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Nonlinear Process Control Using Multiple Models: Relay Feedback Approach

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In this work the relay feedback autotuning is extended to handle process nonlinearity using multiple local models. Local models from relay feedback tests are scheduled using the Takagi−Sugeno fuzzy model, and local controllers are designed accordingly. This results in a gradual model switching between different operating conditions. The characteristics of the fuzzy implications are explored, and analytical expressions for the fuzzy model are derived. The importance of the selection of the scheduled parameters is emphasized, and the necessity of model scheduling for different loops is also explored. One transfer function example and two recycle plant examples are used to illustrate the advantage of the simple model scheduling method. Performance is evaluated according to the regions of robust performance and/or simulations. Results show that the proposed approach provides a simple and workable scheme for model scheduling large-scale systems.

1. Introduction

Intelligent control is now becoming common in the literature and in practice. Control systems with some types of intelligent features begin to appear. Among these features, the abilities to perform automatic tuning in a multivariable environment and to adjust parameters as the operating condition changes are of primary importance in chemical process control. The reason is obvious: chemical processes, generally, are multivariable and nonlinear.

The last decade has seen significant progress in the autotuning of proportional−integral derivative (PID) controllers. Most of approaches are the variation of the Åström−Hägglund relay feedback tests.[1] First, a continuous cycling of the controlled variable is generated from a relay-feedback experiment, and the important process information, ultimate gain (K_u) and ultimate frequency (ω_u), can be extracted directly from the experiment. A controller can be designed according to K_u and ω_u.[19,21,23,24,27] Applications of relay-feedback-based autotuners are shown throughout process industries. The success of these types of autotuners is due to the fact that the tuning mechanism is so *simple* that operators understand how it works. Moreover, it also works well in many multivariable systems.[12]

Chemical processes are often operated at different steady states. Changes in the operating condition are usually initiated by external factors. These parameters are often known a priori, e.g., changes in the production rate or product specification. The objective of process control is to achieve good transition while moving toward a new operating point and yet maintaining robust performance in the face of unknown disturbances. The concept of multiple models provides a useful framework for automated chemical process control.[3,5,7−9,15,16] Since knowledge on process dynamics accumulated as the plant starts operation, provided with an efficient autotuning procedure, multiple models (or multiple sets of controller parameters) can be obtained in a straightforward manner. Conventionally, these models, if they exist, are utilized via a look-up table approach.

The objective of this work is to devise a framework for the control system design such that it works well over the entire operating regime. The automated control system design consists of two steps: (1) automatic tuning at a specific operating condition and (2) automatic model scheduling for the entire operating regime. The relay-feedback-based autotuning is proven reliable in the neighborhood of nominal operating point. For multivariable systems, the autotuning is carried out in a sequential manner. Applications to complex chemical plants are also reported.[11,26] The controller tuning for the entire plant can be carried out effectively. However, if the process is operated over a wide range of operating conditions, the *local* controllers have to be retuned (as a result of large uncertainty bound) to meet *global* performance criterion. Once multiple models are available, the next step is to employ the local model(s) at a corresponding operating condition. Approaches exist for incorporating models at different operating regimes. One is switching to a specific model if a certain condition is met (a crisp switching).[15] The other way is to combine local models using interpolation techniques (a fuzzy switching). In this work, the fuzzy modeling of Takagi and Sugeno[22] are used to schedule local models. It is a fuzzy augmentation of crisp models which provides a nice framework for model scheduling. The linguistic nature of the fuzzy logic provides a better interface between process operators and control system designers. Characteristics of the Takagi−Sugeno model are analyzed, and the importance in the selection of the output variables (model or controller parameters) is also emphasized. A transfer function example and two plant-wide control examples are used to illustrate the combined automatic tuning and model scheduling procedure.

2. Autotuning

Åström and Hägglund[1] suggest the relay-feedback test to generate sustained oscillation as an alternative

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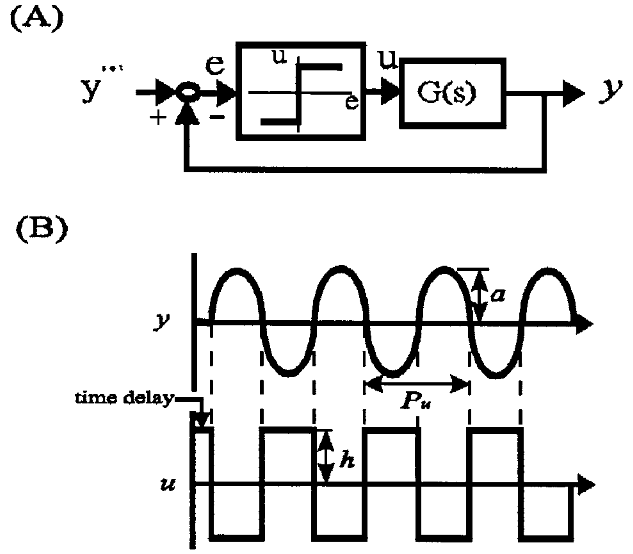


Figure 1. (A) Block diagram for a relay-feedback system and (B) relay-feedback test for a system with positive steady-state gain.

Table 1. Additional Versions of the Ziegler−Nichols Settings for PI Controller

rule	K_c	τ_I
original	$K_u/2.2$	$P_u/1.2$
Tyreus−Luyben	$K_u/3.22$	$2.2P_u$
Shen−Yu	$K_u/3$	$2P_u$

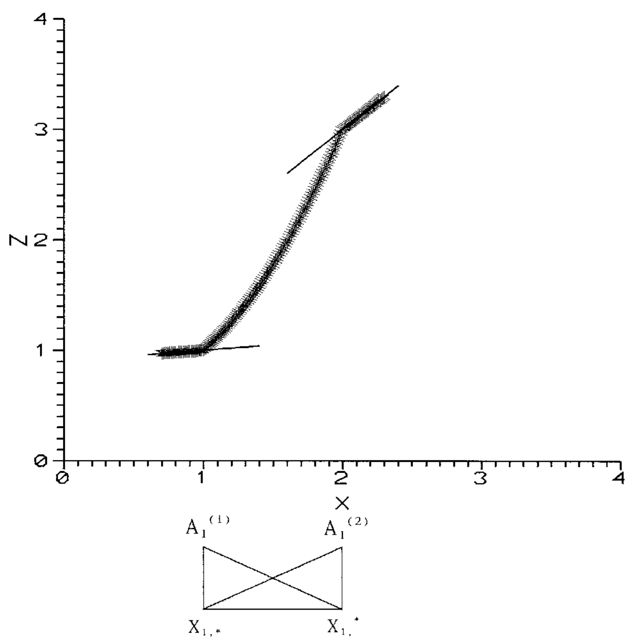


Figure 2. Membership functions and resultant global model from fuzzy modeling (example 1).

to the conventional continuous cycling technique. It is very effective in determining the ultimate gain and ultimate frequency. Luyben[11] popularizes the relay-feedback method and calls this method "ATV" (autotune variation). It has become a standard practice in chemical process control, as can be seen in recent textbooks in process control[11,18] and books also devoted to this subject.[2,26]

Consider a relay-feedback system where $G(s)$ is the process transfer function, y is the controlled output, y^{set} is the set point, e is the error, and u is the manipulated input. An ideal (on−off) relay is placed in the feedback loop. Figure 1B illustrates how the relay-feedback

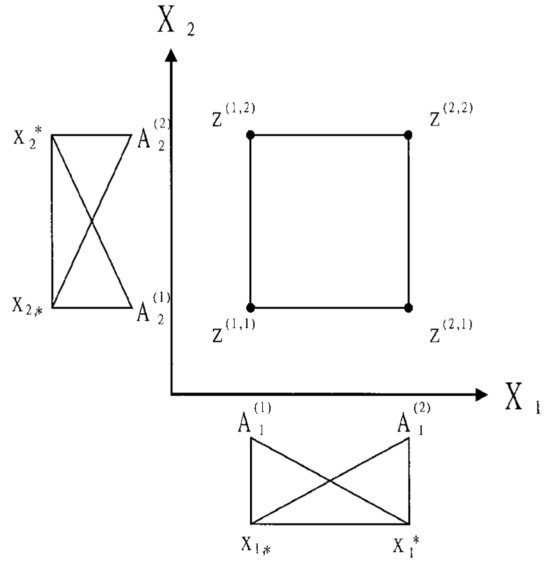


Figure 3. Linear membership functions for a two-input system.

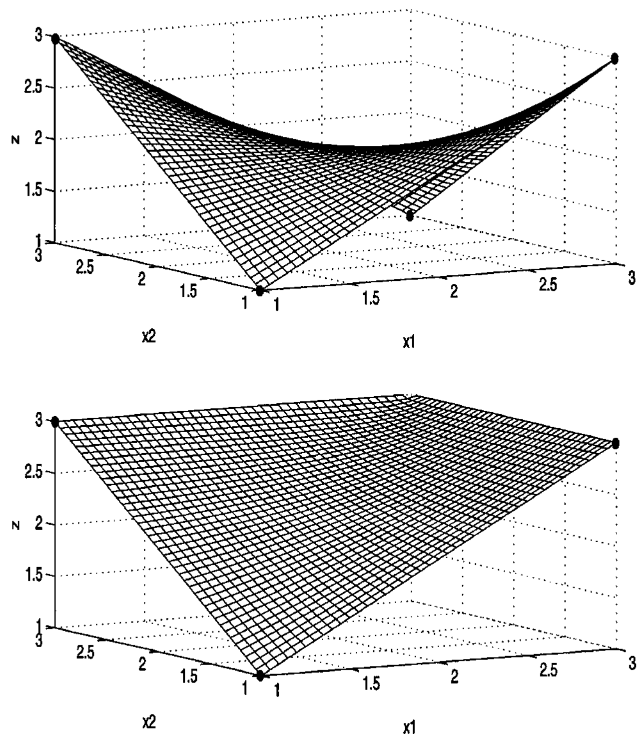


Figure 4. Global bilinear model from fuzzy modeling for example 3 with (A) four data sets and (B) three data sets.

system works. A relay of magnitude h is inserted in the feedback loop. Initially, the input u is increased by h. As the output y starts to increase (after a time delay D), the relay switches to the opposite position, $u = -h$. Because the phase lag is $-\pi$, a limit cycle with a period P_u results (Figure 1). The period of the limit cycle is the ultimate period. Therefore, the ultimate properties from this relay-feedback experiment are

$$\omega_u = 2\pi/P_u \quad (1)$$

$$K_u = 4h/\pi a \quad (2)$$

where h is the height of the relay and a is the amplitude of oscillation. Notice that the relay-feedback tests result in sustained oscillations for open-loop stable systems and most of open-loop unstable systems.[20]

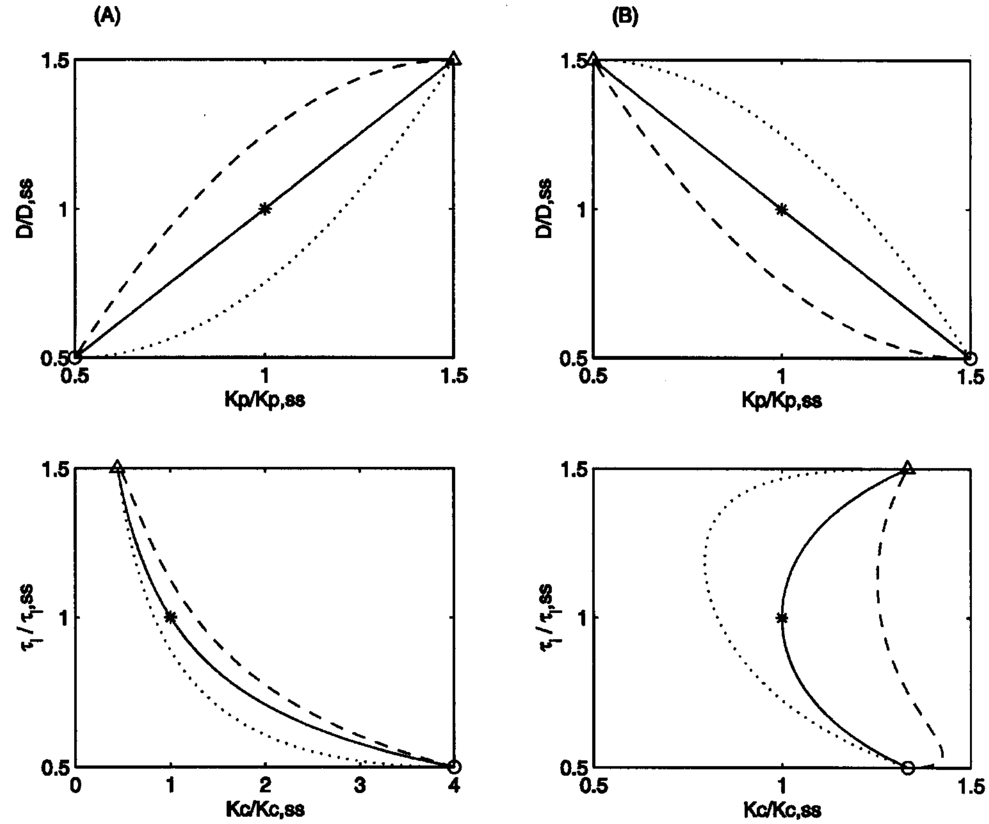


Figure 5. Effect of the selected scheduled (output) variables.

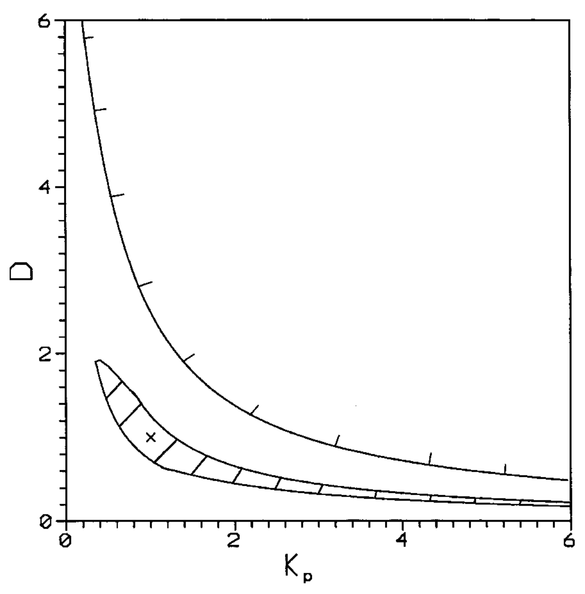


Figure 6. Regime of robust stability (RS) and robust performance (RP, shaded area).

The Ziegler–Nichols tuning is still popular in control engineering practice. It works reasonably well for some loops but tends to be too underdamped for many process control applications. On the basis of the integrator plus time delay system, Tyreus and Luyben[23] proposed a tuning rule which also utilizes the information of K_u and P_u. A different version of Ziegler–Nichols tuning is also proposed.[19] They are proven useful for many plantwide control applications.[12] For a PI controller, the settings are shown in Table 1. Notice that these types of settings tend to work well for first-order systems with a long time constant. This can be seen from the derivation of the Tyreus–Luyben tuning (for the integrator plus time delay process). Therefore, once we have the ultimate gain and ultimate period, the tuning rule can be applied directly. In many cases, that completes the controller tuning.

As will be shown later, in some cases, transfer function models are preferable for the purpose of model scheduling. The ultimate gain (K_u) and ultimate frequency (ω_u) can be used directly to backcalculate the local transfer function model. As pointed out by several authors,[4,11,23] the high-frequency characteristic of the integrator plus time delay model offers an attractive means in modeling *slow* chemical processes. The transfer functions have the following form:

$$G(s) = K_p e^{-Ds}/s \tag{3}$$

The model parameters can be solved directly from the ultimate gain and ultimate frequency.

$$K_p = \frac{\omega_u}{K_u} = \frac{2\pi}{K_u P_u} \tag{4}$$

$$D = \frac{\pi}{2\omega_u} = \frac{P_u}{4} \tag{5}$$

The controller parameters of the modified Ziegler–Nichols tuning can be expressed explicitly in terms of K_p and D. If the settings of Shen and Yu (Table 1) are used, we have

$$K_c = \pi/6K_pD \tag{6}$$

$$\tau_I = 8D \tag{7}$$

In this section, the relay-feedback test is introduced, and steps required to perform the experiment are also

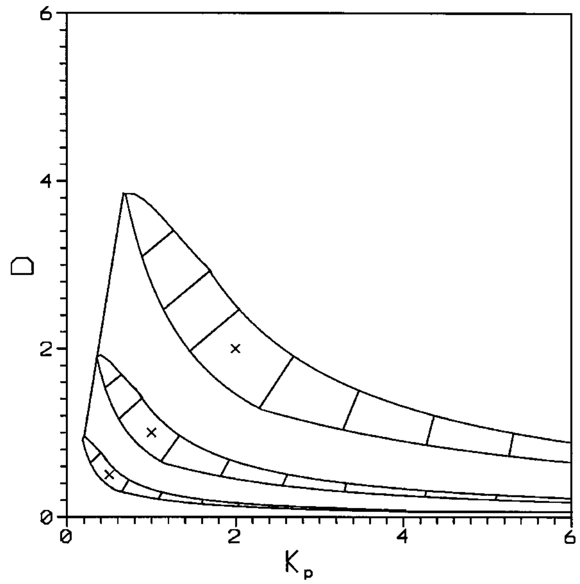


Figure 7. Regions of robust performance at different operating conditions (indicated by ×) for the fixed gain control (the middle shaded area), crisp switching (all three shaded areas), and fuzzy switching (the entire closed region).

given. Once you have obtained the information on the ultimate frequency, the controller settings can be decided using the modified Ziegler–Nichols methods. Moreover, the model parameters of the useful integrator plus time delay model can be found directly (eqs 4 and 5). This completes the tuning and modeling at a given operating condition. In other words, the local controller and local model can be found in a straightforward manner. It is very likely that, after some period of process operation, the autotuning procedure is repeated at different operating conditions. How can we utilize this local information to construct a global model?

3. Model Scheduling

Similar to the gain scheduling, the model scheduling is defined as using different process models as the operating condition changes. The output (or scheduled) variables z are often referred to as model parameters or controller settings, and the input (or scheduling) variables x are the variables that indicate changes in the operating condition. They are often set by the operating condition, e.g., production rate, product specification, process outputs, etc. The model scheduling problem then becomes the following: Given sets of process data ($\mathbf{z}$, $\mathbf{x}$), find the functions $\mathbf{z} = \mathbf{f}(\mathbf{x})$ which can describe the global behavior.

3.1. Takagi–Sugeno Fuzzy Model. The fuzzy modeling of Takagi and Sugeno[22] is employed to construct the global model. It uses fuzzy logic to interpolate between several models. A brief description of the fuzzy set is given. In the fuzzy set, a variable x may belong partially to a set (e.g., a set of high temperature). The membership function (A) characterizes this degree of belonging. A is defined as

$$A(x):\ x \rightarrow [0, 1], \quad x \in X$$

where X, generally, is a subset of R and the grade falls between 0 and 1. The truth value (TV) of a proposition

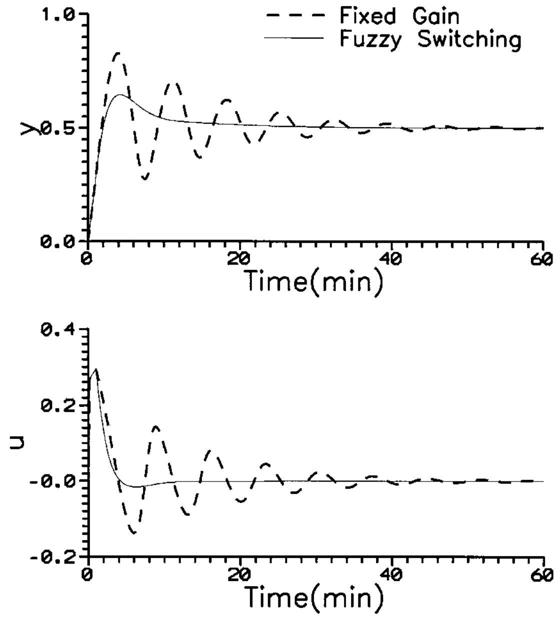


Figure 8. Set-point responses of example 3 using the fixed gain control and fuzzy switching.

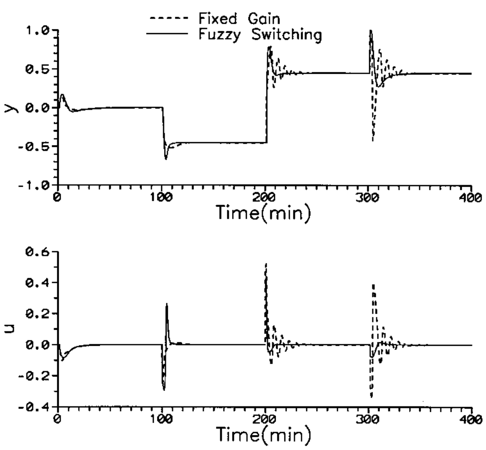


Figure 9. Set-point and load responses of example 3 at different operating points using the fixed gain control and fuzzy switching.

"x_1 is A_1 and x_2 is A_2" is expressed as

$$A_1(x_1) \wedge A_2(x_2) = \min(A_1(x_1), A_2(x_2))$$

where $\wedge$ is the logical .AND. operator.

Takagi and Sugeno suggest that a multivariable system can be represented by the fuzzy implications ($R^{(j)}$). Consider a multivariable system with n input variables (x_i, $i = 1, ..., n$) and one output (z) with k fuzzy implications.

$$R^{(1)}: \quad \text{If } x_1 \text{ is } A_1^{(1)}, \dots \text{ and } x_n \text{ is } A_n^{(1)}, \text{ then } z = p_0^1 + p_1^1 x_1 + \dots + p_n^1 x_n$$

$$R^{(k)}: \quad \text{If } x_1 \text{ is } A_1^{(k)}, \dots \text{ and } x_n \text{ is } A_n^{(k)}, \text{ then } z = p_0^k + p_1^k x_1 + \dots + p_n^k x_n$$

Then, the output z becomes

$$z = \sum_{j=1}^{k} \beta_j (p_0^j + p_1^j x_1 + \dots + p_n{}^j x_n) \tag{8}$$

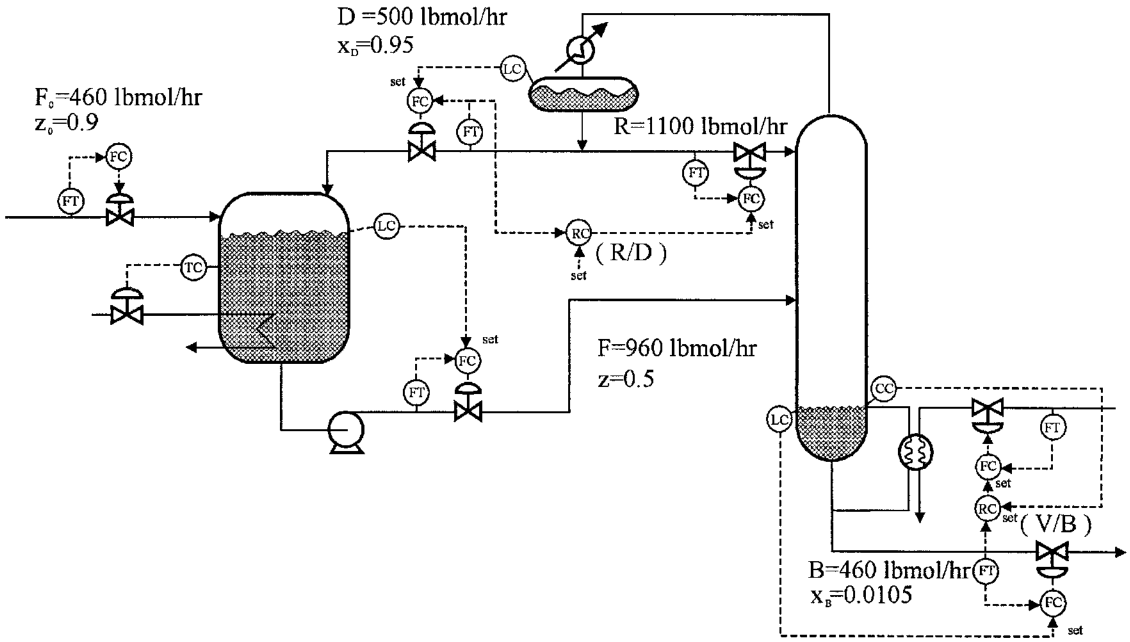


Figure 10. Conventional control structure for a simple recycle plant.

where

$$\beta_j = \frac{A_1^{(j)}(x_1) \wedge \ldots \wedge A_n^{(j)}(x_n)}{\sum_{j=1}^{k}[A_1^{(j)}(x_1) \wedge \ldots \wedge A_n^{(j)}(x_n)]} \tag{9}$$

In this work, the following assumptions are made: (1) the membership function is linear and (2) each regime (except two ends) is defined by two membership functions.

A. Single-Input Systems. The Takagi–Sugeno method offers a general framework to establish a nonlinear (global) model between the scheduling variable x (e.g., production rate, product specification, etc.) and the scheduled variable z (e.g., process steady-state gain, time constants, time delay, etc.). Let us use a single-input–single-output example to analyze the fuzzy model.

Example 1. Suppose the *trend* of the process variable (z) around two operating points is known. We have the following two implications:

$R^{(1)}$: If x is $A^{(1)}$, then $z = 0.1x + 0.9$

$R^{(2)}$: If x is $A^{(2)}$, then $z = x + 1$

The membership functions $A^{(1)}$ and $A^{(2)}$ are given in Figure 2, and the results show that the Takagi–Sugeno model leads to a piecewise nonlinear function between z and x. Analytically, the nonlinear function can be expressed as

$$z = r(x + 1) + (1 - r)(0.1x + 0.9), \quad 1 \le x \le 2 \tag{10}$$

where

$$r = \frac{x^* - x}{x^* - x_*} \tag{11}$$

with x^* and x_* defining the upper and lower bounds of the regime. This is simply a linear combination of two linear functions as shown in Figure 2.

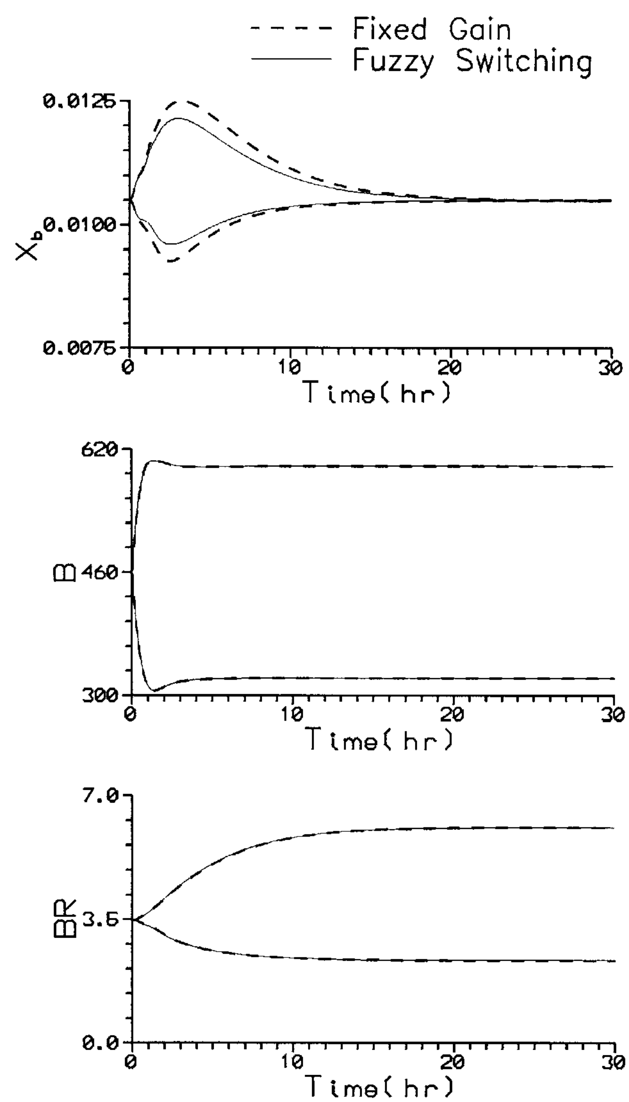


Figure 11. Load responses of the recycle plant for ±30% production rate changes using the fixed gain control and fuzzy switching.

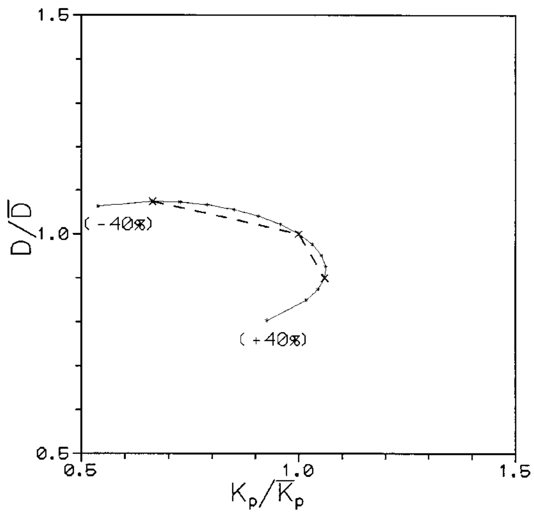


Figure 12. Global model of the recycle plant as production rate varies from −40% to +40% (solid, true value; dashed, from fuzzy modeling).

Several observations can be made immediately. Consider the linear membership functions in Figure 2 where the scheduling variable (x) superimposes the same range.

O1. If the output variable z shows the same trend as the scheduling variable x varies (i.e., the slopes in the consequence of Figure 2 have the same sign), then the resultant nonlinear function is monotonic (i.e., the sign of the slope remains the same).

O2. If the output variable z shows different trends as the scheduling variable x varies (i.e., the slopes have different signs), then the resultant nonlinear function is nonmonotonic.

An even simpler model scheduling mechanism can be devised. If we do not have any knowledge about the trend of the process variable (i.e., the slope in Figure 2), the process variable can simply be set constant around the neighborhood where system identification is performed. Suppose the two data points we have are

Table 2. Nominal Controller Parameters for the Tennessee Eastman Process

loop	unit	K_c	transmitter span
level	reactor	4	100%
	separator	2.35	100%
	stripper	2	100%
pressure	reactor	3.33	3000 kPa
temperature	reactor	12.7	100 °C
	separator	0.96	100 °C
	stripper	108	100 °C
composition	A in recycle	115	100 mol %
	B in recycle	23.1	100 mol %

z^* at x^* and z_* at x_*. Mathematically, we have

$$z = rx^* + (1 - r)x_*, \quad x_* \le x \le x^* \tag{12}$$

This is simply a linear interpolation between these two points. The following observation points out its limitation.

O3. If the trend of the output variable z is not included, then the resultant function is simply linear interpolation of these two different data points which always exhibit monotonic behavior in between.

Actually, the general result is as follows: If the process description in the consequence is a polynomial with an order m, then the resultant function is also a polynomial function to the $m + 1$ power. Despite its limitation, this simple approach offers an attractive alternative in most cases. Another nice feature of the Takagi−Sugeno modeling is that once a new identification result becomes available we can simply add another implication to the original rule sets. The function then becomes a piecewise linear function (e.g., eq 12).

B. Multiple-Input Systems. Systems with multiple scheduling variables are often encountered in practice. For example, both the production rate and the production specification are changed to meet the business condition (e.g., the Tennessee Eastman process is a good example[6,12]). Consider a general dual-input system with two input variables x_1 and x_2 and one output variable z. Suppose we have four experimental results and the corresponding data are $(x_{1,*}, x_{2,*}, z^{(1,1)})$, $(x_1^*, x_{2,*}, z^{(2,1)})$,

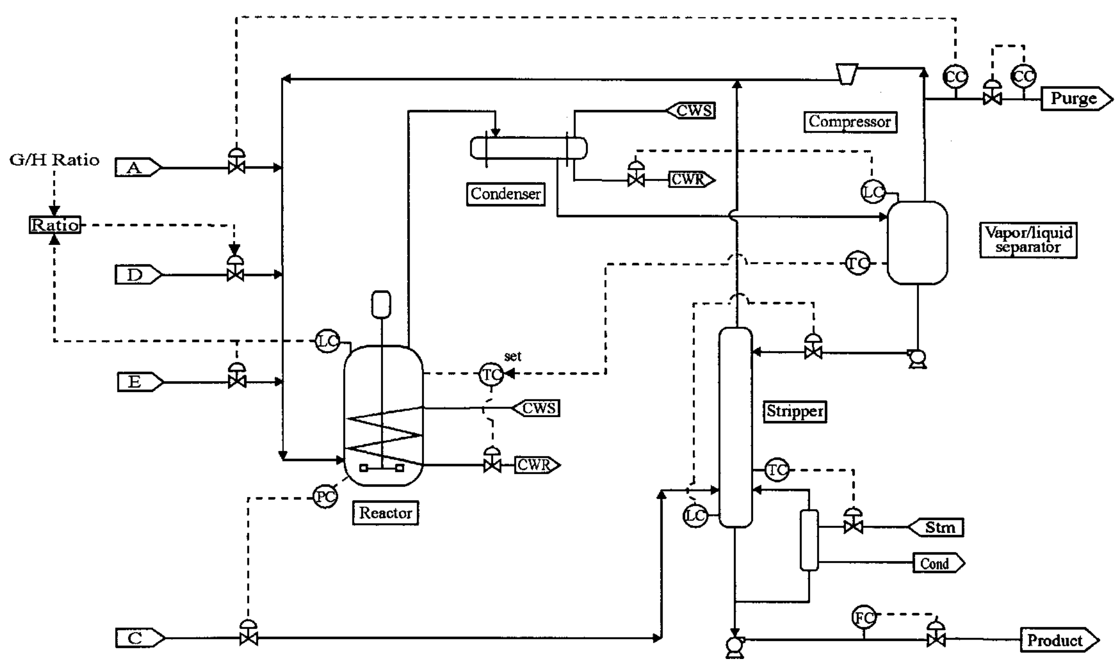


Figure 13. Tennessee Eastman process using Luyben control structure for the case of on-demand product.

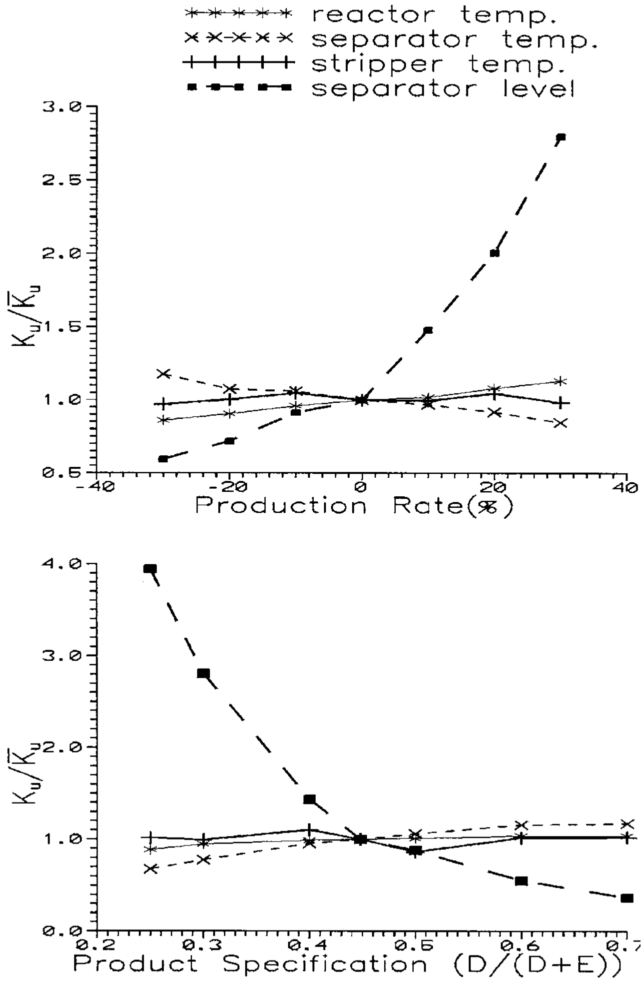


Figure 14. Controller parameters from relay-feedback tests for different operating conditions: changes in the production rate and product specification.

($x_{1,*}$, x_2^*, $z^{(1,2)}$), and (x_1^*, x_2^*, $z^{(2,2)}$). Figure 3 gives the ranges of the two input variables and the membership functions. If these local data are employed in modeling, again, the result of fuzzy implications can be expressed analytically. It becomes a *bilinear* function:

$$z = r_1 r_2 z^{(1,1)} + r_1(1 - r_2)z^{(1,2)} + (1 - r_1)r_2 z^{(2,1)} + (1 - r_1)(1 - r_2)z^{(2,2)} \quad (13)$$

where

$$r_1 = \frac{x_1^* - x_1}{x_1^* - x_{1,*}} \quad \text{and} \quad r_2 = \frac{x_2^* - x_2}{x_2^* - x_{2,*}} \quad (14)$$

Example 2. Consider a system with two inputs (x_1 and x_2) and one output (z). Suppose the *trend* of the output variable is not known and plant tests give the following four data sets: (x_1, x_2, z) = (1, 1, 1), (1, 3, 3), (1, 3, 3), and (3, 3, 1). The four fuzzy implications are similar to that shown above with $x_{1,*}, = x_{2,*} = 1$ and $x_1^* = x_2^* = 3$. Figure 4A shows the resultant bilinear function. □

In practice, we may not have all of the data points. For example, only three data points are available in example 2 where $z^{(1,1)}$ corresponds to the nominal steady state, $z^{(2,1)}$ stands for an increase in the production rate, and $z^{(1,2)}$ represents a change in the product specification. Under this circumstance, we only have three fuzzy implications ($R^{(1)}$, $R^{(2)}$, and $R^{(3)}$). The analytical expression then becomes:

$$z = \frac{r_1 r_2}{r_1 + r_2 - r_1 r_2} z^{(1,1)} + \frac{r_1(1 - r_2)}{r_1 + r_2 - r_1 r_2} z^{(1,2)} + \frac{(1 - r_1)r_2}{r_1 + r_2 - r_1 r_2} z^{(2,1)} \quad (15)$$

With one less data point, the Takagi–Sugeno model gives a good description for the triangular region defined by $z^{(1,1)}$, $z^{(1,2)}$, and $z^{(2,1)}$. However, extrapolation outside this region is less reliable as shown in Figure 4B.

It is obvious the extension of the Takagi–Sugeno model to a multivariable system is fairly straightforward. As expected, with the least process information, the model leads to a bilinear system. However, one should be cautious when the model is extrapolated.

3.2. Selection of a Scheduled Variable. From previous discussion, it becomes clear that the Takagi–Sugeno model interpolates *linearly* among data points. Hence, we need more than two data points to describe a function with nonmonotonic behavior. It generally requires more process information in quantity as well as in quality. Therefore, in building a global model, it is important to select appropriate scheduled variables (z) such that the nonmonotonic behavior can be avoided. Typical output variables in model scheduling are controller parameters and model parameters. It is rather intuitive to use the controller parameters (e.g., K_c and τ_I) as the output variables in the fuzzy modeling. Let us use the linear integrator plus time delay model to illustrate the effect of different scheduled variables. Suppose the T–L tuning (Table 1) is employed to tune the typical slow processes.

Consider the first case where both model parameters (K_p and D) increase as the operating condition changes (i.e., increase in the scheduling variable). Figure 5A shows that the controller parameters also change monotonically as the operating condition varies. However, a better global model can be achieved if the model parameters are selected as the scheduled variables. Numerically, it can be shown using the fuzzy modeling in the previous section for the case with or without a process trend. The second case is that K_p and D change toward different directions as the operating condition changes (Figure 5B). This is a more likely situation in process systems. Because K_p represents the slope of the output responses and D is a measure of time delay, an increase in K_p and a decrease in D implies a faster output response. This is exactly the case in the plantwide control example (next section). However, if the controller parameters are used as the output variable, we have a nonmonotonic behavior in the controller gain K_c as shown in Figure 5B. As mentioned earlier, we need either more identification results or a very precise description of the process trend to find a reasonable global model. If the model parameters are employed as the scheduled variables, only two data points are sufficient to construct a good global model. The examples clearly illustrate the importance in selecting the scheduled variables. For the integrator plus time delay model with the Ziegler–Nichols type of tuning, the model parameters seem to be a better choice as the speed of response changes with the operating condition (this is most likely the case).

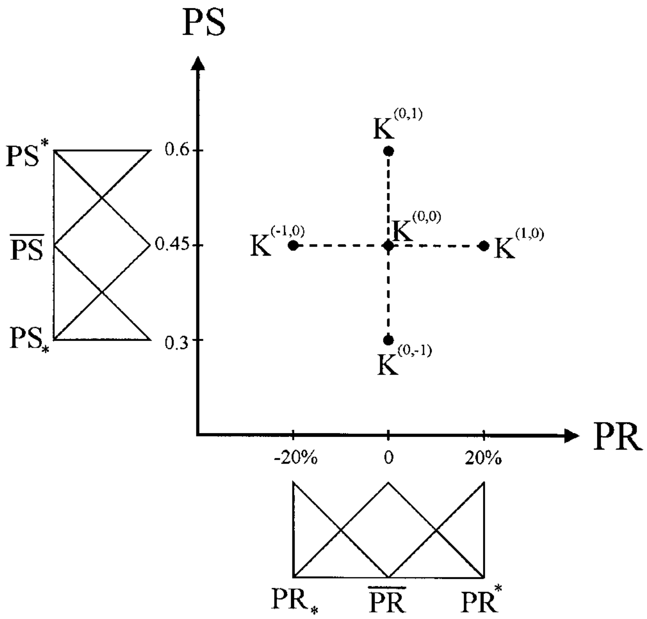


Figure 15. Linear membership functions for the Tennessee Eastman process.

4. Nonlinear Control

4.1. Transfer Function System. In this work, the integrator plus time delay model is chosen (eq 3) to represent slow chemical processes. The controller settings of eqs 6 and 7 give a gain margin (GM) of 2.83 and a phase margin (PM) of 46.1° for all possible model parameters (i.e., $K_p \neq 0$ and $D \neq 0$). First we would like to know how well the nominal controller settings work. Considering the nominal condition of $\bar{K}_p = 1$ and $\bar{D} = 1$, Figure 6 shows the region of robust stability (RS). For example, the closed-loop system becomes unstable when $K_p = 2$ and $D = 2$ (Figure 6), and it remains stable for small values of K_p and D. Figure 6 shows that the settings remain stable for a fairly large region in the parameter space. A more useful assessment is that the region can achieve the robust performance (RP). In this work, a very simple measure of the RP is defined: A system is RP if and only if $2.21 \le \mathrm{GM} \le 3.95$ and $36.1° \le \mathrm{PM} \le 56.1°$. That means we allow the 1/GM and PM to vary by ±0.1 and ±10°, respectively. The following equations describing the magnitude (M) and phase (ϕ) are useful in finding the GM and PM as model parameters change. Substituting nominal tuning constants into the integrator plus time delay model, we have

$$M = \frac{\pi\sqrt{1 + (8\omega\bar{D})^2}}{48(\omega\bar{D})^2}\frac{K_p}{\bar{K}_p} \tag{16}$$

$$\phi = -\pi - \frac{D}{\bar{D}}(\omega\bar{D}) + \tan^{-1}(8\omega\bar{D}) \tag{17}$$

where the overbar stands for the nominal condition. The region of the RP can then be found by solving eqs 16 and 17. The shaded area in Figure 6 indicates the parameter space where the RP can be achieved. In other words, if the process drifts out of the shaded area, the controller has to be retuned for good performance. Therefore, the region of the RP can be used to evaluate the effectiveness of model scheduling approaches.

Suppose the process is operated at three different conditions: high, nominal, and low productions which correspond to $K_p = D = 0.5$, 1, and 2, respectively (indicated by × in Figure 7). We examined three approaches: (1) fixed gain control, (2) crisp switching control, and (3) fuzzy switching control. By crisp switching, we mean the model parameters (and, consequently, the controller parameters) are chosen from one of the three sets if a certain condition in the scheduling variable is met. Fuzzy switching implies the model parameters (and, consequently, the controller parameters) are generated from a fuzzy model (e.g., eq 12). In the fixed gain control, we only have the nominal settings; the region of RP is indicated by the middle shaded area in Figure 7. Performance degradation can be expected as the operating point moves out of the region. If we choose to use the *crisp* model switching among three sets of model parameters, then, at best,

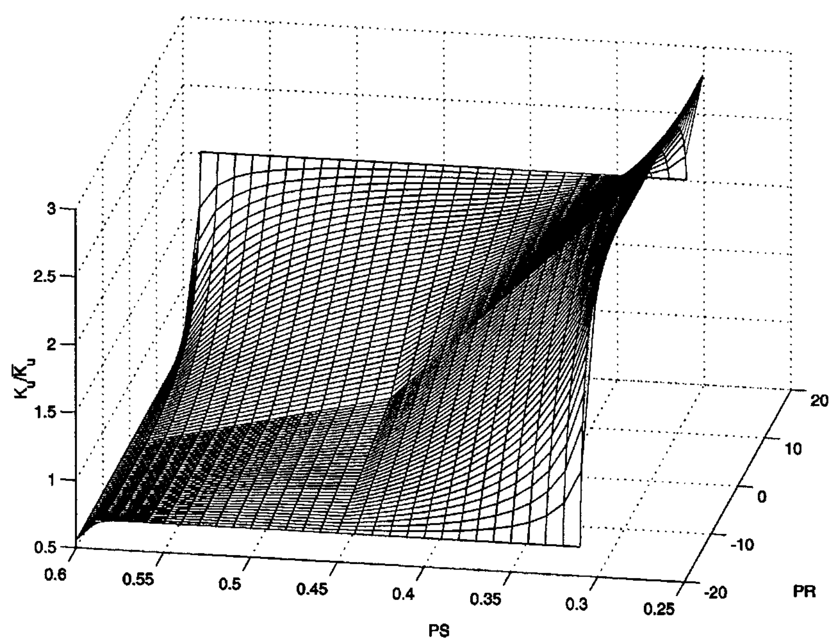
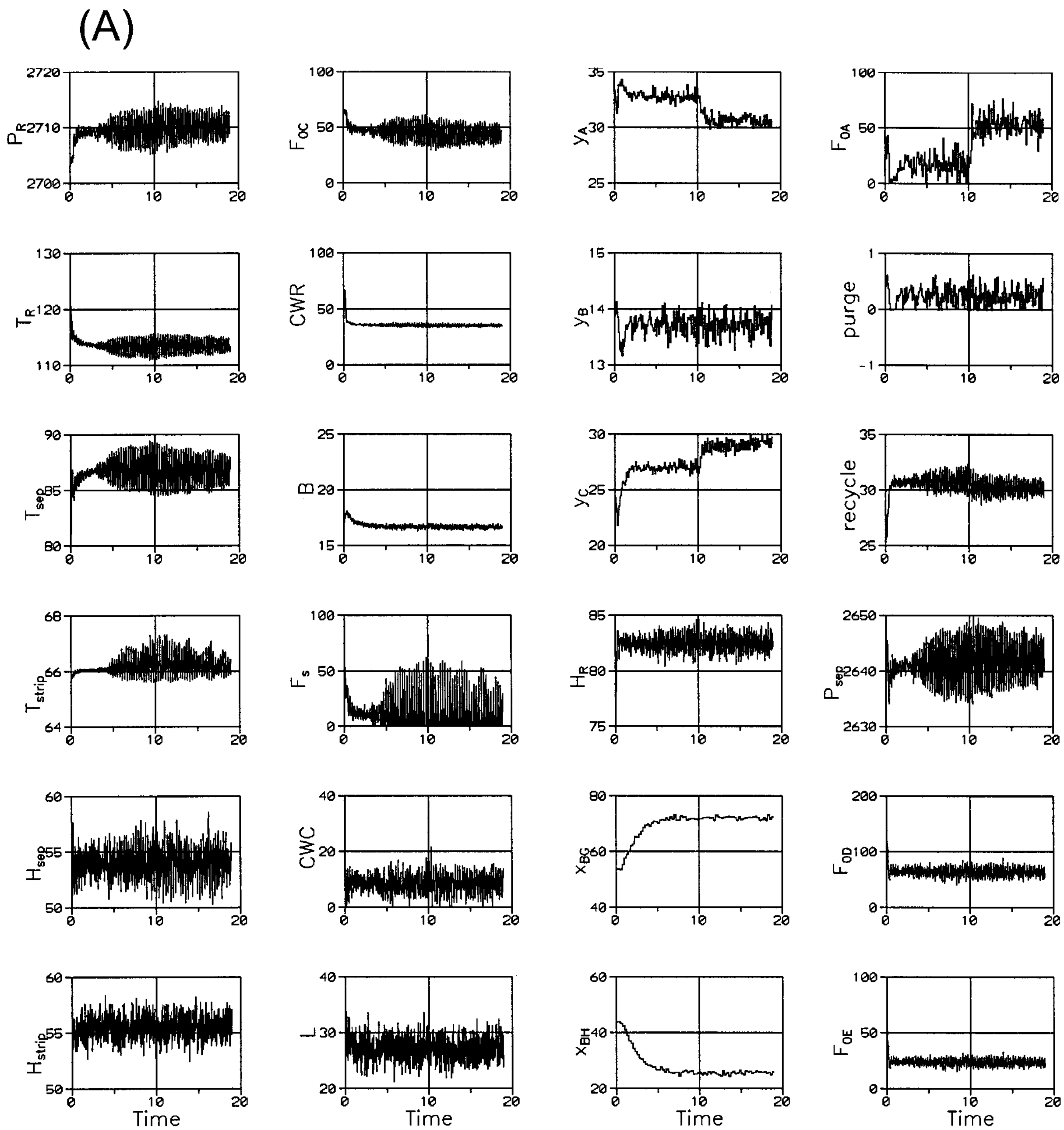


Figure 16. Global model for the separator level ultimate gain of the Tennessee Eastman process as production rate (PR) and product specification (PS) vary (−20% < PR < +20% and 0.3 < D/(D + E) < 0.6).



the regions of RP are these three shaded areas. However, if the local models are scheduled according to the Takagi–Sugeno fuzzy implications, we have a much larger region for the RP, as shown in Figure 7. The degree of sophistication in the consequence of fuzzy rules (e.g., with or without knowledge of process trend) has little effect on the RP region.

Example 3. Consider the following nonlinear system:

$$y = \frac{K_p(y)\, e^{-D(y)s}}{s} u \tag{18}$$

with

$$K_p(y) = y + 1 \qquad \text{and} \qquad D(y) = y + 1 \tag{19}$$

Nominally the system is operated at $y = 0$ and $u = 0$. A PI controller with the T–L tuning is employed, and the results show that the fixed gain control gives oscillatory set-point responses (dashed line in Figure 8). If we obtain new identification results at $y = 1$, a fuzzy model scheduling can be constructed.

$R^{(1)}$: If y is $A^{(1)}$, then $K_p = 2$ and $D = 2$

$R^{(2)}$: If y is $A^{(2)}$, then $K_p = 1$ and $D = 1$

The membership functions are similar to that of Figure 2 except that the range of the scheduling variables (y) is between 0 and 1. The results show that much better set-point responses can be obtained (solid line in Figure 8) when these two local models are scheduled using the simple Takagi–Sugeno fuzzy implications. Figure 9 shows the set-point and load responses when the process is operated at different conditions. Here, a load transfer function of $1/(10s + 1)$ and $L = 1$ are assumed.

4.2. Simple Recycle Plant. The second example is a reactor/separator plant studied by Wu and Yu.[25] The feed to the system is the reactant A, and almost pure product B is taken out from the bottoms of the distil-

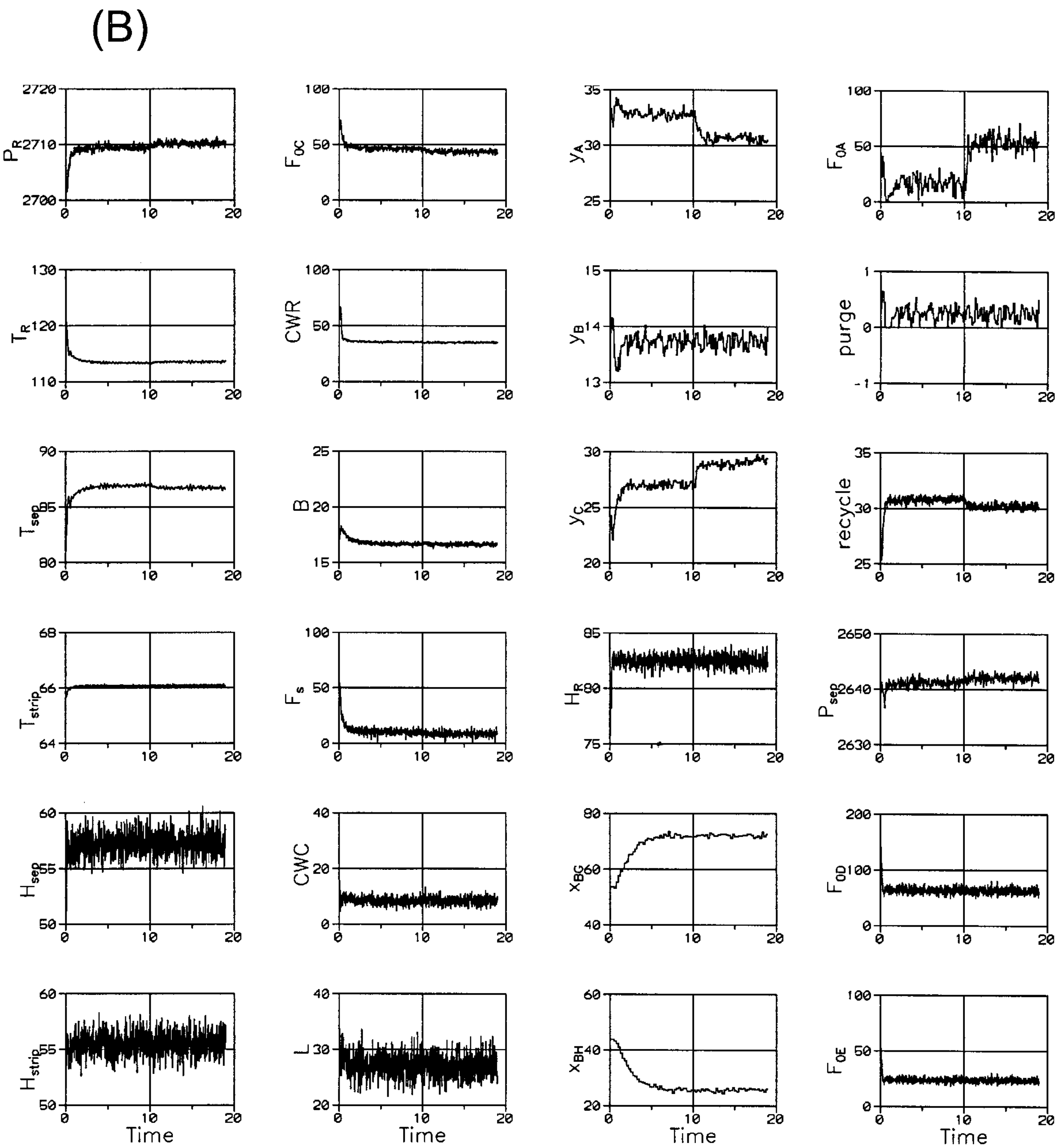


Figure 17. Responses of the Tennessee Eastman process for a simultaneous production rate and product specification changes followed by a load change (IDV(1) at time = 10) using (A) fixed gain control and (B) fuzzy switching.

lation column. The conventional control structure is designed, and the nominal controller parameters are tuned using the sequential tuning approach of Shen-Yu.[26] Figure 10 shows that the control structure and the important controlled variable, product quality (X_b), is maintained by changing the boilup ratio (BR). The nominal production rate (B) is 460 lbmol/h, and as the economic condition changes, the plant produces 70–130% of the nominal rate.

If only the nominal model parameters are available, we use the settings at all possible operating points. The dashed lines in Figure 11 show the closed-loop responses for ±30% changes in the production rate. On the other hand, as the process knowledge accumulates, we have the model parameters at +20% and −30% of the nominal production (Figure 12). The fuzzy modeling can, then, be employed for the model scheduling. The integrator plus time delay model is appropriate for this application. Again, the simplest fuzzy modeling is used. That is, we do not use the information about the trend on process variable.

$R^{(1)}$: If y is PR_*, then $K_p = 10.99 \times 10^{-3}$ and $D = 0.165$

$R^{(2)}$: If y is PR, then $K_p = 16.58 \times 10^{-3}$ and $D = 0.153$

$R^{(3)}$: If y is PR^*, then $K_p = 17.57 \times 10^{-3}$ and $D = 0.137$

PR_*, PR, and PR^* are the membership functions for low, nominal, and high production rates, respectively. They are similar to that of Figure 2 except for the ranges of the scheduling variable (i.e., the production rate). Figure 12 shows that that speed of responses becomes faster as we increase the production rate between the range of 70 and 120% of the nominal production rate. However, ranges of the variations in system parameters are *not* large, especially for D. Therefore, only a slight improvement in closed-loop responses can be obtained using the model scheduling (Figure 11). Notice that for the entire range of the production (−40% to +40%) the model parameters show slight nonmonotonic behavior (much severe behavior can be observed if the controller parameters are used).

4.3. Tennessee Eastman Process. The Tennessee Eastman problem is a realistic complex reactor/separator process.[6] Several control strategies are proposed to solve the challenging problem.[10,12−14,17] A detailed description of the process is given by Downs and Vogel.[6] The essential features of the process include an open-loop unstable reactor with two major reactions (A + C + D → G and A + C + E → H), a separator removes unreacted light components and recycles them back to the reactor and a stripper further separates products from reactants (Figure 13). The temperature, pressure, and levels are all interacting and nonlinear. The process is operated under different modes as the business condition changes. Mainly, we have to run the process under different production rates (PR) and different product specifications (PS, G/H mass ratios). Because we have a wide range of operating conditions, a single set of controller parameters is not expected to work well for the entire region. This is an ideal problem for the application of the multiple models.

The Luyben control structure[10] is employed (Figure 13). In this case, an on-demand product is set by the downstream process. The control structure consists of nine control loops: three level loops (reactor, separator, and stripper), one pressure loop (reactor), three temperature loops (reactor, stripper, and separator), and two composition loops. The integrating nature of the recycle structure leads to the use of simple proportional-only control on all loops.[10] The reactor level and the stripper level are maintained by changing the inlet flow rates; the controllers require little tuning. The Luyben tuning constants are used for these two level loops and the pressure loops (Table 2). It should be noticed that the separator level is maintained by changing the cooling water flow; this manipulated input has strong effects on the separator temperature and pressure as well as the level. Therefore, care should be taken in the tuning of this level loop. Relay-feedback tests are applied to the remaining six loops. The autotuning is carried out sequentially starting from the reactor temperature loop work to the two composition loops.[19] The controller parameters are set to $^1/_3$ of the ultimate gain except for the stripper temperature loop ($^1/_{12}$). Table 2 gives the nominal settings.

The model scheduling mechanism will become very complex if controller settings of all nine loops (or six loops) are scheduled. Therefore, it is important to devise a control structure such that only a minimal number of loops need to be retuned. (Actually, this can be viewed as a performance index of different control structures.) Suppose, after some period of operation, we have performed relay-feedback tests on ±30 production changes (PR = ±30%) with the nominal product specification (PS = 45/55) and we also have ultimate properties for 25/75 and 70/30 product ratios (PS = 25/75 and 70/30). Figure 14 shows that the ultimate gains stay fairly constant for most loops except for the separator level. Therefore, only the controller parameter for the separator level is scheduled. Because we have five data sets, the fuzzy implications thus become

$R^{(1)}$: If PR is PR* and PS is $\bar{\text{P}}$S, then $K = K^{(1,0)}$

$R^{(2)}$: If PR is $\bar{\text{P}}$R and PS is $\bar{\text{P}}$S, then $K = K^{(0,0)}$

$R^{(3)}$: If PR is $\bar{\text{P}}$R and PS is PS*, then $K = K^{(0,1)}$

$R^{(4)}$: If PR is $\bar{\text{P}}$R and PS is PS$_*$, then $K = K^{(0,-1)}$

$R^{(5)}$: If PR is PR$_*$ and PS is $\bar{\text{P}}$S, then $K = K^{(-1,0)}$

Figure 15 shows the corresponding membership functions. This is exactly the three data sets scenario described in section 3 except that we have four triangular regions here. The results of the fuzzy modeling can also be expressed in the form of eq 15 (use three data sets for each region). Figure 16 shows the ultimate gain of the separator level loop as the production rate and product specification changes. Provided with five data sets, the fuzzy implications allow us to move around different operating regions. For example, we have a simultaneous change in the production rate and the product specification (PR = −20% and PS = 65/35). Simulation results (Figure 17) show that much better transient responses and better disturbance rejection (IDV(1) at time > 10) are obtained using multiple local models. Moreover, this is achieved by scheduling only one level loop.

5. Conclusion

In this work, a framework for local autotuning and global model scheduling is proposed. The relay feedback is employed to find local models, and then these models are scheduled using the Takagi−Sugeno fuzzy model. The characteristics of the resultant global model are analyzed. The importance of the selection of the scheduled parameters is emphasized. The proposed techniques are applied to a transfer function model as well as large-scale recycle plants. Issues such as which variables should be selected and how many loops should be scheduled become important when dealing with large-scale systems. Simulation results show that improved performance can be achieved using relatively simple model scheduling.

Acknowledgment

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Nomenclature

a = amplitude of limit cycle
A_i^i = membership function for the ith input variable under jth fuzzy implication
B = production rate
D = time delay
F_{oj} = fresh feed flow rate, j = A, C, D, E
$G(s)$ = nominal process transfer function
F_s = flow rate of steam to the stripper
$G(s)$ = nominal process transfer function
H_R = reactor level
H_{sep} = separator level
H_{strip} = stripper level
h = magnitude of relay output
K_p = steady-state gain

K_u = ultimate gain
L = flow rate of liquid from separator to stripper
M = magnitude of a transfer function
P = reactor pressure
P_{sep} = separator pressure
PR^*, $\bar{PR}$, PR_* = membership function for high, nominal, and low production rates
PS^*, $\bar{PS}$, PS_* = membership function for high, nominal, and G/H (or D/(D + E)) ratio
P_u = ultimate period
Purge = purge flow rate
$R^{(j)}$ = jth fuzzy implication
Recycle = recycle flow rate
T_R = reactor temperature
T_{sep} = separator temperature
T_{strip} = stripper temperature
u = process input
x = input of the fuzzy model (scheduling variable)
x_{Bj} = composition of product, j = G and H
y = process output
y_j = composition of recycle stream, j = A and B
z = output of the fuzzy model (scheduled variable)

Greek Symbols

ϕ = phase angle
ω = frequency
ω_u = ultimate frequency

Acronyms

ATV = autotune variation
GM = gain margin
PM = phase margin
PR = change in production rate (%)
PS = product specification (D/(D + E))
RP = robust performance
RS = robust stability

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