International Journal of Fluid Power 2 (2001) No. 1 pp. 31-36

MEASURED PERFORMANCE EVALUATION OF PID AND NEURAL NET CONTROL OF A HYDRAULICALLY DRIVEN INERTIA LOAD WITH NONLINEAR FRICTION

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Abstract

Hydraulic systems are inherently nonlinear. When used to control an inertial load, which also exhibits nonlinear behaviour due to slip-stick friction at the contact surface, the result is a system which is highly non-linear and poses a difficult control problem. The study described in this paper examines the experimental performance of velocity control of a mass on a sliding contact surface using a servovalve and linear actuator. Conventional PID control is compared to artificial neural net (ANN) based controllers. A modified multi-input PID controller was used to train the ANN controller. The ANN based controller outperformed the PID controller when subjected to a wide variety of input signals. A second ANN co-controller was added to the loop to provide an additional corrective signal in the form of a pulse to give the system an extra surge of input to overcome the stiction friction in the zero velocity cross-over region. Excellent results were achieved with improved accuracy compared to the single ANN controller when subjected to a series of random input signals, indicating the robustness of the ANN controllers.

Keywords: hydraulic, PID, neural network, control, nonlinear

1 Introduction

Friction in hydraulic actuators and valves and in the systems they control can lead to tracking errors and, in some cases, instability in the form of limit cycle oscillations (Bilabdi, 1997; Dupont, 1997; Dupont and Dunlap, 1993; Tafazoli et al, 1996). Various types of simple PD controllers to deal with nonlinear friction have been proposed with varying degrees of success (Dupont, 1997; Dupont and Dunlap, 1993). A limitation of these controllers was the constraint that the system had to operate in a region about which the equations used to design the controller were linearized. Although many other type of controllers such as adaptive or optimal could be applied to the problem, the authors' experience with artificial neural networks (ANN's) and nonlinear control indicated that the nonlinear friction problem could be an application for ANN technology.

The artificial neural network has considerable potential in the ability to deal with the nonlinear systems typically encountered in the fluid power area as a result of the learned behaviour characteristics of the ANN and the lack of a need for formal analytical structure in application. This is an important consideration where an accurate model of certain characteristics is extremely difficult to quantify. Such is the case of nonlinear friction.

The authors have recently explored the utilization of ANN techniques in the control of a highly nonlinear system - in particular, the velocity control of an inertial load with slip-stick friction resulting from a mass sliding on a metal-to-metal contact surface (Qian et al, 1998; Qian et al, 1999). The studies, which were largely simulation based, demonstrated the potential of ANN based controllers for this application.

In this paper, the work is extended to develop an ANN co-controller to improve control in the zero velocity cross-over region. Detailed experimental results are presented for comparative purposes for several controller configurations. It should be mentioned that velocity control is considered here because the nonlinearity of stick-slip is greatly enhanced at the zero velocity crossing point. This is a much more difficult problem of control (in comparison to position control) because of the sensitivity of the hydraulic actuator and load to friction. In addition, it must be emphasized that the input waveforms considered in this study were more demanding than most inputs required in practice. The particular waveforms chosen were very complex and were

This manuscript was received on 20 October 2000 and was accepted after revision for publication on 23 February 2001

specifically chosen to subject the controller to extreme conditions and to enhance the nonlinear effects.

This paper will consider the application of this ANN based co-controller to an hydraulic experimental system where the velocity is the controlled output. The advantages, potential and constraints of such an approach are discussed.

2 Hydraulic Control System

The system that was studied is shown in Fig. 1. An inertial load is driven by means of a double acting, single rod hydraulic actuator controlled by a servo-valve. The measured nonlinear friction characteristics between the force developed and applied by the linear actuator to the load, as a function of mass velocity, is shown in Fig. 2. The presence of Coulomb friction is very evident; further, the nonlinear characteristics are not symmetrical, in part due to the orientation of the load in the experimental system. This particular characteristic was considered to be a good challenge for the application of an ANN controller focusing on the zero velocity cross over point.

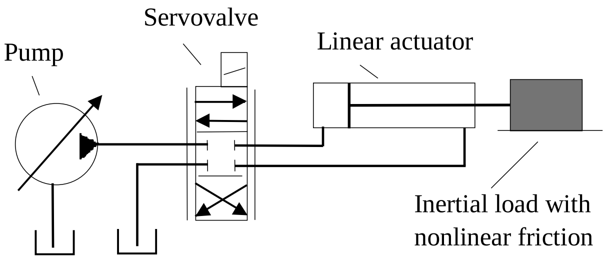

Fig. 1: *Hydraulic system used for velocity control of an inertial load*

3 PID Control

As a first step, conventional controllers were applied to a simulated model of the system. This was considered to be most important in establishing the feasibility of using ANN technology. The describing equations for the valve actuator and load were derived using power bond graphs and based on recognized assumptions and established parametric relationships. To facilitate the dynamic simulation of the hydraulic servo system as well as all the controllers and interfacing devices, the simulation software package Matlab/Simulink© was used. The model was used to develop and tune the controllers through multiple simulations prior to testing on the actual system. As described in Qian et al (1998), the model was found to provide a very accurate representation of its physical counterpart and reproduced the expected nonlinear behaviour in the system.

To establish a "base" upon which a comparison of the proposed ANN controller and co-controller could be made, a PID controller was first implemented. The PID controller was located in the forward part of the control loop and the parameters obtained using the classical Nichols/Ziegler method (Murrill, 1998). A stability study indicated that the controller was stable over the operating conditions investigated. Manual fine tuning was employed to give the best response to a waveform consisting of a series of step inputs as well as a swept sinusoidal signal varying from 0.4 Hz to 8.0 Hz, as shown in Fig. 3. The response of the system to this input after tuning is shown in Fig. 4. It is evident that the system has difficulty following the desired input.

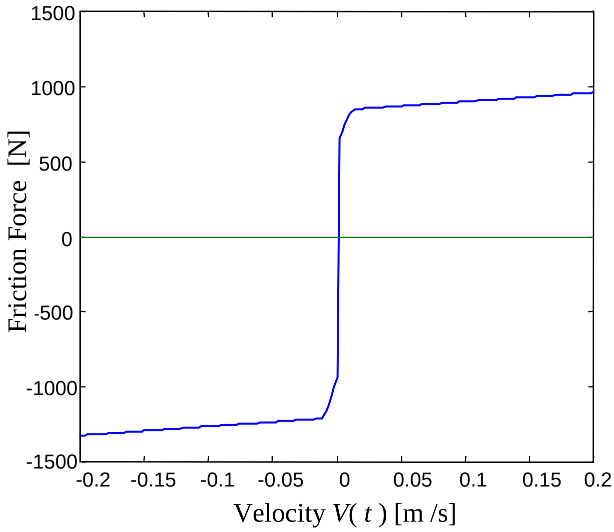

Fig. 2: *Nonlinear friction characteristics of the actuator and load*

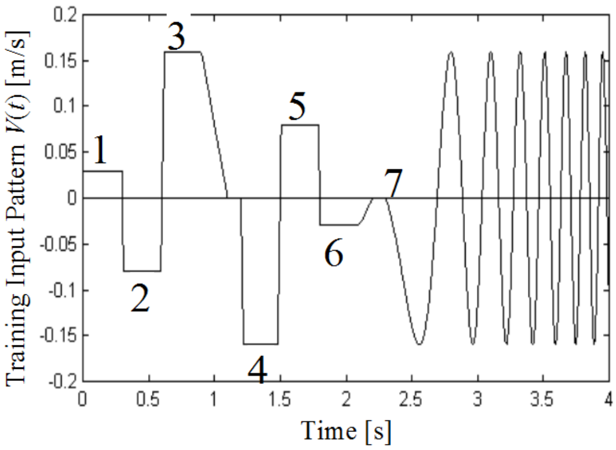

Fig. 3: *Segmented PID control input signal profile*

It should be noted at this time that to provide a measure of comparison for various controllers, the sum of the squared errors (SSE) at sampled points over the whole pattern was calculated. A reduction in the SSE from one trace to the other indicates a general improvement in the tracking ability of the controller. The absolute value of the SSE has little meaning in this instance.

As discussed in Qian et al (1998), a sequential PID controller was developed where a separate set of PID parameter settings was developed for each of the different (numbered) segments of the input signal shown in Fig. 3. The gains were tuned (scheduled) at specific points in the pattern. The results showed an improvement in the ability of the controller to follow the input over a much larger amplitude and frequency range (an SSE of 7.92 compared to 9.91 for the standard PID controller). This controller, however, was very complex to implement and thus, a neural network was trained to learn the PID characteristics over the same input pattern.

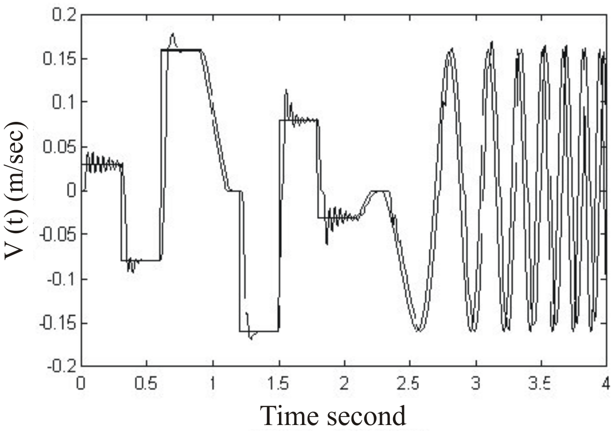

Fig. 4: *Response of the PID controller to the input signal profile*

4 ANN Controller

ANN's have been used extensively as a means to model nonlinear systems using input/output data (Qian et al, 1999; Murrill, 1998). In this study, an ANN was placed in parallel to the segmented PID controller, as illustrated in Fig. 5. By subjecting the ANN to similar input and output signals that the PID controller experienced, the ANN could be readily trained to mimic the performance of the PID controller without disturbing the actual system. Once the neural network was trained and then tested with data it had not seen before to yield acceptable results, the network replaced the sequential PID controller (the SSE for both controllers was comparable). The advantage in this approach was the relative ease in which the neural controller could be implemented. Further, since a stability analysis showed that the PID controller was stable for the gains used, then the stability of the ANN controller was reasonably ensured.

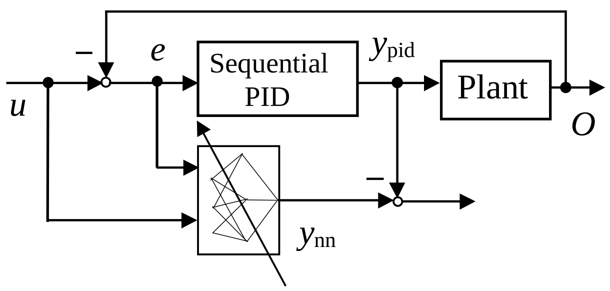

Fig. 5: *Neural net training protocol*

The morphology of the neural network was as follows: the inputs were *e*, *e*(*k*-1), *e*(*k*-2), *e*(*k*-3), *u*(*k*), *u*(*k*-1) and *u*(*k*-2) where the *k*-1, *k*-2 etc. reflect time delays. There were eight neurons in the input layer, nine in the first hidden layer, seven in the second layer and one in the output layer (this morphology was established by trial and error). In an unconventional manner the input signal, *u*(*k*), and two time delayed input signals, *u*(*k*-1) and *u*(*k*-2), were used as inputs to the network as well. This provided additional information regarding the desired amplitude and frequency of the waveform as well as for the sign of the desired velocity signal. An improved system simulated response was obtained.

Central to the functionality of neural networks was the training process. The ANN was batch trained such that the actual training process did not commence until all of the information was processed. The system was subjected to the pattern of interest and the accumulative error between the NN and PID outputs calculated. The weights of the NN were then adjusted using the Levenberg-Marquardt algorithm. This algorithm has been proven to be one of the most efficient training methods and is also available in the Matlab Neural Network Toolbox.

5 ANN Based Co-controller

The response of the system to a 1 Hz sinusoidal input signal is shown in Fig. 6 using the ANN controller. It is apparent that a significant error occurs in the vicinity of the zero velocity cross-over region, due to the nonlinear friction characteristics of the actuator and load.

It was decided that system performance could be improved by the addition of a co-controller which would give the system an input pulse at the zero velocity condition in order to rapidly overcome this friction. This is a common approach to overcoming some of the problems at the zero crossing point. In this study, however, an ANN based co-controller was developed which could be trained to tune the pulse width and amplitude as circumstances required.

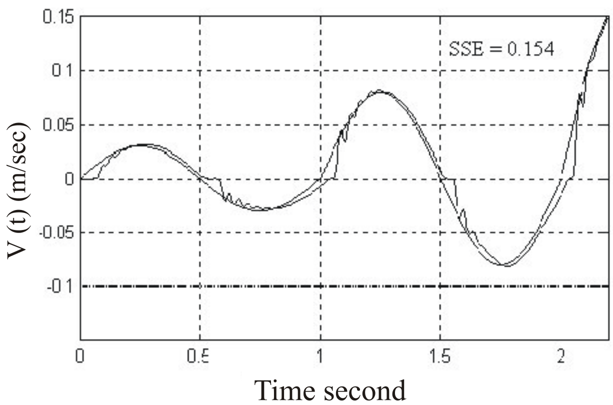

Fig. 6: *Neural net controlled system response to a 1 Hz input signal*

Initially a simple look-up table based co-controller (not ANN based) was employed to assess the effect of the various pulse characteristics on system performance (Qian, 1998). After much investigation, the pulse shape utilized was a half sine wave. Both the pulse amplitude and width were found to be critical factors. Using the system input and output signals as input parameters to the look-up table, a gradient search method was used to determine the best pulse amplitude and width values for the cross over points. As with the original ANN (PID) controller a second ANN was trained to perform the tasks of the look up table. Once an acceptable error between the ANN and look-up table was accomplished through training, the second ANN replaced the look-up table in the circuit. The final operating configuration, after training with both ANN's in the circuit, is shown schematically in Fig. 7. This ANN generated both pulse amplitude and width signals using a half sine wave generator (the pulse generator in Fig. 7).

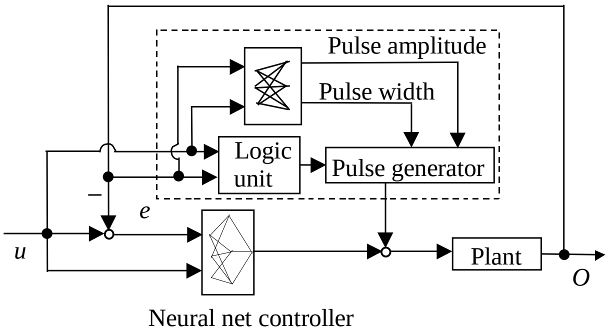

Fig. 7: *Training an ANN for modelling a sequential PID controller*

In addition to the real time system input and output signals, time delayed signals were also used for both ANNs. These signals effectively provided slope and rate of change of slope information and were used in the final system training for the training signal of Fig. 3.

6 Comparative Performance of Controllers

The performance of all three controllers was initially examined using a simulated model of the system. This preliminary study was most useful in establishing the feasibility of the concept and to tune the controllers to expected operating regions in the experimental system. The trained controller was then applied to the experimental system illustrated in Fig. 1. The hydraulic test system was subjected to two different input signals. Because this was a comparison study, attention was placed on replicating experimental operating conditions; further, all tests were repeated to establish confidence in the results. The experimental responses presented here are very representative of the many tests that were conducted.

Many studies were conducted on the experimental system to fine tune the controllers. The SSE's for these tests were very repeatable. However, the real test for the ANN controllers was to evaluate performance using input signals for which they had not been trained. These results are presented here.

Figure 8 shows the comparative performance of the controllers for a triangular input signal. While some differences are apparent from visual inspection, the SSE provides the best measure of comparison. Both of the ANN based controllers out-perform the PID controller with the dual neural net controller providing the most accurate output signal (SSE = 0.1007 PID, SSE = 0.0526 single ANN, SSE = 0.0365 with ANN co-controller).

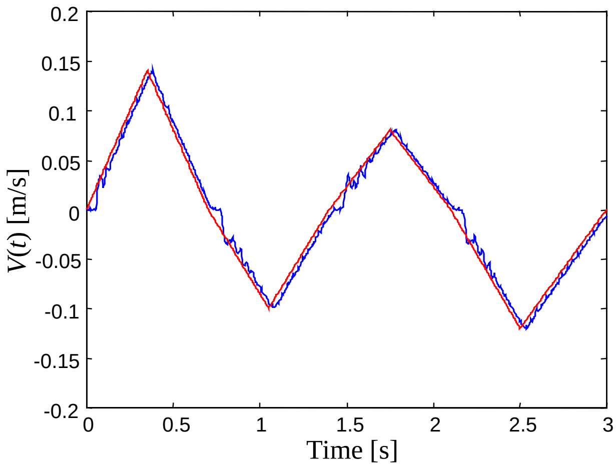

Fig. 8(a): *System experimental response to a triangular wave input using PID control (SSE=0.1007)*

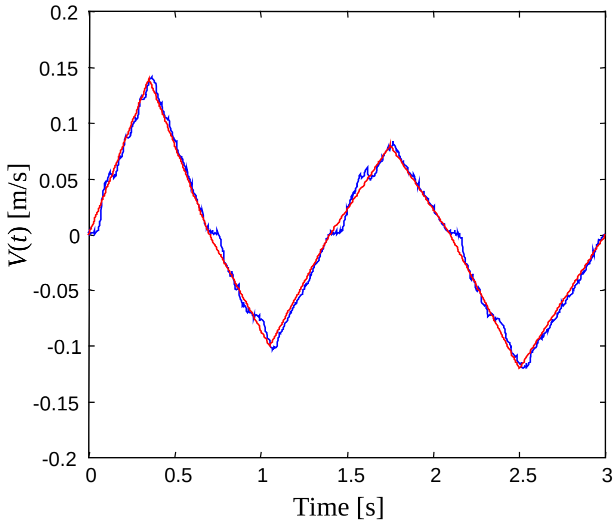

Fig. 8(b): *System experimental response to a triangular wave input using single ANN control (SSE=0.0526)*

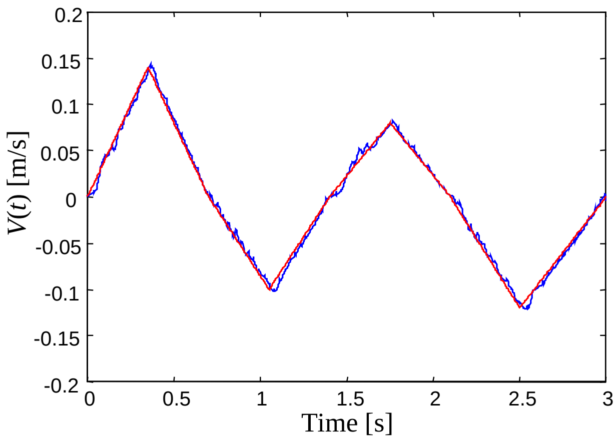

Fig. 8(c): *System experimental response to a triangular wave input using dual ANN control (SSE=0.0365)*

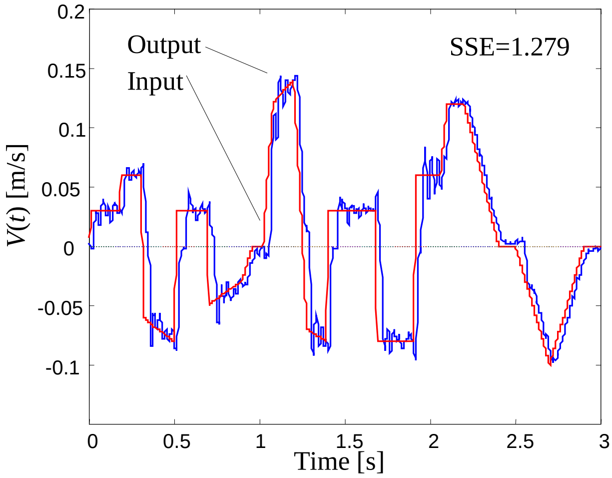

Fig. 9(a): *System experimental response to a random sequence of square, ramp and sinusoidal inputs using PID control (SSE=1.279)*

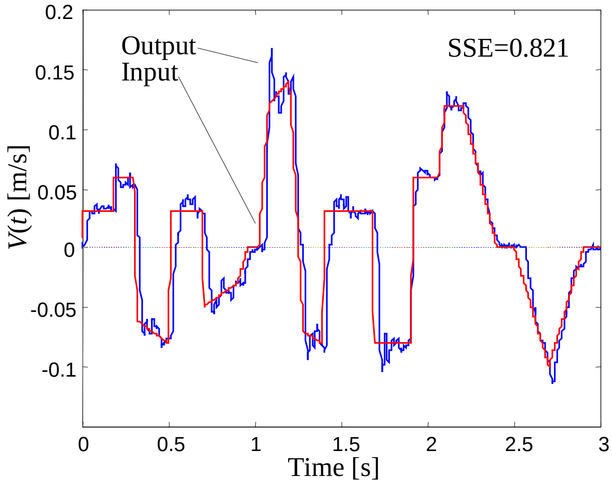

Fig. 9(b): *System experimental response to a random sequence of square, ramp and sinusoidal inputs using single ANN control (SSE=0.821)*

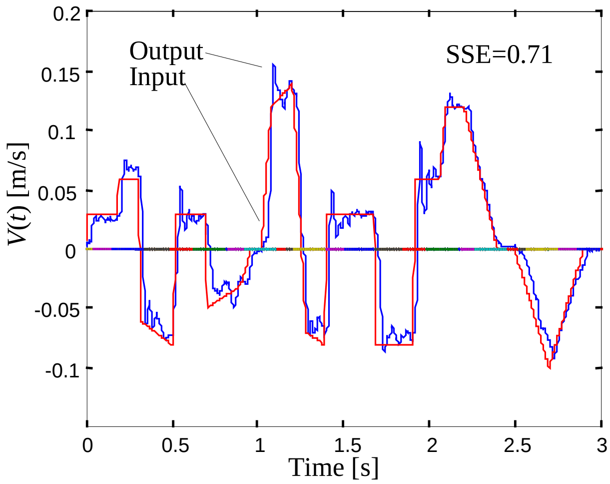

Fig. 9(c): *System experimental response to a random sequence of ramp, square and sinusoidal inputs using dual ANN control (SSE=0.711)*

This same trend is also apparent in Fig. 9 where a more complex input signal was used which consisted of segments of ramp, step and sinusoidal components (SSE = 1.279 PID, SSE = 0.821 single ANN, SSE = 0.711 with ANN co-controller).

7 Discussion and Conclusions

In this study, the use of ANN's to replace a PID controller and a complex look-up table based co-controller has been considered. It must be reiterated that the fixed gain PID controller has been used in this comparison. The sequential PID controller for the regions shown in Fig. 3 was used as the basis to train the ANN. Implementation of this PID controller was specific to the particular wave form chosen; however, the ANN trained to mimic its performance, was found to perform extremely well for any wave form chosen (again, from a comparative point of view). This "generalizing" ability of ANN's is a very powerful attribute for this kind of application.

The ANN was used to replace a complex look-up table based co-controller which was designed to add a variable amplitude and width, half-wave sinusoidal pulse at the zero velocity cross over point in the wave form. As with the PID controller study, the trained ANN co-controller performance was superior to the original co-controller to which it was trained. In this case, the ANN co-controller was able to "interpolate" between the discrete levels set in the look-up table. The most significant results presented in this paper are the improved performance obtained with ANN controllers when the experimental system was subjected to inputs for which the ANN controllers had not been trained. This indicates the truly robust nature of these controllers. Thus it was concluded that the use of the ANN based controller and co-controller could be used to improve the performance of a hydraulic servo-system driving an actuator with nonlinear friction.

Several other conclusions are apparent. First, the computational complexity of the scheduled PID controller and the look-up table co-controller was substantial when compared to the trained ANN systems. This could have significant implications for practical applications. Second, the stability of the system could be reasonably assured since the stability of the original controller could be established analytically. This, statement, however, must be tempered somewhat if the ANN's are allowed to train "on-line" for fine tuning. It is an area that needs continued investigation in the future.

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