Extruder Melt Temperature Control With Fuzzy Logic

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Extruder Melt Temperature Control With Fuzzy Logic

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Abstract: In polymer extrusion, the delivery of a melt which is homogenous in composition and temperature is paramount for achieving high quality extruded products. However, advancements in process control are required to reduce temperature variations across the melt flow which can result in poor product quality. The majority of thermal monitoring methods provide only low accuracy point/bulk melt temperature measurements and cause poor controller performance. Furthermore, the most common conventional proportional-integral-derivative controllers seem to be incapable of performing well over the nonlinear operating region. This paper presents a model-based fuzzy control approach to reduce the die melt temperature variations across the melt flow while achieving desired average die melt temperature. Simulation results confirm the efficacy of the proposed controller.

Keywords: Polymer Extrusion, Melt Temperature Variation, Fuzzy Control.

1. INTRODUCTION

Use of polymer materials has greatly increased over last few decades due to their many attractive properties such as ease of forming into complex shapes, lightweight with high tensile/impact/tear strengths, high temperature resistance, high chemical resistance, high clarity, reprocesseability and low cost. This has resulted in new industrial applications for polymer materials while enabling products to be more cost effective, flexible, and efficient. The extrusion process is used for the production of commodities in diverse industrial sectors such as packaging, household, automotive, aerospace, marine, construction, electrical and electronic, and medical applications. Despite this success, it seems that effective thermal monitoring and control still remains an issue.

1.1 Polymer extrusion process

There are two basic types of polymer processing extruders known as continuous and batch extruders (Rosato, 1998). Of these, single screw continuous extruders are the most commonly used in the plastics industry (Spalding and Hyun, 2003). The basic components of a single screw extruder are shown in Figure 1. The screw is the key component and has been divided into three main functional/geometrical zones (i.e. solids conveying, melting, and metering) based on their primary operations. The material fed into the machine through the hopper is conveyed along the screw while absorbing heat provided by the barrel heaters and through process mechanical work. Eventually, a molten flow of material is forced into the die which forms the material into the desired shape. More details of the mechanisms of polymer extrusion can be found in Rauwendaal (2001).

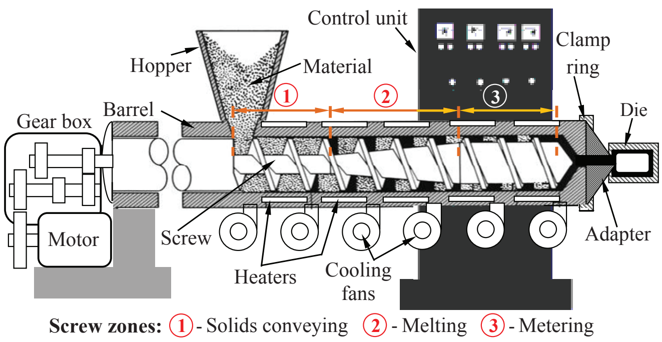

Fig. 1. The basic components of a single screw extruder

1.2 Extrusion melt thermal control

In polymer processing, melt temperature is one of the most important process variables and even small variations can cause poor product quality (Dormeier and Panreck, 1990). Under poor thermal conditions, several processing problems can occur, e.g. thermal degradation, output surging, poor mechanical properties, dimensional instability, poor surface finish and poor optical clarity (Rauwendaal, 2001; Maddock, 1964; Fenner, 1979). Die melt temperature homogeneity depends on the selection of processing conditions, machine geometry, and material properties (Brown et al., 2004b; Kelly et al., 2006; Abeykoon et al., 2010b,a). Moreover, it has been found that melt temperature non-homogeneity increases with screw speed. Therefore, it is a challenging task to run extruders at higher screw speeds although the process energy efficiency then increases (Abeykoon et al., 2010c). Normally, extruders are operated at conservative rates to eliminate poor thermal conditions with resulting poor energy efficiencies. An ideal controller would minimise poor thermal conditions such as melt flow non-homogeneity and achieve the highest possible thermal and energy efficiencies enabling the extruder to run at high speeds.

Varying degrees of success have been achieved in the area of extrusion melt thermal control by manipulation of barrel temperature and screw speed settings using empirical modelling techniques. The majority of schemes have been concentrated on transfer function models mostly in combination with proportional-integral-derivative (PID) approaches (Fingerle, 1978; Muhrer et al., 1983; Previdi et al., 2006). Some other work has used linear time-series regression techniques in process disturbances rejection and melt temperature control (Parnaby et al., 1975; Kochhr and Parnaby, 1977; Hassn and Parnaby, 1981; Patterson and Kerf, 1978; Costin et al., 1982; Germuska et al., 1984; Lin and Lee, 1997). Mercure and Trainor (1989) proposed time dependent partial differential equations to formulate a first principle mathematical model for the extruder barrel temperature control. The controller was implemented by using a PID algorithm and the mathematical model was solved by virtue of a software package. Such linear techniques have demonstrated some potential to reduce fluctuations in melt temperature at a fixed operating point but as the process is highly non-linear (Costin et al., 1982), they are not suitable for the wider operating range which applies in industrial environments.

1.3 Fuzzy logic applications in extrusion thermal control

Fuzzy logic has been widely used in industrial control applications and is becoming increasingly popular in modern process control. It has several advantages including its simplicity, ease of handling non-linear systems, low installation cost and no need for exact numerical involvements (Zhang, 1996-2000; Jantzen, 1998; Fileti et al., 2007). However, only a few researchers have attempted to use fuzzy logic for extrusion thermal control and of these, most have attempted to maintain barrel temperature settings rather than the melt temperature itself. Taur et al. (1995) proposed a fuzzy PID temperature control for extruder barrel temperatures which exhibited good control capabilities. Tasi and Lu (1998) developed a single-loop fuzzy supervisory predictive PID controller also for extruder barrel temperature control. PID gains were estimated using a generalised predictive control technique. A real-time algorithm was applied to achieve control actions incorporating PID and fuzzy supervision. The controller set-point tracking performance was verified by experiments and successful results were achieved with steady state errors of $\pm 0.4^\circ$C and a small overshoot. Recent work by Yusuf et al. (2010) used fuzzy genetic algorithms in extruder barrel temperature control. The membership functions of a fuzzy logic controller were found using a genetic algorithm. Simulation studies showed that the optimised controller gave a much faster settling time with no overshoot.

From the above, it is obvious that there has been much progress in extrusion thermal control over the last few decades. However, most of the existing thermal monitoring and control methods are based on conventional wall-mounted thermocouples. The melt temperature provided by such thermocouples remains a poor performance indicator, one which is highly affected by the metal wall temperature and which provides no insight into process thermal information (Shen et al., 1992; Rauwendaal, 2001). As a result, control techniques based on these poor sensor measurements is likely to produce limited performance. Further, most of the existing control is based on linear PID controller which cannot handle significant process nonlinearities. Due to these problems in existing thermal control, few studies have reported to use other control techniques (i.e. alternative to the conventional PID) such as fuzzy logic for better thermal control performance. The work with artificial intelligence (AI) techniques has mainly focused on barrel set temperature control rather than melt temperature. There is little work reported in literature on melt temperature control methods based on nonlinear and/or thermal profile measurement (i.e. rather than using point/bulk melt temperature measurement methods) techniques. Therefore, extruder melt temperature controls are in need of considerable future development to meet existing production challenges.

In this work, an attempt was made to reduce die melt temperature variations across the melt while achieving desired average die melt temperature by manipulating the screw speed and barrel set temperatures. A non-linear dynamic model based on die melt temperature profile measurements was developed and used to represent the process dynamics within the controller. Feedback from an infrared (IR) temperature sensor was used to ensure the accuracy of temperature profile prediction. The control decisions were made by a set of knowledge-based fuzzy rules. The work was focused on a single screw extruder which is the most common extrusion machine in industry.

2. EQUIPMENT & PROCEDURE

All measurements were carried out on a 63.5mm diameter (D) single screw extruder (Davis Standard BC-60). A barrier flighted screw with a spiral Maddock mixer (DSB-1 general purpose screw) and a 2.5:1 compression ratio (Feed-5D, Compression-13D, Metering-6D) was used to process material. The extruder was fitted with an adaptor prior to a short capillary die with a 6mm bore as illustrated in Figure 1. The barrel has four separate temperature zones equipped with Davis Standard "Dual-Therm" controllers which utilise two thermocouples in each zone for barrel wall temperature control.

Melt temperature profiles at the die were measured using a thermocouple mesh placed in-between the adapter and the die. A work by Brown et al. (2004a) has previously presented this technique in detail and has confirmed that the die melt temperature measurements are symmetrical across the thermocouple mesh centreline when averaged over significantly long periods of time. However, this technique is currently impractical to use in a production environment due to constraints such as its limited durability, access requirements, disruptive effects on melt flow and output, etc. In this study, fifteen radial positions make a complete die melt temperature profile (distances from the die centre line to each radial position: 0mm (T_0), ±3mm (±T_3), ±4.5mm (±$T_{4.5}$), ±8.8mm (±$T_{8.8}$), ±11mm (±T_{11}), ±14.7mm (±$T_{14.7}$), ±16.5mm (±$T_{16.5}$), and ±19mm (±T_{19})). An IR temperature sensor (Dynisco MTX 922) was also used to measure the melt temperature close to the screw tip. A LabVIEW software program was developed to communicate between the experimental instruments and a PC. Screw speed and all temperature signals were acquired at 10Hz using a 16-bit DAQ card, National Instruments (NI) PCI-6035E, through a NI TC-2095 thermocouple connector box and a NI low-noise SCXI-1000 connector box.

Experimental trials were carried out on a virgin high density polyethylene (HDPE), (ExxonMobil HYA-800), (density 0.961g/cm^3, melt flow index -0.7g/10min @ (190°C, 2.16kg)). The extruder temperature settings were fixed as described in Table. 1 under two different barrel set temperature conditions and denoted as A (high temperature) and B (low temperature).

Table 1. Extruder barrel temperature settings

Temperature settings	Set temperatures (°C)						
	Barrel zones				Clamp ring	Adapter	Die
	1	2	3	4			
A	110	130	180	230	230	230	230
B	105	125	175	215	215	215	215

Experiments were started with temperature setting ‘A’ and data was recorded with the screw stationary for 1 minute. Then, the screw speed was increased up to 90rpm with random steps of in-between ±5-±40rpm and the extruder running for about 65 minutes. Then, barrel set temperatures were changed into condition ‘B’ and random step changes of screw speed were applied with the extruder running for about another 64 minutes (i.e. the complete experiments was carried out over 129 minutes continuously). The extruder was allowed to stabilise over 15 minutes after set temperature change while the extruder was running for about 7 minutes over each other different condition. All of these experimental settings were selected in order to generate realistic processing conditions whilst covering the full operating range of the extruder (i.e. 0-100rpm). This therefore allowed investigation of melting performance at low throughputs where melting is dominated by conduction from the barrel and screw, and intermediate and high throughputs where melting is primarily achieved by viscous shearing. Two separate experimental trials were carried out for model training and validation.

3. CONTROLLING MELT TEMPERATURE

The typical variability in the melt temperature profile across the melt flow over different screw speeds is shown in Figure 2. Ideally, these should have flat profiles under all processing conditions. The main purpose of this study is to select and maintain an appropriate processing condition to make the die melt temperature profile as flat as possible (i.e. reduce melt temperature variations across the melt flow). It is clear that screw speed has a significant

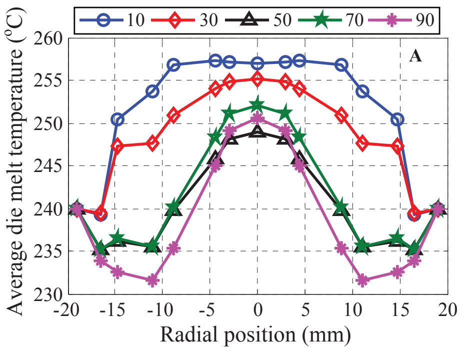

Fig. 2. Die temperature profiles from 10-90rpm:Test A

impact on the shape of the die melt temperature profiles and these effects differ with the barrel set temperatures as well (Kelly et al., 2006; Abeykoon et al., 2010b,a). Furthermore, changes to each barrel zone temperature have different effects on the resulting melt temperature at the output (Stevens and Covas, 1995). This means that most of the existing thermal control methods based on point/bulk temperature measurement feedback are not capable of identifying and hence controlling these radial temperature variations across the melt flow. Moreover, the majority of the existing control strategies try to manipulate screw speed or barrel set temperatures (i.e. all zones together or individual zones) but not both at the same time. A key aim is therefore to develop a thermal control framework based on temperature profile measurements, which manipulates screw speed and individual set temperatures together to reduce undesirable melt temperature variations while maintain the required average temperature levels. Obviously, this type of controller will have to handle the complex nonlinear behaviours of the process. This study uses a model-based control approach and hence the performance of the controller depends on the accuracy of models. In this type of work, use of a control technique like fuzzy logic may be advantageous as it does not require fully accurate models. Another major advantage is that fuzzy logic controller can handle process nonlinearities with a set of linguistic if-then rules which do not require exact numerical boundaries. Due to these and its other advantages mentioned in section 1.3, fuzzy logic was selected as the control technique for this study.

3.1 *Fuzzy logic controller*

In general, fuzzy logic controllers are composed of four main elements: fuzzy rules (i.e. if-then linguistic rules), an inference mechanism, a fuzzification stage, and a defuzzification stage. Further details on the fuzzy logic technique and controller design can be found in Passino and Yurkovich (1998); Zhang (1996-2000); Jantzen (1998); Fileti et al. (2007).

Controller design

For the development of the melt temperature controller, five process inputs (i.e. screw speed and four barrel zone temperatures) were used as the manipulated variables. Two fuzzy logic controllers (named as FLC 1 and FLC 2) provide the required control commands to these process inputs to reduce the die melt temperature variations across the melt flow while achieving desired average die melt temperature. Three error signals (i.e. the melt temperature variance error:$E(T_v)$, the average die melt temperature error:$E(T_m)$, and the mass throughput error:$E(M)$) are given as the inputs to the controllers and they make decisions to minimise these errors based on 30 knowledge-based linguistic if-then fuzzy rules (i.e. 21 rules for FLC 1 and 9 rules for FLC 2). Errors are determined by the following equations.

$$E(T_v) = T_{v,act} - T_{v,max} \tag{1}$$

$$E(\dot{m}) = M_{act} - M_{set} \tag{2}$$

$$E(T_m) = T_{m,act} - T_{m,set} \tag{3}$$

where $T_{v,act}$ is the actual melt temperature variance, $T_{v,max}$ is the maximum allowable melt temperature variance, M_{act} and M_{set} are the actual and set mass throughput rates, $T_{m,act}$ and $T_{m,set}$ are the actual and set average die melt temperatures.

In practice, it is very difficult to measure a die melt temperature profile without disturbing the melt flow and hence a specially developed nonlinear polynomial dynamic model (T_p-model) is used to predict the melt temperature profile and shown in equation (4). In practice, this would operate in place of the thermocouple mesh. For the model selection, a number of different model combinations (i.e. with different orders and number of terms) were studied. Within the model, one past output term and one past input term from each input were used to predict the current output (i.e. n_a=1 and n_b for each input is equal to one). Then the maximum delays (n_k) attributed to each model input have to be determined. Melt temperature changes at each radial position followed by screw speed changes and barrel set temperature changes were observed from the experimentally measured results. Melt temperature changes soon after any change of screw speed. Also, melt temperature is affected by barrel set temperatures but it takes slightly long period of time to change the barrel zone temperatures once any change made. Based on these observations reasonable values were assumed for delays attributed to each input as: d_N=10s, d_{Rp}=0s, d_{T1}=150s, d_{T2}=120s, d_{T3}=90s, and d_{T4}=60s. These delays can be adjusted as required depending on the screw geometry, material, processing condition etc. Then, a 2^{nd} order model with 15 terms (i.e. with a 1.22% normalised prediction error (NPE) on unseen data) was selected to use in controller and given in equation (4).

$$\begin{aligned}\hat{T}_p(t) =& [0.8207 \times \hat{T}_p(t-1)] - [0.0223 \times R_p(t)^2] \\ & -[1.1109 \times R_p(t)] - [0.0008 \times \hat{T}_p(t-1) \times N(t-10)] \\ & +[0.0134 \times R_p(t) \times T_2(t-120)] - [0.0113 \times \hat{T}_p(t-1) \times R_p(t)] \\ & +[0.0081 \times R_p(t) \times T_4(t-60)] + [0.0008 \times N(t-10) \times R_p(t)] \\ & +[0.0639 \times T_3(t-90)] + [0.0033 \times N(t-10) \times T_2(t-120)] \\ & -[0.0006 \times N(t-10)^2] + [0.0043 \times N(t-10) \times T_1(t-150)] \\ & -[0.0037 \times N(t-10) \times T_3(t-90)] + [0.3096 \times T_4(t-60)] \\ & -[0.0012 \times \hat{T}_p(t-1) \times T_2(t-120)]\end{aligned} \tag{4}$$

The actual average die melt temperature ($T_{m,act}$) at each speed was determined by taking the mean of the measured temperature profile. Also, the temperature profile prediction accuracy is corrected from a error generated by a measured (T_{IR}) and a predicted ($\hat{T}_{IR}$) IR sensor readings. The IR temperature prediction model (T_{IR}-model) takes six inputs for its prediction (i.e. N, $T_{m,act}$, T_1, T_2, T_3 and T_4) and the 2^{nd} order 6 terms dynamic T_{IR}-model (with a 0.25% NPE on unseen data) used in controller is given in equation (5).

$$\begin{aligned}\hat{T}_{IR}(t) =& [0.9507 \times \hat{T}_{IR}(t-1)] - [8.8588 \times 10^{-06} \times N(t-10)^2] \\ & +[0.0276 \times T_{m,act}] - [0.0001 \times T_1(t-150) \times T_4(t-60)] \\ & +[9.9513 \times 10^{-05} \times T_3(t-90) \times T_4(t-60)] \\ & +[0.0003 \times T_1(t-150) \times T_2(t-120)]\end{aligned} \tag{5}$$

Although, an IR sensor provides only a point measurement of melt temperature, experimental observations showed that it captures the same pattern of temperature variations as the thermocouple mesh. Therefore, IR temperature measurements can be used as feedback to correct the melt temperature predicted at each radial position across the die.

As it is difficult to make real-time throughput measurements, a nonlinear model (M-model) was developed to predict the mass throughput as a function of process inputs. This is shown in equation (6) and is based on experimental measurements of tests A and B.

$$\begin{aligned}M_{act} =& [3.392 \times 10^{-04} \times N \times T_2 \times T_3] + [0.012 \times N^2] \\ & -[3.105 \times 10^{-07} \times T_4^3]\end{aligned} \tag{6}$$

The average values of three throughput samples collected during the last 3 minutes at each condition were used for model development and validation. The mass throughput prediction model shows 3.18% NPE with the unseen data. The proposed controller structure with all of these models and IR sensor feedback is shown in Figure 3. The combined

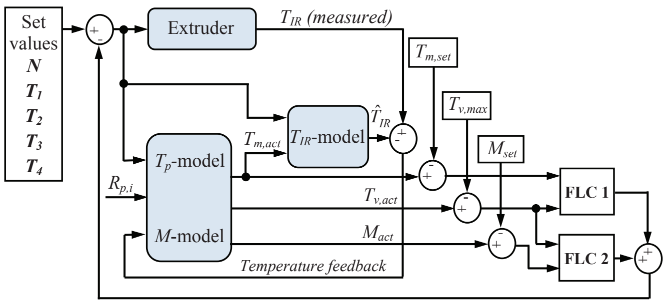

Fig. 3. The purposed controller structure

signal of outputs from both fuzzy logic controllers makes necessary adjustments to the manipulated variables to maintain the process thermal stability.

4. RESULTS & DISCUSSION

The proposed controller was implemented in MATLAB SIMULINK to check its performance on a set of unseen data. All 30 fuzzy rules were formulated by studying the experimental results and they were implemented by using triangular shaped membership functions. The Mamdani inference method (i.e. also known as a singleton output) was used with centre of area (i.e. centroid) fuzzification technique to construct the controller (Mamdani and Assilian, 1975). Measured vales of screw speed, barrel set temperatures and IR temperature were used as inputs to the controller. The set values of the average die melt temperature (i.e. by taking the average of measured die melt melt temperature profiles) and the mass throughput at each speed were determined from experimental results. The maximum allowable melt temperature variance was set as zero to achieve the minimum possible melt temperature fluctuations. Subsequently, the controller responses during disturbances were checked by adding different size of step changes (i.e. 10, 20, 30, 40, and 50 units) to the individual process inputs while others remained unchanged. The controller settled back to the normal conditions just after the step change which showed good disturbance rejection ability.

The controller performance of achieving desired average die melt temperature and reducing die melt temperature variance are shown in Figures 4 and 5 respectively.

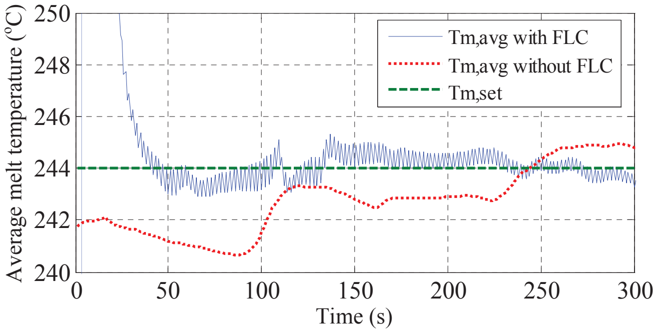

Fig. 4. Variations in average die melt temperature with and without FLC at 30rpm with setting A (Table 1)

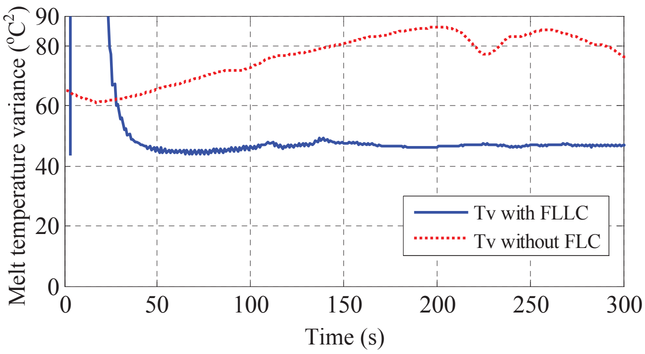

Fig. 5. Die melt temperature variance with and without FLC at 30rpm with setting A (Table 1)

The melt temperature variances were calculated using equation (7) for both experimental and controller predicted temperature profiles with reference to the desired average die melt temperature.

$$Variance = \frac{1}{n}\sum_{i=1}^{n}(T_{(m,act),i} - T_{m,set})^2 \qquad (7)$$

where n is the number of desired radial positions. Adjustments made by the FLC controller (i.e. combined outputs from both FLC 1 and FLC 2 for each manipulating variable) to each process variables to achieve above results are shown in Figure 6.

The experimental extruder was not instrumented with any melt temperature controller and only PID controllers were available to maintain each barrel set temperature in its set value. However, simulation results show that the

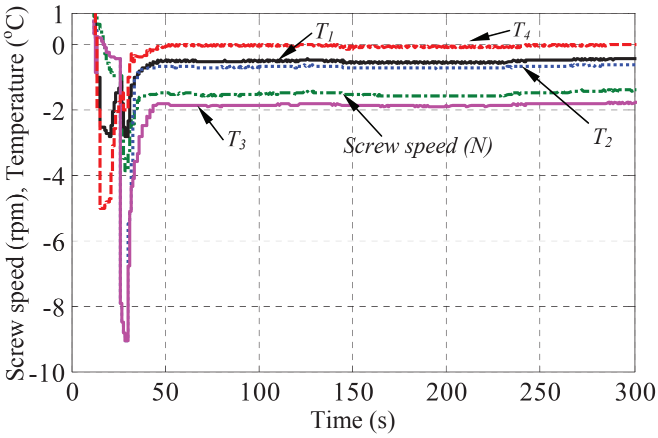

Fig. 6. Controller adjustments to the manipulating variables from their set values at 30rpm with setting A (Set conditions: N=30rpm, T_1=110, T_2=130, T_3=180, T_4=230)

proposed controller makes necessary changes to the screw speed and all barrel zone temperatures to maintain the desired average melt temperature while minimising the melt temperature variance across the melt flow.

The barrier flighted screw geometry used in these experiments seems to give good melting conditions in comparison to the conventional gradual compression screw geometry. The authors observed relatively larger melt temperature variances with a gradual compression screw geometry (the screw geometry most commonly used in industry) and temperature fluctuations increased as screw speed increased (Abeykoon et al., 2010a). Therefore, this type of controller may be highly useful for the reduction of melting fluctuations at such conditions. Evidently, the proposed controller can achieve the desired average die melt temperature while minimising the melt temperature variations across the melt flow. Therefore, this approach may allow extruders to operate at higher screw speeds with higher energy efficiencies. This can be applied to any industrial extruder on the development of the required process models. Further improvements to the controller performance can be achieved in a number of ways, such as improving the accuracy of models used, improving the accuracy of the temperature feedback (i.e. use a more advanced method than IR sensor if available), improving fuzzy rules etc. Moreover, the controller may still have some limitations over changes of machine geometry and material properties. Development of generalised models for different materials and screw geometries are highly desirable in expanding the controller in industrial applications.

5. CONCLUSIONS

A model-based fuzzy control framework to reduce the die melt temperature variance while achieving the desired average die melt temperature was proposed and the simulation results confirmed its efficacy. The controller determines the average melt temperature based on a radial temperature profile of the die melt flow rather than a point-based measurement which is less accurate although common in practice. It is shown that knowledge-based fuzzy rules provide good control capabilities to maintain the melt temperature homogeneity within desired limits by manipulating screw speed and barrel set temperatures in parallel. The controller performances can be further improved by improving the models accuracies, adding more fuzzy rules etc. Therefore, this may offer a new method to operate extruders at high screw speeds whilst achieving both high energy and thermal efficiencies.

6. FUTURE WORK

Development of generalised models should enable use of the controller with different materials and machine geometries and will be addressed under future work. Also, the implementation of the proposed controller on an actual extruder will be carried out to evaluate its performance.

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