Pattern-Based Closed-Loop Quality Control for the Injection Molding Process

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The basis for a novel pattern-based closed-loop control strategy for the injection molding process is presented. The strategy utilizes artificial neural networks (ANNs) embedded within a cascade design to analyze sensor patterns, identify process character and control part quality. The platform for this work, the injection molding process, is an industrially significant, cyclic manufacturing operation. Final part quality of this process is a nonlinear function of many machine and polymer variables. Part quality control of this process is currently attained via single input–single output machine controls supervised by human operators. Presented here is a method that employs ANN technology to improve upon this approach and provide the basis for closed-loop part quality control. In the cascade design, machine controller set-points of an inner loop are updated based on ANN analysis of mold cavity pressure patterns. The controller action maintains the desired pressure pattern set-point of the outer loop associated with desired part quality. Control strategy details are provided along with set-point tracking demonstrations that support feasibility of this pattern-based approach.

INTRODUCTION

The Injection Molding Process

The injection molding process is a nonlinear, multivariable process that forms plastic material into useful parts or components commonly found in a multitude of consumer goods. As the name suggests, molten plastic material is injected into a mold cavity at high speed. Rapid cooling then solidifies the plastic, causing the material to hold the desired shape. Then the cycle begins again. A typical injection molding machine is shown in Fig. 1.

To begin the process, rotation of the reciprocating screw within the barrel charges the injection molding machine. The action of the screw pushes molten plastic already in the barrel toward the tip of the screw and draws more thermoplastic feed material into the barrel from the hopper. Plastic within the barrel melts as a result of electric heating and viscous dissipation. Application of a back pressure prevents the material from discharging through the nozzle until the appointed time.

When the injection start signal is received, pressure in the hydraulic system rises rapidly. This dramatic rise in pressure forces the screw, now referred to as the ram, to move quickly along the axis of the barrel, injecting the molten plastic into a chilled mold. As the plastic begins to cool, the newly molded form shrinks. A holding pressure on the screw is maintained to force more plastic into the mold and "pack out" the part. After the plastic at the entrance to the mold solidifies, the holding pressure is removed and the part remains in the mold to cool. When the part is sufficiently cool, the mold opens and ejects the solid plastic form. Cycle times for this process range from less than one minute for most parts to a few minutes for very large parts.

Producing injection molded parts is often just the first step in producing the consumer goods we see on the market. Assembly of these parts into larger entities is usually necessary and the current trend is towards robotic assembly. Robots, however, cannot identify poor quality parts and remove them on-line as easily as their human counterparts can. Flawed parts can cause costly assembly line shutdowns. To compensate for the lost detection capability, manufacturers are demanding higher quality, tighter tolerance parts from injection molders. Injection molders, in turn, are working to improve their process capabilities to meet these newer demands.

Much of their efforts have focused on tooling: using sophisticated process models to design the mold right the first time and using advanced materials to reduce wear. However, it is difficult, if not impossible, to achieve the desired quality levels solely through tool-
ing improvements alone. Advanced part quality monitoring and control techniques are also needed.

Owing to the complexity of injection molding, process control has historically been approached from a component perspective. Controllers on an injection molding machine are usually dedicated to particular components like heater bands or servo-valves and are operated independently of each other, except for occasional timing considerations. This approach to process control does not guarantee part quality control, even with closed-loop feedback controllers, because part quality is not simply dependent on machine performance.

Lacking a reliable process measure of part quality on which to base closed-loop part quality control, the injection molding industry has resorted to applying open-loop statistical tools to assess processing performance. These tools are applied over and above the existing hardware controllers. The most commonly practiced open loop technique is statistical quality control (SQC). In this technique, quality control personnel routinely sample parts and report back to the operator regarding recent machine performance. Quality control is then achieved through manual set-point adjustments. SQC, although effective, is labor-intensive and characterized by long dead times.

Many molders also practice statistical process control (SPC). As implemented on the plant floor, SPC involves monitoring process parameters from a central control room. If a measured value on a given machine exceeds a statistically pre-defined limit, plant personnel are alerted of a potential problem. With every injection, sampling occurs and response times are shorter than with SQC. The advantage of using SPC along with simple machine feedback control is that polymer data as well as machine data can be evaluated. Unfortunately, this technique relies only on discrete data and still does not account for the effects of process interactions.

For further improvements to be made in part quality control, the problem must be approached from a perspective that addresses the cyclic, nonlinear, multivariable nature of the process. This work presents a novel pattern-based part quality control strategy for injection molding based on such a perspective. Complete cavity pressure sensor data patterns are analyzed in this method using trained artificial neural networks (ANNs). Cavity pressure data patterns are complex functions of machine, polymer and environmental variables known to be related to part quality (1–4). ANNs are proven tools for modeling nonlinear relationships. The ANNs are applied as pattern analysis tools to predict part quality and identify process character. By embedding the ANNs in a cascade control strategy, closed-loop part quality control can be achieved.

**Pattern Recognition for Part Quality Monitoring**

In the 1980s, researchers in injection molding process control began developing closed-loop univariate control strategies based on polymer variables, rather than machine variables. Much of the work focused on polymer pressure control (5–7) because pressure fluctuations during the injection and hold stages are considered to be the predominant cause of poor-quality parts (8). Control strategies based on injection speed (9, 10) and melt temperature (11, 12) were also investigated.

In a review of injection molding process control strategies published in 1987, Agrawal et al. (13) con-
cluded that it was necessary to develop multivariate control strategies and recommended that efforts continue to focus on polymer variables. In the same year, Ricketson and Wang (14) and Wang and Shah (15) implemented a model-based strategy to control injection molded part quality. In both works, multivariate regression models were constructed to relate discrete measurements of polymer variables to part thickness. A few years later, Haussler and Wortberg (16) constructed and trained an ANN to predict part weight and length from a pattern of discrete process measurements. Although they were able to improve part quality monitoring capabilities with the nonlinear model, they did not report implementation of a closed-loop strategy to control part weight or length.

In attempting to expand the number of variables analyzed to determine control actions, some researchers were interested in accounting for the time element of the process. These researchers concentrated on analyzing complete data patterns of a single variable over the course of the injection molding cycle rather than discrete measurements of several variables. Freeh and Meyer (17) laid the groundwork for pattern analysis when they explored the use of the complete mold cavity pressure profile as a means for determining optimum molding conditions. Some time later, Wu et al. (18) analyzed cavity pressure traces in relation to machine parameters and part quality. The cavity pressure traces were reduced to a smaller, discrete patterns of data representing significant features of the traces. A feature based expert system was then developed using this information.

In previous work, the pattern recognition capabilities of ANNs was to analyze cavity pressure data patterns as complete pictures or snapshots to predict part quality applied (19). That work established that ANNs trained on entire data patterns can provide improved part quality monitoring capabilities over currently popular SPC techniques.

**PATTERN-BASED PART QUALITY CONTROL**

Presented here is a methodology to extend the use of pattern recognition to closed-loop part quality control. This method incorporates ANNs specifically trained for control purposes into a cascade strategy. Cascade control is a well-posed problem that has been studied and explored for many years (20). A block diagram of the closed-loop pattern-based control strategy developed is shown in Fig. 2.

On-line, the ANNs analyze measured cavity pressure patterns to assess pattern error. Part quality control is then achieved by adjusting machine set points, in this case barrel temperature and holding pressure set points, associated with inner control loops to maintain the desired cavity pressure pattern of the outer loop.

Upon implementation, ANN analysis is applied within the pattern controller on both the reference and incoming patterns to determine the machine set point errors. Each ANN analysis associates a measured cavity pressure pattern with machine set-points from a pattern map. The ANN determined machine set-points are an estimate of the true machine set-points based on measured polymer information, not machine information, and are referred to as “apparent” machine set-points to denote this unusual perspective. Comparison of apparent machine set-point values then results in a vector of machine set-point errors that can be acted upon by the controller.

**Artificial Neural Networks**

The first step toward achieving closed loop pattern-based control as described involves the construction

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**Fig. 2. Block diagram of the pattern-based cascade control strategy.**
of an ANN-based pattern analyzer. ANNs are powerful pattern recognition tools that can serve as pattern analyzers (21–24). These mathematical models comprise individual processing units, often called neurons, that simulate neural activity. Each processing unit sums weighted inputs and then applies a linear or nonlinear function to the resulting sum to determine the output. The neurons are arranged in layers and are combined through extensive connectivity. One ANN that has received much attention is the back propagation network (BPN) (23).

BPNs have hierarchical feed forward network architectures. In the classical structure of a BPN shown in Fig. 3, the output of each neuron of a layer is sent directly to each neuron in the layer above. While there can be many layers, all pattern recognition and classification tasks can be accomplished with three layers: one layer that receives and distributes the input pattern, one middle or hidden layer that captures the nonlinearities of the input/output relationship, and one layer that produces the output pattern. BPNs also typically contain a bias neuron in the input and hidden layers that produces a constant output of 1.0 and is fully connected to the layer above but receives no input. A 36-5-2 BPN describes a network with 36 input neurons, 5 hidden neurons, and 2 output neurons, exclusive of bias neurons.

BPNs are trained by repeatedly presenting a series of input/output pattern sets to a network. The network gradually "learns" the input-output relationship of interest by adjusting the weights to minimize the error between the actual and predicted output patterns of the training set. To prevent the network from memorizing the training set, a separate data set, called the test set, is used to monitor network performance. When the sum squared error of the test set reaches a minimum, network training is considered complete and the weights are fixed. In this work, the hyperbolic tangent function with limits $[-1, 1]$ is applied along with conjugate gradient optimization technique. For more information regarding the construction of BPNs used in this work, see Cooper et al. (25).

Here, a BPN was trained to serve as the pattern analyzer using a map of patterns representative of the processing window. The patterns within the map, consisting of cavity pressure patterns and their associated machine set-points for barrel temperature and holding pressure, were generated using an injection

![Diagram of a back propagation network](image)

Fig. 3. Architecture of a back propagation network.
molding process model derived from first principles and proven correlations. Use of a process model minimizes the amount of laboratory work required to establish a training database and allows similar databases for different materials, molds or machines to be generated quickly and easily if needed.

The primary drawback of using the process model in a real process control application is its complexity. The model comprises a stiff system of algebraic, integral, and differential equations. This system of equations takes as long as thirty minutes using a Pentium-based personal computer to compute a single pressure pattern. Typical injection molding applications operate on a cycle time of less than one or two minutes. Thus, after validation, the model is used to train an ANN that mimics the model's computational capability. The ANN can then compute model results in seconds, making the model results useful in real-time applications.

**THE INJECTION MOLDING PROCESS MODEL**

The injection molding process model developed for this work builds upon the one-dimensional frameworks of Shankar and Paul (26) and Chiu et al. (27). The process model simulates the dynamic machine and polymer behavior during the filling, packing and cooling stages involved in the molding of a rectangular ASTM flame bar (19). Specifically, cavity pressure sensor patterns are computed as a function of machine controllable variables, mold geometry and polymer properties. Figure 4 is a basic diagram that shows the molded form of the ASTM flame bar and its runner system.

The fundamental equations that comprise the foundation of the lumped parameter model include the equations of continuity, momentum, energy and Newton's Second Law. The correlations include a Tait equation of state, a Cross viscosity model and first order dynamics to describe the ram velocity and holder pressure behavior. The process model is designed to be simple enough to use in real-time monitoring and control applications and yet detailed enough to reliably predict process trends.

**Filling**

Polymer flows as a result of physical displacement by the ram as well as because of the development of a pressure gradient. The continuity equation for a compressible fluid

\[
\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial z} (\rho v_z) = 0
\]  

(1)

is used along with the definition of bulk modulus, \(K_p\)

\[
K_p = \rho \frac{dP_{net}}{d\rho}
\]

(2)

and a Tait equation of state (28–30) to find the relationship between polymer pressure, \(P_{net}\), ram position, \(x\), and polymer flow, \(Q_1\),

\[
\frac{dP_{net}}{dt} = \frac{K_p}{V_{brl}} \left( A_{brl} \frac{dx}{dt} - Q_1 \right)
\]

(3)

\(V_{brl}\) is the volume of polymer remaining in the barrel.

The equations of motion are solved to calculate the flow of polymer from the nozzle into the mold cavity. Assuming incompressible, laminar flow in a cylindrical conduit, the relevant momentum equation is

\[
\frac{\partial P}{\partial t} + \frac{1}{r} \frac{\partial (r \tau_{rz})}{\partial r} = -\frac{\rho}{\partial t} \frac{\partial v_z}{\partial r}
\]

(4)

where \(P\) is the polymer pressure, \(r\) is the conduit radius, \(\tau_{rz}\) is the shear stress acting in the radial direction perpendicular to the axial direction (z), \(\rho\) is the polymer density, and \(v_z\) is the velocity of flow in the axial direction.

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*Fig. 4. Diagram of solid plastic form as ejected from mold.*
Given that the fluid is incompressible, the volumetric flow rate through any polymer-filled cross-sectional area of conduit is equivalent to the polymer flow during filling, \( Q_i \), is found from Equation 7 as (27)

\[
\frac{dQ_i}{dt} = \frac{P_{\text{noz}} - P_{\text{flow front}} - \sum_{i=1}^{5} (F_{s,i}/A_{c,i})}{\rho_{\text{avg}} \sum_{i=1}^{5} (H_{L,i}/A_{c,i})}
\]

(5)

where \( i = 1, \ldots, 5 \) denotes the conduit sections of the nozzle orifice, sprue, runner system, gate, and mold cavity. The pressure at the flow front, \( P_{\text{flow front}} \), is atmospheric and the resistive shear force, \( F_{s,i} \), is the shear stress, \( \tau_{z,i} \), multiplied by the surface area, \( A_{s,i} \).

\[
F_{s,i} = A_{s,i} \tau_{z,i}
\]

(6)

The shear stress for a non-Newtonian fluid is the polymer viscosity, \( \eta_i \), evaluated from the Cross equation (31) multiplied by the shear rate, \( \dot{\gamma}_i \).

\[
\tau_{z,i} = \eta_i \frac{\partial \dot{\gamma}_i}{\partial r} = \eta_i \dot{\gamma}_i
\]

(7)

The position of the flow front and the fractional hydraulic length of the leading section are found at any time given the total volume of polymer present in the conduit and the geometries of the individual sections. When the polymer flow front is at or beyond the point where the cavity pressure transducer is located, the cavity pressure, \( P_c \), is calculated from the Hagen-Poiseille equation for the flow of a non-Newtonian fluid between flat plates as

\[
P_c = \frac{12 \eta_0 Q_i H_{L,c}}{w h^3}
\]

(8)

where \( H_{L,c} \) is the distance between the cavity pressure transducer and the flow front, \( w \) is the cavity width and \( h \) is the cavity height.

**Packing**

When polymer completely fills the conduit, the polymer must be considered a compressible fluid in both the continuity and momentum equations. As a result, the volumetric flow rate, \( Q_i \), must be determined individually for each conduit section.

\[
\frac{dQ_i}{dt} = \frac{P_{t-1} - P_t - (1/2) \sum_{i=1}^{t} (F_{s,i}/A_{c,i})}{(\rho_{t-1}/2) \sum_{i=1}^{t} (H_{L,i}/A_{c,i})}
\]

(9)

For the case \( i = 1 \), \( P_0 \) is the nozzle pressure and \( \rho_0 \) is the density of the polymer in the nozzle.

**Cooling**

During filling, the heat generated by viscous dissipation is assumed to be offset by the heat lost as a result of conduction (32) and, therefore, a constant melt temperature is assumed. Once filled, however, cooling of the polymer melt is significant and the temperature of the polymer in the conduit is determined by solving the equation of energy for unsteady state heat conduction in one direction. Neglecting shear heating, the cooling rate for each section of conduit is

\[
\frac{dT_i}{dt} = \frac{U_{0,i} A_{s,i} (T_i - T_{\text{mold}})}{\rho_i v_i C_{p,i}}
\]

(10)

\( U_{0,i} \) is the overall heat transfer coefficient and \( C_{p,i} \) is the heat capacity evaluated as a function of temperature (30) to account for the effects of crystallization.

As the melt solidifies, polymer flow is restricted and the hydraulic diameter, the cross-sectional area and the surface area of each section are reduced accordingly. The total pressure observed in a given section of conduit, assuming a negligible solid partial pressure contribution, is set equal to the partial pressure of the liquid phase as calculated by the Tait equation.

\[
P_t = P_{\text{t, t}}(1 - \phi_{s,t})
\]

(11)

When polymer in the gate is completely frozen, polymer flow into the mold ceases and a constant polymer density is assumed for the mold cavity. Cooling continues until the mold is opened.

**Model Summary**

The dynamic equations in this model compute mold cavity pressure patterns given a set of machine parameters from the start of injection until cooling is complete. The process model begins under velocity control and then switches over to pressure control based on ram position. Similarly, the model begins by using the continuity and momentum equations for filling the mold and the switches over to the continuity, momentum and energy equations for packing and cooling the mold when the mold fills. Ancillary equations are used to describe mold geometry, polymer viscosity and polymer state changes. Numerical solution of this stiff system is found using a variable step size, semi-explicit Bulirsch-Stoer method (33).

**Process Model Validation**

Two step-test experiments were conducted to validate the injection molding process model constructed. In each of these step-test experiments, the set-point of interest was stepped up, then stepped back down to baseline conditions, then stepped down further and then finally stepped back up to baseline conditions. At the onset of each experiment, the machine was operated at baseline conditions for at least one hour before data was collected to allow for machine equilibration. The barrel temperature set-point values of interest were 246, 241 and 235°C (475, 465 and 455°F) and holding pressure set-point values of interest were...
the significant features of a typical cavity pressure pattern. The model output plotted in Fig. 5 demonstrates that the model reasonably predicts the peak pressure as well as the lag time associated with the progression of the flow front to the transducer.

Validation of the model's ability to correctly predict process trends is provided in Figs. 6 and 7. Figure 6 specifically addresses the model correlation with respect to barrel temperature set-points. The experimental data clearly show that steep injection peaks are found at higher temperature set-points and that injection peaks disappear at lower temperature set-points. The simulation successfully predicts the process trend observed in the data.

Similarly, Fig. 7 addresses the model correlation with respect to holding pressure set-points. As expected, higher cavity pressures were observed during packing for higher holding pressure set-points. Although the magnitude of packing pressure plateau lacks accuracy, the simulation correctly predicts the process trend of interest.

**THE PATTERN ANALYZER**

Having developed and validated a process model, the next step was to train an ANN to serve as the pattern analyzer. Pattern data required to train the ANN was generated by systematically varying the machine set-points in the process model. The holding pressure set-point was varied in steps of 0.41 MPa (60
psig) from 1.89 to 5.20 MPa (260 to 740 psig) and the barrel temperature set-point was varied in steps of 2.2°C (4°F) from 232 to approximately 249°C (449 to 481°F). The 81 resulting cavity pressure patterns and their corresponding machine set-points constitute a pattern map of the processing window. A visual summary of this pattern map is shown in Fig. 8. The center of the map corresponds to the baseline operating condition.

A 36-3-2 BPN was selected for training. Cavity pressure patterns generated by the process model were transformed by cubic spline interpolation into patterns with the desired data point spacing. (Refer to Experimental Details below.) The pattern data was then multiplied by a factor of 0.01 to scale the pressure signal values to between zero and one for input into the BPN. The associated holding pressure and barrel temperature set-points for each cavity pressure pattern were linearly scaled between -0.5 and 0.5 to fit within the sigmoidal [−1, 1] output of the BPN. Hence, the baseline machine set-points were defined by a [0, 0] output pattern.

Forty-one input-output data pattern sets, including the baseline pattern set at the center of the map, were methodically assigned to the training set. The remaining 40 were assigned to the test set. Training began and network convergence was attained after only 34 iterations. Another advantage of using a process model data is that, since there is no noise in the data, the time required to train a network is much less than if real data is used.

**PATTERN SET-POINT TRACKING DEMONSTRATION**

Controllers are designed and tuned to track set point changes and reject disturbances. In order to establish the viability of a control strategy, it is necessary to demonstrate strategy capabilities related to these tasks. In this work, a pattern step-test experiment was conducted to demonstrate the set-point tracking capability of the pattern-based control strategy developed.

In this experiment, the desired cavity pressure pattern set-point was stepped from the baseline pattern to one corresponding to a higher temperature but a lower packing pressure by making the necessary machine set-point adjustments. The pattern set point step change is shown conceptually in Fig. 9. Cavity pressure patterns were collected at each of the steady states and compared to assess the pattern set point tracking capability.

**Materials and Equipment**

Pellet-shaped, unreinforced polybutylene terephthalate (PBT) was molded into ASTM flame bars using a 90 ton Toyo Plastar injection molding machine. The
The machine was programmed to inject plastic melt into the mold under velocity control and then to “pack out” the mold under pressure control. Switchover from velocity to pressure control occurred when the ram position reached the designated stroke value. The machine-mold assembly was instrumented to collect high speed cavity pressure and ram position data during the course of the experiments.

The PBT selected for these experiments, GE Valox® 325, is a semicrystalline material with a melt temperature of 235°C (455°F) and a specific gravity of 1.31. Valox is characterized by comparatively high chemical and thermal resistance properties and is used extensively in the plastics industry for automotive electrical applications. This material was selected for its industrial significance as well as its semicrystalline behavior.

The MoldMaster mold was configured to produce an ASTM flame bar (D 635) approximately 127 mm long, 12.7 mm wide, and 3.8 mm thick. A Dynisco PT44DH 250 kg (550 lb) cavity pressure transducer was inserted behind a 6.35 mm (1/4 in) diameter ejector pin, as shown in Fig. 5. The mold was then installed in a Toyo Ti90G injection molding machine and connected to a ConAir TC1-DI thermolator to maintain the mold coolant water temperature at 49°C (120°F).

In addition, the machine was instrumented with a Kyowa PAV-200KEM33 hydraulic pressure transducer, a Dynisco PT465XL 210 MPa (30,000 psig) nozzle pressure transducer and a Lucas Shaevitz magnetorestrictive linear displacement transducer. Data was collected and displayed on a Gateway 486 personal computer using a Strawberry Tree high-speed data-acquisition system.

**Experimental Details**

Initial processing conditions were determined from the material manufacturer’s literature and refined online. The baseline processing condition was defined as a holding pressure of 3.55 MPa (500 psig) and a barrel temperature of 241°C (465°F). Note that a barrel temperature set-point of 241°C (465°F) refers to a descending series of barrel heater band set points, 241-238-235-232°C (465-460-455-450°F), where the temperature set-point of the nozzle heater band is 241°C. Prior to beginning the experiments, the Valox material was dried in a Conair D30H4 desiccant dryer at 121°C (250°F) for at least 4 hours. The approximate cycle time was 1 minute.

Sensor data was collected at a rate of 25 Hz over a period of 13 seconds beginning from the start of injection for a given shot. Cavity pressure data patterns were adjusted vertically to account for sensor calibration drift and horizontally according to ram position to eliminate lag variability introduced from the hydraulic.
prior to being analyzed by the BPN. The δ vector is found by subtracting an average, real baseline cavity pressure pattern from the model-generated, baseline cavity pressure pattern. The use of δ compensates for plant-model mismatch at the baseline condition and was applied throughout as a constant bias term. Following the “zeroing” procedure, the cavity pressure patterns were analyzed to determine apparent machine set-points.

Results

A single step change in the desired pattern set-point was made and the system response was analyzed. Again, this pattern set-point change is illustrated within the context of the pattern map in Fig. 9. Both set-point patterns are overlaid in Fig. 10 to emphasize the pattern changes that would be observed by an operator. Recall that since desired cavity pressure patterns are associated with desired part quality, the change in desired pattern also corresponds to a change in desired part quality. For this experiment the pattern set-point change resulted in a 0.03% decrease in part length from 124.70 mm to 124.66 mm.

The ability of the pattern-based approach to track pattern set-point changes is evident by comparing steady state cavity pressure pattern data with the desired pattern set-points. Figure 11 shows that the original data pattern very closely matches the original pattern set-point. The success of the method is demonstrated in Fig. 12, which shows that the new, steady state data pattern closely approximates the new pattern set-point. As a result, the part length decreased by the desired 0.04 mm from 124.70 mm to 124.66 mm.

CONCLUSIONS

Tight tolerance part quality control is difficult to achieve in injection molding, even with operator supervision. Presented here was the basis for a closed-loop pattern-based strategy to meet the challenge of injection molding process control. The strategy uses ANNs imbedded within a cascade design to analyze
sensor patterns, identify process character, and control part quality. Adjustments to machine controllable parameters are made following BPN pattern analysis and are based on pattern set-point error. The pattern set-point tracking demonstration provides evidence that this strategy offers potential both from a technical and end-user perspective.

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NOMENCLATURE

\[ A_{inj} = \text{Cross-sectional area of ram in the injection cylinder.} \]
\[ A_{c,i} = \text{Cross-sectional area of i}^{th}\text{section of conduit.} \]
\[ A_{s,i} = \text{Surface area of i}^{th}\text{section of conduit.} \]
\[ C_{p,i} = \text{Heat capacity of polymer of i}^{th}\text{section of conduit.} \]
\[ F_{s,i} = \text{Shear force in the i}^{th}\text{section of the conduit.} \]
\[ h = \text{Mold cavity height.} \]
\[ H_{Lc} = \text{Hydraulic length of the polymer front from the position of the transducer.} \]
\[ H_{Li} = \text{Hydraulic length of the i}^{th}\text{section of the conduit covered by polymer.} \]
\[ K_p = \text{Bulk modulus of the polymer.} \]
\[ P = \text{Pressure of fluid in a conduit.} \]
\[ P_{flow} = \text{Polymer pressure at the front.} \]
\[ P_i = \text{Polymer pressure in the i}^{th}\text{section of conduit.} \]
\[ P_{Tatt} = \text{Liquid polymer pressure in the i}^{th}\text{section of conduit calculated by the Tait equation.} \]
\[ P_{not} = \text{Polymer pressure in the nozzle.} \]
\[ P_i = \text{Polymer pressure in the mold cavity.} \]
\[ \dot{Q}_i = \text{Volumetric flow rate of polymer from the nozzle.} \]
\[ Q, i = \text{Volumetric flow rate of polymer into i}^{th}\text{section of conduit.} \]
\[ r = \text{Radius of conduit.} \]
\[ T_i = \text{Temperature of polymer in i}^{th}\text{section of conduit.} \]
\[ T_{mold} = \text{Temperature of mold.} \]
\[ t = \text{Time during integration.} \]
\[ U_{h,i} = \text{Overall heat transfer coefficient for the i}^{th}\text{section of conduit.} \]
\[ V_{bar} = \text{Volume of polymer in the barrel.} \]
\[ V_i = \text{Volume of i}^{th}\text{section of conduit.} \]
\[ v_s = \text{Screw velocity in axial direction.} \]
\[ v_{ax} = \text{Screw velocity in axial direction for i}^{th}\text{section.} \]
\[ w = \text{Mold cavity width.} \]
\[ x = \text{Screw position (x = 0 when the injection cylinder is charged).} \]
\[ z = \text{Axial direction of polymer flow.} \]

Greek Symbols

\[ \gamma_i = \text{Shear rate in i}^{th}\text{section of conduit.} \]
\[ \eta_i = \text{Viscosity of polymer.} \]
\[ \eta_b = \text{Viscosity of polymer in mold cavity.} \]
\[ \phi_{s,i} = \text{Volume fraction of solid polymer in i}^{th}\text{section of conduit.} \]
\[ \rho = \text{Density of polymer.} \]
\[ \rho_i = \text{Density of polymer in i}^{th}\text{section of conduit.} \]
\[ \rho_{avg} = \text{Average density of polymer in conduit during filling.} \]
\[ \tau_s = \text{Shear stress of fluid in the conduit.} \]
\[ \tau_{ax,i} = \text{Shear stress of fluid in i}^{th}\text{section of the conduit.} \]

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