In-Line Viscosity Control in an Extrusion Process with a Fuzzy Gain Scheduled PID Controller

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ABSTRACT: In the extrusion process, rapidly tracking the set point of quality factor and eliminating its variation to reduce the off-specification product is important. In this study, the fuzzy gain-scheduled proportional-integral-derivative (PID) controller is used to control the melt viscosity during extrusion processing. A second-order model related to the viscosity and the extruder screw speed is developed empirically to approximate the extrusion system. It is concluded that, in comparison to the well-known Zeigler-Nichols PID tuning control scheme, the performances of the proposed control strategy is preferable both in simulation and implementation. © 1999 John Wiley & Sons, Inc. J Appl Polym Sci 74: 541–555, 1999

Key words: PID controller; fuzzy; gain scheduling; viscosity; in-line; extrusion

INTRODUCTION

In polymer extrusion processes, end product quality would change in accordance with process variations. These process variations could result from the variations in the raw material (e.g., variations in regrind level,[1] drying conditions, additive concentration, etc.) or in the performances of the molding machine and auxiliary equipment (e.g., signal fluctuation due to imprecise sensors, inconsistent machine operations, etc). An effective closed-loop control, especially in-line[2] control, to eliminate process variations and to rapidly track the set point of the quality factor is of primary importance.

In control problems, because mechanical, optical, electrical properties, homogeneity, etc., cannot be directly measured in processing, process variables[3] like die pressure drop, flow rate, torque, viscosity, temperature, etc., are generally taken as the quality characteristics. As for the manipulated variable, from the view points of quickly tracking the set point changes and compensating for the property variations, screw speed is usually considered as a better variable to be manipulated for its rapid response. Another factor, such as temperature, which results in the process variations, is usually regarded as an independently steady-state control because of its long time constant.[4,5] The raw material variables are usually used in the sense of optimizing the grade and type of polymer to be processed.[6–9] The dynamic of the extrusion plant is a rather complex process that has lead to various control schemes with modified strategies implemented to perform the quality control.

The selection of the process variable to be controlled is of considerable interest. The use of pressure control has some disadvantages. One of them is that the pressure drop is a function of the die geometry and conditions of the extrusion system (i.e., temperature and throughput) and rheological properties of the polymer. A rather complicated dynamic model would be required to ensure

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the polymeric melt with consistent properties.[10] The temperature control, as mentioned above, is suitably regarded as an independently steady-state control because of its long time constant. The melt viscosity, which is the index of polymer characteristic itself, would be considered rather suitable.

In the early studies, Parnaby et al. used stochastic techniques to obtain the dynamic model of the extrusion process,[11] and used a model reference optimal steady-state adaptive computer control[10] to achieve a mass flow rate and a product quality control, in which the mass flow rate was inferred from the die inlet melt conditions of temperature and pressure. Screw speed, restrictor valve position, and temperature were treaded as the manipulated variables. Wassick et al.[12] designed a nonlinear internal model controller for screw torque control. The manipulated variable used to regulate the screw torque was the screw speed. A nonlinear dynamic model was developed related to the screw speed and screw torque. Ng et al.[13] designed a control strategy based on the discrete optimal regulator solution, and included automatic dead-time compensation to perform pressure control with arranging the extruder gear pump. Recently, Chiu et al.[14] used the minimum variance controller to reduce the melt viscosity variations. Screw speed was treaded as the manipulated variable. The system transfer function and the disturbance dynamic model of the plant were obtained experimentally. Other efforts on quality control in terms of temperature control can also be seen in the literatures, such as Dastych et al.,[15] Tsai et al.,[16] Khalid et al.,[17] Pulkkinen et al.,[18] Taur et al.,[4] Omatu et al.,[5] etc.

Model deriving also plays an important role in control problems. Using the stochastic techniques, though the most reliable method, would involve extensive and time-consuming identification of the extrusion process, because lots of relevant variables have to be considered for deriving an effective dynamic model.[10,19] The theoretical model that was derived from the physical relationship between variables provides a benefit in understanding the extrusion process, but is usually complex or sometimes impossible to be obtained for an extrusion process. A deterministic dynamic model related to the viscosity and the screw speed can be developed empirically, in which the model is determined by injecting a step change in a screw speed and then to evaluate the transfer function from the resulting transient and steady responses. This method provides a comparatively easy way for model identification, although would be an approximate model or sometimes inaccurate because of the complex nature of the extrusion process.

Table I Specifications of the Single Screw Extruder

Specification	Value
Screw diameter (mm)	45
L/D ratio	25
Compression ratio	3.37
Production output rate (kg/h)	4–35
Screw speed (rpm)	0–100

The problem of using an empirical model can be solved by applying some adapted techniques in the controller. The proportional-integral-derivative (PID) controller is the most popular controller in industries because of their simple structure and robust performance in a wide range of operating conditions. The general adaptive PID controllers would require certain knowledge of the process (e.g., the structure of the plant model[20]). Zhao et al.[21] proposed a fuzzy gain scheduling scheme of PID controllers for process control in which human expertise was utilized to on line to determine the controller parameters. This method provides an appropriate tuning method for the approximate model used in this article.

In this study, the fuzzy gain scheduled proportional-integral-derivative (PID) controller is used to control the melt viscosity by manipulating the extruder screw speed. A second order model related to the viscosity and the extruder screw speed is developed empirically to approximate the extrusion system. Simulation and implementation are included. Besides, the well-known Ziegler-Nichols PID tuning rule[22,23] is also implemented for comparison.

EXPERIMENTAL

All the experimental data presented in this article are obtained from runs on a single screw extruder. The specifications of the single screw extruder are shown in Table I. The extruder is also equipped with five pressure transducers that are combined with temperature sensors. Three of them (ASAHI Model TTJ-N67A) are located, re-

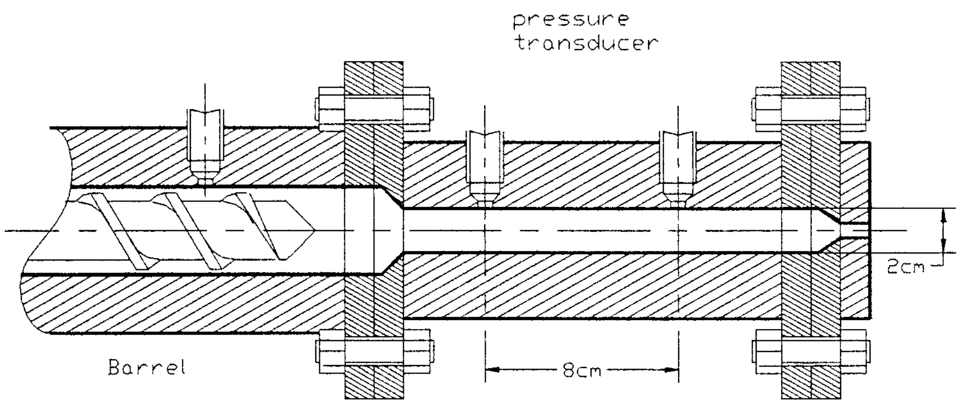


Figure 1 Schematic diagram of the in-line viscometer.

spectively, at the solid polymer transition, the molten, and the melt transition section; the rest (Dynisco Model TPT4636) are located at the die, as shown in Figure 1. A personal computer combined with analog-to-digital (A/D) and digital-to-analog (D/A) converters (AXIOM Model AX5411) and an RS232 interface is used for monitoring and controlling all of the process information from the extruder including temperature, pressure, and screw speed. All of the data acquisition and display software, including the process control algorithms, is written in C programming language. The material used is low-density polyethylene (LDPE).

In-Line Viscosity Measurements

The viscometer is similar to the capillary as shown in Figure 1. The design criteria for the in-line viscometer is basing on avoiding to perturb the production throughput and on achieving real-time measurement of the melt viscosity in the main process stream. The melt viscosity is measured based on the measurement of the pressure drop and the flow rate through the viscometer as is in a capillary.[24] Two pressure transducers (Dynisco Model TPT4636) are installed in the viscometer to measure the pressure drops. The flow rate is decided by continuously predicting the extruder output from measurements of various process variables, which is similar to the method proposed by Kramer.[25] Because the viscometer with fixed geometry is used, the extruder screw speed and the operating temperature are considered as the most influential variables. In this case, The effect of temperature is reflected to the die inlet pressure for convenience. To find the relationship between the flow rate and these two variables,

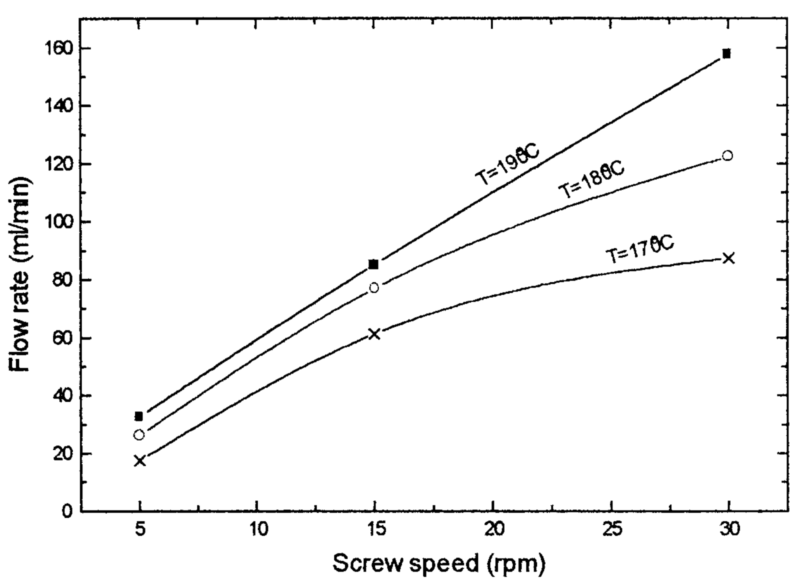


Figure 2 Plot of the flow rate vs. the extruder screw speed for LDPE.

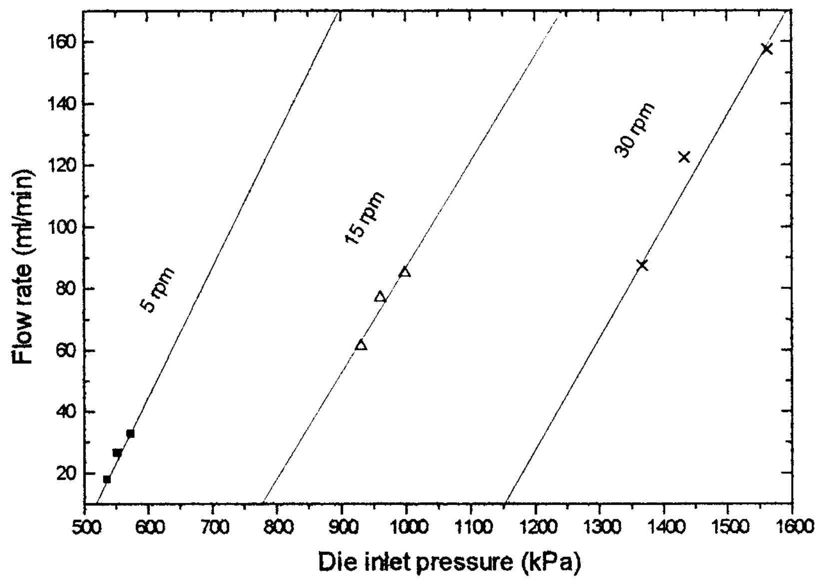


Figure 3 Plot of the flow rate and the die inlet pressure with respect to three screw speeds.

each variable related to the flow rate is individually characterized in advance. Figure 2 shows the relationship between the flow rate and the extruder screw speed for LDPE by means of the viscometer shown in Figure 1. Figure 3 shows the relationship between the flow rate and the die inlet pressure at A fixed screw speed, resulting from three different temperatures. The flow rate was calibrated by using a volumetric graduate. A second order polynomial was decided to fit the curves in Figure 2, and a linear function was also decided to fit the data in Figure 3. Consequently, an equation—as shown in eq. (1)—was used to combine these two functions.

$$Q = C_1 + C_2P + C_3N + C_4NP + C_5N^2 + C_6PN^2 \quad (1)$$

where Q is the flow rate, N is the extruder screw speed, P is the die inlet pressure drop, C_n is the coefficient in which n is a positive integer.

The parameter, C_n, was determined by using the least-square regression[26] with six sets of pretest screw speeds, die inlet pressure drop, and corresponding flow rate data, and is shown in Table II.

Empirical Process Model Development

The empirical model was determined by injecting a step change in screw speed and then to evaluate the system dynamics from the resulting transient and steady responses. A typical viscosity response to the screw speed step change is shown in Figure 4. The behavior of the extrusion processes was adequately described by a second-order difference equation[27] as

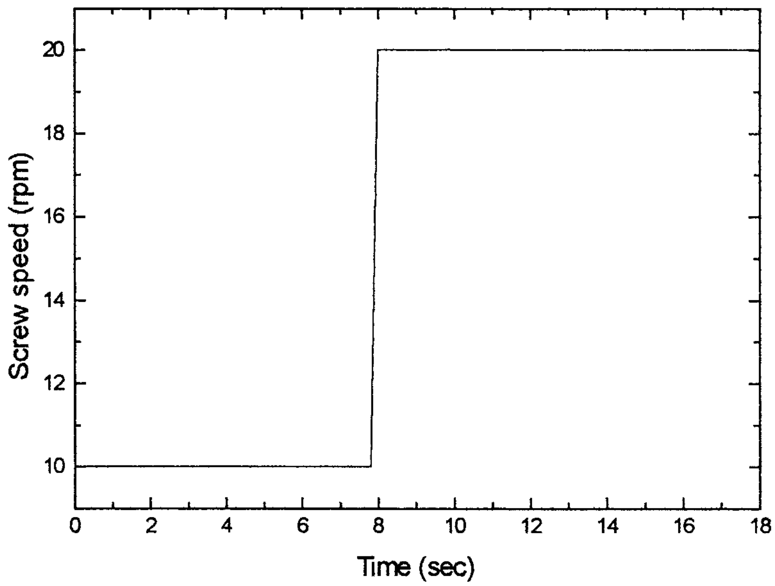
$$y_n = a_1y_{n-1} + a_2y_{n-2} + k(b_1m_{n-1} + b_2m_{n-2}) \quad (2)$$

where y_n represents the process output at which time is equal to nT, in which T is the sample period and n is an integer. k is the process gain. m_{n-1} represents the process input at which time is equal to $(n-1)T$. The values of the coefficients a_1, a_2, b_1 and b_2 can be calculated by using the expressions as

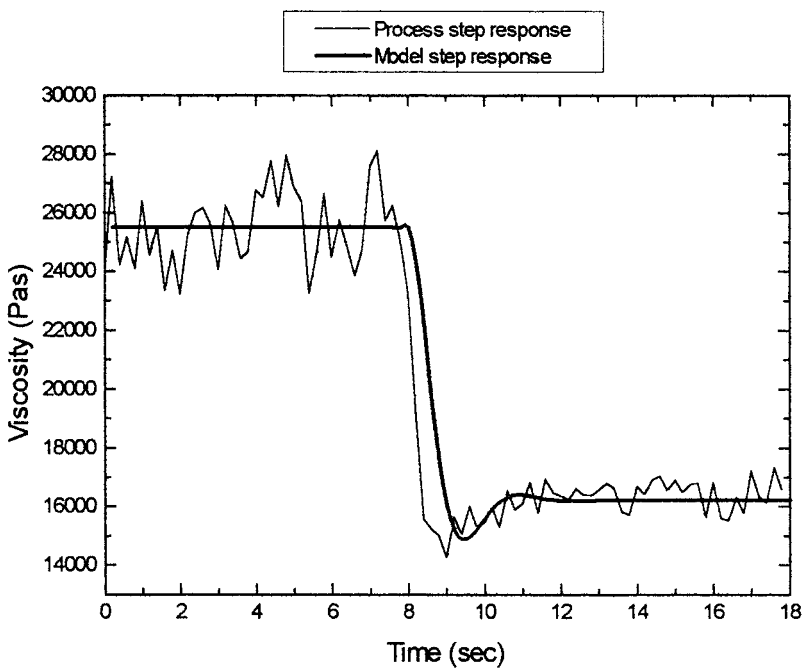
$$a_1 = 2e^{-\zeta\omega_nT}\cos\omega_dT \quad (3)$$

Table II Values of Coefficients in Eq. (1)

Coefficients	Data
C_1	−5.488172054
C_2	0.000008908
C_3	0.766969562
C_4	−0.000000937
C_5	−0.024376642
C_6	0.000000026



(a)



(b)

Figure 4 (a) Step input in screw speed. (b) A typical viscosity response to a step in screw speed.

$$a_2 = -e^{-2\zeta\omega_n T} \tag{4}$$

$$b_1 = 1 - \frac{\zeta\omega_n}{\omega_d} e^{-\zeta\omega_n T} \sin \omega_d T - e^{-\zeta\omega_n T} \cos \omega_d T \tag{5}$$

$$b_2 = e^{-\zeta\omega_n T}\left(e^{-\zeta\omega_n T} + \frac{\zeta\omega_n}{\omega_d} \sin \omega_d T - \cos \omega_d T \right) \tag{6}$$

where

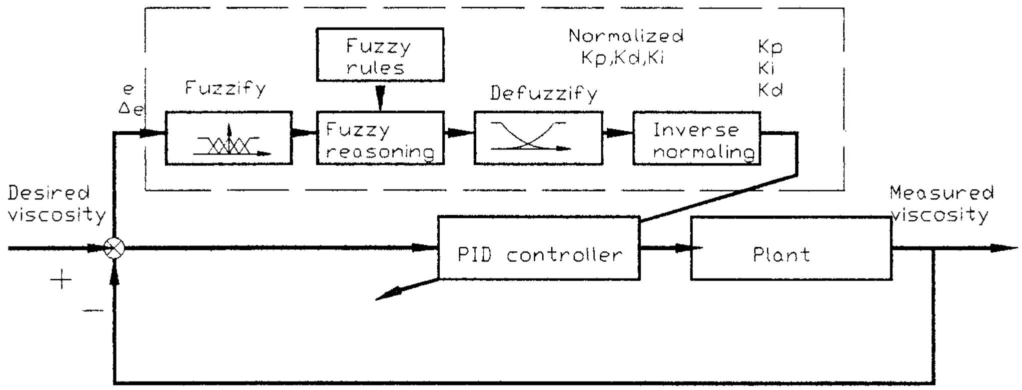


Figure 5 Block diagram of the PID control system with a fuzzy gain scheduler.

$$\omega_d = \omega_n \sqrt{1 - \zeta^2},$$

ω_n and ζ are the natural frequenzy and the damping ratio, respectively.

The process gain k was determined based on the steady-state viscosity change over the screw speed change. The damping ratio and the natural frequency were obtained by trial and error according to the step response in Figure 4. In this case, it was considered a better conjunction with respect to $k = -928.488$, $\omega_n = 2.54$, and $\zeta = 0.53$. The comparison of the actual process output and the model output is also shown in Figure 4.

PID Controller

The discrete time expression for a PID controller combined with error signal input[28] can be written as

$$m_n = K_p e_n + K_i T \sum_{i=1}^{n} e_i + \frac{K_d}{T} \Delta e_n \tag{7}$$

where K_p, K_i, and K_d are the proportional, integral, and derivative gains, respectively, m_n is the control signal at time nT, e_n is the error between the reference and the process output at time nT, and

$$\Delta e_n \equiv e_n - e_{n-1} \tag{8}$$

The following section describes the fuzzy gain scheduling procedure for getting a better performance.

Fuzzy Gain Scheduling[21]

The block diagram of the PID control system with a fuzzy gain scheduler is shown in Figure 5. The

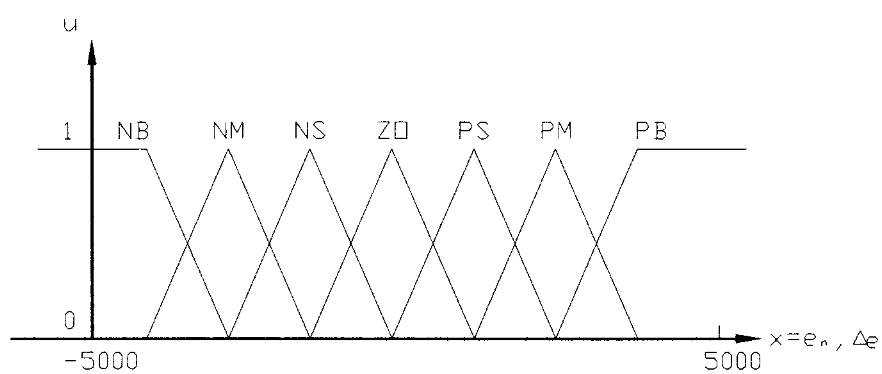


Figure 6 Membership functions for e_n and Δe_n, where NB represents negative big, NM is negative medium, NS is negative small, ZO is zero, PS is positive small, PM is positive medium, PB is positive big.[21]

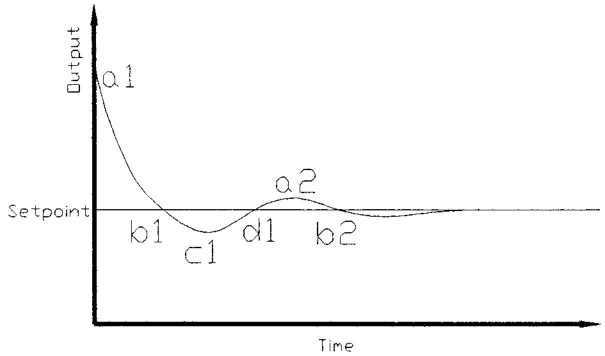


Figure 7 Process step response.

procedure of the fuzzy gain scheduling is divided into the following parts including fuzzification, making fuzzy rules, fuzzy reasoning, defuzzification, and inverse normalization.

Fuzzification

The membership functions (MF) of fuzzy sets for e_n and Δe_n were designed as shown in Figure 6. Seven fuzzy sets, including triangle and trapezoid, were used. The errors and error changes can be transfer into linguistic values by means of mapping them into the membership functions. The linguistic values are then used for fuzzy inferring.

Making Fuzzy Rules

The fuzzy rules were driven based on the step response of the process as shown in Figure 7. For example, around a_1, a big control signal to achieve a fast rise time is needed. To produce a big control signal, the proportional gain is set as a fuzzy set Big, and the derivative gain as a fuzzy set Small. The integral gain is determined according to Zhao et al.[21] by means of the relation between the integral and the derivative time constants of another equivalent expression of PID controller, as shown in eq. (9)

$$G_c(s) = K_p(1 + T_d s + 1/(T_i s)) \tag{9}$$

where $T_i = K_p/K_i$ and $T_d = K_d/K_p$, which are referred to integral and derivative time constants, respectively. By using the relation between the integral time constant and the derivative time constant as in eq. (10), the integral gain can be obtained according to eq. (11).

$$T_i = \alpha T_d \tag{10}$$

$$K_i = K_p/(\alpha T_d) = K_p^2/(\alpha K_d) \tag{11}$$

In eq. (11), a small α would result in a strong integral action. In this case, α is determined by

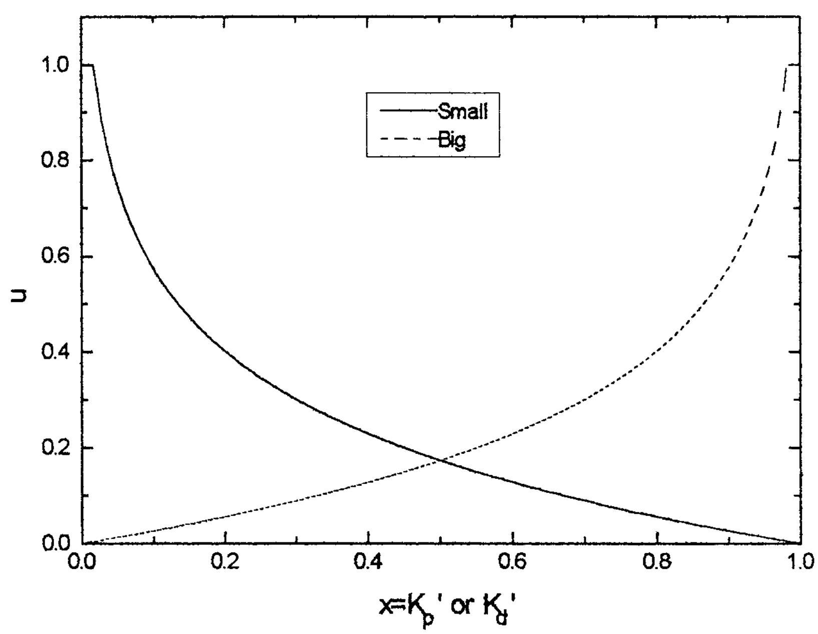


Figure 8 Membership functions for K_p' and K_d'.[21]

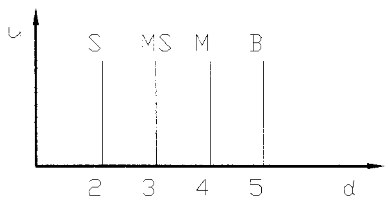


Figure 9 Membership functions for α, where S represents small, MS is medium small, M is Medium, and B is big.[21]

comparison with the well-known Ziegler-Nichols PID tuning rule, as suggested by Zhao et al.,[21] of which is equal to 4. A value of 2 is used for a stronger integral action. For convenience, the gains are limited in the range between 0 and 1. The membership functions of fuzzy sets for the, say, normalized proportional gain K'_p and the normalized derivative gain K'_d, are shown in Figure 8, and have the relation of

$$\mu_{\text{small}}(x) = -\tfrac{1}{4}\ln x \tag{12}$$

$$\mu_{\text{big}}(x) = -\tfrac{1}{4}\ln(1 - x) \tag{13}$$

The membership functions of fuzzy sets for α are shown in Figure 9.

The fuzzy rules are designed in the form of

$$\text{If } e(k) \text{ is } A_i \text{ and } \Delta e(k) \text{ is } B_i, \text{ then } K'_p \text{ is } C_i, \; K'_d \text{ is } D_i, \text{ and } \alpha = \alpha_i,\ i = 1, 2, \ldots, m. \tag{14}$$

Here, A_i, B_i, C_i, and D_i, are fuzzy sets, and α_i is a constant. The fuzzy tuning rules for K'_p K'_d, and α are shown in Tables III, IV, and V, respectively.

Table III Fuzzy Tuning Rules for K'_p[21]

		Δe_n						
		NB	NM	NS	ZO	PS	PM	PB
e_n	NB	B	B	B	B	B	B	B
	NM	S	B	B	B	B	B	S
	NS	S	S	B	B	B	S	S
	ZO	S	S	S	B	S	S	S
	PS	S	S	B	B	B	S	S
	PM	S	B	B	B	B	B	S
	PB	B	B	B	B	B	B	B

Table IV Fuzzy Tuning Rules for K'_d[21]

		Δe_n						
		NB	NM	NS	ZO	PS	PM	PB
e_n	NB	S	S	S	S	S	S	S
	NM	B	S	S	S	S	S	B
	NS	B	B	S	S	S	B	B
	ZO	B	B	B	S	B	B	B
	PS	B	B	S	S	S	B	B
	PM	B	S	S	S	S	S	B
	PB	S	S	S	S	S	S	S

Fuzzy Reasoning

To include both influences of the errors and the error changes on the output, the fuzzy logic used to infer μ_i of the output fuzzy sets is a direct product of the MF values of the two input fuzzy sets A_i and B_i as

$$\mu_i = \mu_{A_i}(e_n) \cdot \mu_{B_i}(\Delta e_n) \tag{15}$$

Defuzzification

A linear combination of all used rules is utilized for defuzzification as in eqs. (16), (17), and (18).

$$K'_p = \sum_{i=1}^{m} \mu_i K'_{p,i} \tag{16}$$

$$K'_d = \sum_{i=1}^{m} \mu_i K'_{d,i} \tag{17}$$

Table V Fuzzy Tuning Rules for α[21]

		Δe_n						
		NB	NM	NS	ZO	PS	PM	PB
e_n	NB	2	2	2	2	2	2	2
	NM	3	3	2	2	2	3	3
	NS	4	3	3	2	3	3	4
	ZO	5	4	3	3	3	4	5
	PS	4	3	3	2	3	3	4
	PM	3	3	2	2	2	3	3
	PB	2	2	2	2	2	2	2

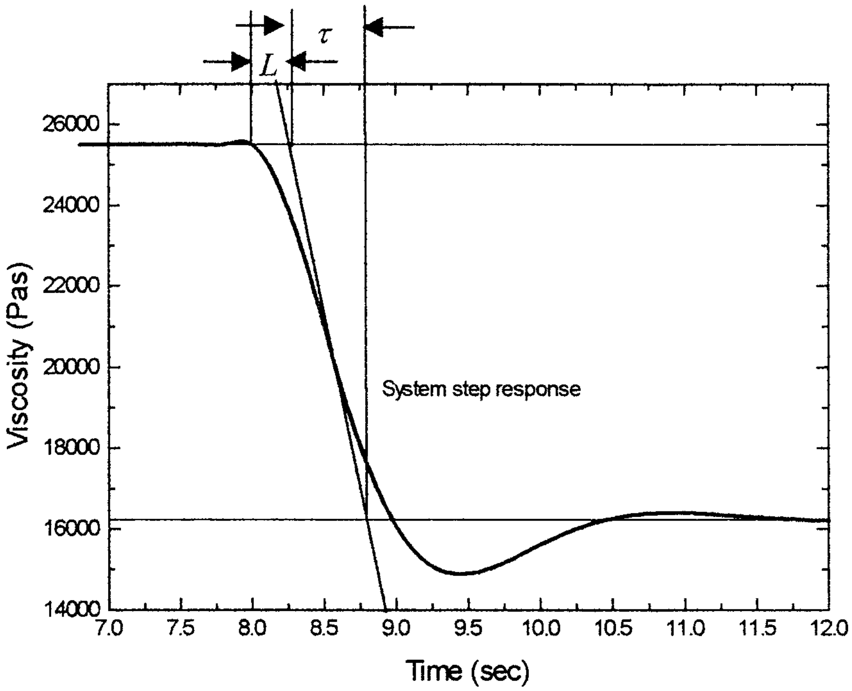


Figure 10 System step response.

$$\alpha = \sum_{i=1}^{m} \mu_i \alpha_i \tag{18}$$

Once K_p', K_d', and α are obtained, the actual proportional and derivative gains can be derived by the following inverse normalization.

Inverse Normalization

In the fuzzy gain scheduling procedure, the normalized gains are consequently derived. The values of K_p' and K_d' are both in the range from zero to 1, of which the relations to the actual gains K_p and K_d can be represented as

$$K_p' = (K_p - K_{p,\min})/(K_{p,\max} - K_{p,\min})$$

$$K_d' = (K_d - K_{d,\min})/(K_{d,\max} - K_{d,\min}) \tag{19}$$

Therefore, K_p and K_d can be calculated by

$$K_p = (K_{p,\max} - K_{p,\min})K_p' + K_{p,\min}$$

$$K_d = (K_{d,\max} - K_{d,\min})K_d' + K_{d,\min} \tag{20}$$

in which $K_{p,\min}$, $K_{p,\max}$, $K_{d,\min}$, and $K_{d,\max}$ represent the maximal and the minimal K_p, the maximal and the minimal K_d, respectively. A rule of thumb for determining them according to simulations is given as

$$K_{p,\min} = \tfrac{1}{2} K_{p,\text{Ziegler–Nichols}}$$

$$K_{p,\max} = 2K_{p,\text{Ziegler–Nichols}}$$

$$K_{d,\min} = \tfrac{1}{2} K_{d,\text{Ziegler–Nichols}}$$

$$K_{d,\max} = 2K_{d,\text{Ziegler–Nichols}} \tag{21}$$

where $K_{p,\text{Ziegler-Nichols}}$ and $K_{d,\text{Niegler-Nichols}}$ represent the proportional and derivative gains that are according to Ziegler-Nichols's first turning rule.[21] In Ziegler-Nichols's first turning rule, the values of the parameters K_p, T_i, and T_d are suggested as

$$K_{p,\text{Ziegler–Nichols}} = 1.2\,\tfrac{\tau}{L}$$

$$T_{i,\text{Ziegler–Nichols}} = 2L$$

$$T_{d,\text{Ziegler–Nichols}} = 0.5L \tag{22}$$

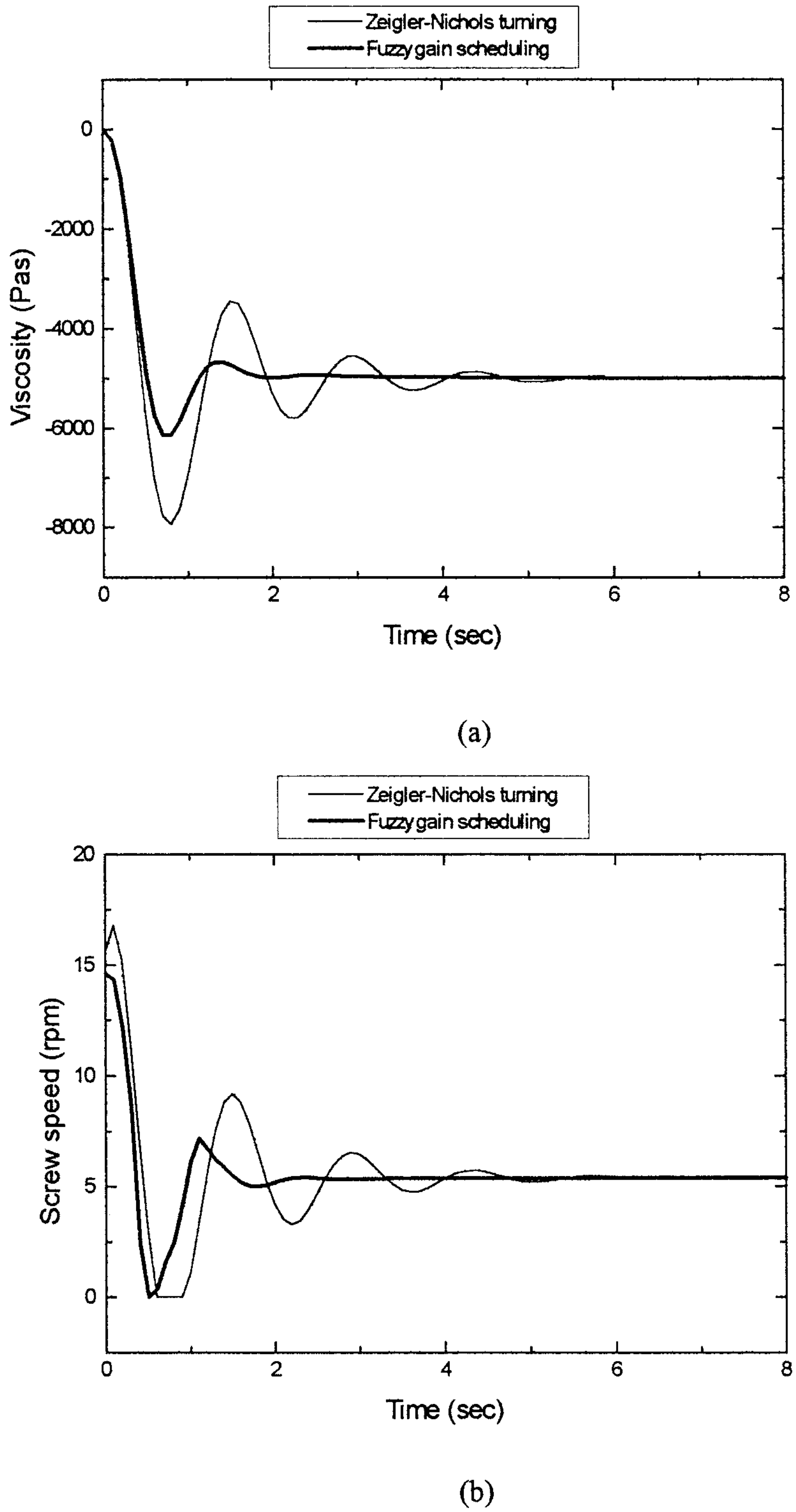


Figure 11 (a) Simulated output. (b) Simulated controller output.

where L and τ represent the effective delay and the time constant that are determined by drawing a tangent line at the inflection point of the step response curve, as shown in Figure 10. K_i is consequently calculated by using eq. (11).

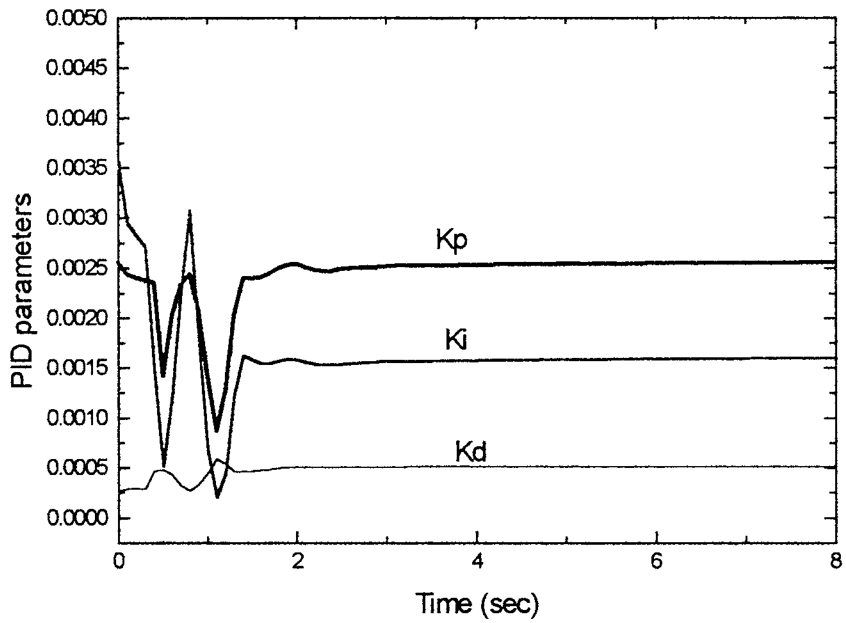


Figure 12 Simulated PID parameters of the fuzzy gain scheduler.

Computer Simulation

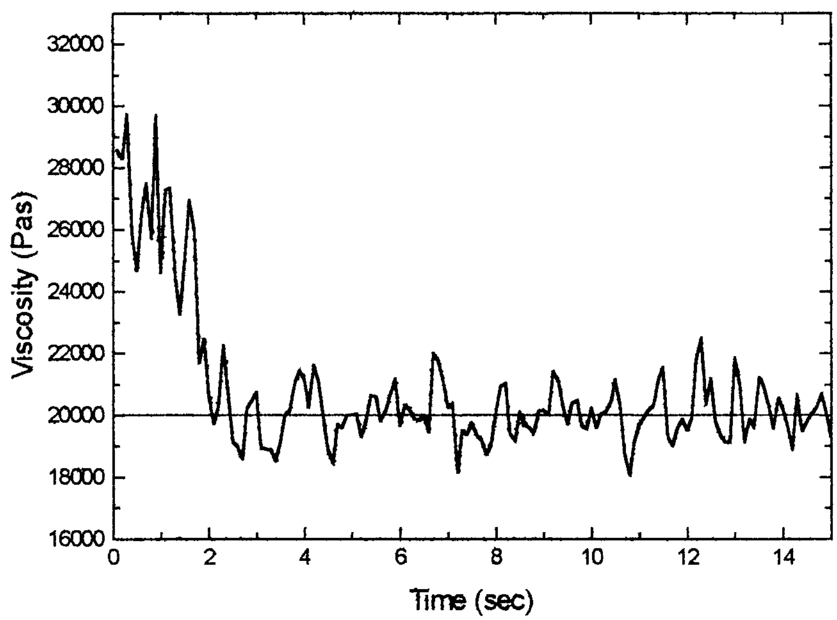
Because the sample period of 0.1 s is need for data acquisition and processing in the physical system, the controller gains would need a reduction so as to have a good approximation.[29] In this case, all controller gains, both in simulation and practical control action, are divided by the process gain *k*. The results obtained according to the Ziegler-Nichols turning rule and the fuzzy gain scheduling method with regard to the step change of 5000 Pas are shown in Figure 11. The controller gains determined by the fuzzy reasoning process are shown in Figure 12. As we can see in Figure 11, better control performance has been drawn from the fuzzy gain scheduling method than from the Ziegler-Nichols turning rule, which is in accordance with conclusions summarized by Zhao et al. The detailed controller performances are shown in Table VI.

EXPERIMENTAL RESULTS AND DISCUSSION

The control system was practically implemented on the LDPE extrusion process basing on the simulations. The temperature was set at 180°C. The step change in viscosity of LDPE was set from 25,000 Pa · s to 20,000 Pa · s at time equal to 1 s. Figure 13 shows a typical measured output and controller output based on the fuzzy gain scheduling PID controller. Figure 14 shows the measured output and controller output based on the Ziegler-Nichols PID turning method. The parameters of controller that turned by the fuzzy gain scheduler are shown in Figure 15. The mean of the result from the fuzzy gain scheduled method from 2–15 s is 20098.89472 (Pas) with a standard deviation of 891.28121 (Pas). A mean of 20192.45886 (Pas) with the standard deviation of 1068.3031 (Pas) for the Ziegler-Nichols turning method is derived in the same time range. In comparison to the Ziegler-Nichols PID turning method, the performance of the fuzzy gain scheduled PID is preferable because of its shorter rising time and smaller variance. Both result in comparison to simulations; the performances of the ex-

Table VI Simulated Performances

	Fuzzy Gain Scheduled	Zeigler–Nichols Turned
Overshoot (%)	21	60
Setting time (s) (with respect to 5% deviation from the set point)	1.5	3.8



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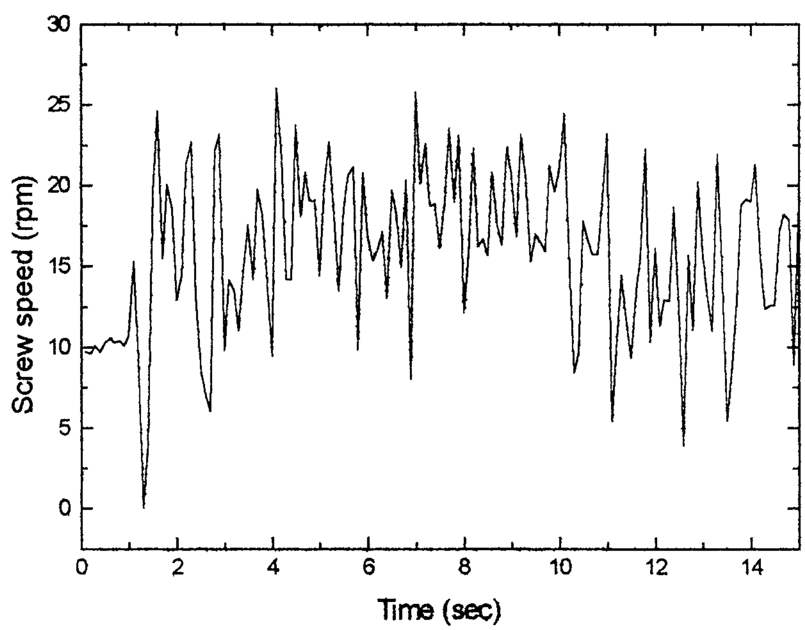
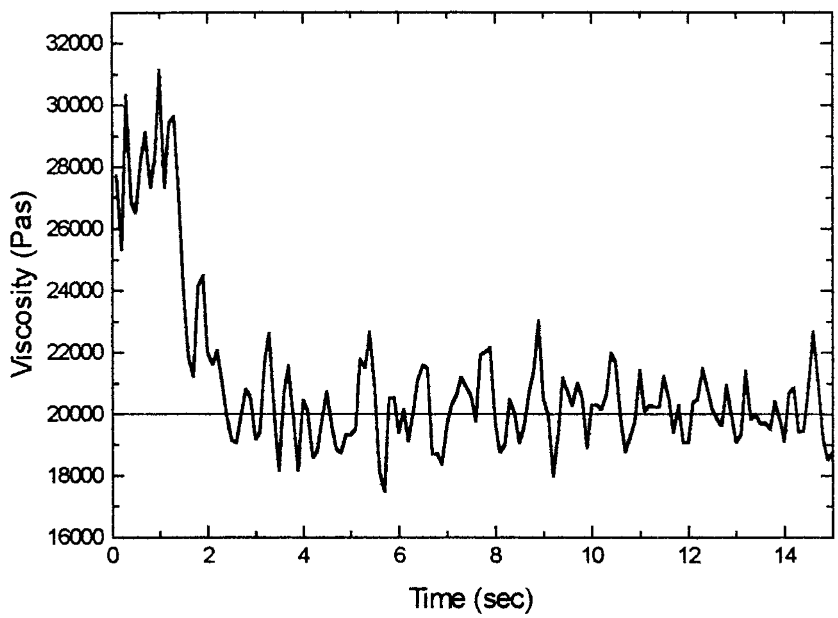
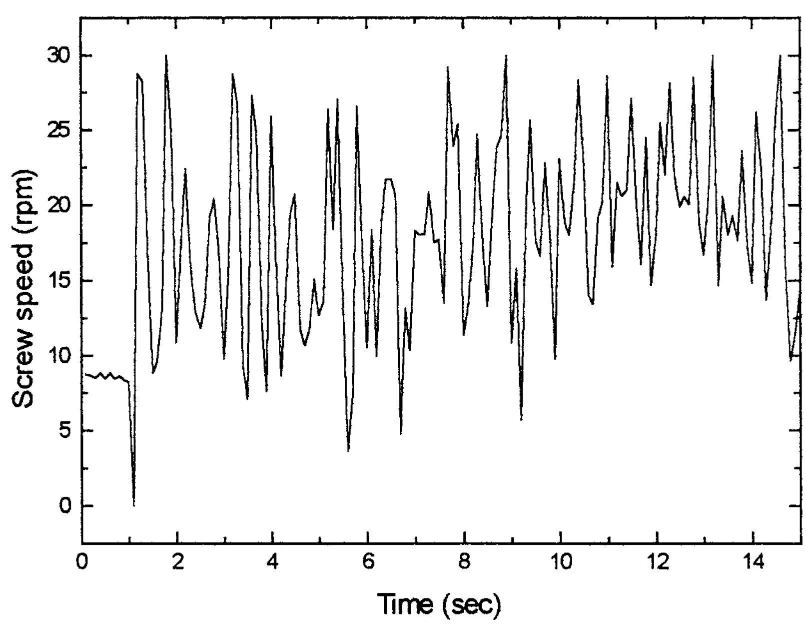


(b)

Figure 13 (a) Process output for fuzzy gain scheduled PID controller. (b) Controller output for fuzzy gain scheduled PID controller.



(a)



(b)

Figure 14 (a) Process output for Ziegler-Nichols turned PID controller. (b) Controller output for Ziegler-Nichols turned PID controller.

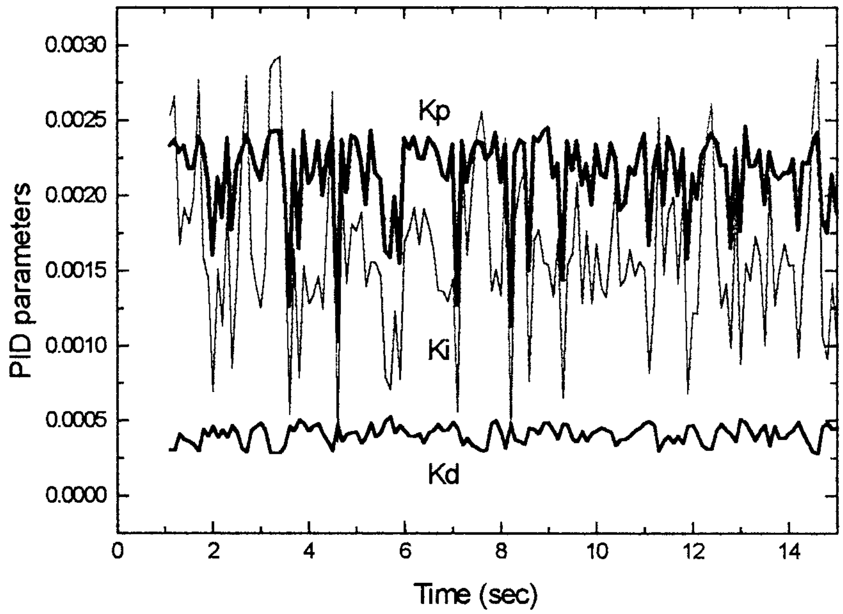


Figure 15 PID parameters of the fuzzy gain scheduler.

perimentals are not in accord with those of simulations due to noises. The noises could result in a big derivative action, and hence, the controller outputs exhibit vibrations, as shown in Figures 13 and 14. Suggestions were made for reduction of the vibrations including removal of the derivative action, providing more precise sensors, a more reliable power supply system, etc., of which are considered as further research.

CONCLUSIONS

This article presents the fuzzy gain scheduled PID control scheme to continuously produce polymers with desired viscosity in an extrusion molding process. The screw speed was taken as the manipulated command and the melt viscosity as the controlled output. On the basis of the results reported in this article it is concluded that the melt viscosity can be properly controlled by the proposed method. In comparison to the Ziegler-Nichols PID turning method, better performances have been drawn both in simulation and implementation of the fuzzy gain scheduled PID method.

Moreover, the noises that come mostly from imprecise pressure transducers and power supply system would result in fluctuations in system output and command. To improve this situation, better and more precise pressure transducers should be used, and the derivative action should be removed. Both improvements are being considered in further research.

NOMENCLATURES

N = extruder screw speed
P = die inlet pressure drop
C_n = coefficients in eq. (1)
y_n = process output at time nT
T = sample period
k = process gain
m_{n-1} = process input at time $(n - 1)T$
a_1, a_2, b_1, b_2 = coefficients in eq. (2)
ω_n = natural frequency
ζ = damping ratio
K_p = proportional gain of PID controller
K_i = integral gain of PID controller
K_d = derivative gain of PID controller
e_n = error between the reference and the process output at time nT
Δe_n = error change at time nT
T_i = integral time constant
T_d = derivative time constant
α = coefficient in eq. (10)

$\mu_{\text{small}}(x)$, $\mu_{\text{big}}(x)$ = membership function of fuzzy set SMALL and BIG
K_p' = normalized proportional gain
K_d' = normalized derivative gain
A_i, B_i, C_i, D_i = fuzzy sets
$K_{p,\text{Ziegler-Nichols}}$ = proportional gain that is according to Ziegler-Nichols's first turning rule
$K_{d,\text{Ziegler-Nichols}}$ = derivative gain that is according to Ziegler-Nichols's first turning rule
L = effective delay in Ziegler-Nichols's first turning rule
τ = time constant in Ziegler-Nichols's first turning rule

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