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Adaptive neuro-fuzzy controller for real-time melt pressure control in polymer extrusion processes

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Abstract— **Melt pressure is a key indicator of melt flow stability and quality in polymer extrusion processes. The melt pressure level affects the degree of mixing and melt pressure stability which in turn influence the melt quality. Meanwhile, short-term melt pressure fluctuations result in dimensional variations in the extruded products in continuous extrusion processes. In industrial polymer extruders, the melt pressure is measured using pressure transducers installed close to the die entry. Process operators ensure the safe operation of the process based on these melt pressure measurements. This study proposes an intelligent control system based on the adaptive neuro-fuzzy inference system to manipulate the screw speed to maintain the melt pressure at a desired level while minimizing melt pressure fluctuations. Data recorded from an actual extrusion process was used to determine the parameters of the membership functions and the rule base of a Sugeno fuzzy inference system using neuro-fuzzy learning. The controller was designed and validated through simulation using Matlab Simulink. The results indicated that the proposed controller was capable of maintaining the desired melt pressure level while minimizing melt pressure fluctuations across different extrusion processing conditions, by manipulating the screw speed. Therefore, this will be an attractive solution to improve the dimensional stability and product quality of extruded products in continuous polymer extrusion processes.**

I. Introduction

POLYMER extrusion is a fundamental process that is used as an initial/intermediate process in manufacturing plastic products such as pipes, films, sheets, tubes, etc. [1]. Although the melt viscosity and the melt temperature distribution across the melt flow are considered as key indicators of the quality of the polymer melt, due to the limitations in the measuring instruments, these parameters are not monitored in real-time in industrial extrusion processes [2]. This inhibits the implementation of real-time quality control strategies resulting in material and energy wastage. Alternatively, in industrial polymer extrusion processes, melt pressure is used as a key indicator of the melt stability as it can be readily measured with a pressure transducer at the adaptor close to the die entry. Process operators use the melt pressure measurements to troubleshoot industrial extrusion processes and to ensure process safety.

The melt pressure level affects the throughput at a given screw speed, leading to variations in the melt temperature, degree of mixing, and melt pressure stability [3]. In continuous polymer extrusion processes, the melt stability directly affects the dimensional stability of the extruded product. Short-term melt pressure fluctuations, which are also known as ‘surging’, lead to dimensional variations in the extruded product in continuous polymer extrusion processes, and hence it is important to minimize these melt pressure fluctuations while maintaining an appropriate level of melt pressure [4]. Changes to the screw design can improve the melt stability of the process significantly [5]. However, proper selection and fine-tuning of extruder process settings for a given screw design and material should be able to further improve the melt stability of industrial extrusion processes.

To understand the pressure development in single-screw extrusion processes, several analytical and empirical models have been developed in past studies [6]-[12]. They are useful in identifying the effect of extrusion process parameters on melt pressure development, which in turn would be beneficial for implementing melt pressure control strategies.

The earliest works on extrusion control systems were focused on controlling the melt temperature and pressure as an indirect means of controlling the melt viscosity [13]. This was due to the difficulties in monitoring melt viscosity in real-time as mentioned earlier. Costin et al. [14] developed a control strategy to control the melt pressure by adjusting the screw speed, based on dynamic transfer function models. In another study, Dahlin feedback controllers were proposed to regulate both melt pressure and temperature with the aim of achieving the desired melt viscosity and extrudate dimensions [15]. The controller exhibited good steady-state control of the melt pressure and temperature. Lin and Lee [16] proposed an integral observer control technique, which incorporated a third-order state-space dynamic model to control melt pressure and temperature by manipulating the screw speed. Work by Previdi et al. [17] introduced classical proportional-integral-derivative (PID) controllers to control the melt

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temperature and pressure. A small-scale laboratory extruder equipped with the proposed controller exhibited better melt pressure control than an extruder equipped with a melt pump. Jiang et al. [18] developed a melt pressure controller based on generalized predictive control. This controller tracked the set points accurately, outperforming commercial PID controllers.

The majority of the reported past studies on controlling the melt pressure in polymer extrusion processes were based on traditional control approaches. With the advancements in artificial intelligence, control techniques based on fuzzy logic [13] and data-driven control [19] have become increasingly popular across a wide range of applications, due to their enhanced performance compared to traditional approaches.

This study introduces a controller based on the adaptive neuro-fuzzy inference system (ANFIS) to control the melt pressure in a single-screw extrusion process in real-time, by manipulating the screw speed. A Sugeno fuzzy inference system (FIS) was designed. The input membership functions and the rule base of the FIS were determined through adaptive neuro-fuzzy training using an experimentally collected dataset from an actual extrusion process. The ability of the controller to maintain a desired melt pressure level and to minimize melt pressure fluctuations were assessed via simulation across multiple processing conditions. To the best of the knowledge of the authors, no previous study has incorporated an ANFIS in developing a melt pressure controller for polymer extruders.

II. Methodology

In this study, a controller was designed and implemented through simulation to control the melt pressure at the die entry of a single-screw extrusion process. The aim of the study was to develop a control mechanism that manipulates the process control variables to maintain the melt pressure at a desired level without significant temporal variations. A control technique based on fuzzy logic was used considering its numerous benefits including the ability to handle complex nonlinearities in the process, the use of human-like reasoning based on a set of linguistic IF-THEN rules, simplicity, and low installation cost [13].

Mamdani and Takagi-Sugeno are widely used fuzzy inference systems that have been used across different control applications [20]. Despite the benefits that typical fuzzy controllers can offer, these fuzzy inference systems require the linguistic rules and membership functions to be defined manually based on expert knowledge of the process. This could be a tedious and time-consuming effort for complex industrial processes, while the performance of the controller may also be adversely affected by the inaccurate formulation of the fuzzy rule base. Hence, in this study, an ANFIS was used to design the controller as it allows the parameters of the membership functions as well as the rule base to be determined using actual process data rather than defining them arbitrarily. This requires a dataset of the extrusion process to allow the controller to learn from process data. Hence, this study was designed to have three key stages: (i) Data collection, (ii) Development of prediction models, and (iii) ANFIS controller design.

A. Data Collection

To collect the required dataset, an experimental trial was carried out on a Davis Standard BC-60 single-screw extruder with a screw diameter (D) of 63.5 mm. A barrier-flighted screw with a spiral Maddock mixer (with a 2.5:1 compression ratio) was used due to its efficient melting and mixing performance. The solids conveying, melting, and melt conveying zones of the screw had lengths of 5*D, 13*D, and 6*D, respectively. A schematic of the extruder is shown in Fig. 1. A virgin HDPE was selected as the polymeric material for the experimental trials (brand name: ExxonMobil HYA 800; density: 0.961 g.cm^{-3}; MFI: 0.7 g/10 min at 190 °C, 2.16 kg).

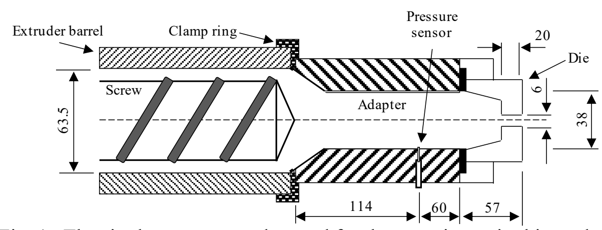


Fig. 1. The single-screw extruder used for the experiment in this study (dimensions are shown in millimeters)

Data collection was carried out under three different barrel set temperature conditions as indicated in Table I. The extruder had four main heating zones (denoted by T_1, T_2, T_3, and T_4) and three additional zones (at the clamp ring, adapter, and die). The temperatures at the three additional heating zones were maintained at the value of the last main heating zone (i.e., T_4). This was done to ensure that the consistency of the polymer melt was maintained until it entered the die. Under each temperature condition, the screw speed was varied between 0 and 90 rpm. Melt pressure was measured using a PT422A Dynisco pressure sensor installed at the adapter close to the die entry as shown in Fig. 1, while the screw speed and barrel set temperature data were recorded from the sensors in the extruder. A detailed explanation of the data collection procedure can be found in a previous study [2] by the authors and hence not discussed here. Based on this procedure, a total of 115,800 data points were collected at a frequency of 10 Hz. The dataset was later down-sampled to a frequency of 1 Hz by averaging over every 10 samples to reduce noise. The pre-processed dataset is shown in Fig. 2.

TABLE I
BARREL SET TEMPERATURES OF THE EXTRUDER

Temperature condition	Barrel set temperatures (°C)						
	Barrel heating zones				Clamp ring	Adapter	Die
	T_1	T_2	T_3	T_4			
A (High)	110	130	180	230	230	230	230
B (Medium)	105	125	175	215	215	215	215
C (Low)	100	120	170	200	200	200	200

B. Development of Prediction Models

Although the melt pressure at the die entry can readily be measured from the melt pressure transducers available on industrial extruders, a modelling technique is required to predict the response of the melt pressure to control decisions made by the controller in a simulation environment. To enable this, a deep learning model proposed by the authors in a previous study [2] was used to predict the melt pressure. Since the procedure for training and validating this model was discussed in detail in the previous study [2], they are not discussed here. The model was constructed by combining a deep autoencoder (DAE) with a multilayer perceptron neural network (NN), which takes in the screw speed and four barrel set temperatures of the extruder as inputs to predict the melt pressure at the die entry. The same fine-tuned hyperparameters reported in the previous study [2] were used to train the model. The trained DAE-NN melt pressure model recorded a training root mean square error (RMSE) of 0.247 and exhibited an RMSE of 0.250 on unseen test data.

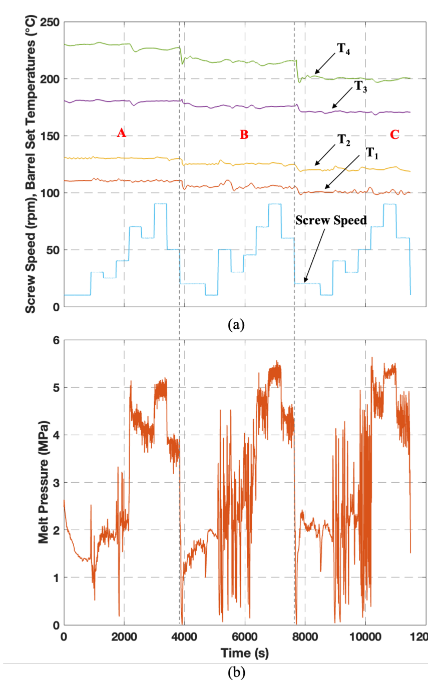


Fig. 2. Pre-processed dataset (a) variation of process settings (b) recorded melt pressure data during the experimental trial

In addition to the melt pressure, the mass throughput of the extruder was also used as an additional control variable to ensure that the extruder operates within the desired operating limits. As confirmed by White and Schott [21], control of melt pressure in the melt conveying zone (i.e., near the die entry) affects the output rate of the extruder. Hence, it is important to make sure that the mass throughput of the extruder is also maintained within desired limits, while controlling the melt pressure. Therefore, another model is required to estimate the mass throughput in real-time during the simulation. A multilayer perceptron neural network was trained to predict the mass throughput using the screw speed and four barrel set temperatures of the extruder as inputs. To train the mass throughput model, the same train and test split used to train the pressure model was used. The hyperparameters of the throughput model were fine-tuned using k-fold cross-validation with a value of k = 10 on the training set. The neural network with the best performance was found to have two hidden layers with 40 neurons per hidden layer. It was trained for 500 iterations with a batch size of 16 at a learning rate of 0.001. The cross-validation results yielded an average training RMSE of 0.889 and an average validation RMSE of 0.903 for this hidden layer configuration. The model exhibited consistent performance across all 10 folds of the training data. Finally, the model with the fine-tuned hyperparameters was trained on the entire training set and tested on the unseen test data. It resulted RMSE values of 0.948 and 1.002 on training and test sets, respectively, indicating good generalization performance on unseen data without overfitting.

C. ANFIS Controller Design

The aim of developing an ANFIS controller is to minimize the melt pressure variations while maintaining a desired melt pressure level at a given screw speed of the extruder. The controller can achieve this by appropriately adjusting the process settings of the extruder (i.e., screw speed and barrel set temperatures). However, due to the multi-input single-output (MISO) nature of ANFIS controllers, only the screw speed was selected as a manipulated variable. Since the influence of barrel set temperatures is negligible compared to the influence of screw speed on both melt pressure and mass throughput, this would not have a negative effect on the performance of the controller. This is further confirmed by the correlation coefficients presented in Table II. Hence, the controller was designed to have one manipulated variable (i.e., screw speed) and two controlled variables (i.e., melt pressure and mass throughput).

TABLE II
CORRELATION COEFFICIENTS OF EXTRUDER PROCESS SETTINGS WITH CONTROLLED VARIABLES

Controlled variable	Barrel set temperatures				Screw speed
	T_1	T_2	T_3	T_4	
Melt pressure	-0.087	-0.025	-0.132	-0.137	0.854
Mass throughput	0.052	0.110	-0.010	-0.048	0.984

Two error signals were generated as shown by Eqs. (1) and (2), and fed to the controller as inputs.

$$E_P = P_{desired} - P_{actual} \tag{1}$$
$$E_M = M_{desired} - M_{actual} \tag{2}$$

Here, E_P and E_M denote the melt pressure error and the mass throughput error respectively. $P_{desired}$ and P_{actual} denote the desired and actual melt pressure values, while $M_{desired}$ and M_{actual} indicate the desired and actual mass throughput values, respectively.

The neuro-fuzzy system was trained using the collected dataset, with the Neuro-Fuzzy Designer toolbox in Matlab. A

Sugeno FIS structure was designed with seven membership functions for each controller input. Triangular-shaped membership functions were chosen for the controller inputs, considering their wide popularity in practical applications [13]. Linear membership functions were chosen for the controller output. Fig. 3 illustrates the designed neuro-fuzzy model used to tune the parameters of the Sugeno FIS. The model converged after 10 iterations and reported an RMSE of 0.010003. The model had learned 49 fuzzy rules and the AND operator was used to combine the two conditions in each rule. The input membership functions learned by the neuro-fuzzy system are illustrated in Figs. 4(a) and 4(b). p_mf1 to p_mf7 represent the input membership functions of the melt pressure error, while m_mf1 to m_mf7 indicate the input membership functions of the mass throughput error. Fig. 4(c) illustrates the output surface.

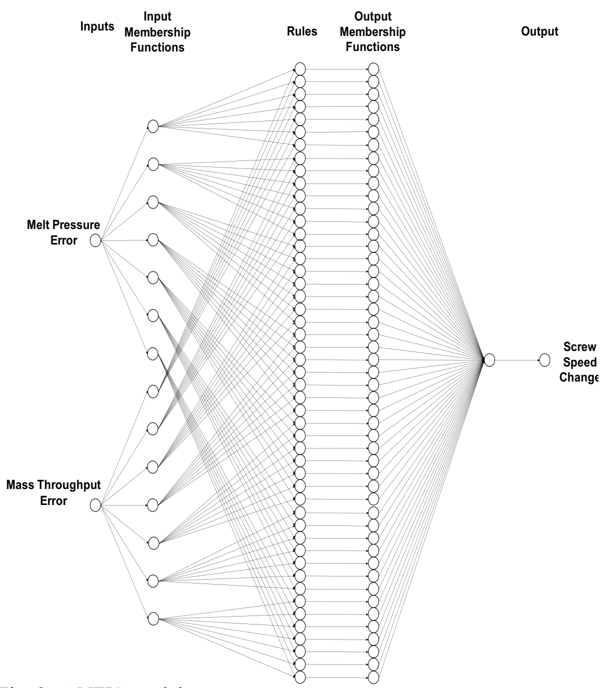


Fig. 3. ANFIS model structure

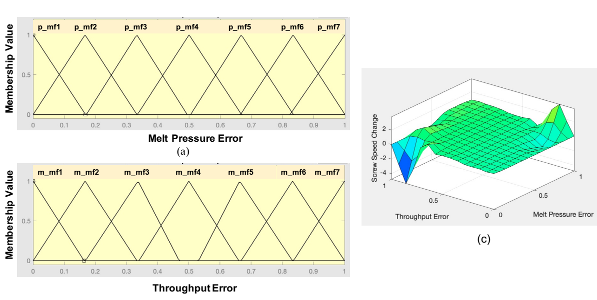


Fig. 4. (a) and (b) Input membership functions, (c) Output surface for the ANFIS

Next, a feedback control system was designed using the tuned ANFIS controller. The controller takes two inputs (i.e., melt pressure error and mass throughput error) and produces a control output (i.e., screw speed change). To assess the performance of the controller, it was implemented on Matlab (R2021b) Simulink. Fig. 5 illustrates the structure of the proposed control system that was evaluated through simulation. The extruder process settings (i.e., barrel set temperatures and screw speed) measured from the extrusion process in real-time are fed to the two prediction models, which in turn provide an estimate of the melt pressure and mass throughput. These predictions are then subtracted from the desired values to calculate the melt pressure error and the mass throughput error. The ANFIS controller then determines the appropriate screw speed change necessary to bring down the errors to zero.

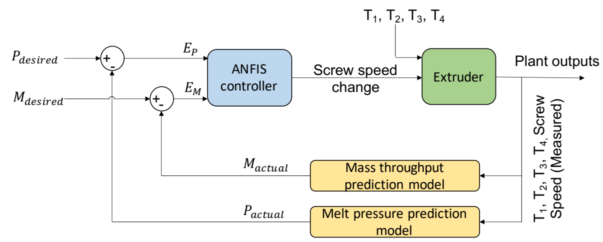


Fig. 5. Proposed feedback control system

III. Results and Discussion

To evaluate the performance of the developed ANFIS controller, its ability to track a desired melt pressure level across a range of different operating conditions was assessed. The melt pressure level and the mass throughput rate with and without the ANFIS controller at different barrel set temperature conditions and screw speeds were recorded and compared. Figs. 6, 7, and 8 illustrate the comparison of the melt pressure level and mass throughput with and without the ANFIS controller, along with the screw speed changes applied by the controller at high, medium, and low barrel set temperature conditions, respectively. Due to the limited space available, only the comparisons of screw speeds of 10, 50, and 90 rpm are presented.

For the purpose of this study, the desired melt pressure level and mass throughput were determined considering the average values at each screw speed. However, it should be noted that these desired values may be changed within an achievable range under each screw speed setting. The melt pressure measurements at each screw speed setting are shown over the period during which the screw speed was held constant at the specified speed without any step changes. As can be observed from Figs. 6-8, the ANFIS controller was able to achieve the desired melt pressure level while minimizing pressure fluctuations, regardless of the barrel set temperature and screw speed conditions.

At the 10 rpm screw rotational speed, regardless of the set temperature condition, both melt pressure and mass throughput were found to be more consistent and closer to the desired values with the ANFIS controller implemented. However, under the medium set temperature condition, the

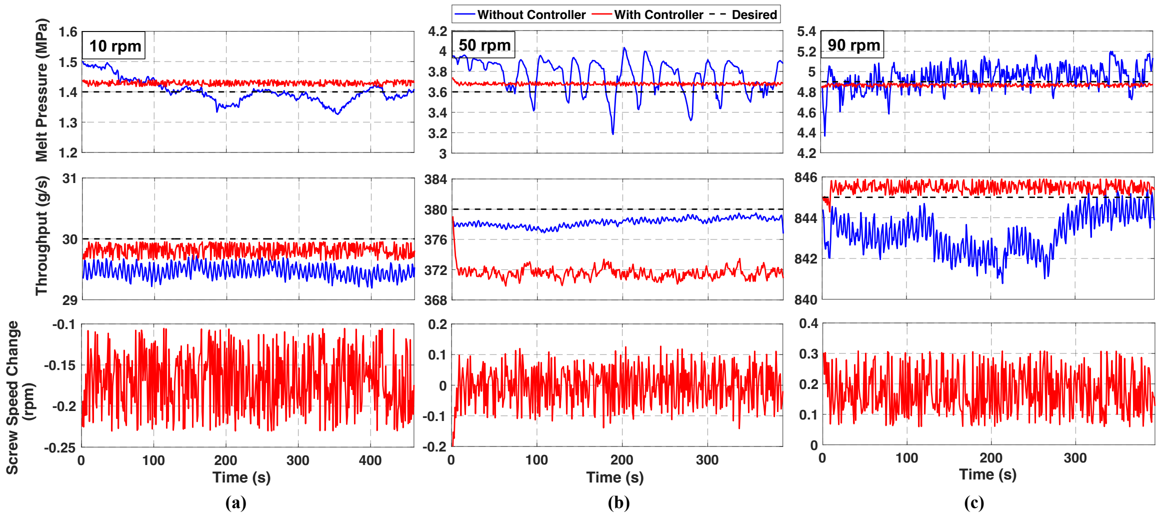


Fig. 6. Performance evaluation of the ANFIS controller at different screw speeds under the high temperature condition (a) 10 rpm (b) 50 rpm (c) 90 rpm

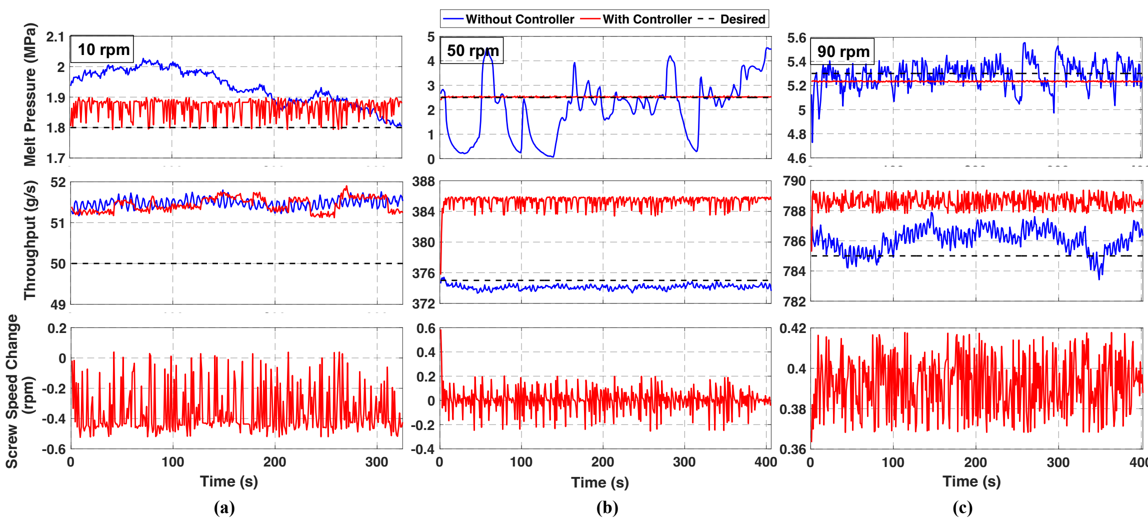


Fig. 7. Performance evaluation of the ANFIS controller at different screw speeds under the medium temperature condition (a) 10 rpm (b) 50 rpm (c) 90 rpm

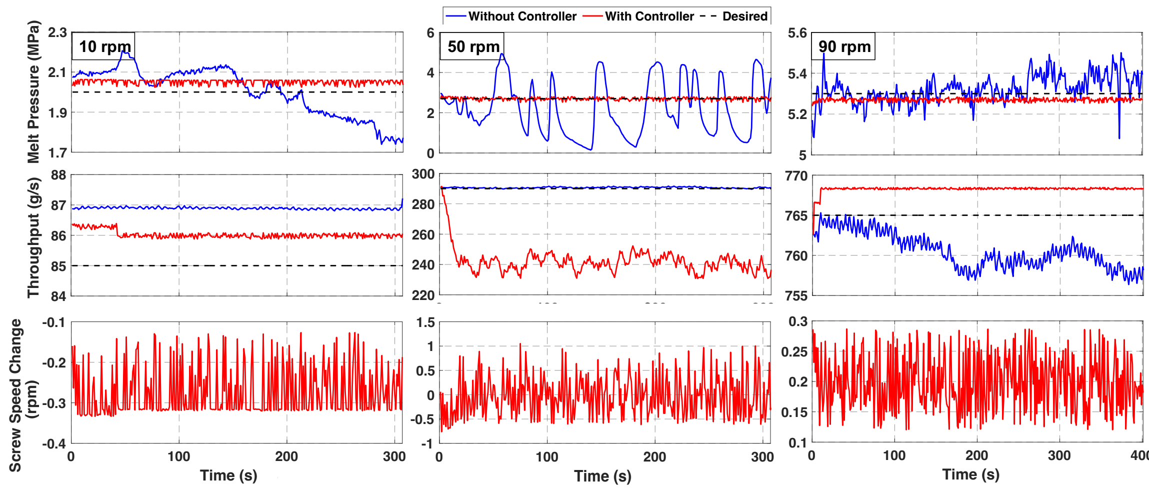
controller resulted in slight melt pressure fluctuations with a magnitude of around 0.1 MPa, although it achieved the desired pressure level.

The controller exhibited the most significant improvement in performance in terms of regulating the desired melt pressure, at the 50 rpm screw speed setting across all set temperature conditions. Without the controller, very high melt pressure fluctuations were observed at the medium and low set temperature conditions. As shown in Figs. 7(b) and 8(b), these fluctuations have magnitudes as high as about 5 MPa. The controller was able to bring down these fluctuations quite significantly, however, this was achieved at the expense of maintaining the desired level of mass throughput. At the medium and low set temperature conditions, the mass throughput showed reductions of about 10 and 50 g/s, respectively. Although this reduction is significant and would affect the production rate of the extruder, this compromise can be justified considering the improvement in melt stability provided by the controller.

Figs. 6(c), 7(c), and 8(c) show that, at the 90 rpm speed setting, the melt pressure fluctuations are smaller than those at the 50 rpm speed but larger than those at the 10 rpm speed without the controller. The implementation of the ANFIS controller has enabled achieving the desired melt pressure level and maintaining that with only very small fluctuations. The controller was successful at getting very close to the desired mass throughput level as well.

IV. Conclusion

This study proposed a control approach based on fuzzy logic and neuro-adaptive learning, to regulate the melt pressure in a single-screw extrusion process. Only the preliminary performance evaluation tests are presented in this paper, as the research is still in its early stages. The ANFIS-based control approach was chosen considering its benefits such as the ability to control nonlinear processes, the ability to design the controller without a mathematical model of the



(a) (b) (c)

Fig. 8. Performance evaluation of the ANFIS controller at different screw speeds under the low temperature condition (a) 10 rpm (b) 50 rpm (c) 90 rpm

system, and the ease with which the FIS parameters and rule base can be determined. At this stage, the proposed controller has only been tested via simulation using Matlab Simulink. The controller exhibited excellent performance in terms of achieving and maintaining the desired melt pressure level while minimizing melt pressure fluctuations, across multiple operating conditions.

Although the controller has exhibited good performance when tested through simulation, it is not yet ready to be incorporated into an actual extrusion process. Further performance evaluations such as the disturbance rejection ability of the controller should be carried out before implementing the controller in an actual extruder. Moreover, the ANFIS controller was trained only on a dataset collected from processing an HDPE material using a barrier-flighted screw. The controller's performance may be affected if the polymeric material or the screw design is changed. Conventional gradual compression and rapid compression screws generally exhibit higher melt thermal instability, and hence it might be more challenging for the controller to regulate the process under such conditions. Hence, the authors will investigate addressing these issues in future work.

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