

Spinline Tension Control in Melt Spinning by Discrete Adaptive Sliding-Mode Controllers

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ABSTRACT: The spinline tension plays a critical role in the development of fiber structures and the quality of as-spun yarns in melt spinning. Implementing a controller to adjust the spinline velocity is helpful to maintain the spinline tension at a target level with small fluctuation, enabling as-spun yarns to possess the desired tenacity and uniform qualities. The spinline tension system is difficult to model and the stochastic disturbance always exists. The discrete adaptive sliding-mode controller can robustly and adaptively deal with the system with the unknown model and stochastic disturbance, such as the spinline tension system. The algorithm estimates the parameters of the controller in the sense of minimizing the deviation from the sliding surface, thus reducing the variation of the tension response

about the desired level. The sliding surface is defined by an asymptotically stable polynomial, and seven stable polynomials are chosen in experiments. The experiments are carried out by using a laboratory type of the melt spinning setup to produce polypropylene as-spun yarns. Compared with the results without control, the proposed controller can not only maintain the mean of the tension response close to the target level but also reduce the standard deviation to the value, which is generally acceptable to the manufacturer. © 2006 Wiley Periodicals, Inc. *J Appl Polym Sci* 100: 3816–3821, 2006

Key words: melt spinning; spinline tension; discrete adaptive sliding-mode controllers

INTRODUCTION

In melt spinning, the spinline tension is a dominant factor to affect the spinline stress. The spinline stress governs the development of fiber structural parameters, including crystallinity and orientation, as well as as-spun yarn qualities, including tenacity, elongation, shrinkage, and dyeability. The spinline tension at a target level yields the good quality in tenacity. The spinline instability causes the nonuniform qualities of as-spun yarns; thus, suffering from downstream operational drawbacks, such as poor drawability, unacceptable broken filament count, and decreased textile processibility. The uniform tension can alleviate the spinline instability. Hence, to enhance uniform qualities of as-spun yarns, it is important to maintain the spinline tension at a desired level with small fluctuation.

Many papers have been devoted to discussing fiber structural parameters by means of mathematical analysis of spinline stress in melt spinning. Dutta and Nadkarni¹ presented that a unique relationship between the as-spun orientation and spinline stress existed for different grades of polypropylene (PP), and

the birefringence was directly proportional to the spinline stress for polyester. Jinan et al.² displayed that the mechanism of crystallization was influenced by the spinning stress, molecular orientation, cooling rate, and thinning of polymer fluid. Zieminski et al.³ used mathematical models to investigate effects of various spinning parameters on the density, crystallinity, orientation, and spinline stress. Chen et al.⁴ presented that the rheological stress affected the development of fiber structures, and the take-up stress was associated with the molecular weight of polymer, spinning temperature, cooling rate, take-up velocity, spinline length, and so on. Bhuvanesh and Gupta⁵ revealed that parameters of momentum balance equations for PP included the spinline tension, velocity, density, and viscosity, throughput, and cross-sectional area, and these parameters were not measured except the spinline tension and velocity in the practical melt spinning process. In general, the spinline tension dominates the spinline stress. The spinline tension is one factor which can be online controlled to affect fiber structures. Therefore, controlling the spinline tension at a desired level is good for enhancing as-spun yarn qualities.

There are many disturbances, such as nonuniform material properties and process conditions, to cause spinline instability in melt spinning. The material properties include viscosity, elasticity, thermal capac-

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ity, and density. The process conditions include the spinline speed, temperature and distance, as well as the temperature and speed of cooled air. These disturbances generally are stochastic. Lee et al.⁶ presented that factors to cause spinning instability involved the spinline tension, spinline cooling, and spinline velocity under the draw resonance dynamics of melt spinning. Kase and Araki⁷ demonstrated that the spinline stability criterion was obtained by a linear transfer function between the spinline tension and spinline velocity. Jung et al.⁸ revealed that the spinline tension was influenced by the disturbances of material properties and process conditions, and thus caused the variation of the take-up cross-sectional area. The severe variation of the take-up cross-sectional area yields filament unevenness, based on Bode diagrams. Devereux and Denn⁹ compared the theoretical and experimental take-up cross-sectional areas by Bode gain diagrams for poly(ethylene terephthalate) and PP. Accordingly, the spinline tension fluctuation constantly results from disturbances of material properties and process conditions, causing nonuniform qualities of as-spun yarns.

For quality as-spun yarns, it is requisite to design a controller to maintain the spinline tension at a desired level with small fluctuation. In practice, we can change the spinline velocity to adjust the spinline tension. However, the relationship between the spinline tension and spinline velocity is difficult to model. The conventional control cannot be applied to the spinline tension system with uncertain parameters and stochastic disturbances. Sliding-mode control offers the advantage of robustness against modeling uncertainties and external disturbances. Furuta¹⁰ investigated the discrete sliding-mode control, with the switching coefficient of the sliding surface, to ensure stability and robustness for a discrete system with plant uncertainties. Chan¹¹ presented the discrete quasisliding-mode tracking controller, which is a nonswitching and nonpredictive type to deal with the system with bounded modeling uncertainties and slowly varying disturbances. By coupling adaptive control with sliding-mode control, the estimation algorithm can make sliding-mode control become more effective to control of the system whose model is unknown. Chan¹² presented the discrete adaptive sliding-mode control for the minimum-phase plant with a bounded disturbance, and the system behavior in the vicinity of the sliding surface was examined. When the bounds of uncertain plant parameters are unknown, Chang¹³ used the adaptive sliding controller to alleviate the chattering drawback for second-order continuous-time systems. If disturbances are not bounded and slowly varying, a large deviation from the sliding surface using sliding-mode control may occur, leading to severe fluctuation of the response. Chan¹⁴ proposed the discrete adaptive sliding-mode control for the

plant with not only uncertain parameters but also stochastic disturbances, which could minimize the deviation from the sliding surface.

A laboratory scale of the melt spinning setup is used to manufacture PP as-spun yarns. The fourth godet-roll speed is adjustable to regulate the spinline tension. For uniform qualities, we implement a controller to maintain the spinline tension at a desired level with small variation. Since dynamics of the spinline tension is a stochastic system and it is difficult to model the system, this investigation adopts a discrete adaptive sliding-mode controller, which can adaptively and robustly handle unknown models with stochastic disturbances, for the spinline tension control. The control scheme employs the nonswitching type of sliding-mode control and controller-parameter estimation to obtain the minimum deviation from the sliding surface. Thus, the tension response at the desired level with reduced variance can be achieved. The sliding surface is defined by an asymptotically stable polynomial which is chosen by a designer. In our experiments, we choose seven stable polynomials for sliding surfaces, and their results in reducing the standard deviations of tension responses are demonstrated.

DISCRETE ADAPTIVE SLIDING-MODE CONTROLLER¹⁴

Consider the single-input single-output (SISO) discrete-time system described by the following ARMAX model:

$$A(z^{-1})y(k) = z^{-1}B(z^{-1})u(k) + C(z^{-1})w(k) \quad (1)$$

where $\{y(k)\}$, $\{u(k)\}$, and $\{w(k)\}$ denote output, input, and white noise sequence, respectively. $A(z^{-1})$, $B(z^{-1})$, and $C(z^{-1})$ are polynomials in the unit delay operator z^{-1} as follows:

$$A(z^{-1}) = 1 + a_1z^{-1} + \dots + a_nz^{-n} \quad (2)$$

$$B(z^{-1}) = b_0 + b_1z^{-1} + \dots + b_mz^{-m}$$

$$C(z^{-1}) = 1 + c_1z^{-1} + \dots + c_pz^{-p}$$

where the orders of $A(z^{-1})$, $B(z^{-1})$, and $C(z^{-1})$, n , m , and p , in the ARMAX model are known, and b_0 is a nonzero constant. Moreover, $B(z^{-1})$ and $C(z^{-1})$ have all zeros inside the unit circle. The sliding surface is defined by $s(k) = 0$, where

$$s(k) = T(z^{-1})(y(k) - y_1(k)) \quad (3)$$

$y_r(k)$ is the bounded reference input and $T(z^{-1}) = 1 + t_1z^{-1} + \dots + t_nz^{-n}$ is the user-specified asymptotically stable polynomial. If the model and disturbance are known, the control law can be given by

$$B(z^{-1})u(k) = -F(z^{-1})y(k) - C(z^{-1})w(k) + T(z^{-1})y_1(k+1) \quad (4)$$

where $F(z^{-1}) = f_0 + f_1z^{-1} + \dots + f_{n-1}z^{-(n-1)}$ is the unique polynomial satisfying $T(z^{-1}) = A(z^{-1}) + z^{-1}F(z^{-1})$. The control law can be written as

$$u(k) = \frac{1}{b_0}[-\phi^T(k)\theta - w(k+1) + y_r(k+1) + \dots + t_n y_r(k-n+1)] \quad (5)$$

where

$$\phi(k) = [y(k), \dots, y(k-n+1), u(k-1), \dots, u(k-m), w(k), \dots, w(k-p+1)]^T$$

$$\theta = [f_0, \dots, f_{n-1}, b_1, \dots, b_m, c_1, \dots, c_p]^T$$

However, if the model and disturbance are unknown, we substitute $C(z^{-1})w(k+1) = [C(z^{-1}) - 1]s(k+1)$ into eq. 4 to give the control law of the form

$$u(k) = \frac{1}{b_0}[-\hat{\phi}(k)\hat{\theta}(k) + y_r(k+1) + \dots + t_n y_r(k-n+1)] \quad (6)$$

where

$$\hat{\phi}(k) = [y(k), \dots, y(k-n+1), u(k-1), \dots, u(k-m), s(k), \dots, s(k-p+1)]^T$$

$$\hat{\theta}(k) = [\hat{f}_0, \dots, \hat{f}_{n-1}, \hat{b}_1, \dots, \hat{b}_m, \hat{c}_1, \dots, \hat{c}_p]^T$$

$\hat{\theta}(k)$ is the estimated parameter-vector of the controller. Minimizing the quadratic cost function $J = \frac{1}{2} \sum_{k=1}^n s(k)^2$ where $s(k) = \phi^T(k-1)\theta - \hat{\phi}^T(k-1)\hat{\theta}(k-1) + w(k)$, yields the recursive algorithm to estimate $\hat{\theta}(k)$ in the sense of minimizing the deviation from the sliding surface, thus leading to reduction of the response fluctuation. The estimation algorithm is shown as follows:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \frac{\hat{\phi}(k-1)}{r(k-1)} s(k) \quad (7)$$

$$r(k) = r(k-1) + \hat{\phi}^T(k)\hat{\phi}(k), r(0) = 1 \quad (8)$$

The estimation algorithm for $\hat{\theta}(k)$ ensures $\|\hat{\theta}(k)\| < \infty$ for all k and $\|\hat{\theta}(k) - \hat{\theta}(k-1)\| \rightarrow 0$ as $k \rightarrow \infty$. The stability of the closed-loop system is guaranteed by zeros of $z^{(n+m)}B(z^{-1})T(z^{-1})$, poles of the closed-loop

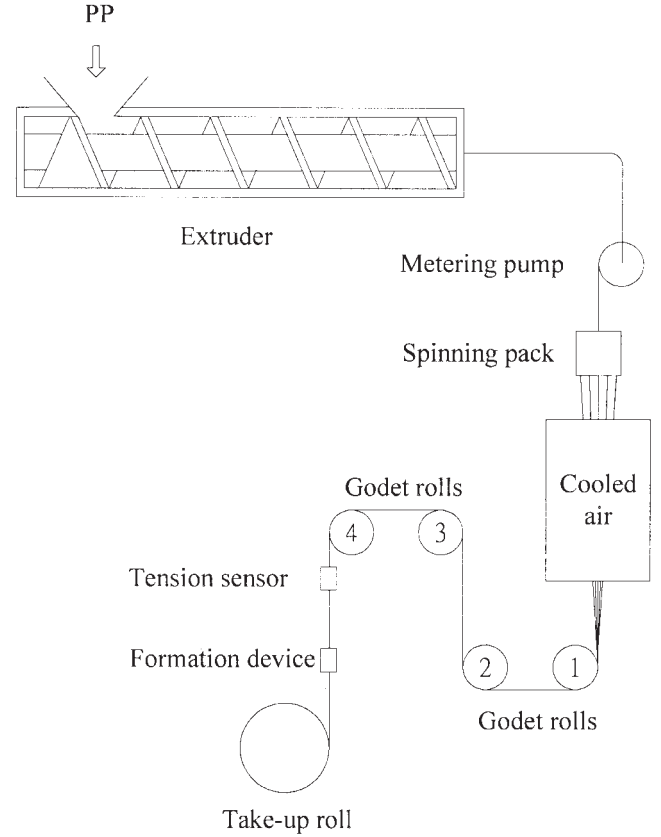


Figure 1 Schematic representation of the melt spinning setup.

system, inside the unit circle, requiring that $B(z^{-1})$ and $T(z^{-1})$ be asymptotically stable.

Since the control law requires the orders of $A(z^{-1})$, $B(z^{-1})$, and $C(z^{-1})$ as well as a nonzero b_0 to be known, they must be identified before designing the control law when the model is unknown. On the basis of the assumed orders, parameters of the ARMAX model can be identified by the recursive least-squares (RLS) algorithm¹⁵ as shown in the following:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \frac{P(k-1)\varphi(k)}{\lambda + \varphi^T(k)P(k-1)\varphi(k)}\varepsilon(k) \quad (9)$$

$$P(k) = \frac{1}{\lambda} \left[P(k-1) - \frac{P(k-1)\varphi(k)\varphi^T(k)P(k-1)}{\lambda + \varphi^T(k)P(k-1)\varphi(k)} \right], P(0) = 1 \quad (10)$$

where

$$\varepsilon(k) = y(k) - \varphi^T(k)\hat{\theta}(k)$$

$$\varphi(k) = [-y(k-1), \dots, -y(k-n), u(k-1), \dots, u(k-m-1), \varepsilon(k-1), \dots, \varepsilon(k-p)]^T$$

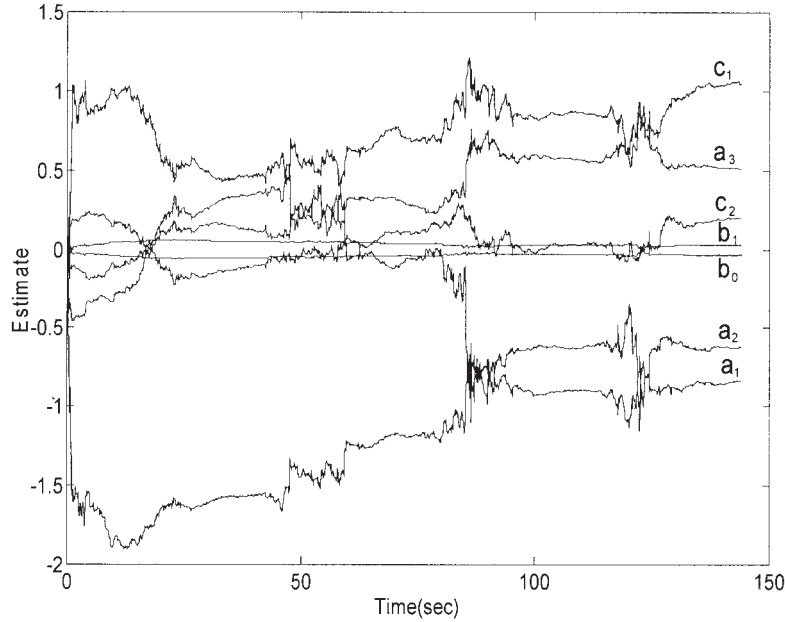


Figure 2 Estimated parameters of the ARMAX model.

$$\hat{\theta}(k) = [\hat{a}_1, \hat{a}_2, \dots, \hat{a}_n, \hat{b}_0, \hat{b}_1, \dots, \hat{b}_m, \hat{c}_1, \hat{c}_2, \dots, \hat{c}_p]^T$$

$\hat{\theta}(k)$ is the estimated parameter-vector of the ARMAX model. The forgetting factor λ typically is the value in the range from 0.97 to 0.995. The best orders of $A(z^{-1})$, $B(z^{-1})$, and $C(z^{-1})$ are determined on the basis of minimization of the Akaike's information criterion (AIC), which is stated as

$$AIC \approx \log_e \left[\left(1 + \frac{2N_{par}}{N_{data}} \right) \sum_{k=1}^N \varepsilon^2(k) \right] \quad (11)$$

where N_{par} is total number of estimated parameters and N_{data} is the length of the collected data. Thus, the identified model is the one which results in the minimum value of AIC. The conditions on the model orders, b_0 , $B(z^{-1})$, and $C(z^{-1})$ are checked based on the best identified model.

EXPERIMENTAL

Our laboratory scale of the melt spinning setup is schematically shown in Figure 1. The extruder is a single crew type with diameter of 25 mm. The outflow rate of the metering pump is 0.6 mL/rev. The spinneret is a metal plate containing 20 holes, each with a capillary diameter of 0.5 mm and aspect ratio of 4. The PP chips are melted in the extruder and discharged into a metering pump. Molten PP flows through a spinneret into a cooled air stream blowing across spinline. The solidified as-spun PP yarn, a bundle of 20 fibers, is then wound on a take-up roll. The setup

settings in our experiments are temperatures in three extruder barrel sections at 211, 222, and 231°C, a die at 241°C, a metering pump at 232°C, a spinneret at 222°C, and cooler air at 25°C as well as speeds of a extruder screw in 22.1 rpm, a metering pump in 30.7 rpm, cooled air in scale 1, a formation in 165 rpm, and a take-up roll in 1800 rpm. A tension sensor is located in the section between the fourth godet roll and take-up roll. The speed of the fourth godet roll is adjustable to regulate the spinline tension in this section.

The ARMAX model with the input of the fourth godet-roll speed and the output of the spinline tension is built to describe the spinline tension system. The system is too complex to model and the stochastic disturbance always exists. Thus, $A(z^{-1})$, $B(z^{-1})$, and $C(z^{-1})$ in the ARMAX model are not known. To check whether the conditions on the use of discrete adaptive sliding-mode controller are met, we employ the system identification and AIC to determine the best model, including the orders of $A(z^{-1})$, $B(z^{-1})$, and $C(z^{-1})$ and parameter values, based on input and output data. To prepare the input-output data, the fourth godet roll is run at the speed from 0 to 1500 rpm in the absolute sinusoid wave with a period of 720 samples, and the data acquisition lasts for four periods. The sampling time is 0.05 s. Thus, a total of 2880 input-output data were collected. Before performing the system identification, the input-output data should be adjusted to be zero-mean, which can be done with the trend function in MATLAB.

When the structure of the tentative model is selected by using n , m , and p from 1 to 5 and the time delay of 1, the parameters of $A(z^{-1})$, $B(z^{-1})$, and $C(z^{-1})$ for each

TABLE I
Experimental Results for our Choices of $T(z^{-1})$

t_1	t_2	Mean	Standard deviation
-0.5	-0.24	100.14	8.08
-0.1	-0.20	100.59	8.25
-0.1	-0.30	98.76	7.73
-0.3	-0.40	99.35	7.48
-0.2	-0.24	101.23	8.26
0.0	-0.25	99.11	8.21

model orders n , m , and p are then estimated by the RLS identification algorithm, with the forgetting factor $\lambda = 0.995$ in eqs. (9) and (10). Hence, there are 125 models with different orders n , m , and p to be identified. Among these identified models, the minimum value of AIC yields the best model. As a consequence, the model orders, $m = 1$, $n = 3$, and $p = 2$, give the AIC value of 13.72, the minimum value of AIC among the 125 identified models, and their parameter estimates are $\hat{a}_1 = -0.8383$, $\hat{a}_2 = -0.6215$, $\hat{b}_0 = -0.0321$, $\hat{b}_1 = 0.0292$, $\hat{c}_1 = 1.0481$, and $\hat{c}_2 = 0.2021$, displayed in Figure 2. On the basis of the best identified model, therefore, \hat{b}_0 is a nonzero constant and the zeros of $B(z^{-1})$ at 0.9097 and $C(z^{-1})$ at -0.7934 and -0.2547 are located inside the unit circle, enabling the discrete adaptive sliding-mode controller to work on the spinline tension control.

In our experiments, the desired level of spinline tension is $y_d(k) = 100g$. Since the tension response usually is in fluctuation, the spinline tension level and its uniformity are evaluated by the mean and standard deviation of tension data. Traditionally, the operator sets the fourth godet-roll speed by personal experience

so that the spinline tension reaches the desired value. We tried to find the fourth godet-roll speed by trial and error so that the spinline tension is close to 100g. Without control, the melt spinning is operated at the fourth godet-roll speed of 600 rpm for 200 s and 4000 tension data are acquired. As a result, the mean of the tension data is 98.51g and the standard deviation is 10.91. This value of standard deviation may cause unacceptable tension variation, thus producing non-uniform quality of as-spun yarns. To improve the tension variation, it is prerequisite to implement the discrete adaptive sliding-mode controller because the controller can reduce the response variance for the stochastic system without the need of modeling, where the spinline tension system is the case.

To estimate the parameters of the controller, we express the controller in the form of eq. (6), based on the identified model orders, $n = 3$, $m = 1$, and $p = 2$, and $b_0 = -0.0321$, where $\hat{\phi}(k) = [y(k), y(k-1), y(k-2), u(k-1), s(k), s(k-1)]$ and $\hat{\theta}(k) = [\hat{f}_0, \hat{f}_1, \hat{f}_2, \hat{b}_1, \hat{c}_1, \hat{c}_2]$. Thus, there are six parameters, $\hat{f}_0, \hat{f}_1, \hat{f}_2, \hat{b}_1, \hat{c}_1$, and \hat{c}_2 , to be estimated by the algorithms as eqs. (7) and (8). Since the zeros of $z^{n+m} B(z^{-1})T(z^{-1})$ are the closed-loop poles and $B(z^{-1}) = -0.0321 + 0.0292z^{-1}$ has a zero at 0.9097, $T(z^{-1}) = 1 + t_1z^{-2} + t_2z^{-2}$, having zeros inside the unit circle, can ensure stability of the closed-loop system. We have seven choices of $T(z^{-1})$ with t_1 and t_2 , listed in Table I, which all have zeros inside the unit circle. As a demonstration, one of the choices is $T(z^{-1}) = 1 - 0.3z^{-1} - 0.4z^{-2}$, which has zeros at 0.8 and -0.5. The experiment starts with the initial estimate of the parameter-vector, $\hat{\theta}(0) = [0.01, 0.01, 0.01, 0.01, 0.01, 0.01]^T$. The control signal is generated based on cur-

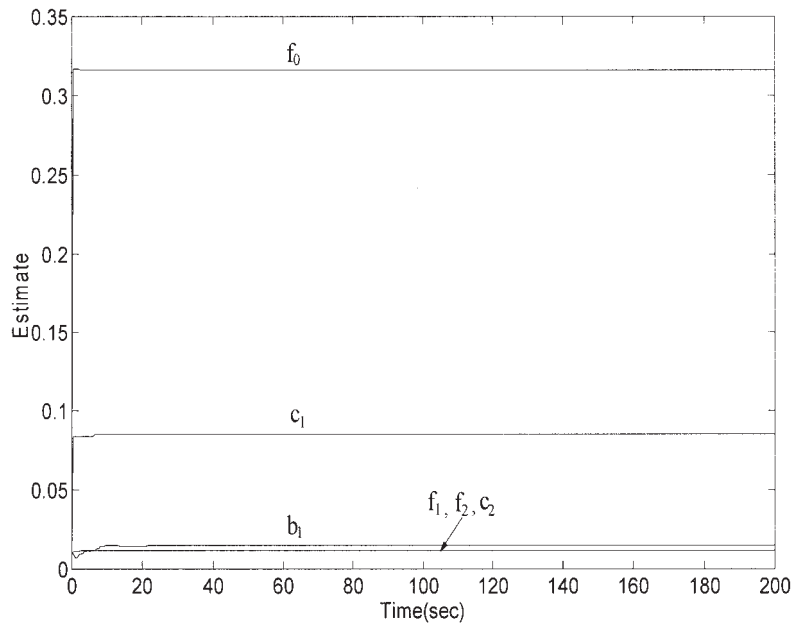


Figure 3 Estimated parameters of the controller.

rent and past outputs and deviations from the sliding-surface, past input, and on-line estimated parameter-vector $\hat{\theta}(k)$. The parameter estimates are shown in Figure 3, and $\hat{\theta}(k)$ finally converges to a constant vector, $[0.316, 0.012, 0.012, 0.015, 0.085, 0.012]^T$. Figure 4 illustrates that the spinline tension response has a mean of 99.35g and standard deviation of 7.48. The speed adjustment of the fourth godet roll is displayed in Figure 5. Compared with the result of no control, obviously, the discrete adaptive sliding-mode controller can reduce the variation of spinline tension, enhancing evenness of the tension. Our choices of $T(z^{-1})$ give tension means and standard deviations as listed in Table I. The means indicate that the tension levels are close to the desired value of 100g. The standard deviations are around 7 or 8, which are generally acceptable to the manufacturer.

CONCLUSIONS

In melt spinning, the spinline tension at a target level with small fluctuation is helpful to produce good and uniform qualities of as-spun yarns. In general, we can change the roll speed to adjust the spinline tension. The spinline tension system constantly suffers from stochastic disturbances. Without the need of modeling, the discrete adaptive sliding-mode control actu-

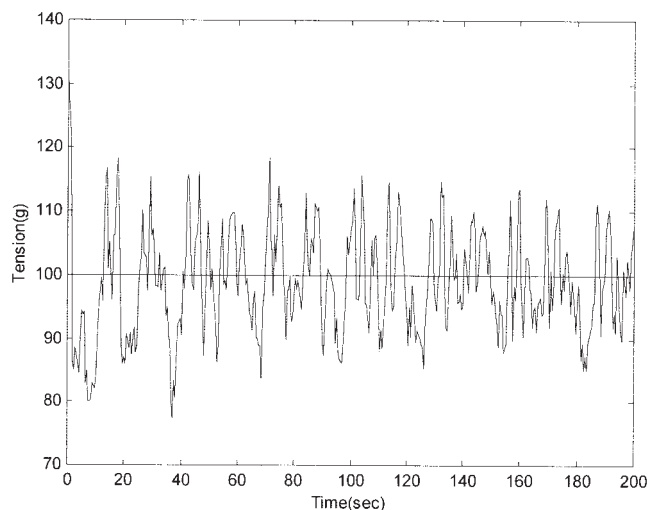


Figure 4 Spinline tension response.

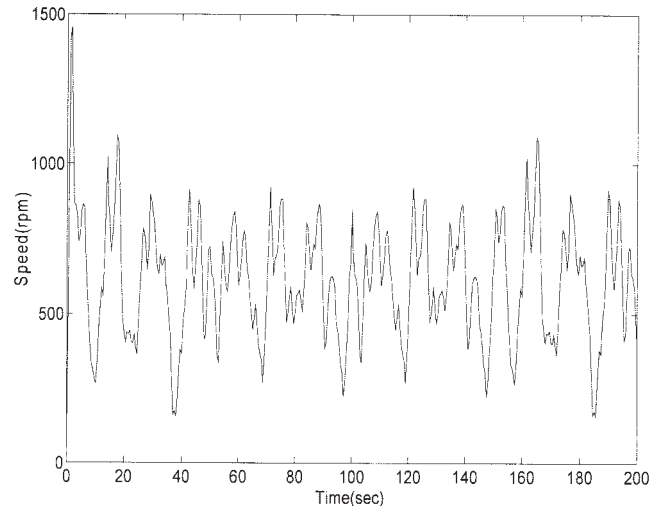


Figure 5 Fourth godet-roll speed.

ally is an effective strategy to reduce the tension variance for the spinline tension system, which is demonstrated by experimental results. The experiment is proceeding in our melt spinning setup to manufacture PP as-spun yarns. As a result, in addition to maintaining the spinline tension close to the desired level of 100g, the proposed controller reduces the standard deviation of the tension variation to the value about 7 or 8, which is smaller than the standard deviation of 10.91 without control.

References

1. Dutta, A.; Nadkarni, V. M. *Text Res J* 1984, 54, 35.
2. Jinan C.; Kikutani, T.; Takaku, A.; Shimizu, J. *J Appl Polym Sci* 1989, 37, 2683.
3. Zieminski, K. F.; Spruiell, J. *J Appl Polym Sci* 1988, 35, 2223.
4. Chen, S.; Yu, W.; Spruiell, J. E. *J Appl Polym Sci* 1987, 34, 1477.
5. Bhuvanesh, Y. C.; Gupta, V. B. *J Appl Polym Sci* 1995, 58, 663.
6. Lee, J. S.; Jung, H. W.; Kim, S. H.; Hyun, J. C. *J Non-Newtonian Fluid Mech* 2001, 99, 159.
7. Kase, S.; Araki, M. *J Appl Polym Sci* 1982, 27, 4439.
8. Jung, H. W.; Song, H. S.; Hyun, J. C. *J Non-Newtonian Fluid Mech* 1999, 87, 165.
9. Devereux, B. M.; Denn, M. M. *Ind Eng Chem Res* 1994, 33, 2384.
10. Furuta, K. *Syst Control Lett* 1990, 14, 145.
11. Chan, C. Y. *Automatica* 1995, 31, 1509.
12. Chan, C. Y. *Automatica* 1997, 33, 999.
13. Chang, K. M. *JSME Int J* 1999, 42, 930.
14. Chan, C. Y. *Automatica* 1999, 35, 1491.
15. Ljung, L. *System Identification Toolbox-User's Guide*; The Mathworks, Inc.: Natick, MA 1997.