Journal Article

A Novel Model-Based Controller for Polymer Extrusion

Abeykoon, C.

Recommended citation:
Abeykoon, C. (2014), 'A Novel Model-Based Controller for Polymer Extrusion', *IEEE Transactions on Fuzzy Systems*, Vol.22, No.6, pp.1413-1430. doi: 10.1109/TFUZZ.2013.2293348

A Novel Model-Based Controller for Polymer Extrusion

Abstract—**Extrusion is a fundamental technique of processing polymeric materials and the thermal homogeneity of the process melt output is a major concern for high quality extruded products. Therefore, accurate process thermal monitoring and control are highly invaluable for product quality control. However, most of the industrial extruders use conventional thermocouples whose measurements are limited to a single point and are highly influenced by barrel metal wall temperature. It has shown that the melt temperature varies considerably with the die radial position and hence point based measurements are not sufficient to determine the actual thermal stability across the melt flow. Therefore, thermal control techniques based on such point/bulk measurements may be limited in performance. Also, the majority of process thermal control methods are based on linear models and are not capable of dealing with process nonlinearities. In this work, a review of previous work relating to extruder melt temperature control is presented while identifying their limitations. A novel model-based control approach is then proposed to control the polymer extrusion process incorporating a melt temperature profile prediction soft sensor and fuzzy logic. The results show that the proposed controller is good in achieving the desired average melt temperature across the melt flow while minimising the melt temperature variance. The adjustments made by the controller to the manipulated variables confirmed that it has the capability of adjusting the suitable variables depending on the different situations encountered. Therefore, this will be a promising alternative to linear control techniques and control techniques based on point/bulk thermal measurements which are common in the present industry.**

Index Terms—**Polymer extrusion, Process monitoring, Melt temperature profile, Modelling, Soft sensor, Model-based control, Fuzzy logic, Performance evaluation.**

I. INTRODUCTION

Extrusion is one of the major methods of processing polymeric materials and is involved in the final production of many polymer products such as pipes, films, sheets, tubes, rods, etc. The screw is the key component of an extrusion machine and has been divided into three main functional/geometrical zones (i.e. solids conveying or feed, melting or compression, and metering or pumping) based on the primary operations of the machine as shown in Figure 1.

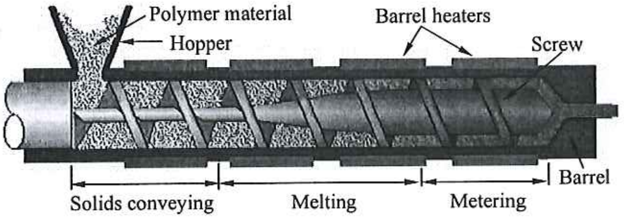

Figure 1. Functional/geometrical zones of a single screw extruder

The transition points between these functional extruder zones and their lengths are often not well identified and are highly dependent upon the processing conditions such as screw speed, pressure, temperature and polymer type. Generally, two basic types of polymer processing extruders are used in the present industry called continuous and batch (discontinuous) extruders [1]. Of these two major categories of extruders, continuous extruders may be the most commonly used in the current industry. However, continuous extruders are poor in control performance compared to reciprocating extrusion processes (i.e. discontinuous processes) such as those used in injection moulding which are well controlled with new technology [2]. Therefore, this study was focused on the development of the control of continuous extruders. Among continuous extruders, single screw continuous extruders are the most commonly used in industry [1] and that is mainly due to their reliability, low purchase and maintenance costs, simplicity of operation and the ability to generate the required pressure [3], [4]. Twin screw extruders are also popular in the polymer processing industry particularly in applications such as mixing, compounding or reacting polymeric materials, etc. More details on single and twin screw extruders and their operation can be found in the literature together with other relevant information on polymer processing [5]–[8]. Generally, the design and process operation of twin screw extruders are more complex than single screw extruders. Also, the process mechanism of twin screw extruders is not as well understood as single screw extruders [5]. Therefore, a single screw extruder was selected for this research due to their wider availability in industrial applications and good understanding of the process mechanism. This enabled a more straightforward approach to testing and improvement of the prospective process controller on a single screw extruder initially. Ultimately, it should be possible to extend the controller's operation to be compatible with multi screw extruders in future extensions of the research.

A. Importance of improved process monitoring and control

Process monitoring and control are extremely important combined aspects within the industry. The key idea behind the process monitoring is to identify the inherent process problems and to develop strategies to control them, both through machine design and process operation. In fact, the performance of a process control strategy depends on the accuracy and the quality of the process monitoring techniques (i.e. depends on how good process problems are identified and understood). An accurate control cannot be achieved if the process cannot be monitored accurately [2]. Overall, process control relates to the selection and tuning of processing conditions to maintain process efficiency and product quality for a specific material and a machine. In general, the main objective of any process controller is to achieve good quality products while achieving a better process efficiency in terms of the use of resources such as material, energy, labour, time, etc.

In polymer extrusion, melt output of the machines should be uniform throughout the process (i.e. the uniformity of the melt temperature over the time and temperature homogeneity across the melt flow) for achieving of good quality products. Temporal thermal variations of melt output may cause to generate variations of melt pressure resulting in output rate variations, non-uniformities of optical/mechanical/chemical properties of the extruded parts, extrudate with un-melted particles, etc [9]. Also, process problems can occur due to the variability of processing materials [10]–[12], machine geometry [13]–[18] and process settings [5], [10], [15], [19], [20]. Obviously, processing problems attributed to the machines' functionality (e.g. screw misalignments, vibrations of machine parts, inaccuracies of screw design) have to be addressed at the stage of machine design and the selection of optimum operating conditions may be the most important factor to achieve the highest possible process efficiency (i.e. in terms of energy and thermal stability) for a given machine and a material. In such a situation, it is invaluable to have a process controller which can accurately detect and control of processing problems.

Although the quality of the melt output (i.e. a thermally homogeneous melt output which is constant in quantity and quality over the time) is the major concern in polymer extrusion, it seems that there are not many control techniques available which make control decisions by observing the actual quality of the melt flow. This may be due to the practical difficulties of monitoring the melt quality across the flow cross-section without disturbing the steadiness of the melt flow. Presently, most polymer processing extruders are equipped with speed controllers (i.e. to maintain the screw speed within its set limit) and temperature controllers (i.e. to maintain the barrel set temperatures within their desired limits). It seems that both of these controllers are commonly used as the major aids of process control to achieve the required melt quality. The feedback for speed control is obtained via instruments such as tachometer generators (i.e. a device which can convert the measured speed into an analog voltage signal) while temperature feedback is usually obtained from the thermocouples attached to the extruder barrel/die wall. In fact, the availability of a controller which makes the necessary control decisions by observing the actual quality of the melt (by using an appropriate monitoring technique) would be highly useful rather than maintaining the barrel set temperatures and/or screw speed within their set limits without obtaining any feedback on the actual melt quality. Therefore, this study was mainly focused to address this requirement.

B. Previous studies on melt temperature control in polymer extrusion

As reported in the literature, history of the extrusion control schemes based on the temperature begins from the late 1970s. Basically, several researchers attempted to control the melt temperature and pressure (i.e. mostly these two parameters are jointly used for developing control strategies) as an indirect approach to control the melt viscosity due to the practical difficulties encountered in real-time monitoring of the melt viscosity. Initially, several researchers used linear Laplace transform techniques to develop control schemes relating to extrusion melt temperature and pressure by implementing proportional-integral-derivative (PID) control algorithms. Later, time series techniques which are capable of developing more sophisticated models allowing to identify and control of process disturbances were used for controlling of the temperature and pressure.

1) Control schemes based on transfer function or time series models: Fontaine [21] developed transfer function models for melt throughput, exit pressure and temperature to changes in the back pressure valve setting, barrel heater power and screw speed. The usefulness of the proposed controller was limited as process signals were pre-filtered to remove some of the inherent fluctuations without considering the relations of these fluctuations with the product quality.

Fingerle [22] attempted to control melt temperature by introducing a special extruder modification. An annular section of adjustable length was added at the end of the extruder barrel, and adjusting the length of the section was used to control the rate of viscous dissipation in the extruder. A controller was implemented with a PID algorithm and gave good temperature control in comparison with a temperature controller based on heat transfer through the barrel. However, this control method involves complex modifications to the extruder which may not industrially possible and hence may limit its practical use.

Dormeier [23] proposed a PID control algorithm to regulate the melt temperature of an extruder with three heating zones. The controller showed better performance than a conventional analog controller but had different tuning parameters for set-point changes and disturbance rejection. Moreover, it was effective in regulating long-term disturbances but was not good at regulating high frequency disturbances.

Muhrer et al. [24] proposed a cascade PI control scheme to control the melt temperature by manipulating barrel zone temperatures. The results showed that the controller was good in reducing the effects of process disturbances on the melt temperature. Moreover, the authors stated that the controller tuning has to be repeated as changing the process operating conditions while re-determining the appropriate process gains (i.e. proportional and integral gains of the controller).

Chan et al. [25], [26] and Nelson et al. [27] proposed Laplace transfer function models (e.g. a first order, a second order and a lead-lag) to describe dynamic responses of an extrusion process. These models assume isothermal processing conditions and hence require detailed knowledge of material rheological properties for their use in process control.

Kochhar and Parnaby [28] and Parnaby et al. [29] modelled the extrusion process parameters by using a time series technique. A control scheme was proposed to control melt temperature by manipulating the screw speed while melt pressure and flow rate were controlled by manipulating the die restrictor valve setting (i.e. not a common feature in extrusion). Simulations were carried out to calculate the control actions which were necessary to correct the temperature drift and stated that the melt temperature predicted by the model was quite close to the measured temperature. Later, Hassan and Parnaby [30] used an adaptive control approach to develop a model reference steady-state computer controller. Process errors were identified by the cascade controller and manipulated the screw speed, die restrictor valve angular position and barrel wall set temperatures via slave servo-mechanisms to achieve the required plant output. The authors claimed that the controller was able to maintain the melt temperature with small variations (i.e. within $\pm1\%$) to the required limits.

Costin et al. [31] used a time series technique to develop dynamic transfer function models between the screw speed and pressure and also to model the disturbances associated with the extruder pressure. A digital PI and self-tuning regulator (STR) algorithms were implemented to regulate the pressure by manipulating the screw speed. A number of screw speed step tests were performed to estimate process time constant and to determine the system linearity while various filters were used to eliminate the signal noise. Signal noise filtering was quite difficult and filter implementation resulted in change of the process transfer function and hence affected to the controller performance. A combination of the STR and a filter failed to control the process and the PI algorithm with a filter gave relatively good results.

Germuska et al. [32] proposed an adaptive and multivariable control approaches to control the melt pressure, melt temperature and extrudate thickness by manipulating the screw speed, die heater power and the mass flow rate. The time series and Laplace transfer function models were used to implement a control scheme incorporating Dahlin feedback controllers (see [33] for details on Dahlin controllers) to control the melt pressure and temperature in order to maintain melt viscosity and extrudate thickness to achieve product dimensional accuracy. The proposed control scheme showed good steady-state control for changes to the melt pressure and temperature set points although the extrudate thickness controller did not perform well due to the noisy thickness measurements.

2) Control schemes based on artificial intelligence techniques: Although artificial intelligence (AI) techniques are still less popular in polymer processing industry, these are highly popular in some of the current industrial applications (more details will be discussed in section II). Taur et al. [34] proposed a fuzzy PID temperature control for extruder barrel temperatures with if-then rules and triangular shaped membership functions which exhibited good control capabilities. Tasi and Lu [35] 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 $\pm0.4°C$ and a small overshoot. Yusuf et al. [36] used fuzzy genetic algorithms in extruder barrel temperature control. The optimum shapes for membership functions of a fuzzy logic controller (FLC) were found using a genetic algorithm (GA). Simulation results showed that the optimised controller gave a much faster settling time with no overshoot. Ravi and Balakrishnan [37], [38] used AI techniques in extruder barrel temperature control. The results showed that a FLC can perform well with a lesser overshoot than a PI controller. Another work carried out by them [39], [40] found that a neuro-fuzzy controller gave better performance than fuzzy logic and PID controllers in extruder barrel temperature control. In fact, all of these studies based on AI techniques have focused only on the control of the barrel set temperatures in their set limits and did not attempt to control the melt temperature.

3) Control schemes based on other techniques: Menges and Meissner [41] proposed three control schemes to control the melt temperature of an extruder at the entrance of the die. A sensor which can make four radial temperature measurements (based on the method proposed by Leeuwen [42]) was used for melt temperature measurements. Of these control schemes, one scheme gave much faster responses but was not industrially compatible as the conical valve which was used to control the melt flow was not a usual industrial device. Moreover, the melt temperature measurement technique used in this work was also undesirable for industrial applications as it was highly disturbing to the steadiness of the melt flow.

Dastych et al. [43] proposed a robust multi-input-multi-output (MIMO) controller and a decentralised discrete model reference adaptive controller for a single screw extruder. The adaptive controller was based on their previous work [44] and it controlled the temperatures of the extruder barrel zones and melt temperature. The performance of both controllers was verified by simulation and the results showed that these can handle uncertainties and time varying or load depending plant parameters better than PID controllers.

Mercure and Trainor [45] formulated a first principle mathematical model of the extruder barrel temperature and proposed a PID controller for melt temperature control. The controller performance was verified by simulation and the authors claimed that it offered a number of advantageous (e.g. reduced settling time, automatic start-up and reduced down time) over conventional controllers. However, the controller performance might be affected by simplifying assumptions and the difficulties of selecting exact boundary conditions for solving differential equations (i.e. boundary conditions may vary with time, temperature, materials, screw speed, etc).

Lin and Lee [46] identified extrusion plant dynamics by a least squares approximation associated with loss and covariance functions, applied to a set of experimental data. The authors used data from Parnaby et al. [29] and identified a single-input-single-output (SISO) third order state-space dynamic model. An integral observer control methodology was proposed incorporating the developed dynamic model, and the extruder screw speed was manipulated to control the melt pressure and temperature. The simulation results showed that the control of pressure and temperature in the limits of ±0.5MPa and $\pm2.5°C$, respectively.

Recent work presented by Previdi et al. [47] proposed a prototype feedback control scheme for melt temperature and pressure in a single screw extruder. The results of the proposed control scheme showed better performance than a pump-equipped extruder which did not have a feedback control system. The authors stated that the proposed control system is a cost-effective alternative for volumetric mechanical pumps while it is also a robust and an accurate solution to extrusion process control within the required limits.

As was discussed in the above, varying degrees of success have been achieved in the area of polymer extrusion control by manipulating the barrel set temperatures and screw speed using empirical modelling techniques. The control of melt quality and throughput has traditionally been attempted by joint regulation of melt pressure and melt temperature. Stable pressure generation ensures a consistent mass flow rate. The control of the melt temperature helps to avoid viscosity fluctuations (for a consistent feed material) and thermal degradation of the material and hence to maintain the melt flow thermal homogeneity. However, the majority of these previous approaches are limited in industrial use due to several constraints such as their complexity, incompatibility with the industrial practices, lack of performance, etc. As it was clearly recognized from the previous work [7], [48], [49], point/bulk temperature measurements provided by the most of the industrially well-established process thermal monitoring techniques are poor in accuracy and these are limited in providing thermal information across the melt flow. Obviously, these limitations in process thermal monitoring cause to poor controller performance as the process controller performance directly relates how well the process information can be monitored. Furthermore, most of the existing process control schemes are based on linear PID controllers which are poor in handling process nonlinearities. Few works reported on AI techniques (i.e. alternatives to the conventional PID) have mainly focused on barrel set temperature control rather than the melt temperature. Moreover, it seems that only a limited amount of work has been reported on process thermal control based on nonlinear and/or thermal profile measurement techniques (i.e. rather than using point/bulk melt temperature measurement methods). Therefore, extruder melt temperature controls are in need of considerable future developments not only to design advanced control techniques but also to improve the thermal monitoring methods (i.e. to obtain accurate temperature feedback for making control decisions) in order to overcome the existing production challenges. In this study, an attempt was made to develop a novel control strategy which can fill two major existing gaps (as discussed in the above) in polymer extrusion thermal monitoring and control:

(i) The controller should based on an advanced thermal monitoring technique (i.e. an alternative to the point/bulk thermal measurements).

(ii) The controller should have the capability of dealing with process nonlinearities.

II. Controlling of the Melt Temperature

The typical variability in the melt temperature profile across the melt flow over different processing conditions was previously discussed by the author [7], [48]–[53] and a few other researchers [15], [19], [54]. If the melt flow is fully homogeneous in temperature, it should have flat melt temperature profiles across the flow cross-section under all processing conditions (i.e. the ideal situation). However, it has been experimentally shown that the process melt temperature significantly varied across the melt flow cross-section. This information confirms the argument that most of the existing thermal control methods based on point/bulk temperature measurement feedback are not capable of identifying these radial temperature variations and hence they are unable to control these variations. Therefore, the study of the entire melt temperature profile as a measure of the process thermal stability is more appropriate than a single point or a bulk measurement to ensure high quality extruded products. Unfortunately, it is quite difficult to monitor a die melt temperature profile within a production environment and most extruders are instrumented only with conventional wall mounted thermocouples. These are highly affected by the barrel wall temperature and also they are not capable of measuring a melt temperature profile or detecting rapid variations in melt temperature [5], [55]. As alternatives to the point/bulk measurements, some of the thermal profile measurement methods (e.g. a traversing thermocouple [55], [56], a thermocouple mesh [54], a fluorescence technique [57]) have been proposed, but these are not yet robust enough to use in a production environment due to constraints such as their complexity, limited durability, access requirements, disruptive effects on the melt flow and output, etc. However, some of these techniques have been used to gatherer valuable process thermal information in a research setting. Therefore, it is clear that the process thermal monitoring in polymer extrusion is still having poor performance and hence process control techniques are also experiencing lack of performance.

In fact, it is clear that not only the level of the melt temperature but also the melt temperature variance across the melt flow has to be controlled (i.e. in parallel with the level) to achieve a better process thermal control. Therefore, the process controller should have the capability to select and maintain appropriate process settings to make the extruder output melt flow temperature profile as flat as possible (i.e. to achieve reduced melt temperature variations across the melt flow) while achieving the desired average melt temperature across the melt flow. As was revealed by previous work [15], [19], [48], [52]–[54], it is clear that the screw speed has a significant impact on the shape of the extruder output melt flow temperature profile and these effects differ with the barrel set temperatures as well. Furthermore, changes to each barrel zone temperature have different effects on the resulting melt temperature at the output [6]. The majority of the existing thermal control strategies try to manipulate screw speed or barrel set temperatures (i.e. all zones together or individually) but not both at the same time. Moreover, it is quite difficult for the process operator to determine in what quantity which parameter has to be adjusted (i.e. manual process adjustments) to avoid some processing problem as changes to one particular parameter change the effects of the all other parameters and may generate another problem due to the highly coupled nature of the process variables. Therefore, a control strategy which considers all of these process variables together to make control decisions would be highly effective.

In the selection of an appropriate control technique, all the above mentioned issues had to be considered as the selected control technique should be compatible with all of these requirements. Overall, the key aim was to develop a process thermal control framework based on the temperature profile measurements which manipulates the screw speed and individual barrel set temperatures together to reduce undesirable melt temperature variations across the melt flow while maintaining the required average temperature levels throughout the process operating period for a given machine and a material. Obviously, this type of controller would have to handle complex nonlinear behaviours of the process and conventional linear PID approaches may not perform well over these situations. In this type of work, use of a control technique like fuzzy logic may be advantageous as a fuzzy logic controller can handle process nonlinearities with a set of linguistic if-then rules which do not require exact numerical boundaries [58]. Moreover, Vlachopoulos [59] and Rauwendaal et al. [60] emphasise the suitability of using the AI techniques (e.g. expert systems, neural networks and fuzzy logic) in the applications of polymer processing industry to overcome the existing challenges in the process modelling and control. Also, fuzzy logic techniques are already used in a large number of practical applications such as process control in other industries (e.g. temperature, pressure and level control, failure diagnosis and distillation column control); house hold applications like washing machines and refrigerators; motor control in power industry; various automobile, robotics and aerospace applications, etc [58], [61]–[63]. As was discussed in section I.B.2, the AI techniques which were used in the extruder barrel temperature control have performed well over conventional PID controllers with a smaller overshoot and a faster settling time. Due to these compatibilities and other well-known advantages (e.g., possibility of defining tasks with multiple rules without integrating into a single analytic control law, simplicity, low installation cost), fuzzy logic was selected as the control technique to use in the prospective process thermal controller of this study. More details on fuzzy logic and fuzzy logic based controller design can be found in the literature [58], [61]–[72].

III. Design of the Controller for the Extruder Melt Temperature Control

In this study, the melt temperature variance across the melt flow (T_v) was the primary variable which should be controlled while achieving the desired average die melt temperature ($T_{m,avg}$). However, making of temperature profile measurements across a melt flow by physical sensors is quite difficult in polymer processes due to several constraints [7], [48]. Therefore, currently there is no way to select control actions by observing a temperature profile of the process melt output based on a measurement made by a physical temperature sensor. To solve this problem, a soft sensor strategy was used to inferentially predict the melt temperature profile across the extruder output melt flow. Overall, this process controller includes two major mechanisms:

(i). An inferential die melt temperature profile prediction mechanism (i.e. a soft sensor to predict melt temperatures at the desired radial positions across the melt flow)

(ii). A control decision making mechanism incorporating fuzzy logic

A. Development of the inferential die melt temperature profile prediction mechanism

A thermocouple mesh technique [48], [54] was used to measure the melt temperature profile across the melt flow as it was good in providing detailed and accurate information on the thermal homogeneity of the extruder output melt flow. It was felt that it is better if it is possible to inferentially predict the melt temperature at the different melt flow radial locations to obtain similar types of measurements to the thermocouple mesh. Therefore, the modelling procedure which was originally introduced by the author [49], [51], [52] was used to develop dynamic models to predict melt temperature profile across the melt flow from readily measurable process parameters in real-time. Although, these models can predict the melt temperature profile, it is still good to have some reference or correction for the predicted melt temperature at the different radial locations to ensure the prediction accuracy. From the experimental results achieved by evaluating the commonly used melt temperature sensors in polymer processing [48], it was found that an infrared (IR) temperature sensor had the closest relationship with the thermocouple mesh measurements among the methods evaluated. Therefore, a combined mechanism of an IR temperature sensor and a feedback model was selected to obtain a temperature feedback to correct the possible errors of the soft sensor's temperature predictions at the different melt flow radial positions. Finally, a soft sensor strategy which is having the structure shown in Figure 2 was investigated to predict a melt temperature profile across the melt flow in real-time.

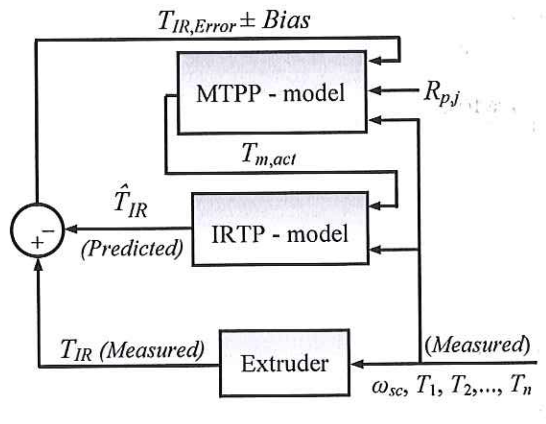

Figure 2. The structure of the proposed soft sensor to predict the melt temperature profile across the extruder output melt flow in real-time

Overall, the proposed soft sensor employs two models for its operation. One model is to predict the melt temperature profile across the melt flow (melt temperature profile prediction model (MTPP - model)) and it takes six process inputs (ω_{sc}, $R_{p,j}$, T_1, T_2, T_3, T_4) for its prediction. Here, ω_{sc} represents the screw speed, R_p is the radial position across the melt flow while T_1-T_4 represent the set temperatures of the extruder barrel zones 1-4. Apart from these 6 inputs, the difference between the predicted and measured IR temperature sensor measurements ($T_{IR,Error}$) with a suitable adjustment (i.e. a positive or a negative bias value specific to each radial position) is also taken as the MTPP - model input with the purpose of the correction of the possible prediction errors. A desired number of radial positions can be defined under the $R_{p,j}$ input as suitable and for this study 15 radial positions (i.e. $j = 1, 2, 3, ..., 15$) were defined. In practice, MTPP - model would operate in place of the thermocouple mesh. The other model (IR temperature prediction model (IRTP - model or feedback model)) also takes 6 inputs (ω_{sc}, $T_{m,act}$, T_1, T_2, T_3, T_4) and predicts the melt temperature given by the IR temperature sensor. Here, the $T_{m,act}$ input is the mean value taken from the predicted melt temperatures of 15 radial positions by the MTPP - model. This die melt temperature profile prediction soft sensor strategy was also originally proposed by the author and more details were discussed previously [73], [74].

B. Development of the control decision making mechanism with fuzzy logic

The procedure of designing of the controller's decision making mechanism is now discussed.

1) Selection of membership functions: In general, any fuzzy set is fully characterised by its own membership functions (MFs). In fact, different shapes of membership functions (e.g. Triangular, Trapezoid, Gaussian and Bell) are available and the most desirable shape for a particular problem has to be selected. There are a few different ways of the selection of membership functions for FLC applications such as intuition, inference, rank ordering, neural networks, genetic algorithms and inductive reasoning [71]. Moreover, Sciascio and Carelli [75] argue that the triangular shaped membership functions may be the most commonly used MFs in fuzzy logic applications due to their simplicity of generation and the consistency property. For this study, triangular shaped MFs were selected due to the easiness of generating both symmetrical and non-symmetrical shapes as well as due to their popularity in practical use. Moreover, the controller's performance was evaluated by using a few other membership functions with different shapes (i.e. trimf, gaussmf and gbellmf) and combinations of membership functions (i.e. zmf-trapmf-smf and zmf-gaussmf-smf) by applying these to the simulation model. However, no significant differences of performance of the controller could be observed by changing the shape of the MFs and hence the results are presented only with triangular shaped MFs.

2) Design of FLC elements : There are four basic elements/steps in designing of a FLC: formulation of rules, fuzzification, inference and defuzzification [58]. The procedures followed in this study to design these elements are presented in this section.

a. Formulation and fuzzification of linguistic rules

In general, two types of commonly used fuzzy operators can be found in FLC design: OR operator and AND operator. The designer can choose a suitable operator based on the design criteria of each problem. In this study, it was required to satisfy all the conditions included in each rule simultaneously and hence the AND operator was selected. A thorough observation of the effects of each process parameter on the level of the melt temperature and temperature variance across the extruder output melt flow was made by using the developed models and the other available data sources. Actually, it was really challenging to generate rules to be compatible with a number of parameters in parallel (i.e. to include a large number of variables in a single rule). Therefore, only two variables were integrated into each individual rule and the use of maximum possible number of rules may enable to make a firm control decision (i.e. a decision which considers a large number of possible situations). Here, the major requirements of developing the FLC were to minimise temperature variations across the extruder output melt flow while achieving the desired average melt temperature; and two inputs to the controller (i.e. two error signals) can be generated based on these two requirements. To widen the scope of the controller's operation, another input to the controller was introduced based on the process mass throughput ($\bar{M}$) error. For this purpose, the measured and predicted (i.e. from a model called $\bar{M}$ - model) mass throughput values were used. Altogether, three error signals (melt temperature variance error: $E(T_v)$, average melt temperature error: $E(T_{m,avg})$, mass throughput error: $E(\bar{M})$) were generated as given in equations (1) to (3) and these were used as the inputs to the controller.

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

$$E(T_{m,avg}) = T_{m,act} - T_{m,set} \tag{2}$$

$$E(\bar{M}) = \bar{M}_{act} - \bar{M}_{set} \tag{3}$$

where $T_{v,act}$ and $T_{v,max}$ are the actual and maximum allowable melt temperature variances across the melt flow, $\bar{M}_{act}$ and $\bar{M}_{set}$ are the actual and set/desired mass throughput rates, $T_{m,act}$ and $T_{m,set}$ are the actual and set/desired average melt temperatures across the melt flow. By combining $E(T_v)$ and $E(T_{m,avg})$, 21 if-then fuzzy rules were developed and implemented in a FLC denoted as FLC 1. Similarly, 9 fuzzy rules were generated from $E(T_{m,avg})$ and $E(\bar{M})$ and implemented in a separate controller denoted as FLC 2. All of these 30 fuzzy rules were formulated by studying the experimental results based on the Mamdani inference method [68] and they were fuzzified by using triangular shaped membership functions. The range of each universe of discourse (i.e. the whole range of the membership functions of each controller input and output) and the arrangement of their membership functions were initially determined based on the experimental information. Later these were modified to improve the controller's performance by observing simulation results and the details of the final selections are given below:

- The range of $E(T_v)$ was set from -50°C^2 to 900°C^2 and seven MFs (i.e. labelled from A to F in the order of magnitude increment) were used within this range as shown in Figure 3. The range of $E(T_v)$ was selected from -50°C^2 by allowing to set the $T_{v,max}$ by between 0-50°C^2.
- $E(T_{m,avg})$ was defined by three MFs in the range of -100°C to 100°C as shown in Figure 4.
- $E(\bar{M})$ was defined by three equally spaced MFs in the range of -200g/s to 200g/s as shown in Figure 5.

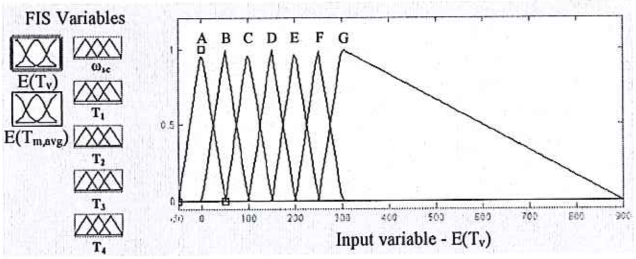

Figure 3. Universe of discourse of the controller input: $E(T_v)$

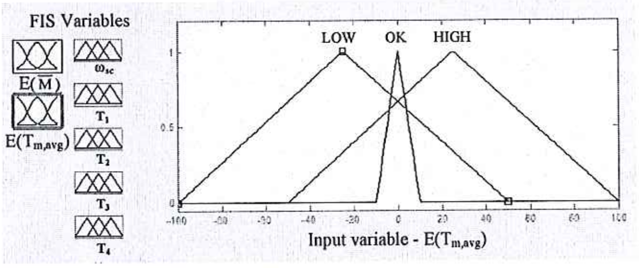

Figure 4. Universe of discourse of the controller input: $E(T_{m,avg})$

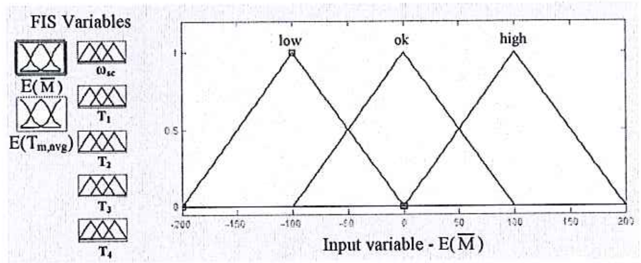

Figure 5. Universe of discourse of the controller input: $E(\bar{M})$

The controller outputs ($\omega_{sc}, T_1, T_2, T_3$ and T_4) were defined in the range of -10rpm to 10rpm (i.e. for ω_{sc}) or -10°C to 10°C (i.e. for T_1, T_2, T_3 and T_4) by using seven equally spaced MFs. These seven MFs were labelled based on the following notation:

VL - Very Low	M - Medium	SH - Slightly High
L - Low		H - High
SL - Slightly Low		VH - Very High

The universe of discourse of each output of the controller is similar in their range and the arrangement of the MFs. The universe of discourse of the screw speed output is shown in Figure 6.

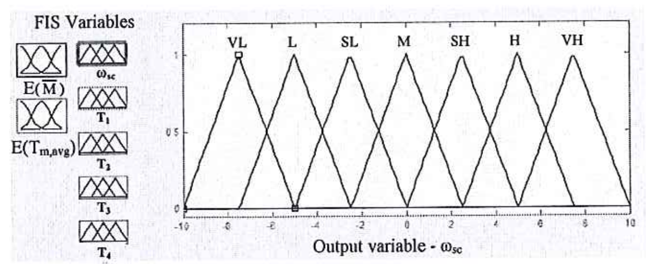

Figure 6. Universe of discourse of the controller output for screw speed

Both FLC 1 and FLC 2 are MIMO controllers (i.e. with two inputs and five outputs) and each output is having its own control surface corresponding to the rule base. As the controller operates, each manipulated variable moves within the corresponding control surface as appropriate to minimise errors which may be generated due to the process fluctuations.

b. The inference mechanism

As mentioned earlier, the Mamdani inference method [68] was chosen in this study to obtain the conclusion of each rule (i.e. to apply implication operator) and to make the final control decision by aggregating the conclusions of all the rules. Moreover, the minimum implication operator (which truncates the consequent's membership function) and the maximum aggregation operator were used for the controller implementation. These two operators were selected as it was realised that these methods are the most appropriate to make control decisions for this particular problem. Moreover, these methods have been widely applied in the previous fuzzy logic applications as well.

c. Defuzzification

The conversion of the aggregate decision into a numerical value is known as the defuzzification (i.e. the quantification of linguistic information). For this particular operation, the centroid method which is one of the most commonly used defuzzification methods was used in this study. In this method, the quantification of the aggregate output into a numerical value is carried out based on the centre of area under the curve of the aggregate fuzzy set [58].

Then, the control decision making mechanism of the prospective model-based controller was implemented by combining all of these basic elements.

IV. The Structure of the Proposed Model-Based Controller

Eventually, the melt temperature profile prediction mechanism (i.e. the soft sensor) and the control decision making mechanism were combined and the structure of the novel model-based controller is shown in Figure 7. As shown in Figure 7, the combined signal of both fuzzy logic controllers' (i.e. FLC 1 and FLC 2) outputs makes necessary adjustments to the manipulated variables to maintain the process thermal stability within the desired limits while achieving the required mass flow rate at each screw speed. Obviously, the screw speed (ω_{sc}), melt temperature from an IR temperature sensor (T_{IR}) and all the barrel zone temperatures (T_1, T_2, T_3 and T_4) can be measured easily in real-time within any practical environment without disturbing the process melt output or without making modifications to the existing extrusion machines. Moreover, these parameters can be measured to a good accuracy by using commercially available sensors. Therefore, it is possible to feed all the required signals easily into the controller for its real-time operation in practice.

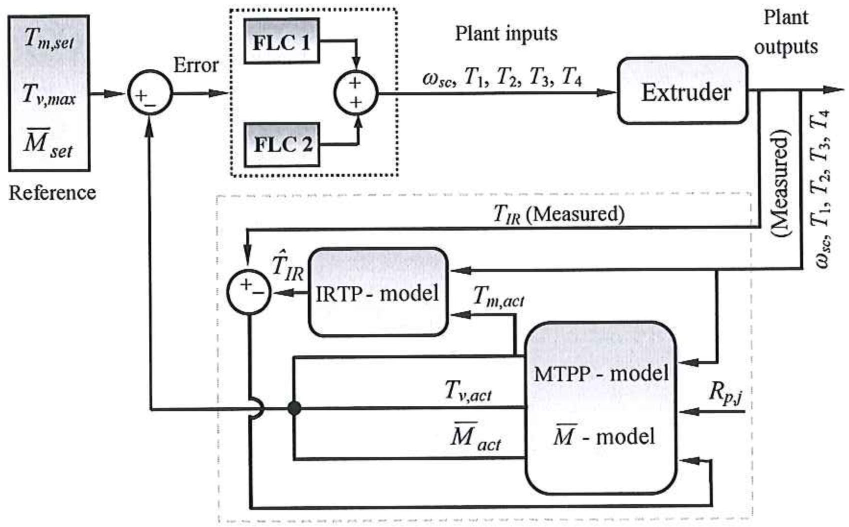

Figure 7. The structure of the proposed model-based controller

V. Implementation of the Controller

A. *Equipment & Procedure*

All measurements were carried out on a highly-instrumented 63.5mm diameter (D) single screw extruder. A barrier flighted (BF) screw with a spiral Maddock mixer (a general purpose screw with a 2.5:1 compression ratio) and a tapered single flighted gradual compression (GC) screw (with a 3:1 compression ratio) were used to process the materials. From here onwards, these two screws are denoted as the BF screw and the GC screw.

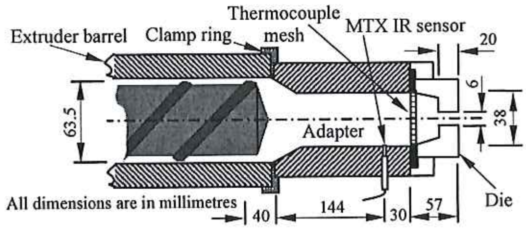

Figure 8. Extruder die, adapter and thermocouple mesh

The extruder was fitted with an adaptor by using a clamp ring prior to a short capillary die with a 6mm diameter bore as shown in Figure 8. The extruder barrel has four separate temperature zones and another three separate temperature zones are available at the clamp ring, adapter and die. Each of these temperature zones is equipped with a separate temperature controller which allows the control of their set temperature individually.

Melt temperature at the different radial locations of the melt flow at the end of the adapter (denoted as die melt temperature throughout this paper) was measured using a thermocouple mesh placed in-between the adapter and die as shown in Figure 8. As it was previously confirmed by Kelly et al. [15], [54]; the die melt temperature measurements are symmetrical across the thermocouple mesh centreline when averaged over a significantly long period of time. Therefore, seven thermocouple junctions (i.e. with 7 positive and 1 negative thermocouple wires) were placed asymmetrically across the melt flow along the diameter of the mesh as shown in Figure 9, and this asymmetric placement of wires gave the opportunity to increase the number of effective temperature measurements across the melt flow by mirroring them over the centreline to obtain the complete die melt temperature profile.

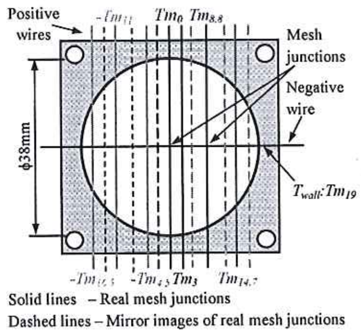

Figure 9. The thermocouple mesh arrangement

The die wall set temperature was used as the melt temperatures at the ±19mm radial positions. Then, the final melt temperature profile was obtained by 15 radial positions (distance from the melt flow centreline to each radial position: 0mm, ±3mm, ±4.5mm, ±8.8mm, ±11mm, ±14.7mm, ±16.5mm and ±19mm) across the melt flow as illustrated in Figure 9. A data acquisition programme developed in LabVIEW was used 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 thermocouple connector box (NI TC-2095) and a low-noise signal conditioning box (NI SCXI-1000).

1) Materials and experimental conditions: Experimental trials were carried out on a virgin high density polyethylene (HDPE), (ExxonMobil HYA 800), (density: 0.961g/cm^3, melt flow index (MFI): 0.7g/10min @ (190°C, 2.16kg)); and a regrind polypropylene (RPP), density: 0.850g/cm^3, MFI: 5.71g/10min @ (230°C, 2.16kg)). The extruder barrel temperature settings were fixed as described in Table I under six different set conditions denoted as A, D (high temperature); B, E (medium temperature); and C, F (low temperature).

Table I
EXTRUDER BARREL TEMPERATURE SETTINGS

Test-(Material)-Screw	Temperature settings	Set temperatures (°C)						
		Barrel zones				Clamp ring	Adapter	Die
		1	2	3	4			
1-HDPE-BF 2-HDPE-GC	A	110	130	180	230	230	230	230
	B	105	125	175	215	215	215	215
	C	100	120	170	200	200	200	200
3-RPP-BF	D	150	190	215	240	240	240	240
	E	145	180	200	220	220	220	220
	F	140	170	185	200	200	200	200

Experiments were started with temperature setting A or D (i.e. setting A for tests 1 and 2, setting D for test 3) and the data was recorded with the screw stationary for 1 minute. Then, the screw speed was increased from 0 to 90rpm with steps of between 5 and 40rpm and for the different barrel set temperatures with the extruder running for 193 minutes in tests 1 and 2, and 151 minutes in test 3 continuously. The extruder was allowed to stabilise for 15 minutes after each set temperature change whereas it was hold for about 7 minutes at each of the other different conditions. These time periods were chosen by considering the time requirement of process to become steady after applying the step changes to the screw speed and/or barrel set temperature. The process settings matrix corresponding to the test 1 is shown in Figure 10.

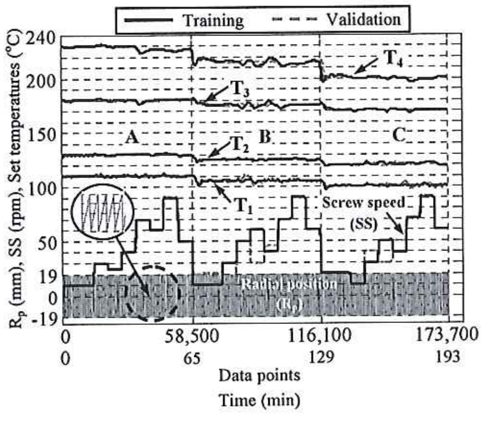

Figure 10. Model input matrices - Test 1

The magnitudes of the applied step changes were also determined by ensuring the process to run under normal conditions after applying these changes. Moreover, all of these settings were selected in order to generate realistic processing conditions whilst covering the full operating range of the extruder (i.e. 0-100rpm). Three samples of process mass throughput were also measured within the last 3 minutes of each processing condition (i.e. after process became steady). The average value of these three samples was taken as the mass throughput at each of these conditions. Separate tests were carried out to collect the data for model training and validation (i.e. 6 different experimental trials altogether). Here, the data collected from test 1 was used for implementing the controller while the data collected from test 2 and test 3 were used for the controller's performance evaluation on an unseen screw geometry and an unseen material, respectively.

B. Modelling technique and the models used in the controller

For this study, the melt temperature of a die redial position which is $j$mm away from the melt flow centreline ($T_{m,j}$) was modelled as a function of screw speed, die radial position and barrel set temperatures as given in equation (4) and this is called the MTPP - model.

$$T_{m,j} = f(\omega_{sc}, R_{p,j}, T_1, T_2, T_3, T_4) \qquad (4)$$

The MTPP - model should predict the melt temperature value of each radial position assigned by the radial position input, and fifteen radial positions make a complete melt temperature profile across the die melt flow for this study. For a given time period, the model should estimate the melt temperature values of these fifteen positions individually by only changing the radial position input while the screw speed and barrel set temperatures remain constant.

A fast recursive algorithm [76] was used to model the process as a general nonlinear discrete-time dynamic MISO system which can be expressed as:

$$y(t) = f(y(t-1), y(t-2), ...y(t-n_1), ...y(t-n_a), u_i(t-n_{ik}), u_i(t-n_{ik}-1), ...u_i(t-n_{ik}-n_1), ...u_i(t-n_{ik}-n_{ib})) \quad (5)$$

where $y(t)$ is the system output at time t, $u_i(t), i = 1, \cdots, m$ are the system input variables at time t (m is the total number of inputs to the system), n_a is the number of poles, n_{ib} is the number of zeros plus 1 and n_{ik} is the corresponding delays (i.e. number of input samples that occur before each input affects the output) of each model input. To determine the delays, melt temperature variations at each redial position followed by the screw speed and barrel set temperature changes were observed from the experimentally measured signals. Based on these observations, values of delays attributed to each input were selected as: $d_{\omega_{sc}}$=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 conditions, etc. Ideally, the modelling algorithm would determine the delays automatically depending on the processing conditions and this will be considered under the future work.

The same modelling procedure was followed for the development of IRTP and mass throughput (i.e. $\bar{M}$ - model) prediction models. The temperature measured by the IR sensor was predicted as a function of the screw speed, barrel set temperatures and the predicted average melt temperature across the melt flow ($T_{m,act}$) by the MTPP model:

$$T_{IR} = f(\omega_{sc}, T_{m,act}, T_1, T_2, T_3, T_4) \qquad (6)$$

The process mass throughput ($\bar{M}$) was modelled as a function of the screw speed and barrel set temperatures:

$$\bar{M} = f(\omega_{sc}, T_1, T_2, T_3, T_4) \qquad (7)$$

Further details on the modelling procedure/technique can be found in the author's previous work [51], [52], [74], [77]–[80].

After studying a number of model combinations (i.e. models with different orders and a number of terms), a 2^{nd} order model with 15 terms (i.e. with a 1.22% normalized prediction error (NPE) on the validation data) and a 2^{nd} order model with 6 terms (i.e. with a 0.25% NPE on the validation data) were selected as MTPP and IRTP models and these are given in equations (8) and (9), respectively.

$$\begin{aligned}\hat{T}_{m,j}(t)=&0.8207 \times \hat{T}_{m,j}(t-1) + 0.3096 \times T_4(t-60)\\ &+0.0081 \times R_{p,j}(t) \times T_4(t-60) - 0.0223 \times R_{p,j}(t)^2\\ &+0.0134 \times R_{p,j}(t) \times T_2(t-120) + 0.0006 \times \omega_{sc}(t-10)^2\\ &-0.0113 \times \hat{T}_{m,j}(t-1) \times R_{p,j}(t) + 0.0638 \times T_3(t-90)\\ &-0.0012 \times \hat{T}_{m,j}(t-1) \times T_2(t-120)\\ &-0.0008 \times \hat{T}_{m,j}(t-1) \times \omega_{sc}(t-10)\\ &+0.0043 \times \omega_{sc}(t-10) \times T_1(t-150)\\ &+0.0008 \times \omega_{sc}(t-10) \times R_{p,j}(t)\\ &+0.0033 \times \omega_{sc}(t-10) \times T_2(t-120)\\ &-0.0037 \times \omega_{sc}(t-10) \times T_3(t-90)\\ &+T_{IR,Error} \pm bias \end{aligned} \quad (8)$$

$$\begin{aligned}\hat{T}_{IR}(t)=&0.9507 \times \hat{T}_{IR}(t-1) + 0.0003 \times T_1(t-150) \times T_2(t-120)\\ &+0.0276 \times \hat{T}_{m,act} - 0.0001 \times T_1(t-150) \times T_4(t-60)\\ &+9.9513 \times 10^{-05} \times T_3(t-90) \times T_4(t-60)\\ &-8.8588 \times 10^{-06} \times \omega_{sc}(t-10)^2 \end{aligned} \quad (9)$$

A 3^{rd} order model with 3 terms (i.e. with a 3.18% NPE on the validation data) was selected as the $\bar{M}$ - model to use in the controller and is shown in equation (10).

$$\begin{aligned}\hat{\bar{M}}=&3.392 \times 10^{-04} \times \omega_{sc} \times T_2 \times T_3 + 0.012 \times \omega_{sc}^2\\ &- 3.105 \times 10^{-07} \times {T_4}^3 \end{aligned} \quad (10)$$

The $\bar{M}$ - model was introduced into the controller with the purpose of increasing the number of linguistic rules which should help to uplift the controller's decision making accuracy. These models' inputs can be updated in real-time to obtain their outputs.

VI. Simulation Results of the Controller and Discussion

The proposed controller was implemented in Matlab-Simulink to check its performance on achieving targets and also to evaluate its responses on a set of unseen data and disturbances. The experimentally measured actual values of the screw speed, barrel set temperatures and the melt temperature measured by an IR temperature sensor were used as inputs to the controller. The set values of the average melt temperature across the melt flow and the mass throughput at each screw speed were determined based on the experimental results. The maximum allowable melt temperature variance ($T_{v,max}$) was set as zero to achieve the possible optimum control action to minimise the melt temperature fluctuations.

A. *The performance of the controller on achieving the desired average melt temperature and reducing the melt temperature variance*

The efficacy of the proposed controller was verified over the different screw speeds, and its performance on achieving the desired average melt temperature ($T_{m,avg}$) and reducing the melt temperature variance (T_v) across the melt flow at different screw speeds are shown in Figures 11-15 together with the adjustments made to the manipulated variables for achieving these set/desired outputs. All of these simulation studies on the controller's performance verification which are shown in this section were carried out on the data collected under the barrel set temperature conditions A and B (see Figure 10). Here, the process signals at 10rpm are shown over 900s while the signals at the other screw speeds are shown over 420s. This is because the experimental measurements were carried over 900s at the 10rpm while the measurements were made only over 420s at the other screw speeds. The process signals in the last 20s at each screw speed are not shown in figures as the screw speed step changes were applied during this time period. As shown in Figures 11-15, the controller has achieved the desired average melt temperature across the melt flow at all the situations tested. Slightly higher average melt temperature fluctuations (i.e. variations of between ±3°C around the set/desired temperature) can be observed at 50rpm and 70rpm speeds than other speeds. Significant reductions of the melt temperature variance can be observed at 30rpm, 70rpm and 90rpm speeds while slight reductions of melt temperature variance have achieved at 10rpm and 50rpm. Of the adjustments made to the manipulated variables, the largest adjustment has been made to the third barrel zone temperature (i.e. T_3) by the controller at 10rpm, 30rpm and 50rpm speeds while this has shifted between T_3 and screw speed (ω_{sc} or SS) at 70rpm and 90rpm screw speeds. Moreover, it is obvious that the controller has responded differently depending on the varying processing behaviours.

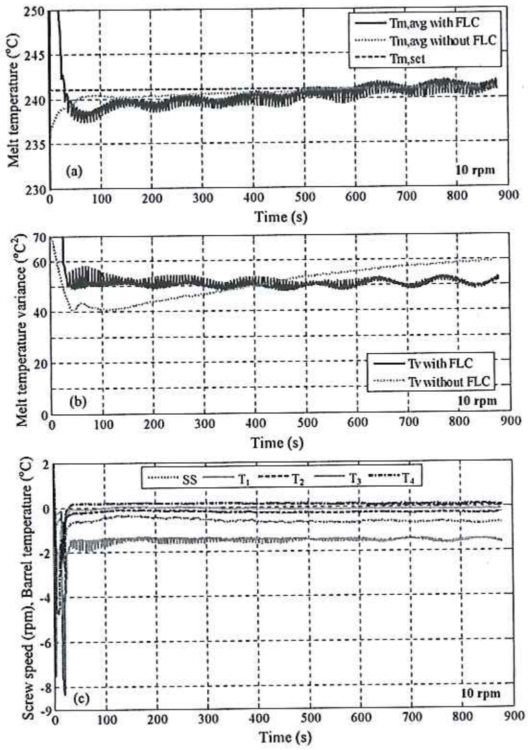

Figure 11. (a). Variations in $T_{m,avg}$ with and without FLC, (b). Melt temperature variance with and without FLC, (c). Controller adjustments to the manipulating variables from their set values (Set conditions: ω_{sc}=10rpm, T_1=110°C, T_2=130°C, T_3=180°C, T_4=230 °C)

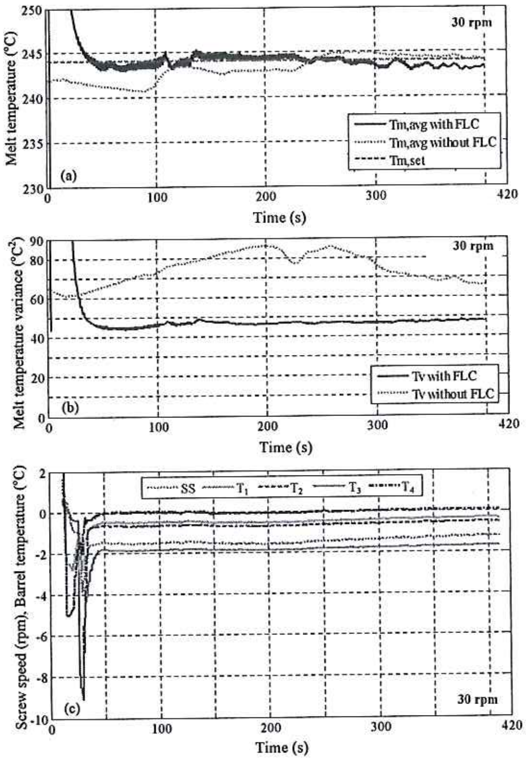

Figure 12. (a). Variations in $T_{m,avg}$ with and without FLC, (b). Melt temperature variance with and without FLC, (c). Controller adjustments to the manipulating variables from their set values (Set conditions: ω_{sc}=30rpm, T_1=110°C, T_2=130°C, T_3=180°C, T_4=230°C)

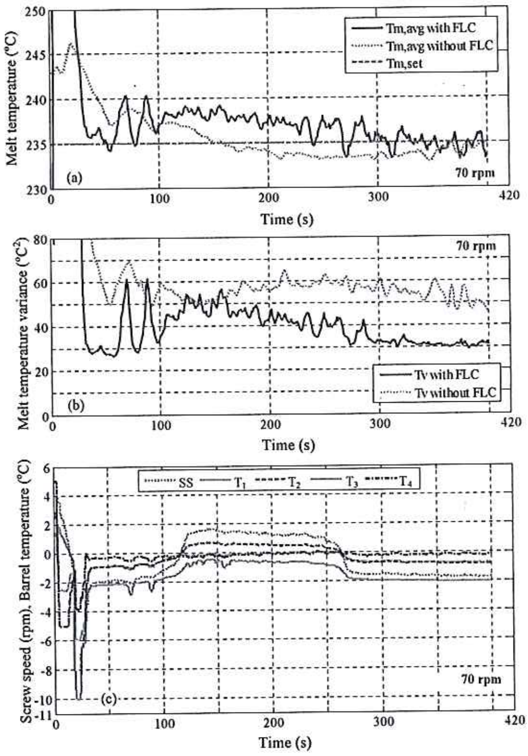

Figure 14. (a). Variations in $T_{m,avg}$ with and without FLC, (b). Melt temperature variance with and without FLC, (c). Controller adjustments to the manipulating variables from their set values (Set conditions: ω_{sc}=70rpm, T_1=110°C, T_2=130°C, T_3=180°C, T_4=230°C)

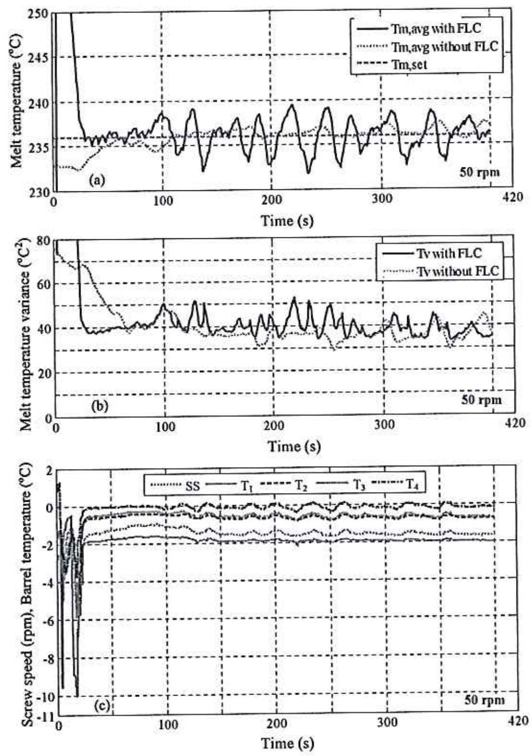

Figure 13. (a). Variations in $T_{m,avg}$ with and without FLC, (b). Melt temperature variance with and without FLC, (c). Controller adjustments to the manipulating variables from their set values (Set conditions: ω_{sc}=50rpm, T_1=110°C, T_2=130°C, T_3=180°C, T_4=230°C)

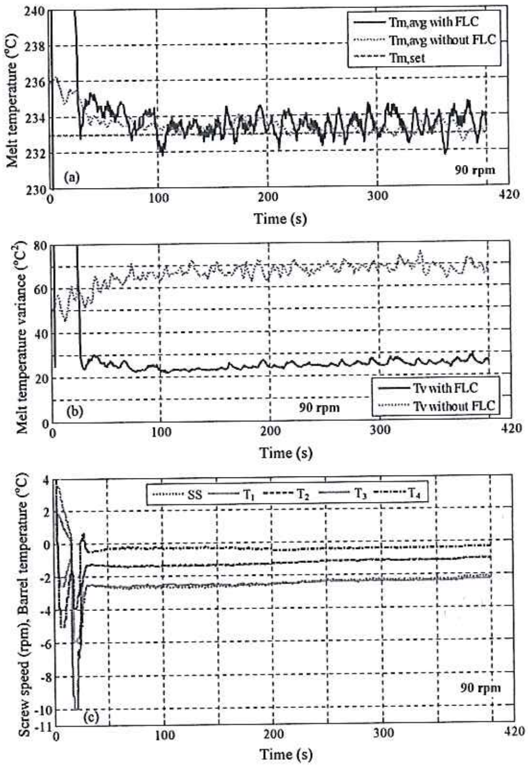

Figure 15. (a). Variations in $T_{m,avg}$ with and without FLC, (b). Melt temperature variance with and without FLC, (c). Controller adjustments to the manipulating variables from their set values (Set conditions: ω_{sc}=90rpm, T_1=110°C, T_2=130°C, T_3=180°C, T_4=230°C)

By observing these simulation results, it is clear that the controller has shown good performance in achieving the desired average melt temperature while minimizing the melt temperature variance. The experimental extruder was not instrumented with any melt temperature controller and only proportional-integral-derivative (PID) controllers were available to maintain the set temperature of each barrel zone in its set value. However, the simulation results show that the 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. Therefore, the newly proposed technique in this study seems to be highly suitable for maintaining the process melt thermal stability in polymer extrusion. As there is no any significant work reported in the literature for polymer extrusion process thermal control based on thermal profile measurements and/or artificial intelligence (AI) techniques, this would be a good starting point for future research on applying such techniques for the development of the polymer processing industry.

A barrier flighted screw with a Maddock mixer was used in the experiment which was carried out to collect the required data for the controller development. Usually, it is known that BF screws perform favourably (e.g. efficient melting and mixing) compared to conventional single flighted screws [10], [15]. In another experiment carried out by the author, relatively larger melt temperature variances were observed with a single flighted GC screw (i.e. the screw geometry most commonly used in industry) and temperature fluctuations increased as screw speed increased. Therefore, this type of controller may be highly useful for reducing/controlling of melting fluctuations at such conditions. Moreover, it seems that a technique like fuzzy logic has the capability of manipulating a number of variables together via a simple controller (i.e. based on linguistic rules) which is highly suitable for a process like polymer extrusion with heavily coupled process variables. Therefore, this approach should allow extruders to achieve the required process thermal stability (hence the melt quality) at higher screw speeds where energy efficiency is higher.

B. The performance of the controller on disturbances

Simulation results on a set of unseen data showed that the controller can perform well on achieving its targets as was discussed in the previous section. Subsequently, the responses of the controller over disturbances were checked by adding different sizes of step changes (i.e. 10, 20 and 30 units) to each individual process variable from their set values while others remained unchanged. Moreover, the responses of the controller were checked on an unseen material and screw geometry and these results are presented in the following sections.

1) Responses of the controller over 20 units of positive step change to the ω_{sc} and T_3: The responses of the controller on 20 units of positive step changes applied at the time of 200s (applied for 20s) to the screw speed and the third barrel zone temperature (T_3) at 30rpm are shown in Figures 16 and 17, respectively.

As shown in Figure 16-(b), the step increase of screw speed by 20rpm has caused to decrease the melt temperature

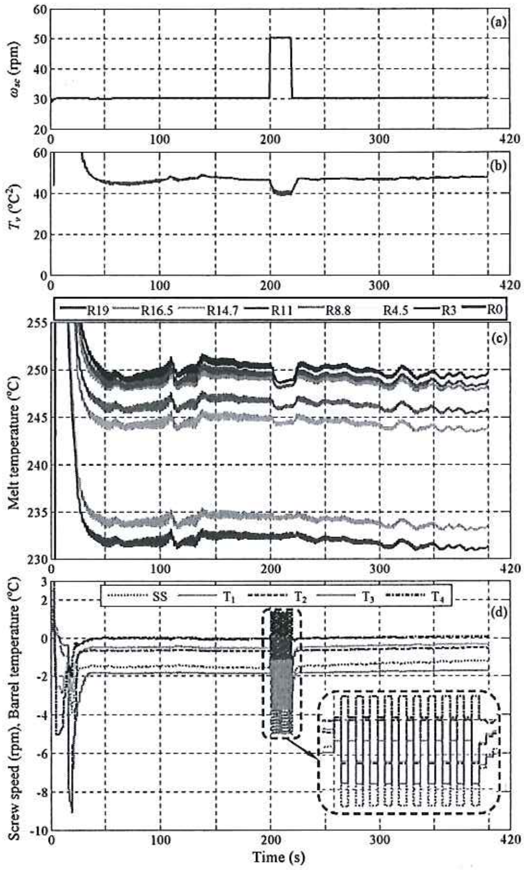

Figure 16. Responses of the controller over 20rpm step change of screw speed from 30rpm: (a). screw speed, (b). melt temperature variance, (c). melt temperature, (d). controller outputs

variance approximately by 7°C^2. However, an increase of the melt temperature variance approximately by 110°C^2 can be observed by following the 20°C step increase to the third barrel zone temperature (T_3) and this is evident by Figure 17-(b).

Moreover, the melt temperatures at all the radial positions have reduced due to the applied positive step changes in both ω_{sc} and T_3. However, these reductions are lower with the screw speed step change than the step change of the third barrel zone temperature. As shown in Figures 16-(d) and 17-(d), the controller has responded immediately after the applied step changes and has made adjustments to the manipulated variables throughout the period of disturbance. Also, it is noticeable that the controller has responded differently over the applied step changes to the screw speed and barrel set temperature. Moreover, the process operation has reached back to its normal conditions after removing the applied step changes to the screw speed and barrel set temperature approximately within 5s and 25s, respectively.

2) Responses of the controller over 20 units of positive step change to the feedback model: In addition to the process manipulated variables, a disturbance was introduced to the feedback model of the controller (IRTP - model) by applying a 20 units of positive step change at the time of 200s (applied

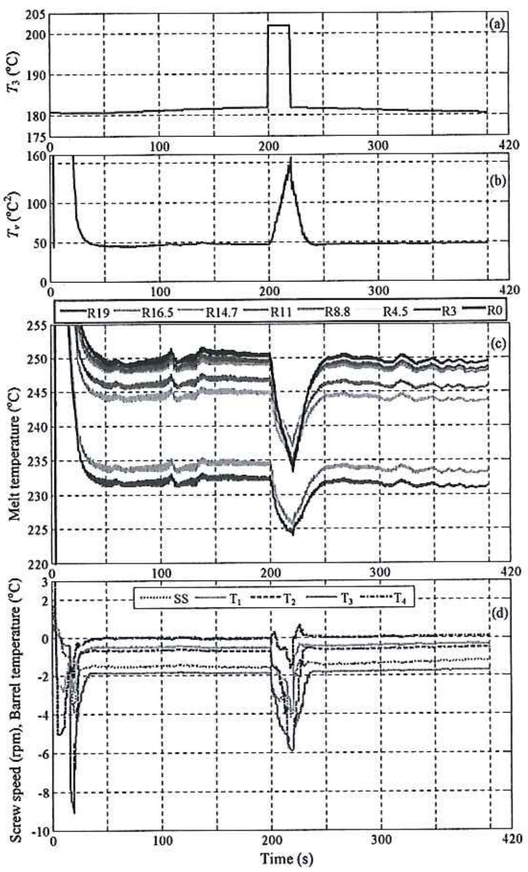

Figure 17. Responses of the controller over 20°C step change to the third barrel zone temperature (T3) from 180°C: (a). temperature at zone 3, (b). melt temperature variance, (c). melt temperature, (d). controller outputs

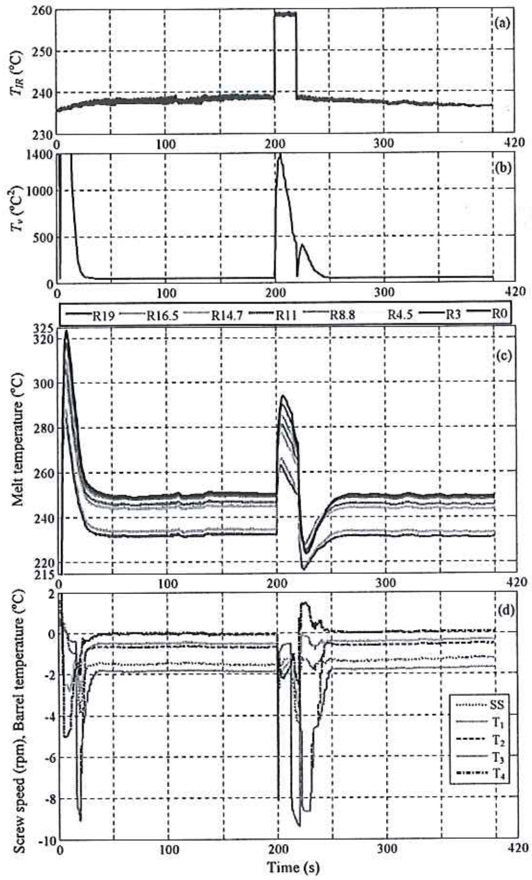

Figure 18. Responses of the controller over 20°C step change to the IR temperature (T_{IR}) input: (a). IR temperature, (b). melt temperature variance, (c). melt temperature, (d). controller outputs

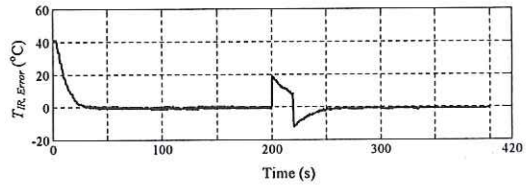

Figure 19. Controller's IR temperature prediction error over 20°C step change to the IR temperature (T_{IR}) input

for 20s) to the measured IR temperature input when the process was operating at 30rpm screw speed. The applied step change to the IR temperature signal, changes occurred to both process melt temperature variance and melt temperature due to the applied step change and the adjustments made by the controller to the manipulated variables followed by the applied step change are shown in Figure 18. Moreover, the effects of the applied step change on the IR temperature prediction ($T_{IR,Error}$) and the average melt temperature across the melt flow ($T_{m,avg}$) are shown in Figures 19 and 20, respectively.

As shown in Figure 18-(b), a significantly higher increment of melt temperature variance across the melt flow (i.e. around 1350°C) than the conditions observed with the screw speed and the third barrel zone temperature can be noticed with the applied step increase by 20°C to the feedback model. This large increment of melt temperature variance has reflected by the changes occurred to the melt temperatures at all the melt flow radial positions as shown in Figure 18-(c). Although, only one spike was observed in the melt temperature variance signals followed by the applied step changes to the ω_{sc} and T_3, two spikes can be observed in the melt temperature variance signal followed by the step change applied to the feedback model. This is an indication of an oscillating behaviour of the controller as it was trying to reach its normal operation by rejecting the disturbance. Therefore, the small spike shown in Figure 18-(b) is relevant to a lagging process operating behaviour (i.e. process output is in a lower level than the set/expected value). As a variance is always positive in sign, it shows a positive spike instead of a negative spike. This oscillatory behaviour can be clearly observed from the process melt temperature and $T_{IR,Error}$ signals as well. The average melt temperature signal (i.e. shown in Figure 20) shows +36°C and -19°C level changes approximately by following this oscillatory behaviour. Moreover, the magnitudes of the adjustments made by the controller to the manipulated variables to compensate for the step change applied to the feedback model are higher than the magnitudes applied for compensating of step changes applied to the screw speed and third barrel zone temperature. These observations emphasise that the feedback

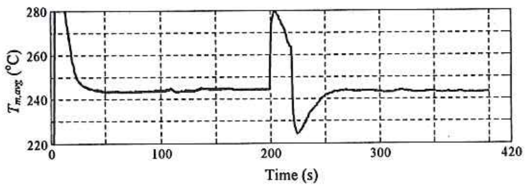

Figure 20. Controller's $T_{m,avg}$ response over 20°C step change to the IR temperature (T_{IR}) input

model has a significant impact on the controller's performance and hence obtaining an accurate feedback is highly important. Although, the disturbance applied on the feedback model shows a significant influence to the controller's operation, the process operation has reached back to its normal conditions approximately after 40s of removing the applied disturbance to the feedback model.

As it was evident, the controller settled back to the normal operating conditions just after removing the applied disturbances on its manipulated variables and the feedback by showing a good disturbance rejection ability. The performance of the controller on disturbances was further evaluated at the other screw speeds by applying both positive and negative step changes to the each manipulated variable and good disturbance rejection capability was observed in all the situations tested.

C. The performance of the controller on an unseen material

The results presented in the above on the controller's performance are relevant to the data obtained from the processing of a HDPE with a BF screw (i.e. collected from test 1) and hence it is called HDPE-BF controller on here onwards. After evaluating the HDPE-BF controller's performance on changes/disturbances to the process variables and the feedback model, its responses to an unseen material were checked by using a set of data obtained from the processing of a regrind polypropylene (RPP) with the same BF screw. However, RPP was processed at a higher barrel temperature setting than used for processing of HDPE as shown in Table I and some other details relevant to the RPP data used to observe the controller's responses are as below:

- Screw speed: 50rpm
- Average melt temperature across the melt flow: 241°C
- Average melt temperature variance across the melt flow: 26.5°C^2

The major problem observed with this unseen material was that the melt temperature profile prediction mechanism within the controller was not able to accurately predict the actual level of average melt temperature across the melt flow and this was confirmed by the very high IR temperature prediction error of around 40°C as evident by Figure 21. As shown in Figure 22, the simulation results show that the predicted average melt temperature is around 189°C although the controller's simulation was carried out by setting the desired average melt temperature as 241°C. Moreover, the difference between the predicted and the actual average melt temperatures is always higher than 50°C. As a result, a very high melt temperature variance (i.e. around 1500°C^2) has caused as shown in Figure 23.

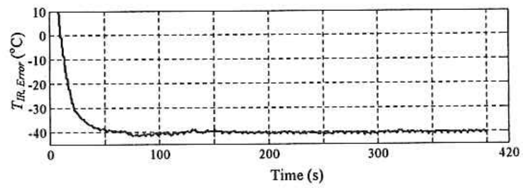

Figure 21. IR temperature prediction error of the HDPE-BF controller on an unseen material (RPP with the same BF screw) at 50rpm

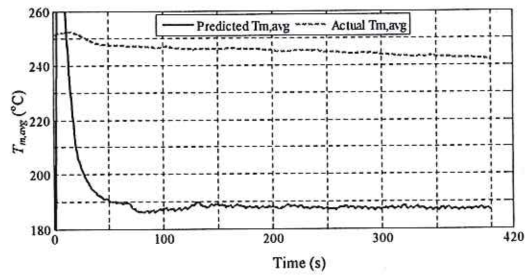

Figure 22. The predicted $T_{m,avg}$ by the HDPE-BF controller on an unseen material (RPP with the same BF screw) and the actual $T_{m,avg}$ (i.e. experimentally measured) at 50rpm

Perhaps, the actual melt temperature that would be achieved by HDPE at the barrel temperature setting which the RPP was processed would be lower than the melt temperature achieved by RPP. Therefore, the models developed for HDPE may not be capable of predicting the RPP temperature level accurately. In such a situation, the controller may not be able to make precise control decisions and some possible reasons which may cause to such poor performance are given below:

- As was realised from the extensive experimental studies [49], the effects of the individual process parameters on process thermal homogeneity are dependent upon material and screw geometry. Therefore, the formulated fuzzy rules may be specific to the screw geometry and material used for experiments and hence decisions made by the controller may not be accurate for another screw geometry or material.
- Errors generated in such situations may be very large in quantity and these may lie out of the defined controller ranges and hence the controller may not be able to respond appropriately. The defined ranges of the HDPE-BF controller inputs: $E(T_v)$: -50°C^2 to 900°C^2, $E(\bar{M})$: -200g/min to 200g/min, $E(T_{m,avg})$: -100°C to 100°C.

In general, it seems that the proposed controller has some limitations on performing its operation over different materials (i.e. which did not use for the model development

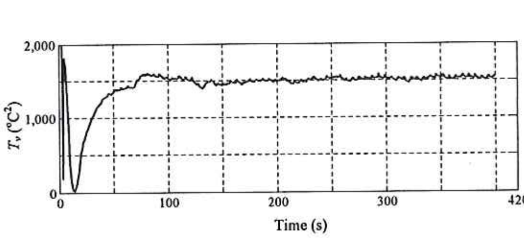

Figure 23. The melt temperature variance achieved by the HDPE-BF controller on an unseen material (RPP with the same BF screw) at 50rpm

experiments). Perhaps, the controller might have shown better performance on this unseen material if both materials were processed under the same process setting.

D. The performance of the controller on an unseen screw geometry

The performance of the HDPE-BF controller on an unseen screw geometry was also evaluated by using a set of data obtained from the processing of the same material (HDPE-HYA800) under the same barrel temperature setting but with a single flighted GC screw. The experimental settings used with the GC screw are shown in Table I and some other details relevant to the data used to evaluate the controller's responses on an unseen screw geometry are as below:

- Screw speed: 50rpm
- Average melt temperature across the melt flow: 227°C
- Average melt temperature variance across the melt flow: 70.5°C^2

The controller shows only around 7°C IR temperature prediction error with the unseen screw geometry as shown in Figure 24 where it was around 40°C with the unseen material tested.

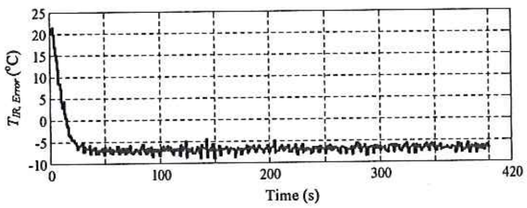

Figure 24. IR temperature prediction error of the HDPE-BF controller on an unseen screw geometry (the same material with a GC screw) at 50rpm

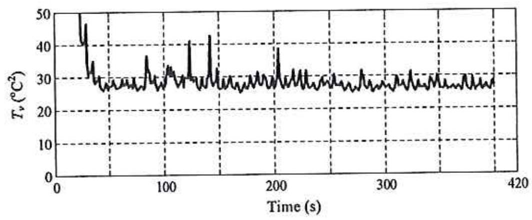

Figure 25. The melt temperature variance achieved by the HDPE-BF controller on an unseen screw geometry (the same material with a GC screw) at 50rpm

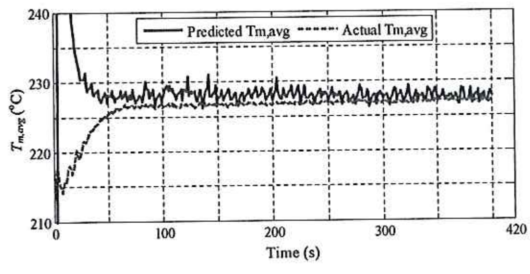

Figure 26. The predicted $T_{m,avg}$ by the HDPE-BF controller on an unseen screw geometry (the same material with a GC screw) and the actual $T_{m,avg}$ (i.e. experimentally measured) at 50rpm

As shown in Figure 25, the melt temperature variance achieved by the controller across the melt flow on the unseen screw geometry is around 28°C^2 and this is around 42°C^2 reduction of the melt temperature variance than achieved by the experiments. Moreover, the difference between the controller predicted and the actual average melt temperatures is only around 2°C as shown in Figure 26 where it was around 54°C with the unseen material tested. However, the difference between the actual (i.e. experimentally measured) average melt temperatures at the conditions of the HDPE-BF controller and the unseen material is lower than the difference between the conditions of the HDPE-BF controller and the unseen screw geometry as shown in Table II.

Table II
ACTUAL AVERAGE TEMPERATURE ACROSS THE MELT FLOW AT DIFFERENT EXPERIMENTAL CONDITIONS AT 50RPM

Condition	Barrel temperature setting/Screw/Material	Actual average melt temperature (°C)
HDPE-BF controller	A-B/BF/HDPE	236
Unseen material	D-E/BF/RPP	241
Unseen screw geometry	A-B/GC/HDPE	227

Therefore, one of the major reasons for having a relatively good performance with the unseen screw geometry may be that both of these experiments were carried out under the same barrel set temperatures with the same material. Perhaps, the effects of material properties on melting (particularly on the level of the melt temperature) may be significant than the effects of screw geometry under the same processing condition in this case. However, it is not reasonable to draw overall conclusions only based on these results as the polymer extrusion is a highly complex and variable process in nature. The processing behaviour may significantly vary based on the material, machine and processing conditions used.

E. The controller's operation in practice

By observing the controller's performance, it is clear that the controller has some limitations on performing over unseen materials and screw geometries. Therefore, the development of generalised models to be compatible with different materials, screw geometries and process settings are highly desirable in expanding the usefulness of the controller in industrial applications and hence recommended for possible future research. Further improvements to the controller's performance may 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 an IR temperature sensor if available), improving fuzzy rules, etc.

At this stage, this control strategy is proposed only for single screw extruders and this technique should be applicable to multi screw extruders as well. In the application of the proposed techniques into the multi screw extruders, the generalised models should be developed by studying their processing behaviours. Although the same model structure/s can be used, additional process and machine geometrical parameters may need to be considered depending on the type of the machine. In fact, there is no fundamental issue of using the thermocouple mesh technique on multi screw extruders but this may depend on the processing speeds, output channel shape and size, access requirements, etc. Obviously these factors can be explored in detail under future work.

In the long run, the drifts of the process may be a problem on the performance of the soft sensing mechanism within the controller and hence it should be compensated either by adapting or re-developing the model/s [81]. Similarly, the accuracy of process measurements is also important for the better performance of the controller. That is because the models developed are based on the measured experimental data and if these measurements are poor in accuracy resulting models would also be poor in accuracy. Moreover, the accuracy and reliability of the decisions made by the controller are also directly related to the quality/accuracy of the process parameter measurements made in real-time. Therefore, the use of highly accurate equipment for process measurements is a major requirement of a model-based control approach. Also, all of the sensors should be calibrated properly while avoiding possible offsets of their readings. A careful attention should be made on the possible effects of signal noise on the controller's performance. As was reported in the literature [21], [31], filtering of the signals should not be carried out only to avoid noise or large fluctuations in the measured signals to make it easy to design the controller. This may cause filtering of the fluctuations which may really affect the process functional quality and hence the decisions made by the controller may not be capable of controlling some of the process fluctuations which may adversely affect on the product quality. In fact, the best practice would be the achievement of the accurate measurements to the highest possible level by improving the quality of the sensors and data acquisitioning (DAQ) devices. If it is obvious that some of the information included in the measured signals are not relevant to the actual process, then these can be filtered by using a properly designed filter. As was observed from the experiments, process measurements such as pressure and temperature were not affected by noise once the DAQ system was properly designed and tuned. However, electrical variables (e.g. currents and voltages) were found to be more easily affected by noise than other measurements. In fact, electrical variables are not involved with the proposed control scheme. Sometimes, it would be difficult for industrial processes to follow all the procedures which are used in an experimental laboratory to make accurate process measurements. However, it would be better to check the accuracy of the sensors from time to time while observing the key process signals on a screen in real-time. Obviously, the real-time observation of the process signals on a screen allows to identify the accuracy of these measurements while making it is easy to determine the process functional quality.

VII. Conclusions

The inability of dealing with process nonlinearities and obtaining of the temperature feedback from less accurate point/bulk temperature sensors are the major shortcomings of the majority of the existing process controllers in polymer extrusion. In this work, a novel model-based control approach was proposed to overcome these shortcomings incorporating a melt temperature profile prediction soft sensor, empirical process models and fuzzy logic. A novel method introduced by the author, a soft sensor for temperature profile prediction, to predict the melt temperature at the different radial positions across the extruder output melt flow in polymer extrusion was used as the thermal monitoring technique of the newly proposed controller. The major purposes of the newly proposed controller were to minimize the melt temperature variations and to achieve the average melt temperature, both across the melt flow, while achieving the desired process output rate at a given speed. One of the major differences of the proposed control strategy over the existing methods is that this controller selects the control actions based on the average melt temperature across the melt flow rather than using a point/bulk measurement (i.e. taken from a sensor attached to the extruder barrel or die wall) which is less accurate although common in practice. Any possible uncertainties that may arise on the controller's performance due to the possible melt temperature prediction errors are avoided by correcting the melt temperature predictions with reference to an actual melt temperature measurement. Therefore, this controller concerns about the actual melt quality to make the control decisions unlike conventional thermal controllers which make control actions mostly based on the temperature of the extruder barrel/die wall (i.e. with reference to the temperatures measured from typical wall mounted thermocouples). Moreover, the proposed controller manipulates the screw speed and each barrel zone temperature by making adjustments to them individually (i.e. all of these variables manipulate in parallel) via a rule-based fuzzy logic control mechanism. Efficacy of the controller by achieving its targets and rejecting disturbances were also tested by simulation and good results were obtained. The controller settled back to the normal conditions within a short period of time (e.g. settled back to the normal conditions just after 40s followed by an applied 20°C positive step change to the feedback) after removing the applied disturbances to the manipulated variables and the feedback. Therefore, this may offer a promising approach to operate extruders at high screw speeds while achieving both high energy and thermal efficiencies simultaneously.

Based on the results achieved, it was felt that a technique like fuzzy logic which is good in handling process nonlinearities based on simple linguistic information is greatly suitable for control of highly complex processes like polymer extrusion with heavily coupled process variables. Therefore, further research on applying AI techniques to polymer process modelling and control is highly recommended. Further evaluation of the controller's performance showed that it has some limitations on performing over unseen materials and screw geometries. These limitations could be avoided by developing generalised models to be compatible with different materials, screw geometries and processing conditions; and further research is underway on this purpose. The possible methods of improving the performance of the controller and extending its application to be compatible with other types of extruders, polymer processes and polymer materials will also be explored under future work.

REFERENCES

[1] D. V. Rosato, *Extruding plastics - A practical processing handbook.* Springer:Verlag, 1998.

[2] P. D. Coates, "In-line rheological measurements for extrusion process control," *Transactions of the Institute of Measurement and Control*, vol. 28, no. 1, pp. 10–16, 1995.

[3] M. A. Spalding and K. S. Hyun, "Troubleshooting mixing problems in single-screw extruders," *SPE ANTEC Technical Papers*, vol. 1, pp. 229–233, 2003.

[4] B. H. Maddock, "A visual analysis of flow and mixing in extruder screws," *SPE Journal*, vol. 15, no. 5, pp. 383–389, 1959.

[5] C. Rauwendaal, *Polymer extrusion*, 4th ed. Hanser:Munich, 2001.

[6] M. J. Stevens and J. A. Covas, *Extruder principles and operation.* Chapman and Hall, 1995.

[7] C. Abeykoon, *Polymer Extrusion: A Study on Thermal Monitoring Techniques and Melting Issues.* Lap Lambert Academic Publishing:Verlag, 2012.

[8] J. L. White, *Twin screw extrusion: Technology and principles.* Hanser:Munich, 1991.

[9] P. H. Squires and F. W. Wolf, "Designing extruders for quality performance," *SPE Journal*, vol. 24, no. 4, pp. 68–73, 1971.

[10] E. C. Brown, A. L. Kelly, and P. D. Coates, "Melt temperature homogeneity in single screw extrusion: effect of material type and screw geometry," *SPE ANTEC Technical Papers*, vol. 1, pp. 183–187, 2004.

[11] C. G. Gogos and M. H. Kim, "Melting phenomena and mechanism in polymer processing equipment," *SPE ANTEC Technical Papers*, vol. 1, 2000, paper No: 475.

[12] R. T. Fenner, *Principals of polymer processing.* Macmillan:London, 1979.

[13] C. Abeykoon, M. McAfee, K. Li, P. J. Martin, and A. L. Kelly, "The inferential monitoring of screw load torque to predict process fluctuations in polymer extrusion," *Journal of Materials Processing Technology*, vol. 211, no. 12, pp. 1907–1918, 2011.

[14] Y. Breaux, J.-Y. Charmeau, and M. Moguedet, "A simple model of throughput and pressure development for single screw," *Journal of Materials Processing Technology*, vol. 209, no. 1, pp. 611–618, 2009.

[15] A. L. Kelly, E. C. Brown, and P. D. Coates, "The effect of screw geometry on melt temperature profile in single screw extrusion," *Polymer Engineering and Science*, vol. 46, no. 12, pp. 1706–1714, 2006.

[16] A. L. Kelly, E. C. Brown, and P. D. Coates, "Melt temperature field measurement in single screw extrusion: influence of melt pressure and die geometry," *SPE ANTEC Technical Papers*, vol. 1, pp. 291–295, 2005.

[17] C. Rauwendaal and G. van der Sluis, "Effect of screw surface on extruder performance," *SPE ANTEC Technical Papers*, vol. 1, pp. 313–316, 2004.

[18] K. Wilczyski, "Evaluating screw performance in a single screw extruder," *Polymer-Plastics Technology and Engineering*, vol. 28, no. 7-8, pp. 671–690, 1989.

[19] A. K. Wood and R. Rasid, "Effect of process variables on melt velocity profiles in extrusion process using single screw plastics extruder," *Plastics, Rubber, & Composites*, vol. 32, no. 5, pp. 193–198, 2003.

[20] H. W. Gitschner and J. Lutterback, "Influences of barrel wall temperature on melt throughput fluctuations in the single screw extruder," *Kunststoffe-German Plastics*, vol. 74, no. 1, pp. 7–8, 1984.

[21] W. Fontaine, Ph.D. dissertation, Ohio State University, Ohio, 1975.

[22] D. Fingerle, "Autogenic melt temperature control system for plastic extrusion," *Journal of Elastomers and Plastics*, vol. 10, no. 4, pp. 293–310, 1978.

[23] S. Dormeier, "Digital temperature control - A way to improve the extrusion process," *SPE ANTEC Technical Papers*, pp. 216–219, 1979.

[24] C. Muhrer, C. Guerrero, and W. I. Patterson, "Extruder temperature behaviour," *SPE ANTEC Technical Papers*, pp. 95–98, 1983.

[25] D. Chan and L. J. Lee, "Dynamic modelling of a single screw plasticating extruder," *SPE ANTEC Technical Papers*, pp. 77–80, 1984.

[26] D. Chan, R. W. Nelson, and L. J. Lee, "Dynamic behaviour of a single screw plasticating extruder part II: Dynamic modelling," *Polymer Engineering and Science*, vol. 26, no. 20, pp. 152–161, 1986.

[27] R. W. Nelson, D. Chan, B. Yang, and L. J. Lee, "Dynamic behaviour of a single screw plasticating extruder part I: Experimental study," *Polymer Engineering and Science*, vol. 26, no. 20, pp. 144–151, 1986.

[28] A. K. Kochhar and J. Parnaby, "Dynamic modelling and control of plastics extrusion processes," *Automatica*, vol. 13, no. 2, pp. 177–183, 1977.

[29] J. Parnaby, A. K. Kochhr, and B. Wood, "Development of computer control strategies for plastic extruders," *Polymer Engineering and Science*, vol. 15, no. 8, pp. 594–605, 1975.

[30] G. A. Hassan and J. Parnaby, "Model reference optimal steady-state adaptive computer control of plastics extrusion processes," *Polymer Engineering and Science*, vol. 21, no. 5, pp. 276–284, 1981.

[31] M. H. Costin, P. A. Taylor, and J. D. Wright, "On the dynamics and control of a plasticating extruder," *Polymer Engineering and Science*, vol. 27, no. 17, pp. 1095–1106, 1982.

[32] D. D. Germuska, P. A. Taylor, and J. D. Wright, "Adaptive and multivariable control of a single screw extrusion system," *The Canadian Journal of Chemical Engineering*, vol. 62, no. 6, pp. 790–801, 1984.

[33] E. B. Dahlin, "Design and tuning digital controllers," *Instruments and Control Systems*, vol. 41, no. 6, pp. 77–83, 1968.

[34] J. S. Taur, C. W. Tao, and C. C. Tasi, "Temperature control of a plastic extrusion barrel using PID fuzzy controllers," *International IEEE/IAS Conference on Industrial Automation and Control: Emerging Technologies, Taipei, Taiwan*, pp. 370–375, 1995.

[35] C. C. Tasi and C. H. Lu, "Fuzzy supervisory predictive PID control of a plastics extruder barrel," *Journal of the Chinese Institute of Engineers*, vol. 21, no. 5, pp. 619–624, 1998.

[36] I. Yusuf, N. Iksan, and N. S. Herman, "A temperature control for plastic extruder used fuzzy genetic algorithms," *International Multi Conference of Engineers and Computer Scientists, Hong Kong*, vol. 2, pp. 1075–1080, 2010.

[37] S. Ravi and P. A. Balakrishnan, "Temperature response control of plastic extrusion plant using Matlab/Simulink," *International Journal of Recent Trends in Engineering and Technology*, vol. 3, no. 4, pp. 135–140, 2010.

[38] S. Ravi and P. A. Balakrishnan, "Stable self tuning genetic fuzzy temperature controller for plastic extrusion system," *International Journal of Reviews in Computing*, vol. 3, pp. 21–28, 2011.

[39] S. Ravi and P. A. Balakrishnan, "Modelling and control of an ANFIS temperature controller for plastic extrusion process," *IEEE International Conference on Communication Control and Computing Technologies*, pp. 314–320, 2010.

[40] S. Ravi and P. A. Balakrishnan, "Design of synthetic optimizing neuro fuzzy temperature controller for dual screw profile plastic extruder using Labview," *Journal of Computer Science*, vol. 7, no. 5, pp. 671–677, 2011.

[41] G. Menges and M. Meissner, "Improvement in extruder melt temperature control," *Journal of Macromolecular Science: Part A - Chemistry*, vol. 6, no. 3, pp. 641–656, 1972.

[42] J. V. Leeuwen, "Stock temperature measurement in plastifying equipment," *Polymer Engineering and Science*, vol. 7, no. 2, pp. 98–109, 1967.

[43] J. Dastych, P. Wiemer, and H. Unbehauen, "Robust and adaptive control of a single screw plastics extruder," *Adaptive Control of Chemical Processes (ADCHEM 88)*, pp. 171–176, 1988.

[44] P. Wiemer and H. Unbehauen, "Decentralized discrete model reference adaptive control," *Proceedings of the 10th IFAC World Congress, Munich, Germany*, vol. 7, pp. 61–66, 1987.

[45] P. K. Mercure and R. Trainor, "Modelling and optimization of extruder temperature control," *Computer Applications in Applied Polymer Science II - American Chemical Society*, pp. 490–506, 1989, 38.

[46] J. J. Lin and G. Lee, "System identification for state feedback integral observer control of polymer plastic extrusion," *Polymer-Plastics Technology and Engineering*, vol. 36, no. 5, pp. 749–775, 1997.

[47] F. Previdi, S. M. Savaresi, and A. Panarotto, "Design of a feedback control system for real-time control of flow in a single-screw extruder," *Control Engineering Practice*, vol. 14, no. 9, pp. 1111–1121, 2006.

[48] C. Abeykoon, P. J. Martin, A. L. Kelly, and E. C. Brown, "An evaluation of melt temperature sensors for polymer extrusion," *Sensors & Actuators A: physical*, vol. 182, pp. 16–27, 2012.

[49] C. Abeykoon, "Modelling and control of melt tempearture in polymer extrusion," Ph.D. dissertation, Queen's University Belfast, United Kingdom, 2011.

[50] C. Abeykoon, P. J. Martin, A. L. Kelly, K. Li, E. C. Brown, and P. D. Coates, "Investigation of the temperature homogeneity of die melt flows in polymer extrusion," *Polymer Engineering and Science*, 2013, DOI: 10.1002/pen.23784.

[51] C. Abeykoon, P. J. Martin, K. Li, and A. L. Kelly, "Dynamic modelling of die melt temperature profile in polymer extrusion: Effects of process settings, screw geometry and material," *Journal of Applied Mathematical Modelling*, 2013, DOI: 10.1016/j.apm.2013.08.004.

[52] C. Abeykoon, K. Li, M. McAfee, P. J. Martin, Q. Niu, A. L. Kelly, and J. Deng, "A new model based approach for the prediction and optimisation of thermal homogeneity in single screw extrusion," *Control Engineering Practice*, vol. 19, no. 8, pp. 862–874, 2011.

[53] C. Abeykoon, M. McAfee, K. Li, A. L. Kelly, and E. C. Brown, "Monitoring the effect of operating conditions on melt temperature homogeneity in single-screw extrusion," *SPE ANTEC Technical Papers*, vol. 1, pp. 1799–1806, 2010.
[54] E. C. Brown, A. L. Kelly, and P. D. Coates, "Melt temperature field measurement in single screw extrusion using thermocouple meshes," *Review of Scientific Instruments*, vol. 75, no. 11, pp. 4742–4748, 2004.
[55] X. Shen, R. Malloy, and J. Pacini, "An experimental evaluation of melt tempearture sensors for thermopalstic extrusion," *SPE ANTEC Technical Papers*, pp. 918–926, 1992.
[56] K. D. Sabota, D. R. Lawson, and J. S. Huizinga, "Advanced temperature measurements in polymer extrusion," SPE ANTEC Tech. Papers, pp. 2832–2842, 1995.
[57] A. J. Bur, M. G. Vangel, and S. C. Roth, "Fluorescence based temperature measurements and applications to real-time polymer processing," *Polymer Engineering and Science*, vol. 41, no. 8, pp. 1380–1389, 2001.
[58] K. M. Passino and S. Yurkovich, *Fuzzy control*. Addison-Wesley, 1998.
[59] J. Vlachopoulos, "Recent progress and future challenges in computer-aided polymer processing analysis and design," *Report Presented at the ATV-Semapp Meeting, Funen, Denmark*, 1998.
[60] C. Rauwendaal, G. Armstrong, and S. Unruh, "High precision extrusion lines," *SPE ANTEC Technical Papers*, vol. 1, pp. 406–410, 1996.
[61] H. Zhang, "Why use fuzzy logic?" Available from: http://www.aptronix.com/de/whyfuzzy.htm, 2011, [Assessed 22/02/2011].
[62] A. M. F. Fileti, A. J. B. Antunes, F. V. Silva, V. Silveira, and J. A. F. R. Pereira, "Experimental investigations on fuzzy logic for process control," *Control Engineering Practice*, vol. 15, no. 9, pp. 1149–1160, 2007.
[63] C. W. D. Silva, "Applications of fuzzy logic in the control of robotic manipulators," *Fuzzy Sets and Systems*, vol. 70, no. 2-3, pp. 223–234, 1995.
[64] L. A. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, no. 3, pp. 338–353, 1965.
[65] L. A. Zadeh, G. J. Klir, and B. Yuan, *Fuzzy sets, fuzzy logic, fuzzy systems: selected papers by Lotfi A. Zadeh*. World Scientific Press, 1996.
[66] J. S. R. Jang, C. T. Sun, and E. Mizutani, *Neuro-Fuzzy and soft computing: A computational approach to learning and machine intelligence*. Prentice Hall, 1997.
[67] J. Jantzen, "Design of fuzzy controllers," *Technical Report: 98-E 864, Technical University of Denmark*, 1998.
[68] E. H. Mamdani and S. Assilian, "An experiment in linguistic synthesis with a fuzzy logic controller," *International Journal of Man-Machine Studies*, vol. 7, no. 1, pp. 1–13, 1975.
[69] S.-J. Wu and C.-T. Lin, "Optimal fuzzy controller design in continuous fuzzy system: global concept approach," *IEEE Transactions on Fuzzy Systems*, vol. 8, no. 6, pp. 713–729, 2000.
[70] S.-J. Wu and C.-T. Lin, "Discrete-time optimal fuzzy controller design: global concept approach," *IEEE Transactions on Fuzzy Systems*, vol. 10, no. 1, pp. 21–38, 2002.
[71] J. R. Timothy, *Fuzzy logic with engineering applications*, 2nd ed. Wiley-Blackwell, 2004.
[72] M. Fazzolari, R. Alcala, Y. Nojima, H. Ishibuchi, and F. Herrera, "A review of the application of multiobjective evolutionary fuzzy systems: Current status and further directions," *IEEE Transactions on Fuzzy Systems*, vol. 21, no. 1, pp. 45–65, 2013.
[73] C. Abeykoon, "A novel soft sensor for real-time monitoring of die melt temperature profile in polymer extrusion," 2012, *Patent Application Number: LK/P/1/16984*.
[74] C. Abeykoon, "A novel soft sensor for real-time monitoring of die melt temperature profile in polymer extrusion," 2013, *Under review of the IEEE Tranactions on Industrial Electronics*.
[75] F. D. Sciascio and R. Carelli, "Fuzzy basis functions for triangle-shaped membership functions: Universal approximation - MISO case," *IFSA 95, Sao Paulo, Brazil*, vol. 11, no. 5, pp. 439–442, 1995.
[76] K. Li, J. Peng, and E. Bai, "A two-stage algorithm for identification of nonlinear dynamic systems," *Automatica*, vol. 42, no. 7, pp. 1189–1197, 2006.
[77] C. Abeykoon, A. L. Kelly, P. J. Martin, and K. Li, "Dynamic modelling of die melt temperature profile in polymer extrusion," *IEEE Conference on Decision and Control, Florence, Italy*, 2013, *Accepted - Submission No: 477*.
[78] C. Abeykon, K. Li, P. J. Martin, and A. L. Kelly, "Monitoring and modelling of the effects of process settings and screw geometry on melt pressure generation in polymer extrusion," *International Journal of System Control and Information Processing*, vol. 1, no. 1, pp. 71–88, 2012.
[79] C. Abeykon, K. Li, P. J. Martin, and A. L. Kelly, "Modeling of melt pressure development in polymer extrusion: Effects of process settings and screw geometry," *3rd IEEE International Conference on Modelling, Identification and Control*, pp. 197–202, 2011.
[80] C. Abeykoon, K. Li, M. McAfee, P. J. Martin, J. Deng, and A. L. Kelly, "Modelling the effects of operating conditions on on die melt temperature homogeneity in single screw extrusion," *UKACC International Conference on Control*, pp. 42–47, 2010.
[81] H. Kaneko and K. Funatsu, "Development of high predictive soft sensor method and the application to industrial polymer processes," *Asia-Pacific Journal of Chemical Engineering*, vol. 7, no. S1, pp. S39–S47, 2012.

Chamil Abeykoon obtained his BSc in Mechanical Engineering from the University of Peradeniya, Sri Lanka, with the award of best performance in Mechanical Engineering in the year 2007. Then, he worked in the same department as an Assistant Lecturer in Mechanical Engineering until commencing his postgraduate studies in the year 2008. He obtained his PhD in Mechanical Engineering in the year 2011 from the Queens University Belfast, United Kingdom, with 18 research publications, a patent application, and a young author best paper award from the IEEE. After his PhD, he worked as a Lecturer in Mechanical Engineering at the University of Peradeniya for a short period. Currently, Chamil is a Research Fellow in Engineering of the University of Bradford, United Kingdom, and he is due to take-up a new position as a Lecturer in Engineering of the Glyndwr University, United Kingdom, from the beginning of the year 2014. So far, he has produced 16 journal papers and 13 conference papers; and his current research interests include process monitoring, modelling and control; soft sensors and soft sensing; process instrumentation; energy efficiency; and heat transfer. Moreover, he is the author of the book *Polymer Extrusion: A Study on Thermal Monitoring Techniques and Melting Issues*. He is an associate member of the IESL, IMechE and ICPM, and also he became a graduate student member of the IEEE in the year 2011. Furthermore, Chamil provides his service to the industry as an engineering consultant to solve problems which comes under his research expertise.