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A case study in intelligent vs. conventional control for a process control experiment[1]

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Abstract

While intelligent control methods such as direct, adaptive, and supervisory fuzzy control have shown some success, there is a significant need to evaluate their performance relative to conventional control approaches, particularly in an experimental setting. Such evaluations help to determine the value of the new intelligent control methods, and provide the engineer with general guidelines on how to apply them to more complex real-world applications. In this work a case study is conducted where comparisons are made between conventional and intelligent controllers for a process control experiment in our laboratory. Nominal, disturbance, and plant failure conditions are studied and the advantages and disadvantages of each of the approaches is highlighted.

Keywords: Intelligent control; fuzzy control; feedback linearization; adaptive control; process control

1. Introduction

Recently, excitement over the field of intelligent control has risen due to progress in the areas of fuzzy control, neural networks, genetic algorithms, and expert systems to name a few (Antsaklis and Passino, 1993; Passino, 1995, 1996a). Unfortunately, the contributions of these areas have been difficult to assess due to the relatively little work focused on determining the advantages of these new approaches relative to existing conventional control techniques (Passino 1996, 1993). Often, engineers need both theoretical and experimental comparative analysis to determine the advantages and disadvantages of new control methods. In some applications (e.g., safety-critical ones) engineers are hesitant to employ a new approach without being assured that the technique has a firm theoretical foundation and a track-record of success in a variety of applications.

Clearly, a complete engineering cost-benefit analysis which includes comparative analysis of intelligent versus conventional control methods is beyond the scope of this or any other piece of work. Here the focus is on comparative analysis of fuzzy control versus several conventional control methods in a single experimental test bed. In particular, comparisons are made between conventional on-off, proportional, feedback linearizing, adaptive feedback linearizing control, direct, adaptive, and supervisory fuzzy control methods for a liquid level control problem. Hence, the focus is on a simulation-based and experimental comparison between conventional and fuzzy control methods. For a more philosophical comparison between these methods, where a wide range of issues are discussed, see Passino (1993) and Passino (1995). It must be emphasized that you must be careful not to over-generalize the results of this paper. While similar characteristics have been seen for other applications you clearly cannot generalize all the conclusions to all other applications.

It is assumed that the reader has a good understanding of fuzzy control (e.g., see Passino and Yurkovich, 1998; Driankov et al., 1993), and point the reader to Ross (1995); Kandel and Langholz (1993); Yen et al. (1995); Sugeno (1985); Marks (1994); Yager and Zadeh (1992) for additional studies of applications of fuzzy control. The adaptive fuzzy control technique that that is used, "fuzzy model reference learning control," is explained in Layne

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and Passino (1992, 1993 and 1996) and other applications of this method can be found in Layne et al. (1993), Kwong et al. (1995), Moudgal et al. (1995) and Lennon and Passino (1995). Other methods for adaptive fuzzy control are covered in the above referenced books and in Graham and Newell (1988), Graham and Newell (1989), Procyk and Mamdani (1979), Scharf and Mandic (1985), Tanscheit and Scharf (1988), Isaka et al. (1988), Daley and Gill (1987) and Wang et al. (1997). Other fuzzy supervisory control approaches are given in Ollero and Garcia-Cerezo (1989), de Silva (1991), Garcia-Benitz et al. (1993), Moudgal et al. (1994) and Murphy et al. (1996). Overall, our case study is similar in spirit to the one found in Heckenthaler and Engell (1994) where the authors perform a comparative analysis of a variety of controllers for a specific application.

In the next section, the process control experiment is explained by describing the experimental setup, giving a model of the system, and describing the experimental conditions. Following this the seven control techniques mentioned above are introduced. Then the results will be presented and discussed. Next, advantages and disadvantages of the techniques as they apply to this experiment, a computational complexity comparison, and our recommendation for which type of controller performed best in this experiment are presented. Finally, the paper is concluded with a broad discussion of the results, and future research directions are identified.

2. Process control experiment

The process control experiment in our laboratory has been designed to emulate systems found in chemical processes by providing the ability to study liquid level control with various disturbances and plant variations. In this section the experimental setup is described, give a model of the system, supply a description of the experimental conditions, and discuss our control objectives.

2.1. Experimental setup

The process control experiment consists of two tanks as shown in Fig. 1. The first tank, which is called the "fill" tank, contains a liquid whose volume is to be controlled. Note that this volume is proportional to the liquid level. The liquid volume is denoted by L_f and it is measured in gallons. When full, the fill tank contains 10 gallons of liquid. The reference input, which is a desired level, is denoted by L_d. The second tank is a "reservoir" tank which contains the liquid that will be pumped into and out of the fill tank. The reservoir tank is the same size as the fill tank. There are two controlled pumps and another pump that is used for creating a disturbance. The first pump is a variable-rate DC pump (which is denoted by P_r) which pumps liquid from the reservoir tank into the fill tank. The next pump is an AC pump (which is denoted by P_f) which can only be turned off and on. This pump will be used to control the amount of liquid leaving the fill tank. The last pump, another variable-rate DC pump (which is denoted by P_d), is used to create a disturbance by removing liquid from the fill tank. The control input to the system is a single voltage u where a positive value of sufficient magnitude will cause the DC pump P_r to pump liquid into the fill tank and a negative u of sufficient magnitude will cause the AC pump P_f to pump liquid out of the fill tank. A Gateway 2000 486DX2 66 MHz PC computer is used to run all control algorithms in the implementation. The process control experiment is interfaced to the PC through a Keithley Instruments DAS20 data acquisition board. The sampling period is 0.25 seconds for all the experiments. There are other electronics that perform filtering on the level measurements, pulse width modulation for the pumps, optical isolation, and power, but for brevity these electronics will not be discussed.

It is interesting to note that there are several characteristics of the experiment which cause problems with regulating the liquid level. First, a styrofoam ball on the end of a plastic rod (which is free to rotate about a fixed

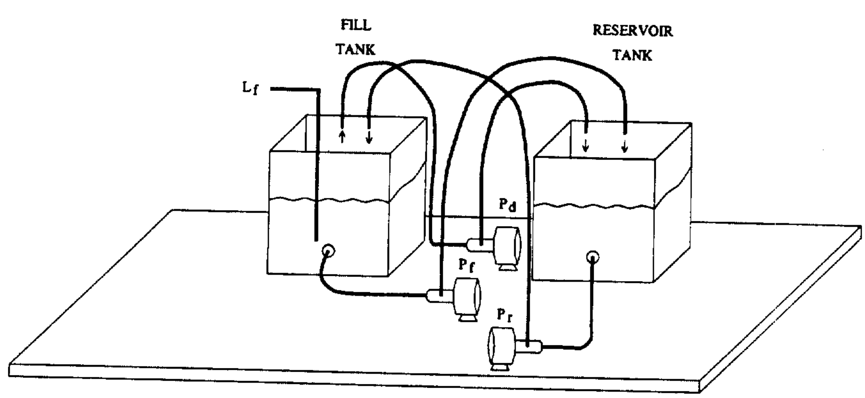

Fig. 1. Process control experiment.

point) along with a potentiometer is used to measure liquid level. If liquid is pumped into and out of the tank in a series of pulses, waves are created which cause problems with level measuring (the styrofoam ball only measures the level at a point on the surface in the tank, not the entire surface), which in turn makes regulating the liquid level more difficult. Second, the pumps have a significant "dead zone" nonlinearity so that if the voltage level is not large enough, no liquid is pumped. This problem is further magnified in that the AC pump P_f has a much larger dead zone than that of the DC pump P_r. Both of these pumps are responsible for control actions. Third, there are, of course, saturation nonlinearities on the rate at which the pumps can transfer water between the tanks. Fourth, there is significant noise in the system that seems to arise mainly from the pumps. This noise tends to propagate by first causing problems with the level measuring, which in turn causes chattering in the control output, which further causes the pumps to add more noise to the system. Fifth, there tends to be some delay in the system when the pumps are being turned on and off. Finally, there is a small disturbance in the plant such that when the pumps are turned off, water may flow in either direction through the pumps. This flow is due to the liquid level differential between the two tanks. For example, if the fill tank has more liquid in it than the reservoir tank, then the liquid will slowly flow into the reservoir tank. For all the experiments it is ensured that more water is in the fill tank so that this "leak" will flow out of the fill tank. Since the "leak" is relatively small it is ignored in our model and in the development of our conventional controllers.

In the next subsection, these nonlinearities are more carefully quantified by providing a mathematical model of the system.

2.2. Model

Using some basic modeling ideas, it has been found that a reasonably good model of the experiment is given by

$$\dot{L}_f = \alpha_r(u) - \alpha_f(L_f) \tag{1}$$

where $\alpha_f(L_f)$ is a level-dependent disturbance caused by pump P_d (one that is created by the user), $\alpha_r(u)$ represents the combined effects of the pumps P_f and P_r, u is a voltage input (with values between -8.5 Volts and 10.0 Volts) which controls pumps P_f and P_r, and L_f is the liquid level in the fill tank. Also,

$$\alpha_r(u) = R(u) \tag{2}$$

and

$$\alpha_f(L_f) = \begin{cases} 0.87R(d(L_f)) & \text{if } d(L_f) \geqslant 0 \\ 0 & \text{if } d(L_f) < 0 \end{cases} \tag{3}$$

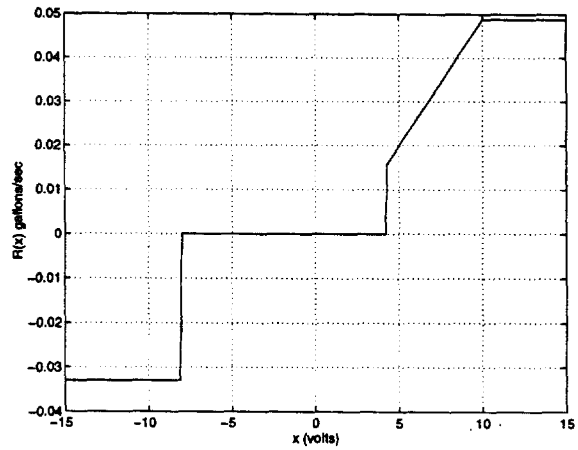

Fig. 2. Plot of $R(x)$.

where $d(L_f)$ represents the disturbance to the liquid level (in our experiments the user can pick the disturbance) and

$$R(x) = \begin{cases} -0.0333 & \text{if } x < -8.0 \\ 0.0000 & \text{if } -8.0 \leqslant x \leqslant 4.3 \\ 0.0058x - 0.0092 & \text{if } 4.3 < x < 10.0 \\ 0.0488 & \text{if } 10.0 \leqslant x \end{cases} \tag{4}$$

as shown in Fig. 2.

The function $R(x)$ represents the flow rate of the pumps. For Eq. (3) the DC pump P_d was not as efficient as the DC pump P_r and an efficiency factor of 0.87 was determined experimentally to represent the difference (compare Eqs. (2) and (3)). The DC pump P_r turns on when an input signal of 4.3 volts or higher is used. At 10 Volts, the DC pump P_r saturates, so the flow rate never goes beyond 0.0488 gallons/sec. The AC pump P_f turns on when a voltage of -8.0 volts or lower is applied. All control values u were saturated between the values of -8.5 volts and 10.0 volts. Since the AC pump can only be turned on and off, a voltage had to be chosen to represent when the pump was on. At 8.0 volts, the DC pump P_r has approximately the same flow rate as the AC pump has when it is on so this value was used (the DC pump has a flow rate of approximately 0.0372 gallons/sec at this voltage).

The disturbance was chosen to be

$$d(L_f) = \frac{15.0}{\pi} \tan^{-1}(L_f) \tag{5}$$

for two reasons. First, it is desired to have a disturbance that takes on values between 5.0 volts and 9.0 volts since this helps to ensure that the model operates in a controllable region (so that the pump does not operate in its dead zones). Second, it is desired to have a disturbance which is dependent on the volume of liquid since the disturbance is viewed as an effect from a human operator or other subsystem that will generally remove more liquid from the tank when there is more liquid available. The function in Eq. (5) meets both of these requirements. Note that this disturbance only gives us the 5.0 to 9.0 volt range for our P_d pump input when the level is above 2 gallons. Because of this fact, our reference input is restricted to be above 2 gallons.

The simulations were done with a fourth-order Runge-Kutta algorithm with an integration step size of 0.25 seconds. The control output was only updated once every 0.25 seconds to better imitate the controllers used in implementation.

2.3. Experimental conditions

Each controller was allowed to control the process control system for three different experimental conditions. Each test run involved tracking a desired liquid volume reference input L_d, which was a square wave of a frequency of 0.005 Hz that switched between 5 and 6 gallons. The reference input was slow enough for well-designed controllers to succeed in regulating the level, yet the change in volume was large enough to force the plant to exhibit its nonlinear characteristics. Similar results are obtained for most other amplitudes (note the restriction above). The three different plant setups were:

- Nominal plant (i.e., $\alpha_f(L_f) = 0$),
- Plant with disturbance (i.e., $\alpha_f(L_f) = 0.87d(L_f)$), and
- Plant with a degradation on the DC pump P_r or what will be called a "pump failure," (For this setup, let $\alpha_f(L_f) = 0$ and the input to the pump P_r was multiplied by 0.6, a 60% reduction in the efficiency of the DC pump P_r.) Such a failure may result from build-up of particulates in the filters of the pump as contaminated liquid passes through them.

Note that other experimental conditions were tested but are not reported here in the interest of brevity. The results here are representative of the quality of the results found for other test cases including the case when different amplitude square waves were used for the desired liquid volume reference input.

2.4. Control objectives

The control objectives for the process control experiment are to keep the steady-state error small, to have little or no chattering on the control output, and to use a low amount of control energy. The most important of these control objective is having a small steady-state error (this problem is one of regulating liquid level). A performance measure will be developed in Section 5 to quantify this objective. The next important control objective is to reduce chattering on the control output, to prolong the life of the pumps. This objective is difficult to quantify, so it will only be measured qualitatively. The amount of control energy is important because of power consumption. A performance measure will be developed in Section 5 for this objective. For implementation purposes, the interest is not in the transient responses because the controllers showed very similar transient responses relative to the differences seen between the controllers' steady-state responses.

3. Conventional control

In this section four conventional control techniques are presented: on-off, proportional, feedback linearizing, and adaptive feedback linearizing control. Here, only the control laws are presented; the results of the controllers' performance will be presented in Section 5.

3.1 On-off control

The first controller, and probably the simplest studied, is the on-off controller. This controller follows the simple control law

$$u = \begin{cases} 10 & \text{if } L_f \leqq L_d \\ -8.5 & \text{if } L_f > L_d \end{cases} \tag{6}$$

where L_f is the measured liquid volume and L_d is the desired liquid volume. This control law was easy to develop and also turned out to be an effective controller for most disturbances and plant variations (see Section 5 for full details). The only drawback of this controller was that it used the most control energy for all the experimental setups, and caused chattering in the control output to a high degree. Clearly, this effect is a negative characteristic, as chattering the control output can age the pumps rapidly.

3.2 Proportional control

The next control method presented is a proportional controller. The control law is

$$u = K_p(L_d - L_f) \tag{7}$$

where the proportional gain K_p was experimentally determined to be 350 in implementation and 1000 in simulation. Again, this controller is easy to develop, and more importantly tends to use less control energy than the on-off controller. In fact, this method used the least amount of control energy for the nominal plant in implementation as will be seen in Section 5. Proportional integral derivative (PID), PI, and PD controllers were also studied, but these techniques offered few, if any, advantages over the proportional control for a number of reasons. The sensors on the system tended to be very noisy, so any derivative of the level tended to be of little value because of noise. The integral term was not needed, because in almost all cases no constant steady-state error occurred in implementation, and the integral term tended to slow the system's response and cause overshoot. Note, however, that there were two cases which did have a noticeable constant steady-state error. These were the feedback linearizing controller for the nominal plant and pump failure setup. In both cases including the integral term caused poorer performance than not including it.

3.3 Feedback Linearizing Control

The next conventional controller studied makes use of feedback linearization (Vidyasagar, 1993). This controller was designed assuming that *complete* knowledge of the disturbance in Eq. (5) is available since if this term is ignored, the feedback linearization procedure produces a simple proportional controller (which has already been studied). Notice that due to the nonlinearity in Eq. (4), Eq. (1) does not fit the form for feedback linearization. For instance, notice that if u is small the system is not controllable due to the dead zone in the pumps. Clearly, the theory does not apply directly. It can be assumed, however, that the system will operate in a region where the theory does hold (e.g., $R(x) = 0.0058x - 0.0092$). Proceeding along these lines the control law used for the feedback linearizing controller is

$$u = 0.87\frac{15.0}{\pi}\tan^{-1}(L_f) + 0.13\frac{0.0092}{0.0058} + K_p(L_d - L_f)\,. \tag{8}$$

Substituting Eq. (8) into Eq. (1) you obtain

$$\dot{L}_f = R\left(0.87\frac{15.0}{\pi}\tan^{-1}(L_f) + 0.13\frac{0.0092}{0.0058} + K_p(L_d - L_f)\right) - 0.87R\left(\frac{15.0}{\pi}\tan^{-1}(L_f)\right) \tag{9}$$

which simplifies to

$$\dot{L}_f = 0.0058K_p(L_d - L_f)\,. \tag{10}$$

Note that the above derivations make use of the fact that as long as the input voltage to pumps P_r and P_d stays between 5 volts and 9 volts, the assumption above holds and the flow rate of the pumps $R(x)$ can be approximated as

$$R(x) = 0.0058x - 0.0092\,. \tag{11}$$

Since the differential equation can be put into this form for some operating conditions, the system is feedback linearizable with certain disturbances (such as the one given in Eq. (5)). In addition, letting $e = L_d - L_f$ and for constant L_d, $\dot{L}_d = 0$, the differential equation (Eq. (7)) becomes

$$\dot{e} = -0.0058K_pe\,. \tag{12}$$

This final differential equation shows the system to be asymptotically stable (for $K_p > 0$). The gain K_p is a tuning gain which was experimentally determined to be 80 in implementation and 1000 in simulation.

Section 5 will show that the control law in Eq. (8) performed best with the known disturbance (i.e., the one in Eq. (5)) in simulation and implementation. However, when the controller was used with the nominal plant, it performed poorly. Because this method performed so well with a known disturbance, two methods are introduced that utilize some of the structure of the feedback linearization, but modify it to accommodate other disturbances, and the nominal plant. One such method will be discussed in the next subsection and another in the section on intelligent control methods.

3.4. Adaptive feedback linearizing control

The last conventional controller studied is an adaptive controller. Because of the success of the feedback linearizing controller for the disturbance case, two adaptive approaches based on this technique were attempted. The first approach, adaptive feedback linearization, is presented here. The second approach is explained in the next section. The adaptive feedback linearizing approach used here is discussed in Sastry and Bodson (1989) and Sastry and Isidori (1989).

Several assumptions need to be made to use the adaptive feedback linearizing methodology. First, use $R(x) = 0.0058x - 0.0092$. Second, it is assumed that the disturbance has $d(L_f) \geqslant 0$. With the disturbance in Eq. (5) the $R(x)$ assumption will hold. Without the disturbance this control law would result in an adaptive proportional controller with an offset. Finally, the update law found in Sastry and Isidori (1989) is modified to include projection (Sastry and Bodson, 1989). With the above assumptions, the plant becomes

$$\dot{x} = R(u) - 0.87R(d(x)) \tag{13}$$

$$y = x \tag{14}$$

where $d(x)$ is the same as in Eq. 5, $R(x) = 0.0058x - 0.0092$, and x is L_f. Expanding Eq. 13 results in

$$\dot{x} = 0.0058u - 0.0092 - 0.87\left(0.0058\frac{15.0}{\pi}\tan^{-1}(x)\right) + 0.87(0.0092) \tag{15}$$

which becomes

$$\dot{x} = 0.0058u - 0.87\left(0.0058\frac{15.0}{\pi}\tan^{-1}(x)\right) - 0.13\,(0.0092). \tag{16}$$

Letting $f(x) = -0.87(0.0058(15.0/\pi)\tan^{-1}(x)) - 0.13(0.0092)$, $g(x) = 0.0058$, and $h(x) = x$, then $\dot{x} = f(x) + g(x)u$ and $y = h(x)$. From these equations, one obtains $L_g h(x) \neq 0$ (where $L_g h(x)$ is the Lie derivative of $h(x)$ with respect to g) and thus this system has a relative degree of 1 (Sastry and Bodson, 1989; Sastry and Isidori, 1989). Further, using the notation in (Sastry and Bodson, 1989; Sastry and Isidori, 1989) and letting $\theta_1^1 = 0.87(0.0058(15.0/\pi))$, $\theta_2^1 = 0.13(0.0092)$, $\theta_1^2 = 0.0058$, $f_1(x) = -\tan^{-1}(x)$, $f_2(x) = -1$, and $g_1(x) = 1$ gives

$$f(x) = \sum_{i=1}^{2} \theta_i^1 f_i(x) \tag{17}$$

and

$$g(x) = \theta_1^2 g_1(x) \tag{18}$$

where the θ_i^1, $i = 1, 2$ and θ_1^2 can be treated as unknown parameters. The estimates of $f(x)$ and $g(x)$ are $\hat{f}(x)$ and $\hat{g}(x)$ respectively. The estimates can be written as

$$\hat{f}(x) = \sum_{i=1}^{2} \hat{\theta}_i^1 f_i(x) \tag{19}$$

and

$$\hat{g}(x) = \hat{\theta}_1^2 g_1(x) \tag{20}$$

where f_i, $i = 1, 2$ and g_1 are assumed to be known. The $\hat{\theta}_i^1$ are estimates of θ_i^1 and $\hat{\theta}_1^2$ is an estimate of θ_1^2. The control law then becomes

$$u = \frac{1}{\widehat{L_g h}}(-\widehat{L_f h} + v) \tag{21}$$

where

$$\widehat{L_f h} = \sum_{i=1}^{2} \hat{\theta}_i^1 L_{f_i} h \tag{22}$$

and

$$\widehat{L_g h} = \hat{\theta}_1^2 L_{g_1} h \tag{23}$$

where $L_{f_1}h = -\tan^{-1}(x)$, $L_{f_2}h = -1$, $L_{g_1}h = 1$, and $v = \dot{L}_d + \alpha(L_d - y)$. The variable α is a tuning parameter which was experimentally determined to be 0.35 for implementation and 2.0 in simulation.

The adaptive update law for the estimates $\hat{\theta}$ ($\hat{\theta} = [\hat{\theta}_1^1, \hat{\theta}_2^1, \hat{\theta}_1^2]^T$) is of a gradient type with

$$\dot{\hat{\theta}} = \gamma(y - L_d)\, w \tag{24}$$

where γ is the adaptive gain and $w = [w_1^T, w_2^T]^T$ where

$$w_1 = [L_{f_1}h, L_{f_2}h]^T \text{ and} \tag{25}$$

$$w_2 = L_{g_1}h\left(\frac{-\widehat{L_f h} + v}{\widehat{L_g h}}\right). \tag{26}$$

Table 1
Bounds on the true values of θ

Variable	Upper bound	Lower bound
θ_1^1	0.0500	0.0000
θ_2^1	0.0100	0.0005
θ_1^2	0.0080	0.0020

The adaptive gain γ was experimentally determined to be 0.045 in implementation and 0.2 in simulation.

The projection algorithm makes use of the assumption that upper and lower bounds on the true values of θ_1^1, θ_2^1, and θ_1^2 are known. The range of possible estimates are thus restricted to this region. The projection algorithm is implemented in the following manner: if $\hat{\theta}_1^1 > \hat{\theta}_{1\,\max}^1$ then $\hat{\theta}_1^1 = \hat{\theta}_{1\,\max}^1$ else if $\hat{\theta}_1^1 < \hat{\theta}_{1\,\min}^1$ then $\hat{\theta}_1^1 = \theta_{1\,\min}^1$ else $\hat{\theta}_1^1$ is updated as above. Here $\hat{\theta}_{1\,\max}^1$ and $\hat{\theta}_{1\,\min}^1$ are our upper and lower bounds. $\hat{\theta}_2^1$ and $\hat{\theta}_1^2$ are updated in a similar manner. Table 1 contains the bounds that were used in both simulation and implementation. Note, that these bounds contain the true values for θ_1^1, θ_2^1, and θ_1^2 in simulation for all the plant setups (assuming that $R(x) = 0.0058x - 0.0092$).

As will be seen in Section 5, this method performed well when controlling the plant in the presence of the known disturbance both in implementation and simulation, but poorly when faced with the pump failure in implementation. Compared to the other adaptive controllers, it did not perform well for the nominal plant setup in implementation and simulation. A possible cause of these problems is parameter uncertainty. To overcome this problem one possibility is to add unconventional correcting schemes (e.g., a means to "turn off" the adaptation during certain transient regions). However, it was desirable to present this approach without departing from its basic theoretical framework as established in Sastry and Bodson (1989); Sastry and Isidori (1989) so such a correcting scheme was not used. As will be seen in Section 5, an approach which does turn off its adaptation mechanism during the transient region performs remarkably well (this method is the fuzzy supervisory controller).

4. Intelligent control

Many advantages which are inherent in intelligent control can be attributed to its ability to allow designers to easily incorporate heuristic knowledge of how to best control a system into a controller. This knowledge could come from a human operator who has manually performed the control task, or from a control engineer who has done mathematical, simulation-based, or experimental analysis of the plant and candidate controllers for it. After a considerable amount of studying how our process control system operates (that included our experiments in conventional control), it was determined that the best controller for the nominal plant would be one which, for large errors, used the pumps at full flow rate, and for the steady-state area, one which pumped liquid into the tank slowly (lowest flow rate) until the level was above the desired level, and then let the small leaking (as mentioned earlier) cause the liquid level to fall below the desired level. Although the output is oscillating, this control design is probably the best control method which can be done for the nominal plant because of the considerable amount of dead zone in the actuators. Such heuristic knowledge is exploited in some of the intelligent control methods below.

The three intelligent control techniques which will be discussed in this section are fuzzy control, fuzzy model reference learning control (FMRLC), and a fuzzy supervisory control.

4.1. Fuzzy control

Fuzzy control has emerged as a practical alternative for many applications. To design fuzzy controllers one specifies a set of rules (a rule base) that indicates what the plant input should be, given the current inputs to the fuzzy controller. While in operation, the fuzzy controller's inputs are fuzzified to form fuzzy sets that can be used by the inference mechanism. The inference mechanism then decides what rules to apply for these inputs by matching the fuzzified inputs to the premises of the rules in the rule base. The inference mechanism provides a fuzzy set that indicates the certainty that the plant input should take on various values. Then, defuzzification is used to convert the fuzzy set produced by the inference mechanism into a crisp output to be used by the plant.

The fuzzy controller developed here has two inputs and a single output. It uses singleton fuzzification. The minimum operator is used to represent premise and implication. The center of gravity technique is used for the defuzzification. Furthermore, there are 9 evenly spaced triangular membership functions over $[1, -1]$ on each input. Also, there are 81 triangular membership functions on the output universe of discourse, and the outermost membership functions peak at -8.5 and 10.0 volts.

A block diagram of the fuzzy control system is shown in Fig. 3. The two fuzzy controller inputs were error in volume $(L_d - L_f)$ and volume of liquid L_f. The gain on error in volume, K_p, was determined experimentally to be 400 in simulation and 20 in implementation. To utilize more rules, level values in the range [4.83, 6.17] were mapped to $[-1, 1]$ by performing the following operation: $(L_f - 5.5)\ 1.5$. The second input, volume of liquid, was used because of the leaking mentioned earlier. This leaking depended on the relative volume of liquid in the two tanks, where larger liquid level differences in the tanks resulted in larger leaks. So, for the same amount of error at two different levels, there was a slight difference in how much liquid the pumps should be pumping. Furthermore, the disturbance presented in Eq. (5) was also level-dependent, and with the FMRLC the second input would greatly help its performance, and so using the second input on the direct fuzzy controller allowed for a better comparison between the two methods.

Although the use of L_f for the fuzzy controller would seem to limit the ability of this controller to track reference inputs out of this range (i.e., outside of the range [4.83, 6.17]), by changing the fuzzy controller input $(L_f - 5.5)\ 1.5$ to $(L_f - 5.0)\ 0.18$ and increasing the number of input membership functions on the level input, any reference input between 0 and 10 could be tracked (the tanks can only hold ten gallons).

Finally, notice that the nonlinear control surface induced by the fuzzy controller that is shown in Fig. 6(a) results in an implementation of the control objectives stated at the beginning of this section. For small negative errors, the pump P_f is never turned on, and for small positive errors, the pump P_r is turned on at its lowest rate, thus satisfying the second control objective. For large errors, the corresponding pump was turned on at its maximum rate, thus satisfying the first control objective.

4.2. Fuzzy model reference learning control

Fuzzy model reference learning control (FMRLC) has been effectively used in several applications as a means to "tune" fuzzy controllers on-line to try to make the fuzzy controllers more robust to plant variations and to improve disturbance rejection (Layne and Passino, 1992, 1993, 1996; Layne et al., 1993; Kwong et al., 1995; Moudgal et al., 1995; Lennon and Passino, 1995). It is

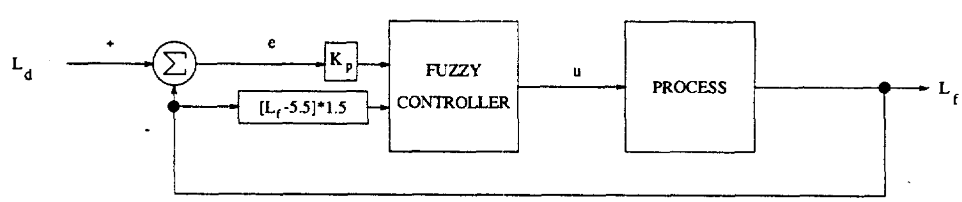

Fig. 3. Block diagram of fuzzy control system.

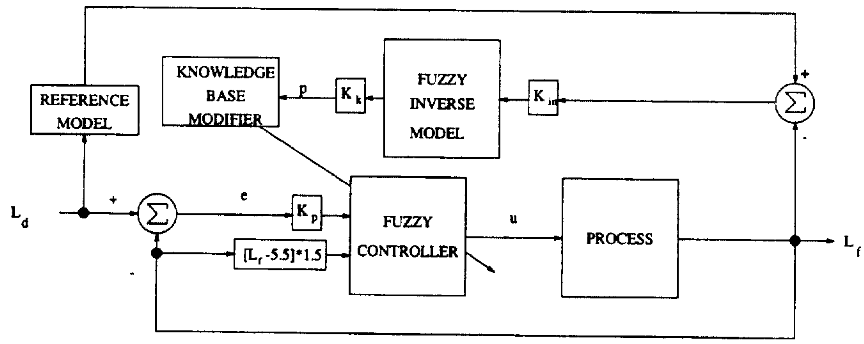

Fig. 4. FMRLC for the tank.

assumed that the reader has access to these publications for an introduction to the FMRLC and hence a basic understanding of the FMRLC method.

The block diagram of the FMRLC is shown in Fig. 4. The fuzzy controller in Fig. 4 has the same structure as the fuzzy controller described in the previous subsection, and since it provided a reasonably good performance it is used to initialize the FMRLC. The gain K_p was determined to be 20 in implementation and 12 in simulation. The use of the second input becomes more important for the FMRLC because, as mentioned before, the disturbance is a function of the volume of liquid in the tank. With this information, the amount of control voltage needed to compensate for the disturbance can be better tuned.

The reference model for the FMRLC is simply a unity gain which represents our desire to perfectly track the reference input L_d. In experimental work it was found that using other reference models usually only slowed the system down (i.e., the rise time decreased) and never improved performance in the steady state region.

The fuzzy inverse model is a single-input, single-output fuzzy system with nine input and output membership functions. The input to the fuzzy inverse model was scaled with a gain K_{in} which was experimentally found to have a value of 20 in implementation and a value of 35 in simulation. The input membership functions were triangular and evenly distributed over $[1, -1]$, with the ones at the outermost edges saturated in the usual manner. The output membership function centers followed a power spacing law over $[1, \ -1]$. In particular, the output near zero error is small, and increases according to a square function (membership function centers were proportional to $(L_d - L_f)^2$). To see how the fuzzy inverse model behaves, see Fig. 5. Again, the minimum operator was used to represent the premise and implication, and center of gravity was used for the defuzzification. The output of the fuzzy inverse model was further scaled with a gain K_k which was tuned to be 2.0 in simulation and 4.5 in implementation, and was used as an input to the knowledge base modifier. The scaling gains of the input

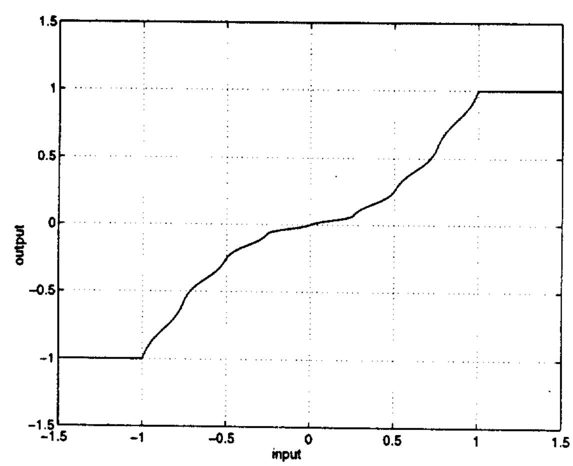

Fig. 5. Input-output map for the fuzzy inverse model.

and output of the fuzzy inverse model resulted from using tuning ideas from the FMRLC construction procedures in Layne and Passino (1993); Kwong et al. (1995).

The FMRLC knowledge base modifier modifies the output centers (or consequences) of the fuzzy controller (for more details see Layne and Passino, 1993). For this experiment, it was found that modifying the rules that were on two time periods before gave the best response. If the previous rule was used (one time period before) then the controller tunes itself to behave like an on-off controller. This phenomenon occurred because if the error were positive then the control output's center would increase, and as time went on the center would continue to increase until it reached its maximum value (limits were placed on the maximum and minimum values that the knowledge base modifier could modify the output centers). Similarly, if the error was negative, the output center on the negative side would be decreased until it reached its minimum value. The resulting on-off type control forced the volume to go high then go low by extreme values. By modifying the output centers from two time periods before, the FMRLC did not exhibit the behavior of an on-off controller. For example, the

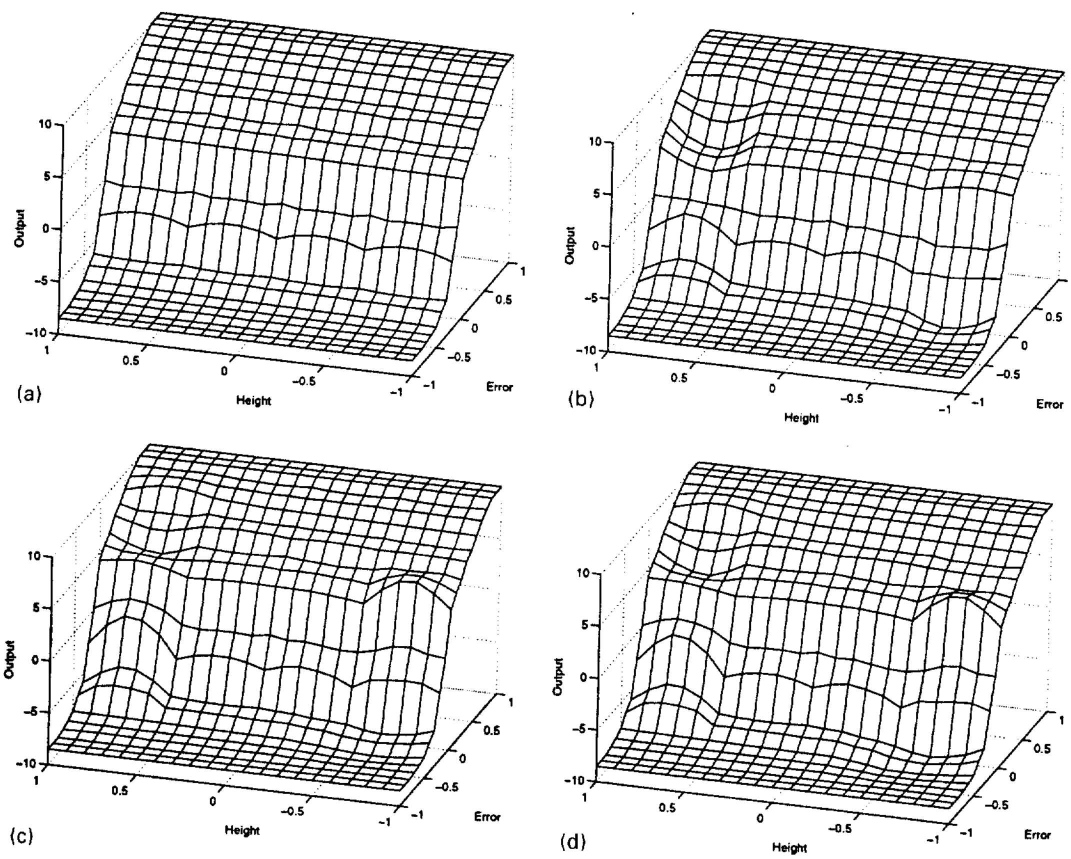

Fig. 6. Control surface for the FMRLC controlling the nominal plant. (a) Fuzzy controller surface at 0 sec. (b) Fuzzy controller surface at 150 sec. (c) Fuzzy controller surface at 250 sec. (d) Fuzzy controller surface at 400 sec.

one-time-period modification makes changes based on the current sensor readings, and since it takes about one time period to determine whether the current control action was effective or not this method does not work well. However, in the two-time-period modification, the controller looks at the next level measurement and if the error is still positive then the output center is increased; however, if the control action was "high" enough to cause the level to be negative, then the output center is decreased. This approach achieved our control objective; it operated the pumps in a manner which controlled the pumps to barely overshoot the reference input.

While the full results of using the FMRLC will be shown in Section 5, here it is illustrated how the FMRLC tunes a fuzzy controller. The control surface for the fuzzy controller of the previous section that was used to initialize the FMRLC is shown in Fig. 6(a). The subsequent plots in Figs. 6(b)–(d) show how the FMRLC tunes the fuzzy controller in implementation (similar results are seen when tuning the fuzzy controller in simulation). From these it is seen that the initial fuzzy control design was a close "guess" to the tuned values (although in Section 5 it will be seen that the re-shaping of the surface achieved by the FMRLC has a significant impact on performance to make it perform better than the direct fuzzy controller in implementation). Another important point to notice is that by 250 seconds into the trial, the control surface stayed constant. In the fuzzy controller presented earlier the output centers were tuned to our best "guess," while the centers of the FMRLC's fuzzy controller were tuned to values that operated best within the system. The main difference being that even in the nominal experimental setup, it was not possible to exactly place the centers where they would be most effective; the FMRLC did tend to place the centers where they would be most effective. As seen in Fig. 6 the majority of the tuning occurred where the error was small, and the movement of the centers was also relatively small.

From the simulation results it is seen that the FMRLC only performed better than the fuzzy controller for the disturbance case. One plausible reason for this occurrence is the high gain on the error used by the fuzzy controller. The FMRLC had problems with such a high gain on this input. An FMRLC could be designed with a high gain comparable to the fuzzy controller, but such an FMRLC would have very low gains on the learning mechanism (results for the disturbance case would not have been achieved, and a high gain on the input fuzzy system is not practical in implementation). Thus, a tradeoff was necessary between the gains on the fuzzy system and the learning mechanism. Generally, it has been found that if one has a very good understanding of the plant, then higher gains can be used on the fuzzy controller (i.e., high gain feedback) and lower gains on the adaptation. On the other hand, if one has a poor understanding of the plant dynamics then it may be desirable to have lower gains on the controller, and higher gains in the adaptation loop.

4.3. Fuzzy supervisory control

The fuzzy supervisory controller was developed to try to capitalize on (i) all the knowledge that had been gained from the other approaches about how to perform good control, and (ii) the excellent performance the feedback linearizing controller displayed for handling the plant with a disturbance. To overcome the problems of not "knowing" the system well, two gains are actively tuned during run-time. A block diagram of the fuzzy supervisory controller is shown in Fig. 7. The control law for the fuzzy supervisory control technique is

$$u = f_1 L_f + K_p (L_d - L_f) + g_1 (L_d - L_f). \tag{27}$$

The gain K_p was determined to be 150 in implementation and 1000 in simulation. The gains, f_1 and g_1, are tuned by single-input single-output fuzzy systems. Both fuzzy systems use singleton fuzzification, the minimum operator to represent premise and implication, and center of gravity for defuzzification. They both have nine evenly spaced triangular membership functions over [1, − 1] on each

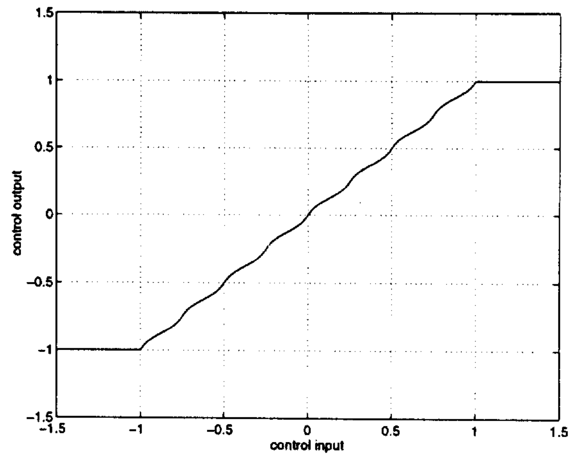

Fig. 8. Input-output map for the fuzzy systems in the fuzzy supervisor.

input, with the membership functions at the outermost edges saturated in the usual manner, and use nine evenly spaced triangular membership functions over [1, − 1] on the output universe of discourse. The control surface for both fuzzy systems is shown in Fig. 8. The only difference between the two fuzzy systems is that one of the fuzzy system's input gain, K_1, was 20 in implementation and 150 in simulation, and the other fuzzy system's input gain K_2 was only scaled by 10 in implementation and 50 in simulation.

The gain f_1 is adjusted up or down to compensate for any disturbances (it also ends up compensating for any plant variations). Tuning f_1 is accomplished by a fuzzy system. The adaptation law for f_1 is

$$f_1(k+1) = f_1(k)\gamma(1 - |y_1|)y_1 \tag{28}$$

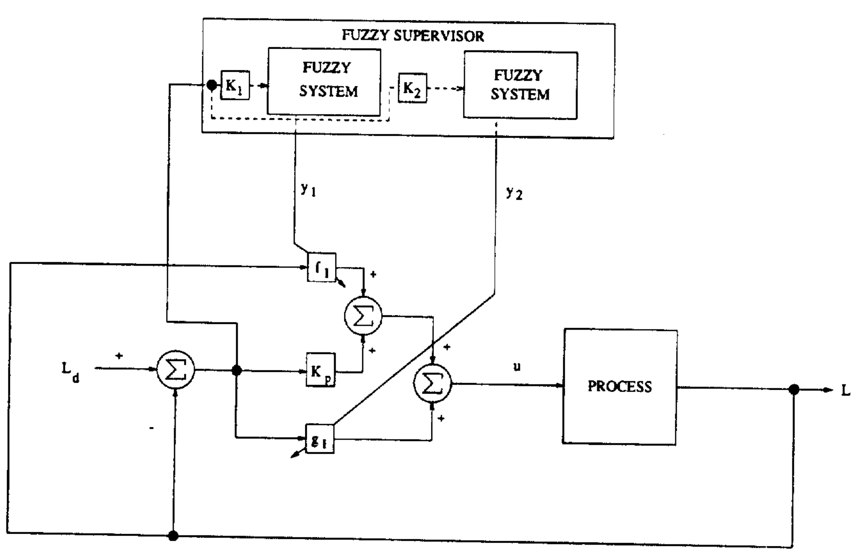

Fig. 7. Fuzzy supervisory controller block diagram.

where y_1 is one of the outputs of the fuzzy supervisor (see Fig. 7), and γ was a tuning factor on the learning rate. The value of γ was experimentally determined to be 0.04 in implementation and 1.0 in simulation. The $(1 - |y_1|)$ term is used to turn the adaptation on and off. It tunes the controller when it is within a certain region around the steady-state value. When it is far away (in the transient region), it is not tuned. The last term, y_1, stops the tuning when the output is near the desired level. In effect, the adaptation mechanism does not tune when the output is far away from the desired output, and when it is very close to the desired output. It only tunes when it is "somewhat" close.

The gain g_1 is tuned to be either a small-(zero-) or high-gain proportional controller. This part of the control law was used to ensure that the output stayed within certain values of the desired output. For regions of large error the gain g_1 was 500 in implementation and 2000 in simulation, and for regions of small error the gain g_1 was zero. The adaptation law for g_1 was the following

$$g_1 = K_3 |y_2| \tag{29}$$

where y_2 was the other output of the fuzzy supervisor (see Fig. 7), and K_3 was 500 for implementation or 2000 for the simulations.

The fuzzy supervisory controller developed above specifically duplicated the large error response that was desired by "turning" on and off a high-gain proportional controller, and for small errors, it operated similarly to the feedback linearizing controller. By acting like the feedback linearizing controller for small errors, the needed response of "just turning on" the pump when the level was slightly below the desired level is effectively duplicated. For most cases, the f_1 gain was large enough so that for small positive errors the DC pump P_r turned on slightly, and for small negative errors none of the pumps were turned on. Thus, this controller again duplicated the desired design, with the added possibility that it would duplicate the feedback linearizing results for most disturbances.

5. Simulation and experimental results

Because the quality of the responses is difficult to assess by simply observing the graphs of the responses, a means of quantifying the quality of the responses from the raw data is used. The two quantitative performance measures used are a sum of the errors squared over the two time periods 250 to 300 seconds and 350 to 400 seconds (this measure is denoted by $\sum e^2$), and sum of control output squared (this is denoted by $\sum u^2$) over the same two time periods (note that for the error performance measure $\sum e^2$ any values within 0.01 in implementation are judged to be approximately the same. Any values of $\sum u^2$ within 1000 in implementation of each other would be judged to be nearly the same). These time periods were chosen for several reasons. First, they allow the adaptive control techniques time to "learn" how to best control the plant. Second, they do not take into account the transient response. Performance of the controllers in the transient regions were very nearly the same (all controllers when faced with large errors immediately output a large control voltage). It is important to note that the control voltage measure of performance ($\sum u^2$) in some cases can be very misleading because of the dead zones of the pumps. For example, a constant output of -5 volts would have a worse performance measure than a constant output of -1 volts; however, both of these controllers use the same amount of "pump power" since in both instances neither pump would be on. Another measure of the performance of the controllers (though only shown graphically) was its ability to meet the steady-state error and keep the control output from chattering. This requirement proved important, because if the pumps were turning on and off, a considerable amount of mechanical and electrical noise entered the system, causing the level sensor not to operate effectively. By eliminating noise, better sensor readings could be obtained. Also note, extreme chattering is considered a disadvantage because it can age the pumps rapidly.

In this section results for each experimental setup for both simulation and implementation are compared and a recommendation is provided for the controller which performed the best. For the sake of brevity, only tabulated numerical results for the on-off controller were included in this work, and no plots were included.

5.1 Simulation results

The simulation results are presented in this subsection. Constraints were placed on the proportional gains of the controllers. In simulation, proportional components of the controllers studied could be tuned to be unrealistically high. It is known from implementation studies that high proportional gain controllers simply act like on-off controllers because of the noise in the system. It is for this reason that a limit of 1000 was set on all proportional components of the controllers.

5.1.1 Nominal plant

The numerical results for the seven controllers for the nominal plant in simulation can be found in Table 2, and the corresponding responses of the six controllers (the seven minus the on-off controller) can be found in Fig. 9. As can be seen from these results, the fuzzy controller performed the best at reducing steady state-error. A reason for this fact is that the fuzzy controller is able to reflect the necessary nonlinear control needed for controlling this plant (e.g., the dead zones of the actuators).

Table 2
Numerical simulation results for nominal plant

Control technique	$\sum e^2$	$\sum u^2$
On-off control	1.6×10^{-2}	3.5×10^4
Proportional control	2.2×10^{-3}	2.2×10^3
Feedback linearizing control	2.7×10^{-2}	2.1×10^3
Adaptive feedback linearizing control	1.3×10^{-3}	1.1×10^4
Fuzzy control	5.1×10^{-5}	6.2×10^3
FMRLC	2.5×10^{-4}	2.4×10^3
Fuzzy supervisory control	5.7×10^{-3}	1.4×10^4

In this instance, the use of the control output performance measure is somewhat misleading. The fuzzy supervisory controller has a large amount of control output when compared to the feedback linearization controller. Between the times 250–300 seconds, the output of the fuzzy supervisor outputs a -7 volt signal, while the feedback linearization technique outputs a -2 volt signal. In both cases these signals are within the dead zone. So no energy is being used by the pumps for pumping.

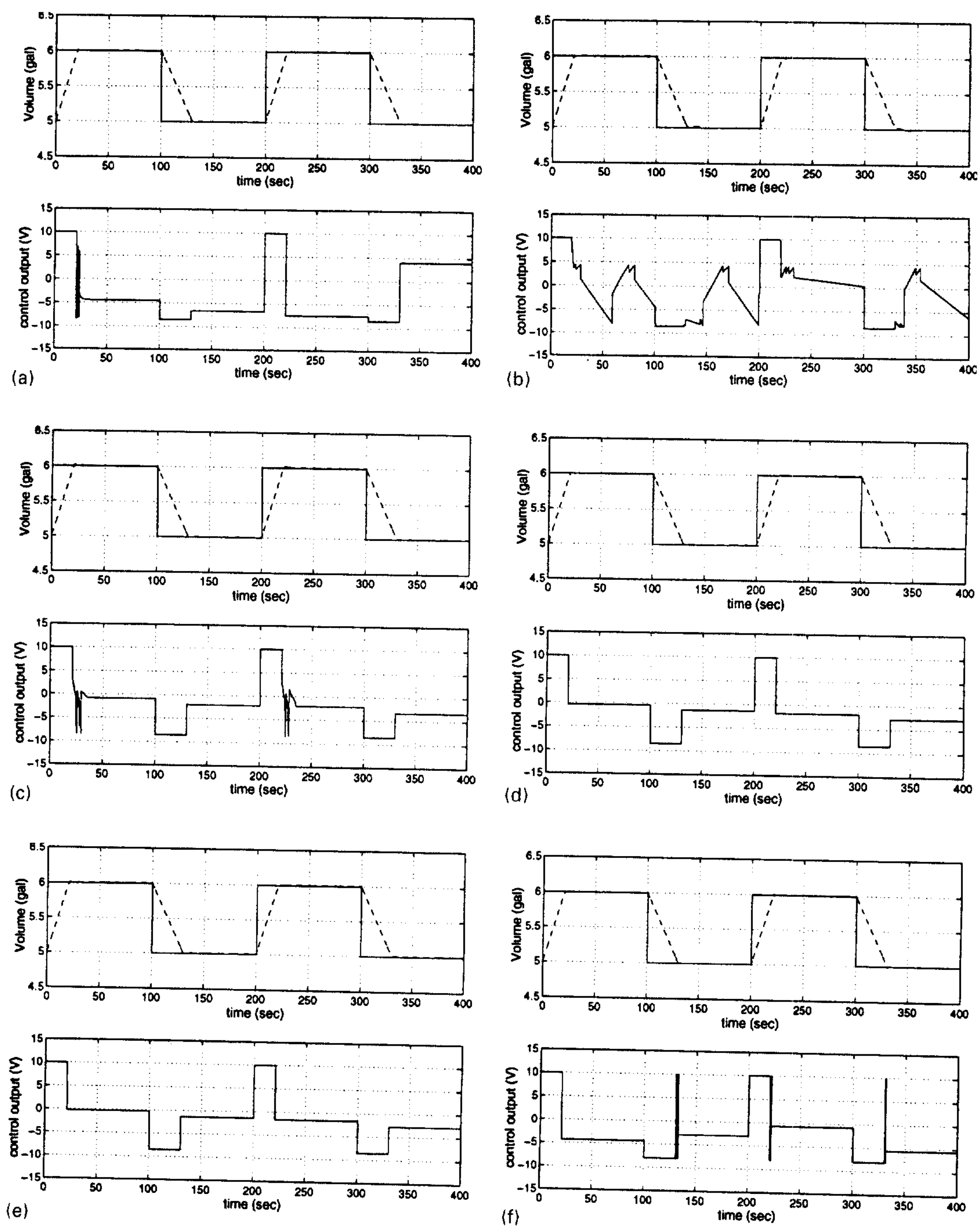

Fig. 9. Simulation results for no disturbance and no pump failure (i.e. nominal plant). (a) Fuzzy supervisory control. (b) FMRLC. (c) Adaptive feedback linearizing control. (d) Fuzzy control. (e) Feedback linearizing control. (f) Proportional control.

5.1.2. Plant with disturbance

The numerical results for the seven controllers for the plant with a disturbance in simulation can be found in Table 3, and the corresponding responses of the six controllers can be found in Fig. 10. Several of the controllers were able to reduce the steady-state error considerably. Among these techniques were all three adaptive techniques (FMRLC, fuzzy supervisory, and adaptive feedback linearization) and the feedback linearization. However, the feedback linearizing technique performed the best by producing no steady-state error as measured by our performance measure. Note that the adaptive and non-adaptive feedback linearization techniques were designed for the disturbance case. All controllers, except the on-off controller, used about the same amount of control energy. The reason for the adaptive controllers performing so well is due to the fact the plant with disturbance is controllable at most time instances. These controllers are

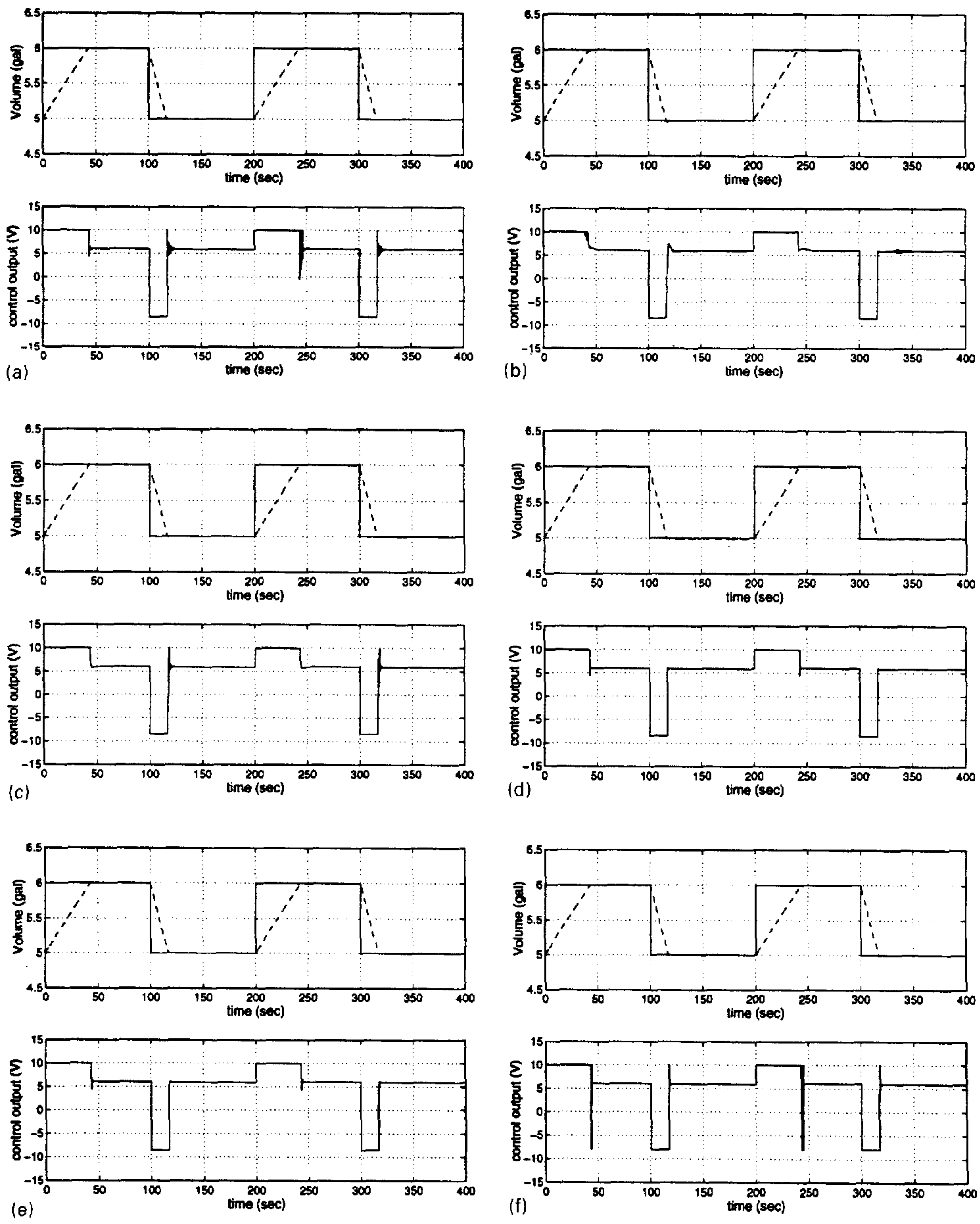

Fig. 10. Simulation results for disturbance and no pump failure. (a) Fuzzy supervisory control. (b) FMRLC. (c) Adaptive feedback linearizing control. (d) Fuzzy control. (e) Feedback linearizing control. (f) Proportional control.

Table 3
Numerical simulation results for plant with disturbance

Control technique	$\sum e^2$	$\sum u^2$
On-off control	2.2×10^{-2}	3.7×10^4
Proportional control	5.9×10^{-2}	1.4×10^4
Feedback linearizing control	0.0	1.4×10^4
Adaptive feedback linearizing control	3.0×10^{-5}	1.4×10^4
Fuzzy control	4.7×10^{-4}	1.4×10^4
FMRLC	5.6×10^{-5}	1.4×10^4
Fuzzy supervisory control	9.1×10^{-9}	1.4×10^4

Table 4
Numerical simulation results for plant with pump failure.

Control technique	$\sum e^2$	$\sum u^2$
On-off control	7.7×10^{-3}	3.5×10^4
Proportional control	9.4×10^{-3}	9.4×10^3
Feedback linearizing control	3.0×10^{-2}	9.7×10^3
Adaptive feedback linearizing control	7.8×10^{-3}	5.3×10^3
Fuzzy control	1.1×10^{-4}	9.1×10^3
FMRLC	4.0×10^{-3}	5.0×10^3
Fuzzy supervisory control	1.5×10^{-4}	1.9×10^2

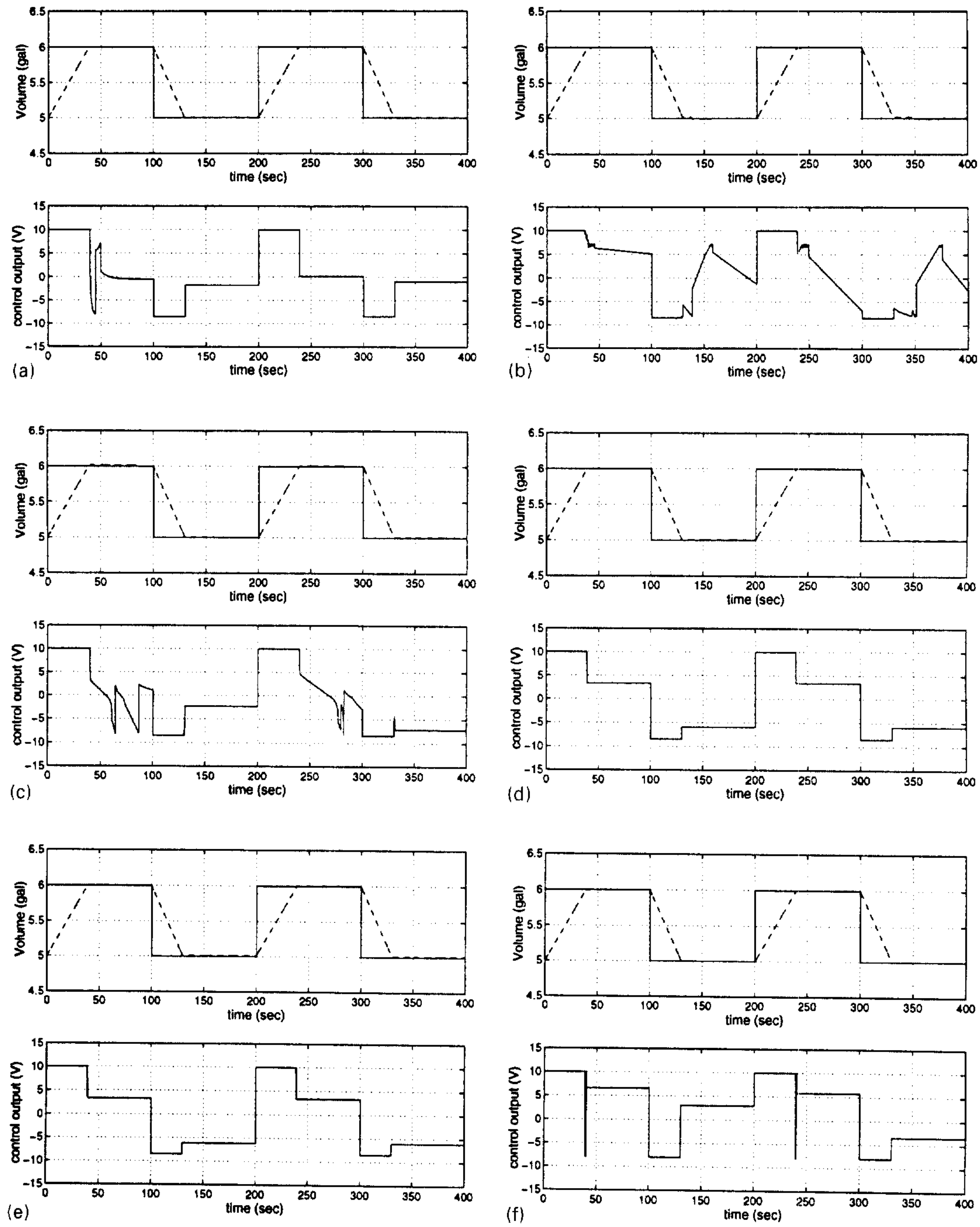

Fig. 11. Simulation results for no disturbance with pump failure. (a) Fuzzy supervisory control. (b) FMRLC. (c) Adaptive feedback linearizing control. (d) Fuzzy control. (e) Feedback linearizing control. (f) Proportional control.

then able to adapt to tune the necessary parameters to allow for no steady-state error (the error in level actually went to zero near the end of each step portion).

5.1.3 Pump failure condition

The numerical results for the seven controllers for the plant with a pump failure in simulation can be found in Table 4, and the corresponding responses of the six controllers can be found in Fig. 11. The fuzzy controller and fuzzy supervisory controller performed the best. Again, the fuzzy controller's ability to map the necessary nonlinear surface needed for control helped considerably. Also, in this instance the control output performance measure is misleading.

5.2. Experimentation results

In this subsection the results of implementing the seven controllers in the experimental test bed are presented. Additional tuning was done on many of the controllers to optimize their performance in the presence of some of the plant dynamics that were not modeled (e.g., the noise in the system and the pump delays). In many of the tuning instances reducing the gains on the error terms and slowing down the learning of the adaptive techniques occurred. The tuning that was necessary is explained in Section 6.

It is emphasized that, in implementation, the control voltage measure of performance was a meaningful measure performance. Because of the presence of noise and the small leakage, the controllers seldom caused their respective control outputs to remain in a dead-zone region.

5.2.1. Nominal plant

The numerical results for the seven controllers for the nominal plant can be found in Table 5, and the corresponding responses of the six controllers can be found in Fig. 12. As can be seen from these results, the fuzzy supervisory control and the FMRLC performed better than any other controllers considering the steady-state error. Both of these controllers perform about the same, in so far as they use the smallest amount of control energy. However, the fuzzy supervisory control technique tended to keep the control output from chattering. The controller which used the least amount of control energy was the proportional controller. Note that, from $t = 50$ to 100 seconds, the FMRLC tunes its fuzzy controller to decrease the amount of chattering and this continues to be evident from $t = 230$ to 250 seconds.

5.2.2. Plant with disturbance

The results of the experiment with the disturbance can be seen in Fig. 13 and in Table 6. From these results, it can easily be seen that the feedback linearization technique performed the best, with the FMRLC, supervised fuzzy controller, and the adaptive feedback controller performing almost as well. However, both the feedback linearizing controller and adaptive feedback linearizing controller were designed to account for the very "disturbance" that was induced (i.e., in the development of the controllers perfect knowledge of the disturbance is assumed). The two adaptive intelligent control techniques did not have *a priori* knowledge of the disturbance. The adaptive feedback linearizing and fuzzy supervisory controllers used the least amount of control energy. Both intelligent adaptive control techniques had the same amount of steady-state error, and the fuzzy supervisory controller used slightly less control energy.

Table 5

Numerical implementation results for nominal plant.

Control technique	$\sum e^2$	$\sum u^2$
On-off control	8.7×10^{-2}	3.4×10^4
Proportional control	3.6×10^{-2}	4.4×10^3
Feedback linearizing control	1.2×10^0	7.1×10^3
Adaptive feedback linearizing control	6.5×10^{-2}	1.2×10^4
Fuzzy control	2.3×10^{-2}	5.1×10^3
FMRLC	8.1×10^{-3}	5.2×10^3
Fuzzy supervisory control	8.8×10^{-3}	5.8×10^3

5.2.3. Pump failure condition

The results of the experiment with the pump failure can be seen in Fig. 14 and in Table 7. Again, the FMRLC and fuzzy supervisory control techniques out-performed the other techniques as far as steady-state error is concerned. The fuzzy supervisory technique did slightly better in reducing the steady-state error; however, the FMRLC technique used less control energy. However, looking at the time period from 150 to 200 seconds, the FMRLC has problems coping with the pump delays. Fortunately, the FMRLC is able to adapt to overcome these delays, as is evident for the rest of the experiment. Due to the heavy reliance on *a priori* knowledge of the plant dynamics, the feedback linearization and adaptive feedback linearization approaches performed significantly worse.

6. Lessons learned

Here, advantages and disadvantages of each type of controller are presented, a comparison of the controllers based on computational complexity is given, and our recommendation for the controller that performed the best in this experiment is provided.

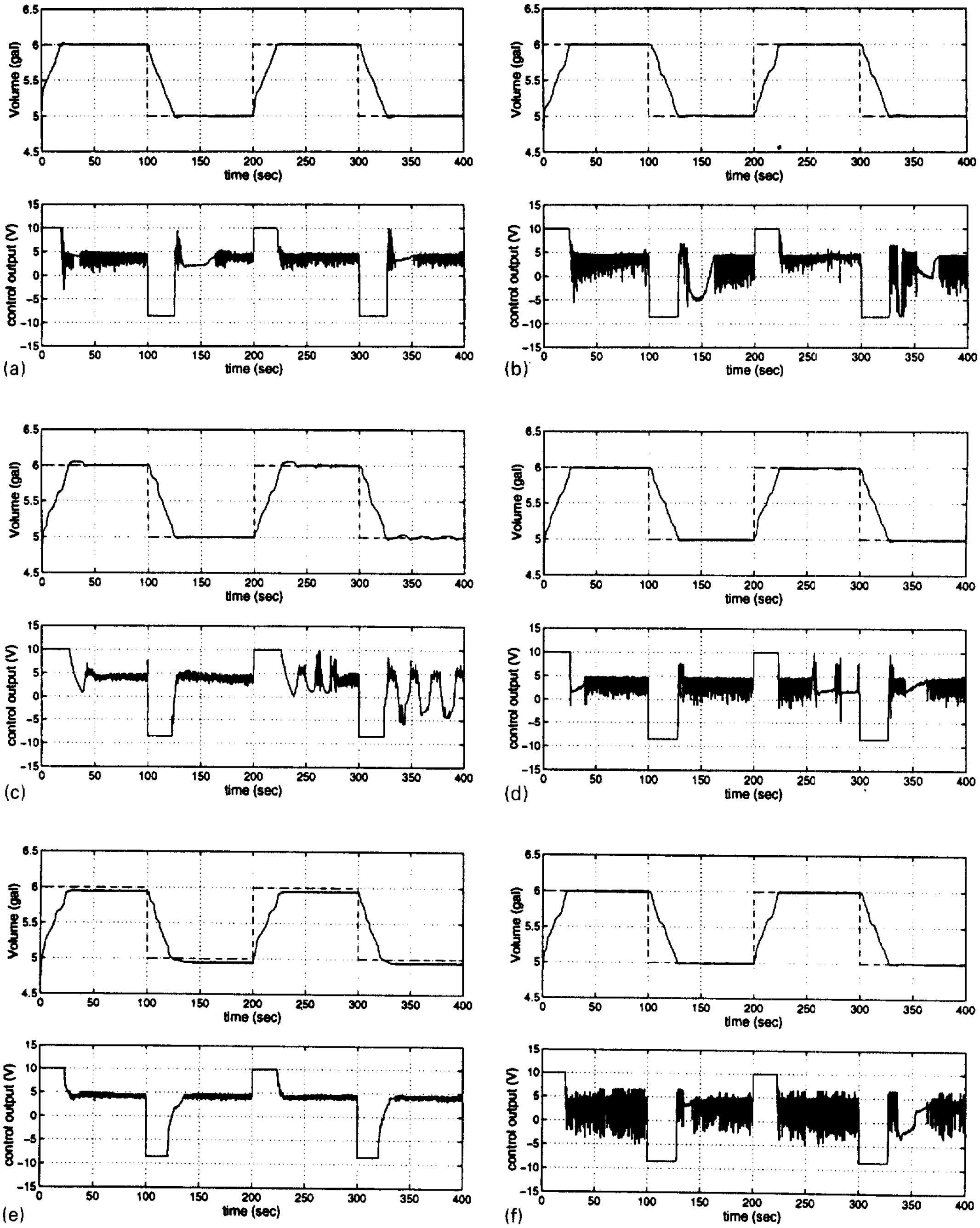

Fig. 12. Implementation results for no disturbance and no pump failure (i.e. nominal plant). (a) Fuzzy supervisory control. (b) FMRLC. (c) Adaptive feedback linearizing control. (d) Fuzzy control. (e) Feedback linearizing control. (f) Proportional control.

6.1. On-off control

The advantage of the on-off controller is that it was the easiest to develop. It also tended to have a low steady-state error. However, it caused chattering on the control output, which caused considerable noise in the level measuring (the steady-state error would have been better had this noise not been introduced). The main disadvantage of this controller was that it used the most control energy for all cases. Simulation and implementation designs for this controller were identical.

6.2. Proportional control

The advantages of the proportional controller are that it did about the same as the on-off controller in keeping the steady-state error small, and at the same time reduced the amount of control energy used. The disadvantage of

Table 6
Numerical implementation results for plant with disturbance.

Control technique	$\sum e^2$	$\sum u^2$
On-off control	9.9×10^{-2}	3.7×10^4
Proportional control	1.2×10^{-1}	1.4×10^4
Feedback linearizing control	1.5×10^{-2}	1.1×10^4
Adaptive feedback linearizing control	2.9×10^{-2}	1.2×10^4
Fuzzy control	1.1×10^{-1}	1.4×10^4
FMRLC	1.8×10^{-2}	1.3×10^4
Fuzzy supervisory control	1.8×10^{-2}	1.2×10^4

the proportional controller is that it tended to perform poorly with the disturbance or the pump failure present in implementation. The implementation of this controller used a gain of 350, while the simulation used a gain of 1000. A smaller gain on the proportional controller was used for coping with noise. As mentioned earlier, a large gain on a proportional component of a controller caused the controller to behave similar to an on-off controller.

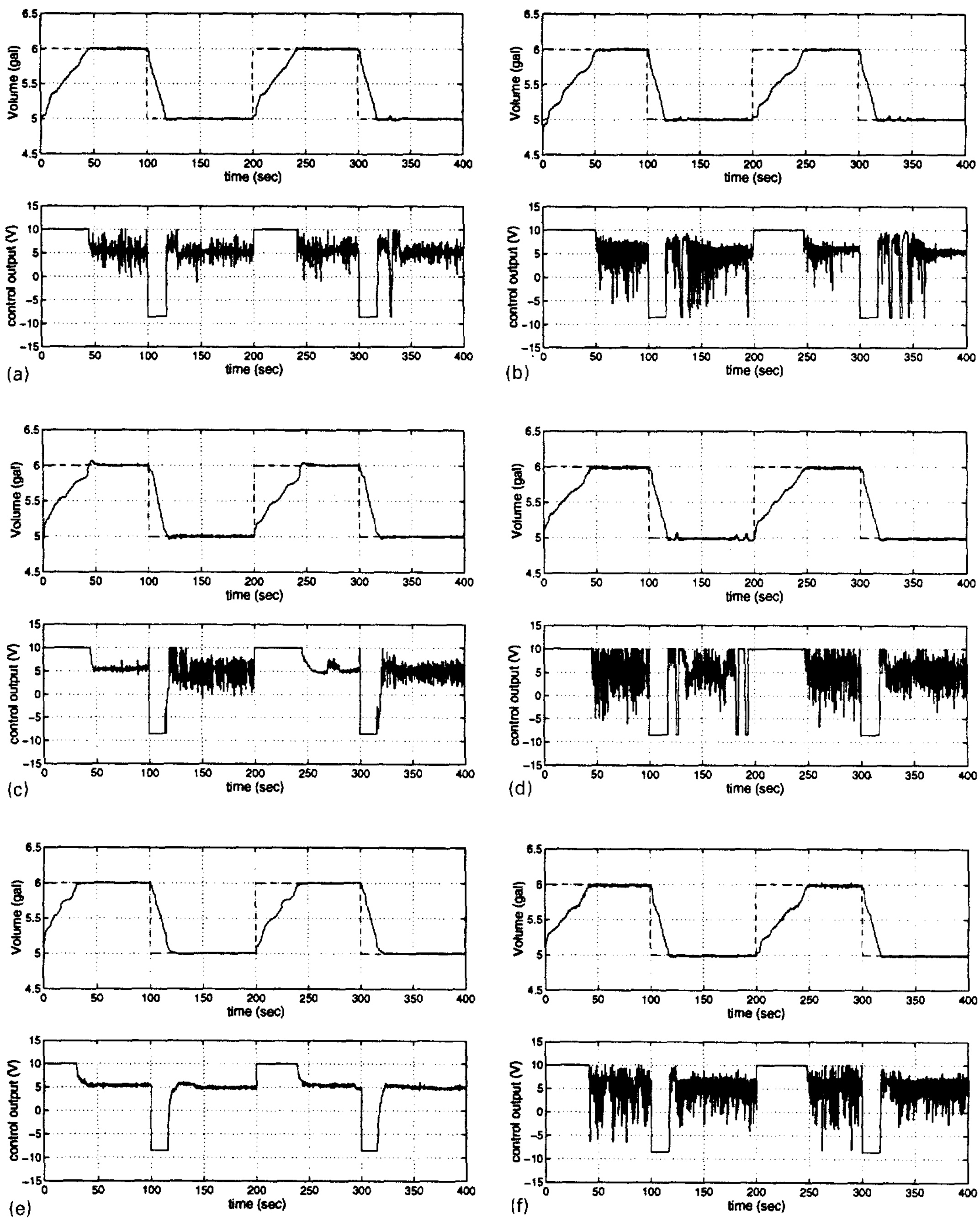

Fig. 13. Implementation results for disturbance and no pump failure. (a) Fuzzy supervisory control. (b) FMRLC. (c) Adaptive feedback linearizing control. (d) Fuzzy control. (e) Feedback linearizing control. (f) Proportional control.

Table 7
Numerical implementation results for plant with pump failure

Control technique	$\sum e^2$	$\sum u^2$
On-off control	5.0×10^{-2}	3.7×10^4
Proportional control	1.2×10^{-1}	1.5×10^4
Feedback linearizing control	3.4×10^0	2.1×10^4
Adaptive feedback linearizing control	1.1×10^0	2.3×10^4
Fuzzy control	1.4×10^{-1}	2.0×10^4
FMRLC	1.6×10^{-2}	1.3×10^4
Fuzzy supervisory control	9.3×10^{-3}	1.9×10^4

6.3. Feedback linearizing control

The advantage of the feedback linearizing controller was that it was able to perform the best when a known disturbance was used. Its performance was good, due to the fact that it did not cause chattering on the control output, and thus did not introduce much noise into the system in implementation. The disadvantage of this control technique lies in its inability to cope with variations in the plant (as is standard with feedback linearization

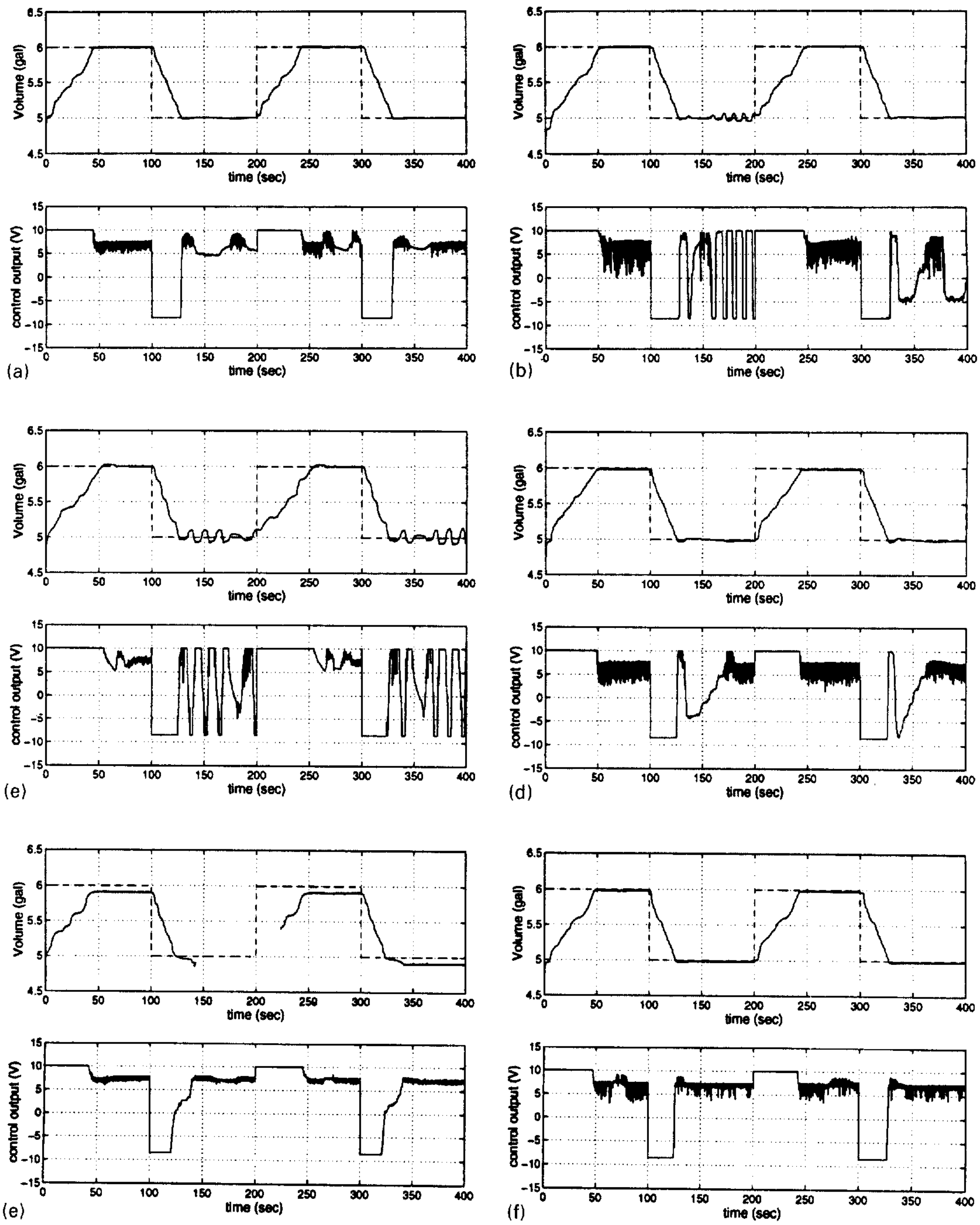

Fig. 14. Implementation results for no disturbance with pump failure. (a) Fuzzy supervisory control. (b) FMRLC. (c) Adaptive feedback linearizing control. (d) Fuzzy control. (e) Feedback linearizing control. (f) Proportional control.

approaches). The simulation and implementation results showed that the feedback linearizing controller has problems coping with the nominal plant, and the experimental setup with the pump failure. The simulation and implementation of this controller were nearly identical, except for the use of a higher proportional gain in simulation and a tuning of the gain on the disturbance (i.e., the 0.87 relative efficiency coefficient was tuned to 0.80 for implementation). The need for the proportional gain change is the same as for the proportional controller.

6.4. *Adaptive feedback linearizing control*

The advantage of the adaptive feedback linearizing controller was seen in its ability in simulation to drive the steady-state error to zero for the disturbance case. Its disadvantages resulted from its inability to cope with the plant with a pump failure in implementation. This controller was designed for the disturbance case, yet it did not perform better than either of the intelligent adaptive or feedback linearization techniques for this plant setup. As seen from Fig. 14(c), this control technique produced visible oscillations in the liquid level. These oscillations were primarily due to the delay in the pumps and this control technique's adaptation process.

The two intelligent adaptive techniques' adaptation schemes were such that their learning process were not affected by these delays. Both of the intelligent techniques were able to adapt slowly because of their architecture. The FMRLC approach has a "remembering" mechanism, such that at different levels in the tank, different parameters are learned (transient and steady-state regions had their own parameters). The fuzzy supervisory controller did not learn when a large error was present (the steady-state parameters were only learned when the plant was in the steady-state region). The adaptive feedback linearizing control technique adjusted the same parameters throughout all levels in the tank, and thus had to adapt quickly to learn in both the transient and steady-state regions.

Finally, note that designs for simulation and implementation were the same except for changing the learning and proportional gains. The learning gain γ was decreased from 0.2 in simulation to 0.045 in implementation. The proportional gain α was also decreased from 2.0 in simulation to 0.35 in implementation to further help in improving performance.

6.5. *Fuzzy control*

The fuzzy control technique performed the best among the non-adaptive techniques for controlling the nominal plant. Its ability to perform so well with the nominal experimental setup stems from our ability to heuristically add knowledge of how to control the plant into the fuzzy controller. A disadvantage of using this controller (and the other non-adaptive techniques) was its inability to cope with the disturbance and the pump failure as effectively as the two intelligent adaptive techniques did.

6.6. *Fuzzy model reference learning control*

The FMRLC technique performed, in most conditions, as well as or better than all the other controllers (excluding the fuzzy supervisory controller). It performed only slightly worse than the feedback linearizing controller for the disturbance case, even though it had no *a priori* knowledge of the disturbance. The ability of this technique to perform so well is primarily due to the fact that it can adapt differently in each region of operation (transient and steady-state). One disadvantage to this technique is that it uses a relatively high amount of computational resources. However, the FMRLC was implementable within the sampling period, and hence this is not a significant disadvantage.

FMRLC designs for simulation and implementation differed in the choice of the scaling gains. The simulation design made use of high gains on the learning mechanism to help cope with plant variations. The implementation design used lower gains on the learning mechanism to avoid effects from the pump delays. The lower learning gains allowed for slightly higher gains on the proportional components.

6.7. *Fuzzy supervisory control*

The fuzzy supervisory technique performed the best in the majority of trials, both in simulation and implementation. It performed only slightly worse than the feedback linearizing controller for the disturbance case, even though it had no *a priori* knowledge of the disturbance. The ability of this technique to perform so well is primarily due to the fact that it employs a specially designed adaptation mechanism, such that it only tuned while the process was in its steady-state region. During the transient regions it simply acted as an on-off controller. Designs for simulation and implementation were quite similar, except for the use of higher gains on the proportional components, and the use of higher gains on the adaptation process, thus allowing it to learn faster for simulation.

6.8. *Computational complexity*

The computational complexity of the seven algorithms can be best represented by letting the complexity of the feedback linearization be denoted by N (the computation complexity here is based on the relative amount of processor use). The complexity of the on-off controller and proportional controllers was slightly less than N. The complexity of the fuzzy and the fuzzy supervisory controllers was about $5N$, the complexity of the FMRLC and the adaptive feedback linearizing controller was about 10N (all of these values are only approximations; the implemented fuzzy systems use an algorithm that allows for few computations because of the fact that only two input membership functions on each input are ever on). The differences in the computation time may be great, but the ability of modern processors greatly reduces the effect. In fact, it is quite easy to implement all the controllers using the same sampling period of 0.25 seconds.

6.9. Recommendations

From the results in the previous section, the fuzzy supervisory controller is recommended for implementation for this experiment. The fuzzy supervisory controller performed equally with the FMRLC when using our quantitative performance measures only, but the fuzzy supervisory controller also had lower amounts of chattering as compared to the FMRLC control method. This advantage is considered a significant benefit in that the chattering can cause excessive wear on the pumps. Although the fuzzy supervisory controller did not perform as well as the feedback linearizing controller for the disturbance setup, both in the performance measure (though this is a very minute difference) and the level of chattering, it is believed that if the fuzzy supervisory controller were given additional information about the plant it could perform as well.

7. Concluding remarks

In this work four conventional control techniques (including one adaptive technique) and three intelligent control techniques (two were adaptive techniques) were presented. Each of these controllers was tested in simulation and three separate experimental setups and a comparative analysis was performed. The fuzzy supervisory control technique tended to perform the best.

Possible future research directions include

- Expanding the experimental setup to include control of temperature and liquid level,
- Performing some theoretical analysis on stability and robustness,
- Experimenting with additional nonlinear control techniques, and
- Using other intelligent control techniques (current work includes an indirect adaptive fuzzy control technique (Spooner and Passino, 1996) and a genetic model reference adaptive control technique (Porter and Passino, 1994).

Overall, it seems that the primary advantages of the intelligent control methods lie in the ease with which our heuristic ideas about how to achieve good control could be incorporated. It remains to be seen if this advantage holds for other applications. Clearly, in some cases there may be significant advantages to conventional methods, especially if one has a good mathematical model of the process.

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References

Antsaklis, P., & Passino, K. (1993). *An Introduction to Intelligent and Autonomous Control.* Norwell, MA: Kluwer Academic Publishers.

Daley, S., & Gill, K.F. (1987). Atitude control of a spacecraft using an extended self-organizing fuzzy logic controller. *Proc. Institute of Mechanical Engineers, 201*(C2), 97–106.

de Silva, C.W. (1991). An analytical framework for knowledge-based tuning of servo controllers. *Engineering Applications in Artificial Intelligence, 4*(3), 177–181.

Driankov, D., Hellendoorn, H., & Reinfrank, M. (1993). *An Introduction to Fuzzy Control.* NY: Springer-Verlag.

Garcia-Benitez, E., Yurkovich, S. & Passino, K. (1993). Rule-based supervisory control of a two-link flexible manipulator. *Journal of Intelligent and Robotic Systems, 7*, 195–213.

Graham, P., & Newell, R. (1988). Fuzzy identification and control of a liquid level rig, *Fuzzy Sets and Systems, 26*, 255–273.

Graham, P., & Newell, R. (1989). Fuzzy adaptive control of a first-order process. *Fuzzy Sets and Systems, 31*, 47–65.

Heckenthaler, T. & Engell, S. (1994). Approximately time optimal control of a two-tank system. *IEEE Control System Magazine, 14*, 24–30.

Isaka, S., Sebald, A., Karimi, A., Smith, N., & Quinn, M. (1988). On the design and performance evaluation of adaptive fuzzy controllers. In *Proc. of the IEEE Conf. on Decision and Control*, (Austin, TX), 1068–1069.

Kandel, A., & Langholz, G. (1993). *Fuzzy Control Systems.* Boca Raton, FL: CRC Press.

Kwong, W., Passino, K., Laukonen, E., & Yurkovich, S. (1995). 'Expert supervision of fuzzy learning systems for fault tolerant aircraft control.' *Special Issue on Fuzzy Logic in Engineering Applications, Proceedings of the Inst. of Electrical and Electronics Engineers (IEEE), 83*, 466–483.

Layne, J., & Passino, K. (1992). Fuzzy model reference learning control, in *1st IEEE Conf. on Control Applications*, (Dayton, OH), 686–691.

Layne, J., & Passino, K. (1993). Fuzzy model reference learning control for cargo ship steering. *IEEE Control Systems Magazine, 13*, 23–34.

Layne J., & Passino, K. (1996). Fuzzy model reference learning control, *International Journal of Intelligent and Fuzzy Systems, 4*(1), 33–47.

Layne, J., Passino, K. & Yurkovich, S. (1993). Fuzzy learning control for anti-skid braking systems. *IEEE Trans. on Control Systems Techology, 1*, 122–129.

Lennon W. & Passino, K. (1995). Intelligent control for brake systems. In *IEEE Int. Symp. on Intelligent Control*, (Monterey, CA), pp. 499–504.

Marks, R.J. (ed.) (1994). *Fuzzy Logic Technology and Applications*. New York: IEEE Press.

Moudgal, V., Kwong, W., Passino, K., & Yurkovich, S. (1995). Fuzzy learning control for a flexible-link robot. *IEEE Transactions on Fuzzy Systems, 3*, 199–210.

Moudgal, V., Passino, K., & Yurkovich, S. (1994). Rule-based control for a flexible-link robot. *IEEE Trans. on Control Systems Technology, 2*, 392–405.

Murphy, T.F., Yurkovich, S. & Chen, S.-C. (1996). Intelligent control for paper machine moisture control. In *Proc. of the IEEE Conf. on Control Applications*, (Dearborn, MI), 826–833.

Ollero, A. & Garcia-Cerezo, A.J. (1989). Direct digital control, auto-tuning and supervision using fuzzy logic. *Fuzzy Sets and Systems, 12*, 135–153.

Passino, K. (1993). Bridging the gap between conventional and intelligent control. *Special Issue on Intelligent Control, IEEE Control Systems Magazine, 13*, 12–18.

Passino, K. (1995). Intelligent control for autonomous systems, *IEEE Spectrum, 32*, 55–62.

Passino, K. (1996a). Intelligent control. In *The Control Handbook* (W. Levine, ed.), pp. 999–1001, Boca Raton: CRC Press.

Passino, K. (1996b). Towards bridging the perceived gap between conventional and intelligent control, In *Intelligent Control: Theory and Applications*, ch. 1, pp. 1–27, IEEE Press, Gupta, M.M. and Sinha, N.K. (editors).

Passino, K.M., & Yurkovich, S. (1998). *Fuzzy Control*. Menlo Park, CA: Addison Wesley Longman.

Porter, L., & Passino, K. (1994). Genetic model reference learning control. In *IEEE International Symposium on Intelligent Control*, (Columbus, Ohio), pp. 219–224.

Procyk, K., & Mamdani, E. (1979). A linguistic self-organizing process controller. *Automatica, 15*, 15–30.

Ross, T. (1995). *Fuzzy Logic in Engineering Applications*. NY: McGraw-Hill.

Sastry, S. & Bodson, M. (1989). *Adaptive Control Stability, Convergence, and Robustness*. Englewood Cliffs, NJ: Prentice Hall.

Sastry, S. & Isidori, A. (1989). Adaptive control of linearizable system. *IEEE Transactions on Automatic Control, 34*, 1123–1131.

Scharf, E., & Mandic, N. (1985). The application of a fuzzy controller to the control of a multi-degree-of-freedom robot arm. In *Industrial Applications of Fuzzy Control*, pp. 41–62, Amsterdam, The Netherlands: Elsevier

Spooner, J.T. & Passino, K.M. (1996). Stable adaptive control using fuzzy systems and neural networks. *IEEE Trans. on Fuzzy Systems, 4*, 339–359.

Sugeno, M. (ed.) (1985). *Industrial Applications of Fuzzy Control*. North Holland: Elsevier Science Publishers B.V.

Tanscheit, R., & Scharf, E. (1988). Experiments with the use of a rule-based self-organising controller for robotics applications. *Fuzzy Sets and Systems, 26*, 195–214.

Vidyasagar, M. (1993). *Nonlinear System Analysis*. Englewood Cliffs, New Jersey: Prentice Hall, second ed.

Wang, L.-X. (1997). *A Course in Fuzzy Systems and Control*. Englewood Cliffs, NJ: Prentice-Hall.

Yager, R.R., & Zadeh, L.A. (1992). *An Introduction to Fuzzy Logic Applications in Intelligent Systems*. New York: Kluwer Academic Publishers.

Yen, J., Langari, R., & Zadeh, L. (1995). *Industrial Applications of Fuzzy Logic and Intelligent Systems*. NY: IEEE Press.