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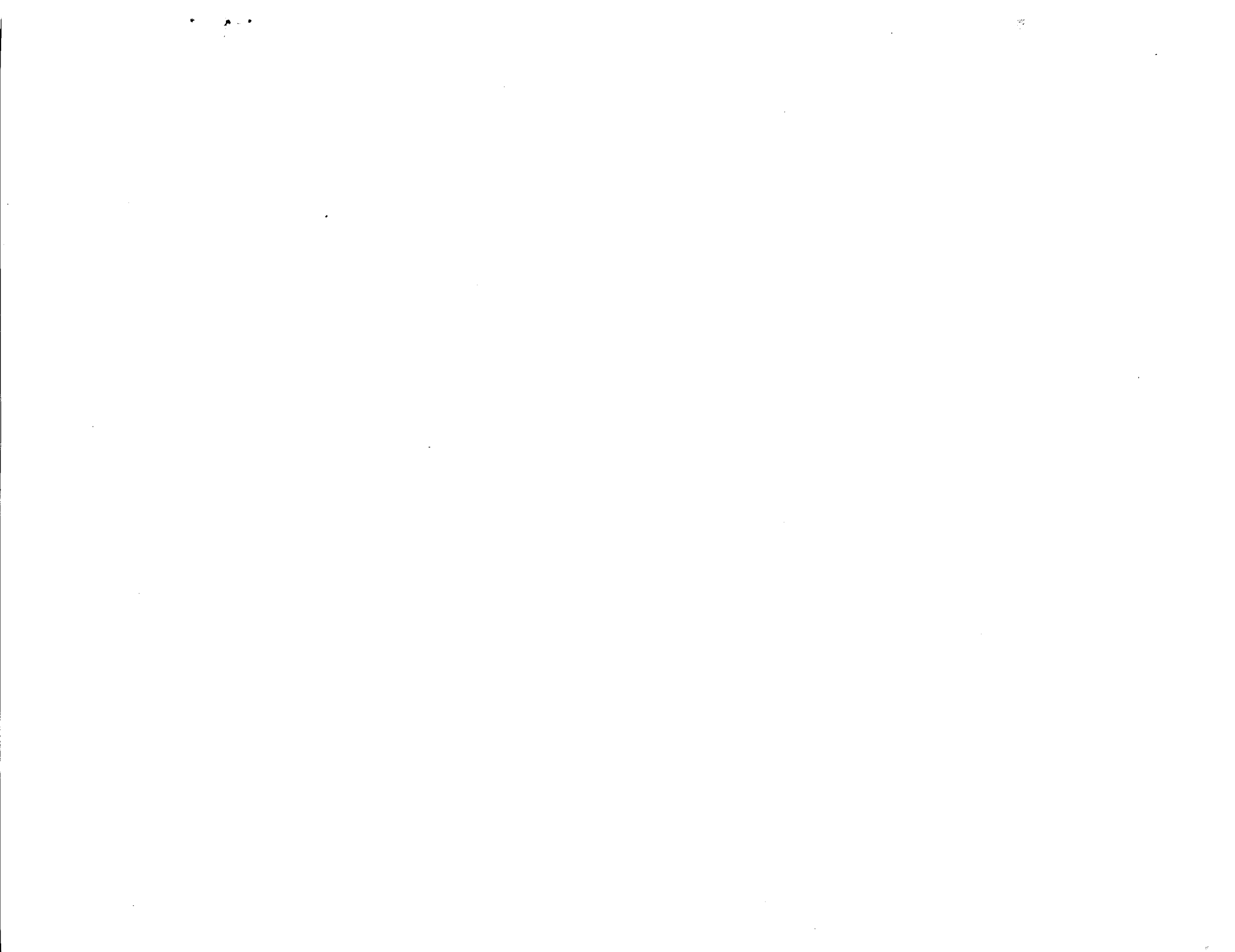
Adaptive Performance Seeking Control Using Fuzzy Model Reference Learning Control and Positive Gradient Control

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ADAPTIVE PERFORMANCE SEEKING CONTROL USING FUZZY MODEL REFERENCE LEARNING CONTROL AND POSITIVE GRADIENT CONTROL

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1. Abstract

Performance Seeking Control attempts to find the operating condition that will generate optimal performance and control the plant at that operating condition. In this paper a nonlinear multivariable Adaptive Performance Seeking Control (APSC) methodology will be developed and it will be demonstrated on a nonlinear system. The APSC is comprised of the Positive Gradient Control (PGC) and the Fuzzy Model Reference Learning Control (FMRLC). The PGC computes the positive gradients of the desired performance function with respect to the control inputs in order to drive the plant set points to the operating point that will produce optimal performance. The PGC approach will be derived in this paper. The feedback control of the plant is performed by the FMRLC. For the FMRLC, the conventional fuzzy model reference learning control methodology is utilized, with guidelines generated here for the effective tuning of the FMRLC controller.

2. Introduction

Control techniques utilized to drive the plant to produce optimal performance are found in an area that is called Performance Seeking Control (PSC).⁽¹⁻⁷⁾ Conventional PSC control approaches compute the optimal performance off-line utilizing some control algorithm like linear programming, a gradient, or some neural net method. The optimal operating point or trajectory is then passed to an on-line feedback controller for the control of the process. The APSC structure proposed in this paper, Fig. 1, is in essence a PSC approach, but because the computations are entirely performed on-line, in a closed loop control fashion, it is more appropriately classified here as an adaptive control approach.

In this paper it will be shown that an on-line APSC has been realized through the computation of the positive gradients, (for a desired performance function) with respect to the plant control inputs. These gradients are used to drive the plant set points in a closed loop fashion. When this optimal operating condition is reached the gradients of the performance function with respect to the control inputs will all be zero, and the control will stop driving the process set points any further. In this work, the combined effect of PGC and FMRLC with its ability to perform nonlinear control, with fast on-line learning of the control law, will be exploited.

During the past several years, fuzzy control has emerged as one of the most active and promising control areas, especially because of the ability of fuzzy control in controlling highly nonlinear, time variant, and ill-defined systems. The works of Mamdani and his colleagues on fuzzy control⁽¹²⁻¹⁵⁾ was motivated by Zadeh's work on the theory of fuzzy sets,⁽¹⁶⁻¹⁹⁾ and its application to linguistics and systems analysis. The work of Procyk and Mamdani on the linguistic self-organizing controller⁽²⁰⁾ as well as refinements to this algorithm made by others, was later modified and extended by Layne to what it is called FMRLC.⁽²¹⁾ The FMRLC structure, Fig. 2, has learning capabilities and differs conceptually from adaptive control primarily by its ability to memorize learned experiences. The FMRLC algorithm will be utilized here for nonlinear, multivariable feedback control, and some guidelines will be generated for the effective tuning of the FMRLC controller. In this paper the PGC and FMRLC controllers will be combined to form the new on-line APSC structure shown in Fig. 1.

3.0 Adaptive Performance Seeking Control

The APSC structure proposed in this paper is shown in Fig. 1. The feedback control of the state variables is performed by the FMRLC in a nonlinear multivariable control structure shown in more detail in Fig. 2. The APSC is initialized with a switch in the open position, and the set points, r_i , are controlled remotely. When the switch is closed, the control of the set points is automatically

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updated by the APSC. It should be noted that in this operating mode the remote portion of the set points can still be updated as in a trim control fashion. The APSC remains continuously active even when the maximum performance has been reached by preventing the gradient from falling exactly to zero. This is shown by the limit bands built around zero in Fig. 1. The limit band of the control derivatives is chosen larger than the corresponding limit band of the performance function in order to prevent large gradient excursions for very small changes in the control inputs. In addition, the limit bands around zero will prevent the maximum point due to a certain gradient direction from being approached in the limit sense. This will provide for the establishment of a new gradient direction towards the maximum performance point. The dashed line blocks in Fig. 1 are derivative approximations.

3.1 Plant Description

To facilitate the development of this control methodology the following nonlinear system is presented and analyzed:

$$\begin{aligned}\dot{x}_1 &= -2x_1x_2 + 3x_2 + u_1 \\ \dot{x}_2 &= x_1^2 - x_2^3 + u_2\end{aligned}\quad (1)$$

where (x_1, x_2) , (u_1, u_2) are the states of the system and the control inputs respectively.

The process in (1) is chosen to be nonlinear, stable, with strong cross coupling of the control inputs to the controlled variables. Further, a performance function is selected to demonstrate this control structure which is a function of the states and with the properties of continuity, convexity, and quadratic, where:

$$f(x_1, x_2) = -(x_1 - c_1)^2 - (x_2 - c_2)^2 + c_3^2 \quad (2)$$

This function describes an elliptic paraboloid, with a maximum easily determined by inspection to be equal to c_3^2 at $(x_1, x_2) = (c_1, c_2)$, where c_1, c_2, c_3 are constants. The performance function in (2) could have also been extracted from a corresponding performance index as the argument inside the integral of the performance index, except for the fact that the desire here is to maximize this function instead of minimizing it. In addition a typical performance index could contain a penalty function for control expenditure, but this portion of the control development will not be carried out in this paper.

The process itself (i.e. with zero control input) is determined to be stable by using the Liapunov Direct method, with the Liapunov function: $V(x_1, x_2) = ax_1^{2m} + bx_2^{2n}$. With the choices of $m=1, n=1, a=1, b=2$, which simplifies $\dot{V}(x)$, $V(x_1, x_2) = x_1^2 + 2x_2^2$ which is positive definite. $\dot{V}(x) = \nabla V(x(t))^T g(\dot{x}(t))$, and with no control input, $\dot{V}(x_1, x_2) = -4x_2^4 + 6x_1x_2$ which is negative semi-definite as long as the inequality $2x_2^3 \geq 3x_1$ is satisfied.

Section 3 will cover the development of the APSC control structure shown in Fig. 1, with the derivation of the PGC and the discussion of the FMRLC control approach. In section 4 the simulation results for the APSC structure will be presented. Section 5 will cover the conclusion.

3.2 Positive Gradient Control

Based on the process in Eq. (1) and the performance function in Eq. (2): let f be a function of two variables x_1 and x_2 . Also, for simplicity let x_1 be a function of an independent variable u_1 and x_2 be a function of an independent variable u_2 . It is desired to find the point (x_1^*, x_2^*) , where f assumes its maximum value, $f(x_1^*, x_2^*)$. A necessary condition for (x_1^*, x_2^*) to be a point where f has a relative maximum is that the differential of f vanish at (x_1^*, x_2^*) , that is,

$$\begin{aligned}df(x_1^*, x_2^*) &= \left[\frac{\partial f}{\partial x_1} \frac{dx_1}{du_1} (x_1^*, x_2^*) \right] \Delta u_1 \\ &+ \left[\frac{\partial f}{\partial x_2} \frac{dx_2}{du_2} (x_1^*, x_2^*) \right] \Delta u_2 \\ \underline{\Delta} \left[\frac{\partial f}{\partial u} (x^*) \right]^T \Delta u &= 0\end{aligned}\quad (3)$$

$\partial f / \partial u$ is the gradient of f with respect to u . Since u_1 and u_2 are independent, the components of Δu are independently arbitrary and (3) implies

$$\frac{\partial f}{\partial u} (x^*) = 0. \quad (4)$$

In Fig. 1, instead of using the gradient $\partial f / \partial u_i$ to control the set points of the states, the derivative expression f / \dot{u}_i is utilized. To use the gradient expression would require the knowledge of an analytic function

$f(x_1, x_2, \dots, x_n, u_1, u_2, \dots, u_m)$ defined at every point $(x_1, x_2, \dots, x_n, u_1, u_2, \dots, u_m)$. The substitution of the derivative expression in place of the gradient of f necessitates an analysis to compare their behavior, in order to determine whether the derivative expression will produce the desirable results. For simplicity, let's assume that f is a function of two variables, u_1 and u_2 , which are in turn a function of t . The derivative expression of

$$\frac{\dot{f}}{\dot{u}_1} = \left(\frac{\partial f}{\partial u_1} \frac{du_1}{dt} + \frac{\partial f}{\partial u_2} \frac{du_2}{dt} \right) \bigg/ \frac{du_1}{dt} \quad (5)$$

can be expanded in the limit sense as:

$$\frac{\dot{f}}{\dot{u}_1} = \left[\frac{f(u_1 + \Delta u_1, u_2) - f(u_1, u_2)}{\Delta u_1} \frac{\Delta u_1}{\Delta t} + \frac{f(u_1, u_2 + \Delta u_2) - f(u_1, u_2)}{\Delta u_2} \frac{\Delta u_2}{\Delta t} \right] \bigg/ \frac{\Delta u_1}{\Delta t} \quad (6)$$

After some cancellation of terms Eq. (6) reduces to:

$$\frac{\dot{f}}{\dot{u}_1} = \frac{f(u_1 + \Delta u_1, u_2) - f(u_1, u_2)}{\Delta u_1} + \frac{f(u_1, u_2 + \Delta u_2) - f(u_1, u_2)}{\Delta u_1} \quad (7)$$

Similarly the gradient of f with respect to u_1 can be expressed as:

$$\frac{\partial f}{\partial u_1} = \frac{f(u_1 + \Delta u_1, u_2) - f(u_1, u_2)}{\Delta u_1} \quad (8)$$

Inspection of Eqs. (7) and (8) shows that the two differ by the second term in Eq. (7) which is absent in Eq. (8). Now let's examine how the control is expected to behave with the substitution of (7) for (8). The gradient of the performance function with respect to the control input u_1 in Eq. (8) represents the desirable direction of control adjustment of the state x_1 set point which maximizes the function f . When the first term of Eq. (7) is much greater than its second term, Eq. (7) reduces to Eq. (8). In the worst case, when the second term in Eq. (7) is much larger than its first term, the state x_1 is adjusted primarily due to the change of f relative to the control input u_2 instead of u_1 . If the second term in Eq. (7) is positive greater than the first term, and the state x_1 still needs to move in a positive

direction in order to maximize the function f , then the state x_1 is commanded to move in the right direction. If the state x_1 is already at or past the point that would maximize the function f , then a positive second term in Eq. (7) would move the state in the wrong direction. However, moving the state in the wrong direction relative to maximizing the function f will cause the numerator sign of the second term in Eq. (7) to become negative, thereby forcing the state to move back in the right direction.

The gradient vector is normal to the elevation contours and at each point it has the direction of maximum increase of the function f . The vector representing the derivative approximation to the gradient will not be exactly normal to the elevation contours of f , nevertheless, the derivative vector establishes a certain positive ascending direction towards maximizing f . This approximate PGC methodology can also be thought as providing a series of excitations to the control system, with each excitation forcing the states closer to the optimum performance point.

Based on the above, controlling the process in the positive gradient direction will essentially follow an ascending path on the performance surface described by the performance function in (2), much like a hill climbing problem. When a positive direction path is established the control will follow this trajectory to the point where climbing stops. At this point a new positive gradient direction is established and climbing towards the maximum point resumes. This process is repeated until finally the maximum performance point is reached. When this maximum performance point is reached the gradient $\partial f / \partial u$ in (4) will be zero and the control will cease to update the process set point, thereby allowing the process to settle on this operating point. With the limit bands built around the zero points shown in Fig. 1, the control will be making small excursions around this maximum performance point in order to continuously hunt for this maximum. In this proposed control structure the plant model is not needed for the actual control of the process. However, for the fuzzy controller, a rather simple fuzzy model of the plant is constructed. This will be discussed in the next section.

3.3 Fuzzy Model Reference Learning Control

Fuzzy control theory will not be covered in depth in this paper. For more detail discussions in these areas see Refs. 11 to 22. The FMRLC structure (Ref. 20), shown in Fig. 2, employs an inverse fuzzy model of the process and modifies the knowledge base through the knowledge base modifier mechanism in order for the process output $y(kt)$ to match the reference model output $y_m(kt)$. In this section the basic design procedure of the FMRLC for the process in Eq. (1) will be discussed.

For the MIMO system discussed in this paper two decoupled FMRLC controllers are constructed. A coupled FMRLC controller could be utilized instead, however, the dimensions of the knowledge bases would have increased equivalent to the number of the inputs to the fuzzy controller. In addition to the basic FMRLC structure shown in Fig. 2, a pole at zero frequency was placed at the output of each decoupled controller. This is needed for zero steady state error. Each decoupled FMRLC controller contains 6 adjustable gains. Therefore, some discussion in this section will be devoted to establishing some guidelines for the effective tuning of the control gains. Typical inputs to the fuzzy controller are the error $e(kT)$ and the error derivative $c(kT)$, but other types of inputs can be chosen such as integration of the error. The membership functions for all the inputs to the fuzzy controllers and the inverse models have been chosen with triangular shape, normalized, and uniformly distributed in each Universe of Discourse, as shown in Fig. 3. In Fig. 3, E^j signifies a membership function or linguistic value associated with a specific input to the fuzzy controller, where μ gives the certainty that an element of that particular input may be classified heuristically as E^j . Figure 4 shows the rule base constructed for the inverse fuzzy models. From this rule base it can be deduced that the Consequent membership functions corresponding to the inverse model output variable $y_f(kT)$ have similar distribution to the membership

functions shown in Fig. 3. The knowledge base (rule base) contains the centers of the membership functions which are triangular shaped for this problem, with a base width of 0.4 as seen in Fig. 3. One of the important consideration in the construction of the inverse knowledge base is that the inverse fuzzy model exhibits the proper directionality associated with the controlled process. The knowledge base associated with the fuzzy controllers initially contains all zeros, which reflects no knowledge of how to control the process. This knowledge base is updated automatically as the FMRLC controller learns how to control the process.

The selection of the FMRLC gains is an important step in the design process, as the ability of the controller to track the reference model will heavily depend on the particular choices of the gains. The gains g_e and g_{y_e} are chosen so that the ranges of these inputs are mapped to a normalized universe of discourse in the range of $[-1,1]$. For instance an appropriate choice for the value of the gain g_e would be $1/\text{range}(e(kT))$. A good choice for the value of the gain g_c is found to be approximately equal to $10/(\text{range}(e(kT))/T)$, which is equal to $10/(\text{max change}(r(kT))/T)$, where $r(kT)$ is the set point and T is the sampling time. The smaller the choice for the values of the gains g_e and g_c , the more the control action is concentrated towards the center region of the rule base, resulting in

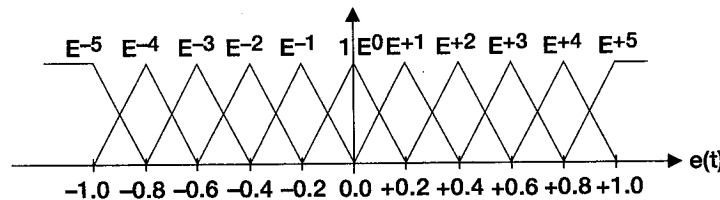


Figure 3.—Membership functions.

$P_{i,j,k}$		Y_c^k										
		-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Y_c^j	-5	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-0.8	-0.6	-0.4	-0.2	0.0
	-4	-1.0	-1.0	-1.0	-1.0	-1.0	-0.8	-0.6	-0.4	-0.2	0.0	+0.2
	-3	-1.0	-1.0	-1.0	-1.0	-0.8	-0.6	-0.4	-0.2	0.0	+0.2	+0.4
	-2	-1.0	-1.0	-1.0	-0.8	-0.6	-0.4	-0.2	0.0	+0.2	+0.4	+0.6
	-1	-1.0	-1.0	-0.8	-0.6	-0.4	-0.2	0.0	+0.2	+0.4	+0.6	+0.8
	0	-1.0	-0.8	-0.6	-0.4	-0.2	0.0	+0.2	+0.4	+0.6	+0.8	+1.0
	+1	-0.8	-0.6	-0.4	-0.2	0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0
	+2	-0.6	-0.4	-0.2	0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0
	+3	-0.4	-0.2	0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0	+1.0
	+4	-0.2	0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0	+1.0	+1.0
	+5	0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0	+1.0	+1.0	+1.0

Figure 4.—Inverse fuzzy model rule base.

better control tracking at the expense of an increased control rate of the control variable $u(kT)$. The gain, g_{y_c} , effects the damping of the process response: If it's too small the response will be oscillatory, if it's too large, the process will be unable to keep up with the reference model. A good choice for the value of the gain, g_{y_c} , is found to lie somewhere in the range of $[1/(4\omega_n), 1/(2\omega_n)]$, where, ω_n , is the natural frequency of the process. The output gains, g_u and g_f , are chosen so that the corresponding Normalized Universe of Discourse maps to the range of the output variables of the fuzzy controller. For instance, both g_u and g_f are selected to be equal to the range of the control input variable, $u(kT)$. This choice for the output gains allows both $u(kT)$ and $y_f(kT)$ to take on values as large as the largest control input.

The selection of the reference model shown in Fig. 2, represents the desired performance of the FMRLC feedback control system. The reference model is selected here to have a natural frequency, ω_m , equal to the process natural frequency, ω_n , with a relatively low step value for the open loop response. With the process being nonlinear, its response time can strongly depend on the magnitude of the control input. Therefore, it may not be desirable to select a reference model significantly faster than the process response time relative to a low control input value, or else we may be asking for relatively large control rates. A first order model for the selection of the reference model has been found to be adequate.

$$G_{RM} = \frac{\omega_m}{s + \omega_m} \quad (9)$$

4.0 APSC Simulation

The APSC simulation consists of two parts. The first part is the simulation of the FMRLC and the corresponding tuning of its gains as discussed in section 3.3. The second part is the simulation of the overall APSC controller shown in Fig. 1 with the combined FMRLC and PGC control structure.

4.1 FMRLC Control Simulation

Based on the discussion in section 3.3, the control parameters for the two decoupled FMRLC controllers have been selected with the following values:

$$\begin{bmatrix} g_{e1} & g_{y_c1} & g_{c1} & g_{y_c2} & g_{u1} & g_{f1} & \omega_{m1} \\ g_{e1} & g_{y_c2} & g_{c2} & g_{y_c1} & g_{u2} & g_{f2} & \omega_{m2} \end{bmatrix} = \begin{bmatrix} 0.25 & 0.25 & 0.1 & 0.125 & 10 & 10 & 2 \\ 0.25 & 0.25 & 0.1 & 0.125 & 10 & 10 & 2 \end{bmatrix}$$

The defuzzification approach used in this simulation is the so called "Center of Gravity." Figure 5 shows the response of the decoupled FMRLC controller with simultaneous step set point changes. This response shows the tracking capabilities of the FMRLC. The set point tracking response was used to tune the controller as was discussed in section 3.3. The knowledge base of the fuzzy controller started with all zero entries, reflecting that initially there was no knowledge of how to control the system. The learning rate is quite fast as is evident from the responses of the states and control inputs in Fig. 5. The resulting knowledge base of the decoupled controller corresponding to the state x_2 (that was learned from the simulation in Fig. 5) is shown in Fig. 6. The zero elements associated with this knowledge base is an indication that the controller, for this particular simulation, has not had the opportunity to venture into these areas of its knowledge space.

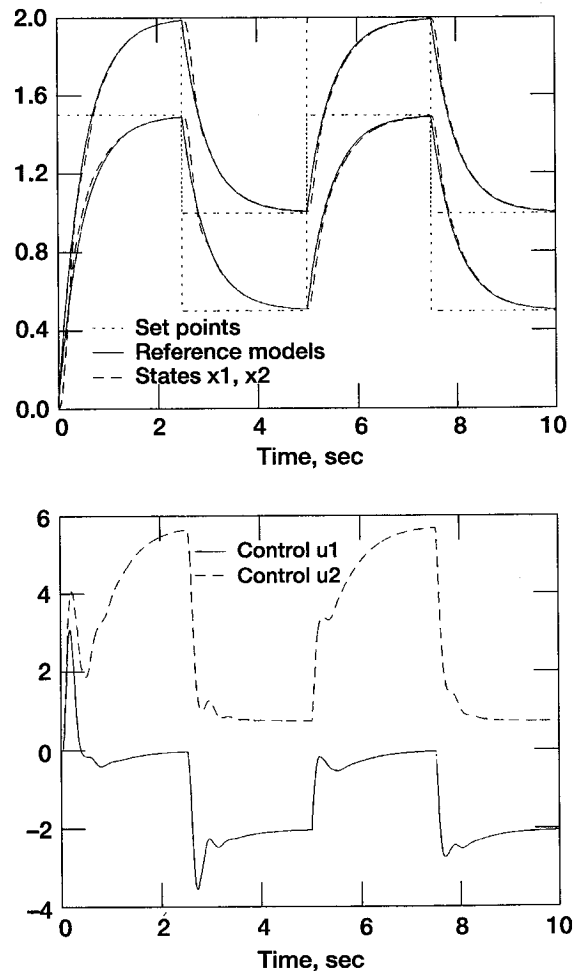


Figure 5.—FMRLC close loop step response.

$P_{i,j,k}$		C^k										
		-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
E^j	-5	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	-4	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	-3	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	-2	-.265	-.265	.000	.000	-.273	-.931	-.931	.083	.000	.000	.000
	-1	-.265	-.265	.000	.000	-.273	-.665	-.076	.477	.000	.000	.000
	0	.000	.000	.000	-.048	-.444	.134	.924	.394	.000	.000	.000
	+1	.000	.000	-.360	-.950	-.186	.532	.128	.000	.000	.134	.134
	+2	.000	.000	-.396	-.802	.913	.974	.128	.000	.000	.134	.134
	+3	.000	.000	-.037	.100	.939	1.000	.000	.000	.000	.000	.000
	+4	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	+5	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000

Figure 6.—Automatically generated rule base for state x_2 .

4.2 APSC Control Simulation

The objective of this control simulation is to drive the states in (1) to the operating point that will maximize the performance function in (2) starting from some arbitrary initial conditions $(x_1(0), x_2(0), u_1(0), u_2(0))$. The resulting state trajectory will not be optimal since this approach employs an adaptive control structure and no classical optimization techniques like linear programming, or steepest descent gradients are used here.

Additional control parameter values used in this simulation as depicted in Fig. 1 are: $K_i = 0.5$, $\tau = 0.25$. The switch shown in Fig. 1 is closed at $t = 1.0$ sec. Before the switch closes the set points are preset to the values $(r_1, r_2) = (1.0, 1.0)$ to start the simulation. After the switch closes the setpoints are updated automatically. The control moves the states towards the positive gradient of the performance function with respect to the control inputs in order to find the operating point that will maximize the performance function. For this simulation the constants of the performance function in (2) have been set to $(c_1, c_2, c_3) = (2.5, 2.0, \sqrt{5.0})$ which causes the optimal performance value to be $f^* = 5.0$ at $(x_1^*, x_2^*) = (2.5, 2.0)$.

Figure 7 shows the performance function as it moves to its maximum obtained value, and Fig. 8 shows the two states as they transition to the operating point corresponding to the performance function in Fig. 7. It is evident from Fig. 8 that this transition to the optimal operating point occurs as a series of responses that more closely resemble first order type system responses. Figure 9 shows the input control response for the same simulation. Figure 10 shows the combined state trajectory on the three-dimensional performance surface of Eq. (2). Figure 11 shows a contour map depicting elevation contours of the performance

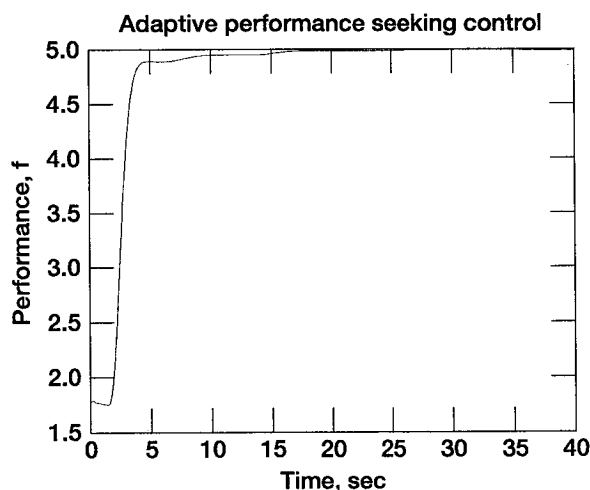


Figure 7.—Performance function.

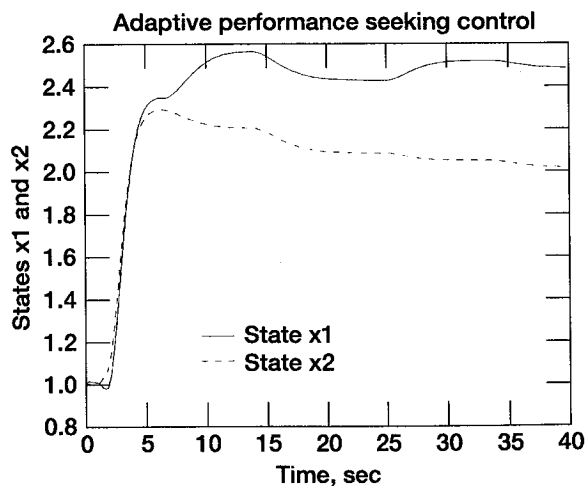


Figure 8.—State trajectories.

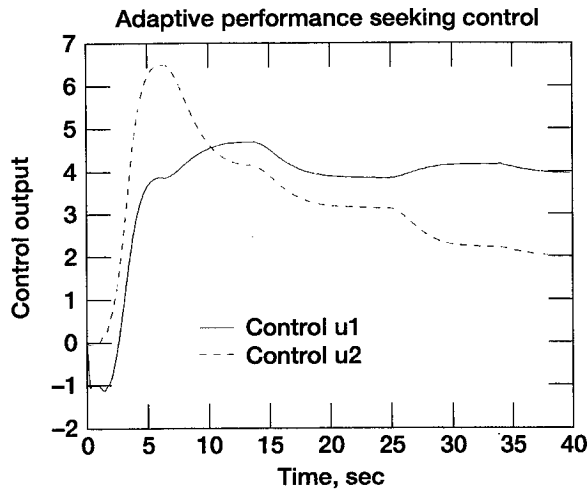


Figure 9.—Control trajectories.

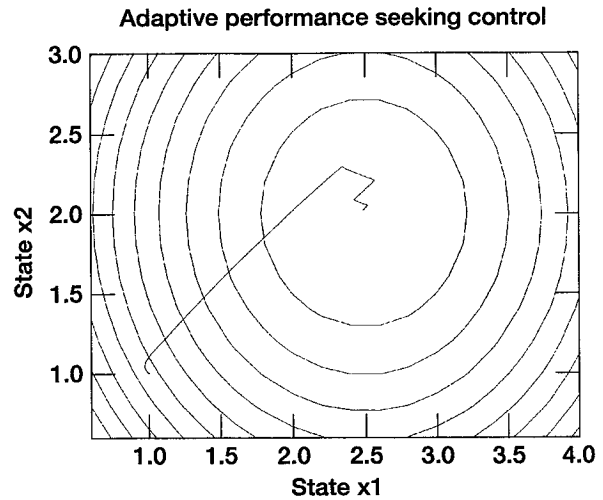


Figure 11.—Combined state trajectory ascent through elevation contours.

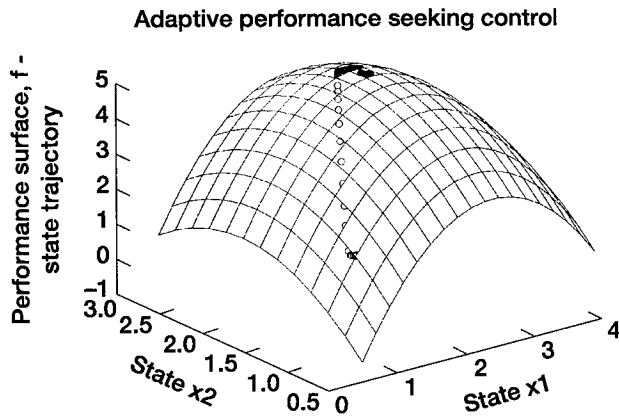


Figure 10.—Combined state trajectory ascent.

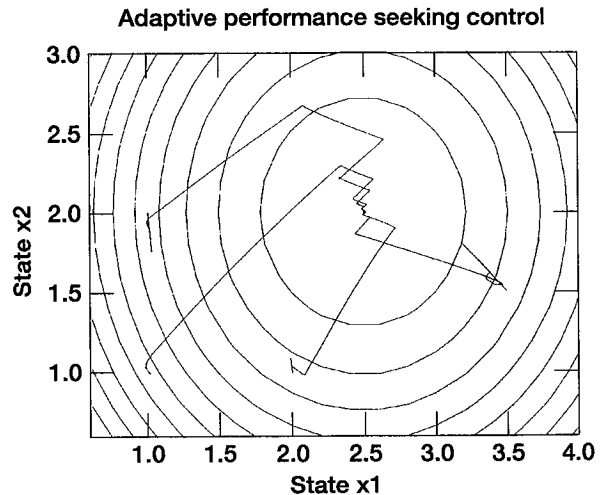


Figure 12.—Ascent of multiple state trajectories.

function in Eq. (2), and the combined state trajectory to the highest elevation point. It is evident from Fig. 11 that the ascent to the top of the performance surface follows a series of ascending paths, where a certain path ends and a new path is established when climbing ceases in that particular direction. This type of ascent is the direct result of following a positive gradient path, where the rate of ascent is proportional to the magnitude of the gradients at each time instant. Figure 12 shows different state trajectories starting from various initial conditions and all converging to the highest elevation point on the performance elevation contour map.

For these simulations, the knowledge bases of the two decoupled FMRLC controllers were also initialized with zeros, but the resulting knowledge bases from the simulation in Fig. 6 could have been used as the starting point.

5.0 Conclusion

In this paper a nonlinear process was used to help develop an Adaptive Performance Seeking Control methodology. This methodology utilizes the Fuzzy Model Reference Learning Control method and an approximate Positive Gradient Control approach which was developed in this paper. The simulation results presented in this paper showed that the FMRLC, with the discussed tuning guidelines, provides for an effective way to control nonlinear and tightly coupled processes. The results also show that the approximate Positive Gradient Controller within the closed loop Adaptive Performance Seeking Control structure effectively drives the process to operate at the point that generates maximum performance.

Since a mathematical model of the plant was not used in the control structure described in this paper, and since relative to the plant only its natural frequency information was utilized to tune the controller, it would be expected that this control structure would be adaptive to changes in the plant dynamics to the extent that there are no large variations to the plant natural frequency. In addition, since the APSC controller continuously hunts for the operating condition that generates maximum performance, it may become feasible to perform engine control without the need of extensive testing to derive engine control schedules.

For future work it would be important to study adaptiveness of this control methodology to plant model variations, stability, convergence, and robustness in more detail. Further, experimental validation of this method would be needed, with processes that exhibit more complex system dynamics.

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