinder and large flow deadband in the valve. The tracking ability to ramp and cosine set-points was found to be good due to the inherent integral action of the algorithm. What also became apparent was that a third-order model can adequately represent industrial hydraulic functions, which is consistent with the observation made previously based on either nonlinear simulations or experiments.[2,8,9]

The influence of GPC design parameters was also experimentally studied and observations were made. The maximum output horizon was shown to be more effective, than other controller's parameters, in stabilizing the systems response. The on-line estimation was, however, required certain measures in order to ensure numerical accuracy as well as control stability during periods of insufficient excitation. Bounding the elements related to covariance matrix, **P**, and switching off the estimation when the control signal lies within its deadband are features that were added to conventional least squares estimator to ensure the numerical stability of the estimation. Finally, off-line parameter estimation was shown to be very helpful to yield initial values for the parameters, so that the adaptive controller was well behaved at start-up.

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