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VELOCITY CONTROL OF OPEN CENTER HYDRAULIC SYSTEM USING NEURAL NETWORK ALGORITHM

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ABSTRACT

Real-time learning control of a hydraulic actuator is studied using a cerebellar model articulation controller (CMAC) neural network architecture. Experiments are conducted on a one degree of freedom hydraulic cylinder. The main applications considered are the earth moving equipment applications. The electrohydraulic valve used to control the flow in the hydraulic circuit is an open-center, non-pressure compensated type valve, the type used in most earth moving vehicles. Large hysteresis and deadband are observed in the hydraulic system which result in large delay and poor dynamic tracking performance. Experimental results on the control of the hydraulic actuator are compared between the CMAC controller and a conventional PI controller with model based feedforward valve transform.

Keywords: control, hydraulic, neural network, CMAC, earth moving equipment

INTRODUCTION

The earth moving industry is one of the major applications of hydraulic systems. Due to the harsh working environment, high power demands, and required mobility, there is no other feasible actuation system to substitute the hydraulic power. The earthmoving industry has been investing in significant efforts to develop high performance hydraulic actuator control systems. Significant non-linearities in hydraulic systems make it difficult to design optimized controllers which can provide high performance control at various working conditions. Changes in load, working temperature and/or aging of hydraulic components cause variations in system behavior characteristics. Deadband, saturation, non-linear gain, hysteresis, backlash and granularity are well-known non-linear input-output characteristics of hydraulic actuator components. Those non-linearities result in limit cycle, oscillations, lower accuracy, power loss and/or instability in operation.

Even though the conventional PID control algorithm is a conservative and reliable method, it can not provide optimum dynamic performance due to these non-linearities. Systems which have uncertain nonlinear dynamics, such as electrohydraulic (EH) systems, require nonlinear control since they cannot be stabilized via linear control (**1**), a number of adaptive control algorithms have been investigated and applied to the EH systems to improve the dynamic control performance (**2**). Model reference adaptive control algorithms using local (**3**) or global (**4**) linearization methods require accurate system model, off-line modeling and system identification. The variations of non-linearities caused by the aging and wear of the components cannot be compensated by these approaches. On the other hand, self-tuning adaptive control algorithms are less sensitive to the modeling error, and they are also able to compensate for the variations of the system parameters. However, self-tuning adaptive control algorithms have been developed to tune the values of initial (**5**) or full-time (**2, 6, 7, 8**) estimator parameters. Therefore the performance largely depends on the estimator design. Recently, fuzzy logic control algorithms have been proposed to deal with the system uncertainties of the EH actuators (**9, 10**). Even though accurate mathematical system model is not needed in fuzzy logic controller, appropriate expertise and experiences are necessary for optimal controller design.

In earth moving equipment, PID control algorithm was implemented with a model based feedforward compensation to deal with variations of deadband and system gain (**11**). Since the model based compensation requires accurate model of hydraulic systems, the off-line modeling and identification for each individual product is very time consuming and costly (**11**). Furthermore, implementation of feedforward compensation requires periodic calibration.

In this paper, the cerebellar model articulation controller (CMAC) neural network algorithm is proposed and implemented for a hydraulic actuator control. The laboratory experiment setup resembles on the tilt cylinder of the WTL. The application of this research is not limited to the tilt motion control of wheel type loaders but applicable to a variety of earth moving equipment and other hydraulic actuators used in heavy duty industries. The self learning ability of neural networks can approximate non-linearity of the system dynamics and adapt system dependencies (12). The CMAC learning controller is very advantageous for the real time implementation due to its simpler and faster learning convergence than other artificial neural network architectures. The goal is to improve the dynamic control performance compared to the performance levels currently achieved by PID control algorithms, reduce off-line modeling and, system identification requirements through the use of learning capability of the CMAC neural network algorithm.

SYSTEM MODELING

One example of earthmoving equipment is the wheel type loader (WTL). The main role of the WTL is to load soil or other material from a pile to a truck at a construction or mining field. The loading arm (called the linkage) of the WTL has two degrees of freedom of motion. Lift is the motion to move the bucket up and down while tilt is for rotation of the bucket. The schematic of a typical EH valve controlled hydraulic circuit for the lift and tilt cylinders in a WTL is shown in figure 1. Since there is only one pump to actuate both the lift and the tilt cylinders, and the lift spool is located after the tilt spool in series, the flow can reach the lift cylinder only when the pump-to-tank area of the tilt spool is not completely shut off. In this configuration, called *tilt priority*, the amount of lift extension is limited by the level of tilt command. The use of the open-center type directional valve is essential in this manner. Open-center type valves have larger deadband compared to that of closed-center valves.

The schematic diagram of the one degree of freedom electro-hydraulic control system used in the experiments is shown in figure 2. The system consists of a pump and relief valve (safety valve) unit, an open-center non-pressure compensated EH directional control valve, a hydraulic cylinder and a PC-bus based real-time control system. The measured data are the cylinder position, the rod end (RE) and the head end (HE) pressures, and the rotational speed of the pump, and are sampled through a four channel A/D converter. A/D and D/A converters are 16-bit resolution. The real-time control algorithm runs on the Intel 486/50 MHz microprocessor of the PC. Control action is calculated according to the tracking error and sensor data, and is sent through D/A converter to the amplifier of the solenoids of the directional EH control valve. The solenoids then activate the valve spool, which causes fluid to flow to the RE or HE of the cylinder according to the control action.

The mathematical model of the one degree of freedom (DOF) hydraulic actuator control system shown in figure 2 is as follows. For the extension motion of the cylinder, flow rates across all orifice areas are described as

$$Q_p = \omega_{engine} * q_{pump},$$
$$Q_{pt} = C_d * \sqrt{2/\rho} * A_{pt} * \sqrt{X_3 - P_t},$$
$$Q_{pc} = C_d * \sqrt{2/\rho} * A_{pc} * \sqrt{X_3 - X_4},$$
$$Q_{ct} = C_d * \sqrt{2/\rho} * A_{ct} * \sqrt{X_5 - P_t},$$

and equations of force balance on the piston-rod-load inertia are

$$\dot{X}_1 = X_2,$$
$$\dot{X}_2 = \frac{1}{M} * [X_4 * H_{area} - X_5 * R_{area} - F_{ext}].$$

Pressure changes in the cylinder due to bulk modulus of hydraulic fluid are determined by

$$\dot{X}_3 = \frac{\beta}{V_{hose}} * [Q_p - Q_{pt} - Q_{pc}],$$
$$\dot{X}_4 = \frac{\beta}{X_1 * H_{area}} * [Q_{pc} - X_2 * H_{area}],$$
$$\dot{X}_5 = \frac{\beta}{(l_{stroke} - X_1) * R_{area}} * [-Q_{ct} + X_2 * R_{area}],$$

where

A_{pt} : Pump to tank spool area,
A_{pc} : Pump to cylinder spool area,
A_{ct} : Cylinder to tank spool area,
Q_p : Pump flow,
Q_{pc} : Flow across pump to cylinder area,
Q_{pt} : Flow across pump to tank area,
Q_{ct} : Flow across cylinder to tank area,
M : Piston mass,
H_{area} : Cylinder head end area,
R_{area} : Cylinder rod end area,

l_{stroke} : Total cylinder movement,
V_{hose} : Pump to tank hose volume,
q_{pump} : Pump volume displacement per revolution,
$X_1=x$: Piston displacement,
$X_2=x'$: Piston velocity,
$X_3=P_1$: Pump pressure,
$X_4=P_2$: Cylinder head end pressure,
$X_5=P_3$: Cylinder rod end pressure.

The retraction motion of the cylinder can be described by:

$$Q_p = \omega_{engine} * q_{pump},$$
$$Q_{pt} = C_d * \sqrt{2/\rho} * A_{pt} * \sqrt{X_3 - P_t},$$
$$Q_{pc} = C_d * \sqrt{2/\rho} * A_{pc} * \sqrt{X_3 - X_5},$$
$$Q_{ct} = C_d * \sqrt{2/\rho} * A_{ct} * \sqrt{X_4 - P_t},$$
$$\dot{X}_1 = X_2,$$
$$\dot{X}_2 = \frac{1}{M} * [X_4 * H_{area} - X_5 * R_{area} - F_{ext}],$$
$$\dot{X}_3 = \frac{\beta}{V_{hose}} * [Q_p - Q_{pt} - Q_{pc}],$$
$$\dot{X}_4 = \frac{\beta}{X_1 * H_{area}} * [-Q_{ct} - X_2 * H_{area}],$$
$$\dot{X}_5 = \frac{\beta}{(l_{stroke} - X_1) * R_{area}} * [Q_{pc} + X_2 * R_{area}].$$

As the external load varies, the spool command required to match that load with specific cylinder velocity varies as well. This results in the variation in the deadband and velocity/spool displacement gain as shown in the modulation curve in figure 3. The modulation curve shows the steady-state relationship between spool displacement and cylinder velocity under various external loads and pump speed (flow rate). It is obvious from figure 3 that both external load and pump speed (flow rate) have significant effects on the deadband and system gain. The frequency response of the one DOF hydraulic system is shown in figure 4. Natural frequency of the hydraulic system varies significantly as a function of external load (Fig. 4). Note that figure 4 does not include deadband effect.

REAL-TIME CONTROL ALGORITHMS

Two different classes of control algorithms are studied and compared in real-time experiments: 1. industry standard proportional-integral (PI) controller with a feedforward valve transform compensation, 2. cerebellar model articulation control (CMAC) algorithm. Figure 5 shows the block diagram of the hydraulic control system. The CMAC control algorithm is added parallel to the PI controller in the feedforward loop.

PI Control Algorithm

When the PI controller alone is used as the control algorithm, the CMAC algorithm is turned off (Fig. 5). However, since the open-center type directional control BH valve has a large deadband (Fig. 3), PI controller alone can barely move the spool out of the deadband when very low speeds are commanded. A model based feedforward compensation, called *the valve transform*, is then added parallel to the PI controller (11). The valve transform model can be estimated from the modulation curve (Fig. 3), and is a function of velocity, cylinder force and engine flow. The valve transform gives the spool command such that the spool can move out of the deadband and gives a reasonable velocity tracking at a given working condition.

CMAC Neural Network Control Algorithm

The CMAC control algorithm was modeled after the structure and functions of various cells and fibers in the human cerebellum (13). The algorithm is essentially an adaptive table lookup scheme since it can modify the contents in the memory table by using a learning algorithm. CMAC has generalization capability that similar inputs excite many of the same memory locations thus producing similar outputs. From figure 5, CMAC algorithm works as follows:

1. Sample the input vector which may contains both desired and feedback signal information. Since the deadband and the gain of the system is a function of pump speed and external load (Fig. 3), the input vector of CMAC is then composed of desired velocity, pump speed, and cylinder force. Instead of external load, cylinder force is used as input to the CMAC algorithm because the external load is difficult to measure directly in the actual application. The cylinder force is estimated using the measured values of HE and RE pressures.

2. Find corresponding memory locations for that input vector using a mapping algorithm, the total number of memory locations mapped for a sample of input space is called the generalization size (n_g) of the algorithm. The deadband of the hydraulic actuator occurs only when there is a change in the direction of the cylinder motion or there is a change in the sign of the velocity, and has a significant effect over the

small velocity region. Thus, a square root mapping function was used for desired velocity input such that the small velocity region is amplified and the large velocity region is compressed as far as memory usage is concerned. Since the pump speed is proportional to the cylinder velocity, the pump speed input state is mapped linearly. The steady-state relationship between external force and cylinder velocity was found to have a discontinuity and abrupt gain change over the small force region. Therefore, a square root function is used to map the cylinder force input state

3. Response from CMAC is then the summation of the contents of these n_g active memory locations.

4. Update the contents of these active memory locations by a learning algorithm which is based on the tracking error.

5. Repeat until a learning accuracy criterion is satisfied.

EXPERIMENTAL RESULTS

PID controller and CMAC neural network based controller with or without feedforward valve transform are implemented, tested and compared on one degree of freedom electro-hydraulic actuator control system lab setup. Only fixed load condition was tested at this stage.

As mentioned in previous section, deadband and system gain are largely affected by the external load and pump speed. Since it is very difficult to obtain accurate modulation curves from experiments due to the limitation of the piston travel range, a fixed nominal valve transform was used in this study. A fixed simple valve transform will also provide us the opportunity to test the learning and compensation ability of the CMAC controller for the inaccuracy of the valve transform. The values were obtained from the voltage-to-flow curve shown in figure 6. To get this curve, hydraulic cylinder was disconnected and the flow was measured without load at full pump speed (12.5 gpm). Very large hysteresis at the start of motion in both directions and very large deadband is clearly observed. The hysteresis is due to the friction at the valve spool-sleeve contact. The total deadband observed in the experiment was approximately 1.8 to 2.8 VDC. For the nominal valve transform, compensated value of deadband was set to 1.7 to 2.9 VDC and gains on both direction was set to 2.33 VDC s/m.

Extensive set of experiments were conducted on the laboratory setup for many hours to test the reliability of the real-time control system. Only a few results will be presented to summarize the performance achieved by the CMAC control algorithm. Figure 7 shows the tracking performance of the PI control system with nominal feedforward valve transform. Large delay in tracking and tracking error are obvious in Figure 7. Without valve transform, PI control cannot even move the spool out of the deadband. Figure 8 shows the tracking when the CMAC control is turned on. Tracking delay and tracking error are significantly reduced by adding CMAC to the control loop. CMAC contribution to the control action is also shown in figure 8, note that CMAC algorithm starts with a blank memory table. CMAC gives consistent control contribution even after many cycles. When CMAC is implemented without valve transform, similar results as shown in figure 8 can be observed. However, the contribution of CMAC in control action is larger since CMAC takes care of the control contribution that is no longer provided by the valve transform. Both experiments shown in figures 7 and 8 are conducted under constant pump speed and constant external load.

The experiments under varying pump speed are shown in figures 9 and 10. The pump speed was varied between 60% to 100% of the maximum speed. Tracking response of PI control system is shown in figure 9. The pump speed significantly affects the gain of the system (Fig. 3). PI control cannot compensate this variation of the system gain, as can be seen from the changing of tracking top velocities. The tracking response of the CMAC control system under varying pump speed is also shown in figure 9. The experiment is started with blank CMAC memory table. CMAC could learn and compensate for the change of the system gain. However, it takes more time for CMAC to converge in this case than it does in the constant pump speed case shown in figure 8.

Figure 10 shows the tracking response of the CMAC control with pre-trained CMAC memory table. The CMAC table was trained at three different pump speeds: 60%, 80%, and 100% of the maximum speed. At each pump speed, the CMAC was trained by running 10 cycles of desired velocity profile. It is obvious that CMAC could track the desired velocity command right from the beginning. The delay in tracking was significantly reduced compared to previous figures.

CONCLUSIONS

Due to its highest power density compared to other kinds of actuation methods, hydraulic power is the main actuation method used in high power applications such as earth moving, farming and mining equipment. However, nonlinear characteristics of the hydraulic components make it difficult to design an optimized controller which can provide high dynamic performance over a wide range of working conditions. A typical EH control system used in earth moving vehicles is considered in this study. The industrial standard PI control cannot effectively deal with the hydraulic non-linearity such as deadband and variation of the system gain. Large delay and tracking errors were observed in tracking a command under the PI control with model based valve transform feedforward compensation. Adding CMAC neural network control to the PI control improved the tracking performance significantly. Within 5 to 10 cycles of desired velocity profile, CMAC learned nonlinearities of the system and give superior tracking performance to the PI control. The CMAC control can perform better if it starts with a pre-trained memory table.

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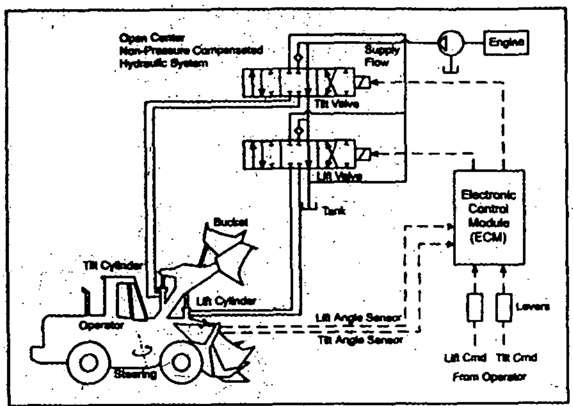

Figure 1 - WTL electro-hydraulic control system

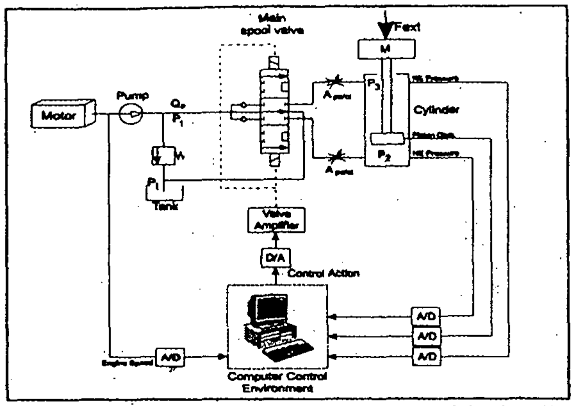

Figure 2 - Schematic diagram of one DOF hydraulic actuator control system

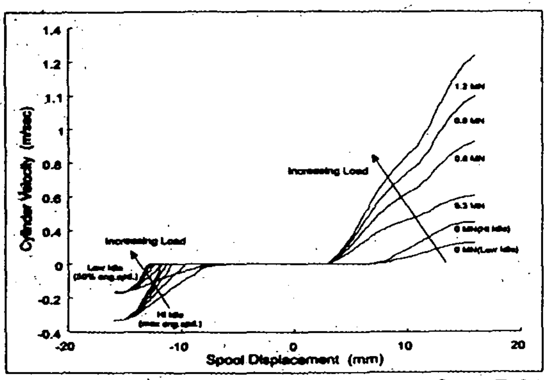

Figure 3 - Simulated modulation curve of one DOF hydraulic system

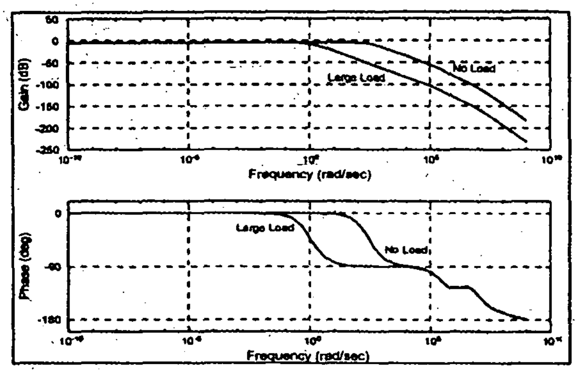

Figure 4 – Frequency response of one DOF hydraulic system

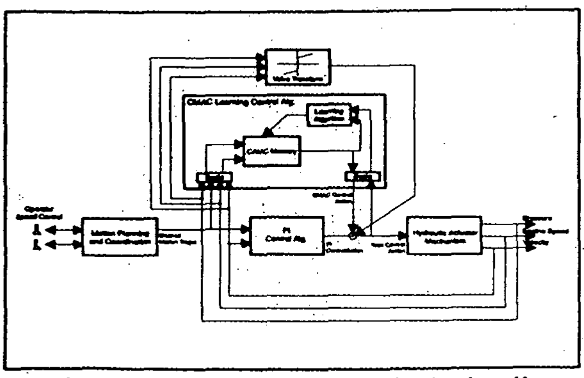

Figure 5 - Block diagram of the hydraulic control system

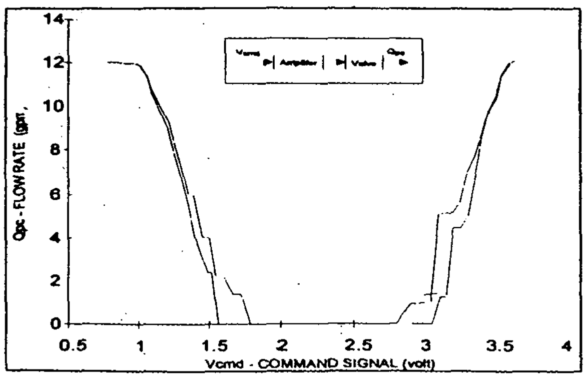

Figure 6 - Actual voltage-to-flow curve at maximum pump speed

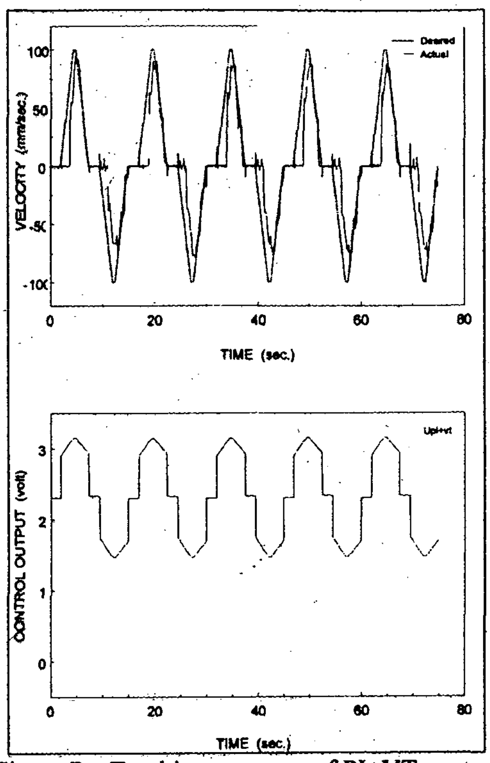

Figure 7 – Tracking response of PI+VT control system under constant external load and pump speed

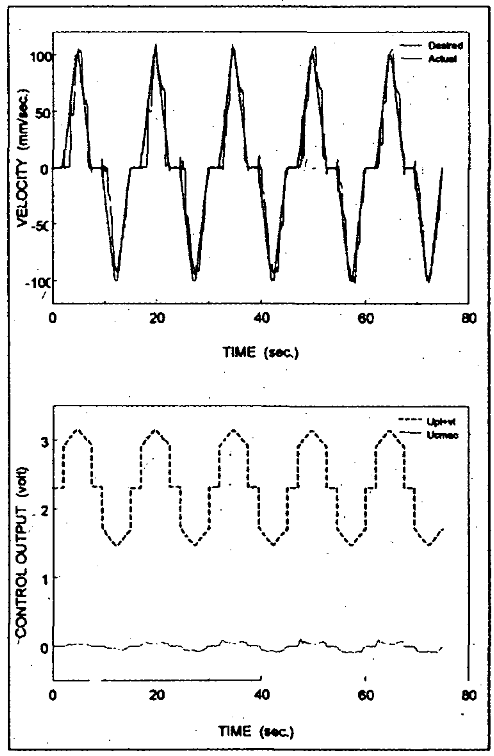

Figure 8 – Tracking reponse of PI+VT=CMAC system under constant external load and pump speed

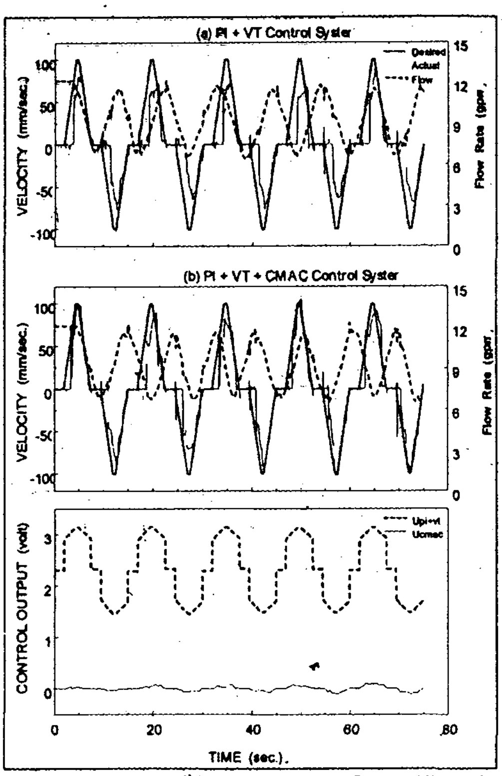

Figure 9 – Tracking response of PI+VT and PI+VT+CMAC system under constant external load and varying pump speed

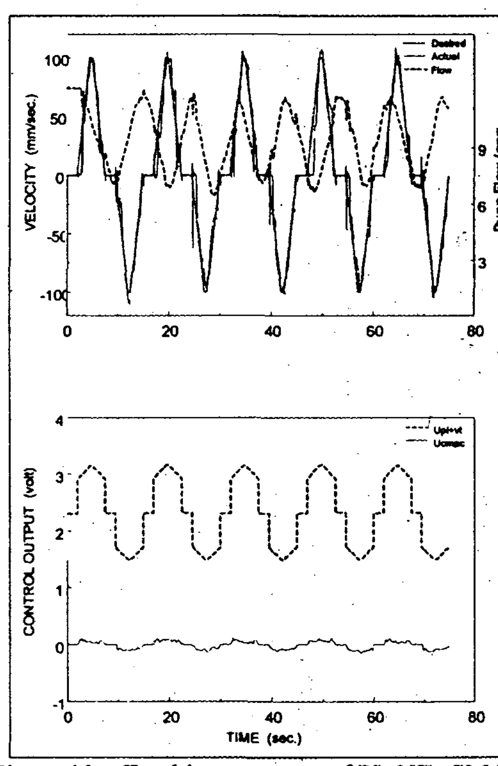

Figure 10 – Tracking response of PI+VT+CMAC system under constant load and varying pump speed with pre-trained CMAC memory table