Chapter 92
Fuzzy Controller Design with Fault Diagnosis System Condition On-line Monitor Using Neural Network

Xiaochun Lou

Abstract This chapter presents a practical method to design and implement a fuzzy controller with system condition on-line monitor for temperatures of continuous soaking process in sugar plant. A new fuzzy control strategy is proposed to improve the control performances. The proposed strategy utilizes an innovative idea based on sectionalizing the error signal of the step response into four different functional zones. The supporting philosophy behind these four functional zones is to decompose the desired control objectives in terms of rising time, settling time and steady-state error measures maintained by an appropriate PID-type controller in each zone. Then, fuzzy membership factors are defined to configure the control signal on the basis of the fuzzy weighted PID outputs of all four zones. A method of system condition on-line monitor using neural network is presented, base on dead time, peak time, percent overshoot, steady state error, rise times, and gain of system step response. The obtained results illustrate the effectiveness of the proposed fuzzy control scheme in improving the performance and intelligent maintenance of the implemented control systems for temperatures of continuous soaking process in sugar plant.

Keywords Fuzzy controller · On-line monitor · Neural network

92.1 Introduction

The continuous soaking process (CSP) is an important step in sugar plant. The CSP is carried out in Fig. 92.1. The soaking machine have actuating medium input of the beet threads from belt balance and the input waters from water chest, and

X. Lou (✉)
Hangzhou Vocational and Technical College, 310018 Hangzhou, Zhejiang, China
e-mail: hznwb@163.com

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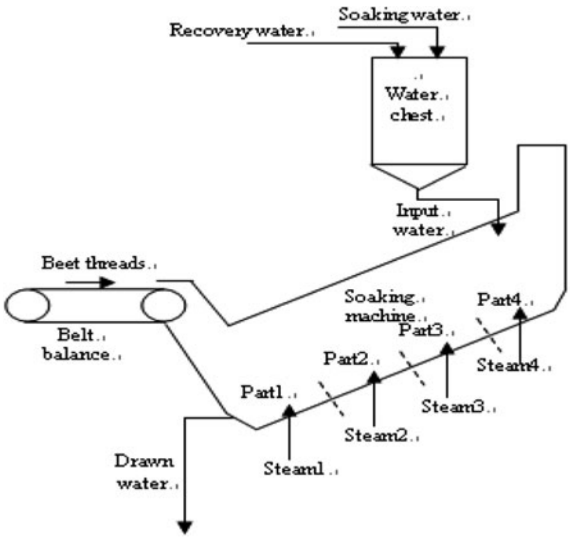


Fig. 92.1 Continuous soaking process

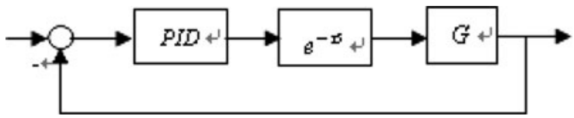
produce output of drawn water, its beet threads levees of four ports are constrained, its temperatures of four ports are controlee by heating steam, the input water is composed of soaking water and recovery water. The controlee variables are flow of drawn water, temperatures of four ports, flow of input water, and water level of water chest, mass of beet threads. The operating variables are four ports flow of heating steam, flow of input water, flow of soaking water, motor speed in belt propeller. The major disturbances are beet threads quantity to get into soaking machine and recovery water quantity [1].

Due to time delay, the temperatures controls of four ports are large influence to product quality. The chapter is an attempt to study this problem.

To analyse this observation, consider the general time delay system in Fig. 92.2.

To improve the control performance under the control delay degradation effect, appropriate control methods should be developed. Although considerable research interest has been paid to the implementation of advanced controllers, PID controllers are still being used in the majority of industrial processes. This is mainly due to the fact that the PID control schemes have a simple structure which can be easily understood and maintained by field engineer. However the tuning of conventional PID remains a difficult task due to insufficient knowledge of the analytical process dynamics. Therefore many classical PID control loops suffer from poor tuning due to the nonlinear and time-varying nature of industrial process. As a consequence, recourse to the automatic PID tuning approach is unavailable in most practical situations for maintaining a consistent performance in the presence of real process uncertainty. This is attracting recent attention from researchers and practicing engineers [2].

Fig. 92.2 General time delay system diagram



Currently, the fuzzy logic control technique has demonstrated great promise to provide a reasonable and effective alternative to the classical controllers in the face of proven model complexity and uncertainty. In this direction, fuzzy PID control type has been the subject of intense interest during the last two decades because of its ability to induce the familiar conventional PID control law on the basis of approximate fuzzy reasoning. Hence, it has received considerable attention in the field of process control to improve its performance in dealing with process model uncertainties compared to its alternative conventional PID counterparts [3].

In the fuzzy PID control approach, the fuzzy rules can be implemented either as an error driven direct control action type or a gain scheduling type [4]. The error driven type controllers constitute the majority in which the rules are expressed to produce the controller output. The gain scheduling type controllers are based on fuzzy tuning rules to adjust the PID gains. Different research attempts have been made to develop fuzzy PID controllers with automatic tuning concepts [5].

This chapter proposes a new fuzzy PID control tuning methodologies in which the fuzzy PID control function is partitioned into four fuzzy regional-based PD, P, PID, PI whose contributions in derivation of the overall PID control output are adjusted on the basis of their fuzzy membership values. Then, the chapter is an attempt to undertake the demonstrations of how control strategies can be practically implemented on real industrial processes.

92.2 Fuzzy Controller Design

92.2.1 Fuzzy Control Strategy

PID control is by far the most commonly used control scheme in process control applications. This scheme, however, suffers from poor parameter tuning, resulting in degraded performance. Real processes are essentially nonlinear and their dynamics change with the operating point, calling for an adaptive PID tuning mechanism. Furthermore, the PID control designer needs to consider the time delay characteristics. For invariable PID tuning, control performance would be degraded due to the stochastic nature of the time delay as experimentally illustrated in the previous section. It has been observed that fuzzy PID controllers can represent better control performances in the time delay processes compared to their conventional counterparts [6]. In the fuzzy PID scheduler, the error signal

plays a decisive role in defining membership values and the control action mainly depends on gain scheduling [7–9]. The proposed method is based on

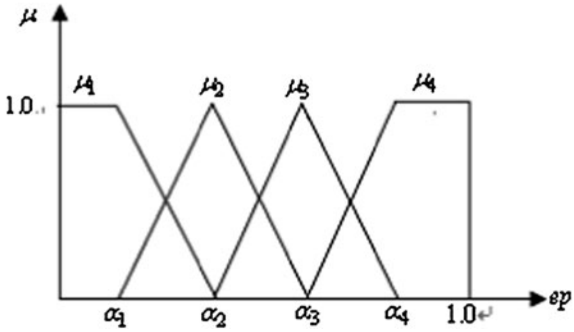


Fig. 92.3 Proposed membership function based on error percent signal

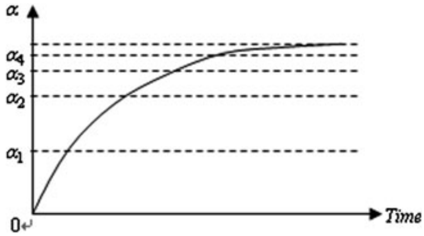


Fig. 92.4 Desired PID zones functionality

sectionalizing the error percent signal of the step response into three functional zones and fuzzy membership factors are used to configure the overall control signal contributed from the PID outputs of all zones. These functional zones have been derived from our desired functional expectation of PID controller in different zones. To discriminate among the operating zones of the four different PID type controllers, four membership variables (i.e.μ_1, μ_2, μ_3, and μ_4) are defined as shown in Fig. 92.3.

The desired PID controller for the first zone is a PD type due to a large error signal to speed up the response, leading to a minimum rising time. In the second zone, P type is suitable for leading to a minimum rising time when a largish error signal to speed up the response. Next, the controller should minimize the settling time without oscillation or instability; therefore the PI type should be applied in the third zone. Finally, in the case of a small error signal in the fourth zone, a PI type controller should be applied to eliminate or minimize the steady state error. The supporting philosophy of defining these four functional zones is to decompose the desired control objectives in terms of three important control performance measures, which are the rising time, settling time and steady state error maintained by an appropriate PID controller in each zone. The proposed desired PID functionality is depicted in Fig. 92.4 in which $\alpha_1, \alpha_2, \alpha_3$ and α_4 denote the parameters to be determined by designer in order to specify the zones boundaries.

This fuzzy PID control structure offers more robustness due to its ability to set proper actuator high and low limits in the predefined functional zones

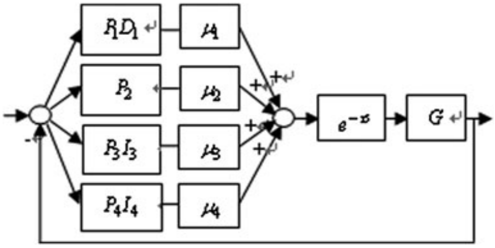


Fig. 92.5 Fuzzy PID control algorithm

(i.e., actuator low limit in zone 1 and actuator high limit in zone 4). The robustness advantage could be become more obvious in the case of large time delays. Fuzzy membership factors are used to configure the overall control signal by aggregating the weighted PID outputs of all zones to facilitate a gradual bump-less control transfer between two adjacent control zones, as depicted in Fig. 92.5. In order to increase stability assurance, the proportional gain of the PID controller should be reduced when the feedback signal approaches the set-point. P_1 and D_1indicate the proportional gain and derivative factor of the *PD* type controller which is enabled in the first and second zones. P_2 is the proportional gain of the *P* type controller which is enabled in the second and third zones.P_3, I_3 and D_3 are the proportional gain, derivative factor and integral coefficient of the *PID* type controller which is enabled in the third and fourth zones while P_4 and I_4 are the proportional gain and integral factor of *PI* type controller which is enabled only in the fourth zone. Therefore, the output of fuzzy *PID* controller can be determined as follows in terms of the fuzzy aggregated contribution of each regional *PID* type controller:

$$\begin{aligned} u_c &= \mu_1(P_1(e + D_1\,\dot{e})) + \mu_2(P_2 e) + \mu_3(P_3(e + I_3 \textstyle\int edt + D_3 e)) + \mu_4(P_4(e + I_4 \textstyle\int edt)) \\ &= (\mu_1 P_1 + \mu_2 P_2 + \mu_3 P_3 + \mu_4 P_4)e + (\mu_1 P_1 D_1 + \mu_3 P_3 D_3)\,\dot{e} + (\mu_3 P_3 I_3 + \mu_4 P_4 I_4)\textstyle\int edt \end{aligned} \tag{92.1}$$

where u_c is the overall output of fuzzy PID control signal which is applicable for all zones. Therefore, the output of fuzzy PID control signal for each zone $(u_{c1}, u_{c2}, u_{c3}, u_{c4})$ is derived as follows:

Zone 1:

$$u_{c1} = \mu_1(P_1(e + D_1\,\dot{e})) \tag{92.2}$$

Zone 2:

$$u_{c2} = (\mu_1 P_1 + \mu_2 P_2 + \mu_3 P_3)e + (\mu_1 P_1 D_1)\,\dot{e} + \mu_3 P_3 I_3 \textstyle\int edt \tag{92.3}$$

Zone 3:

$$u_{c3} = (\mu_2 P_2 + \mu_3 P_3 + \mu_4 P_4)e + (\mu_3 P_3 I_3 + \mu_4 P_4 I_4)\textstyle\int edt \tag{92.4}$$

Zone 4:

$$u_{c4} = (\mu_3 P_3 + \mu_4 P_4)e + (\mu_3 P_3 I_3 + \mu_4 P_4 I_4)\int edt \tag{92.5}$$

Examining Eqs. 92.2–92.5 reveals that the proposed fuzzy controller behaves like a gain scheduling PID controller with the following general characteristics:

In the early stage of the response in zone 1 when $\mu_1 = 1$ and $\mu_2 = \mu_3 = \mu_4 = 0$ the controller acts as a PD controller with maximum proportional and derivative gains leading to a fast rising response without overshooting or instability concerns.

As the response moves into zone 2, μ_1 decreases and μ_2 increases leading to a reduction derivative gains and also an increase in the proportional gain to a faster rising response without overshooting or instability concerns.

As the response moves into zone 3, μ_2 decreases and μ_3 increases leading to a reduction of proportional gains and also an increase in the integral gain to make the controller achieve the final steady state error elimination.

As the response enters zone 4, the fuzzy controller behaves as a PI controller. Thus, the steady state-state error is eliminated by the gradual increase in integral gain, the gradual decrease of proportional gain and the absence of derivative gain when the system is about to settle down.

92.2.2 Error Percent Determination

The error percent is defined as follows:

$$ep = \frac{S.P - P.V}{S.P - P.V_0} \tag{92.6}$$

where $P.V_0$ denotes the process value when the set-point changes. Therefore, the complete error percent signal *ep* is partitioned into three fuzzy sets, as shown in Fig. 92.3, by the following four membership variables:

For

$$ep \geq \alpha_1 : \mu_1 = 1, \mu_2 = \mu_3 = \mu_4 = 0; \tag{92.7}$$

For

$$\alpha_2 \leq ep \leq \alpha_1 : \mu_2 = \frac{\alpha_1 - ep}{\alpha_1 - \alpha_2}, \mu_1 = 1 - \mu_2, \mu_3 = \mu_4 = 0; \tag{92.8}$$

For

$$\alpha_3 \leq ep \leq \alpha_2 : \mu_3 = \frac{\alpha_2 - ep}{\alpha_2 - \alpha_3}, \mu_2 = 1 - \mu_3, \mu_1 = \mu_4 = 0; \tag{92.9}$$

For

$$\alpha_4 \leq ep \leq \alpha_3 : \mu_4 = \frac{\alpha_3 - ep}{\alpha_3 - \alpha_4}, \mu_3 = 1 - \mu_4, \mu_1 = \mu_2 = 0; \tag{92.10}$$

For

$$ep \leq \alpha_4 : \mu_4 = 1, \mu_1 = \mu_2 = \mu_3 = 0. \tag{92.11}$$

In this chapter, the membership variables are utilized to set the proper actuator limits to enhance the desired control system operation. This could be implemented as a low limit for the actuator set-point in zone 1 and a high limit for the actuator set point in zone 4. This limitation scheme has an obvious operational advantage. In zone 1, the process output value is far from the desired set-point. Thus, proper setting of the actuator lower limit can cause a fast rising time response. However, there is a small error between the desired set-point and the actual process value in zone 4. Therefore, reducing the actuator high limit can prevent instability. The operational benefit of this scheme becomes more obvious with large time delays.

92.3 System Condition On-line Monitor Using Neural Network

The system parameters of dead time (τ), peak time (t_p), percent overshoot (M_p), steady state error (e_{ss}), rise times (t_r), and gain (K) are shown to depend on the system condition. They are fixed when systems do normally. To bring about a improvement of intelligent maintenance, we use the system parameters to identified normal or faulted system by means of neural network.

92.3.1 Network Structure

Figure 92.6 shows the neural network structure by means of research determine.

The six inputs to the network included all of the aforesaid step response features. Neurons in the hidden layer used hyperbolic tangent activation functions. The linear output neurons estimate the system condition according to the following relation:

$$y = \sum_{j=1}^{4} w_{jk} \tan\ h\left(\sum_{i=0}^{6} w_{ij} x_i\right) + w_0 z_0 \tag{92.12}$$

where x_i is the input and y is the network output. w_{ij} is the adjustable weight between input i and hidden neuron j and w_{jk} is the adjustable weight between hidden neuron j and output neuron k. Note that the bias terms are absorbed into Eq. 92.12 by setting x_0=1 and $z_0 = 1$.

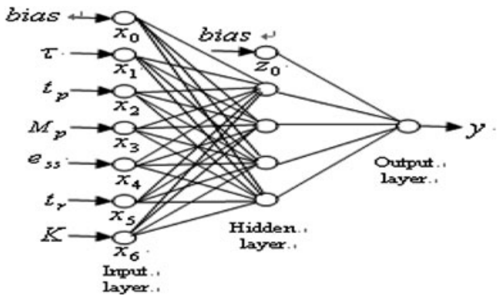


Fig. 92.6 Neural network structure

92.3.2 Training Data

The faulty operating conditions were chosen to reflect a wide range of variation in the severity of each failure mode. While possible in practice, situations where two or more faults occur simultaneously were not considered here due to the exceedingly large number of possible fault combinations. This represents a potential limitation of the approach. Step response tests were carried out to ascertain the six performance parameters associated with each operating condition, such as normal operating condition and faulty operating conditions of controller, sensor, actuator and controlled object. The test signal consisted of a series of steps. The set point was increased 10% from current values and back to the 10% after the testing. This sequence was repeated 15 times so that the slight variations in the responses would be captured.

92.3.3 Network Training

The algorithm was implemented by first assigning the weights random numbers on the interval [− 0.5, 0.5]. The weights were then scaled as follows:

$$w_{ij,new} = \frac{0.6\sqrt[6]{4}}{\sqrt{\sum_{i=1}^{6} w_{ij}^2}} w_{ij,old}, \quad i = 1, \ldots, 6, \quad j = 1, \ldots, 4 \tag{92.13}$$

the bias weights, w_{0j}, were given random initial values on the interval $[-0.6\sqrt[6]{4}, 0.6\sqrt[6]{4}]$. The remaining adjustable parameters were given random initial values on the interval [1,1].

The goal of training is to minimize the mean squared error between the desired network outputs and the actual network outputs which is written for batch mode training, where the error is evaluated over the entire training data set, as

$$E(T) = \frac{1}{P}\sum_{p=1}^{P}(d_p - y_p(T))^2 \tag{92.14}$$

where d_p is the desired output corresponding to input vector X_p,$y_p(T)$ is the network output corresponding to input vector X_p after training epoch T, and P is the total number of input/output vectors in the training data set. To minimize (92.14), the gradient descent method with momentum was employed. The weights were updated according to

$$\Delta W(T) = -\eta \nabla E\big|_{W(T)} + \mu \Delta W(T-1) \tag{92.15}$$

In Eq. 92.15, W is the matrix of adjustable weights, η is the learning rate, m is the momentum term, ∇ is the gradient operator and $\Delta W(T) = W(T) - W(T-1)$. To accelerate convergence, the learning rate was continuously adjusted during training as follows:

$$\eta_{new} = \begin{cases} \rho\eta_{old}, \Delta E\langle 0 \\ \sigma\eta_{old}, \Delta E\rangle 0 \end{cases} \tag{92.16}$$

where ΔE is the change in the network error, $E_{new} - E_{old}$, resulting from the last weight update. Parametersρ and σ were set to standard values of 1.1 and 0.5, respectively. Setting the momentum term, μ, in (92.15) to 0.9 was also found to increase the speed of learning.

The experimental results proved that the trained network has the capability to detect and identify the various magnitudes of the faults of interest, as they occur singly. Furthermore, the results indicate that the network can accurately estimate fault levels unseen during the training process. This information is vital to a process system condition monitoring strategy since it can be used to detect problems and assist in the timely scheduling of repairs to the system, before a severe failure occurs.

92.4 Practical Implementation

Figure 92.1 shows a temperatures control system in sugar plant processes with large time delay. The controlled variables are temperatures of four ports. The operating variables are four ports flow of heating steam.

Four different PID controllers are employed in different time response zones. The PID parameters in this experiment have been set as follows: P_1 (Proportional gain) = 8, $D_1 = T_{d1}$ (derivative time) = 480 ms, P_2 (Proportional gain) = 7, P_3 (Proportional gain) = 4, $(I_3)^{-1} = T_{i3}$ (Integral time) = 1 s, P_4 (Proportional gain) = 3, $(I_4)^{-1} = T_{i4}$ (Proportional gain) = 0.5 s, Cycle time = 500 ms.

Furthermore, α parameters, determining the boundary of the functional zones in Fig. 92.4, are specified as follow: $\alpha_1 = 0.5$, $\alpha_2 = 0.2$, $\alpha_3 = 0.15$, $\alpha_3 = 0.05$.

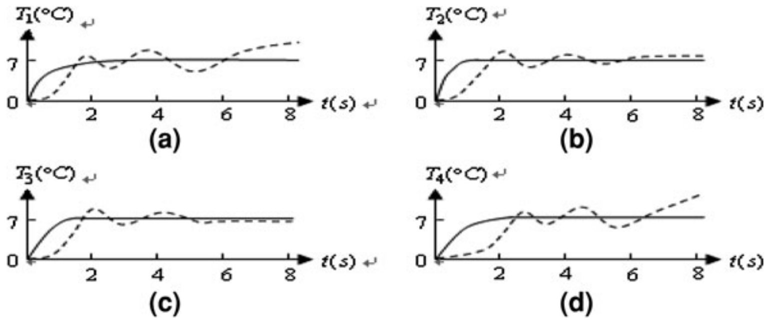


Fig. 92.7 Effect compare

Table 92.1 Condition on-line monitor experimental results

Number	y	Fault by off-line check
1	0.00	Normal condition
2	0.10	Controller open circuit
3	0.11	Control software chaos
4	0.15	Controller short circuit
5	0.30	Sensor open circuit
6	0.36	Sensor wander
7	0.38	Sensor short circuit
8	0.50	Supply pressure of actuator
9	0.63	Percent vent blockage of actuator
10	0.66	Percent diaphragm leakage of actuator
11	0.80	Controlled object leak
12	0.89	Controlled object performance wander
13	0.91	Controlled object blockage

In Fig. 92.7, the solid line shows a effect of the fuzzy PID controller, the dotted line shows a effect of rule PID. The practical observations indicate the promising capability of the proposed fuzzy PID control scheme. System condition on-line monitor experimental results are listed in Table 92.1 along with the normal condition and 13 faulty conditions.

92.5 Conclusions

In this chapter, a new fuzzy PID control approach is proposed to improve the control performance due to the time delay degradation effect. The proposed method is based on sectionalizing the error signal of the step response into four functional zones and fuzzy membership factors are used to configure the control signal by aggregating the weighted PID outputs of all zones to facilitate a gradual bump-less control transfer between two adjacent control zones, and that A method of system condition on-line monitor using neural network is presented. The obtained results illustrate the effectiveness of the proposed fuzzy control scheme in improving the performance and intelligent maintenance of the implemented control systems for temperatures of continuous soaking process in sugar plant.

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